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Geometric Algorithms for Intervals and Related Problems

Shimin Li
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GEOMETRIC ALGORITHMS FOR INTERVALS AND RELATED PROBLEMS

by

Shimin Li

A dissertation submitted in partial fulfillment
of the requirements for the degree

of

DOCTOR OF PHILOSOPHY

in

Computer Science

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2018
ABSTRACT

Geometric Algorithms for Intervals and Related Problems

by

Shimin Li, Doctor of Philosophy
Utah State University, 2018

Major Professor: Haitao Wang, Ph.D.
Department: Computer Science

In this dissertation, we study several problems related to intervals and develop efficient algorithms for them. Interval problems have many applications in reality because many objects, values, and ranges are intervals in nature, such as time intervals, distances, line segments, probabilities, etc. Problems on intervals are gaining attention also because intervals are among the most basic geometric objects, and for the same reason, computational geometry techniques find useful for attacking these problems. Specifically, the problems we study in this dissertation includes the following: balanced splitting on weighted intervals, minimizing the movements of spreading points, dispersing points on intervals, multiple barrier coverage, and separating overlapped intervals on a line. We develop efficient algorithms for these problems and our results are either first known solutions or improve the previous work.

In the problem of balanced splitting on weighted intervals, we are given a set of $n$ intervals with non-negative weights on a line and an integer $k \geq 1$. The goal is to find $k$ points to partition the line into $k + 1$ segments, such that the maximum sum of the interval weights in these segments is minimized. We give an algorithm that solves the problem in $O(n \log n)$ time. Our second problem is on minimizing the movements of spreading points. In this problem, we are given a set of points on a line and we want to spread the points on the line so that the minimum pairwise distance of all points is no smaller than a given value $\delta$. The objective is to minimize the maximum moving distance of all points. We solve the problem in $O(n)$ time. We also solve the cycle version of the problem in linear time. For the third problem, we are given a set of $n$...
non-overlapping intervals on a line and we want to place a point on each interval so that the minimum pairwise distance of all points are maximized. We present an $O(n)$ time algorithm for the problem. We also solve its cycle version in $O(n)$ time. The fourth problem is on multiple barrier coverage, where we are given $n$ sensors in the plane and $m$ barriers (represented by intervals) on a line. The goal is to move the sensors onto the line to cover all the barriers such that the maximum moving distance of all sensors is minimized. Our algorithm for the problem runs in $O(n^2 \log n \log \log n + nm \log m)$ time. In a special case where the sensors are all initially on the line, our algorithm runs in $O((n+m) \log(n+m))$ time. Finally, for the problem of separating overlapped intervals, we have a set of $n$ intervals (possibly overlapped) on a line and we want to move them along the line so that no two intervals properly intersect. The objective is to minimize the maximum moving distance of all intervals. We propose an $O(n \log n)$ time algorithm for the problem.

The algorithms and techniques developed in this dissertation are quite basic and fundamental, so they might be useful for solving other related problems on intervals as well.
In this dissertation, we study several problems related to intervals and develop efficient algorithms for them. Interval problems have many applications in reality because many objects, values, and ranges are intervals in nature, such as time intervals, distances, line segments, probabilities, etc. Problems on intervals are gaining attention also because intervals are among the most basic geometric objects, and for the same reason, computational geometry techniques find useful for attacking these problems. Specifically, the problems we study in this dissertation includes the following: balanced splitting on weighted intervals, minimizing the movements of spreading points, dispersing points on intervals, multiple barrier coverage, and separating overlapped intervals on a line. We develop efficient algorithms for these problems and our results are either first known solutions or improve the previous work.

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well.
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Shimin Li
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CHAPTER 1

INTRODUCTION

In this dissertation, we study several problems related to intervals and develop efficient algorithms for them. Interval problems have many applications in reality because many objects, values, and ranges are intervals in nature, such as time intervals, distances, line segments, probabilities, etc. Problems on intervals are gaining attention also because intervals are among the most basic geometric objects, and for the same reason, computational geometry techniques find useful for attacking these problems.

In the rest of this chapter, we first briefly introduce the field of computational geometry and the topic of intervals, and we then present an overview on the problems we study in this dissertation. Finally, we will give an outline of the dissertation.

1.1 Computational Geometry

Computational geometry is a branch of computer science focusing on algorithm design, analysis, and implementation for solving geometric problems. The observations on the properties of the geometric objects in those problems play a critical role in the process of developing algorithms. The active research areas in computational geometry include both purely theoretical problems and problems arose from applications in the real world. Some important applications of computational geometry include computer graphics, geographic information systems, computer-aided engineering, computer vision, robotics, data analysis, facility location, and others. Refer to [1–4] for several great books on computational geometry.

1.2 Problems on Intervals

Certain objects and values in real applications can be treated as geometric intervals, such as time intervals, line segments, distances, probabilities, etc. Therefore, computational geometry techniques may be used to solve problems on intervals. Interval
problems are in general very basic and the topic has been studied extensively in computational geometry and other fields. Algorithms for interval problems have many important applications, such as scheduling [5–11], and mobile sensor barrier coverage [12–17].

1.3 An Overview of Our Problems

In this section, we give an overview on the problems we study in this dissertation. The details can be found in subsequent chapters.

1.3.1 Balanced Splitting on Weighted Intervals

This problem is motivated from load balancing in temporal and multi-version database systems. The problem can be formulated as follows. Let $I$ be a set of $n$ intervals on a line $L$, where each interval has a non-negative weight. For any given integer $k \geq 1$, we want to find $k$ points on $L$ to partition $L$ into $k+1$ segments, such that the maximum cost of these segments is minimized, where the cost of each segment $s$ is defined to be the sum of the weights of the intervals in $I$ that intersect $s$. Previously, an $O(n \log n)$ time algorithm was given for a special case where the weights of all intervals are the same. We present an $O(n \log n)$ time algorithm for the general case where the intervals may have different weights.

Our results on this problem have been published in a journal [18]. Refer to Chapter 2 for the details.

1.3.2 Minimizing the Movements of Spreading Points

Given a set $P$ of $n$ points sorted on a line $L$ and a distance value $\delta > 0$, the problem is to move the points of $P$ along $L$ such that the distance of any two points of $P$ is at least $\delta$ and the maximum movement of all points of $P$ is minimized. Using the greedy strategy, we present an $O(n)$ time algorithm for this problem. Further, we extend our algorithm to solve (in $O(n)$ time) the cycle version of the problem where all points of $P$ are on a cycle $C$. Previously, only weakly polynomial-time algorithms were known for these problems based on linear programming (of $n$ variables and $\Theta(n)$ constraints). In addition, we present a linear-time algorithm for another similar facility-location moving problem, which also improves the previous work.
Our results on this problem have been published in a conference [19]. Refer to Chapter 3 for the details.

1.3.3 Dispersing Points on Intervals

In certain applications, the movements of the points may be restricted. We consider a variation of the previous problem by adding some constraints on the movement of points. Given \( n \) pairwise disjoint intervals sorted on a line, we want to find a point in each interval such that the minimum pairwise distance of these points is maximized. We present a linear time algorithm for the problem. Further, we also solve in linear time the cycle version of the problem where the intervals are given on a cycle.

Our results on this problem have been published in a conference [20] and a journal [21]. Refer to Chapter 4 for the details.

1.3.4 Multiple Barrier Coverage

This problem is motivated from mobile sensor barrier coverage in wireless sensor networks. Given a set \( B \) of \( m \) line segments (called “barriers”) on a horizontal line \( L \) and another set \( S \) of \( n \) horizontal line segments of the same length in the plane, we want to move all segments of \( S \) to \( L \) so that their union covers all barriers and the maximum movement of all segments of \( S \) is minimized. Previously, an \( O(n^3 \log n) \)-time algorithm was given for the problem but only for the case \( m = 1 \). In this dissertation, we propose an \( O(n^2 \log n \log n + nm \log m) \)-time algorithm for any value \( m \), which improves the previous work even for \( m = 1 \). We then consider a line-constrained version of the problem in which the segments of \( S \) are all initially on the line \( L \). Previously, an \( O(n \log n) \)-time algorithm was known for the case \( m = 1 \). We present an algorithm of \( O((n + m) \log(n + m)) \) time for any \( m \), which generalizes the previous work.

Our results on this problem have been published in a conference [22]. Refer to Chapter 5 for the details.

1.3.5 Separating Overlapped Intervals on a Line

This is a general case of the spreading points problem on a line. Given \( n \) intervals on a line \( \ell \), we consider the problem of moving these intervals on \( \ell \) such that after the
movement no two intervals overlap and the maximum moving distance of the intervals is minimized. The difficulty for solving the problem lies in determining the order of the intervals in an optimal solution. By interesting observations, we show that it is sufficient to consider at most \( n \) “candidate” lists of ordered intervals. Further, although explicitly maintaining these lists takes \( \Omega(n^2) \) time and space, by more observations and a pruning technique, we present an algorithm that can compute an optimal solution in \( O(n \log n) \) time and \( O(n) \) space. We also prove an \( \Omega(n \log n) \) time lower bound for solving the problem, which implies the optimality of our algorithm.

Our results on this problem has been submitted to a conference and is still under review. Refer to Chapter 6 for the details.

1.4 Dissertation Outline

The rest of this dissertation is organized as follows. We present our algorithm for the balanced splitting on weighted intervals problem in Chapter 2. The algorithms for minimizing the movements of spreading points are discussed in Chapter 3. In Chapter 4, we give the results on dispersing points on intervals. Our algorithms for covering multiple barriers are described in Chapter 5. Chapter 6 presents the algorithm for the problem of separating overlapped intervals. Finally, the future work is discussed in Chapter 7.
CHAPTER 2

BALANCED SPLITTING ON WEIGHTED INTERVALS

2.1 Introduction

We consider the problem of splitting weighted intervals in a balanced way in this chapter. The results in this chapter have been published in a journal [18].

2.1.1 Problem Definitions and Our Results

Let $I$ be a set of $n$ intervals on a line $L$, where each interval has a non-negative weight. Given an integer $k \geq 1$, we want to find $k$ points on $L$ to partition $L$ into $k + 1$ segments, such that the maximum cost of these segments is minimized, where the cost of each segment $s$ is the sum of the weights of the intervals in $I$ that “properly” intersect $s$ (i.e., the intersection contains more than one point). The formal definition is given below.

Let $I = \{I_1, I_2, \ldots, I_n\}$ be a set of $n$ intervals on a line $L$, and each interval $I_i$ has a weight $w_i \geq 0$. For simplicity, we assume $L$ is the $x$-axis, and depending on the context, any real value $x \in \mathbb{R}$ is also considered as the point on $L$ with coordinate $x$, and vice versa. Each interval $I_i$ is represented as $[l_i, r_i]$ with $l_i < r_i$, where $l_i$ is its left endpoint and $r_i$ is its right endpoint. Note that we consider each $I_i$ as a closed interval including both endpoints.

For an integer $k \geq 1$, consider any $k$ points $x_1, x_2, \ldots, x_k$ on $L$ with $x_1 < x_2 < \cdots < x_k$, and we refer to these $k$ points as splitters. For simplicity of discussion, let $x_0 = -\infty$ and $x_{k+1} = +\infty$. The above $k$ splitters partition the line $L$ into $k + 1$ open segments: $s_i = (x_{i-1}, x_i)$ for $i = 1, 2, \ldots, k + 1$. For each segment $s_i$, we define its cost $C(s_i)$ as the sum of the weights of the intervals of $I$ that intersect $s_i$ (e.g., see Fig. 2.1). Note that since each $s_i$ is an open segment (i.e., it does not contain its two endpoints) and each interval of $I$ is closed, if an interval $I_i$ intersects $s_i$, then their intersection contains
The interval splitting problem is to find $k$ points/splitters $x_1, x_2, \ldots, x_k$ to partition $L$ into $k+1$ open segments (as defined above) such that the maximum cost of all segments (i.e., $\max_{i=1}^{k+1} C(s_i)$) is minimized (e.g., see Fig. 2.1).

Previously, Le et al. [23] gave an $O(n \log n)$ time algorithm for a special case of this problem where $w_i = 1$ for each $1 \leq i \leq n$. Their algorithm, which is based on the observation that the maximum cost in any optimal solution must be an integer in $[1, n]$, does not work for our more general problem (see Section 2.4 for more discussions). In this chapter, by developing new algorithmic techniques, we solve the general case in $O(n \log n)$ time.

2.1.2 Applications and Related Work

As discussed in [23], the interval splitting problem has applications in load balancing for storing and processing data in temporal and multi-version databases. If we consider the $x$-axis $L$ as the time, each interval represents a time period during which an object in databases is associated with the same value. Since an object may be associated with different values during different time periods, the task is to store and process a large number of intervals in a distributed store. To this end, one can split the intervals into “buckets” (corresponding to the segments of $L$ in our problem) such that intervals from the same buckets can be stored in one node and processed by one core from a cluster of machines. One challenging problem is to achieve load-balancing in this process, i.e., no single node and core should store and process too many intervals. This is exactly (the special case of) our interval splitting problem. If each object has a weight, which may represent the difficulty or importance for storing and processing the object (and
its corresponding intervals), then the problem becomes the general case of the interval splitting problem. Refer to [23] and the references therein for more discussions on temporal and multi-version databases.

The interval splitting problem is related to the classical interval scheduling problems. In the interval scheduling, each interval represents the time period during which a task needs to be executed. A subset of intervals is compatible if no two intervals overlap. One basic problem is to find a largest compatible set, and the problem can be solved by a simple greedy algorithm as shown in [7]. There are many other variations of problem; e.g., see [7, 24–27].

Since problems related to intervals are normally very fundamental, there are many powerful tools dealing with these problems, such as interval graphs [28], interval trees [29], segment trees [1], etc. Unfortunately, none of these techniques seems useful for solving our interval splitting problem.

As discussed in [23], the interval splitting problem is also related to many other problems, e.g., finding optimal splitters for a set of one dimensional points [30], the array partitioning problems [31, 32], etc.

2.1.3 Our Approach

We observe that there must exist an optimal solution in which every splitter is at the endpoint of an interval in $I$. This observation implies that the objective value (i.e., the maximum cost of all segments $s_i$) of the optimal solution must be determined by two interval endpoints along with $-\infty$ and $+\infty$. This immediately gives $\Theta(n^2)$ candidate values for the optimal objective value since there are $2n$ interval endpoints. We can easily find the optimal objective value from these candidate values if we can solve the decision version of the problem: Given any value $c$, determine whether we can find $k$ splitters such that the maximum cost of all segments $s_i$ is no more than $c$.

Assume the $2n$ interval endpoints have already been sorted. We first present a greedy algorithm that can solve the decision version in $O(n)$ time. Then we use this algorithm to find the optimal objective value from the above candidate values. One difficulty is that since there are $\Theta(n^2)$ candidate values, computing them needs $\Omega(n^2)$ time. To reduce the running time, we manage to implicitly organize all the candidate
values in $O(n)$ arrays and each array contains $O(n)$ elements in sorted order, and further, we give a data structure that can compute any candidate value in $O(1)$ time after $O(n)$ time preprocessing. Using this data structure and our decision algorithm, we apply a technique, called binary search on sorted arrays [33], to compute the optimal objective value in the above $O(n)$ sorted arrays. These efforts together lead to an $O(n \log n)$ time algorithm for solving the interval splitting problem.

The rest of this chapter is organized as follows. We introduce some notations, definitions, and observations in Section 2.2. The algorithm for the decision problem is given in Section 2.3. In Section 2.4, we solve the interval splitting problem, which is referred to as the optimization problem. Section 2.5 concludes this chapter.

2.2 Preliminaries

For ease of discussion, we make a general position assumption that no two intervals of $\mathcal{I}$ share the same endpoint, and our techniques can be easily adapted to the degenerate case.

We use an open segment to refer to a segment on $L$ that does not include its endpoints. For any open segment $s$, let $\mathcal{I}(s)$ denote the set of intervals of $\mathcal{I}$ intersecting $s$, and let $C(s)$ denote the sum of the weights of the intervals in $\mathcal{I}(s)$ and we also call $C(s)$ the cost of $s$. For any point $x$ on $L$, we let $\mathcal{I}(x)$ denote the set of intervals of $\mathcal{I}$ each of which contains $x$ in its interior, and let $C(x)$ denote the sum of the weights of the intervals in $\mathcal{I}(x)$.

Let $X = \{x_1, x_2, \ldots, x_t\}$ be a set of points/splitters on $L$ with $x_1 < x_2 < \cdots < x_t$, where $t$ may or may not be equal to $k$. These splitters partition $L$ into $t + 1$ open segments, and we denote by $C(X)$ the maximum cost of these open segments and $C(X)$ is referred to as the cost of $X$. We use $C_{opt}$ to denote the cost of the set of splitters in any optimal solution of the interval splitter problem (for $k$ splitters), and $C_{opt}$ is also referred to as the optimal objective value.

Let $E$ denote the set of all $2n$ endpoints of the intervals of $\mathcal{I}$. Due to our general position assumption, no two points of $E$ have the same position. Let $e_1, e_2, \ldots, e_{2n}$ be the list of the points of $E$ sorted on $L$ from left to right.

We first prove Lemma 2.2.1. A similar observation has been made by Le et al. [23].
for the special case where the weights of all intervals of $I$ are 1, and here we extend their result to the general case.

Lemma 2.2.1. For the interval splitting problem, there must exist an optimal solution in which every splitter is at the endpoint of an interval in $I$ (i.e., every splitter is in $E$).

Proof. Consider any optimal solution and assume $X = \{x_1, x_2, \ldots, x_k\}$ are the set of splitters sorted on $L$ from left to right. We assume no two splitters in $X$ have the same position since otherwise we could consider splitters at the same position as a single splitter.

If $X \subseteq E$, then we are done with the proof. Otherwise, consider any splitter $x$ in $X$ but not in $E$ (i.e., $x \in X \setminus E$). For ease of discussions, we assume $x \in (e_1, e_{2n})$. Hence, there is some $i$ with $1 \leq i \leq k - 1$ such that $x \in (e_i, e_{i+1})$. If the open interval $(e_i, e_{i+1})$ contains some other splitters in $X$, then among such splitters, we let $x$ represent the one closest to $e_i$. Hence, there is no splitter in the interval $(e_i, x)$ (e.g., see Fig. 2.2).

An easy observation is that if we move $x$ to $e_i$, the value $C(X)$ does not increase. Since $X$ is an optimal solution, we further conclude $C(X)$ does not change and we have obtained another optimal solution after $x$ moves to $e_i$. Notice that in the new optimal solution, the size $|X \setminus E|$ become one less than before. If in the new optimal solution the size $|X \setminus E|$ is zero, then we are done with the proof (i.e., we have found an optimal solution in which all splitters are in $E$); otherwise, we repeatedly apply the above “moving technique” until $|X \setminus E|$ becomes zero. The lemma thus follows.

For any two points $p$ and $q$ on $L$, let $\overline{pq}$ be the open line segment whose endpoints are $p$ and $q$ (but $\overline{pq}$ does not include its endpoints). Recall that $I(\overline{pq})$ is the set of
intervals of $I$ that intersect $pq$, and $C(pq)$ is the sum of the weights of the intervals in $I(pq)$.

From now on, we let $E$ also include the two infinite points $-\infty$ and $+\infty$ on $L$. Let $S_E$ consists of all values $C(pq)$ for any two points $p$ and $q$ in $E$. Lemma 2.2.1 implies the following corollary.

Corollary 2.2.2. $C_{opt} \in S_E$.

**Proof.** By Lemma 2.2.1, there is an optimal solution in which the set $X$ of splitters is a subset of $E$. Hence, $C_{opt} = C(X)$. The splitters of $X$ partition $L$ into open segments and there must be a segment $s_i$ such that $C(X) = C(s_i)$. Clearly, both endpoints of $s_i$ are in $E$. By the definition of $S_E$, $C(s_i) = C_{opt}$ must be in $S_E$. □

For any value $c$, if there exists a set $X$ of at most $k$ splitters such that $C(X) \leq c$, then we call $c$ a *feasible value* and call $X$ a *feasible splitter set* with respect to $c$. For any given value $c$, the decision version of our interval splitting problem is to determine whether $c$ is a feasible value, and if yes, find a feasible splitter set. For differentiation, we refer to our original interval splitting problem as the optimization version.

In the sequel, we will first present our algorithm for the decision problem in Section 2.3 and then solve the optimization problem in Section 2.4.

### 2.3 The Decision Problem

In this section, we solve the decision version of the problem. Our algorithm runs in $O(n)$ time after the points in $E$ are sorted. Note that Le et al. [23] also gave a linear time algorithm (after the points in $E$ are sorted), but their algorithm only works for the special case. Our algorithm solves the general case. In the following, we assume the points of $E$ have been sorted.

Our algorithm uses the greedy approach. Let $c$ be any given value. If $c$ is a feasible value, the algorithm will find from left to right at most $k$ splitters $x_1, x_2, \ldots$, that are feasible for $c$; otherwise it will report that $c$ is not feasible.

Recall that for any point $x \in L$, $I(x)$ is the set of intervals of $I$ each of which contains $x$ in its interior, and $C(x)$ is the sum of the weights of the intervals in $I(x)$. 
We first give the following lemma, which will be useful later for proving the correctness of our algorithm.

Lemma 2.3.1. **If there is a point** $q$ **on** $L$ **with** $C(q) > c$, **then** $c$ **is not a feasible value.**

*Proof.* Assume to the contrary that $c$ is a feasible value. Let $X = \{x_1, x_2, \ldots, x_k\}$ be a feasible splitter set. Thus we have $C(X) \leq c$. Let $x_0 = -\infty$ and $x_{k+1} = +\infty$. Assume $q$ is in $[x_{i-1}, x_i)$ for some index $i$. Let $s_i$ be the open interval $(x_{i-1}, x_i)$. Depending on whether $q = x_{i-1}$, there are two cases.

1. If $q \neq x_{i-1}$, then $q \in s_i$. Based on their definitions, we have $I(q) \subseteq I(s_i)$, and thus $C(q) \leq C(s_i)$. Note that $C(X) \geq C(s_i)$. Since $C(q) > c$, we obtain $C(X) \geq C(s_i) \geq C(q) > c$, which contradicts with that $C(X) \leq c$.

2. If $q = x_{i-1}$, then $q$ is not in $s_i$. Let $q'$ be a point to the right of $q$ and infinitesimally close to $q$. Clearly, $q' \in s_i$. Further, it always holds that $C(q') \geq C(q)$. Consequently, we obtain $C(X) \geq C(s_i) \geq C(q') \geq C(q) > c$, which again contradicts with $C(X) \leq c$.

The lemma is thus proved. 

We first describe the main idea of our algorithm and then flesh out the details. The algorithm starts with setting $x_0$ to $-\infty$ (note that $x_0$ is not a splitter). Assume $x_{i-1}$ has already been computed for any $1 \leq i \leq k$. Our algorithm sweeps a point $x$ from $x_{i-1}$ to the right as far as possible to find $x_i$. For any $x > x_{i-1}$, recall that $C(x_{i-1}x)$ is the sum of the weights of the intervals in $I$ that intersect the open segment $x_{i-1}x = (x_{i-1}, x)$.

During the rightward sweeping of $x$, as long as $C(x_{i-1}x) \leq c$, we continue to move $x$ rightwards. But if moving $x$ rightwards will make the value $C(x_{i-1}x)$ larger than $c$, then we stop and put the next splitter $x_i$ at the current position of $x$; if the above situation happens when $x = x_{i-1}$, then we terminate the algorithm and conclude that $c$ is not a feasible solution. If $x$ has moved to the right of all intervals of $I$, then we terminate the algorithm and conclude that $c$ is feasible value. In addition, if the algorithm has already put $k$ splitters (i.e., $k = i - 1$) but still need to put the next splitter $x_{k+1}$, then we conclude that $c$ is not a feasible solution and terminate the algorithm. The details on how to implement the algorithm are given below.
Our algorithm will maintain an invariant that each splitter (i.e., \(x_i\) for \(1 \leq i \leq k\)) computed by the algorithm is at the left endpoint of an interval of \(I\). Assume \(x_{i-1}\) has just been computed and \(x\) is at \(x_{i-1}\). In order to compute the value \(C(x_{i-1})\) during the rightward sweeping of \(x\), we need to know the value \(C(x_{i-1})\). We assume \(C(x_{i-1})\) is already known when \(x\) is at \(x_{i-1}\). Initially when \(i = 1\), we set \(x_{i-1} = -\infty\) and \(C(-\infty) = 0\). Further, during the sweeping of \(x\), we will maintain the value \(C(x_i)\), which will be used to compute \(C(x_i)\) once the next splitter \(x_i\) is determined. We will show that after \(x_i\) is determined, \(x_i\) is at the left endpoint of an interval and \(C(x_i)\) is computed correctly.

During the sweeping of \(x\), an event happens when \(x\) encounters a point of \(E\). Suppose we have just computed \(x_{i-1}\). For the case where \(i \geq 2\), before we sweep \(x\) rightwards, we first process this beginning event for \(x = x_{i-1}\) as follows.

For any interval \(I \in \mathcal{I}\), we use \(w(I)\) to denote its weight.

Since \(i \geq 2\), by our algorithm invariant, \(x_{i-1}\) is the left endpoint of an interval, denoted by \(I\). Also recall that \(C(x_{i-1})\) is known. If \(C(x_{i-1}) + w(I) > c\), then we conclude that \(c\) is not a feasible solution and terminate the algorithm. The correctness is proved in the following lemma.

**Lemma 2.3.2.** If \(C(x_{i-1}) + w(I) > c\), then \(c\) is not a feasible value.

**Proof.** Consider any point \(q\) to the right of \(x_{i-1}\) and infinitesimally close to \(x_{i-1}\). Since \(x_{i-1}\) is the left endpoint of \(I\), it holds that \(\mathcal{I}(q) = \mathcal{I}(x_{i+1}) \cup \{I\}\), and thus, \(C(q) = C(x_{i-1}) + w(I)\). It follows that \(C(q) > c\). By Lemma 2.3.1, \(c\) is not a feasible value. \(\Box\)

If \(C(x_{i-1}) + w(I) \leq c\), then we are “safe” to move \(x\) rightwards. We also set \(C(x_{i-1}) = C(x) = C(x_{i-1}) + w(I)\). One can verify that the above values are correct when \(x\) is moving rightwards before the next event happens. This finishes our processing on the beginning event for \(x = x_{i-1}\).

Below, we discuss the general events after the beginning event. Suppose the next event is at a point \(e\) in \(E\) (with \(x_{i-1} < e < +\infty\)) and assume that \(C(x)\) and \(C(x_{i-1})\) have been correctly maintained for \(x\) right before \(x\) arrives at \(e\). We process the event \(e\) as follows. Let \(I\) be the interval for which \(e\) is its endpoint. Depending on whether \(e\) is the right or left endpoint of \(I\), there are two cases.
1. If $e$ is the right endpoint of $I$, then we update $C(x)$ by setting $C(x) = C(x) - w(I)$ and continue to move $x$ rightwards and proceed on the next event after $e$. Note that we do not need to change the value $C(x_{i-1})$.

If $e$ is the rightmost point of $E$, then we terminate the algorithm and conclude that $c$ is a feasible value, and the set of $i - 1$ splitters $x_1, x_2, \ldots, x_{i-1}$ that have been computed so far is a feasible splitter set.

2. If $e$ is the left endpoint of $I$, then we first check whether $C(x_{i-1}) + w(I) \leq c$. If yes, we set $C(x) = C(x) + w(I)$ and $C(x_{i-1}) = C(x_{i-1}) + w(I)$, and continue to move $x$ rightward and proceed on the next event after $e$.

If $C(x_{i-1}) + w(I) > c$, we need to put the next splitter $x_i$ at $e$. But if $i = k + 1$, then we terminate the algorithm and conclude that $c$ is not a feasible value because we are only allowed to have $k$ splitters. If $i < k + 1$, then we let $x_i = e$ and proceed on finding the next splitter $x_{i+1}$. Note that $x_i$ is at the left endpoint of $I$, which maintains the algorithm invariant. Also, it is easy to see that $C(x_i) = C(x)$.

This finishes the description of our algorithm. For the running time, since the points of $E$ have already been sorted, after processing each event, we can find the next event point in constant time. Also, processing each event takes only constant time. Hence, the total time of the algorithm is $O(n)$. The correctness of the algorithm can be seen from Lemma 2.3.2 as well as the fact that our algorithm always tries to push the splitters rightward on $L$ as far as possible.

As a summary, we have the following result.

Theorem 2.3.3. Suppose the endpoints of all intervals in $I$ have been sorted. The decision version of the interval splitting problem can be solved in $O(n)$ time.

2.4 The Optimization Problem

In this section, we solve the optimization version of the interval splitting problem, with the help of Corollary 2.2.2 and Theorem 2.3.3. In the following, we refer to our algorithm for the decision problem in Theorem 2.3.3 as the decision algorithm.

Recall that $C_{opt}$ is the optimal objective value. If we know the value $C_{opt}$, then we can compute an optimal solution by using our decision algorithm. Specifically, we apply
our decision algorithm on $c = C_{opt}$, and the algorithm will find a feasible splitter set, which is an optimal solution. Hence, to solve the optimization problem, the key is to compute $C_{opt}$, which is our focus below.

Note that in the special case where the weight of each interval of $I$ is 1, an easy observation is that $C_{opt}$ must be an integer in $[1, n]$. Thus, using the decision algorithm, we can easily compute $C_{opt}$ in $O(n \log n)$ time by doing binary search on the integer sequence from 1 to $n$. This is exactly the approach used in [23] (by using their own decision algorithm, which works only for the special case). In our general problem, however, this approach does not work because $C_{opt}$ may not be an integer. We propose a new approach, as follows.

2.4.1 Computing the Optimal Objective Value $C_{opt}$

Recall that the set $S_E$ consists of all values $C(pq)$ for any two points $p$ and $q$ in $E$. By Corollary 2.2.2, we have $C_{opt} \in S_E$. One straightforward way to compute $C_{opt}$ is to first compute all values in the set $S_E$ and sort them. Then, using our decision algorithm in Theorem 2.3.3, we can compute $C_{opt}$ by doing binary search on the sorted list of the values in $S_E$. However, since $|S_E| = \Theta(n^2)$, this approach takes $\Omega(n^2)$ time. In the following, we give an $O(n \log n)$ time algorithm.

Recall that $E$ also includes $-\infty$ and $+\infty$. We first organize the values in $S_E$ into $O(n)$ sorted arrays and each array has $O(n)$ elements. Note that our algorithm does not do this organization explicitly.

Let $e_0, e_1, \ldots, e_{2n+1}$ be the list of the values of $E$ sorted on $L$ from left to right, with $e_0 = -\infty$ and $e_{2n+1} = +\infty$. For any $i$ and $j$ with $0 \leq i < j \leq 2n + 1$, define $w(i, j) = C(e_i e_j)$. Clearly, $S_E = \{w(i, j) | 0 \leq i < j \leq 2n + 1\}$. Below is a self-evident observation that shows a monotonicity property of $w(i, j)$.

**Observation 2.4.1.** For any $i$, if $i < j_1 \leq j_2$, then $w(i, j_1) \leq w(i, j_2)$.

For each $i = 0, 1, \ldots, 2n + 1$, we define an array $A_i[0 \cdots 2n + 1]$ of $2n + 2$ elements as follows. For each $j$ with $0 \leq j \leq 2n + 1$, define $A_i[j]$ to be $w(i, j)$ if $i < j$ and 0 otherwise. By Observation 2.4.1, elements in each array $A_i$ are sorted in ascending
order. It is not difficult to see that \( S_E \) is the union of all elements in the arrays \( A_i \), \( 0 \leq i \leq 2n + 1 \), i.e., \( S_E = \bigcup_{i=0}^{2n+1} A_i \).

Since \( C_{opt} \in S_E \), our goal is to find \( C_{opt} \) in \( \bigcup_{i=0}^{2n+1} A_i \). To this end, although we cannot afford to explicitly compute all elements of these arrays, based on the following Lemma 2.4.2, with linear time preprocessing, we can obtain any element of these arrays in constant time whenever we need it.

**Lemma 2.4.2.** With \( O(n) \) time preprocessing, for any query \((i, j)\) with \( i < j \), we can compute the value \( w(i, j) = A_i[j] \) in constant time.

Before proving Lemma 2.4.2, we show how to compute \( C_{opt} \) with the help of Lemma 2.4.2. We use a technique, called *binary search on sorted arrays*, which was developed in [33]. We first briefly discuss this technique.

Assume there is a “black-box” decision procedure \( \sigma \) available such that given any value \( \alpha \), \( \sigma \) can report whether \( \alpha \) is a feasible value in \( O(T) \) time, and further, if \( \alpha \) is a feasible value, then any value larger than \( \alpha \) is also a feasible value. Given a set of \( M \) arrays \( B_i \), \( 1 \leq i \leq M \), each containing \( N \) elements in sorted order, the goal is to find the smallest feasible value \( \delta \) in \( \bigcup_{i=1}^{M} B_i \). Suppose given its indices, any element of these arrays can be obtained in constant time. An algorithm is presented in [33] with the following result.

**Lemma 2.4.3.** [33] The smallest feasible value \( \delta \) in \( \bigcup_{i=1}^{M} B_i \) can be found in \( O((M + T) \log(MN)) \) time.

For solving our problem, we can use the above result to find \( C_{opt} \) in \( \bigcup_{i=0}^{2n+1} A_i \) as follows. The following observation is self-evident.

**Observation 2.4.4.** If a value \( c \) is a feasible value for the decision problem, then any value larger than \( c \) is also a feasible value.

Hence, \( C_{opt} \) is the smallest feasible value in \( \bigcup_{i=0}^{2n+1} A_i \). Our linear time decision algorithm in Theorem 2.3.3 can play the role of the black-box \( \sigma \) with \( T = O(n) \). Further, we have already shown that given any \( i \) and \( j \), we can compute the element \( A_i[j] \) in constant time. Therefore, we can apply the technique in Lemma 2.4.3 (with \( M = N = 2n + 2 \) and \( T = O(n) \)) to compute \( C_{opt} \) in \( O(n \log n) \) time.
In summary, we have the following result.

Theorem 2.4.5. The optimization version of the interval splitting problem can be solved in $O(n \log n)$ time.

2.4.2 Proving Lemma 2.4.2

It remains to prove Lemma 2.4.2. Consider any query $(i, j)$ with $i < j$. Our goal is to compute $w(i, j) = C(e_i e_j)$. We begin with some observations.

Recall that $e_0, e_1, \ldots, e_{2n+1}$ are the sorted list of points of $E$. For each $t$ with $0 \leq t \leq 2n + 1$, define $I_t$ to be the set of intervals of $I$ whose left endpoints are strictly to the left of $e_t$. Recall that for any point $x$ on $L$, $I(x)$ is the set of intervals of $I$ each of which contains $x$ in its interior. Also recall that $I(e_i e_j)$ is the set of intervals of $I$ that intersect the open segment $e_i e_j$. We have the following lemma.

Lemma 2.4.6. $I(e_i e_j) = I(e_i) \cup (I_j \setminus I_i)$ and $I(e_i) \cap (I_j \setminus I_i) = \emptyset$.

Proof. We first prove $I(e_i e_j) = I(e_i) \cup (I_j \setminus I_i)$. To this end, we show below that any interval in $I(e_i e_j)$ must be in $I(e_i) \cup (I_j \setminus I_i)$, and vice versa.

1. Consider any interval $I \in I(e_i e_j)$. We prove that $I$ must be in $I(e_i) \cup (I_j \setminus I_i)$.

Let $l$ and $r$ be the left and right endpoints of $I$, respectively. By definition, $I$ intersects the open segment $e_i e_j$. Hence, $l < e_j$, implying that $I \in I_j$. If $I \notin I_i$, it is vacuously true that $I \in I(e_i) \cup (I_j \setminus I_i)$. Otherwise, it must be that $l < e_i$. Since $I$ intersects the open segment $e_i e_j$, we can also get $r > e_i$. Therefore, it holds that $l < e_i < r$, implying that $e_i$ is contained in the interior of $I$, and thus $I \in I(e_i)$.

Therefore, in any case, we obtain $I \in I(e_i) \cup (I_j \setminus I_i)$.

2. Consider any interval $I \in I(e_i) \cup (I_j \setminus I_i)$. We prove that $I$ must be in $I(e_i e_j)$.

Let $l$ and $r$ be the left and right endpoints of $I$, respectively.

If $I \in I_j \setminus I_i$, then due to $I \in I_j$, we obtain $l < e_j$, and due to $I \notin I_i$, we obtain $e_i \leq l$. Hence, we have $e_i \leq l < e_j$. Since $l < r$, $I$ must intersect the open segment $e_i e_j$, and thus $I \in I(e_i e_j)$.

If $I \notin I_j \setminus I_i$, then $I$ must be in $I(e_i)$, implying that $e_i \in (l, r)$. Therefore, $I$ must intersect the open segment $e_i e_j$, and $I \in I(e_i e_j)$. 

The above proves that $\mathcal{I}(e_i e_j) = \mathcal{I}(e_i) \cup (\mathcal{I}_j \setminus \mathcal{I}_i)$.

Next, we show that $\mathcal{I}(e_i) \cap (\mathcal{I}_j \setminus \mathcal{I}_i) = \emptyset$. Indeed, for any interval $I = [l, r] \in \mathcal{I}_j \setminus \mathcal{I}_i$, as discussed above, it holds that $e_i \leq l < e_j$, implying that $e_i$ cannot be in the interior of $I$, and thus, $I \not\in \mathcal{I}(e_i)$. On the other hand, for any interval $I = [l, r] \in \mathcal{I}(e_i)$, since $e_i$ is in the interior of $I$, we have $l < e_i$; thus, $I$ must be in $\mathcal{I}_i$, implying that $I$ cannot be in $\mathcal{I}_j \setminus \mathcal{I}_i$.

The lemma thus follows. 

The preceding lemma implies the following approach for computing the value $C(e_i e_j)$. For each $t$ with $0 \leq t \leq 2n + 1$, let $C_t$ be the sum of the weights of the intervals in $\mathcal{I}_t$. By Lemma 2.4.6, we can obtain $C(e_i e_j) = C(e_i) + (C_j - C_i)$. Hence, if the values $C(e_i)$, $C_j$, and $C_i$ are already known, we can compute $C(e_i e_j)$ in constant time. In the sequel, we present an algorithm that can compute $C(e_i)$ and $C_t$ for all $t = 0, 1, \ldots, 2n + 1$ in $O(n)$ time. The algorithm is similar to our decision algorithm in Section 2.3 (the decision algorithm can compute $C(e_i)$, but here we also need to compute $C_t$).

The algorithm sweeps a point $x$ from $-\infty$ to $+\infty$. An event happens when $x$ encounters a point, say, $e_t$, in $E$, and for processing the event, we will compute $C(e_t)$ and $C_t$. During the sweeping of $x$, we will maintain two values for $x$: $C(x)$, i.e., the sum of the weights of the intervals of $\mathcal{I}$ that contain $x$ in their interior, and $C'(x)$, which is the sum of the weights of the intervals whose left endpoints are strictly to the left of $x$.

Initially, when $x = -\infty$, we have $C(x) = C'(x) = 0$. Consider a general step that the next event is at $e_t$. We assume that the values $C(x)$ and $C'(x)$ have been correctly maintained right before $x$ arrives at $e_t$. Note that $e_t$ is an endpoint of an interval of $\mathcal{I}$, and let $I$ denote the interval (and let $w(I)$ be the weight of $I$). Depending on whether $e_t$ is the left or the right endpoint of $e_t$, there are two cases.

If $e_t$ is the right endpoint of $I$, we first set $C(e_t) = C(x) - w(I)$ and $C_t = C'(x)$. Then we update $C(x) = C(x) - w(I)$, and we do not need to change $C'(x)$. One can verify that all these values have been correctly computed. We then proceed on the next event after $e_t$.

If $e_t$ is the left endpoint of $I$, then we set $C(e_t) = C(x)$ and $C_t = C'(x)$. We also update $C(x) = C(x) + w(I)$ and $C'(x) = C'(x) + w(I)$ because once $x$ crosses $e_t$, $e_t$ is
strictly to the left of \( x \). We proceed on the next event after \( e_t \).

The algorithm is done once \( x \) passes the rightmost point of \( E \). Since the points of \( E \) have already been sorted, the algorithm runs in \( O(n) \) time.

As a summary, in \( O(n) \) time we can compute \( C(e_t) \) and \( C_t \) for all \( t = 0, 1, \ldots, 2n+1 \), after which, given any query \((i, j)\) with \( i < j \), we can compute \( w(i, j) \) in constant time. Lemma 2.4.2 is thus proved.

2.5 Conclusions

In this chapter, we present an efficient algorithm for solving the interval splitting problem. While the previous work [23] only deals with the special/unweighted case, our algorithm works for the general/weighted case. Besides its applications in load balancing for storing and processing data in temporal and multi-version databases, the interval splitting problem itself is an interesting and basic problem on intervals. Our techniques may be used for solving other related problems as well.
3.1 Introduction

We consider the following points-spreading problem in this chapter. The results in this chapter have been published in a conference [19].

3.1.1 Problem Definitions and Our Results

Given a set $P$ of $n$ points sorted on a line $L$ and a distance value $\delta \geq 0$, we wish to move the points of $P$ along $L$ such that the distance of any two points of $P$ is at least $\delta$ and the maximum movement of all points of $P$ is minimized. The above is the line version. We also consider the cycle version of the problem, where all points of $P$ are given sorted cyclically on a cycle (one may view $C$ as a simple closed curve). We wish to move the points of $P$ on $C$ such that the distance of any two points of $P$ along $C$ is at least $\delta$ and the maximum movement of all points of $P$ along $C$ is minimized. Note that since $C$ is a cycle, the distance of any two points of $C$ is defined to be the length of the shortest path on $C$ between the two points.

Both versions of the problem have been studied before. By modeling them as linear programming problems (with $n$ variables and $\Theta(n)$ constraints), Dumitrescu and Jiang [34] gave the first-known polynomial-time algorithms for both problems. Since there only exist weakly polynomial-time algorithms for linear programming [35, 36], it would be interesting to design strongly polynomial-time algorithms for the points-spreading problem. In this chapter, we solve both versions of the problem not only in strongly polynomial time but also in $O(n)$ time (which is optimal). Our algorithms are based on a greedy strategy.

In addition, we consider a somewhat related problem, called the facility-location movement problem, defined as follows. Suppose we have a set of $k$ “server” points and
another set of \( n \) “client” points sorted on \( L \). We wish to move all servers and all clients on \( L \) such that each client co-locates with a server and the maximum moving distance of all servers and clients is minimized. Dumitrescu and Jiang [34] solved this problem in \( O((n + k) \log(n + k)) \) time. We present an \( O(n + k) \) time algorithm based on their approach.

3.1.2 Related Work

The 2D version of the points-spreading problem was proposed by Demaine et al. [37] (also called “movement to independence” problem in [34, 37]). The problem in 2D is NP-hard and an approximation algorithm was given in [37]; the algorithm was improved later by Dumitrescu and Jiang [34].

The points-spreading problem is related to the points dispersion problems which involve arranging a set of points as far away from each other as possible subject to certain constraints. For example, Fiala et al. in [38] studied such a problem in which one wants to place \( n \) given points, each inside its own, prespecified disk, with the objective of maximizing the distance between the closest pair of these points. The problem was shown to be NP-hard [38]. Approximation algorithms were given for this problem by Cabello [39]. Dumitrescu and Jiang [40] gave improvement on the approximation algorithms and also proposed algorithms for the problem in high-dimensional spaces. In fact, Fiala et al. [38] studied the dispersion problems on a more general problem settings. Another variation of the dispersion problems is to select a subset of facilities from a set of given facilities to maximize the minimum distance (or some other distance function) among all pairs of selected facilities [41, 42]. The problem is generally NP-hard (e.g., in 2D) but polynomial time algorithms are available in the one-dimensional space [41, 42]. In addition, Chandra and Halldórsson [43] studied dispersion problems in other problem settings.

The facility-location movement problem was first introduced by Demaine et al. [37] in graphs, which was proved to be NP-hard. A 2-approximation algorithm was presented in [37] for this problem in graphs, and later it was shown that the 2-approximation ratio cannot be improved unless \( P=NP \) [44]. Dumitrescu and Jiang [34] studied the geometric version of this problem in the plane, and they showed that the problem is NP-hard to
approximate within 1.8279. Fixed parameter algorithms (with \( k \) as the parameter) were also given in [34].

3.1.3 Our Approach

For solving the line version of the points-spreading problem, essentially we first solve a “one-direction” case of the problem in which points are only allowed to move rightwards, by using a simple greedy algorithm. Suppose \( d \) is the maximum movement in the solution of the above one-direction case. Then, we show that an optimal solution to the original problem can be obtained by shifting each point of \( P \) leftwards by the distance \( d/2 \).

For solving the cycle version of the problem, essentially we also first solve a one-direction case in which points are only allowed to move counterclockwise on \( C \). If \( d \) is the maximum movement in the solution of the one-direction case, then we also show that an optimal solution to the original problem can be obtained by shifting each point of \( P \) clockwise by \( d/2 \). However, unlike the line version, the one-direction case of the problem becomes more difficult on the cycle. One straightforward idea is to cut the cycle \( C \) at a point of \( P \) (and extend \( C \) as a line) and then apply the algorithm for the one-direction case of the line version. However, the issue is that the last point may be too close to or even “cross” the first point if we put all points back on \( C \). By observations, we show that if such a case happens, we can run the line-version algorithm for another round and the second round is guaranteed to find an optimal solution. Overall, the algorithm is still simple, but it is challenging to discover the idea and prove the correctness.

For solving the facility-location movement problem, Dumitrescu and Jiang [34] presented an \( O((n + k) \log(n + k)) \) time algorithm using dynamic programming. By discovering a monotonicity property on the dynamic programming, we improve Dumitrescu and Jiang’s algorithm to \( O(n + k) \) time.

The rest of this chapter is organized as follows. In Section 3.2, we present our algorithm for the line version of the points-spreading problem. The cycle version of the problem is solved in Section 3.3. Section 3.4 discusses our solution for the facility-location movement problem.
3.2 The Line Version of the Points-Spreading Problem

In the line version, the points of $P$ are given sorted on the line $L$. Without loss of generality, we assume $L$ is the $x$-axis and $P = \{p_1, p_2, \ldots, p_n\}$ are sorted by their $x$-coordinates from left to right. For each $i \in [1, n]$, let $x_i$ denote the location (or $x$-coordinate) of $p_i$ on $L$. For any two locations $x$ and $x'$ of $L$, denote by $|xx'|$ the distance between $x$ and $x'$, i.e., $|xx'| = |x - x'|$.

Our goal is to move each point $p_i \in P$ to a new location $x'_i$ on $L$ such that the distance of any pair of two points of $P$ is at least $\delta$ and the maximum moving distance, i.e., $\max_{1 \leq i \leq n} |x_ix'_i|$, is minimized. For simplicity of discussion, we make a general position assumption that no two points of $P$ are at the same location in the input. The degenerate case can also be handled by our techniques but the discussions would be more tedious.

We refer to a configuration as a specification of the location of each point $p_i$ of $P$ on $L$. For example, in the input configuration each $p_i$ is at $x_i$. Let $F_0$ denote the input configuration. A configuration is feasible if the distance between any pair of points of $P$ is at least $\delta$.

Denote by $d_{opt}$ the maximum moving distance in any optimal solution. If the input configuration $F_0$ is feasible, then we do not need to move any point, implying that $d_{opt} = 0$. Since the points of $P$ are sorted, we can check whether $F_0$ is feasible in $O(n)$ time by checking the distance between every adjacent pair of points of $P$. If $F_0$ is not feasible, then $d_{opt} > 0$. In the following, we assume $F_0$ is not feasible, and thus $d_{opt} > 0$.

We first present some observations, based on which our algorithm will be developed.

3.2.1 Observations

For any two indices $i < j$ in $[1, n]$, define

$$w(i, j) = (j - i) \cdot \delta - |x_ix_j|.$$ 

As discussed in Dumitrescu and Jiang [34], there exists an optimal solution in which the order of all points of $P$ is the same as that in the input configuration $F_0$. Based on this property, we prove Lemma 3.2.1 regarding the value $d_{opt}$. 

Lemma 3.2.1. \( d_{\text{opt}} \geq \max_{1 \leq i < j \leq n} \frac{w(i,j)}{2} \).

Proof. Consider any optimal solution \( OPT \) in which the order of all points of \( P \) is the same as that in \( F_0 \). For each \( 1 \leq i \leq n \), let \( x^*_i \) be the location of \( p_i \) in \( OPT \).

Consider any \( i \) and \( j \) with \( 1 \leq i < j \leq n \). Our goal is to prove \( d_{\text{opt}} \geq w(i,j)/2 \).

Since the points of \( P \) in \( OPT \) have the same order as in \( F_0 \), for each \( k \) with \( i < k \leq j \), we have \( |x^*_k - x^*_i| \geq \delta \) because \( OPT \) is a feasible solution. Hence, \( |x^*_i x^*_j| = \sum_{k=i+1}^j |x^*_k - x^*_i| \geq (j - i) \cdot \delta \).

If \( |x^*_i x^*_j| - |x_i x_j| \leq 0 \), then \( |x_i x_j| \geq |x^*_i x^*_j| \geq (j - i) \cdot \delta \). Thus, \( w(i,j) \leq 0 \). Since \( d_{\text{opt}} > 0 \), \( d_{\text{opt}} \geq w(i,j)/2 \) holds.

If \( |x^*_i x^*_j| - |x_i x_j| > 0 \), then the difference of \( |x^*_i x^*_j| \) and \( |x_i x_j| \) are due to the moving of \( p_i \) and \( p_j \). It is not difficult to see that \( \max\{|x_i x_j^*|, |x_j x_i^*|\} \geq (|x^*_i x^*_j| - |x_i x_j|)/2 \) (the equality happens when \( p_i \) moves leftwards by distance \((|x^*_i x^*_j| - |x_i x_j|)/2 \) and \( p_j \) moves rightwards by the same distance). Since \( d_{\text{opt}} \geq \max\{|x_i x_j^*|, |x_j x_i^*|\} \), it holds that \( d_{\text{opt}} \geq (|x^*_i x^*_j| - |x_i x_j|)/2 \). Due to \( |x^*_i x^*_j| \geq (j - i) \cdot \delta \), we obtain that \( d_{\text{opt}} \geq w(i,j)/2 \).

The lemma thus follows. \( \square \)

Lemma 3.2.2. If there exist \( i \) and \( j \) with \( 1 \leq i < j \leq n \) and a feasible configuration \( F' \) in which each point \( p_k \in P \) moves rightwards to \( x'_k \) (i.e., \( x_k \leq x'_k \)) such that \( w(i,j) = \max_{1 \leq k \leq n} |x_k x'_k| \), then we can obtain an optimal solution by shifting each point of \( P \) in \( F' \) leftwards by distance \( w(i,j)/2 \).

Proof. Let \( F'' \) denote the configuration obtained by shifting each point of \( P \) in \( F' \) leftwards by distance \( w(i,j)/2 \).

Consider any point \( p_k \in P \). Let \( x''_k \) denote the location of \( p_k \) in \( F'' \), i.e., \( x''_k = x'_k - w(i,j)/2 \). In order to prove that \( F'' \) is an optimal solution, by Lemma 3.2.1, it is sufficient to show that \( |x_k x''_k| \leq w(i,j)/2 \), as follows.

Indeed, since \( 0 \leq x'_k - x_k \leq w(i,j) \), i.e., \( x'_k \) is to the right of \( x_k \) at most \( w(i,j) \), after \( p_k \) is moved leftwards by \( w(i,j)/2 \) to \( x''_k \), \( x''_k \) must be within distance \( w(i,j)/2 \) from \( x_k \). Hence, \( |x_k x''_k| \leq w(i,j)/2 \). The lemma thus follows. \( \square \)

We call a feasible configuration that satisfies the condition in Lemma 3.2.2 a canonical configuration (such as \( F' \) in Lemma 3.2.2). Due to Lemma 3.2.2, to solve the problem
in linear time, it is sufficient to find a canonical configuration in linear time, which is our focus below.

3.2.2 Computing a Canonical Configuration

In this section, we present a linear-time algorithm that can find a canonical configuration. Comparing with the original problem, now we only need to consider the rightward movements.

Initially, we set $x_1' = x_1$. Then we consider the rest of the points $p_2, p_3, \ldots, p_n$ from left to right. For each $i$ with $2 \leq i \leq n$, suppose we have already moved $p_{i-1}$ to $x_{i-1}'$. Then, we set $x_i' = \max\{x_i, x_{i-1}' + \delta\}$, and move $p_i$ to $x_i'$. Refer to Fig. 3.1 for an example. The algorithm finishes after all points of $P$ have been considered. Clearly, the algorithm runs in $O(n)$ time. Let $F'$ denote the resulting configuration (i.e., each $p_i$ is at $x_i'$).

In the following lemma, we show that $F'$ is a canonical configuration.

Lemma 3.2.3. $F'$ is a canonical configuration.

Proof. First of all, based on our way of setting $x_i'$ for $i = 1, 2, \ldots, n$, it can be easily seen that every two points of $P$ in $F'$ are at least $\delta$ away from each other. Thus, $F'$ is a feasible configuration. Note that $x_i' \geq x_i$ for any $i \in [1, n]$.

Next, we show that there exist $i$ and $j$ with $1 \leq i < j \leq n$ such that $w(i, j) = d_{\text{max}}$, where $d_{\text{max}} = \max_{1 \leq k \leq n} |x_kx_k'|$.

Recall that $d_{\text{max}} > 0$. Suppose the moving distance of $p_j$ is the maximum, i.e., $d_{\text{max}} = |x_jx_j'|$. Let $i$ be the largest index such that $i < j$ and $p_i$ does not move in the algorithm (i.e., $x_i = x_i'$). Note that such a point $p_i$ must exist as $x_1 = x_1'$ and $x_j' > x_j$.

For any point $p_k \in P$, if $p_k$ is moved (rightwards) in $F'$ (i.e., $x_k < x_k'$), then according to our way of setting $x_k'$, it must hold that $x_k' - x_{k-1}' = \delta$. By the definition
of $i$, for each point $p_k$ with $k \in [i + 1, j]$, $p_k$ is moved in $F'$, and thus $x'_k - x'_{k-1} = \delta$. Therefore, we obtain

$$|x'_i x'_j| = x'_j - x'_i = \sum_{i+1 \leq k \leq j} (x'_k - x'_{k-1}) = (j - i) \cdot \delta.$$  

Since $x'_i = x_i$ and $x_j < x'_j$, we have $|x_i x'_j| = |x_i x_j| + |x_j x'_j|$. Hence, $d_{max} = |x_j x'_j| = |x_i x'_j| - |x_i x_j| = (j - i) \cdot \delta - |x_i x_j| = w(i, j)$. This proves the lemma.

Combining Lemmas 3.2.2 and 3.2.3, we conclude this section with the following theorem.

**Theorem 3.2.4.** *The line version of the points-spreading problem is solvable in $O(n)$ time.*

*Remark:* One may verify that our algorithm for computing the canonical configuration $F'$ essentially solves the following *one-direction case* of the line version problem: Move the points of $P$ rightwards such that any pair of points of $P$ are at least $\delta$ away from each other and the maximum moving distance of all points of $P$ is minimized.

### 3.3 The Cycle Version of the Points-Spreading Problem

In the cycle version, the points of $P = \{p_1, p_2, \ldots, p_n\}$ are on a cycle $C$ sorted cyclically, say, in the counterclockwise order. We use $|C|$ to denote the length of $C$. For any two locations $x$ and $x'$ on $C$, the distance between $x$ and $x'$, denoted by $|xx'|$, is the length of the shortest path between $x$ and $x'$ on $C$. Clearly, $|xx'| \leq |C|/2$. For each $i \in [1, n]$, we use $x_i$ to denote the location of $p_i$ on $C$ in the input. Our goal is to move each point $p_i \in P$ to a new location $x'_i$ such that the distance of any pair of two points of $P$ on $C$ is at least $\delta$ and the maximum moving distance, i.e., $\max_{1 \leq i \leq n} |x_i x'_i|$, is minimized.

We assume $|C| \geq \delta \cdot n$ since otherwise there would be no solution. Again, for simplicity of discussion, we make a general position assumption that no two points of $P$ are at the same location on $C$ in the input.
As in the line version, we refer to a configuration as a specification of the location of each point of \( P \) on \( C \). A configuration is feasible if the distance between any pair of points of \( P \) is at least \( \delta \). Let \( F_0 \) denote the input configuration.

Denote by \( d_{opt} \) the maximum moving distance in any optimal solution. If \( F_0 \) is feasible, then \( d_{opt} = 0 \). We can also check whether \( F_0 \) is feasible in \( O(n) \) time. If \( F_0 \) is not feasible, then \( d_{opt} > 0 \). In the following, we assume \( F_0 \) is not feasible, and thus \( d_{opt} > 0 \).

To solve the cycle version of the problem, we extend our algorithm (and observations) for the line version in Section 3.2. Namely, we first move all points of \( P \) on \( C \) counterclockwise to obtain a “canonical configuration”, and then shift all points clockwise. However, as will be seen later, the problem becomes much more difficult on the cycle.

Consider any two locations \( x \) and \( x' \) on \( C \). We define \( C(x, x') \) as the portion of \( C \) from \( x \) to \( x' \) counterclockwise. We use \( |C(x, x')| \) to denote the length of \( C(x, x') \). Note that \( |x x'| = \min\{|C(x, x')|, |C(x', x)|\} \).

As in the line version, we first give some observations, based on which our algorithms will be developed.

### 3.3.1 Observations

For any two indices \( i \neq j \) in \([1, n]\), define

\[
w(i, j) = \left[(n + j - i) \mod n\right] \cdot \delta - |C(x_i, x_j)|.\]

In words, if \( i < j \), then \( w(i, j) = (j - i) \cdot \delta - |C(x_i, x_j)| \); otherwise, \( w(i, j) = (n + j - i) \cdot \delta - |C(x_i, x_j)| \). Since \( |C| \geq \delta \cdot n \), it can be verified that \( w(i, j) \leq |C| \).

As discussed in [34], there exists an optimal solution in which the order of all points of \( P \) is the same as that in the input configuration \( F_0 \). Using this property, we prove Lemma 3.3.1, which is analogous to Lemma 3.2.2 for the line version.

**Lemma 3.3.1**. \( d_{opt} \geq \max_{1 \leq i, j \leq n} \frac{w(i, j)}{2} \).
Lemma 3.2.3 for the line version.

Consider any optimal solution OPT in which the order of all points of P is the same as that in the input configuration $F_0$. For each $1 \leq k \leq n$, let $x_k^*$ be the location of $x_k$ in $OPT$.

Consider any two indices $i \neq j$ in $[1, n]$. To prove the lemma, the goal is to show that $d_{opt} \geq w(i, j)/2$. Depending on whether $i < j$, there are two cases. Below we only prove the case $i < j$, and the other case is very similar.

First of all, we claim that $|C(x_i^*, x_j^*)| \geq (j - i) \cdot \delta$. Indeed, consider any $k \in [i + 1, j]$. Since OPT is an optimal solution, $|x_{k-1}^* - x_k^*| \geq \delta$ holds. Because $|x_{k-1}^* - x_k^*| = \min\{|C(x_{k-1}^*, x_k^*)|, |C(x_k^*, x_{k-1}^*)|\}$, we obtain that $|C(x_k^*, x_{k-1}^*)| \geq \delta$. Since the order of the points of $P$ in OPT is the same as that in $F_0$, we have $C(x_i^*, x_j^*) = \bigcup_{k=i+1}^j C(x_k^*, x_{k-1}^*)$ and $|C(x_i^*, x_j^*)| = \sum_{k=i+1}^j |C(x_k^*, x_{k-1}^*)| \geq (j - i) \cdot \delta$. The claim is thus proved.

In the sequel, we prove $d_{opt} \geq w(i, j)/2 = [(j - i) \cdot \delta - |C(x_i, x_j)|]/2$.

If $|C(x_i^*, x_j^*)| - |C(x_i, x_j)| \leq 0$, then since $|C(x_i^*, x_j^*)| \geq (j - i) \cdot \delta$, it holds that $|C(x_i, x_j)| \geq (j - i) \cdot \delta$. Hence, $w(i, j) \leq 0$, and it follows that $d_{opt} \geq w(i, j)/2$.

If $|C(x_i^*, x_j^*)| - |C(x_i, x_j)| > 0$, then the difference of $|C(x_i^*, x_j^*)|$ and $|C(x_i, x_j)|$ is due to the moving of $p_i$ and $p_j$. Because the order of the points of $P$ in OPT is the same as that in $F_0$, the smallest moving distance of these two points happens when $x_i$ and $x_j$ move towards opposite directions (i.e., $x_i$ moves clockwise and $x_j$ moves counterclockwise) by the same distance $(|C(x_i^*, x_j^*)| - |C(x_i, x_j)|)/2$. Therefore, we obtain $\max\{|x_i - x_i^*|, |x_j - x_j^*|\} \geq (|C(x_i^*, x_j^*)| - |C(x_i, x_j)|)/2$. Since $d_{opt} \geq \max\{|x_i - x_i^*|, |x_j - x_j^*|\}$, it holds that $d_{opt} \geq (|C(x_i^*, x_j^*)| - |C(x_i, x_j)|)/2$. Finally, because $|C(x_i^*, x_j^*)| \geq (j - i) \cdot \delta$, we obtain $d_{opt} \geq w(i, j)/2$. 

Based on Lemma 3.3.1, we obtain the following lemma, which is analogous to Lemma 3.2.3 for the line version.

Lemma 3.3.2. If there exist $i \neq j$ in $[1, n]$ and a feasible configuration $F'$ in which each point $p_k \in P$ is at location $x_k^*$ such that $w(i, j) = \max_{1 \leq k \leq n} |C(x_k^*, x_k^*)|$, then we can obtain an optimal solution by shifting every point of $P$ in $F'$ clockwise by distance $w(i, j)/2$.

Proof. Let $F''$ denote the configuration obtained by shifting every point of $P$ in $F'$ clockwise by distance $w(i, j)/2$. 
Consider any point \( p_k \in P \). Let \( x_k'' \) denote the location of \( x_k \) in \( F'' \). On the one hand, 
\[ |C(x_k, x_k'')| \leq w(i, j) \] since \( w(i, j) = \max_{1 \leq k \leq n} |C(x_k, x_k')| \). On the other hand, since the above shifting moves \( p_k \) from \( x_k' \) clockwise to \( x_k'' \) by distance \( w(i, j)/2 \) (recall that \( w(i, j) \leq |C| \)), it holds that either 
\[ |C(x_k, x_k'')| \leq w(i, j)/2 \text{ or } |C(x_k', x_k)| \leq w(i, j)/2. \]
Consequently, 
\[ |x_k x_k''| = \min\{|C(x_k, x_k'')|, |C(x_k', x_k)|\} \leq w(i, j)/2. \]

The above shows that \( \max_{1 \leq k \leq n} |C(x_k, x_k'')| \leq w(i, j)/2 \), i.e., the maximum moving distance of all points of \( P \) in \( F'' \) is no more than \( w(i, j)/2 \). By Lemma 3.3.1, \( F'' \) is an optimal solution. The lemma is thus proved. \( \square \)

We call a feasible configuration that satisfies the condition in Lemma 3.3.2 a canonical configuration. In light of Lemma 3.3.2, to solve the problem in linear time, it is sufficient to find a canonical configuration in linear time, which is our focus below.

3.3.2 Computing a Canonical Configuration

In this section, we present a linear-time algorithm that can find a canonical configuration. Comparing with the original problem, now we only need to consider the counterclockwise movements.

Recall that the points \( p_1, p_2, \ldots, p_n \) are ordered on \( C \) counterclockwise in the input configuration \( F_0 \). For convenience of discussion, we define coordinates for locations on \( C \) in the following way. We define \( x_1 \) as the origin with coordinate zero. For any other location \( x \in C \), the coordinate of \( x \) is defined to be \( |C(x_1, x)| \). Hence each location of \( C \) has a coordinate no greater than \( |C| \).

Our algorithm has two rounds. In the first round, we will use the same approach as for the line version of the problem, and let \( F_1 \) denote the resulting configuration. However, the issue is that in \( F_1 \) the new location of \( p_n \) may be too close to \( p_1 \) or \( p_n \) may even “cross” \( p_1 \), which might make \( F_1 \) not feasible. If \( p_n \) does not cross \( p_1 \) and \( p_n \) is at least \( \delta \) away from \( p_1 \) in \( F_1 \), then we will show that \( F_1 \) is a canonical configuration. Otherwise, we will proceed to the second round, which is to (starting from the configuration \( F_1 \)) consider all points again from \( p_1 \) and use the same strategy to set the new locations of the points. We will show that the configuration \( F_2 \) obtained after the second round is a canonical configuration. The details are given below.
The first round

In the first round, we will move each point \( p_i \in P \) from \( x_i \) along \( C \) counterclockwise to a new location \( x_i' \). The way we set \( x_i' \) here is similar to that in the line version and the difference is that we have to take care of the cycle situation. Specifically, \( x_1' = x_1 \), i.e., \( p_1 \) does not move. For each \( i \in [2, n] \), suppose we have already moved \( p_{i-1} \) to \( x_{i-1}' \), then we define \( x_i' \) as follows:

\[
x_i' = \begin{cases} 
    x_i & \text{if } x_i \geq x_{i-1}' + \delta \\
    (x_{i-1}' + \delta \mod |C|) & \text{if } x_i < x_{i-1}' + \delta. 
\end{cases} \tag{3.1}
\]

This finishes the first round of our algorithm. Denote by \( F_1 \) the resulting configuration.

Note that if \( x_{i-1}' + \delta > |C| \), then since \( x_i \leq |C| \), according to Equation (3.1), \( x_i' = (x_{i-1}' + \delta \mod |C|) \), which is equal to \( x_{i-1}' + \delta - |C| \); in this case, we say that the counterclockwise movement of \( p_i \) crosses the origin \( x_1 \).

Lemma 3.3.3. If \( p_n \) does not cross \( x_1 \) (\( = x_1' \)) in the first round of the algorithm and \( |C(x_n', x_1')| \geq \delta \), then \( F_1 \) is a canonical configuration.

Proof. First of all, we show that \( F_1 \) is a feasible configuration, i.e., the distance between any two points of \( P \) in \( F_1 \) is at least \( \delta \). Consider any two indices \( i \) and \( j \). Without loss of generality, assume \( i < j \). Our goal is to show that \( |x_i'x_j'| \geq \delta \). To this end, it is sufficient to show that \( |C(x_i', x_j')| \geq \delta \) and \( |C(x_j', x_i')| \geq \delta \).

On the one hand, \( C(x_i', x_j') \) contains \( x_{i+1}' \), implying that \( C(x_i', x_{i+1}') \subseteq C(x_i', x_j') \) and thus \( |C(x_i', x_{i+1}')| \leq |C(x_i', x_j')| \). According to our first round algorithm (i.e., Equation (3.1)), it holds that \( |C(x_i', x_{i+1}')| \geq \delta \). Thus, \( |C(x_i', x_j')| \geq \delta \).

On the other hand, since \( p_n \) does not cross \( x_1 = x_1' \), \( C(x_j', x_i') \) contains both \( x_n' \) and \( x_1' \), and in other words, \( C(x_n', x_1') \subseteq C(x_j', x_i') \). Due to \( |C(x_n', x_1')| \geq \delta \), we obtain \( |C(x_j', x_i')| \geq |C(x_n', x_1')| \geq \delta \).

Therefore, \( F_1 \) is a feasible configuration.

Let \( d_{\text{max}}' \) be the maximum counterclockwise movement of all points of \( P \) in the first round, i.e., \( d_{\text{max}}' = \max_{1 \leq k \leq n} |C(x_k, x_k')| \). To show that \( F_1 \) is canonical configuration, we also need to show that there exist \( i \) and \( j \) such that \( d_{\text{max}}' = w(i, j) \). In the following,
we will find two indices \(i\) and \(j\) with \(i < j\) such that \(d_{\text{max}}^{\prime} = w(i, j)\). Recall that when \(i < j\), \(w(i, j) = (j - i) \cdot \delta - |C(x_i, x_j)|\).

Since the input configuration \(F_0\) is not feasible, it must hold that \(d_{\text{max}}^{\prime} > 0\). Let \(j\) be the index such that \(d_{\text{max}}^{\prime} = |C(x_j, x'_j)|\). Let \(i\) be the largest index such that \(i < j\) and \(x'_i = x_i\). Note that such an index \(i\) must exist since \(x_1 = x'_1\).

According to the definition of \(i\), each point \(x_k\) with \(i + 1 \leq k \leq j\) is moved in the first round algorithm, which implies that \(|C(x'_k, x'_k)| = \delta\) according to Equation (3.1). Hence, we obtain \(|C(x'_i, x'_j)| = \sum_{k=i+1}^j |C(x'_k, x'_k)| = (j - i) \cdot \delta\). On the other hand, since the movement of \(p_n\) does not cross \(x_1\) and \(p_i\) does not move, the movement of \(p_j\) does not cross \(x_1 = x'_i\). Thus, \(C(x'_i, x'_j) = C(x_i, x_j) \cup C(x_j, x'_i)\) and \(|C(x'_i, x'_j)| = |C(x_i, x_j)| + |C(x_j, x'_i)|\).

Therefore, we obtain \(d_{\text{max}}^{\prime} = |C(x_j, x'_j)| = |C(x'_i, x'_j)| - |C(x_i, x_j)| = (j - i) \cdot \delta - |C(x_i, x_j)| = w(i, j)\).

We conclude that \(F_1\) is a canonical configuration. \(\square\)

According to Lemma 3.3.3, if \(p_n\) does not cross \(x_1 = x'_1\) in the first round and \(|C(x'_n, x'_1)| \geq \delta\) in \(F_1\), then we have found a canonical configuration and our algorithm stops. Otherwise, we proceed to the second round, as follows.

The second round

In the second round, we will move each point \(p_i \in P\) from \(x'_i\) counterclockwise to a new location \(x''_i\), defined as follows.

We first define \(x''_1\). Recall that we proceed to the second round because either \(p_n\) crosses \(x_1 = x'_1\) in the first round or \(|C(x'_n, x'_1)| < \delta\). In either case we define

\[
x''_1 = (x'_n + \delta) \mod |C|.
\]  

(3.2)

Hence, \(|C(x'_n, x''_1)| = \delta\).

For each \(i = 2, 3, \ldots, n\), suppose \(p_{i-1}\) has been moved to \(x''_{i-1}\); then we move \(p_i\) from \(x'_i\) counterclockwise to \(x''_i\), with

\[
x''_i = \max\{x'_i, (x''_{i-1} + \delta) \mod |C|\}
\]  

(3.3)
This finishes the second round of our algorithm. Let $F_2$ be the resulting configuration. In the sequel we show that $F_2$ is a canonical configuration.

Recall that $|C| \geq n \cdot \delta$. We first have the following observation on the first round of the algorithm.

**Observation 3.3.4.** There must be a point $p_i$ with $i \in [2, n]$ such that $p_i$ does not move in the first round of the algorithm (i.e., $x_i = x'_i$).

**Proof.** Assume to the contrary that every point $p_i$ with $i \in [2, n]$ is moved in the first round. Then, by our first round algorithm (i.e., Equation (3.1)), $|C(x'_i, x'_i)| = \delta$ for each $2 \leq i \leq n$. Hence, $|C(x'_1, x'_n)| = \sum_{i=2}^{n} |C(x'_i, x'_i)| = (n - 1) \cdot \delta$. Further, since either $p_n$ crosses $x_1 = x'_1$ or $|C(x'_n, x'_1)| < \delta$, we obtain that $n \cdot \delta > |C|$, which contradicts with the fact that $|C| \geq n \cdot \delta$. \hfill \qed

**Observation 3.3.5.** If a point $p_i$ does not move in the second round, then for each point $p_j$ with $j \in [i, n]$, $p_j$ does not move in the second round either.

**Proof.** If $i = n$, then the observation trivially follows. We assume $i < n$.

According to the first round algorithm, it holds that $|C(x'_i, x'_i)| \geq \delta$ for any $i \in [2, n]$. Since $p_i$ does not move in the second round, $x''_i = x'_i$ holds. Due to $|C(x'_i, x'_{i+1})| \geq \delta$, according to our second round algorithm (e.g., Equation (3.3)), $x''_{i+1} = x'_{i+1}$. By the same reasoning, $x''_j = x'_j$ for any $j \in [i + 1, n]$, which leads to the observation. \hfill \qed

With Observations 3.3.4 and 3.3.5, we can prove the following lemma.

**Lemma 3.3.6.** Suppose $k$ is the largest index such that $p_k$ does not move in the first round of the algorithm; then $p_k$ does not move in the second round of the algorithm either, i.e., $x_k = x'_k = x''_k$.

**Proof.** According to the first round algorithm, it holds that $|C(x'_i, x'_i)| \geq \delta$ for any $i \in [2, n]$.

By Observation 3.3.4, $k \in [2, n]$. We first discuss the case where $k \in [3, n - 1]$. Indeed, this is the most general case. As shown later, the case where $k = 2$ or $k = n$ can be proved by similar but simpler techniques.
By the definition of \( k \), the points \( p_{k+1}, p_{k+2}, \ldots, p_n \) are moved in the first round. Hence, for each \( i \in [k + 1, n] \), according to our first round algorithm (i.e., Equation (3.1)), \(|C(x'_i - 1, x'_i)| = \delta\). Thus,

\[
|C(x'_k, x''_n)| = \sum_{i=k+1}^{n} |C(x'_i - 1, x'_i)| = (n - k) \cdot \delta.
\]  

(3.4)

Recall that \( p_1 \) is moved in the second round, and according to Equation (3.2),

\[
|C(x'_n, x''_1)| = \delta.
\]  

(3.5)

If there is any \( i \in [2, k - 1] \) such that \( p_i \) does not move in the second round, then by Observation 3.3.5, \( p_k \) does not move in the second round either, which leads to the lemma.

Otherwise, since every point \( p_i \) with \( i \in [2, k - 1] \) is moved in the second round, according to our second round algorithm (i.e., Equation (3.3)), \(|C(x''_{i-1}, x''_i)| = \delta\) holds. Hence, we obtain

\[
|C(x''_k, x''_{k-1})| = \sum_{i=2}^{k-1} |C(x''_i - 1, x''_i)| = (k - 2) \cdot \delta.
\]  

(3.6)

Based on Equations (3.4), (3.5), and (3.6), we obtain \(|C(x'_k, x''_k)| + |C(x'_n, x''_n)| + |C(x'_1, x''_{k-1})| = (n - 1) \cdot \delta\). This implies that in the second round the counterclockwise movement of \( p_{k-1} \) from \( x'_{k-1} \) to \( x''_{k-1} \) does not cross \( x_k = x'_k \), due to \(|C| \geq n \cdot \delta\). Further, \(|C(x''_{k-1}, x'_k)| = |C| - |C(x'_{k-1}, x'_{k-1})| = |C| - (|C(x'_k, x''_k)| + |C(x'_n, x''_n)| + |C(x'_1, x''_{k-1})|) = |C| - (n - 1) \cdot \delta \geq \delta\). According to our second round algorithm (i.e., Equation (3.3)), \( x''_k = x'_k \), i.e., \( p_k \) does not move in the second round.

The above proves the lemma for the case where \( k \in \{3, n - 1\} \).

If \( k = 2 \) or \( k = n \), the proof is very similar.

If \( k = 2 \), then we still have Equations (3.4) and (3.5). Thus, \(|C(x'_2, x''_n)| + |C(x'_n, x''_2)| = (n - 1) \cdot \delta\). This implies that in the second round the counterclockwise movement of \( p_1 \) from \( x'_1 \) to \( x''_1 \) does not cross \( x_2 = x'_2 \), due to \(|C| \geq n \cdot \delta\). Further, \(|C(x''_1, x'_2)| = |C| - (|C(x'_2, x''_n)| + |C(x'_n, x''_2)|) = |C| - (n - 1) \cdot \delta \geq \delta\). According
to our second round algorithm (i.e., Equation (3.3)), \(x''_2 = x'_2\), i.e., \(p_2\) does not move in the second round. Hence, the lemma is proved.

If \(k = n\), then we still have Equations (3.5) and (3.6). Thus, \(|C(x''_n, x''_1)| + |C(x''_1, x''_{n-1})| = (n - 1) \cdot \delta\). This implies that in the second round when \(p_{n-1}\) moved from \(x'_{n-1}\) to \(x''_{n-1}\), \(p_{n-1}\) does not cross \(x_n = x'_n\), due to \(|C| \geq n \cdot \delta\). Further, \(|C(x''_{n-1}, x''_n)| = |C| - |C(x''_n, x''_{n-1})|\) = \(|C| - (|C(x''_n, x'_1)| + |C(x''_1, x''_{n-1})|)\) = \(|C| - (n - 1) \cdot \delta \geq \delta\). According to our second round algorithm (i.e., Equation (3.3)), \(x''_n = x'_n\), i.e., \(p_n\) does not move in the second round. Hence, the lemma follows.

In summary, \(p_k\) does not move in the second round of the algorithm. \(\square\)

Recall that \(F_2\) is the configuration after the second round of the algorithm. Our goal is to prove that \(F_2\) is a canonical configuration. Based on the proof of Lemma 3.3.6, we have the following two corollaries.

**Corollary 3.3.7. The configuration \(F_2\) is feasible.**

**Proof.** Suppose \(p_k\) is the point specified in Lemma 3.3.6. Hence, \(k \in [2, n]\) and \(p_k\) does not move in the two rounds of our algorithm. We only prove the case where \(k \in [2, n - 1]\), and the case \(k = n\) can be proved by similar (but simpler) techniques.

After the first round, it holds that \(|C(x'_{i-1}, x'_i)| \geq \delta\) for each \(i \in [k + 1, n]\). Since \(x_k\) does not move in the second round, by Observation 3.3.5, \(x''_i = x'_i\) for any \(i \in [k, n]\). Hence, for each \(i \in [k + 1, n]\), it holds that \(|C(x''_{i-1}, x''_i)| \geq \delta\).

On the other hand, according to our second round algorithm, \(|C(x''_n, x''_1)| \geq \delta\) and \(|C(x''_{i-1}, x''_i)| \geq \delta\) for each \(i \in [2, k]\). Since \(x''_n = x''_1\), it holds that \(|C(x''_n, x''_1)| = |C(x''_n, x''_1)| \geq \delta\).

The above discussion leads to the following observation: \(x''_1, x''_2, \ldots, x''_n\) are ordered counterclockwise on \(C\), and further, for each \(i \in [2, n]\), \(|C(x''_{i-1}, x''_i)| \geq \delta\), and \(|C(x''_n, x''_1)| \geq \delta\).

To show that \(F_2\) is feasible, our goal is to prove that \(|x''_i x''_j| \geq \delta\) for any \(i \neq j \in [1, n]\). Consider any \(i \neq j \in [1, n]\). Without loss of generality, we assume \(i < j\). To prove \(|x''_i x''_j| \geq \delta\), it is sufficient to show that \(|C(x''_i, x''_j)| \geq \delta\) and \(|C(x''_j, x''_i)| \geq \delta\).
The above observation implies that $C(x_i', x_{i+1}') \subseteq C(x_i'', x_j')$ and $|C(x_i'', x_j')| \geq |C(x_i', x_{i+1}')| \geq \delta$. On the other hand, $C(x_n'', x_1') \subseteq C(x_j'', x_i')$. Since $|C(x_n'', x_1')| \geq \delta$, we have $|C(x_j'', x_i')| \geq |C(x_n'', x_1')| \geq \delta$.

Therefore, $|x_i''x_j''| \geq \delta$ holds. The corollary thus follows.

**Corollary 3.3.8.** The total counterclockwise moving distance of each point of $P$ in the two rounds of the algorithm is at most $|C| - \delta$, which implies that $|C(x_i', x_i'')| \leq |C| - \delta$ for each $1 \leq i \leq n$.

**Proof.** By Lemma 3.3.6, suppose $p_k$ does not move in the two rounds of our algorithm. For each other point $p_i$ with $i \neq k$, since $p_k$ does not move in the algorithm, the counterclockwise movement of $p_i$ in the two rounds of the algorithm does not cross $x_k$.

Further, as shown in the proof of Corollary 3.3.7, both $|C(x_k', x_i'')| \geq \delta$ and $|C(x_i'', x_k')| \geq \delta$ hold. Hence, the maximum counterclockwise movement of $p_i$ in the two rounds is no more than $|C| - \delta$. The corollary follows.

Finally, the next lemma shows that $F_2$ is a canonical configuration.

**Lemma 3.3.9.** The configuration $F_2$ is a canonical configuration.

**Proof.** Corollary 3.3.7 has already shown that $F_2$ is a feasible configuration. To prove the lemma, it is sufficient to prove that there exist $i$ and $j$ in $[1, n]$ such that $d_{\text{max}} = w(i, j)$, where $d_{\text{max}} = \max_{1 \leq k \leq n} |C(x_k', x_k'')|$.

Let $j$ be the index such that $d_{\text{max}} = |C(x_j', x_j'')|$. We define another index $i$ as follows. If $j = 1$, or $j > 1$ but all points of $p_1, p_2, \ldots, p_{j-1}$ are moved in the two rounds of the algorithm, let $i$ be the largest index in $[j + 1, n]$ such that $p_i$ does not move in the two rounds of the algorithm; otherwise (i.e., $j > 1$ and at least one point of $p_1, p_2, \ldots, p_{j-1}$ does not move in the two rounds of the algorithm), let $i$ be the largest index in $[1, j - 1]$ such that $p_i$ does not move in the two rounds of the algorithm. By Lemma 3.3.6, such an index $i$ must exist. In the following, we prove that $d_{\text{max}} = w(i, j)$.

Depending on whether $i \in [1, j - 1]$ or $i \in [j + 1, n]$, there are two cases.

1. If $i \in [1, j - 1]$, then by the definition of $i$, all points $p_{i+1}, p_{i+2}, \ldots, p_j$ are moved in the algorithm. Since $p_i$ does not move in the second round, by Observation 3.3.5, for each $k \in [i + 1, n]$, $x_k$ does not move in the second round. This implies
that every point of \( p_{i+1}, p_{i+2}, \ldots, p_j \) is moved in the first round of the algorithm. According to our first round algorithm, \( |C(x'_{k-1}, x'_k)| = \delta \) for each \( k \in [i+1, j] \).

Hence, \( |C(x_i, x''_j)| = |C(x''_j, x''_j)| = \sum_{k=i+1}^{j} |C(x''_{k-1}, x''_k)| = (j - i) \cdot \delta \) (because \( x''_k = x''_k \) for each \( k \in [i, n] \)).

Since \( i < j \) and \( x_i = x'_i = x''_i, C(x_i, x''_j) = C(x_i, x_j) \cup C(x_j, x''_j) \). Thus, \( |C(x_j, x''_j)| = |C(x_i, x''_j)| - |C(x_i, x_j)| = (j - i) \cdot \delta - |C(x_i, x_j)| \), which is equal to \( w(i, j) \) since \( i < j \).

Hence, the lemma is proved for this case.

2. If \( i \in [j + 1, n] \), we only discuss the general case where \( i < n \). The special case where \( i = n \) can be proved by similar (but simpler) techniques.

Consider any point \( p_k \) with \( k \in [i+1, n] \). Since \( p_i \) does not move in the two rounds of the algorithm, by Observation 3.3.5, \( p_k \) does not move in the second round.

According to the definition of \( i \), \( p_k \) is moved in the algorithm. Hence, \( p_k \) is moved in the first round. According to our first round algorithm (i.e., Equation (3.1)), \( |C(x'_{k-1}, x'_k)| = \delta. \) Further, since \( x''_k = x'_k \), \( |C(x''_{k-1}, x''_k)| = \delta \) holds. Therefore, \( |C(x''_k, x''_n)| = \sum_{k=i+1}^{n} |C(x''_{k-1}, x''_k)| = (n - i) \cdot \delta. \)

Since \( p_1 \) is moved in the second round, by Equation (3.2), \( |C(x''_1, x''_1)| = \delta. \) We have shown above that \( p_k \) does not move in the second round for any \( k \in [i+1, n] \).

Hence, \( x''_n = x'_n \) and \( |C(x''_n, x''_1)| = \delta. \)

If \( j = 1 \), then \( |C(x''_1, x''_1)| = |C(x''_1, x''_1)| + |C(x''_n, x''_1)| = (n + 1 - i) \cdot \delta. \) Further, since \( p_i \) does not move in the algorithm (i.e., \( x''_i = x''_i = x_1 \)), \( d_{\text{max}} = |C(x_1, x''_1)| = |C(x_i, x''_1)| - |C(x_1, x_1)| = (n + 1 - i) \cdot \delta - |C(x_i, x_1)| \), which is equal to \( w(i, 1) \). The lemma thus follows.

In the following, we discuss the case \( j > 1 \).

Consider any point \( p_k \) with \( k \in [2, j] \).

We claim that \( p_k \) is moved in the second round (i.e., \( x''_k \neq x''_k \)). We prove the claim by induction. Indeed, by the definition of \( i \), \( p_k \) is moved in the two rounds of the algorithm. Recall that \( p_1 \) is moved in the second round. For any \( k \in [2, j] \), suppose \( p_{k-1} \) is moved in the second round. Assume to the contrary that \( p_k \) does not move
in the second round. Then, \( p_k \) must be moved in the first round. According to our first round algorithm (i.e., Equation (3.1)), \(|C(x'_{k-1}, x'_k)| = \delta\). Since \( p_{k-1} \) is moved in the second round, \( p_k \) must be moved as well.

In light of the above claim and according to our second round algorithm, \(|C(x''_{k-1}, x''_k)| = \delta\) for each \( k \in [2, j] \). Therefore, we derive \(|C(x''_1, x''_j)| = \sum_{k=2}^j |C(x''_{k-1}, x''_k)| = (j - 1) \cdot \delta\).

Based on the above discussions, \(|C(x''_i, x''_j)| = |C(x''_i, x''_n)| + |C(x''_n, x''_j)| + |C(x''_1, x''_j)| = (n + j - i) \cdot \delta\). Since \( x_i = x''_i \), \( d_{\text{max}} = |C(x_j, x'_j)| = |C(x_i, x'_j)| - |C(x_i, x_j)| = (n + j - i) \cdot \delta - |C(x_i, x_j)| \), which is equal to \( w(i, j) \).

As a summary, \( F_2 \) is a canonical configuration. \( \square \)

Clearly, both rounds of our algorithm run in \( O(n) \) time. Combining Lemmas 3.3.2, 3.3.3, and 3.3.9, we have the following result.

**Theorem 3.3.10.** The cycle version of the points-spreading problem is solvable in \( O(n) \) time.

**Remark:** One may verify that our algorithm for computing the canonical configuration \( F_2 \) essentially solves the following one-direction case of the cycle version problem: Move the points of \( P \) counterclockwise such that any pair of points of \( P \) are at least \( \delta \) away from each other and the maximum counterclockwise moving distance of all points of \( P \) is minimized.

### 3.4 The Facility-Location Movement Problem

In this section, we present our linear-time algorithm for the facility-location movement problem. In this problem, we are given a set \( S \) of \( k \) “server” points and a set \( Q \) of \( n \) “client” points sorted on a line \( L \), and the goal is to move all servers and clients on \( L \) such that each client co-locates with a server and the maximum moving distance of all servers and clients is minimized.

As shown by Dumitrescu and Jiang [34], the problem is equivalent to finding \( k \) intervals (i.e., line segments) on \( L \) such that each interval contains at least one server, each client is covered by at least one interval, and the maximum length of these intervals
is minimized. In the following, we will focus on solving this interval coverage problem (also called constrained \( k \)-center problem in [34]).

Dumitrescu and Jiang [34] presented an \( O((n+k)\log(n+k)) \) time algorithm using dynamic programming. We discover a monotonicity property on their dynamic programming scheme, and consequently improve their algorithm to \( O(n+k) \) time. Below, we first review the algorithm in [34] and then show our improvement.

3.4.1 Preliminaries

Without loss of generality, we assume \( L \) is the \( x \)-axis. For any two points \( p \) and \( q \) on \( L \) with \( p \) to the left of \( q \), we use \([p, q]\) to denote the interval on \( L \) with left endpoint at \( p \) and right endpoint at \( q \). An easy observation is that there exists an optimal solution consisting of \( k \) intervals in \( \{[p, q] \mid p, q \in S \cup P\} \). For any two points \( p \) and \( q \) on \( L \), let \( d(p, q) \) denote the distance between them.

Let \( S = \{s_1, s_2, \ldots, s_k\} \) be the set of servers sorted on \( L \) from left to right. Let \( Q = \{q_1, q_2, \ldots, q_n\} \) be the set of clients sorted on \( L \) from left to right. For ease of exposition, we assume no two points in \( S \cup Q \) are at the same location.

The servers of \( S \) partition the clients of \( Q \) into \( k+1 \) subsets, defined as follows. For each \( i \in [1, k-1] \), let \( Q_i \) be the subset of the clients of \( Q \) between \( s_i \) and \( s_{i+1} \) on \( L \). In addition, we let \( Q_0 \) be the subset of the clients of \( Q \) to the left of \( s_1 \), and let \( Q_k \) be the subset of the clients of \( Q \) to the right of \( s_k \). Since both \( S \) and \( Q \) are already given sorted, we can obtain the subsets \( Q_0, Q_1, \ldots, Q_k \) in \( O(n+k) \) time. In the following, for simplicity of discussion, we assume \( Q_i \) is not empty for each \( i \in [0, k] \). This implies that the rightmost client \( q_n \) is to the right of the rightmost server \( s_k \) and the leftmost client \( q_1 \) is to the left of the leftmost server \( s_1 \). For each \( i \in [1, k] \), let \( Q'_i = \{s_i\} \cup Q_i \).

3.4.2 A Dynamic Programming Algorithm

Consider any \( Q'_i \) with \( 1 \leq i \leq k \). Let \( q \) be any point in \( Q'_i \). Consider the subproblem at \( q \): Finding \( i \) intervals on \( L \) such that each interval contains at least one server of \( \{s_1, s_2, \ldots, s_i\} \), each client to the left of \( q \) (including \( q \) if \( q \neq s_i \)) must be covered by at least one interval, and the maximum length of these \( i \) intervals is minimized. Define \( \alpha(q) \) as the maximum length of the intervals in an optimal solution of the above subproblem

\[
\alpha(q) = \max \{d(s, q) \mid s \in \{s_1, s_2, \ldots, s_i\}\}
\]
at $q$. Our goal for the interval coverage problem is to solve the subproblem at $q_n$ and compute the value $\alpha(q_n)$.

For any point $q \in S \cup Q$, we use $r(q)$ to denote right neighboring point of $q$ on $L$ in $S \cup Q$ (i.e., the closest point of $S \cup Q$ to $q$ strictly to the right of $q$). Note that after merging $S$ and $Q$ into one sorted list, we can obtain $r(q)$ for each $q \in S \cup Q$ in constant time.

Initially, for each $q \in Q'_1$, $\alpha(q) = d(q_1, q)$ (recall that $q_1$ is to the left of $s_1$).

In general, consider any $q \in Q'_i$ for any $2 \leq i \leq k$. It holds that

$$\alpha(q) = \min_{q' \in Q'_{i-1}} \max\{\alpha(q'), d(r(q'), q)\}.$$ 

In words, in order to solve the subproblem at $q$, we use the $i - 1$ intervals for the subproblem at $q'$ along with an additional interval $[r(q'), q]$. To compute $\alpha(q)$, Dumitrescu and Jiang [34] used the following observation: As we consider the points $q'$ of $Q'_{i-1}$ from left to right, $\alpha(q')$ is monotonically increasing and $d(r(q'), q)$ is monotonically decreasing. Hence, if $\alpha(q')$ for all $q' \in Q'_{i-1}$ are known, $\alpha(q)$ can be computed in $O(\log |Q'_{i-1}|)$ time by binary search.

In this way, the value $\alpha(q_n)$ can be computed in $O((n + k) \log(n + k))$ time (more precisely, $O((n + k) \log n)$ time) and an optimal solution can be found correspondingly.

### 3.4.3 An Improved Implementation

We give an $O(n + k)$ time implementation for the above dynamic programming scheme. To this end, we find a new monotonicity property in Lemma 3.4.1.

Consider any point $q \in Q'_i$ such that $r(q)$ is still in $Q'_i$. For any point $q' \in Q'_{i-1}$, define $f(q') = \max\{\alpha(q'), d(r(q'), q)\}$. Hence, $\alpha(q) = \min_{q' \in Q'_{i-1}} f(q')$. Let $g(q)$ be the point in $Q'_{i-1}$ such that $\alpha(q) = f(g(q))$ (if there is more than one such point, we let $g(q)$ refer to the rightmost one).

**Lemma 3.4.1.** Either $g(r(q)) = g(q)$ or $g(r(q))$ is strictly to the right of $g(q)$.

**Proof.** We only give an “intuitive” proof. Recall that as we consider the points $q'$ of $Q'_{i-1}$ from left to right, $\alpha(q')$ is monotonically increasing and $d(r(q'), q)$ is monotonically decreasing. Intuitively, $g(q)$ corresponds to the intersection of the two functions $\alpha(q')$.
and \(d(r(q'), q)\) for \(q' \in Q'_{i-1}\) (e.g., see Fig. 3.2). Similarly, for the point \(r(q)\), which is still in \(Q'_i\), \(g(r(q))\) corresponds to the intersection of the two functions \(\alpha(q')\) and \(d(r(q'), r(q))\) for \(q' \in Q'_{i-1}\). An observation is that we can obtain the function \(d(r(q'), r(q))\) by shifting \(d(r(q'), q)\) upwards by the value \(d(q, r(q))\) (e.g., see Fig. 3.2). This implies that \(g(r(q))\) cannot be strictly to the left of \(g(q)\). The lemma thus follows.

\[\square\]

Lemma 3.4.1 essentially says that if we consider all points \(q \in Q'_i\) from left to right, then \(g(q)\) in \(Q'_{i-1}\) are also sorted on \(L\) from left to right. Due to this monotonicity property on \(g(q)\), we can compute \(g(q)\) and \(\alpha(q)\) for all \(q \in Q'_i\) in a total of \(O(|Q'_{i-1}| + |Q'_i|)\) time by scanning the points of \(Q'_{i-1}\) from left to right. More specifically, suppose we have computed \(g(q)\) and \(\alpha(q)\) for some \(q \in Q'_i\); then if \(r(q)\) is still in \(Q'_i\), we can compute \(g(r(q))\) and \(\alpha(r(q))\) by scanning the points of \(Q'_{i-1}\) starting from \(g(q)\) to the right.

In this way, the value \(\alpha(q_n)\) can be computed in \(O(n + k)\) time, and an optimal solution can be found correspondingly. Hence, we have the following theorem.

**Theorem 3.4.2.** *If all servers and clients are sorted on the line \(L\), then the facility-location movement problem can be solved in \(O(n + k)\) time.*

As an application, our algorithm for Theorem 3.4.2 can be used to solve the cycle version of the same problem, where all servers and clients are given on a cycle. Dumitrescu and Jiang [34] showed that the cycle version can be solved by solving at most \((n + k)/k\) instances of the above line version of the problem (more specifically, there must be an adjacent pair of servers such that there are at most \(n/k\) clients between them; cutting the cycle between each adjacent pair of the above clients will result in an instance of the line version, with a total of no more than \((n + k)/k\) instances). By using their line-version algorithm of \(O((n + k) \log(n + k))\) time, Dumitrescu and Jiang [34]
solved the cycle version of the problem in $O(\frac{1}{k}(n+k)^2 \log(n+k))$ time. By applying our improved algorithm for the line version, the cycle version can be solved in $O(\frac{1}{k}(n+k)^2)$ time.
CHAPTER 4

DISPERSING POINTS ON INTERVALS

4.1 Introduction

The problems of dispersing points have been extensively studied and can be classified to different categories by their different constraints and objectives, e.g., [41, 42, 45–48]. In this chapter, we consider problems of dispersing points on intervals in linear domains including lines and cycles. The results in this chapter have been published in a conference [20] and a journal [21].

4.1.1 Problem Definitions and Our Results

Let $I$ be a set of $n$ intervals on a line $\ell$, and no two intervals of $I$ intersect. The problem is to find a point in each interval of $I$ such that the minimum distance of any pair of points is maximized. We assume the intervals of $I$ are given sorted on $\ell$. In this chapter we present an $O(n)$ time algorithm for this problem.

As an application of the problem, consider the following scenario. Suppose we are given $n$ pairwise disjoint intervals on $\ell$ and we want to build a facility on each interval. As the facilities can interfere with each other if they are too close (e.g., if the facilities are hazardous), the goal is to choose locations for these facilities such that the minimum pairwise distance among these facilities is minimized. Clearly, this is an instance of our problem.

We also consider the cycle version of the problem where the intervals of $I$ are given on a cycle $C$. The intervals of $I$ are also pairwise disjoint and are given sorted cyclically on $C$. Note that the distance of two points on $C$ is the length of the shorter arc of $C$ between the two points. By making use of our “line version” algorithm, we solve this cycle version problem in linear time as well.
4.1.2 Related Work

To the best of our knowledge, we have not found any previous work on the two problems studied in this chapter. Our problems essentially belong to a family of geometric dispersion problems, which are NP-hard in general in two and higher dimensional space. For example, Baur and Fekete [49] studied the problems of distributing a number of points within a polygonal region such that the points are dispersed far away from each other, and they showed that the problems cannot be approximated arbitrarily well in polynomial time, unless P=NP.

Wang and Kuo [42] considered the following two problems. Given a set $S$ of points and a value $d$, find a largest subset of $S$ in which the distance of any two points is at least $d$. Given a set $S$ of points and an integer $k$, find a subset of $k$ points of $S$ to maximize the minimum distance of all pairs of points in the subset. It was shown in [42] that both problems in 2D are NP-hard but can be solved efficiently in 1D. Refer to [50–54] for other geometric dispersion problems. Dispersion problems in various non-geometric settings were also considered [41,45–48]. These problems are in general NP-hard; approximation and heuristic algorithms were proposed for them.

On the other hand, problems on intervals usually have applications in other areas. For example, some problems on intervals are related to scheduling because the time period between the release time and the deadline of a job or task in scheduling problems can be considered as an interval on the line. From the interval point of view, Garey et al. [6] studied the following problem on intervals: Given $n$ intervals on a line, determine whether it is possible to find a unit-length sub-interval in each input interval, such that these sub-intervals do not intersect. An $O(n \log n)$ time algorithm was given in [6] for this problem. The optimization version of the above problem was also studied [55,56], where the goal is to find a maximum number of intervals that contain non-intersecting unit-length sub-intervals. Chrobak et al. [55] gave an $O(n^5)$ time algorithm for the problem, and later Vakhania [56] improved the algorithm to $O(n^2 \log n)$ time. The online version of the problem was also considered [5]. Other optimization problems on intervals have also been considered, e.g., see [6,8,10,11].
4.1.3 Our Approach

For the line version of the problem, our algorithm is based on a greedy strategy. We consider the intervals of $\mathcal{I}$ incrementally from left to right, and for each interval, we will “temporarily” determine a point in the interval. During the algorithm, we maintain a value $d_{\text{min}}$, which is the minimum pairwise distance of the “temporary” points that so far have been computed. Initially, we put a point at the left endpoint of the first interval and set $d_{\text{min}} = \infty$. During the algorithm, the value $d_{\text{min}}$ will be monotonically decreasing. In general, when the next interval is considered, if it is possible to put a point in the interval without decreasing $d_{\text{min}}$, then we put such a point as far left as possible. Otherwise, we put a point on the right endpoint of the interval. In the latter case, we also need to adjust the points that have been determined temporarily in the previous intervals that have been considered. We adjust these points in a greedy way such that $d_{\text{min}}$ decreases the least. A straightforward implementation of this approach can only give an $O(n^2)$ time algorithm. In order to achieve the $O(n)$ time performance, during the algorithm we maintain a “critical list” $\mathcal{L}$ of intervals, which is a subset of intervals that have been considered. This list has some properties that help us implement the algorithm in $O(n)$ time.

We should point out that our algorithm is fairly simple and easy to implement. In contrast, the rationale of the idea is quite involved and it is not an easy task to argue its correctness. Indeed, discovering the critical list is the most challenging work and it is the key idea for solving the problem in linear time.

To solve the cycle version, the main idea is to convert the problem to a problem instance on a line and then apply our line version algorithm. More specifically, we make two copies of the intervals of $\mathcal{I}$ to a line and then apply our line version algorithm on these $2n$ intervals on the line. The line version algorithm will find $2n$ points in these intervals and we show that a particular subset of $n$ consecutive points of them correspond to an optimal solution for the original problem on $\mathcal{C}$.

In the following, we will present our algorithms for the line version in Section 4.2. The cycle version is discussed in Section 4.3. Section 4.4 concludes.
4.2 The Line Version

Let $I = \{I_1, I_2, \ldots, I_n\}$ be the set of intervals sorted from left to right on $\ell$. For any two points of $p$ and $q$ on $\ell$, we use $|pq|$ to denote their distance. Our goal is to find a point $p_i$ in $I_i$ for each $1 \leq i \leq n$, such that the minimum pairwise distance of these points, i.e., $\min_{1 \leq i < j \leq n} |p_ip_j|$, is maximized.

For each interval $I_i$, $1 \leq i \leq n$, we use $l_i$ and $r_i$ to denote its left and right endpoints, respectively. We assume $\ell$ is the $x$-axis. With a little abuse of notation, for any point $p \in \ell$, depending on the context, $p$ may also refer to its coordinate on $\ell$. Therefore, for each $1 \leq i \leq n$, it is required that $l_i \leq p_i \leq r_i$.

For simplicity of discussion, we make a general position assumption that no two endpoints of the intervals of $I$ have the same location (our algorithm can be easily extended to the general case). Note that this implies $l_i < r_i$ for any interval $I_i$.

The rest of this section is organized as follows. In Section 4.2.1, we discuss some observations. In Section 4.2.2, we give an overview of our algorithm. The details of the algorithm are presented in Section 4.2.3. Finally, we discuss the correctness and analyze the running time in Section 4.2.4.

4.2.1 Observations

Let $P = \{p_1, p_2, \ldots, p_n\}$ be the set of sought points. Since all intervals are disjoint, $p_1 < p_2 < \ldots < p_n$. Note that the minimum pairwise distance of the points of $P$ is also the minimum distance of all pairs of adjacent points.

Denote by $d_{opt}$ the minimum pairwise distance of $P$ in an optimal solution, and $d_{opt}$ is called the optimal objective value. We have the following lemma.

**Lemma 4.2.1.** $d_{opt} \leq \frac{r_j - l_i}{j - i}$ for any $1 \leq i < j \leq n$.

**Proof.** Assume to the contrary that this is not true. Then there exist $i$ and $j$ with $i < j$ such that $d_{opt} > \frac{r_j - l_i}{j - i}$. Consider any optimal solution OPT. Note that in OPT, $p_i, p_{i+1}, \ldots, p_j$ are located in the intervals $I_i, I_{i+1}, \ldots, I_j$, respectively, and $|p_ip_j| \geq d_{opt} \cdot (j - i)$. Hence, $|p_ip_j| > r_j - l_i$. On the other hand, since $l_i \leq p_i$ and $p_j \leq r_j$, it holds that $|p_ip_j| \leq r_j - l_i$. We thus obtain contradiction. 

The preceding lemma leads to the following corollary.
Corollary 4.2.2. Suppose we find a solution (i.e., a way to place the points of $P$) in which the minimum pairwise distance of $P$ is equal to $\frac{r_j - l_i}{j - i}$ for some $1 \leq i < j \leq n$. Then the solution is an optimal solution.

Our algorithm will find such a solution as stated in the corollary.

4.2.2 The Algorithm Overview

Our algorithm will consider and process the intervals of $I$ one by one from left to right. Whenever an interval $I_i$ is processed, we will “temporarily” determine $p_i$ in $I_i$. We say “temporarily” because later the algorithm may change the location of $p_i$.

During the algorithm, a value $d_{\text{min}}$ and two indices $i^*$ and $j^*$ will be maintained such that $d_{\text{min}} = (r_{j^*} - l_{i^*})/(j^* - i^*)$ always holds.

Initially, we set $p_1 = l_1$ and $d_{\text{min}} = \infty$, with $i^* = j^* = 1$. In general, suppose the first $i - 1$ intervals have been processed; then $d_{\text{min}}$ is equal to the minimum pairwise distance of the points $p_1, p_2, \ldots, p_{i-1}$, which have been temporarily determined. In fact, $d_{\text{min}}$ is the optimal objective value for the sub-problem on the first $i - 1$ intervals.

During the execution of algorithm, $d_{\text{min}}$ will be monotonically decreasing. After all intervals are processed, $d_{\text{min}}$ is $d_{\text{opt}}$. When we process the next interval $I_i$, we temporarily determine $p_i$ in a greedy manner as follows. If $p_{i-1} + d_{\text{min}} \leq l_i$, we put $p_i$ at $l_i$. If $l_i < p_{i-1} + d_{\text{min}} \leq r_i$, we put $p_i$ at $p_{i-1} + d_{\text{min}}$. If $p_{i-1} + d_{\text{min}} > r_i$, we put $p_i$ at $r_i$. In the first two cases, $d_{\text{min}}$ does not change. In the third case, however, $d_{\text{min}}$ will decrease.

Further, in the third case, in order to make the decrease of $d_{\text{min}}$ as small as possible, we need to move some points of $\{p_1, p_2, \ldots, p_{i-1}\}$ leftwards. By a straightforward approach, this moving procedure can be done in $O(n)$ time. But this will make the entire algorithm run in $O(n^2)$ time.

To have any hope of obtaining an $O(n)$ time algorithm, we need to perform the above moving “implicitly” in $O(1)$ amortized time. To this end, we need to find a way to answer the following question: Which points of $p_1, p_2, \ldots, p_{i-1}$ should move leftwards and how far should they move? To answer the question, the crux of our algorithm is to maintain a “critical list” $L$ of interval indices, which bears some important properties that eventually help us implement our algorithm in $O(n)$ time.
In fact, our algorithm is fairly simple. The most “complicated” part is to use a linked list to store \( L \) so that the following three operations on \( L \) can be performed in constant time each: remove the front element; remove the rear element; add a new element to the rear. Refer to Algorithm 1 for the pseudocode.

Although the algorithm is simple, the rationale of the idea is rather involved and it is also not obvious to see the correctness. Indeed, discovering the critical list is the most challenging task and the key idea for designing our linear time algorithm. To help in understanding and give some intuition, below we use an example of only three intervals to illustrate how the algorithm works.

Initially, we set \( p_1 = l_1, d_{\text{min}} = \infty, i^* = j^* = 1, \) and \( L = \{1\} \).

To process \( I_2 \), we first try to put \( p_2 \) at \( p_1 + d_{\text{min}} \). Clearly, \( p_1 + d_{\text{min}} > r_2 \). Hence, we put \( p_2 \) at \( r_2 \). Since \( p_1 \) is already at \( l_1 \), which is the leftmost point of \( I_1 \), we do not need to move it. We update \( j^* = 2 \) and \( d_{\text{min}} = r_2 - l_1 \). Finally, we add 2 to the rear of \( L \). This finishes the processing of \( I_2 \).

Next we process \( I_3 \). We try to put \( p_3 \) at \( p_2 + d_{\text{min}} \). Depending on whether \( p_2 + d_{\text{min}} \) is to the left of \( I_3 \), in \( I_3 \), or to the right of \( I_3 \), there are three cases (e.g., see Fig. 4.1).

1. If \( p_2 + d_{\text{min}} \leq l_3 \), we set \( p_3 = l_3 \). We reset \( L \) to \( \{3\} \). None of \( d_{\text{min}}, i^* \), and \( j^* \) needs to be changed in this case.

2. If \( l_3 < p_2 + d_{\text{min}} \leq r_3 \), we set \( p_3 = p_2 + d_{\text{min}} \). None of \( d_{\text{min}}, i^* \), and \( j^* \) needs to be changed. Further, the critical list \( L \) is updated as follows.

We first give some “motivation” on why we need to update \( L \). Assume later in the algorithm, say, when we process the next interval, we need to move both \( p_2 \) and \( p_3 \) leftwards simultaneously so that \( |p_1 p_2| = |p_2 p_3| \) during the moving (this is for making \( d_{\text{min}} \) as large as possible). The moving procedure stops once either \( p_2 \)
arrives at $l_2$ or $p_3$ arrives at $l_3$. To determine which case happens first, it suffices to determine whether $l_2 - l_1 > \frac{l_3 - l_1}{2}$.

(a) If $l_2 - l_1 > \frac{l_3 - l_1}{2}$, then $p_2$ will arrive at $l_2$ first, after which $p_2$ cannot move leftwards any more in the rest of the algorithm but $p_3$ can still move leftwards.

(b) Otherwise, $p_3$ will arrive at $l_3$ first, after which $p_3$ cannot move leftwards any more. However, although $p_2$ can still move leftwards, doing that would not help in making $d_{\min}$ larger.

We therefore update $\mathcal{L}$ as follows. If $l_2 - l_1 > \frac{l_3 - l_1}{2}$, we add 3 to the rear of $\mathcal{L}$. Otherwise, we first remove 2 from the rear of $\mathcal{L}$ and then add 3 to the rear.

3. If $r_3 < p_2 + d_{\min}$, we set $p_3 = r_3$. Since $|p_2p_3| < d_{\min}$, $d_{\min}$ needs to be decreased.

To make $d_{\min}$ as large as possible, we will move $p_2$ leftwards until either $|p_1p_2|$ becomes equal to $|p_2p_3|$ or $p_2$ arrives at $l_2$. To determine which event happens first, we only need to check whether $l_2 - l_1 > \frac{r_3 - l_1}{2}$.

(a) If $l_2 - l_1 > \frac{r_3 - l_1}{2}$, the latter event happens first. We set $p_2 = l_2$ and update $d_{\min} = r_3 - l_2$ ($= |p_2p_3|$), $i^* = 2$, and $j^* = 3$. Finally, we remove 1 from the front of $\mathcal{L}$ and add 3 to the rear of $\mathcal{L}$, after which $\mathcal{L} = \{2, 3\}$.

(b) Otherwise, the former event happens first. We set $p_2 = l_1 + \frac{r_3 - l_1}{2}$ and update $d_{\min} = (r_3 - l_1)/2$ ($= |p_1p_2| = |p_2p_3|$) and $j^* = 3$ ($i^*$ is still 1). Finally, we update $\mathcal{L}$ in the same way as the above second case. Namely, if $l_2 - l_1 > \frac{r_3 - l_1}{2}$, we add 3 to the rear of $\mathcal{L}$; otherwise, we remove 2 from $\mathcal{L}$ and add 3 to the rear.

One may verify that in any case the above obtained $d_{\min}$ is an optimal objective value for the three intervals.

As another example, Fig. 4.2 illustrates the solution found by our algorithm on six intervals.

4.2.3 The Algorithm

We are ready to present the details of our algorithm. For any two indices $i < j$, let $P(i, j) = \{p_i, p_{i+1}, \ldots, p_j\}$.
Initially we set $p_1 = l_1$, $d_{\text{min}} = \infty$, $i^* = j^* = 1$, and $\mathcal{L} = \{1\}$. Suppose interval $i - 1$ has just been processed for some $i > 1$. Let the current critical list be $\mathcal{L} = \{k_s, k_{s+1}, \ldots, k_t\}$ with $1 \leq k_s < k_{s+1} < \cdots < k_t \leq i - 1$, i.e., $\mathcal{L}$ consists of $t - s + 1$ sorted indices in $[1, i - 1]$. Our algorithm maintains the following invariants.

1. The “temporary” location of $p_{i-1}$ is known.
2. $d_{\text{min}} = (r_{j^*} - l_{i^*})/(j^* - i^*)$ with $1 \leq i^* \leq j^* \leq i - 1$.
3. $k_t = i - 1$.
4. $p_{k_s} = l_{k_s}$, i.e., $p_{k_s}$ is at the left endpoint of the interval $I_{k_s}$.
5. The locations of all points of $P(1, k_s)$ have been explicitly computed and finalized (i.e., they will never be changed in the later algorithm).
6. For each $1 \leq j \leq k_s$, $p_j$ is in $I_j$.
7. The distance of every pair of adjacent points of $P(1, k_s)$ is at least $d_{\text{min}}$.
8. For each $j$ with $k_s + 1 \leq j \leq i - 1$, $p_j$ is “implicitly” set to $l_{k_s} + d_{\text{min}} \cdot (j - k_s)$ and $p_j \in I_j$. In other words, the distance of every pair of adjacent points of $P(k_s, i - 1)$ is exactly $d_{\text{min}}$.
9. The critical list $\mathcal{L}$ has the following priority property: If $\mathcal{L}$ has more than one element (i.e., $s < t$), then for any $h$ with $s \leq h \leq t - 1$, Inequality (4.1) holds for any $j$ with $k_h + 1 \leq j \leq i - 1$ and $j \neq k_h + 1$.

$$\frac{l_{k_{h+1}} - l_{k_h}}{k_{h+1} - k_h} > \frac{l_j - l_{k_h}}{j - k_h}.$$  \hfill (4.1)

We give some intuition on what the priority property implies. Suppose we move all points in $P(k_s + 1, i - 1)$ leftwards simultaneously such that the distances between
all adjacent pairs of points of \( P(k_s, i - 1) \) keep the same (by the above eighth invariant, they are the same before the moving). Then, Inequality (4.1) with \( h = s \) implies that \( p_{k + 1} \) is the first point of \( P(k_s + 1, i - 1) \) that arrives at the left endpoint of its interval. Once \( p_{k + 1} \) arrives at the interval left endpoint, suppose we continue to move the points of \( P(k_s + 1, i - 1) \) leftwards simultaneously such that the distances between all adjacent pairs of points of \( P(k_s + 1, i - 1) \) are the same. Then, Inequality (4.1) with \( h = s + 1 \) makes sure that \( p_{k + 2} \) is the first point of \( P(k_s + 1, i - 1) \) that arrives at the left endpoint of its interval. Continuing the above can explain the inequality for \( h = s + 2, s + 3, \ldots, t - 1 \).

The priority property further leads to the following observation.

**Observation 4.2.3.** For any \( h \) with \( s \leq h \leq t - 2 \), the following holds:

\[
\frac{l_{k+1} - l_k}{k_{h+1} - k_h} > \frac{l_{k+2} - l_{k+1}}{k_{h+2} - k_{h+1}}.
\]

**Proof.** Note that \( k + 1 \leq k_{h+1} < k_{h+2} \leq i - 1 \). Let \( j = k_{h+2} \). By Inequality (4.1), we have

\[
\frac{l_{k+1} - l_k}{k_{h+1} - k_h} > \frac{l_{k+2} - l_{k+1}}{k_{h+2} - k_{h+1}}.
\]  

(4.2)

Note that for any four positive numbers \( a, b, c, d \) such that \( a < c \), \( b < d \), and \( \frac{a}{b} > \frac{c}{d} \), it holds that \( \frac{a}{b} > \frac{c - a}{d - b} \). Applying this to Inequality (4.2) will obtain the observation. \( \Box \)

**Remark.** By Corollary 4.2.2, Invariants (2), (6), (7), and (8) together imply that \( d_{\min} \) is the optimal objective value for the sub-problem on the first \( i - 1 \) intervals.

One may verify that initially after \( I_1 \) is processed, all invariants trivially hold (we finalize \( p_1 \) at \( l_1 \)). In the following we describe the general step of our algorithm to process the interval \( I_i \). We will also show that all algorithm invariants hold after \( I_i \) is processed.

Depending on whether \( p_{i-1} + d_{\min} \) is to the left of \( I_i \), in \( I_i \), or to the right of \( I_i \), there are three cases.
The case $p_{i-1} + d_{\min} \leq l_i$

In this case, $p_{i-1} + d_{\min}$ is to the left of $I_i$. We set $p_i = l_i$ and finalize it. We do not change $d_{\min}$, $i^*$, or $j^*$. Further, for each $j \in [k_s + 1, i - 1]$, we explicitly compute $p_j = l_{k_s} + d_{\min} \cdot (j - k_s)$ and finalize it. Finally, we reset $\mathcal{L} = \{i\}$.

**Lemma 4.2.4.** In the case $p_{i-1} + d_{\min} \leq l_i$, all algorithm invariants hold after $I_i$ is processed.

**Proof.** Recall that $\mathcal{L} = \{i\}$ after $I_i$ is processed. Hence, $k_s = k_t = i$. For the sake of differentiation, we use $\mathcal{L}' = \{k'_s, k'_s + 1, \ldots, k'_t\}$ to denote the critical list before we process $I_i$.

1. Since $p_i$ is known, Invariant (1) hold.

2. For Invariant (2), since the same invariant holds before we process $I_i$ and none of $d_{\min}$, $i^*$, and $j^*$ is changed when we process $I_i$, Invariant (2) trivially holds after we process $I_i$.

3. Since $k_t = i$, the third invariant holds.

4. Recall that $p_{k_s} = p_i = l_i$, which is the fourth invariant.

5. To prove Invariant (5), since the same invariant holds before $I_i$ is processed, it is sufficient to show that the points of $P(k'_s + 1, i)$ have been explicitly computed and finalized in the step of processing $I_i$, which is clearly true according to our algorithm.

6. To prove Invariant (6), since the same invariant holds before $I_i$ is processed, it is sufficient to show that each point $p_j$ of $P(k'_s + 1, i)$ is in $I_j$.

   Indeed, consider any $j \in [k'_s + 1, i]$. If $j = i$, then since $p_j = l_j$, it is true that $p_j$ is in $I_j$. If $j < i$, then by Invariant (8) of $\mathcal{L}'$, $l_{k'_s} + d_{\min} \cdot (j - k'_s)$ is in $I_j$. According to our algorithm, in the step of processing $I_i$, $p_j$ is explicitly set to $l_{k'_s} + d_{\min} \cdot (j - k'_s)$. Hence, $p_j$ is in $I_j$.

7. To prove Invariant (7), since the same invariant holds before $I_i$ is processed, it is sufficient to show that $|p_{i-1}p_i| \geq d_{\min}$, which is clearly true according to our algorithm.
8. Invariant (8) trivially holds since $k_s + 1 > i$ (i.e., there is no $j$ such that $k_s + 1 \leq j \leq i$).

9. Invariant (9) also holds since $L$ has only one element.

This proves that all algorithm invariants hold. The lemma thus follows.

The case $l_i < p_{i-1} + d_{\text{min}} \leq r_i$

In this case, $p_{i-1} + d_{\text{min}}$ is in $I_i$. We set $p_i = p_{i-1} + d_{\text{min}}$. We do not change $d_{\text{min}}, i^*, j^*$. We update the critical list $L$ by the following *rear-processing procedure* (because the elements of $L$ are considered from the rear to the front).

If $s = t$, i.e., $L$ only has one element, then we simply add $i$ to the rear of $L$. Otherwise, we first check whether the following inequality is true.

$$\frac{l_{k_t} - l_{k_{t-1}}}{k_t - k_{t-1}} > \frac{l_i - l_{k_{t-1}}}{i - k_{t-1}}. \quad (4.3)$$

If it is true, then we add $i$ to the end of $L$.

If it is not true, then we remove $k_t$ from $L$ and decrease $t$ by 1. Next, we continue to check whether Inequality (4.3) (with the decreased $t$) is true and follow the same procedure until either the inequality becomes true or $s = t$. In either case, we add $i$ to the end of $L$. Finally, we increase $t$ by 1 to let $k_t$ refer to $i$.

This finishes the rear-processing procedure for updating $L$.

Lemma 4.2.5. *In the case $l_i < p_{i-1} + d_{\text{min}} \leq r_i$, all algorithm invariants hold after $I_i$ is processed.*

*Proof.* For the sake of differentiation, we use $L' = \{k'_s, k'_{s+1}, \ldots, k'_t\}$ to denote the critical list before we process $I_i$. After $I_i$ is processed, we have $L = \{k_s, k_{s+1}, \ldots, k_t\}$.

According to our algorithm, $L$ is obtained from $L'$ by possibly removing some elements of $L'$ from the rear and then adding $i$ to the end. Hence, $k_h = k'_h$ for any $h \in [s, t-1]$ and $k_t = i$. In particular, $k_s = k'_s$ since $L$ has at least two elements (i.e., $s < t$).

1. Since the “temporary” location of $p_i$ is computed, the first invariant holds.

2. The second invariant trivially holds since none of $d_{\text{min}}, i^*$, and $j^*$ is changed when we process $I_i$. 


3. Since \( k_t = i \), Invariant (3) holds.

4. To prove Invariant (4), we need to show that \( p_{k_s} = l_{k_s} \). Since the same invariant holds for \( \mathcal{L}' \), \( p_{k'_s} = l_{k'_s} \). Due to \( k_s = k'_s \), we obtain \( p_{k_s} = l_{k_s} \).

5. Invariant (5) trivially holds since \( k_s = k'_s \) and the same invariant holds before \( I_t \) is processed.

6. Similarly, since \( k_s = k'_s \), Invariant (6) holds.

7. Similarly, since \( k_s = k'_s \), Invariant (7) holds.

8. To prove Invariant (8), we need to show that \( p_j \) is implicitly set to \( l_{k_s} + d_{\text{min}} \cdot (j - k_s) \) and \( p_j \in I_j \) for each \( j \in [k_s + 1, i] \).

Recall that \( k_s = k'_s \) and \( d_{\text{min}} \) does not change when we process \( I_t \). Since the same invariant holds before \( I_j \) is processed, for \( j \in [k_s + 1, i - 1] \), it is true that \( p_j \) is implicitly set to \( l_{k_s} + d_{\text{min}} \cdot (j - k_s) \) and \( p_j \in I_j \). For \( j = i \), since \( p_i = p_{i-1} + d_{\text{min}} \) and \( p_i \in I_i \), \( p_i = l_{k_s} + d_{\text{min}} \cdot (i - k_s) \).

Hence, this invariant also holds.

The above has proved that the first eight invariants hold. It remains to prove the last invariant, i.e., the priority property of \( \mathcal{L} \). Our goal is to show that for any \( h \in [s, t - 1] \), Inequality (4.1) holds for any \( j \in [k_h + 1, i] \) with \( j \neq k_{h+1} \).

Consider any \( h \in [s, t - 1] \) and any \( j \in [k_h + 1, i] \) with \( j \neq k_{h+1} \). Since \( h \leq t - 1 \), \( k'_h = k_h \). Depending on whether \( h \leq t - 2 \) or \( h = t - 1 \), there are two cases.

The case \( h \leq t - 2 \). In this case, \( h + 1 \leq t - 1 \) and thus \( k'_{h+1} = k_{h+1} \).

If \( j \leq i - 1 \), then \( j \in [k_h + 1, i - 1] = [k'_h + 1, i - 1] \). Since the priority property holds for \( \mathcal{L}' \), we have \( \frac{l_{k'_h + 1} - l_{k'_h}}{k'_{h+1} - k'_h} > \frac{l_{j} - l_{k'_h}}{j - k'_h} \). As \( k'_h = k_h \) and \( k'_{h+1} = k_{h+1} \), Inequality (4.1) hold for \( j \) and \( h \).

If \( j = i \), then Inequality (4.1) can be proved with the help of Observation 4.2.3, as follows.

Since \( h \leq t - 2 \) and \( s \leq h < t - 1 \), \( k_s \) is not \( k_{t-1} \). Since \( k_{t-1} \) is not removed from \( \mathcal{L} \), according to our algorithm, Inequality (4.3) must be true with replacing \( t \) by \( t - 1 \), i.e., \( \frac{l_{k_{t-1} - 1} - l_{k_{t-2}}}{k_{t-1} - k_{t-2}} > \frac{l_{j} - l_{k_{t-2}}}{j - k_{t-2}} \).
Further, recall that \( k_m = k'_m \) for all \( m \in [s,t-1] \). Due to the priority property of \( \mathcal{L}' \) and by Observation 4.2.3, we obtain \( \frac{l_{k_{h+1}} - l_{k_h}}{k_{h+1} - k_h} > \frac{l_{k_{t-1}} - l_{k_{t-2}}}{k_{t-1} - k_{t-2}} \).

Combining the above two inequalities gives us

\[
\frac{l_{k_{h+1}} - l_{k_h}}{k_{h+1} - k_h} > \frac{l_i - l_{k_{t-2}}}{i - k_{t-2}}. \tag{4.4}
\]

Depending on whether \( h < t - 2 \), there are further two subcases.

1. If \( h = t - 2 \), then Inequality (4.4) is Inequality (4.1) for \( j = i \). So we are done with the proof.

2. If \( h < t - 2 \), then, \( k_h < k_{t-2} \leq i - 1 \). Recall that \( k'_h = k_h \) and \( k'_{t-2} = k_{t-2} \). Due to the priority property of \( \mathcal{L}' \) and by setting \( j = k'_{t-2} \) in Inequality (4.1), we obtain

\[
\frac{l_{k'_{h+1}} - l_{k'_h}}{k'_{h+1} - k'_h} > \frac{l_{k'_{t-2}} - l_{k'_{t-2}}}{k'_{t-2} - k'_h}.
\]

Again, because \( k'_h = k_h, \ k'_{h+1} = k_{h+1}, \) and \( k'_{t-2} = k_{t-2} \), we have

\[
\frac{l_{k_{h+1}} - l_{k_h}}{k_{h+1} - k_h} > \frac{l_{k_{t-2}} - l_{k_{t-2}}}{k_{t-2} - k_h}. \tag{4.5}
\]

Note that for any positive numbers \( x, a, b, c, d \) such that \( x > \frac{a}{b} \) and \( x > \frac{c}{d} \), it always holds that \( x > \frac{a+c}{b+d} \). Applying this to Inequalities (4.4) and (4.5) leads to

\[
\frac{l_{k_{h+1}} - l_{k_h}}{k_{h+1} - k_h} > \frac{l_i - l_{k_h}}{i - k_h},
\]

which is Inequality (4.1) for \( j = i \).

This proves Inequality (4.1) for the case \( h \leq t - 2 \).

The case \( h = t - 1 \). In this case, \( k_{h+1} = k_t = i \). Due to \( j \neq k_{h+1}, j \neq i \).

If none of the elements of \( \mathcal{L}' \) was removed when we updated \( \mathcal{L} \), i.e., \( \mathcal{L} = \mathcal{L}' \cup \{i\} \), then \( k_{t-1} = k'_t \). Since \( k'_t = i - 1, k_h = k_{t-1} = k'_t = i - 1 \). Therefore, \( k_h + 1 = i \), and there is no \( j \) with \( k_h + 1 \leq j \leq i \) and \( j \neq k_{h+1} = k_t = i \). Hence, we have nothing to prove for Inequality (4.1) in this case.

In the following, we assume at least one element was removed from \( \mathcal{L}' \) when we updated \( \mathcal{L} \). Since \( k'_{t-1} = k_{t-1} \) is the last element of \( \mathcal{L}' \) remaining in \( \mathcal{L} \), \( k'_t \) is the
last element removed from $L'$ when we process $I_i$. According to the algorithm, $k'_t$ was removed because Inequality (4.3) was not true, i.e., the following holds

$$\frac{l_{k'_t} - l_{k'_t-1}}{k'_t - k'_{t-1}} \leq \frac{l_i - l_{k'_t-1}}{i - k'_{t-1}}.$$

(4.6)

Recall that $k_h + 1 \leq j \leq i$, $j \neq i$, and $k_h = k_{t-1} = k'_t$. Due to the priority property of $L'$ and by setting $h = t - 1$ in Inequality (4.1), we obtain

$$\frac{l_{k'_t} - l_{k'_t-1}}{k'_t - k'_{t-1}} > \frac{l_j - l_{k'_t-1}}{j - k'_{t-1}}.$$

(4.7)

Combining Inequalities (4.6) and (4.7), we obtain

$$\frac{l_i - l_{k'_t-1}}{l_{k'_t} - l_{k'_t-1}} > \frac{l_i - l_{k'_t-1}}{l_j - l_{k'_t-1}} = \frac{l_i - l_{k'_t-1}}{j - k'_{t-1}},$$

which is Inequality (4.1) for $h$ and $j$ since $h = t - 1$, $k'_t = k_t = i$, and $k'_{t-1} = k_{t-1}$.

The above proves that the priority property holds for the updated list $L'$.

This proves that all algorithm invariants hold after $I_i$ is processed. \qed

The case $p_{i-1} + d_{\min} > r_i$

In this case, $p_{i-1} + d_{\min}$ is to the right of $I_i$. We first set $p_i = r_i$. Then we perform the following front-processing procedure (because it processes the elements of $L$ from the front to the rear).

If $L$ has only one element (i.e., $s = t$), then we stop.

Otherwise, we check whether the following is true

$$\frac{l_{k_{s+1}} - l_{k_s}}{k_{s+1} - k_s} \geq \frac{r_i - l_{k_s}}{i - k_s}.$$

(4.8)

If it is true, then we perform the following finalization step: for each $j = k_s + 1, k_s + 2, \ldots, k_{s+1}$, we explicitly compute $p_j = l_{k_s} + \frac{l_{k_{s+1}} - l_{k_s}}{k_{s+1} - k_s} \cdot (j - k_s)$ and finalize it. Further, we remove $k_s$ from $L$ and increase $s$ by 1. Next, we continue the same procedure as above (with the increased $s$), i.e., first check whether $s = t$, and if not, check whether Inequality (4.8) is true. The front-processing procedure stops if either $s = t$ (i.e., $L$ only has one element) or Inequality (4.8) is not true.

After the front-processing procedure, we update $d_{\min} = (r_i - l_{k_s})/(i - k_s)$, $i^* = k_s$, and $j^* = i$. Finally, we update the critical list $L$ using the rear-processing procedure,
in the same way as in the above second case where $l_i < p_{i-1} + d_{\min} \leq r_i$. We also “implicitly” set $p_j = l_{k_s} + d_{\min} \cdot (j - k_s)$ for each $j \in [k_s + 1, \hat{i}]$ (this is only for the analysis and our algorithm does not do so explicitly).

This finishes the processing of $I_i$.

Lemma 4.2.6. In the case $p_{i-1} + d_{\min} > r_i$, all algorithm invariants hold after $I_i$ is processed.

*Proof.* Let $\mathcal{L} = \{k_s, k_{s+1}, \ldots, k_t\}$ be the critical list after $I_i$ is processed. For the sake of differentiation, we use $\mathcal{L}' = \{k'_s, k'_{s+1}, \ldots, k'_{t'}\}$ to denote the critical list before we process $I_i$.

According to our algorithm, $\mathcal{L}$ is obtained from $\mathcal{L}'$ by the following two main steps: (1) the front-processing step that possibly removes some elements of $\mathcal{L}'$ from the front; (2) the rear-processing step that possibly removes some elements of $\mathcal{L}'$ from the rear and then adds $\hat{i}$ to the rear. Hence, $k_t = \hat{i}$.

Let $w$ be the index of $\mathcal{L}'$ such that $k_s = k'_w$. If $w \neq s$, then $k'_s, k'_{s+1}, \ldots, k'_{w-1}$ are not in $\mathcal{L}$.

The first invariant. Since the “temporary” location of $p_i$ is computed with $p_i = r_i$, the first invariant holds.

The second invariant. By our way of updating $d_{\min}$, $i^*$, and $j^*$, it holds that $d_{\min} = (r_{j^*} - l_{i^*})/(j^* - i^*)$, with $1 \leq i^* \leq j^* \leq \hat{i}$. Hence, the invariant holds.

The third invariant. Since $k_t = \hat{i}$, the third invariant trivially holds.

The fourth invariant. We need to show that $p_{k_s} = l_{k_s}$.

If $s = w$, then $k_s = k'_s$ and $k_s$ is also the first element of $\mathcal{L}'$. Since the fourth invariant holds before $I_i$ is processed, $p_{k'_s} = l_{k'_s}$. Thus, we obtain $p_{k_s} = l_{k_s}$.

If $s \neq w$, then when $k'_{w-1}$ was removed from $\mathcal{L}$ in the algorithm, the finalization step explicitly computed $p_j = l_{k'_{w-1}} + \frac{l_{k_w} - l_{k'_{w-1}}}{k_w - k'_{w-1}} \cdot (j - k'_{w-1})$ for each $j \in [k'_{w-1} + 1, k'_w]$. Once can verify that $p_{k'_w} = l_{k'_w}$. Since $k'_w = k_s$, we obtain $p_{k_s} = l_{k_s}$.

This proves that the fourth invariant also holds.

The fifth invariant. Our goal is to show that all points in $P(1, k_s)$ have been finalized. Since all points in $P(1, k'_s)$ have been finalized before we process $I_i$, it is
sufficient to show that the points for \( P(k_s' + 1, k_s) \) were finalized in the step of processing \( I_i \).

If \( w = s \), then \( k_s = k_s' \) and we are done with the proof. Otherwise, for each \( h \in [s, w - 1] \), when \( k'_h \) was removed from \( \mathcal{L} \), the finalization step finalized the points in \( P(k'_h + 1, k'_{h+1}) \). Hence, all points of \( P(k'_s + 1, k'_w) \) \( (= P(k'_s + 1, k_s)) \) were finalized. Hence, the fifth invariant holds.

The sixth invariant. Our goal is to show that for any \( p_j \) with \( j \in [1, k_s] \), \( p_j \) is in \( I_j \).

Note that the position of \( p_j \) is not changed for any \( j \leq k'_s \) when we process the interval \( I_i \). Since the same invariant holds before we process \( I_i \), \( p_j \) is in \( I_j \) for any \( j \in [1, k'_s] \). Hence, if \( k_s = k'_s \), we are done with proof. Otherwise, it is sufficient to show that \( p_j \) is in \( I_j \) for any \( j \in [k'_s + 1, k_s] \).

For \( j = k_s \), since \( p_j = l_j \), it is trivially true that \( p_j \) is in \( I_j \). In the following, we assume \( j \in [k'_h, k'_{h+1}) \) for some \( h \in [s, w - 1] \) (recall that \( k_s = k'_w \)).

According to our algorithm, \( p_j = l_{k'_h} + \frac{l_{k'_{h+1}} - l_{k'_h}}{k'_{h+1} - k'_h} \cdot (j - k'_h) \). Let \( d'_{min} \) be the value of \( d_{min} \) before \( I_i \) is processed. Let \( p'_j \) be the original “temporary” location of \( p_j \) before \( I_i \) is processed. Since the eighth invariant holds before \( I_i \) is processed, we have \( p'_j = l_{k'_s} + d'_{min} \cdot (j - k'_s) \) and \( p'_j \in I_j \).

We first show that \( p_j \leq p'_j \), i.e., comparing with its original location, \( p_j \) has been moved leftwards in the step of processing \( I_i \). This can be easily seen from the intuitive understanding of the algorithm. We provide a formal proof below.

Since Invariant (8) holds before \( I_i \) is processed, \( p_{k'_s+1} \) was implicitly set to \( l_{k'_s} + d'_{min} \cdot (k'_{s+1} - k'_s) \), which is in \( I_{k'_s+1} \). Hence, \( l_{k'_s} + d'_{min} \cdot (k'_{s+1} - k'_s) \geq l_{k'_s+1} \). Thus, \( d'_{min} \geq \frac{l_{k'_{s+1}} - l_{k'_s}}{k'_{s+1} - k'_s} \). Consequently, \( p'_j = l_{k'_s} + d'_{min} \cdot (j - k'_s) \geq l_{k'_s} + \frac{l_{k'_{s+1}} - l_{k'_s}}{k'_{s+1} - k'_s} \cdot (j - k'_s) \).

Since the priority property holds for \( \mathcal{L}' \), by Observation 4.2.3, \( \frac{k'_{s+1} - k'_s}{l_{k'_{s+1}} - l_{k'_s}} \geq \frac{l_{k'_{s+1}} - l_{k'_s}}{k'_{s+1} - k'_s} \).

Hence, \( p_j = l_{k'_h} + \frac{l_{k'_{h+1}} - l_{k'_h}}{k'_{h+1} - k'_h} \cdot (j - k'_h) \leq l_{k'_h} + \frac{l_{k'_{s+1}} - l_{k'_h}}{l_{k'_{s+1}} - l_{k'_s}} \cdot (j - k'_h) \).

Now to prove \( p_j \leq p'_j \), it is sufficient to prove \( \frac{k'_{s+1} - k'_s}{l_{k'_{s+1}} - l_{k'_s}} \geq \frac{l_{k'_{s+1}} - l_{k'_s}}{k'_{s+1} - k'_s} \), which is true by Inequality (4.1) (replacing \( h \) and \( j \) in Inequality (4.1) by \( s \) and \( k'_h \), respectively) due to the priority property of \( \mathcal{L}' \).
The above proves that $p_j \leq p'_j$. Since $p'_j \in I_j$, $p'_j \leq r_j$, and thus, $p_j \leq r_j$. To prove $p_j \in I_j$, it remains to prove $p_j \geq l_j$.

If $j = k'_h$, then $p_j = l_j$ and we are done with the proof. Otherwise, due to the priority property of $\mathcal{L}'$ and by applying Inequality (4.1), we have \[ \frac{l_{k'_h+1} - l_{k'_h}}{k'_h+1 - k'_h} > \frac{l_j - l_{k'_h}}{j - k'_h}. \]

Therefore, $p_j = l_{k'_h} + \frac{l_{k'_h+1} - l_{k'_h}}{k'_h+1 - k'_h} \cdot (j - k'_h) > l_j$.

This proves that $p_j$ is in $I_j$. Thus, the sixth invariant holds.

The seventh invariant.. The goal is to show that the distance of any pair of adjacent points of $P(1, k_s)$ is at least $d_{\text{min}}$.

Let $d'_{\text{min}}$ be the value of $d_{\text{min}}$ before we process $I_i$. We first prove $d'_{\text{min}} > d_{\text{min}}$.

Indeed, if $k_s = k'_s$, then since the eighth invariant holds before $I_i$ is processed, $d'_{\text{min}} = \frac{r_i - l_{k'_s}}{r_i - k'_s}$, where $p'_{i-1}$ is the location of $p_{i-1}$ before we process $I_i$. Recall that $p'_{i-1} + d''_{\text{min}} > r_i$. Hence, we have $d'_{\text{min}} > \frac{r_i-d'_{\text{min}}-l_{k'_s}}{r_i-1-k'_s}$. We can further deduce $d'_{\text{min}} > \frac{r_i-l_{k'_s}}{r_i-1-k'_s}$. Since $d_{\text{min}} = \frac{r_i-l_{k'_s}}{r_i-1-k'_s}$, we obtain $d'_{\text{min}} > d_{\text{min}}$.

If $k_s \neq k'_s$, then $k'_{w-1}$ was removed from $\mathcal{L}'$, Inequality (4.8) must hold for $s = w-1$, i.e., \[ \frac{l_{k'_w} - l_{k'_{w-1}}}{k'_w - k'_{w-1}} > \frac{r_i - l_{k'_{w-1}}}{r_i - k'_{w-1}}. \] Note that for any four positive numbers $a, b, c, d$ with $\frac{a}{b} > \frac{c}{d}$, $a < c$, and $b < d$, it always holds that $\frac{a}{b} > \frac{c-a}{d-b}$. Applying this to the above inequality gives us \[ \frac{l_{k'_w} - l_{k'_{w-1}}}{k'_w - k'_{w-1}} > \frac{r_i - l_{k'_{w-1}}}{r_i - k'_{w-1}}. \]

Since $d_{\text{min}} = \frac{r_i-l_{k'_s}}{r_i-1-k'_s}$ and $k_s = k'_w$, we obtain $\frac{l_{k'_w} - l_{k'_{w-1}}}{k'_w - k'_{w-1}} > d_{\text{min}}$.

On the other hand, before $I_i$ is processed, according to the eighth invariant, $l_{k'_i} + d'_{\text{min}} \cdot (k'_{s+1} - k'_s)$ is in $I_{k'_i+1}$. Hence, $l_{k'_i} + d'_{\text{min}} \cdot (k'_{s+1} - k'_s) \geq l_{k'_{s+1}}$ and $d'_{\text{min}} = \frac{l_{k'_{s+1}} - l_{k'_s}}{k'_{s+1} - k'_s}$.

Further, due to the priority property of $\mathcal{L}'$ and by Observation 4.2.3, it holds that \[ \frac{l_{k'_w} - l_{k'_{w-1}}}{k'_w - k'_{w-1}} \geq \frac{l_{k'_{s+1}} - l_{k'_{s-1}}}{k'_{s+1} - k'_{s-1}}. \]

Combining our above discussions, we obtain $d'_{\text{min}} > d_{\text{min}}$.

Next, we proceed to prove Invariant (7).

Since Invariant (7) holds before $I_i$ is processed, the distance of every pair of adjacent points of $P(1, k'_s)$ is at least $d'_{\text{min}}$. To prove that the distance of every pair of adjacent points of $P(1, k_s)$ is at least $d_{\text{min}}$, since $d'_{\text{min}} > d_{\text{min}}$, if $k_s = k'_s$, then we are done with the proof, otherwise it is sufficient to show that the distance of every pair of adjacent points of $P(k'_s, k_s)$ is at least $d_{\text{min}}$. 
Consider any \( h \in [s, w - 1] \). When \( k'_h \) is removed from \( \mathcal{L} \), according to the finalization step, every pair of adjacent points of \( P(k'_h, k'_{h+1}) \) is \( \frac{l'_{k'_{h+1}} - l'_{k'_h}}{k'_{h+1} - k'_{h}} \). Due to the priority property of \( \mathcal{L}' \) and by Observation 4.2.3, \( \frac{l'_{k'_{h+1}} - l'_{k'_h}}{k'_{h+1} - k'_{h}} \geq \frac{l'_{k'_{w}} - l'_{k'_{w-1}}}{k'_{w} - k'_{w-1}} \). Recall that we have proved above that \( l'_{k'_{w}} - l'_{k'_{w-1}} > d_{\text{min}} \). Hence, we obtain that the distance of every pair of adjacent points of \( P(k'_h, k'_{h+1}) \) is at least \( d_{\text{min}} \). This further implies that the distance of every pair of adjacent points of \( P(k'_s, k'_{w}) \) \((= P(k'_s, k_s))\) is at least \( d_{\text{min}} \).

Hence, the seventh invariant holds.

The eighth invariant. Consider any \( j \in [k_s, i] \). Based on our algorithm, \( p_j \) is implicitly set to \( l_{k_s} + d_{\text{min}} \cdot (j - k_s) \). Hence, to prove the invariant, it remains to show that \( p_j \) is in \( I_j \).

If \( j = i \), then since \( p_i = r_i \), it is true that \( p_j \in I_j \). In the following, we assume \( j < i - 1 \).

Let \( p'_j \) be the “temporary” location of \( p_j \) before \( I_i \) is processed. Since the eighth invariant holds before \( I_i \) is processed, \( p'_j = l_{k'_j} + d'_{\text{min}} \cdot (j - k'_j) \) and \( p'_j \in I_j \). Again, let \( d''_{\text{min}} \) be the value of \( d_{\text{min}} \) before we process \( I_i \). Recall that we have proved above that \( d''_{\text{min}} > d_{\text{min}} \).

We claim that \( p_j \leq p'_j \). Indeed, if \( k_s = k'_s \), then \( p_j \leq p'_j \) follows from \( d''_{\text{min}} > d_{\text{min}} \).

Otherwise, note that \( p'_j = l_{k'_s} + d''_{\text{min}} \cdot (k'_w - k'_s) + d''_{\text{min}} \cdot (j - k'_s) = p'_{k'_w} + d''_{\text{min}} \cdot (j - k'_w) \), where \( p'_{k'_w} \) is the “temporary” location of \( p_{k'_w} \) before \( I_i \) is processed. Since \( k'_w = k_s \), we have \( p'_j = p'_{k'_w} + d''_{\text{min}} \cdot (j - k_s) \).

Since Invariant (8) holds before \( I_i \) is processed, \( p'_{k'_w} \) is in \( I_{k'_w} \). Hence, \( p'_{k'_w} \geq l_{k_s} \).

Therefore, we obtain \( p'_j \geq l_{k_s} + d''_{\text{min}} \cdot (j - k_s) \geq l_{k_s} + d_{\text{min}} \cdot (j - k_s) = p_j \).

This proves the above claim that \( p_j \leq p'_j \).

Since \( p'_j \in I_j \) and \( p_j \leq p'_j \), we obtain \( p_j \leq r_j \). To prove \( p_j \in I_j \), it remains to show \( p_j \geq l_j \), as follows.

According to our algorithm, \( k_s \) was not removed from \( \mathcal{L} \) either because \( k_s \) is the last element of \( \mathcal{L}' \) or because Inequality (4.8) is not true.

In the former case, it holds that \( k_s = i - 1 \). Since \( j \in [k_s, i - 1] \), \( j = k_s \). Due to \( p_{k_s} = l_{k_s} \), we obtain \( p_j \geq l_j \).

In the latter case, \( k_s \) is not the last element of \( \mathcal{L}' \) that is in \( \mathcal{L} \). Since \( k'_w = k_s \), we have \( k'_w+1 = k_{s+1} \). Due to the priority property of \( \mathcal{L}' \) and by Inequality (4.1) (with
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h = w), we have \( \frac{l_{w+1} - l_{w}}{k_w} \geq \frac{l_j - l_{k_j}}{j - k_s} \). Since \( k_s = k'_w \) and \( k_{s+1} = k'_ {w+1} \), it holds that 
\( \frac{l_{w+1} - l_w}{k_{w+1} - k_s} \geq \frac{l_j - l_{k_j}}{j - k_s} \). Since Inequality (4.8) is not true, we further obtain 
\( \frac{r_i - l_{k_s}}{r_i - k_s} \geq \frac{l_j - l_{k_j}}{j - k_s} \).
Recall that \( d_{\text{min}} = \frac{r_i - l_k}{r_i - k_s} \). Hence, \( d_{\text{min}} \geq \frac{l_j - l_{k_j}}{j - k_s} \) and \( p_j = l_{k_s} + d_{\text{min}} \cdot (j - k_s) \geq l_j \).

This proves that the eighth invariant holds.

The ninth invariant. Our goal is to prove that the priority property holds for \( L' \).
Since the priority property holds for \( L' \), intuitively we only need to take care of the “influence” of \( i \) (i.e., some elements were possibly removed from the rear of \( L' \) and \( i \) was added to the rear in the rear-processing procedure). Note that although some elements were also possibly removed from the front of \( L' \) in the front-processing procedure, this does not affect the priority property of the remaining elements of the list. Hence, to prove that the priority property holds for \( L \), we have exactly the same situation as in Lemma 4.2.5. Hence, we can use the same proof as that for Lemma 4.2.5. We omit the details.

This proves that all algorithm invariants hold after \( I_i \) is processed. The lemma thus follows. \(\square\)

The above describes a general step of the algorithm for processing the interval \( I_i \).
In addition, if \( i = n \) and \( k_s < n \), we also need to perform the following additional finalization step: for each \( j \in [k_s + 1, n] \), we explicitly compute \( p_j = l_{k_s} + d_{\text{min}} \cdot (j - k_s) \) and finalize it. This finishes the algorithm.

4.2.4 The Correctness and the Time Analysis

Based on the algorithm invariants and Corollary 4.2.2, the following lemma proves the correctness of the algorithm.

Lemma 4.2.7. The algorithm correctly computes an optimal solution.

Proof. Suppose \( P = \{p_1, p_2, \ldots, p_n\} \) is the set of points computed by the algorithm. Let \( d_{\text{min}} \) be the value and \( L = \{k_s, k_{s+1}, \ldots, k_l\} \) be the critical list after the algorithm finishes.

We first show that for each \( j \in [1, n] \), \( p_j \) is in \( I_j \). According to the sixth algorithm invariant of \( L' \), for each \( j \in [1, k_s] \), \( p_j \) is in \( I_j \). If \( k_s = n \), then we are done with the proof. Otherwise, for each \( j \in [k_s + 1, n] \), according to the additional finalization step
after $I_n$ is processed, $p_j = l_k + d_{\text{min}} \cdot (j - k)$, which is in $I_j$ by the eighth algorithm invariant.

Next we show that the distance of every pair of adjacent points of $P$ is at least $d_{\text{min}}$. By the seventh algorithm invariant, the distance of every pair of adjacent points of $P(1, k)$ is at least $d_{\text{min}}$. If $k = n$, then we are done with the proof. Otherwise, it is sufficient to show that the distance of every pair of adjacent points of $P(k, n)$ is at least $d_{\text{min}}$, which is true according to the additional finalization step after $I_n$ is processed.

The above proves that $P$ is a feasible solution with respect to $d_{\text{min}}$, i.e., all points of $P$ are in their corresponding intervals and the distance of every pair of adjacent points of $P$ is at least $d_{\text{min}}$.

To show that $P$ is also an optimal solution, based on the second algorithm invariant, it holds that $d_{\text{min}} = \frac{r_j^* - l_i^*}{j - i}$. By Corollary 4.2.2, $d_{\text{min}}$ is an optimal objective value. Therefore, $P$ is an optimal solution.

The running time of the algorithm is analyzed in the proof of Theorem 4.2.8. The pseudocode is given in Algorithm 1.

**Theorem 4.2.8.** Our algorithm computes an optimal solution of the line version of points dispersion problem in $O(n)$ time.

**Proof.** In light of Lemma 4.2.7, we only need to show that the running time of the algorithm is $O(n)$.

To process an interval $I_i$, according to our algorithm, we only spend $O(1)$ time in addition to two possible procedures: a front-processing procedure and a rear-processing procedure. Note that the front-processing procedure may contain several finalization steps. There may also be an additional finalization step after $I_n$ is processed. For the purpose of analyzing the total running time of the algorithm, we exclude the finalization steps from the front-processing procedures.

For processing $I_i$, the front-processing procedure (excluding the time of the finalization steps) runs in $O(k + 1)$ time where $k$ is the number of elements removed from the front of the critical list $L$. An easy observation is that any element can be removed from $L$ at most once in the entire algorithm. Hence, the total time of all front-processing procedures in the entire algorithm is $O(n)$. 

Algorithm 1: The algorithm for the line version of the problem

**Input:** $n$ intervals $I_1, I_2, \ldots, I_n$ sorted from left to right on $\ell$

**Output:** $n$ points $p_1, p_2, \ldots, p_n$ with $p_i \in I_i$ for each $1 \leq i \leq n$

1. $p_1 \leftarrow l_1$, $i^* \leftarrow 1$, $j^* \leftarrow 1$, $d_{\text{min}} \leftarrow \infty$, $\mathcal{L} \leftarrow \{1\}$
2. for $i \leftarrow 2$ to $n$ do
   3.   if $p_{i-1} + d_{\text{min}} \leq l_i$ then
      4.     $p_i \leftarrow l_i$, $\mathcal{L} \leftarrow \{i\}$
   5.   else /* $p_{i-1} + d_{\text{min}} > r_i$ */
      6.     $p_i \leftarrow r_i$, $k_s \leftarrow$ the front element of $\mathcal{L}$
      7.     while $|\mathcal{L}| > 1$ do /* the front-processing procedure */
          8.       if $l_{k_{s+1}} - l_k_s > r_i - l_k_s$ then
              9.         for $j \leftarrow k_s + 1$ to $k_{s+1}$ do
                  10.            $p_j \leftarrow l_{k_s} + \frac{l_{k_{s+1}} - l_k_s}{k_{s+1} - k_s} \cdot (j - k_s)$
                11.        remove $k_s$ from $\mathcal{L}$, $k_s \leftarrow$ the front element of $\mathcal{L}$
          12.       else break;
          13.     $i^* \leftarrow k_s$, $j^* \leftarrow i$, $d_{\text{min}} \leftarrow \frac{r_j - l_{i^*}}{j^* - i^*}$
      14.   while $|\mathcal{L}| > 1$ do /* the rear-processing procedure */
          15.     $k_t \leftarrow$ the rear element of $\mathcal{L}$
          16.     if $l_{k_t} - l_{k_t-1} > \frac{l_i - l_{k_t-1}}{i - k_{t-1}}$ then break;
          17.     remove $k_t$ from $\mathcal{L}$
          18.     add $i$ to the rear of $\mathcal{L}$
      19.   $k_s \leftarrow$ the front element of $\mathcal{L}$
      20. if $k_s < n$ then
          21.     for $j \leftarrow k_s + 1$ to $n$ do
              22.       $p_j \leftarrow l_k_s + d_{\text{min}} \cdot (j - k_s)$

Similarly, for processing $I_i$, the rear-processing procedure runs in $O(k + 1)$ time where $k$ is the number of elements removed from the rear of $\mathcal{L}$. Again, since any element can be removed from $\mathcal{L}$ at most once in the entire algorithm, the total time of all rear-processing procedures in the entire algorithm is $O(n)$.

Clearly, each point is finalized exactly once in the entire algorithm. Hence, all finalization steps in the entire algorithm together take $O(n)$ time.

Therefore, the algorithm runs in $O(n)$ time in total.
4.3 The Cycle Version

In the cycle version, the intervals of \( I = \{I_1, I_2, \ldots, I_n\} \) in their index order are sorted cyclically on \( C \). Recall that the intervals of \( I \) are pairwise disjoint.

For each \( i \in [1, n] \), let \( l_i \) and \( r_i \) denote the two endpoints of \( I_i \), respectively, such that if we move from \( l_i \) to \( r_i \) clockwise on \( C \), we will always stay on \( I_i \).

For any two points \( p \) and \( q \) on \( C \), we use \( |\vec{pq}| \) to denote the length of the arc of \( C \) from \( p \) to \( q \) clockwise, and thus the distance of \( p \) and \( q \) on \( C \) is \( \min\{|\vec{pq}|, |\vec{qp}|\} \).

For each interval \( I_i \in I \), we use \( |I_i| \) to denote its length; note that \( |I_i| = |\vec{l_ir_i}| \). We use \( |C| \) to denote the total length of \( C \).

Our goal is to find a point \( p_i \) in \( I_i \) for each \( i \in [1, n] \) such that the minimum distance between any pair of these points, i.e., \( \min_{1 \leq i < j \leq n} |p_i p_j| \), is maximized.

Let \( P = \{p_1, p_2, \ldots, p_n\} \) and let \( d_{opt} \) be the optimal objective value. It is obvious that \( d_{opt} \leq \frac{|C|}{n} \). Again, for simplicity of discussion, we make a general position assumption that no two endpoints of the intervals have the same location on \( C \).

4.3.1 The Algorithm

The main idea is to convert the problem to a problem instance on a line and then apply our line version algorithm. More specifically, we copy all intervals of \( I \) twice to a line \( \ell \) and then apply our line version algorithm on these \( 2n \) intervals. The line version algorithm will find \( 2n \) points in these intervals. We will show that a subset of \( n \) points in \( n \) consecutive intervals correspond to an optimal solution for our original problem on \( C \). The details are given below.

Let \( \ell \) be the \( x \)-axis. For each \( 1 \leq i \leq n \), we create an interval \( I'_i = [l'_i, r'_i] \) on \( \ell \) with \( l'_i = |\vec{l_1l_i}| \) and \( r'_i = l'_i + |I_i| \), which is actually a copy of \( I_i \). In other words, we first put a copy \( I'_1 \) of \( I_1 \) at \( \ell \) such that its left endpoint is at 0 and then we continuously copy other intervals to \( \ell \) in such a way that the pairwise distances of the intervals on \( \ell \) are the same as the corresponding clockwise distances of the intervals of \( I \) on \( C \). The above only makes one copy for each interval of \( I \). Next, we make another copy for each interval of \( I \) in a similar way: for each \( 1 \leq i \leq n \), we create an interval \( I'_{i+n} = [l'_{i+n}, r'_{i+n}] \) on \( \ell \) with \( l'_{i+n} = l'_i + |C| \) and \( r'_{i+n} = r'_i + |C| \). Let \( \mathcal{I}' = \{I'_1, I'_2, \ldots, I'_{2n}\} \). Note that the intervals of \( \mathcal{I}' \) in their index order are sorted from left to right on \( \ell \).
Lemma 4.3.1. It holds that \( p \) to the left of \( i \) whether \( p \to i \) since \( p \to i \) always exists since \( k \) is necessary to guarantee the correctness of our algorithm for the cycle version. A consequence of this change is that after the algorithm finishes, if \( d_{\min} \) is still equal to \( \frac{|C|}{n} \), then \( d_{\min} \) may not be the optimal objective value for the above line version problem, but if \( d_{\min} < \frac{|C|}{n} \), then \( d_{\min} \) must be the optimal objective value. As will be clear later, this does not affect our final solution for our original problem on the cycle \( C \). Let \( P' = \{p'_1, \ldots, p'_{2n}\} \) be the points computed by the line version algorithm with \( p'_i \in I'_i \) for each \( i \in [1, 2n] \).

Let \( k \) be the largest index in \([1, n]\) such that \( p'_k = l'_k \). Note that such an index \( k \) always exists since \( p'_1 = l'_1 \). Due to that we initialize \( d_{\min} = \frac{|C|}{n} \) in our line version algorithm, we can prove the following lemma.

**Lemma 4.3.1.** It holds that \( p'_{k+n} = l'_{k+n} \).

**Proof.** We prove the lemma by contradiction. Assume to the contrary that \( p'_{k+n} \neq l'_{k+n} \). Since \( p'_{k+n} \in I'_{k+n} \), it must be that \( p'_{k+n} > l'_{k+n} \). Let \( p'_i \) be the rightmost point of \( P' \) to the left of \( p'_{k+n} \) such that \( p'_i \) is at the left endpoint of its interval \( I'_i \). Depending on whether \( i \leq n \), there are two cases.

1. If \( i > n \), then let \( j = i - n \). Since \( i < k + n, j < k \), we claim that \( |p'_j p'_k| < |p'_{j+n} l'_{n+k}| \).

   Indeed, since \( p'_j \geq l'_j \) and \( p'_k = l'_k \), we have \( |p'_j p'_k| \leq |l'_j l'_k| \). Note that \( |l'_j l'_k| = |l'_{j+n} l'_{n+k}| \). On the other hand, since \( p'_{j+n} = l'_{j+n} \) and \( p'_{k+n} > l'_{k+n} \), it holds that \( |p'_{j+n} p'_{k+n}| > |l'_{j+n} l'_{k+n}| \). Therefore, the claim follows.

Let \( d \) be the value of \( d_{\min} \) right before the algorithm processes \( I'_i \). Since during the execution of our line version algorithm \( d_{\min} \) is monotonically decreasing, it holds that \( |p'_j p'_k| \geq d \cdot (k - j) \). Further, by the definition of \( i \), for any \( m \in [i+1, k+n] \), \( p'_m > l'_m \). Thus, according to our line version algorithm, the distance of every adjacent pair of points of \( p'_i, p'_{i+1}, \ldots, p'_{k+n} \) is at most \( d \). Thus, \( |p'_j p'_{k+n}| \leq d \cdot (k+n - i) \). Since \( j = i - n \), we have \( |p'_{j+n} p'_{k+n}| \leq d \cdot (k - j) \). Hence, we obtain \( |p'_j p'_k| \geq |p'_{j+n} p'_{k+n}| \).

However, this contradicts with our above claim.
2. If \( i \leq n \), then by the definition of \( k \), we have \( i = k \). Let \( d \) be the value of \( d_{\text{min}} \) right before the algorithm processes \( I'_i \). By the definition of \( i \), the distance of every adjacent pair of points of \( p'_k, p'_{k+1}, \ldots, p'_{n+k} \) is at most \( d \). Hence, \( |p'_k p'_{k+n}| \leq n \cdot d \).

Since \( p'_k = l'_k \) and \( p'_{n+k} > l'_{n+k} \), we have \( |p'_k p'_{n+k}| > |l'_{n+k}| = |C| \). Therefore, we obtain that \( n \cdot d > |C| \).

However, since we initially set \( d_{\text{min}} = |C|/n \) and the value \( d_{\text{min}} \) is monotonically decreasing during the execution of the algorithm, it must hold that \( n \cdot d \leq |C| \). We thus obtain contradiction.

Therefore, it must hold that \( p'_{n+k} = l'_{n+k} \). The lemma thus follows. \( \square \)

We construct a solution set \( P \) for our cycle version problem by mapping the points \( p'_k, p'_{k+1}, \ldots, p'_{n+k-1} \) back to \( C \). Specifically, for each \( i \in [k, n] \), we put \( p_i \) at a point on \( C \) with a distance \( l'_i \) clockwise from \( l_i \); for each \( i \in [1, k-1] \), we put \( p_i \) at a point on \( C \) at a distance \( p'_{i+n} - l'_{i+n} \) clockwise from \( l_i \). Clearly, \( p_i \) is in \( I_i \) for each \( i \in [1, n] \).

Hence, \( P \) is a “feasible” solution for our cycle version problem. Below we show that \( P \) is actually an optimal solution.

Consider the value \( d_{\text{min}} \) returned by the line version algorithm after all intervals of \( T' \) are processed. Since the distance of every pair of adjacent points of \( p'_k, p'_{k+1}, \ldots, p'_{n+k} \) is at least \( d_{\text{min}} \), \( p'_k = l'_k \), \( p'_{n+k} = l'_{n+k} \) (by Lemma 4.3.1), and \( |l'_{n+k}| = |C| \), by our way of constructing \( P \), the distance of every pair of adjacent points of \( P \) on \( C \) is at least \( d_{\text{min}} \).

Recall that \( d_{\text{opt}} \) is the optimal object value of our cycle version problem. The following lemma implies that \( P \) is an optimal solution.

Lemma 4.3.2. \( d_{\text{min}} = d_{\text{opt}} \).

Proof. Since \( P \) is a feasible solution with respect to \( d_{\text{min}} \), \( d_{\text{min}} \leq d_{\text{opt}} \) holds.

If \( d_{\text{min}} = |C|/n \), since \( d_{\text{opt}} \leq |C|/n \), we obtain \( d_{\text{opt}} \leq d_{\text{min}} \). Therefore, \( d_{\text{opt}} = d_{\text{min}} \), which leads to the lemma.

In the following, we assume \( d_{\text{min}} \neq |C|/n \). Hence, \( d_{\text{min}} < |C|/n \). According to our line version algorithm, there must exist \( i^* < j^* \) such that \( d_{\text{min}} = \frac{r'_{j^*} - l'_{i^*}}{j^* - i^*} \). We assume there is no \( i \) with \( i^* < i < j^* \) such that \( d_{\text{min}} = \frac{r'_{j} - l'_{i}}{j - i} \) since otherwise we could change
of the algorithm is $O(n)$ because the line version algorithm runs in $O(n)$ time. As a summary, we have the following theorem.

**Theorem 4.3.3.** The cycle version of the points dispersion problem is solvable in $O(n)$ time.

### 4.4 Concluding Remarks

In this chapter we present a linear time algorithm for the point dispersion problem on disjoint intervals on a line. Further, by making use of this algorithm, we also solve the same problem on a cycle in linear time.

It would be interesting to consider the general case of the problem in which the intervals may overlap. In fact, for the line version, if we know the order of the intervals
in which the sought points in an optimal solution are sorted from left to right, then we can apply our algorithm to process the intervals in that order and the obtained solution is an optimal solution. For example, if no interval is allowed to contain another completely, then there must exist an optimal solution in which the sought points from left to right correspond to the intervals ordered by their left (or right) endpoints. Hence, to solve the general case of the line version problem, the key is to find an order of intervals. This is also the case for the cycle version.
5.1 Introduction

In this chapter, we study algorithms for the problems for covering multiple barriers. These are basic geometric problems and have applications in barrier coverage of mobile sensors in wireless sensor networks. For convenience, in the following we introduce and discuss the problems from the mobile sensor barrier coverage point of view. The results in this chapter have been published in a conference [22].

5.1.1 Problem Definitions and Our Results

Let $L$ be a line, say, the $x$-axis. Let $B$ be a set of $m$ pairwise disjoint segments, called barriers, sorted on $L$ from left to right. Let $S$ be a set of $n$ sensors in the plane, and each sensor $s_i \in S$ is represented by a point $(x_i, y_i)$. If a sensor is moved on $L$, it has a sensing/covering range of length $r$, i.e., if a sensor $s$ is located at $x$ on $L$, then all points of $L$ in the interval $[x-r, x+r]$ are covered by $s$ and the interval is called the covering interval of $s$. The problem is to move all sensors of $S$ onto $L$ such that each point of every barrier is covered by at least one sensor and the maximum movement of all sensors of $S$ is minimized, i.e., the value $\max_{s_i \in S} \sqrt{(x_i - x'_i)^2 + y_i^2}$ is minimized, where $x'_i$ is the location of $s_i$ on $L$ in the solution (its $y$-coordinate is 0 since $L$ is the $x$-axis). We call it the multiple-barrier coverage problem, denoted by MBC.

We assume that covering range of the sensors is long enough so that a coverage of all barriers is always possible. Note that we can check whether a coverage is possible in $O(m + n)$ time by an easy greedy algorithm (e.g., try to cover all barriers one by one from left to right using sensors in such a way that their covering intervals do not overlap except at their endpoints).

Previously, only the special case $m = 1$ was studied and the problem was solved in
In this chapter, we propose an $O(n^2 \log n \log \log n + nm \log m)$-time algorithm for any $m$, which improves the algorithm in [57] by almost a linear factor even for the special case $m = 1$.

We further consider a *line-constrained* version of the problem where all sensors of $S$ are initially on $L$. Previously, only the special case $m = 1$ was studied and the problem was solved in $O(n \log n)$ time [33]. We present an $O((n + m) \log(n + m))$ time algorithm for any $m$, and the running time matches that of the algorithm in [33] when $m = 1$.

### 5.1.2 Related Work

Sensors are basic units in wireless sensor networks. The advantage of allowing the sensors to be mobile increases monitoring capability compared to those static ones. One of the most important applications in mobile wireless sensor networks is to monitor a barrier to detect intruders in an attempt to cross a specific region. Barrier coverage [57, 58], which guarantees that every movement crossing a barrier of sensors will be detected, is known to be an appropriate model of coverage for such applications. Mobile sensors normally have limited battery power and therefore their movements should be as small as possible.

Dobrev et al. [59] studies several problems on covering multiple barriers in the plane. They showed that these problems are generally NP-hard when sensors have different ranges. They also proposed polygonal-time algorithms for several special cases of the problems, e.g., barriers are parallel or perpendicular to each other, and sensors have some constrained movements. In fact, if sensors have different ranges, by an easy reduction from the Partition Problem as in [59], we can show that our problem MBC is NP-hard even for the line-constrained version and $m = 2$.

Other previous work has been focused on the line-constrained problem with $m = 1$. Czyzowicz et al. [60] first gave an $O(n^2)$ time algorithm, and later, Chen et al. [33] solved the problem in $O(n \log n)$ time. If sensors have different ranges, Chen et al. [33] presented an $O(n^2 \log n)$ time algorithm. For the *weighted case* where sensors have weights such that the moving cost of a sensor is its moving distance times its weight, Wang and Zhang [61] gave an $O(n^2 \log n \log \log n)$ time algorithm for the case where sensors have the same range.
The \textit{min-sum} version of the line-constrained problem with \( m = 1 \) has also been studied, where the objective is to minimize the sum of the moving distances of all sensors. If sensors have different ranges, then the problem is NP-hard \cite{62}. Otherwise, Czyzowicz et al. \cite{62} gave an \( O(n^2) \) time algorithm, and Andrews and Wang \cite{63} improved the algorithm to \( O(n \log n) \) time. The \textit{min-num} version of the problem was also studied, where the goal is to move the minimum number of sensors to form a barrier coverage. Mehrandish et al. \cite{16, 17} proved that the problem is NP-hard if sensors have different ranges and gave polynomial time algorithms otherwise.

Bhattacharya et al. \cite{13} studied a circular barrier coverage problem in which the barrier is a circle and the sensors are initially located inside the circle. The goal is to move sensors to the circle to form a regular \( n \)-gon (so as to cover the circle) such that the maximum sensor movement is minimized. An \( O(n^{3.5} \log n) \)-time algorithm was given in \cite{13} and later Chen et al. \cite{14} improved the algorithm to \( O(n \log^3 n) \) time. The min-sum version of the problem was also studied \cite{13, 14}.

5.1.3 Our Approach

To solve the problem MBC, one major difficulty is that we do not know the order of the sensors of \( S \) on \( L \) in an optimal solution. Therefore, our main effort is to find such an order. To this end, we first develop a decision algorithm that can determine whether \( \lambda \geq \lambda^* \) for any value \( \lambda \), where \( \lambda^* \) is the maximum sensor movement in an optimal solution. Our decision algorithm runs in \( O(m + n \log n) \) time. Then, we solve the problem MBC by “parameterizing” the decision algorithm in a way similar in spirit to parametric search \cite{64}. The high-level scheme of our algorithm is very similar to those in \cite{33, 61}, but many low-level computations are different.

The line-constrained version of the problem is much easier due to an order preserving property: there exists an optimal solution in which the order of the sensors is the same as in the input. This leads to a linear-time decision algorithm using the greedy strategy. Also based on this property, we can find a set \( \Lambda \) of \( O(n^2 m) \) “candidate values” such that \( \Lambda \) contains \( \lambda^* \). To avoid computing \( \Lambda \) explicitly, we implicitly organize the elements of \( \Lambda \) into \( O(n) \) sorted arrays such that each array element can be found in \( O(\log m) \) time. Finally, by applying the matrix search technique in \cite{65}, along with our linear-time
decision algorithm, we compute $\lambda^*$ in $O((n + m) \log(n + m))$ time. We should point out that implicitly organizing the elements of $\Lambda$ into sorted arrays is the key and also the major difficulty for solving the problem, and our technique may be interesting in its own right.

The rest of this chapter is organized as follows. We introduce some notation in Section 6.3. In Section 5.3, we present our algorithm for the line-constrained problem. In Section 5.4, we present our decision algorithm for the problem MBC. Section 5.5 solves the problem MBC. We conclude this chapter in Section 5.6, with remarks that our techniques can be used to reduce the space complexities of some previous algorithms in [33, 61].

5.2 Preliminaries

We denote the barriers of $\mathcal{B}$ by $B_1, B_2, \ldots, B_m$ sorted on $L$ from left to right. For each $B_i$, let $a_i$ and $b_i$ denote the left and right endpoints of $B_i$, respectively. For ease of exposition, we make a general position assumption that $a_i \neq b_i$ for each $B_i$. The degenerated case can also be handled by our techniques, but the discussions would be more tedious.

With a little abuse of notation, for any point $x$ on $L$ (the $x$-axis), we also use $x$ to denote its $x$-coordinate, and vice versa. We assume that the left endpoint of $B_1$ is at 0, i.e., $a_1 = 0$. Let $\beta$ denote the right endpoint of $B_m$, i.e., $\beta = b_m$.

We denote the sensors of $\mathcal{S}$ by $s_1, s_2, \ldots, s_n$ sorted by their $x$-coordinates. For each sensor $s_i$ located on a point $x$ of $L$, $x - r$ and $x + r$ are the left and right endpoints of the covering interval of $s_i$, respectively, and we call them the left and right extensions of $s_i$, respectively.

Again, let $\lambda^*$ be the maximum sensor movement in an optimal solution. Given $\lambda$, the decision problem is to determine whether $\lambda \geq \lambda^*$, or equivalently, whether we can move each sensor with distance at most $\lambda$ such that all barriers can be covered. If yes, we say that $\lambda$ is a feasible value. Thus, we also call it a feasibility test on $\lambda$.

5.3 The Line-Constrained Version of MBC

In this section, we present our algorithm for the line-constrained MBC. As in the
special case \( m = 1 \) \cite{60}, a useful observation is that the order preserving property holds: There exists an optimal solution in which the order of the sensors is the same as in the input. Due to this property, we first give a linear-time greedy algorithm for feasibility tests.

Lemma 5.3.1. Given any \( \lambda > 0 \), we can determine whether \( \lambda \) is a feasible value in \( O(n + m) \) time.

Proof. We first move every sensor rightwards for distance \( \lambda \). Then, every sensor is allowed to move leftwards at most \( 2\lambda \) but is not allowed to move rightwards any more. Next we use a greedy strategy to move sensors leftwards as small as possible to cover the currently uncovered leftmost barrier. To this end, we maintain a point \( p \) on a barrier that we need to cover such that all barrier points to the left of \( p \) are covered but the barrier points to the right of \( p \) are not. We consider the sensors \( s_i \) and the barriers \( B_j \) from left to right.

Initially, \( i = j = 1 \) and \( p = a_1 \). In general, suppose \( p \) is located at a barrier \( B_j \) and we are currently considering \( s_i \). If \( p \) is at \( \beta \), then we are done and \( \lambda \) is feasible. If \( p \) is located at \( b_j \) and \( j \neq m \), then we move \( p \) rightwards to \( a_{j+1} \) and proceed with \( j = j + 1 \). In the following, we assume that \( p \) is not at \( b_j \). Let \( x_i^r = x_i + \lambda \), i.e., the location of \( s_i \) after it is moved rightwards by \( \lambda \).

1. If \( x_i^r + r \leq p \), then we proceed with \( i = i + 1 \).
2. If \( x_i^r - r \leq p < x_i^r + r \), we move \( p \) rightwards to \( x_i^r + r \).
3. If \( x_i^r - 2\lambda - r \leq p < x_i^r - r \), then we move \( s_i \) leftwards such that the left extension of \( s_i \) is at \( p \), and we then move \( p \) to the right extension of \( s_i \).
4. If \( p < x_i^r - 2\lambda - r \), then we stop the algorithm and report that \( \lambda \) is not feasible.

Suppose the above moved \( p \) rightwards (i.e., in the second and third cases). Then, if \( p \geq \beta \), we report that \( \lambda \) is feasible. Otherwise, if \( p \) is not on a barrier, then we move \( p \) rightwards to the left endpoint of the next barrier. In either case, \( p \) is now located at a barrier, denoted by \( B_j \), and we increase \( i \) by one. We proceed as above with \( B_j \) and \( s_i \). It is easy to see that the algorithm runs in \( O(n + m) \) time. \( \square \)
Let $OPT$ be an optimal solution that preserves the order of the sensors. For each $i \in [1, n]$, let $x'_i$ be the position of $s_i$ in $OPT$. We say that a set of $k$ sensors are in \textit{attached positions} if the union of their covering intervals is a single interval of length equal to $2rk$. The following lemma is self-evident and is an extension of a similar observation for the case $m = 1$ in [60].

Lemma 5.3.2. There exists a sequence of sensors $s_i, s_{i+1}, \ldots, s_j$ in attached positions in $OPT$ such that one of the following three cases holds. (a) The sensor $s_j$ is moved to the left by distance $\lambda^*$ and $x'_i = a_k + r$ for some barrier $B_k$ (i.e., the sensors from $s_i$ to $s_j$ together cover the interval $[a_k, a_k + 2r(j - i + 1)]$). (b) The sensor $s_i$ is moved to the right by $\lambda^*$ and $x'_j = b_k - r$ for some barrier $B_k$. (c) The sensor $s_i$ is moved rightwards by $\lambda^*$ and $s_j$ is moved leftwards by $\lambda^*$.

Cases (a) and (b) are symmetric in the above lemma. Let $\Lambda_1$ be the set of all possible distance values introduced by $s_j$ in Case (a). Specifically, for any pair $(i, j)$ with $1 \leq i \leq j \leq n$ and any barrier $B_k$ with $1 \leq k \leq m$, define $\lambda(i, j, k) = x_j - (a_k + 2r(j - i) + r)$. Let $\Lambda_1$ consists of $\lambda(i, j, k)$ for all such triples $(i, j, k)$. We define $\Lambda_2$ symmetrically be the set of all possible values introduced by $s_i$ in Case (b). We define $\Lambda_3$ as the set consisting of the values $[x_j - x_i - 2r(j - i)]/2$ for all pairs $(i, j)$ with $1 \leq i < j \leq n$. Clearly, $|\Lambda_3| = O(n^2)$ and both $|\Lambda_1|$ and $|\Lambda_2|$ are $O(mn^2)$. Let $\Lambda = \Lambda_1 \cup \Lambda_2 \cup \Lambda_3$.

By Lemma 5.3.2, $\lambda^*$ is in $\Lambda$, and more specifically, $\lambda^*$ is the smallest feasible value of $\Lambda$. Hence, we can first compute $\Lambda$ and then find the smallest feasible value in $\Lambda$ by using the decision algorithm. However, that would take $\Omega(mn^2)$ time. To reduce the time, we will not compute $\Lambda$ explicitly, but implicitly organize the elements of $\Lambda$ into certain sorted arrays and then apply the matrix search technique proposed in [65], which has been widely used, e.g., [66,67]. Since we only need to deal with sorted arrays instead of more general matrices, we review the technique with respect to arrays in the following lemma.

Lemma 5.3.3. [65] Given a set of $N$ sorted arrays of size at most $M$ each, we can compute the smallest feasible value of these arrays with $O(\log N \log M)$ feasibility tests and the total time of the algorithm excluding the feasibility tests is $O(\tau \cdot N \cdot \log \frac{2M}{N})$, where $\tau$ is
the time for evaluating each array element (i.e., the number of array elements that need
to be evaluated is $O(N \cdot \log \frac{2M}{N})$).

With Lemma 5.3.3, we can compute the smallest feasible values in the three sets $\Lambda_1$, $\Lambda_2$, and $\Lambda_3$, respectively, and then return the smallest one as $\lambda^*$. For $\Lambda_3$, Chen et al. [33] (see Lemma 14) gave an approach to order in $O(n \log n)$ time the elements of $\Lambda_3$ into $O(n)$ sorted arrays of $O(n)$ elements each such that each array element can be obtained in $O(1)$ time. Consequently, by applying Lemma 5.3.3, the smallest feasible value of $\Lambda_3$ can be computed in $O((n + m) \log n)$ time.

For $\Lambda_1$ and $\Lambda_2$, in the case $m = 1$, the elements of each set can be easily ordered into $O(n)$ sorted arrays of $O(n)$ elements each [33]. However, in our problem for general $m$, the problem becomes significantly more difficult if we want to obtain a subquadratic-time algorithm. Indeed, this is the main challenge of our method. In what follows, our main effort is to prove the following lemma.

**Lemma 5.3.4.** For the set $\Lambda_1$, in $O(m \log m)$ time, we can implicitly form a set $A$ of $O(n)$ sorted arrays of $O(m^2 n)$ elements each such that each array element can be computed in $O(\log m)$ time and every element of $\Lambda_1$ is contained in one of the arrays. The same applies to the set $\Lambda_2$.

We note that our technique for Lemma 5.3.4 might be interesting in its own right and may find other applications as well. Before proving Lemma 5.3.4, we first prove the following result..

**Theorem 5.3.5.** The line-constrained version of MBC can be solved in $O((n + m) \log (n + m))$ time.

**Proof.** It is sufficient to compute $\lambda^*$, after which we can apply the decision algorithm on $\lambda^*$ to obtain an optimal solution.

Let $\Lambda'_1$ denote the set of all elements in the arrays of $A$ specified in Lemma 5.3.4. Define $\Lambda'_2$ similarly with respect to $\Lambda_2$. By Lemma 5.3.4, $\Lambda_1 \subseteq \Lambda'_1$ and $\Lambda_2 \subseteq \Lambda'_2$. Since $\lambda^* \in \Lambda_1 \cup \Lambda_2 \cup \Lambda_3$, we also have $\lambda^* \in \Lambda'_1 \cup \Lambda'_2 \cup \Lambda_3$. Hence, $\lambda^*$ is the smallest feasible value in $\Lambda'_1 \cup \Lambda'_2 \cup \Lambda_3$. Let $\lambda_1$, $\lambda_2$, and $\lambda_3$ be the smallest feasible values in the sets $\Lambda'_1$, $\Lambda'_2$, and $\Lambda_3$, respectively. As discussed before, $\lambda_3$ can be computed in $O((n + m) \log n)$ time. By
Lemma 5.3.4, applying the algorithm in Lemma 5.3.3 can compute both \( \lambda_1 \) and \( \lambda_2 \) in \( O((n+m)(\log m + \log n)) \) time. Note that \( (n+m)(\log m + \log n) = \Theta((n+m) \log(n+m)) \).

The theorem thus follows. \( \square \)

5.3.1 Proving Lemma 5.3.4

In this section, we prove Lemma 5.3.4. We will only prove the case for \( \Lambda_1 \), since the other case for \( \Lambda_2 \) is symmetric. Recall that \( \Lambda_1 = \{ (i, j, k) \mid 1 \leq i \leq j \leq n, 1 \leq k \leq m \} \), where \( \lambda(i, j, k) = x_j - (a_k + 2r(j - i) + r) \).

For any \( j \) and \( k \), let \( A[j, k] \) denote the list \( \lambda(i, j, k) \) for \( i = 1, 2, \ldots, j \), which is sorted in increasing order. With a little abuse of notation, let \( A[j] \) denote the union of the elements in \( A[j, k] \) for all \( k \in [1, m] \). Clearly, \( \Lambda_1 \) is the union of \( A[j] \) for all \( 1 \leq j \leq n \).

In the following, we will organize the elements in each \( A[j] \) into a sorted array \( B[j] \) of size \( O(nm^2) \) such that given any index \( t \), the \( t \)-th element of \( B[j] \) can be computed in \( O(\log m) \) time, which will prove Lemma 5.3.4. Our technique relies on the following property: the difference of every two adjacent elements in each list \( A[j, k] \) is the same, i.e., \( 2r \).

Notice that for any \( k \in [1, m - 1] \), the first element of \( A[j, k] \) is larger than the first element of \( A[j, k + 1] \), and similarly, the last element of \( A[j, k] \) is larger than the last element of \( A[j, k + 1] \). Hence, the first element of \( A[j, m] \), i.e., \( \lambda(1, j, m) \), is the smallest element of \( A[j] \) and the last element of \( A[j, 1] \), i.e., \( \lambda(j, j, 1) \), is the largest element of \( A[j] \). Let \( \lambda_{\min}[j] = \lambda(1, j, m) \) and \( \lambda_{\max}[j] = \lambda(j, j, 1) \).

For each \( k \in [1, m] \), we extend the list \( A[j, k] \) to a new sorted list \( B[j, k] \) with the following property: (1) \( A[j, k] \) is a sublist of \( B[j, k] \); (2) the difference every two adjacent elements of \( B[j, k] \) is \( 2r \); (3) the first element of \( B[j, k] \) is in \( [\lambda_{\min}[j], \lambda_{\min}[j] + 2r] \); (4) the last element of \( B[j, k] \) is in \( (\lambda_{\max}[j] - 2r, \lambda_{\max}[j]) \). Specifically, \( B[j, k] \) is defined as follows. Note that \( \lambda(1, j, k) \) and \( \lambda(j, j, k) \) are the first and last elements of \( A[j, k] \), respectively. We let \( \lambda(1, j, k) = \left\lfloor \frac{\lambda(1, j, k) - \lambda_{\min}[j]}{2r} \right\rfloor \cdot 2r + \lambda(1, j, k) \) and \( \lambda(j, j, k) = \left\lceil \frac{\lambda_{\max}[j] - \lambda(j, j, k)}{2r} \right\rceil \cdot 2r \) be the first and last elements of \( B[j, k] \), respectively. Then, the \( h \)-th element of \( B[j, k] \) is equal to \( \lambda(1, j, k) = \left\lfloor \frac{\lambda(1, j, k) - \lambda_{\min}[j]}{2r} \right\rfloor \cdot 2r + 2r \cdot (h - 1) \) for any \( h \in [1, \alpha[j]] \), where \( \alpha[j] = 1 + \left\lceil \frac{\lambda_{\max}[j] - \lambda_{\min}[j]}{2r} \right\rceil \). Hence, \( B[j, k] \) has \( \alpha[j] \) elements. One can verify that \( B[j, k] \) has the above four properties. Note that we can implicitly create the lists \( B[j, k] \) in
Lemma 5.3.7. For any $t$ with $1 \leq t \leq \alpha[j] \cdot m$, the $t$-th smallest element of $B[j]$ is the $h_t$-th element of the list $B[j, \sigma_j(k_t)]$, where $h_t = \lfloor \frac{t}{m} \rfloor$ and $k_t = t \mod m$.

Proof. Consider any $h$ with $1 \leq h \leq \alpha[j]$. Denote by $B_{h}[j, k]$ the $h$-th element of $B[j, k]$ for each $k \in [1, m]$. By our definition of $B[j, k]$, $B_{h}[j, k] \in [\lambda_{\min}[j] + 2r(h - 1), \lambda_{\min}[j] + 2rh)$. Therefore, for any $h' < h$, it holds that $B_{h'}[j, k] < B_{h}[j, k']$ for any $k$ and $k'$ in $[1, m]$. On the other hand, by the definition of $\sigma_j$, $B_{h}[j, \sigma(k)] \leq B_{h}[j, \sigma(k')]$ for any $1 \leq k < k' \leq m$.

Based on the above discussion, one can verify that the lemma statement holds. \qed

By the preceding lemma, if the permutation $\sigma_j$ is known, we can obtain the $t$-th smallest element of $B[j]$ in $O(1)$ time for any index $t$. Computing $\sigma_j$ can be done in $O(m \log m)$ time by sorting. If we apply the sorting algorithm on every $j \in [1, n]$, then we would need $O(nm \log m)$ time. Fortunately, the following lemma implies that we only need to do the sorting once.

Lemma 5.3.7. The permutation $\sigma_j$ is unique for all $j \in [1, n]$.

Proof. Consider any $j_1, j_2$ in $[1, n]$ with $j_1 \neq j_2$ and any $k_1, k_2$ in $[1, m]$ with $k_1 \neq k_2$. For any $j$ and $k$, let $B_{1}[j, k]$ denote the first element of $B[j, k]$. To prove the lemma, it is sufficient to show that $B_{1}[j_1, k_1] < B_{1}[j_1, k_2]$ if and only if $B_{1}[j_2, k_1] < B_{1}[j_2, k_2]$.

Recall that $B_{1}[j, k] = \lambda(1, j, k) - \left(\frac{\lambda(1, j, k) - \lambda_{\min}[j]}{2r}\right) \cdot 2r$ and $\lambda(1, j, k) = x_j - (a_k + 2rj - r)$. Thus, $B_{1}[j, k] = x_j - a_k + r - \left(\frac{x_j - a_k + r - \lambda_{\min}[j]}{2r}\right) \cdot 2r$. Further, since $\lambda_{\min}[j] = \lambda(1, j, m) = x_j - (am + 2rj - r)$, $B_{1}[j, k] = x_j - a_k + r - \left(\frac{an - a_k + 2rj}{2r}\right) \cdot 2r = x_j - a_k + r - \left(\frac{am - a_k}{2r}\right) \cdot 2r - 2rj$.

Therefore, $B_{1}[j_1, k_1] - B_{1}[j_1, k_2] = a_{k_2} - a_{k_1} + \left(\frac{am - a_{k_2}}{2r}\right) - \left(\frac{am - a_{k_1}}{2r}\right) \cdot 2r$ and $B_{1}[j_2, k_1] - B_{1}[j_2, k_2] = a_{k_2} - a_{k_1} + \left(\frac{am - a_{k_2}}{2r}\right) - \left(\frac{am - a_{k_1}}{2r}\right) \cdot 2r$. Hence, $B_{1}[j_1, k_1] -
\[ B_1[j_1, k_2] = B_1[j_2, k_1] - B_1[j_2, k_2], \]
which implies that \( B_1[j_1, k_1] < B_1[j_1, k_2] \) if and only if \( B_1[j_2, k_1] < B_1[j_2, k_2]. \)

In summary, after \( O(m \log m) \) time preprocessing to compute the permutation \( \sigma_j \) for any \( j \), we can form the arrays \( B[j] \) for all \( j \in [1, n] \) such that given any \( j \in [1, n] \) and \( t \in [1, \alpha[j] \cdot m] \), we can compute \( t \)-th smallest element of \( B[j] \) in \( O(1) \) time. However, we are not done yet, because we do not have a reasonable upper bound for \( \alpha[j] \), which is equal to \( 1 + \lceil \frac{\lambda_{\text{max}}[j] - \lambda_{\text{min}}[j]}{2r} \rceil = 1 + \lceil \frac{\lambda(j,j,1) - \lambda(1,j,m)}{2r} \rceil = j + \lceil \frac{a_m - a_1}{2r} \rceil \). To address the issue, in the sequel, we will partition the indices \( k \in [1, m] \) into groups and then apply our above approach to each group so that the corresponding \( \alpha[j] \) values can be bounded, e.g., by \( O(mn) \).

The Group Partition Technique. We consider any index \( j \in [1, m] \).

We partition the indices \( 1, 2, \ldots, m \) into groups each consisting of a sequence of consecutive indices, such that each group has the following \textit{intra-group overlapping property}:

For any index \( k \) that is not the largest index in the group, the first element of \( A[j, k] \) is smaller than or equal to the last element of \( A[j, k+1] \), i.e., \( \lambda(1, j, k) \leq \lambda(j, j, k+1) \). Further, the groups have the following \textit{inter-group non-overlapping property}: For the largest index \( k \) in a group that is not the last group, the first element of \( A[j, k] \) is larger than the last element of \( A[j, k+1] \), i.e., \( \lambda(1, j, k) > \lambda(j, j, k+1) \).

We compute the groups in \( O(m) \) time as follows. Initially, add 1 into the first group \( G_1 \). Let \( k = 1 \). While the first element of \( A[j, k] \) is smaller than or equal to the last element of \( A[j, k+1] \), we add \( k+1 \) into \( G_1 \) and reset \( k = k + 1 \). After the while loop, \( G_1 \) is computed. Then, starting from \( k + 1 \), we compute \( G_2 \) and so on until index \( m \) is included in the last group. Let \( G_1, G_2, \ldots, G_l \) be the \( l \) groups we have computed. Note that \( l \leq m \).

Consider any group \( G_g \) with \( 1 \leq g \leq l \). We process the lists \( A[j][k] \) for all \( k \in G_g \) in the same way as discussed before. Specifically, for each \( k \in G_g \), we create a new list \( B[j][k] \) from \( A[j][k] \). Based on the new lists in the group \( G_g \), we form the sorted array \( B_g[j] \) with a total of \( |G_g| \cdot \alpha_g[j] \) elements, where \( |G_g| \) is the number of indices of \( G_g \) and \( \alpha_g[j] \) is corresponding \( \alpha[j] \) value as defined before but only on the group \( G_g \), i.e., if \( k_1 \) and \( k_2 \) are the smallest and largest indices of \( G_g \) respectively, then \( \alpha_g[j] = \)
1 + \left\lceil \frac{\lambda(j,j,k_j) - \lambda(1,j,k_1)}{2r} \right\rceil$. Let $B[j]$ be the sorted list of all elements in the lists $B_g[j]$ for all groups. Due to the intra-group overlapping property of each group, it holds that $\alpha_g \leq |G_g| \cdot n$. Thus, the size of $B[j]$ is at most $\sum_{g=1}^{l} |G_g|^2 \cdot n$, which is at most $m^2 n$ since $\sum_{g=1}^{l} |G_g| = m$.

Suppose we want to find the $t$-th smallest element of $B[j]$. As preprocessing, we compute a sequence of values $\beta_g[j]$ for $g = 1, 2, \ldots, l$, where $\beta_g[j] = \sum_{g'=1}^{g} \alpha_{g'}[j] \cdot |G_{g'}|$, in $O(m)$ time. To compute the $t$-th smallest element of $B[j]$, we first do binary search on the sequence $\beta_1[j], \beta_2[j], \ldots, \beta_l[j]$ to find in $O(\log l)$ time the index $g$ such that $t \in (\beta_{g-1}[j], \beta_g[j])$. Due to the inter-group non-overlapping property of the groups, the $t$-th smallest element of $B[j]$ is the $(t - \beta_{g-1}[j])$-th element in the array $B_g[j]$, which can be found in $O(1)$ time. As $l \leq m$, the total time for computing the $t$-th smallest element of $B[j]$ is $O(\log m)$.

The above discussion is on any single index $j \in [1, n]$. With $O(m \log m)$ time preprocessing, given any $t$, we can find the $t$-th smallest value of $B[j]$ in $O(\log m)$ time.

For all indices $j \in [1, n]$, it appears that we have to do the group partition for every $j \in [1, n]$, which would take quadratic time. To resolve the problem, we show that it is sufficient to only use the group partition based on $j = n$ for all other $j \in [1, n-1]$. The details are given below.

Suppose from now on $G_1, G_2, \ldots, G_l$ are the groups computed as above with respect to $j = n$. We know that the inter-group non-overlapping property holds respect to the index $n$. The following lemma shows that the property also holds with respect to any other index $j \in [1, n-1]$.

**Lemma 5.3.8.** The inter-group non-overlapping property holds for any $j \in [1, n-1]$.

**Proof.** Consider any $j \in [1, n-1]$ and any $k$ that is the largest index in a group $G_g$ with $g \in [1, l-1]$. The goal is to show that the first element of $A[j,k]$ is larger than the last element of $A[j,k+1]$, i.e., $\lambda(1,j,k) > \lambda(j,j,k+1)$. Since the groups are defined with respect to the index $n$, it holds that $\lambda(1,n,k) > \lambda(n,n,k+1)$.

Recall that $\lambda(i,j,k) = x_j - (a_k + 2r(j-i)+r)$. Therefore, $\lambda(1,j,k) - \lambda(j,j,k+1) = a_{k+1} - a_k + 2r(1-j)$ and $\lambda(1,n,k) - \lambda(n,n,k+1) = a_{k+1} - a_k + 2r(1-n)$. Since
Proof. Consider any \( G \) with \( 1 \leq g \leq l \) and any \( j \in [1, n] \). For each \( g \in G \), we create a new list \( B[j][k] \) based on \( A[j][k] \) in the same way as discussed before. Based on the new lists, we form the sorted array \( B_g[j] \) of \( |G_g| \cdot \alpha_g[j] \) elements. We also define the value \( \beta_g[j] \) in the same way as before. The following lemma shows that \( \alpha_g[j] \) and \( \beta_g[j] \) can be computed based on \( \alpha_g[n] \) and \( \beta_g[n] \).

Lemma 5.3.9. For any \( j \in [1, n-1] \) and \( g \in [1, l] \), \( \alpha_g[j] = \alpha_g[n] - n + j \) and \( \beta_g[j] = \beta_g[n] + \delta_g \cdot g \cdot (j - n) \), where \( \delta_g = \sum_{g=1}^{g} |G_g| \).

Proof. Consider any \( g \in [1, l] \). Let \( k_1 \) and \( k_2 \) be the smallest and the largest indices in \( G_g \), respectively. By definition, \( \alpha_g[j] = 1 + \lceil \frac{\lambda(j,j,k_1) - \lambda(1,j,k_2)}{2r} \rceil = 1 + \lceil \frac{a_{k_2} - a_{k_1} + 2r(j-1)}{2r} \rceil = j + \lceil \frac{a_{k_2} - a_{k_1}}{2r} \rceil \). Therefore, for any \( j \in [1, n-1] \), \( \alpha_g[j] = \alpha_g[n] - n + j \).

By definition, \( \beta_g[j] = \alpha_1[j] \cdot |G_1| + \alpha_2[j] \cdot |G_2| + \cdots + \alpha_g[j] \cdot |G_g| = (\alpha_1[n] - n + j) \cdot |G_1| + (\alpha_2[n] - n + j) \cdot |G_2| + \cdots + (\alpha_g[n] - n + j) \cdot |G_g| = \beta_g[n] + (j - n) \cdot g \cdot (|G_1| + |G_2| + \cdots + |G_g|) = \beta_g[n] + \delta_g \cdot g \cdot (j - n) \).

For each group \( G_g \), we compute the permutation for the lists \( B[n,k] \) for all \( k \) in the group. Computing the permutations for all groups takes \( O(m \log m) \) time. As also preprocessing, we first compute \( \delta_g, \alpha_g(n) \) and \( \beta_g(n) \) for all \( g \in [1, l] \) in \( O(m) \) time. By Lemma 5.3.9, for any \( j \in [1, n] \) and any \( g \in [1, l] \), we can compute \( \alpha_g[j] \) and \( \beta_g[j] \) in \( O(1) \) time. Because the lists \( B[n,k] \) for all \( k \) in each group \( G_g \) have the intra-group overlapping property, it holds that \( \alpha_g[n] \leq |G_g| \cdot n \). Hence, \( \sum_{g=1}^{l} \alpha_g[n] \leq mn \). For any \( j \in [1, n-1] \), by Lemma 5.3.9, \( \alpha_g[j] < \alpha_g[n] \), and thus \( \sum_{g=1}^{l} \alpha_g[j] \leq mn \). Recall that \( B[j] \) is the sorted array of all elements in \( B_g[j] \) for \( g \in [1, l] \). Thus, \( B[j] \) has at most \( m^2 n \) elements.

For any \( j \in [1, n] \) and any \( t \in [1, \sum_{g=1}^{l} |G_g| \cdot \alpha_g[j]|) \), suppose we want to compute the \( t \)-th smallest element of \( B[j] \). Due to the inter-group non-overlapping property in Lemma 5.3.8, we can still use the previous binary search approach. For the running time, since we can obtain each \( \beta_g[j] \) for any \( g \in [1, l] \) in \( O(1) \) time by Lemma 5.3.9, we can still compute the \( t \)-th smallest element of \( B[j] \) in \( O(\log m) \) time.

This proves Lemma 5.3.4.
5.4 The Decision Problem of MBC

In this section, we present an $O(m+n \log n)$-time algorithm for the decision problem of MBC: given any value $\lambda > 0$, determine whether $\lambda \geq \lambda^*$. Our algorithm for MBC in Section 5.5 will make use of this decision algorithm. The decision problem may have independent interest because in some applications each sensor has a limited energy $\lambda$ and we want to know whether their energy is enough for them to move to cover all barriers.

Consider any value $\lambda > 0$. We assume that $\lambda \geq \max_{1 \leq i \leq n} |y_i|$ since otherwise some sensor cannot reach $L$ by moving $\lambda$ (and thus $\lambda$ is not feasible). For any sensor $s_i \in S$, define $x'_i = x_i + \sqrt{\lambda^2 - y_i^2}$ and $x'_i = x_i - \sqrt{\lambda^2 - y_i^2}$. Note that $x'_i$ and $x'_i$ are respectively the rightmost and leftmost points of $L$ $s_i$ can reach with respect to $\lambda$. We call $x'_i$ the rightmost (resp., leftmost) $\lambda$-reachable location of $s_i$ on $L$. For any point $x$ on $L$, we use $p^+(x)$ to denote a point $x'$ such that $x' > x$ and $x'$ is infinitesimally close to $x$.

The high-level scheme of our algorithm is similar to that in [61]. We first describe the algorithm and then show its correctness. Finally, we discuss its implementation.

5.4.1 The Algorithm Description

We use a configuration to refer to a specification on where each sensor $s_i \in S$ is located. For example, in the input configuration, each $s_i$ is at $(x_i, y_i)$.

We begin with moving each sensor $s_i$ to $x'_i$ on $L$. Let $C_0$ denote the resulting configuration. In $C_0$, each sensor $s_i$ is not allowed to move rightwards but can move leftwards on $L$ by a maximum distance $2\sqrt{\lambda^2 - y_i^2}$.

If $\lambda \geq \lambda^*$, our algorithm will compute a subset of sensors with their new locations to cover all barriers of $B$ and the maximum movement of each sensor of in the subset is at most $\lambda$.

For each step $i$ with $i \geq 1$, let $C_{i-1}$ be the configuration right before the $i$-th step. Our algorithm maintains the following invariants. (1) We have a subset of sensors $S_{i-1} = \{s_{g(1)}, s_{g(2)}, \ldots, s_{g(i-1)}\}$, where for each $1 \leq j \leq i-1$, $g(j)$ is the index of the sensor $s_{g(j)}$ in $S$. (2) In $C_{i-1}$, each sensor $s_k$ of $S_{i-1}$ is at a new location $x'_k \in [x'_k, x'_k]$, and all other sensors are still in their locations of $C_0$. (3) A value $R_{i-1}$ is maintained such that $0 \leq R_{i-1} < \beta$, $R_{i-1}$ is on a barrier, every barrier point $x < R_{i-1}$ is covered by
a sensor of \( S_{i-1} \) in \( C_{i-1} \). (4) If \( R_{i-1} \) is not at the left endpoint of a barrier, then \( R_{i-1} \) is covered by a sensor of \( S_{i-1} \) in \( C_{i-1} \). (5) The point \( p^+(R_{i-1}) \) is not covered by any sensor in \( S_{i-1} \).

Initially when \( i = 1 \), we let \( S_0 = \emptyset \) and \( R_0 = 0 \), and thus all algorithm invariants hold for \( C_0 \). The \( i \)-th step of the algorithm finds a sensor \( s_{g(i)} \in S \setminus S_{i-1} \) and moves it to a new location \( x'_{g(i)} \in [x^l_{g(i)}, x^r_{g(i)}] \) and thus obtains a new configuration \( C_i \). The details are given below.

Define \( S_{i1} \) to be the set of sensors that cover the point \( p^+(R_{i-1}) \) in \( C_{i-1} \), i.e., \( S_{i1} = \{ s_k \mid x^l_k - r \leq R_{i-1} < x^r_k + r \} \). By the algorithm invariant (5), no sensor in \( S_{i-1} \) covers \( p^+(R_{i-1}) \). Thus, \( S_{i1} \subseteq S \setminus S_{i-1} \). If \( S_{i1} \neq \emptyset \), then we choose an arbitrary sensor in \( S_{i1} \) as \( s_{g(i)} \) (e.g., see Fig. 5.1) and let \( x'_{g(i)} = x^r_{g(i)} \). We then set \( R_i = x'_{g(i)} + r \), i.e., \( R_i \) is at the right endpoint of the covering interval of \( s_{g(i)} \). Note that \( C_i \) is \( C_{i-1} \) because \( s_{g(i)} \) is not moved.

If \( S_{i1} = \emptyset \), then we define \( S_{i2} = \{ s_k \mid x^l_k - r \leq R_{i-1} < x^r_k - r \} \) (i.e., \( S_{i2} \)) consists of those sensors \( s_k \) that does not cover \( R_{i-1} \) when it is at \( x^r_k \) but is possible to do so when it is at some location in \([x^l_k, x^r_k]\). If \( S_{i2} \neq \emptyset \), we choose the leftmost sensor in \( S_{i2} \) as \( s_{g(i)} \) (e.g., see Fig. 5.2), and let \( x'_{g(i)} = R_{i-1} + r \) (i.e., we move \( s_{g(i)} \) to \( x'_{g(i)} \) and thus obtain \( C_i \)). If \( S_{i2} = \emptyset \), then we conclude that \( \lambda < \lambda^* \) and terminate the algorithm.

Hence, if \( S_{i1} = S_{i2} = \emptyset \), the algorithm will stop and report \( \lambda < \lambda^* \). Otherwise, a sensor \( s_{g(i)} \) is found from either \( S_{i1} \) or \( S_{i2} \), and it is moved to \( x'_{g(i)} \). In either case, \( R_i = x'_{g(i)} + r \) and \( S_i = S_{i-1} \cup \{ s_{g(i)} \} \). If \( R_i \geq \beta \), then we terminate the algorithm and report \( \lambda \geq \lambda^* \). Otherwise, we further perform the following jump-over procedure: We check whether \( R_i \) is located at the interior of any barrier; if not, then we set \( R_i \) to the left endpoint of the barrier right after \( R_i \).

This finishes the \( i \)-th step of our algorithm. One can verify that all algorithm invariants are maintained. As there are \( n \) sensors in \( S \), the algorithm will finish in at most \( n \) steps.

5.4.2 The Algorithm Correctness

The correctness proof is similar to that for the algorithm in [61], so we briefly discuss it.
If the decision algorithm reports $\lambda \geq \lambda^*$, say, in the $i$-th step, then according to our algorithm, the configuration $C_i$ is a feasible solution. Below, we show that if the algorithm reports $\lambda < \lambda^*$, then $\lambda$ is indeed not a feasible value.

We first note that due to our jump-over procedure and our general position assumption, $R_i$ cannot be at the right endpoint of a barrier, and thus $p^+(R_i)$ must be a point of a barrier.

An interval on $L$ is said to be left-aligned if its left side is closed and equal to 0 and its right side is open. The algorithm correctness will be easily shown with the following Lemma 5.4.1. The proof of the lemma is very similar to Lemma 1 in [61], so we omit it.

**Lemma 5.4.1.** Consider any configuration $C_i$. Suppose $S'_i$ is the set of sensors in $S$ whose right extensions are at most $R_i$ in $C_i$. Then, the interval $[0, R_i)$ is the largest possible left-aligned interval such that all barrier points in the interval can be covered by the sensors of $S'_i$ with respect to $\lambda$ (i.e., the moving distance of each sensor of $S'_i$ is at most $\lambda$).

Suppose our algorithm reports $\lambda < \lambda^*$ in the $i$-th step. We show that $\lambda$ is not a feasible value. Indeed, according to our algorithm, $R_{i-1} < \beta$ and $S_{i1} = S_{i2} = \emptyset$ in the configuration $C_{i-1}$. Let $S'_{i-1}$ be the set of sensors whose right extensions are at most $R_{i-1}$ in $C_{i-1}$. On the one hand, by Lemma 5.4.1 (replacing index $i$ in the lemma by $i-1$), $[0, R_{i-1})$ is the largest left-aligned interval such that all barrier points in the interval that can be covered by the sensors in $S'_{i-1}$. On the other hand, since both $S_{i1}$ and $S_{i2}$ are empty, no sensor in $S \setminus S'_{i-1}$ can cover the point $p^+(R_{i-1})$. Recall that $p^+(R_{i-1})$ is a barrier point not covered by any sensor in $S_{i-1}$. Due to $R_{i-1} < \beta$, we conclude that sensors of $S$ cannot cover all barrier points in the interval $[0, p^+(R_{i-1})] \subseteq [0, \beta]$ with
respect to $\lambda$. Thus, $\lambda$ is not a feasible value. This establishes the correctness of our decision algorithm.

5.4.3 The Algorithm Implementation

The implementation is similar to that in [61] and we briefly discuss it. We first implement the algorithm in $O(m + n \log n)$ time, and then we reduce the time to $O(m + n \log \log n)$ under certain assumptions.

We first move each sensor $s_i$ to $x^r_i$ and thus obtain the configuration $C_0$. Then, we sort the extensions of all sensors in $C_0$ together with the endpoints of all barriers. To maintain the set $S_{i1}$ during the algorithm, we sweep a point $p$ on $L$ from left to right. During the sweeping, when $p$ encounters the left (resp., right) extension of a sensor, we insert the sensor into $S_{i1}$ (resp., delete it from $S_{i1}$). In this way, in each $i$-th step of the algorithm, when $p$ is at $R_{i-1}$, $S_{i1}$ is available.

If $S_{i1} \neq \emptyset$, we pick an arbitrary sensor in $S_{i1}$ as $s_{g(i)}$. To store the set $S_{i1}$, since sensors have the same range, the earlier a sensor is inserted into $S_{i1}$, the earlier it is deleted from $S_{i1}$. Thus, we can simply use a first-in-first-out queue to store $S_{i1}$ such that each insertion/deletion can be done in constant time. We can always pick the front sensor in the queue as $s_{g(i)}$.

If $S_{i1} = \emptyset$, then we need to compute $S_{i2}$. To maintain $S_{i2}$ during the sweeping of $p$, we do the following. Initially when we do the sorting as discussed above, we also sort the $n$ values $x^l_i - r$ for all $1 \leq i \leq n$. During the sweeping of $p$, if $p$ encounters a point $x^l_k - r$ for some sensor $s_k$, we insert $s_k$ to $S_{i2}$, and if $p$ encounters a left extension of some sensor $s_k$, we delete $s_k$ from $S_{i2}$. In this way, when $p$ is at $R_{i-1}$, $S_{i2}$ is available. If $S_{i2} \neq \emptyset$, we need to find the leftmost sensor in $S_{i2}$ as $s_{g(i)}$, for which we use a balanced binary search tree $T$ to store all sensors of $S_{i2}$ where the “key” of each sensor $s_k$ is the value $x^r_k$. $T$ can support each of the following operations on $S_{i2}$ in $O(\log n)$ time: inserting a sensor, deleting a sensor, finding the leftmost sensor.

If $s_{g(i)}$ is from $S_{i1}$, then we do not need to move $s_{g(i)}$. We proceed to sweep $p$ as usual. If $s_{g(i)}$ is from $S_{i2}$, we need to move $s_{g(i)}$ leftwards to $x^l_{g(i)} = R_{i-1} + r$. Since $s_{g(i)}$ is moved, we should also update the original sorted list including the extensions of all sensors in $C_0$ to guide the future sweeping of $p$. To avoid the explicit update, we use a
flag table for all sensor extensions in $C_0$. Initially, every table entry is valid. If $s_{g(i)}$ is moved, then we set the table entries of the two extensions of the sensor invalid. During the sweeping of $p$, when $p$ encounters a sensor extension, we first check the table to see whether the extension is still valid. If yes, then we proceed as usual; otherwise we ignore the event. This only costs extra constant time for each event. In addition, we calculate $R_i$ as discussed before, and the jump-over procedure can be implemented in $O(1)$ time since the barrier endpoints are also sorted.

To analyze the running time, since the barriers are given sorted on $L$, the sorting step takes $O(m + n \log n)$. Since there are $O(n)$ operations on the tree $T$, the total time of the algorithm is $O(m + n \log n)$. Thus we obtain the following result.

Theorem 5.4.2. Given any value $\lambda$, we can determine whether $\lambda \geq \lambda^*$ in $O(m + n \log n)$ time.

Our algorithm in Section 5.5 will perform feasibility tests multiple times, for which we have the following result.

Lemma 5.4.3. Suppose the values $x_{ri}$ for all $i = 1, 2, \ldots, n$ are already sorted, we can determine whether $\lambda \geq \lambda^*$ in $O(m + n \log \log n)$ time for any $\lambda$.

Proof. Our $O(m + n \log n)$ time implementation is dominated by two parts. The first part is the sorting. The second part is on performing the operations on the set $S_{i2}$, each taking $O(\log n)$ time by using the tree $T$. The rest of the algorithm together takes $O(n + m)$ time. Now that the values $x_{ri}$ for all $i = 1, 2, \ldots, n$ are already sorted, the sorting step takes $O(n + m)$ time since the barriers are already given sorted.

Recall that the keys of the sensors of $T$ are the values $x_k$. Let $Q = \{x_k \mid 1 \leq k \leq n\}$. For each sensor $s_k$, we use $\text{rank}(s_k)$ to denote the rank of $x_k$ in $Q$ (i.e., $\text{rank}(s_k) = t$ if $x_k$ is the $t$-th smallest value in $Q$). Since $Q$ is already sorted, all sensor ranks can be computed in $O(n)$ time. It is easy to see that the leftmost sensor of $T$ is the sensor with the smallest rank. Therefore, we can also use the ranks as the keys of sensors of $T$, and the advantage of doing so is that the rank of each sensor is an integer in $[1, n]$. Hence, instead of using a balanced binary search tree, we can use an integer data structure, e.g., the van Emde Boas Tree (or vEB tree for short) [29], to maintain $S_{i2}$. The vEB tree can support each of the following operations on $S_{i2}$ in $O(\log \log n)$ time [29]: inserting
a sensor, deleting a sensor, and finding the sensor with the smallest rank. Using a vEB tree, all operations on $S_{i2}$ in the algorithm can be performed in $O(n \log \log n)$ time. The lemma thus follows.

5.5 Solving the Problem MBC

In this section, we solve the problem MBC. It suffices to compute $\lambda^*$. The high-level scheme of our algorithm is similar to that in [61], although some low-level details are different.

In this section, we use $x_i^r(\lambda)$ to refer to $x_i^r$ for any $\lambda$, so that we consider $x_i^r(\lambda)$ as a function on $\lambda \in [0, \infty]$, which actually defines a half of the upper branch (on the right side of the $y$-axis) of a hyperbola. Let $\sigma$ be the order of the values $x_i^r(\lambda^*)$ for all $i \in [1, n]$.

To make use of Lemma 5.4.3, we first run a preprocessing step in Lemma 5.5.1.

**Lemma 5.5.1.** With $O(n \log^3 n + m \log^2 n)$ time preprocessing, we can compute $\sigma$ and an interval $(\lambda^*_1, \lambda^*_2]$ containing $\lambda^*$ such that $\sigma$ is also the order of the values $x_i^r(\lambda)$ for any $\lambda \in (\lambda^*_1, \lambda^*_2]$. 

**Proof.** To compute $\sigma$, we apply Megiddo’s parametric search [64] to sort the values $x_i^r(\lambda^*)$ for $i \in [1, n]$, using the decision algorithm in Theorem 5.4.2. Indeed, recall that $x_i^r(\lambda) = x_i + \sqrt{\lambda^2 - y_i^2}$. Hence, as $\lambda$ increases, $x_i^r(\lambda)$ is a (strictly) increasing function. For any two indices $i$ and $j$, there is at most one root on $\lambda \in [0, \infty)$ for the equation: $x_i^r(\lambda) = x_j^r(\lambda)$. Therefore, we can apply Megiddo’s parametric search [64] to do the sorting. The total time is $O((\tau + n) \log^2 n)$, where $\tau$ is the running time of the decision algorithm. By Theorem 5.4.2, $\tau = O(m + n \log n)$. Hence, the total time for computing $\sigma$ is $O(m \log^2 n + n \log^3 n)$.

In addition, Megiddo’s parametric search [64] will return an interval $(\lambda^*_1, \lambda^*_2]$ such that it contains $\lambda^*$ and $\sigma$ is also the order of the values $x_i^r(\lambda)$ for any $\lambda \in (\lambda^*_1, \lambda^*_2]$. 

Note that $\lambda^*$ is the smallest feasible value. As $\lambda^* \in (\lambda^*_1, \lambda^*_2]$, our subsequent feasible tests will be only on values $\lambda \in (\lambda^*_1, \lambda^*_2)$ because if $\lambda \leq \lambda^*_1$, then $\lambda$ is not feasible and if $\lambda \geq \lambda^*_2$, then $\lambda$ is feasible. Lemmas 5.4.3 and 5.5.1 together lead to the following result.

**Lemma 5.5.2.** Each feasibility test can be done in $O(m + n \log \log n)$ time for any $\lambda \in (\lambda^*_1, \lambda^*_2)$. 

To compute $\lambda^*$, we “parameterize” our decision algorithm with $\lambda$ as a parameter. Although we do not know $\lambda^*$, we execute the decision algorithm in such a way that it computes the same subset of sensors $s_{g(1)}, s_{g(2)}, \ldots$ as would be obtained if we ran the decision algorithm on $\lambda = \lambda^*$.

Recall that for any $\lambda$, step $i$ of our decision algorithm computes the sensor $s_{g(i)}$, the set $S_i = \{s_{g(1)}, s_{g(2)}, \ldots, s_{g(i)}\}$, and the value $R_i$, and obtains the configuration $C_i$. In the following, we often consider $\lambda$ as a variable rather than a fixed value. Thus, we will use $S_i(\lambda)$ (resp., $R_i(\lambda)$, $s_{g(i)}(\lambda)$, $C_i(\lambda)$, $x_i^r(\lambda)$) to refer to the corresponding $S_i$ (resp., $R_i$, $s_{g(i)}$, $C_i$, $x_i^r$). Our algorithm has at most $n$ steps. Consider a general $i$-th step for $i \geq 1$. Right before the step, we have an interval $(\lambda_{i-1}^1, \lambda_{i-1}^2]$ and a sensor set $S_{i-1}(\lambda)$, such that the following algorithm invariants hold.

1. $\lambda^* \in (\lambda_{i-1}^1, \lambda_{i-1}^2]$.

2. The set $S_{i-1}(\lambda)$ is the same (with the same order) for all values $\lambda \in (\lambda_{i-1}^1, \lambda_{i-1}^2)$.

3. $R_{i-1}(\lambda)$ on $\lambda \in (\lambda_{i-1}^1, \lambda_{i-1}^2)$ is either constant or equal to $x_j + \sqrt{\lambda^2 - y_j^2} + c$ for some constant $c$ and some sensor $s_j$ with $1 \leq j \leq i - 1$, and $R_{i-1}(\lambda)$ is maintained by the algorithm.

4. $R_{i-1}(\lambda) < \beta$ for any $\lambda \in (\lambda_{i-1}^1, \lambda_{i-1}^2)$.

Initially when $i = 1$, we let $\lambda_0^1 = \lambda^*$ and $\lambda_0^2 = \lambda^*$. Since $S_0(\lambda) = \emptyset$ and $R_0(\lambda) = 0$ for any $\lambda$, by Lemma 5.5.1, all invariants hold for $i = 1$. In general, the $i$-th step will either compute $\lambda^*$, or obtain an interval $(\lambda_i^1, \lambda_i^2] \subseteq (\lambda_{i-1}^1, \lambda_{i-1}^2]$ and a sensor $s_{g(i)}(\lambda)$ with $S_i(\lambda) = S_{i-1}(\lambda) \cup \{s_{g(i)}(\lambda)\}$. The running time of the step is $O((m + n \log \log n)(\log n + \log m))$. The details are given below.

5.5.1 The Algorithm

We assume $\lambda^* \neq \lambda_{i-1}^2$ and thus $\lambda^*$ is in $(\lambda_{i-1}^1, \lambda_{i-1}^2)$. Our following algorithm can proceed without this assumption and we make the assumption only for explaining the rationale of our approach. Since $\lambda^* \in (\lambda_{i-1}^1, \lambda_{i-1}^2)$, according to our algorithm invariants, for all $\lambda \in (\lambda_{i-1}^1, \lambda_{i-1}^2)$, $S_{i-1}(\lambda)$ is the same as $S_{i-1}(\lambda^*)$. We simulate the
decision algorithm on $\lambda = \lambda^*$. To determine the sensor $s_{\bar{g}(i)}(\lambda^*)$, we first compute the set $S_i(\lambda^*)$, as follows.

Consider any sensor $s_k$ in $S \setminus S_{i-1}(\lambda)$. Its position in $C_{i-1}(\lambda)$ is $x_k^r(\lambda) = x_k + \sqrt{\lambda^2 - y_k^2}$, which is an increasing function of $\lambda$. Thus, both the left and the right extensions of $s_k$ in $C_{i-1}(\lambda)$ are increasing functions of $\lambda$. Suppose $f(\lambda)$ is either the left or the right extension of $s_k$ in $C_{i-1}(\lambda)$. According to our algorithm invariants, $R_{i-1}(\lambda)$ on $\lambda \in (\lambda_{i-1}^1, \lambda_{i-1}^2)$ is either constant or equal to $x_j + \sqrt{\lambda^2 - y_j^2} + c$ for some constant $c$ and some sensor $s_j$. We claim that there is at most one value $\lambda$ in $(\lambda_{i-1}^1, \lambda_{i-1}^2)$ such that $R_{i-1}(\lambda) = f(\lambda)$. Indeed, if $R_{i-1}(\lambda)$ is constant, then this is obviously true; otherwise, this is also true because each of $f(\lambda)$ and $R_{i-1}(\lambda)$ on $\lambda \in [0, \infty)$ defines a half branch of a hyperbola (and thus they have at most one intersection in $(\lambda_{i-1}^1, \lambda_{i-1}^2)$).

Let $S' = S \setminus S_{i-1}(\lambda)$. If we increase $\lambda$ from $\lambda_{i-1}^1$ to $\lambda_{i-1}^2$, an “event” happens if $R_{i-1}(\lambda)$ is equal to the left or right extension value of a sensor $s_k \in S'$ at some value of $\lambda$ (called an event value), and $S_{i+1}(\lambda)$ does not change between any two adjacent events. To compute $S_{i+1}(\lambda^*)$, we first compute all event values, and this can be done in $O(n)$ time by using the function $R_{i-1}(\lambda)$ and all left and right extension functions of the sensors in $S'$. Let $\Lambda$ denote the set of all event values, and we also add $\lambda_{i-1}^1$ and $\lambda_{i-1}^2$ to $\Lambda$. We then sort all values in $\Lambda$. Using the feasibility test in Lemma 5.5.2, we do binary search to find two adjacent values $\lambda_1$ and $\lambda_2$ in the sorted list of $\Lambda$ such that $\lambda^* \in (\lambda_1, \lambda_2)$. Note that $(\lambda_1, \lambda_2] \subseteq (\lambda_{i-1}^1, \lambda_{i-1}^2]$. Since $|\Lambda| = O(n)$, the binary search uses $O(\log n)$ feasibility tests, which takes overall $O(m \log n + n \log n \log \log n)$ time.

We make another assumption that $\lambda^* \neq \lambda_2$. Again, this assumption is only for the explanation and the following algorithm can proceed without this assumption. Under the assumption, for any $\lambda \in (\lambda_1, \lambda_2)$, the set $S_{i+1}(\lambda)$ is exactly $S_{i+1}(\lambda^*)$. Hence, we can compute $S_{i+1}(\lambda^*)$ by taking any $\lambda \in (\lambda_1, \lambda_2)$ and explicitly computing $S_{i+1}(\lambda)$ in $O(n)$ time.

The above has computed $S_{i+1}(\lambda^*)$. If $S_{i+1}(\lambda^*) \neq \emptyset$, we take any sensor of $S_{i+1}(\lambda^*)$, as $s_{\bar{g}(i)}(\lambda^*)$. Further, we let $\lambda_{i+1}^1 = \lambda_1$, $\lambda_{i+1}^2 = \lambda_2$, and $S_i(\lambda) = S_{i-1}(\lambda) \cup \{s_{\bar{g}(i)}(\lambda^*)\}$.

If $S_{i+1}(\lambda^*) = \emptyset$, then we need to compute the set $S_{i+2}(\lambda^*)$. Since $\lambda^* \in (\lambda_1, \lambda_2) \subseteq (\lambda_{i-1}^1, \lambda_{i-1}^2)$, according to our algorithm invariants, $R_{i-1}(\lambda)$ is a nondecreasing function on $\lambda \in (\lambda_1, \lambda_2)$. For each sensor $s_k \in S$, $x_k - \sqrt{\lambda^2 - y_k^2} - r$ is a decreasing function
Lemma 5.5.3. If the same for all $\lambda$, $S$ on $\lambda$, $O$ (R, $S$ and the set $S$ way to compute $S$ two assumptions on $\lambda$ follows. Which can be found by performing three feasibility tests. Otherwise, we proceed as the sensor $s_i$ after the first $i$ steps, i.e., the decision algorithm to cover all barriers.

On the other hand, according to our algorithm invariants, $R_{i-1}(\lambda) < \beta$ for all $\lambda \in (\lambda_{i-1}^1, \lambda_{i-1}^2)$. Since $\lambda^* \in (\lambda_1^1, \lambda_2^2) \subseteq (\lambda_{i-1}^1, \lambda_{i-1}^2)$, $R_{i-1}(\lambda^*) < \beta$, but this contradicts with that all barriers are covered by the sensors of $S_i(\lambda^*)$ after the first $i - 1$ steps of the decision algorithm. 

By Lemma 5.5.3, if $S_i(\lambda) = \emptyset$, then $\lambda^*$ is the smallest feasible value of $\{\lambda_{i-1}^1, \lambda_2, \lambda_2^2\}$, which can be found by performing three feasibility tests. Otherwise, we proceed as follows.

We make the third assumption that $\lambda^* \neq \lambda_2^2$. Thus, $\lambda^* \in (\lambda_1^1, \lambda_2^2)$ and $S_i(\lambda^*) = S_i(\lambda)$ for any $\lambda \in (\lambda_1^1, \lambda_2^2)$. Next, we compute $s_{g(i)}(\lambda^*)$, i.e., the leftmost sensor of $S_i(\lambda^*)$. Although $S_i(\lambda)$ is the same for all $\lambda \in (\lambda_1^1, \lambda_2^2)$, the leftmost sensor of $S_i(\lambda)$ may not be the same for all $\lambda \in (\lambda_1^1, \lambda_2^2)$. For each sensor $s_k \in S_i(\lambda)$ and any

$$R_{i-1}(\lambda) = x_k - \sqrt{\lambda^2 - \frac{g_k^2}{2}}. $$

If we increase $\lambda$ from $\lambda_1$ to $\lambda_2$, an “event” happens when $R_{i-1}(\lambda)$ is equal to $x_k - \sqrt{\lambda^2 - \frac{g_k^2}{2}}$ for some sensor $s_k \in S'$ at some event value $\lambda$, and the set $S_{i/2}(\lambda)$ is fixed between any two adjacent events. Hence, we use the following way to compute $S_{i/2}(\lambda^*)$. 

We first compute the set $\Lambda$ of all event values, and also add $\lambda_1$ and $\lambda_2$ to $\Lambda$. After sorting all values of $\Lambda$, by using our decision algorithm, we do binary search to find two adjacent values $\lambda_1'$ and $\lambda_2'$ in the sorted list of $\Lambda$ with $\lambda^* \in (\lambda_1', \lambda_2')$. Note that $(\lambda_1', \lambda_2') \subseteq (\lambda_1, \lambda_2)$. Since $|\Lambda| = O(n)$, the binary search calls the decision algorithm $O(\log n)$ times, which takes $O(m \log n + n \log n \log \log n)$ time in total. Since $S_{i/2}(\lambda)$ is the same for all $\lambda \in (\lambda_1', \lambda_2')$. We take an arbitrary value $\lambda \in (\lambda_1', \lambda_2')$ and compute $S_{i/2}(\lambda)$ explicitly in $O(n)$ time. 

Lemma 5.5.3. If $S_{i/2}(\lambda) = \emptyset$, then $\lambda^*$ is in $\{\lambda_{i-1}^2, \lambda_2, \lambda_2^2\}$. 

Proof. If $S_{i/2}(\lambda) = \emptyset$, assume to the contrary that $\lambda^* \notin \{\lambda_{i-1}^2, \lambda_2, \lambda_2^2\}$. Then, our previous two assumptions on $\lambda^*$ are true and $\lambda^* \in (\lambda_1', \lambda_2')$. According to our algorithm invariants, $S_{i/2}(\lambda^*) = S_{i/2}(\lambda) = \emptyset$. This means that if we applied the decision algorithm on $\lambda = \lambda^*$, the sensor $s_{g(i)}(\lambda^*)$ would not exist. In other words, the decision algorithm would stop after the first $i - 1$ steps, i.e., the decision algorithm would only use sensors in $S_{i-1}(\lambda^*)$ to cover all barriers.

By Lemma 5.5.3, if $S_{i/2}(\lambda) = \emptyset$, then $\lambda^*$ is the smallest feasible value of $\{\lambda_{i-1}^2, \lambda_2, \lambda_2^2\}$, which can be found by performing three feasibility tests. Otherwise, we proceed as follows.

We make the third assumption that $\lambda^* \neq \lambda_2^2$. Thus, $\lambda^* \in (\lambda_1', \lambda_2')$ and $S_{i/2}(\lambda^*) = S_{i/2}(\lambda)$ for any $\lambda \in (\lambda_1', \lambda_2')$. Next, we compute $s_{g(i)}(\lambda^*)$, i.e., the leftmost sensor of $S_{i/2}(\lambda^*)$. Although $S_{i/2}(\lambda)$ is the same for all $\lambda \in (\lambda_1', \lambda_2')$, the leftmost sensor of $S_{i/2}(\lambda)$ may not be the same for all $\lambda \in (\lambda_1', \lambda_2')$. For each sensor $s_k \in S_{i/2}(\lambda)$ and any
Lemma 5.5.4. If it is not true that $\lambda \in (\lambda'_1, \lambda'_2)$, the location of $s_k$ in the configuration $C_{i-1}(\lambda)$ is $x_k^r(\lambda)$. As discussed before, $x_k^r(\lambda)$ for $\lambda \in (\lambda'_1, \lambda'_2)$ defines a piece of the upper branch of a hyperbola in the 2D coordinate system in which the $x$-coordinates correspond to the $\lambda$ values and the $y$-coordinates correspond to $x_k^r(\lambda)$ values.

We consider the lower envelope $\mathcal{L}$ of the functions $x_k^r(\lambda)$ defined by all sensors $s_k$ of $S_{i2}(\lambda)$. For each point $q$ of $\mathcal{L}$, suppose $q$ lies on the function defined by a sensor $s_k$ and $q$’s $x$-coordinate is $\lambda_q$. If $\lambda = \lambda_q$, then the leftmost sensor of $S_{i2}(\lambda)$ is $s_k$. This means that each curve segment of $\mathcal{L}$ defined by one sensor corresponds to the same leftmost sensor of $S_{i2}(\lambda)$. Based on this observation, we compute $s_{g(i)}(\lambda^*)$ as follows.

Since the functions $x_k^r(\lambda)$ and $x_j^r(\lambda)$ of two sensors $s_k$ and $s_j$ have at most one intersection in $(\lambda'_1, \lambda'_2)$, the number of vertices of the lower envelope $\mathcal{L}$ is $O(n)$ and $\mathcal{L}$ can be computed in $O(n \log n)$ time [68–70]. Let $\Lambda$ be the set of the $x$-coordinates of the vertices of $\mathcal{L}$. We also add $\lambda'_1$ and $\lambda'_2$ to $\Lambda$. After sorting all values of $\Lambda$, by using our decision algorithm, we do binary search on the sorted list of $\Lambda$ to find two adjacent values $\lambda''_1$ and $\lambda''_2$ such that $\lambda^* \in (\lambda''_1, \lambda''_2]$. Note that $(\lambda''_1, \lambda''_2] \subseteq (\lambda'_1, \lambda'_2]$. Since $\lambda''_1$ and $\lambda''_2$ are two adjacent values of the sorted $\Lambda$, by our above analysis, there is a sensor that is always the leftmost sensor of $S_{i2}(\lambda)$ for all $\lambda \in (\lambda''_1, \lambda''_2]$. To find the sensor, we can take any value $\lambda$ in $(\lambda''_1, \lambda''_2]$ and explicitly compute the locations of sensors in $S_{i2}(\lambda)$. The above computes $s_{g(i)}(\lambda^*)$ in $O(m \log n + n \log n \log \log n)$ time.

Finally, we let $\lambda'_1 = \lambda''_1$, $\lambda'_2 = \lambda''_2$, and $S_i(\lambda) = S_{i-1}(\lambda) \cup \{s_{g(i)}(\lambda^*)\}$.

If the above computes $\lambda^*$, then we terminate the algorithm. Otherwise, we obtain an interval $(\lambda'_1, \lambda'_2] \subseteq (\lambda'_{i-1}, \lambda'_{i-1})$ that contains $\lambda^*$ and the set $S_i(\lambda)$. If $s_{g(i)}(\lambda) \in S_{i1}(\lambda)$, then $R_i(\lambda)$ is equal to $x_{g(i)} + \sqrt{\lambda^2 - y_{g(i)}^2} + r$. If $s_{g(i)}(\lambda) \in S_{i2}(\lambda)$, then $R_i(\lambda) = R_{i-1}(\lambda) + 2r$. By the third algorithm invariant, $R_i(\lambda)$ is either constant or equal to $x_j + \sqrt{\lambda^2 - y_j^2} + c'$ for some constant $c'$ and some sensor $s_j$ with $1 \leq j \leq i - 1$.

If it is not true that $R_i(\lambda) < \beta$ for all $\lambda \in (\lambda'_1, \lambda'_2)$, then we preform some additional processing as follows. We first have the following lemma.

Lemma 5.5.4. If it is not true that $R_i(\lambda) < \beta$ for all $\lambda \in (\lambda'_1, \lambda'_2)$, then $R_i(\lambda)$ is strictly increasing on $(\lambda'_1, \lambda'_2)$ and there is a single value $\lambda' \in (\lambda'_1, \lambda'_2)$ such that $R_i(\lambda') = \beta$. 
Proof. The proof is almost the same as that of Lemma 4 in [61] and we include it here for the sake of completeness.

Since it is not true that $R_i(\lambda) < \beta$ for all $\lambda \in (\lambda^1_i, \lambda^2_i)$, either $R_i(\lambda) > \beta$ for all $\lambda \in (\lambda^1_i, \lambda^2_i)$, or there is a value $\lambda' \in (\lambda^1_i, \lambda^2_i)$ with $R_i(\lambda') = \beta$. We first argue that the former case cannot happen.

Assume to the contrary that $R_i(\lambda) > \beta$ for all $\lambda \in (\lambda^1_i, \lambda^2_i)$. Then, $R_i(\lambda') > \beta$ for any $\lambda' \in (\lambda^1_i, \lambda^2_i)$ since $\lambda^* \in (\lambda^1_i, \lambda^2_i]$. But this would imply that we have found a feasible solution using only sensors in $S_i(\lambda)$ and the maximum movement of all sensors in $S_i(\lambda)$ is at most $\lambda' < \lambda^*$, contradicting with that $\lambda^*$ is the maximum moving distance in an optimal solution.

Hence, there is a value $\lambda' \in (\lambda^1_i, \lambda^2_i)$ with $R_i(\lambda') = \beta$. Next, we show that $R_i(\lambda)$ must be a strictly increasing function. Assume to the contrary this is not true. Then, $R_i(\lambda)$ must be constant on $(\lambda^1_i, \lambda^2_i)$. Thus, $R_i(\lambda) = \beta$ for all $\lambda \in (\lambda^1_i, \lambda^2_i)$. Since $\lambda^* \in (\lambda^1_i, \lambda^2_i]$, let $\lambda' \in (\lambda^1_i, \lambda^2_i)$ be any value in $(\lambda^1_i, \lambda^*)$. Hence, $R_i(\lambda') = \beta$, and as above, $\lambda'$ is a feasible value. However, $\lambda' < \lambda^*$ incurs contradiction. \qed

By Lemma 5.5.4, we compute the value $\lambda' \in (\lambda^1_i, \lambda^2_i)$ such that $R_i(\lambda') = \beta$. This means that all barriers are covered by the sensors of $S_i(\lambda')$ in $C_i(\lambda')$, and thus $\lambda'$ is a feasible value and $\lambda^* \in (\lambda^1_i, \lambda^2_i]$. Because $R_i(\lambda)$ is strictly increasing, $R_i(\lambda) < \beta$ for all $\lambda \in (\lambda^1_i, \lambda')$. We update $\lambda^2_i$ to $\lambda'$.

In either case, $R_i(\lambda) < \beta$ now holds for all $\lambda \in (\lambda^1_i, \lambda^2_i)$. Finally, we perform the jump-over procedure, as follows.

If $R_i(\lambda)$ is a constant and $R_i(\lambda)$ is not in the interior of a barrier, then we set $R_i(\lambda)$ to the left endpoint of the next barrier. If $R_i(\lambda)$ is an increasing function, then we do the following. If we increase $\lambda$ from $\lambda^1_i$ to $\lambda^2_i$, an event happens if $R_i(\lambda)$ is equal to the left or right endpoint of a barrier at some event value of $\lambda$. During the increasing of $\lambda$, between any two adjacent events, $R_i(\lambda)$ is either always in the interior of a barrier or is always between two barriers. We compute all event values in $O(m)$ time by using the function $R_i(\lambda)$ and the endpoints of all barriers. Let $\Lambda$ denote the set of all event values, and we also add $\lambda^1_i$ and $\lambda^2_i$ to $\Lambda$. After sorting all values in $\Lambda$, using the decision algorithm in Lemma 5.5.2, we do binary search on the sorted list of $\Lambda$ to find two
adjacent values $\lambda_1$ and $\lambda_2$ such that $\lambda^* \in (\lambda_1, \lambda_2]$. Note that $(\lambda_1, \lambda_2] \subseteq (\lambda_1^i, \lambda_2^i]$. Since $|\Lambda| = O(m)$, the binary search calls the decision algorithm $O(\log m)$ times, which takes overall $O(m \log m + n \log n \log m)$ time. Finally, we reset $\lambda_1^i = \lambda_1$ and $\lambda_2^i = \lambda_2$.

This completes the $i$-th step of the algorithm, which runs in $O((m + n \log \log n) \cdot (\log m + \log n))$ time. If $\lambda^*$ is not computed in this step, then it can be verified that all algorithm variants are maintained (the analysis is similar to that in [61], so we omit it). The algorithm will compute $\lambda^*$ after at most $n$ steps. The total time of the algorithm is $O(n \cdot (m + n \log \log n) \cdot (\log m + \log n))$, which is bounded by $O(nm \log m + n^2 \log n \log n)$ as shown in the following theorem. Note that the space of the algorithm is $O(n)$.

**Theorem 5.5.5.** The problem MBC can be solved in $O(nm \log m + n^2 \log n \log \log n)$ time and $O(n)$ space.

**Proof.** As discussed before, the running time of the algorithm is $O(n \cdot (m + n \log \log n) \cdot (\log m + \log n))$, which is $O(nm \log m + n^2 \log n \log n + nm \log n + n^2 \log m \log n \log n)$. We claim that $nm \log n + n^2 \log m \log n = O(nm \log m + n^2 \log n \log n)$. Indeed, if $m \leq n \log n$, then $nm \log n = O(n^2 \log n \log n)$ and $n^2 \log m \log n = O(n^2 \log n \log n)$; otherwise, $nm \log n = O(nm \log m)$ and $n^2 \log m \log n = O(nm \log m)$.

$\square$

### 5.6 Concluding Remarks

As mentioned before, the high-level scheme of our algorithm for MBC is similar to those in [33, 61]. However, a new technique we propose in this chapter can help reduce the space complexities of the algorithms in [33, 61]. Specifically, Chen et al. [33] solved the line-constrained problem in $O(n^2 \log n)$ time and $O(n^2)$ space for the case where $m = 1$ and sensors have different ranges. Wang and Zhang [61] solved the line-constrained problem in $O(n^2 \log n \log \log n)$ time and $O(n^2)$ space for the case where $m = 1$, sensors have the same range, and sensors have weights. If we apply the similar preprocessing as in Lemma 5.5.1, then the space complexities of both algorithms [33, 61] can be reduced to $O(n)$ while the time complexities do not change asymptotically.
In addition, by slightly changing our algorithm for MBC, we can also solve the following problem variant: Find a subset $S'$ of sensors of $S$ to move them to $L$ to cover all barriers such that the maximum movement of all sensors of $S'$ is minimized (and sensors of $S \setminus S'$ do not move). We omit the details.
6.1 Introduction

We consider the following separating overlapped intervals problem on a line in this chapter. The results in this chapter were submitted to a conference in 2018 and is now still under review.

6.2 Problem Definitions and Our Results

Let \( \mathcal{I} \) be a set of \( n \) intervals on a real line \( \ell \). We say that two intervals overlap if their intersection contains more than one point. In this chapter, we consider an interval separation problem: move the intervals of \( \mathcal{I} \) on \( \ell \) such that no two intervals overlap and the maximum moving distance of these intervals is minimized.

If all intervals of \( \mathcal{I} \) have the same length, then after the left endpoints of the intervals are sorted, the problem can be solved in \( O(n) \) time by an easy greedy algorithm [19]. For the general problem where intervals may have different lengths, to the best of our knowledge, the problem has not been studied before. In this chapter, we present an \( O(n \log n) \) time and \( O(n) \) space algorithm for it. We also show an \( \Omega(n \log n) \) time lower bound for solving the problem under the algebraic decision tree model, and thus our algorithm is optimal.

As a basic problem and like many other interval problems, the interval separation problem potentially has many applications. For example, one possible application is on scheduling, as follows. Suppose there are \( n \) jobs that need to be completed on a machine. Each job requests a starting time and a total time for using the machine (hence it is a time interval). The machine can only work on one job at any time, and once it works on one job, it is not allowed to switch to other jobs until the job is finished. If the requested time intervals of the jobs have any overlap, then we have to change
the requested starting times of some intervals. In order to minimize deviations from their requested time intervals, one scheduling strategy could be changing the requested starting times (either advance or delay) such that the maximum difference between the requested starting times and the scheduled starting times of all jobs is minimized. Clearly, the problem is an instance of the interval separation problem. The problem also has applications in the following scenario. Suppose a wireless sensor network has \( n \) wireless mobile devices on a line and each device has a transmission range. We want to move the devices along the line to eliminate the interference such that the maximum moving distance of the devices is minimized (e.g., to save the energy). This is also an instance of the interval separation problem.

6.2.1 Applications and Related Work

Many interval problems have been used to model scheduling problems. We give a few examples. Given \( n \) jobs, each job requests a time interval to use a machine. Suppose there is only one machine and the goal is to find a maximum number of jobs whose requested time intervals do not have any overlap (so that they can use the machine). The problem can be solved in \( O(n \log n) \) time by an easy greedy algorithm [71]. Another related problem is to find a minimum number of machines such that all jobs can be completed [71]. Garey et al. [6] studied a scheduling problem, which is essentially the following problem. Given \( n \) intervals on a line, determine whether it is possible to find a unit-length sub-interval in each input interval, such that no two sub-intervals overlap. An \( O(n \log n) \) time algorithm was given in [6] for it. An optimization version of the problem was also studied [55, 56], where the goal is to find a maximum number of intervals that contain non-overlapping unit-length sub-intervals. Other scheduling problems on intervals have also been considered, e.g., see [5, 6, 8–11, 71].

Many problems on wireless sensor networks are also modeled as interval problems. For example, a mobile sensor barrier coverage problem can be modeled as the following interval problem. Given on a line \( n \) intervals (each interval is the region covered by a sensor at the center of the interval) and another segment \( B \) (called “barrier”), the goal is to move the intervals such that the union of the intervals fully covers \( B \) and the maximum moving distance of all intervals is minimized. If all intervals have the
same length, Czyzowicz et al. [60] solved the problem in \( O(n^2) \) time and later Chen et al. [33] improved it to \( O(n \log n) \) time. If intervals have different lengths, Chen et al. [33] solved the problem in \( O(n^2 \log n) \) time. The min-sum version of the problem has also been considered. If intervals have the same length, Czyzowicz et al. [62] gave an \( O(n^2) \) time algorithm, and Andrews and Wang [63] solved the problem in \( O(n \log n) \) time. If intervals have different lengths, then the problem becomes NP-hard [33]. Refer to [12–17] for other interval problems on mobile sensor barrier coverage.

Our interval separation problem may also be considered as a coverage problem in the sense that we want to move intervals of \( I \) to cover a total of maximum length of the line \( \ell \) such that the maximum moving distance of the intervals is minimized.

6.2.2 Our Approach

We consider a one-direction version of the problem in which intervals of \( I \) are only allowed to move rightwards. We show (in Section 6.3) that the original “two-direction” problem can be reduced to the one-direction problem in the following way: If OPT is an optimal solution of the one-direction problem and \( \delta_{\text{opt}} \) is the maximum moving distance of all intervals in OPT, then we can obtain an optimal solution for the two-direction problem by moving each interval in OPT leftwards by \( \delta_{\text{opt}}/2 \).

Hence, it is sufficient to solve the one-direction problem. It turns out that the difficulty is mainly on determining the order of intervals of \( I \) in OPT. Indeed, once such an “optimal order” is known, it is quite straightforward to compute the positions of the intervals in OPT in additional \( O(n) \) time (i.e., consider the intervals in the order one by one and put each interval “as left as possible”). If all intervals have the same length, then such an optimal order is obvious, which is the order of the intervals sorted by their left endpoints in the input. Indeed, this is how the \( O(n) \) time algorithm in [19] works.

However, if the intervals have different lengths, which is the case we consider in this chapter, then determining an optimal order is substantially more challenging. At first glance, it seems that we have to consider all possible orders of the intervals, whose number is exponential. By several interesting (and even surprising) observations, we show that we only need to consider at most \( n \) ordered lists of intervals. Consequently, a straightforward algorithm can find and maintain these “candidate” lists in \( O(n^2) \) time.
and space. We call it the “preliminary algorithm”, which is essentially a greedy algorithm. The algorithm is relatively simple but it is quite involved to prove its correctness. To this end, we extensively use the “exchange argument”, which is a standard technique for proving correctness of greedy algorithms (e.g., see [71]).

To further improve the preliminary algorithm, we discover more observations, which help us “prune” some “redundant” candidate lists. More importantly, the remaining lists have certain monotonicity properties such that we are able to implicitly compute and maintain them in $O(n \log n)$ time and $O(n)$ space, although the number of the lists can still be $\Omega(n)$. Although the correctness analysis is fairly complicated, the algorithm is still quite simple and easy to implement (indeed, the most “complicated” data structure is a binary search tree).

The rest of the chapter is organized as follows. In Section 6.3, we give notation and reduce our problem to the one-direction case. In Section 6.4, we give our preliminary algorithm, whose correctness is proved in Section 6.5. The improved algorithm is presented in Section 6.6. In Section 6.7, we conclude the chapter and prove the $\Omega(n \log n)$ time lower bound by a reduction from the integer element distinctness problem [72,73].

6.3 Preliminaries

We assume the line $\ell$ is the $x$-axis. The one-direction version of the interval separation problem is to move intervals of $I$ on $\ell$ in one direction (without loss of generality, we assume it is the right direction) such that no two intervals overlap and the maximum moving distance of the intervals is minimized. Let OPT denote an optimal solution of the one-direction version and let $\delta_{opt}$ be the maximum moving distance of all intervals in OPT. The following lemma gives a reduction from the general “two-direction” problem to the one-direction problem.

Lemma 6.3.1. An optimal solution for the interval separation problem can be obtained by moving every interval in OPT leftwards by $\delta_{opt}/2$.

Proof. Let SOL be the solution obtained by moving every interval in OPT leftwards by $\delta_{opt}/2$. Our goal is to show that SOL is an optimal solution for our original problem. Let
\( \delta \) be the maximum moving distance of all intervals in SOL. Since no intervals in OPT have been moved leftwards (with respect to their input positions), we have \( \delta = \delta_{opt}/2 \).

Assume to the contrary that SOL is not optimal. Then, there exists another solution SOL’ for the original problem in which the maximum interval moving distance is \( \delta’ < \delta \). By moving every interval of SOL’ rightwards by \( \delta’ \), we can obtain a feasible solution SOL’’ for the one-direction problem in which no interval has been moved leftwards (with respect to their input positions) and the maximum interval moving distance of SOL’’ is at most \( 2\delta’ \), which is smaller than \( \delta_{opt} \) since \( \delta’ < \delta \). However, this contradicts with that OPT is an optimal solution for the one-direction case. \( \square \) \( \square \)

By Lemma 6.3.1, once we have an optimal solution for the one-direction problem, we can obtain an optimal solution for our original problem in additional \( O(n) \) time. In the following, we will focus on solving the one-direction case.

We first sort all intervals of \( \mathcal{I} \) by their left endpoints. For ease of exposition, we assume no two intervals have their left endpoints located at the same position (otherwise we could break ties by also sorting their right endpoints). Let \( \mathcal{I} = \{I_1, I_2, \ldots, I_n\} \) be the sorted intervals by their left endpoints from left to right. For each (integer) \( i \in [1, n] \), denote by \( l_i \) and \( r_i \) the (physical) left and right endpoints of \( I_i \), respectively. Denote by \( x_i^l \) and \( x_i^r \) the \( x \)-coordinates of \( l_i \) and \( r_i \) in the input, respectively. Note that for each \( i \in [1, n] \), the two physical endpoints \( l_i \) and \( r_i \) may be moved during the algorithm, but the two coordinates \( x_i^l \) and \( x_i^r \) are always fixed. Denote by \( |I_i| \) the length of \( I_i \), i.e., \( |I_i| = x_i^r - x_i^l \).

For convenience, when we say the position of an interval, we refer to the position of the left endpoint of the interval.

With respect to a subset \( \mathcal{T}' \) of \( \mathcal{I} \), by a configuration of \( \mathcal{T}' \), we refer to a specification of the position of each interval of \( \mathcal{T}' \). For example, in the input configuration of \( \mathcal{I} \), interval \( I_i \) is at \( x_i^l \) for each \( i \in [1, n] \). Given a configuration \( \mathcal{C} \) of \( \mathcal{T}' \), for each interval \( I_i \in \mathcal{T}' \), if \( l_i \) is at \( x \) in \( \mathcal{C} \), then we call the value \( x - x_i^l \) the displacement of \( I_i \), denoted by \( d(i, \mathcal{C}) \), and if \( d(i, \mathcal{C}) \geq 0 \), then we say that \( I_i \) is valid in \( \mathcal{C} \). We say that \( \mathcal{C} \) is feasible if the displacement of every interval of \( \mathcal{T}' \) is valid and no two intervals of \( \mathcal{T}' \) overlap in \( \mathcal{C} \). The maximum displacement of the intervals of \( \mathcal{T}' \) in \( \mathcal{C} \) is called the max-displacement of \( \mathcal{C} \), denoted by
δ(C). Hence, finding an optimal solution for the one-direction problem is equivalent to computing a feasible configuration of I whose max-displacement is minimized; such a configuration is also called an optimal configuration.

For convenience of discussion, depending on the context, we will use the intervals $I_i$ of $\mathcal{I}$ and their indices $i$ interchangeably. For example, $\mathcal{I}$ may also refer to the set of indices $\{1, 2, \ldots, n\}$.

Let $L_{opt}$ be the list of intervals of $\mathcal{I}$ in an optimal configuration sorted from left to right. We call $L_{opt}$ an optimal list. Given $L_{opt}$, we can compute an optimal configuration in $O(n)$ time by an easy greedy algorithm, called the left-possible placement strategy. Consider the intervals following their order in $L_{opt}$, and for each interval, place it on $\ell$ as left as possible so that it does not overlap with the intervals that are already placed on $\ell$ and its displacement is non-negative. The following lemma formally gives the algorithm and proves its correctness.

Lemma 6.3.2. Given an optimal list $L_{opt}$, we can compute an optimal configuration in $O(n)$ time by the left-possible placement strategy.

Proof. We first describe the algorithm and then prove its correctness.

We consider the indices one by one following their order in $L_{opt}$. Consider any index $i$. If $I_i$ is the first interval of $L_{opt}$, then we place $I_i$ at $x_{i1}$ (i.e., $I_i$ stays at its input position). Otherwise, let $I_j$ be the previous interval of $I_i$ in $L_{opt}$. So $I_j$ has already been placed on $\ell$. Let $x$ be the current $x$-coordinate of the right endpoint $r_j$ of $I_j$. We place the left endpoint $l_i$ of $I_i$ at $\max\{x_{i1}, x\}$. If $I_i$ is the last interval of $L_{opt}$, then we finish the algorithm. Clearly, the algorithm can be easily implemented in $O(n)$ time.

Let $\mathcal{C}$ be the configuration of all intervals obtained by the above algorithm. Recall that $\delta(\mathcal{C})$ denote the max-displacement of $\mathcal{C}$. Below, we show that $\mathcal{C}$ is an optimal configuration.

Indeed, since $L_{opt}$ is an optimal list, there exists an optimal configuration $\mathcal{C}'$ in which the order of the indices of $\mathcal{I}$ follows that in $L_{opt}$. Hence, the max-displacement of $\mathcal{C}'$ is $\delta_{opt}$. According to our greedy strategy for computing $\mathcal{C}$, it is not difficult to see that the position of each interval $I_i$ of $\mathcal{I}$ in $\mathcal{C}$ cannot be strictly to the right of its position in
\( C' \). Therefore, the displacement of each interval in \( C \) is no larger than that in \( C' \). This implies that \( \delta(C) \leq \delta_{\text{opt}} \). Therefore, \( C \) is an optimal configuration.

Due to Lemma 6.3.2, we will focus on computing an optimal list \( L_{\text{opt}} \).

For any subset \( \mathcal{I}' \) of \( \mathcal{I} \), an (ordered) list of \( \mathcal{I}' \) refers to a permutation of the indices of \( \mathcal{I}' \). Let \( L \) be a list of \( \mathcal{I} \) and let \( L' \) be a list of \( \mathcal{I}' \) with \( \mathcal{I}' \subseteq \mathcal{I} \). We say that \( L' \) is consistent with \( L \) if the relative order of indices of \( \mathcal{I}' \) in \( L \) is the same as that in \( L' \). If \( L' \) is consistent with an optimal list \( L_{\text{opt}} \) of \( \mathcal{I} \), then we call \( L' \) a canonical list of \( \mathcal{I}' \).

For any \( 1 \leq i \leq j \leq n \), we use \( \mathcal{I}[i, j] \) to denote the subset of consecutive intervals of \( \mathcal{I} \) from \( i \) to \( j \), i.e., \( \{i, i + 1, \ldots, j\} \).

6.4 The Preliminary Algorithm

In this section, we describe an algorithm that can compute an optimal list in \( O(n^2) \) time and space. The correctness of the algorithm is mainly discussed in Section 6.5.

Our algorithm considers the intervals of \( \mathcal{I} \) one by one by their index order. After each interval \( I_i \) is processed, we obtain a set \( \mathcal{L} \) of at most \( i \) lists of the indices of \( \mathcal{I}[1, i] \), such that \( \mathcal{L} \) contains at least one canonical list of \( \mathcal{I}[1, i] \). For each list \( L \in \mathcal{L} \), a feasible configuration \( C_L \) of the intervals of \( \mathcal{I}[1, i] \) is also maintained. As will be clear later, \( C_L \) is essentially the configuration obtained by applying the left-possible placement strategy on the intervals of \( \mathcal{I}[1, i] \) following their order in \( L \). For each \( j \in [1, i] \), we let \( x^L_j(C_L) \) and \( x^R_j(C_L) \) respectively denote the \( x \)-coordinates of \( l_j \) and \( r_j \) in \( C_L \) (recall that \( l_j \) and \( r_j \) are the left and right endpoints of the interval \( I_j \), respectively). Recall that \( \delta(C_L) \) denotes the max-displacement of \( C_L \), i.e, the maximum displacement of the intervals of \( \mathcal{I}[1, i] \) in \( C_L \).

Initially when \( i = 1 \), we have only one list \( L = \{1\} \) and let \( C_L \) consist of the single interval \( I_1 \) at its input position, i.e., \( x^L_1(C_L) = x^R_1 \). Clearly, \( \delta(C_L) = 0 \). We let \( \mathcal{L} \) consist of the only list \( L \). It is vacuously true that \( L \) is a canonical list of \( \mathcal{I}[1, 1] \).

In general, assume interval \( I_{i-1} \) has been processed and we have the list set \( \mathcal{L} \) as discussed above. In the following, we give our algorithm for processing \( I_i \). Consider a list \( L \in \mathcal{L} \). Note that \( C_L \) has been computed, which is a feasible configuration of \( \mathcal{I}[1, i - 1] \). The value \( \delta(C_L) \) is also maintained. Let \( m \) be the last index in \( L \). Note that
Figure 6.1. Illustrating the three main cases. The (black) solid segments show intervals in their input positions and the (red) dashed segments shows interval $I_m$ in $C_L$.

$m < i$. Depending on the values of $x^l_i$, $x^r_i$, $x^r_m$, and $x^l_m(C_L)$, there are three main cases (e.g. see Fig. 6.1).

Case I: $x^r_i \geq x^r_m$ (i.e., the right endpoint $r_i$ of $I_i$ is to the right of $r_m$ in the input). In this case, we update $L$ by appending $i$ to the end of $L$. Further, we update the configuration $C_L$ by placing $l_i$ at $\max\{x^r_m(C_L), x^l_i\}$ (which follows the left-possible placement strategy). We let $L'$ denote the original list of $L$ before $i$ is inserted and let $C_{L'}$ denote the original configuration of $C_L$. We update $\delta(C_L)$ by the following observation.

**Observation 6.4.1.** $C_L$ is a feasible configuration and $\delta(C_L) = \max\{\delta(C_{L'}), x^l_i(C_L) - x^l_i\}$.

**Proof.** By our way of setting $I_i$ in $C_L$, $I_i$ is valid and does not overlap with any other interval in $C_L$. Hence, $C_L$ is feasible. Comparing with $C_{L'}$, $C_L$ has one more interval $I_i$. Therefore, $\delta(C_L)$ is equal to the larger value of $\delta(C_{L'})$ and the displacement of $I_i$ in $C_L$, which is $x^l_i(C_L) - x^l_i$.

The following lemma will be used to show the correctness of our algorithm and its proof is deferred to Section 6.5.

**Lemma 6.4.2.** If $L'$ is a canonical list of $\mathcal{I}[1, i - 1]$, then $L$ is a canonical list of $\mathcal{I}[1, i]$.

Case II: $x^r_i < x^r_m$ and $x^l_i \leq x^l_m(C_L)$.. In this case, we update $L$ by inserting $i$ right before $m$. Let $x = x^l_m(C_L)$. We update $C_L$ by setting $l_i$ at $x$ and setting $l_m$ at $x + |I_i|$. We let $L'$ denote the original list of $L$ before inserting $i$ and let $C_{L'}$ denote the original $C_L$. We update $\delta(C_L)$ by the following observation. Note that $x^l_m(C_L)$ now refers to the position of $l_m$ in the updated $C_L$.

**Observation 6.4.3.** $C_L$ is a feasible configuration and $\delta(C_L) = \max\{\delta(C_{L'}), x^l_i(C_L) - x^l_m\}$.
Lemma 6.4.6. If $l_i$ is at $x$ in $C_L$, $I_i$ is valid in $C_L$. Comparing with its position in $C_{L'}$, $I_m$ has been moved rightwards; since $I_m$ is valid in $C_{L'}$, $I_m$ is also valid in $C_L$. Note that no two intervals overlap in $C_L$. Therefore, $C_L$ is a feasible configuration.

Comparing with $C_{L'}$, $C_L$ has one more interval $I_i$ and $I_m$ has been moved rightwards in $C_L$. Therefore, $\delta(C_L)$ is equal to the maximum of the following three values: $\delta(C_{L'})$, the displacement of $I_i$ in $C_L$, and the displacement of $I_m$ in $C_L$. Observe that the displacement of $I_i$ is smaller than that of $I_m$. This is because $l_m$ is to the left of $l_i$ in the input (since $m < i$) while $l_m$ is to the right of $l_i$ in $C_L$. Thus, it holds that

$$\delta(C_L) = \max\{\delta(C_{L'}), x_i^l(C_L) - x_i^r, x_m^l(C_L) - x_m^r\}. \qedhere$$

The proof of the following lemma is deferred to Section 6.5.

Lemma 6.4.4. If $L'$ is a canonical list of $I[1, i - 1]$, then $L$ is a canonical list of $I[1, i]$.

Case III: $x_i^r < x_m^l$ and $x_i^l > x_m^r(C_L)$. In this case, we first update $L$ by appending $i$ to the end of $L$ and update $C_L$ by placing the left endpoint of $I_i$ at $x_m^r(C_L)$. Let $L'$ be the original list $L$ before we insert $i$ and let $C_{L'}$ be the original configuration of $C_L$.

Further, we create a new list $L^*$, which is the same as $L$ except that we switch the order of $i$ and $m$. Thus, $m$ is the last index of $L^*$. Correspondingly, the configuration $C_{L^*}$ is the same as $C_L$ except that $l_i$ is at $x_i^r$, i.e., its position in the input, and $l_m$ is at $x_m^r$. We say that $L^*$ is the new list generated by $L'$. We do not put $L^*$ in the set $\mathcal{L}$ at this moment (but $L$ is in $\mathcal{L}$).

Observation 6.4.5. Both $C_L$ and $C_{L^*}$ are feasible; $\delta(C_L) = \max\{\delta(C_{L'}), x_i^l(C_L) - x_i^r\}$ and $\delta(C_{L^*}) = \max\{\delta(C_{L'}), x_m^l(C_{L^*}) - x_m^r\}$.

Proof. By a similar argument as in Observation 6.4.1, $C_L$ is feasible and $\delta(C_L) = \max\{\delta(C_{L'}), x_i^l(C_L) - x_i^r\}$. By a similar argument as in Observation 6.4.3, $C_{L^*}$ is feasible and $\delta(C_{L^*}) = \max\{\delta(C_{L'}), x_m^l(C_{L^*}) - x_m^r\}$. We omit the details. \qedhere

The proof of the following lemma is deferred to Section 6.5.

Lemma 6.4.6. If $L'$ is a canonical list of $I[1, i - 1]$, then one of $L$ and $L^*$ is a canonical list of $I[1, i]$. 

After each list \( L \) of \( \mathcal{L} \) is processed as above, let \( \mathcal{L}^* \) denote the set of all new generated lists in Case III. Recall that no list of \( \mathcal{L}^* \) has been added into \( \mathcal{L} \) yet. Let \( L_{\text{min}}^* \) be the list of \( \mathcal{L}^* \) with the minimum value \( \delta(C_{L_{\text{min}}^*}) \). The proof of the following lemma is deferred to Section 6.5.

Lemma 6.4.7. If \( \mathcal{L}^* \) has a canonical list of \( I[1, i] \), then \( L_{\text{min}}^* \) is a canonical list of \( I[1, i] \).

Due to Lemma 6.4.7, among all lists of \( \mathcal{L}^* \), we only need to keep \( L_{\text{min}}^* \). So we add \( L_{\text{min}}^* \) to \( \mathcal{L} \) and ignore all other lists of \( \mathcal{L}^* \). We call \( L_{\text{min}}^* \) a new list of \( \mathcal{L} \) produced by our algorithm for processing \( I_i \) and all other lists of \( \mathcal{L} \) are considered as the old lists.

Remark. Lemma 6.4.7 is a key observation that helps avoid maintaining an exponential number of lists.

This finishes our algorithm for processing the interval \( I_i \). Clearly, \( \mathcal{L} \) has at most one more new list. After \( I_n \) is processed, the list \( L \) of \( \mathcal{L} \) with minimum \( \delta(C_L) \) is an optimal list.

According to our above description, the algorithm can be easily implemented in \( O(n^2) \) time and space. The proof of Theorem 6.4.8 gives the details and also shows the correctness of the algorithm based on Lemmas 6.4.2, 6.4.4, 6.4.6, and 6.4.7.

Theorem 6.4.8. An optimal solution for the one-direction problem can be found in \( O(n^2) \) time and space.

Proof. To implement the algorithm, we can use a linked list to represent each list of \( \mathcal{L} \). Consider a general step for processing interval \( I_i \).

For any list \( L \in \mathcal{L} \), inserting \( i \) to \( L \) can be easily done in \( O(1) \) time for each of the three cases. The configuration \( C_L \) and the value \( \delta(C_L) \) can also be updated in \( O(1) \) time. If \( L \) generates a new list \( L^* \), then we do not explicitly construct \( L^* \) but only compute the value \( \delta(C_{L^*}) \), which can be done in \( O(1) \) time by Observation 6.4.5. Once every list \( L \in \mathcal{L} \) has been processed, we find the list \( L_{\text{min}}^* \in \mathcal{L}^* \). Then, we explicitly construct \( L^* \) and \( C_{L^*} \) in \( O(n) \) time.

Hence, each general step for processing \( I_i \) can be done in \( O(n) \) time since \( \mathcal{L} \) has at most \( n \) lists. Thus, the total time and space of the algorithm is \( O(n^2) \).

For the correctness, after a general step for processing \( I_i \), Lemmas 6.4.2, 6.4.4, 6.4.6, and 6.4.7 together guarantee that the set \( \mathcal{L} \) has at least one canonical list of \( I[1, i] \). After
\( j = 6 \quad k = 10 \)

\[ L_{opt} : \cdots, k = 10, 8, 14, 5, 4, 12, j = 6, \cdots \]

\[ L_{opt}^1[j, k] = \{8, 5, 4\} \quad L_{opt}^2[j, k] = \{k = 10, 14, 12\} \]

\[ L_{opt}' : \cdots, 8, 5, 4, j = 6, 14, k = 10, 12, \cdots \]

Figure 6.2. Illustrating an inversion \((j, k)\) of \(L_{opt}\) and an example for Lemma 6.5.1: the intervals \(j\) and \(k\) are shown in their input positions.

\( I_n \) is processed, since \( C_L \) is essentially obtained by the left-possible placement strategy for each list \( L \in \mathcal{L} \), if \( L \) is the list of \( \mathcal{L} \) with the smallest \( \delta(C_L) \), then \( L \) is an optimal list and \( C_L \) is an optimal configuration by Lemma 6.3.2. \( \square \)

### 6.5 The Correctness of the Preliminary Algorithm

In this section, we establish the correctness of our preliminary algorithm. Specifically, we will prove Lemmas 6.4.2, 6.4.4, 6.4.6, and 6.4.7. The major analysis technique is the exchange argument, which is quite standard for proving correctness of greedy algorithms (e.g., see [71]).

Let \( L \) be a list of all indices of \( \mathcal{I} \). For any two indices \( j, k \in [1, n] \), let \( L[j, k] \) denote the sub-list of all indices of \( L \) between \( j \) and \( k \) (including \( j \) and \( k \)).

For any \( 1 \leq j < k \leq n \), we say that \((j, k)\) is an inversion of \( L \) if \( x_j^r \leq x_k^r \) and \( k \) is before \( j \) in \( L \) (\( k \) and \( j \) are not necessarily consecutive in \( L \); e.g., see Fig. 6.2 with \( L = L_{opt} \)). For an inversion \((j, k)\), we further introduce two sets of indices \( L^1[j, k] \) and \( L^2[j, k] \) as follows (e.g., see Fig. 6.2 with \( L = L_{opt} \)). Let \( L^1[j, k] \) consist of all indices \( i \in L[j, k] \) such that \( i < k \) and \( i \neq j \); let \( L^2[j, k] \) consist of all indices \( i \in L[j, k] \) such that \( i \geq k \). Hence, \( L^1[j, k], L^2[j, k], \) and \( \{j\} \) form a partition of the indices of \( L[j, k] \).

We first give the following lemma, which will be extensively used later.

**Lemma 6.5.1.** Let \( L_{opt} \) be an optimal list of all indices of \( \mathcal{I} \). If \( L_{opt} \) has an inversion \((j, k)\), then there exists another optimal list \( L_{opt}' \) that is the same as \( L_{opt} \) except that the sublist \( L_{opt}[j, k] \) is changed to the following: all indices of \( L^1_{opt}[j, k] \) are before \( j \) and all indices of \( L^2_{opt}[j, k] \) are after \( j \) (in particular, \( k \) is after \( j \), so \((j, k)\) is not an inversion any more in \( L_{opt}' \)), and further, the relative order of the indices of \( L^1_{opt}[j, k] \) in \( L_{opt}' \) is the same as that in \( L_{opt} \) (but this may not be the case for \( L^2_{opt}[j, k] \)). E.g., see Fig. 6.2.
Many proofs given later in the chapter will utilize Lemma 6.5.1 as a basic technique for “eliminating” inversions in optimal lists. Before giving the proof of Lemma 6.5.1, which is somewhat technical, lengthy, and tedious, we first show that Lemma 6.4.2 can be easily proved with the help of Lemma 6.5.1.

6.5.1 Proof of Lemma 6.4.2.

Assume \( L' \) is a canonical list of \( I[1, i-1] \). Our goal is to prove that \( L \) is a canonical list of \( I[1, i] \).

Since \( L' \) is a canonical list, by the definition of a canonical list, there exists an optimal configuration \( C \) in which the order of the intervals of \( I[1, i-1] \) is the same as that in \( L' \). Let \( L_{opt} \) be the list of indices of the intervals of \( I \) in \( C \). If \( i \) is after \( m \) in \( L_{opt} \), then \( L \) is consistent with \( L_{opt} \) and thus is a canonical list of \( I[1, i] \). In the following, we assume \( i \) is before \( m \) in \( L_{opt} \).

Since \( m < i \), \( x_m^r \leq x_i^r \), and \( i \) is before \( m \) in \( L_{opt} \), \((m, i)\) is an inversion in \( L_{opt} \). Let \( L'_{opt} \) be another optimal list obtained by applying Lemma 6.5.1 on \((m, i)\). Refer to Fig. 6.3. We claim that \( L \) is consistent with \( L'_{opt} \), which will prove that \( L \) is a canonical list. We prove the claim below.

Indeed, note that \( L' \) is consistent with \( L_{opt} \). Comparing with \( L_{opt} \), by Lemma 6.5.1, only the indices of the sublist \( L_{opt}[m, i] \) have their relative order changed in \( L'_{opt} \). Since all indices of \( L' \) are smaller than \( i \), by definition, all indices of \( L' \) that are in \( L_{opt}[m, i] \) are contained in \( L'_{opt}[m, i] \). By Lemma 6.5.1, the relative order of the indices of \( L'_{opt}[m, i] \) in \( L'_{opt} \) is the same as that in \( L_{opt} \), and further, all indices of \( L'_{opt}[m, i] \) are still before \( m \) in \( L'_{opt} \). This implies that the relative order of the indices of \( L' \) does not change from \( L_{opt} \) to \( L'_{opt} \). Hence, \( L' \) is consistent with \( L'_{opt} \). On the other hand, by Lemma 6.5.1, \( i \) is after \( m \). Thus, \( L \) is consistent with \( L'_{opt} \). This proves the claim and thus proves
Lemma 6.4.2.

6.5.2 Proof of Lemma 6.5.1

In this section, we give the proof of Lemma 6.5.1.

We partition the set $L_{opt}^2[j, k] \setminus \{k\}$ into two sets $S_1$ and $S_2$, defined as follows (e.g., see Fig. 6.4). Let $S_1$ consists of all indices $t$ of $L_{opt}^2[j, k] \setminus \{k\}$ such that $x_t^r \leq x_j^r$ (i.e., $r_t$ is to the left of $r_j$ in the input). Let $S_2$ consists of all indices of $L_{opt}^2[j, k] \setminus \{k\}$ that are not in $S_1$. Note that $L_{opt}[j, k] = L_{opt}^1[j, k] \cup S_1 \cup S_2 \cup \{j, k\}$. To simplify the notation, let $S = L_{opt}[j, k]$ and $S_0 = L_{opt}^1[j, k]$ (e.g., see Fig. 6.4).

We only consider the general case where none of $S_0$, $S_1$, and $S_2$ is empty since other cases can be analyzed by similar but simpler techniques.

In the following, from $L_{opt}$, we will subsequently construct a sequence of optimal lists $L_0, L_1, L_2, L_3$, such that eventually $L_3$ is the list $L_{opt}'$ specified in the statement of Lemma 6.5.1 (e.g., see Fig. 6.5).

The List $L_0$

For any adjacent indices $h$ and $g$ of $L_{opt}[j, k] \setminus \{j, k\}$ such that $h$ is before $g$ in $L_{opt}$, we say that $(h, g)$ is an exchangeable pair if one of the three cases happen: $g \in S_0$ and $h \in S_1$; $g \in S_1$ and $h \in S_2$; $g \in S_0$ and $h \in S_2$.

In the following, we will perform certain “exchange operations” to eliminate all exchangeable pairs of $L_{opt}$, after which we will obtain another optimal list $L_0$ in which for any $i_0 \in S_0$, $i_1 \in S_1$, $i_2 \in S_2$, $i_0$ is before $i_1$ and $i_2$ is after $i_1$, and all other indices of $L_0$ have the same positions as in $L_{opt}$ (e.g., see Fig. 6.5).
Consider any exchangeable pair \((h, g)\) of \(L_{opt}\). Let \(L'\) be another list that is the same as \(L_{opt}\) except that \(h\) and \(g\) exchange their order. We call this an exchange operation. In the following, we show that \(L'\) is an optimal list.

Since \(L_{opt}\) is an optimal list, there is an optimal configuration \(C\) in which the order of the intervals is the same as \(L_{opt}\). Consider the configuration \(C'\) that is the same as \(C\) except that we exchange the order of \(h\) and \(g\) in the following way (e.g., see Fig. 6.6): \(x_g^l(C') = x_h^l(C)\) and \(x_g^r(C') = x_h^r(C)\), i.e., the left endpoint \(l_g\) of \(I_g\) in \(C\) is at the same position as \(l_h\) in \(C\) and the right end point \(r_h\) of \(I_h\) in \(C'\) is at the same position as \(r_g\) in \(C\). Clearly, the order of intervals in \(C'\) is the same as that in \(L'\). In the following, we show that \(C'\) is an optimal configuration, which will prove that \(L'\) is an optimal list.

We first show that \(C'\) is feasible. Recall that intervals \(h\) and \(g\) are adjacent in \(L_{opt}\) and also in \(L'\). By our way of setting \(I_g\) and \(I_h\) in \(C'\), the segments of \(\ell\) “spanned” by \(I_h\) and \(I_g\) in both \(C\) and \(C'\) are exactly the same (e.g., the segments between the two vertical dotted lines in Fig. 6.6). Since no two intervals of \(\mathcal{I}\) overlap in \(C\), no two intervals overlap in \(C'\) as well.

Next, we show that every interval of \(\mathcal{I}\) is valid in \(C'\). To this end, it is sufficient to show that \(I_h\) and \(I_g\) are valid in \(C'\) since other intervals do not change positions from \(C\) to \(C'\). For \(I_h\), comparing with its position in \(C\), \(I_h\) has been moved rightwards in \(C'\), and thus \(I_h\) is valid in \(C'\). For \(I_g\), since \((h, g)\) is an exchangeable pair, \(g\) is either in \(S_0\) or in \(S_1\). In either case, \(x_g^l \leq x_k^l\). On the other hand, \(I_k\) is to the left of \(I_g\) in \(C'\), which implies that \(x_k^r(C') \leq x_g^l(C')\). Since \(I_k\) does not change position from \(C\) to \(C'\) and \(I_k\)
is valid in $C$, we have $x^i_k \leq x^i_k(C) = x^i_k(C')$. Combining the above discussion, we have $x^i_g \leq x^i_k \leq x^i_k(C) = x^i_k(C') \leq x^i_g(C')$. Thus, $I_g$ is valid in $C'$. This proves that $C'$ is a feasible configuration.

We proceed to show that $C'$ is an optimal configuration by proving that the max-displacement of $C'$ is no more than the max-displacement of $C$, i.e., $\delta(C') \leq \delta(C)$. Note that $\delta(C) = \delta_{opt}$ since $C$ is an optimal configuration. Comparing with $C$, $I_g$ has been moved leftwards and $I_h$ has been moved rightwards in $C'$. Therefore, to prove $\delta(C') \leq \delta_{opt}$, it suffices to show that the displacement of $I_h$ in $C'$, i.e., $d(h, C')$, is at most $\delta_{opt}$. Since $(h, g)$ is an exchangeable pair, $h$ is either in $S_1$ or in $S_2$. In either case, $x^l_j \leq x^l_h$. On the other hand, $I_j$ is to the right of $I_h$ in $C'$, which implies that $x^l_h(C') \leq x^l_j(C')$. Consequently, we have $d(h, C') = x^l_h(C') - x^l_h \leq x^l_j(C') - x^l_j = d(j, C')$. Since $I_j$ does not change position from $C$ to $C'$, $d(h, C') \leq d(j, C') = d(j, C) \leq \delta_{opt}$. This proves that $C'$ is an optimal configuration and $L'$ is an optimal list.

If $L'$ still has an exchangeable pair, then we keep applying the above exchange operations until we obtain an optimal list $L_0$ that does not have any exchangeable pairs.

Hence, $L_0$ has the following property: for any $i_t \in S_t$ for $t = 0, 1, 2$, $i_0$ is before $i_1$ and $i_2$ is after $i_1$, and all other indices of $L_0$ have the same positions as in $L_{opt}$. Further, notice that our exchange operation never changes the relative order of any two indices in $S_t$ for each $0 \leq t \leq 2$. In particular, the relative order of the indices of $S_0$ in $L_{opt}$ is the same as that in $L_0$.

The List $L_1$

Let $L_1$ be another list that is the same as $L_0$ except that $k$ is between the indices of $S_0$ and the indices of $S_1$ (e.g., see Fig. 6.5). In the following, we show that $L_1$ is also an optimal list. This can be done by keeping performing exchange operations between $k$ and its right neighbor in $S_0$ until all indices of $S_0$ are to the left of $k$. The details are given below.

Let $g$ be the right neighboring index of $k$ in $L_0$ and $g$ is in $S_0$. Let $L'$ be the list that is the same as $L_0$ except that we exchange the order of $k$ and $g$. In the following, we show that $L'$ is an optimal list.

Since $L_0$ is an optimal list, there is an optimal configuration $C$ in which the order
of the indices of the intervals is the same as $L_0$. Consider the configuration $C'$ that is the same as $C$ except that we exchange the order of $k$ and $g$ in the following way: $x_l^j(C') = x_l^k(C)$ and $x_r^g(C') = x_r^g(C)$ (e.g., see Fig. 6.7; similar to that in Section 6.5.2).

In the following, we show that $C'$ is an optimal solution, which will prove that $L'$ is an optimal list.

We first show that $C'$ is feasible. By the similar argument as in Section 6.5.2, no two intervals overlap in $C'$. Next we show that every interval is valid in $C'$. It is sufficient to show that both $I_k$ and $I_g$ are valid. For $I_k$, comparing with its position in $C$, $I_k$ has been moved rightwards in $C'$ and thus $I_k$ is valid in $C'$. For $I_g$, since $g \in S_0$, by the definition of $S_0$, $x_l^j \leq x_l^k$ (e.g., see the left side of Fig. 6.7). Since $x_r^k \leq x_r^g(C) = x_r^g(C')$, we obtain that $x_l^j \leq x_l^g(C')$ and $I_g$ is valid in $C'$.

We proceed to show that $C'$ is an optimal configuration by proving that $\delta(C') \leq \delta(C) = \delta_{opt}$. Comparing with $C$, $I_g$ has been moved leftwards and $I_k$ has been moved rightwards in $C'$. Therefore, to prove $\delta(C') \leq \delta_{opt}$, it suffices to show that $d(k, C') \leq \delta_{opt}$. Recall that $l_j$ is to the left of $l_k$ in the input. Note that $k$ is to the left of $j$ in $L'$. Hence, $l_k$ is to the left of $l_j$ in $C'$. Thus, $d(k, C') \leq d(j, C')$. Note that $d(j, C') = d(j, C)$ since the position of $I_j$ does not change from $C$ to $C'$. Therefore, we obtain $d(k, C') \leq d(j, C) \leq \delta_{opt}$. This proves that $C'$ is an optimal configuration and $L'$ is an optimal list.

If the right neighbor of $k$ in $L'$ is still in $S_0$, then we keep performing the above exchange until all indices of $S_0$ are to the left of $k$, at which moment we obtain the list $L_1$. Thus, $L_1$ is an optimal list.

The List $L_2$

Let $L_2$ be another list that is the same as $L_1$ except that $j$ is between the indices of $S_1$ and the indices of $S_2$ (e.g., see Fig. 6.5). This can be done by keeping performing exchange operations between $j$ and its left neighbor in $S_2$ until all indices of $S_2$ are to
the right of \( j \), which is symmetric to that in Section 6.5.2. The details are given below.

Let \( h \) be the left neighbor of \( j \) in \( L_1 \) and \( h \) is in \( S_2 \). Let \( L_1' \) be the list that is the same as \( L_1 \) except that we exchange the order of \( h \) and \( j \). In the following, we show that \( L_1' \) is an optimal list.

Since \( L_1 \) is an optimal list, there is an optimal configuration \( C \) in which the order of the indices of the intervals is the same as \( L_1 \). Consider the configuration \( C' \) that is the same as \( C \) except that we exchange the order of \( j \) and \( h \) in the following way: 
\[
x_j^l(C') = x_h^l(C) \text{ and } x_j^r(C') = x_h^r(C) \quad (\text{e.g., see Fig. 6.8}).
\]
In the following, we show that \( C' \) is an optimal solution, which will prove that \( L_1' \) is an optimal list.

We first show that \( C' \) is feasible. By the similar argument as before, no two intervals overlap in \( C' \). Next we show that every interval is valid in \( C' \). It is sufficient to show that both \( I_j \) and \( I_h \) are valid. For \( I_h \), comparing with its position in \( C \), \( I_h \) has been moved rightwards in \( C' \) and thus \( I_h \) is valid in \( C' \). For \( I_j \), since \( h \in S_2 \), by the definition of \( S_2 \), 
\[
x_j^l \leq x_h^l(C) = x_h^l(C').
\]
We obtain that \( x_j^l \leq x_j^l(C') \) and \( I_j \) is valid in \( C' \).

We proceed to show that \( C' \) is an optimal configuration by proving that 
\[
\delta(C') \leq \delta(C) = \delta_{opt}.
\]
Comparing with \( C \), \( I_j \) has been moved leftwards and \( I_h \) has been moved rightwards in \( C' \). Therefore, to prove \( \delta(C') \leq \delta_{opt} \), it suffices to show that 
\[
d(h, C') \leq \delta_{opt}.
\]
Since \( h \) is in \( S_2 \), 
\[
x_j^r \leq x_h^r(C).
\]
Since \( x_h^r(C') = x_j^r(C) \), we deduce 
\[
d(h, C') = x_h^r(C') - x_h^r(C) \leq x_j^r(C) - x_j^r = d(j, C) \leq \delta_{opt}.
\]
This proves that \( C' \) is an optimal configuration and \( L_1' \) is an optimal list.

If the left neighbor of \( j \) in \( L_1' \) is still in \( S_2 \), then we keep performing the above exchange until all indices of \( S_2 \) are to the right of \( j \), at which moment we obtain the list \( L_2 \). Thus, \( L_2 \) is an optimal list.

The List \( L_3 \)

Let \( L_3 \) be the list that is the same as \( L_2 \) except that we exchange the order of \( k \).
Recall that an optimal list, we obtain that \( C \) is valid. Comparing with \( \delta \), we shift each interval \( S \) leftwards by its absolute value); third, we set \( I_k \) is at the same position as \( r_j \) in \( C \). Clearly, the interval order of \( C' \) is the same as \( L_3 \). In the following, we show that \( C' \) is an optimal configuration, which will prove that \( L_3 \) is an optimal list.

Since \( L_2 \) is an optimal list, there is an optimal configuration \( C \) in which the order of the indices of intervals is the same as \( L_2 \). Consider the configuration \( C' \) that is the same as \( C \) except the following (e.g., see Fig. 6.9): First, we set \( x_j^1(C') = x_k^1(C) \); second, we shift each interval of \( S \) leftwards by distance \( |I_k| - |I_j| \) (if this value is negative, we actually shift rightwards by its absolute value); third, we set \( x_j^r(C') = x_j^r(C) \) (i.e., \( r_k \) is before \( j \) in \( C \)). Clearly, the interval order of \( C' \) is the same as \( L_3 \). In the following, we show that \( C' \) is an optimal configuration, which will prove that \( L_3 \) is an optimal list.

We first show that \( C' \) is feasible. By our way of setting positions of intervals in \( S \cup \{j, k\} \), One can easily verify that no two intervals of \( C' \) overlap. Next we show that every interval is valid in \( C' \). It is sufficient to show that all intervals in \( S \cup \{j, k\} \) are valid. Comparing with \( C \), \( I_k \) has been moved rightwards in \( C' \). Thus, \( I_k \) is valid in \( C' \). Recall that \( x_j^l \leq x_k^l \) and \( x_j^l(C') = x_k^l(C) \). Since \( x_k^l \leq x_j^l(C) \) (because \( I_k \) is valid in \( C \)), we obtain that \( x_j^l \leq x_j^l(C') \) and \( I_j \) is valid in \( C' \). Consider any index \( t \in S \). By the definition of \( S \), \( x_t^l \leq x_j^r \). Since \( j \) is to the left of \( t \) in \( C' \), we have \( x_j^r(C') \leq x_k^l(C') \). Since \( x_j^r \leq x_j^r(C') \) (because \( I_j \) is valid in \( C' \)), we obtain that \( x_t^l \leq x_j^r(C') \leq x_k^l(C') \) and thus \( I_t \) is valid in \( C' \). This proves that \( C' \) is feasible.

We proceed to show that \( C' \) is an optimal configuration by proving that \( \delta(C') \leq \delta(C) = \delta_{opt} \). It is sufficient to show that for any \( t \in S \cup \{j, k\} \), \( d(t, C') \leq \delta_{opt} \). Comparing with \( C \), \( I_j \) has been moved leftwards in \( C' \), and thus, \( d(j, C') \leq d(j, C) \leq \delta_{opt} \). Recall that \( x_j^r \leq x_k^r \) and \( x_j^r(C') = x_j^r(C) \). We can deduce \( d(k, C') = x_k^l(C') - x_k^l \leq x_j^r(C') - x_j^r \leq d(j, C) \leq \delta_{opt} \). Consider any \( t \in S \). By the definition of \( S \), \( x_t^l \geq x_k^l \). On the other hand, since \( t \) is to the left of \( k \) in \( C' \), \( x_t^l(C') \leq x_k^l(C') \). Therefore, we obtain that \( d(t, C') = x_t^l(C') - x_t^l \leq x_k^l(C') - x_k^l = d(k, C') \). We have proved above that \( d(k, C') \leq \delta_{opt} \),
and thus \( d(t, C') \leq \delta_{opt} \). This proves that \( C' \) is an optimal configuration and \( L_3 \) is an optimal list.

Notice that \( L_3 \) is the list \( L'_{opt} \) specified in the lemma statement. Indeed, in all above lists from \( L_{opt} \) to \( L_3 \), the relative order of the indices of \( S_0 \) (which is \( L_{opt}^1[j, k] \)) never changes. This proves Lemma 6.5.1.

6.5.3 Proof of Lemma 6.4.4

In this section, we prove Lemma 6.4.4. Assume \( L' \) is a canonical list of \( I[1, i-1] \). Our goal is to prove that \( L \) is also a canonical list of \( I[1, i] \).

Since \( L' \) is a canonical list, there exists an optimal configuration \( C \) in which the order the intervals of \( I[1, i-1] \) is the same as that in \( L' \). Let \( L_{opt} \) be the list of indices of the intervals of \( I \) in \( C \). If, in \( L_{opt} \), \( i \) is before \( m \) and after every index of \( I[1, i-1] \setminus \{m\} \), then \( L \) is consistent with \( L_{opt} \) and thus is a canonical list of \( I[1, i] \), so we are done with the proof.

In the following, we assume \( L \) is not consistent with \( L_{opt} \). There are two cases. In the first case, \( i \) is after \( m \) in \( L_{opt} \). In the second case, \( i \) is before \( j \) in \( L_{opt} \) for some \( j \in I[1, i-1] \setminus \{m\} \). We analyze the two cases below. In each case, by performing certain exchange operations and using Lemma 6.5.1, we will find an optimal list of all intervals of \( I \) such that \( L \) is consistent with the list (this will prove that \( L \) is a canonical list of \( I[1, i] \)).

The First Case

Assume \( i \) is after \( m \) in \( L_{opt} \). Let \( S \) denote the set of indices strictly between \( m \) and \( i \) in \( L_{opt} \) (so neither \( m \) nor \( i \) is in \( S \)). Since all indices of \( I[1, i-1] \) are before \( m \) in \( L_{opt} \), it holds that \( j > i \) for each index \( j \in S \). Let \( S' \) be the set of indices \( j \) of \( S \) such that \( x'_j \geq x'_i \). Note that for each \( j \in S' \), the pair \( (i, j) \) is an inversion. We consider the general case where neither \( S \) nor \( S' \) is empty since the analysis for other cases is similar but easier.

Let \( j \) be the rightmost index of \( S' \). Again, \( (i, j) \) is an inversion. By Lemma 6.5.1, we can obtain another optimal list \( L'_{opt} \) such that \( j \) is after \( i \) and positions of the indices other than those in \( S \) are the same as before in \( L_{opt} \). Further, the indices strictly between
Consider the list $L'_1$ that is the same as $L_0$ except that we exchange the positions of $m$ and $i$, i.e., the indices of $S_0$ are now after $i$ and before $m$. In the following, we prove that $L'_1$ is an optimal list. Note that $L$ is consistent with $L'_1$, and thus once we prove that $L'_1$ is an optimal list, we also prove that $L$ is a canonical list of $I[1,i]$. The technique for proving that $L'_1$ is an optimal list is similar to that in Section 6.5.2. The details are given below.

Since $L_0$ is an optimal list, there is an optimal configuration $C$ in which the order of the indices of intervals is the same as $L_0$. Consider the configuration $C'$ that is the same as $C$ except the following (e.g., see Fig. 6.10): First, we set $x^l_i(C') = x^l_m(C)$; second, we shift each interval of $S_0$ leftwards by distance $|I_m| - |I_i|$ (again, if this value is negative, we actually shift rightwards by its absolute value); third, we set $x^r_m(C') = x^r_i(C)$. Clearly, the interval order in $C'$ is the same as $L_1$. In the following, we show that $C'$ is an optimal configuration, which will prove that $L'_1$ is an optimal list.

We first show that $C'$ is feasible. As in Section 6.5.2, no two intervals of $C'$ overlap. Next, we show that every interval is valid in $C'$. It is sufficient to show that all intervals in $S_0 \cup \{m,i\}$ are valid since other intervals do not change positions from $C$ to $C'$. Comparing with its position in $C$, $I_m$ has been moved rightwards in $C'$. Thus, $I_m$ is valid in $C'$.

Recall that in Case II of our algorithm, it holds that $x^l_i \leq x^l_m(C_{L'})$, where $C_{L'}$ is the configuration of only the intervals of $I[1,i-1]$ following their order in $L'$. Since $C_{L'}$ is the configuration constructed by the left-possible placement strategy and the order of the indices of $I[1,i-1]$ in $C$ is the same as $L'$, it holds that $x^l_m(C_{L'}) \leq x^l_m(C)$. Hence,
we obtain $x_i^r \leq x_m^l(C)$. Since $x_i^r(C') = x_m^l(C)$, $x_i^r \leq x_i^r(C')$ and $I_i$ is valid in $C'$. Consider any index $j \in S_0$. Recall that $I_j$ is contained in $I_i$ in the input. Thus, $x_j^r \leq x_i^r$. Since $i$ is to the left of $j$ in $C'$, we have $x_i^r(C') \leq x_j^r(C')$. Since $x_i^r \leq x_i^r(C')$ (because $I_i$ is valid in $C'$), we obtain that $x_j^r \leq x_j^r(C')$ and $I_j$ is valid in $C'$. This proves that $C'$ is feasible.

We proceed to show that $C'$ is an optimal configuration by proving that $\delta(C') \leq \delta(C) = \delta_{opt}$. It suffices to show that for any $j \in S_0 \cup \{m, i\}$, $d(j, C') \leq \delta_{opt}$. Comparing with $C$, $I_i$ has been moved leftwards in $C'$, and thus $d(i, C') \leq d(i, C) \leq \delta_{opt}$. Since $x_i^r \leq x_m^r$, we can deduce $d(m, C') = x_m^r(C') - x_m^r \leq x_i^r(C) - x_i^r = d(i, C) \leq \delta_{opt}$. Consider any $j \in S_0$. Recall that $x_j^r \geq x_m^r$. On the other hand, since $j$ is to the left of $m$ in $C'$, $x_j^r(C') \leq x_m^r(C')$. Therefore, $d(j, C') = x_j^r(C') - x_j^r \leq x_m^r(C') - x_m^r = d(m, C')$. We have proved above that $d(m, C') \leq \delta_{opt}$, and thus $d(j, C') \leq \delta_{opt}$.

This proves that $C'$ is an optimal configuration and $L_1$ is an optimal list. As discussed above, this also proves that $L$ is a canonical list of $I[1, i]$. This finishes the proof of the lemma in the first case.

The Second Case

In the second case, $i$ is before $j$ in $L_{opt}$ for some $j \in I[1, i - 1] \setminus \{m\}$. We assume there is no other indices of $I[1, i - 1]$ strictly between $i$ and $j$ in $L_{opt}$ (otherwise, we take $j$ as the leftmost such index to the right of $i$).

Let $\hat{L}_0$ be the list of indices of $I[1, i]$ following their order in $L_{opt}$. Therefore, $\hat{L}_0$ is a canonical list. Let $\hat{L}_1$ be the list the same as $\hat{L}_0$ except that the order of $i$ and $j$ is exchanged. In the following, we first show that $\hat{L}_1$ is also a canonical list of $I[1, i]$. The proof technique is very similar to the above first case.

Let $S$ denote the set of indices strictly between $i$ and $j$ in $L_{opt}$. By the definition of $j$, $k > i > j$ holds for each index $k \in S$. Let $S'$ be the set of indices $k$ of $S$ such that $x_k^r \geq x_j^r$. Hence, for each $k \in S'$, the pair $(j, k)$ is an inversion of $L_{opt}$. We consider the general case where neither $S$ nor $S'$ is empty (otherwise the proof is similar but easier).

As in Section 6.5.3, starting from the rightmost index of $S'$, we keep applying Lemma 6.5.1 to the inversion pairs and eventually obtain an optimal list $L_0$ in which for any index $k$ of $L_0$ strictly between $i$ and $j$, $(j, k)$ is not an inversion and thus $x_k^r < x_j^r$. 
(hence $I_k \subseteq I_j$ in the input as $j < k$). Let $S_0$ denote the set of indices strictly between $i$ and $j$ in $L_0$.

Consider the list $L_1$ that is the same as $L_0$ except that we exchange the positions of $i$ and $j$, i.e., the indices of $S_0$ are now after $j$ and before $i$. In the following, we prove that $L_1$ is an optimal list, which will also prove that $\widehat{L}_1$ is a canonical list of $I[1, i]$ since $\widehat{L}_1$ is consistent with $L_1$.

Since $L_0$ is an optimal list, there is an optimal configuration $C$ in which the order of the intervals is the same as $L_0$. Consider the configuration $C'$ that is the same as $C$ except the following (e.g., see Fig. 6.11): First, we set $x^l_j(C') = x^l_i(C)$; second, we shift each interval of $S_0$ leftwards by distance $|I_i| - |I_j|$; third, we set $x^r_j(C') = x^r_j(C)$. Clearly, the interval order of $C'$ is the same as $L_1$. Below, we show that $C'$ is an optimal configuration, which will prove that $L_1$ is an optimal list.

We first show that $C'$ is feasible. As before, no two intervals of $C'$ overlap. Next we prove that all intervals in $S_0 \cup \{i, j\}$ are valid in $C'$. Comparing with its position in $C$, $I_i$ has been moved rightwards in $C'$ and thus is valid. Since $j < i$, $x^l_j < x^l_i$. Since $x^l_j(C') = x^l_i(C)$ and $x^l_i \leq x^l_i(C)$ (because $I_i$ is valid in $C$), we obtain $x^l_j \leq x^l_j(C')$ and $I_j$ is valid in $C'$. Consider any index $k \in S_0$. Recall that $x^l_k \leq x^r_k \leq x^r_j$. Since $k$ is to the right of $j$ in $C'$, we have $x^r_j(C') \leq x^r_k(C')$. Since $x^r_j \leq x^r_j(C')$, we obtain that $x^l_k \leq x^l_k(C')$ and $I_k$ is valid in $C'$. This proves that $C'$ is feasible.

We proceed to show that $C'$ is an optimal configuration by proving that for any $k \in S_0 \cup \{i, j\}$, $d(k, C') \leq \delta(C) = \delta_{opt}$. Comparing with $C$, $I_j$ has been moved leftwards in $C'$, and thus $d(j, C') \leq d(j, C) \leq \delta_{opt}$. Since $m < i$, $l_m$ is to the left of $r_i$ in the input. Since $I_m$ is to the right of $I_i$ in $C'$, $l_m$ is to the right of $r_i$ in $C'$. This implies that $d(i, C') \leq d(m, C')$. Since $I_m$ does not change position from $C$ to $C'$, $d(m, C') = d(m, C) \leq \delta_{opt}$. Thus, we obtain $d(i, C') \leq \delta_{opt}$. Consider any $k \in S_0$. Since $i < k$, $x^l_i \leq x^l_k$. On the other hand, since $k$ is to the left of $i$ in $C'$, $x^l_k(C') \leq x^l_i(C')$. Therefore, we deduce

![Figure 6.11](image-url)
\(d(k, C') = x^l_k(C') - x^l_k \leq x^l_i(C') - x^l_i = d(i, C').\) We have proved above that \(d(i, C') \leq \delta_{opt},\) and thus \(d(k, C') \leq \delta_{opt}.\)

This proves that \(C'\) is an optimal configuration and \(L_1\) is an optimal list. As discussed above, this also proves that \(\widehat{L}_1\) is a canonical list of \(I[1,i]\).

If the right neighbor \(j\) of \(i\) in \(\widehat{L}_1\) is not \(m\), then by the same analysis as above, we can show that the list obtained by exchanging the order of \(i\) and \(j\) is still a canonical list of \(I[1,i]\). We keep applying the above exchange operation until we obtain a canonical list \(\widehat{L}_2\) of \(I[1,i]\) such that the right neighbor of \(i\) in \(\widehat{L}_2\) is \(m\). Note that \(\widehat{L}_2\) is exactly \(L\), and thus this proves that \(L\) is a canonical list of \(I[1,i]\). This finishes the proof for the lemma in the second case.

Lemma 6.4.4 is thus proved.

6.5.4 Proof of Lemma 6.4.6

We prove Lemma 6.4.6. Assume that \(L'\) is a canonical list of \(I[1,i-1]\). Our goal is to prove that either \(L\) or \(L^*\) is a canonical list of \(I[1,i]\).

As \(L'\) is a canonical list, there exists an optimal list \(L_{opt}\) of \(I\) whose interval order is consistent with \(L'\). Let \(\widehat{L}_0\) be the list of indices of \(I[1,i]\) following the same order in \(L_{opt}\). If \(\widehat{L}_0\) is either \(L\) or \(L^*\), then we are done with the proof. Otherwise, \(i\) must be before \(j\) in \(\widehat{L}_0\) for some index \(j \in I[1,i-1] \setminus \{m\}\). By using the same proof as in Section 6.5.3, we can show that \(L^*\) is a canonical list of \(I[1,i]\). We omit the details.

6.5.5 Proof of Lemma 6.4.7

In this section, we prove Lemma 6.4.7. Assume \(\mathcal{L}^*\) has a canonical list \(L_0\) of \(I[1,i]\). Recall that \(L^*_{\text{min}}\) is the list of \(\mathcal{L}^*\) with the smallest max-displacement. Our goal is to prove that \(L^*_{\text{min}}\) is also a canonical list of \(I[1,i]\).

Recall that for each list \(L \in \mathcal{L}^*\), \(i\) and \(m\) are the last two indices with \(m\) at the end, and further, in the configuration \(C_L\) (which is obtained by the left-possible placement strategy on the intervals in \(I[1,i]\) following their order in \(L\)), \(x^l_i(C_L) = x^l_i\) and \(x^l_m(C_L) = x^r_i\). Also, each list of \(\mathcal{L}^*\) is generated in Case III of the algorithm and we have \(I_i \subseteq I_m\) in the input.
Since $L_0$ is a canonical list of $I[1, i]$, there is an optimal list $L_{\text{opt}}$ of $I$ that is consistent with $L_0$. Let $S$ be the set of indices of $I[i + 1, n]$ before $i$ in $L_{\text{opt}}$. We consider the general case where $S$ is not empty (otherwise the proof is similar but easier). Let $j$ be the rightmost index of $S$ in $L_{\text{opt}}$. Let $L'_{\text{opt}}$ be the list that is the same as $L_{\text{opt}}$ except that we move $j$ right after $i$. In the following, we show that $L'_{\text{opt}}$ is also an optimal list.

Since $L_{\text{opt}}$ is an optimal list, there is an optimal configuration $C$ in which the order of the indices of intervals is the same as $L_{\text{opt}}$. Recall that $L_{\text{opt}}[j, i]$ is consists of indices of $L_{\text{opt}}$ between $j$ and $i$ inclusively. Consider the configuration $C'$ that is the same as $C$ except the following (e.g., see Fig. 6.12): First, for each index $k \in L_{\text{opt}}[j, i] \setminus \{j\}$, move $I_k$ leftwards by distance $|I_j|$; second, move $I_j$ rightwards such that $l_j$ is at $r_i$ (after $I_i$ is moved leftwards in the above first step, so that $I_i$ is connected with $I_j$). Note that the order of intervals of $I$ in $C'$ is exactly $L'_{\text{opt}}$. In the following, we show that $C'$ is an optimal configuration, which will also prove that $L'_{\text{opt}}$ is an optimal list.

We first show that $C'$ is feasible. By our way of setting the positions of intervals in $L_{\text{opt}}[j, i]$, no two intervals overlap in $C'$. Next, we show that every interval is valid in $C'$. It is sufficient to show that $I_k$ is valid in $C'$ for every index $k$ in $L_{\text{opt}}[j, i]$ since all other intervals do not move from $C$ to $C'$. Comparing with its position in $C$, $I_j$ has been moved rightwards in $C'$ and thus is valid. Suppose $k \neq j$. By the definition of $j$, $k < j$ and thus $x_k^l \leq x_j^l$. By our way of constructing $C'$, $x_j^l(C) \leq x_k^l(C')$. Since $I_j$ is valid in $C$, it holds that $x_j^l \leq x_j^l(C)$. Thus, we obtain that $x_k^l \leq x_k^l(C')$ and $I_k$ is valid. This proves that $C'$ is feasible.

We proceed to show that $C'$ is an optimal configuration by proving that $\delta(C') \leq \delta(C) = \delta_{\text{opt}}$. It is sufficient to show that for any index $k \in L_{\text{opt}}[j, i]$, $d(k, C') \leq \delta_{\text{opt}}$. If $k$ is not $j$, then comparing with $C$, $I_k$ has been moved leftwards, and thus $d(k, C') \leq d(k, C) \leq \delta_{\text{opt}}$. In the following, we show that $d(j, C') \leq \delta_{\text{opt}}$. Indeed, since $m < i < j$, it holds that $x_m^l \leq x_j^l$. On the other hand, $I_m$ is to the right of $I_j$ in $C'$, and thus,

![Diagram](image-url)
\(x^1_j(C') \leq x^1_m(C').\) Therefore, we have \(d(j, C') = x^1_j(C') - x^1_j \leq x^1_m(C') - x^1_m = d(m, C').\) Since the position of \(l_m\) is the same in \(C\) and \(C',\) \(d(m, C') = d(m, C) \leq \delta_{opt}.\) Thus, we have \(d(j, C') \leq \delta_{opt}.\) This proves that \(C'\) is an optimal configuration and \(L'_{opt}\) is an optimal list.

If there are still indices of \([i, i + 1, n)\] before \(i\) in \(L'_{opt},\) then we keep applying the above exchange operations until we obtain an optimal list \(L''_{opt}\) that does not have any index of \([i, i + 1, n)\] before \(i,\) and in other words, the indices of \(L''_{opt}\) before \(i\) are exactly those in \([i, i - 1)\setminus\{m\}.\)

Since \(L''_{opt}\) is an optimal list, there is an optimal configuration \(C''\) whose interval order is the same as \(L''_{opt}.\) Let \(C'''\) be a configuration that is the same as \(C''\) except the following: For each interval \(I_k\) with \(k \in [i, i - 1)\setminus\{m\},\) we set its position the same as its position in \(C_{L_{min}^*}\) (which is the configuration obtained by our algorithm for the list \(L_{min}^*\)). Recall that the position of \(I_i\) in \(C_{L_{min}^*}\) is the same as that in the input. On the other hand, \(x^1_j \leq x^1_m(C'').\) Therefore, \(C''\) is still a feasible configuration. We claim that \(C'''\) is also an optimal configuration. To see this, the maximum displacement of all intervals in \([i, i - 1)\setminus\{m\}\) in \(C'''\) is at most \(\delta(C_{L_{min}^*}).\) Recall that \(\delta(C_{L_{min}^*}) \leq \delta(C_{L_0}).\) Further, since \(L_0\) is a canonical list, it holds that \(\delta(C_{L_0}) \leq \delta_{opt}.\) Thus, we obtain \(\delta(C_{L_{min}^*}) \leq \delta_{opt}.\)

Consequently, the maximum displacement of all intervals in \([i, i - 1)\setminus\{m\}\) in \(C'''\) is at most \(\delta_{opt}.\) Since only intervals of \([i, i - 1)\setminus\{m\}\) in \(C'''\) change positions from \(C''\) to \(C''',\) we obtain \(\delta(C''') \leq \delta_{opt}\) and thus \(C'''\) is an optimal configuration.

According to our construction of \(C''',\) the order of the intervals of \([i, i]\) in \(C'''\) is exactly \(L_{min}^*.\) Therefore, \(L_{min}^*\) is a canonical list of \([i, i].\) This proves Lemma 6.4.7.

### 6.6 The Improved Algorithm

In this section, we improve our preliminary algorithm to \(O(n \log n)\) time and \(O(n)\) space. The key idea is that based on new observations we are able to prune some “redundant” lists from \(L\) after each step of the algorithm (actually Lemma 6.4.7 already gives an example for pruning redundant lists). More importantly, although the number of remaining lists in \(L\) can still be \(\Omega(n)\) in the worst case, the remaining lists of \(L\) have certain monotonicity properties such that we are able to implicitly maintain them in \(O(n)\) space and update them in \(O(\log n)\) amortized time for each step of the algorithm.
for processing an interval $I_i$.

In the following, we first give some observations that will help us to perform the pruning procedure on $\mathcal{L}$.

### 6.6.1 Observations

In this section, unless otherwise stated, let $\mathcal{L}$ be the set after a step of our preliminary algorithm for processing an interval $i$. Recall that for each list $L \in \mathcal{L}$, we also have a configuration $C_L$ that is built following the left-possible placement strategy. We use $x(C_L)$ to denote the $x$-coordinate of the right endpoint of the rightmost interval of $L$ in $C_L$.

For any two lists $L_1$ and $L_2$ of $\mathcal{L}$, we say that $L_1$ *dominates* $L_2$ if the following holds: If $L_2$ is a canonical list of $\mathcal{I}[1,i]$, then $L_1$ must also be a canonical list of $\mathcal{I}[1,i]$. Hence, if $L_1$ dominates $L_2$, then $L_2$ is “redundant” and can be pruned from $\mathcal{L}$.

The subsequent two lemmas give ways to identify redundant lists from $\mathcal{L}$. In general, Lemma 6.6.1 is for the case where two lists have different last indices while Lemma 6.6.2 is for the case where two lists have the same last index (notice the slight differences in the lemma conditions).

**Lemma 6.6.1.** Suppose $L_1$ and $L_2$ are two lists of $\mathcal{L}$ such that the last index of $L_1$ is $m'$, the last index of $L_2$ is $m$ (with $m \neq m'$), and $x_{m'} \leq x_m$. Then, if $\delta(C_{L_1}) \leq d(m, C_{L_2})$ and $x(C_{L_1}) \leq x(C_{L_2})$, then $L_1$ dominates $L_2$.

**Proof.** Assume $L_2$ is a canonical list of $\mathcal{I}[1,i]$. Our goal is to prove that $L_1$ is also a canonical list of $\mathcal{I}[1,i]$. It is sufficient to construct an optimal configuration in which the order the intervals of $\mathcal{I}[1,i]$ is $L_1$. We let $h$ denote the left neighboring index of $m'$ in $L_1$ and let $g$ denote the left neighboring index of $m$ in $L_2$.

Since $L_2$ is a canonical list, there is an optimal list $Q$ that is consistent with $L_2$. Let $S$ denote the set of indices of $\mathcal{I}[i+1,n]$ before $g$ in $Q$. We consider the general case where $S$ is not empty (otherwise the proof is similar but easier).

By the similar analysis as in the proof of Lemma 6.4.7 (we omit the details), we can obtain an optimal list $Q_1$ that is the same as $Q$ except that all indices of $S$ are now right after $g$ in $Q_1$ (i.e., all indices of $Q$ before $g$ except those in $S$ are still before $g$ in
\[ Q_2 : \ldots g, S', m, k, \ldots \]
\[ Q_3 : \ldots h, S', m', k, \ldots \]

Figure 6.13. Illustrating the two lists \( Q_2 \) and \( Q_3 \), where \( k \) is the right neighboring index of \( m \) in \( Q_2 \) and \( k \) is also right neighboring index of \( m' \) in \( Q_3 \). In \( Q_2 \) (resp., \( Q_3 \)), the indices strictly before \( S' \) are exactly those in \( I[i, i] \setminus \{m\} \) (resp., \( I[i, i] \setminus \{m'\} \)).

\( Q_1 \) with the same relative order, and all indices of \( Q \) after \( g \) are now after indices of \( S \) in \( Q_1 \) with the same relative order). Therefore, in \( Q_1 \), the indices before \( g \) are exactly those in \( I[i, i] \setminus \{m\} \).

Recall that \( Q_1[g, m] \) denote the sublist of \( Q_1 \) between \( g \) and \( m \) including \( g \) and \( m \). If there is an index \( j \) in \( Q_1[g, m] \) such that \((m, j)\) is an inversion, then as in the proof of Lemma 6.4.2, we keep applying Lemma 6.5.1 on all such indices \( j \) from right to left to obtain another optimal list \( Q_2 \) such that for each \( j \in Q_2[g, m], (m, j) \) is not an inversion. Note that the indices before and including \( g \) in \( Q_1 \) are the same as those in \( Q_2 \). Let \( S' \) denote the set of indices of \( Q_2[g, m] \setminus \{g, m\} \). Again, we consider the general case where \( S' \) is not empty. Note that \( S' \subseteq I[i + 1, n] \). For each \( j \in S' \), since \((m, j)\) is not an inversion and \( m < j \), it holds that \( x^r_j < x^r_m \).

Let \( Q_3 \) be another list that is the same as \( Q_2 \) except the following (e.g., see Fig 6.13): First, we move \( m' \) right after the indices of \( S' \) and move \( m \) before the indices of \( S' \) (i.e., the indices of \( Q_3 \) from the beginning to \( m' \) are indices of \( I[i, i] \setminus \{m'\} \), indices of \( S' \), and \( m' \)); second, we re-arrange the indices of \( I[i, i] \setminus \{m'\} \) (which are all before indices of \( S' \) in \( Q_3 \)) in exactly the same order as in \( L_1 \). In this way, \( L_1 \) is consistent with \( Q_3 \). In the following, we show that \( Q_3 \) is an optimal list, which will prove that \( L_1 \) is a canonical list of \( I[i, i] \) and thus prove the lemma.

Since \( Q_2 \) is an optimal list, there is an optimal configuration \( C_2 \) whose interval order is \( Q_2 \). Consider the configuration \( C_3 \) whose interval order follows \( Q_3 \) and whose interval positions are the same as those in \( C_2 \) except the following: First, for each index \( j \in I[i, i] \setminus \{m'\} \), we set the position of \( I_j \) in the same as its position in \( C_{L_1} \) (i.e., the configuration obtained by our algorithm for \( L_1 \)); second, we place the intervals of \( S' \) such that they do not overlap but connect together (i.e., the right endpoint co-locates with the left endpoint of the next interval) following their order in \( Q_2 \) and the left endpoint of the leftmost interval of \( S' \) is at the right endpoint of \( I_h \) (recall that \( h \) is the left
neighbor of \( m' \) in \( L_1 \), which is also the rightmost interval of \( I[1, i] \setminus \{m'\} \) in \( Q_3 \); e.g., see Fig. 6.13); third, we set the left endpoint of \( I_m' \) at the right endpoint of the rightmost interval of \( S' \). Therefore, all intervals before and including \( m' \) do not have any overlap in \( C_3 \), and the intervals of \( S' \cup \{h, m'\} \) essentially connect together. In the following, we show that \( C_3 \) is an optimal configuration, which will prove that \( Q_3 \) is an optimal list.

We first show that \( C_3 \) is feasible. We begin with proving that no two intervals overlap. Let \( k \) be the right neighboring interval of \( m \) in \( Q_2 \) (e.g., see Fig. 6.13), and \( k \) now becomes the right neighboring interval of \( m' \) in \( Q_3 \). To prove no two intervals of \( C_3 \) overlap, it is sufficient to show that \( I_m' \) and \( I_k \) do not overlap, i.e., \( x_{m'}^r(3) \leq x_k^l(3) \).

Note that \( x_k^l(3) = x_k^l(2) \) and \( x_{m'}^r(2) \leq x_k^l(2) \). Hence, it suffices to prove \( x_{m'}^r(3) \leq x_m^r(2) \).

We claim that in the configuration \( C_{L_1} \), \( t_m' \) is at \( r_h \). Indeed, since \( x_{m'}^r \leq x_m^r \) and \( I_m \) is to the left of \( I_m' \) in \( C_{L_1} \), it holds that \( x_{m'}^r \leq x_m^r(3) \). Since \( C_{L_1} \) is constructed based on the left-possible placement strategy, we have \( x_{m'}^r(3) = x_h^r(3) \), which proves the claim.

Recall that by the definition of \( x(C_{L_1}) \), we have \( x(C_{L_1}) = x_{m'}^r(3) \). Let \( l \) be the total length of all intervals of \( S' \). By our way of constructing \( C_3 \), it holds that \( x_{m'}^r(3) = x_{m'}^r(3) + l = x(C_{L_1}) + l \). On the other hand, since \( L_2 \) is consistent with \( Q_2 \) and \( C_{L_2} \) is constructed based on the left-possible placement strategy, it holds that \( x(C_{L_2}) + l \leq x_{m'}^r(2) \). By the lemma condition, \( x(C_{L_1}) \leq x(C_{L_2}) \). Hence, we obtain \( x_{m'}^r(3) = x(C_{L_1}) + l \leq x(C_{L_2}) + l \leq x_{m'}^r(2) \). Thus, \( I_m \) and \( I_k \) do not overlap in \( C_3 \).

We proceed to prove that every interval of \( C_3 \) is valid. For any interval before \( h \) and including \( h \) in \( Q_3 \), since its position in \( C_3 \) is the same as that in \( C_{L_1} \), it is valid. For interval \( m' \), since it is valid in \( C_{L_1} \) and \( x_{m'}^r(3) = x_{m'}^r(3) + l \), it is also valid in \( C_3 \). Consider any interval \( j \in S' \). Recall that \( x_j^l < x_{m'}^r \). Since \( I_m \) is to the left of \( I_j \) in \( C_3 \), comparing with its input position, \( I_j \) must have been moved rightwards in \( C_3 \). Thus, \( I_j \) is valid. For any interval after \( m' \), its position is the same as in \( C_2 \), and thus it is valid.

The above proves that \( C_3 \) is feasible. In the following, we show that \( C_3 \) is an optimal configuration by proving that \( \delta(C_3) \leq \delta(C_2) = \delta_{opt} \). It is sufficient to show that for any interval \( j \) before and including \( m' \) in \( C_3 \), \( d(j, C_3) \leq \delta_{opt} \).
Consider any interval \( j \) before and including \( h \) in \( C_3 \). We have \( d(j, C_3) = d(j, C_{L_1}) \leq \delta(C_{L_1}) \). By lemma condition, \( \delta(C_{L_1}) \leq d(m, C_{L_2}) \leq \delta(C_{L_2}) \). Since \( L_2 \) is consistent with \( Q_2 \) and \( C_{L_2} \) is constructed based on the left-possible placement strategy, it holds that \( \delta(C_{L_2}) \leq \delta_{opt} \). Therefore, \( d(j, C_3) \leq \delta_{opt} \).

Consider interval \( m' \). In the following, we show that \( d(m', C_3) \leq d(m, C_2) \), which will lead to \( d(m', C_3) \leq \delta_{opt} \) since \( d(m, C_2) \leq \delta_{opt} \).

By lemma condition, \( d(m', C_{L_1}) \leq \delta(C_{L_1}) \leq d(m, C_{L_2}) \). As discussed above, \( x_{m'}(C_3) = x_{m'}(C_{L_1}) + l \). Therefore, \( d(m', C_3) = d(m', C_{L_1}) + l \). On the other hand, as discussed above, \( x_{m}(C_2) \geq x_{m'}(C_{L_2}) + l \). Therefore, \( d(m, C_2) \geq d(m, C_{L_2}) + l \).

Due to \( d(m', C_{L_1}) \leq d(m, C_{L_2}) \), we obtain \( d(m', C_3) \leq d(m, C_2) \).

Consider any index \( j \in S' \). Recall that \( m' \leq i < j \) as \( S' \subseteq \mathcal{I}[i+1, n] \). Therefore, \( x_{m'} \leq x_j \). On the other hand, \( l_{m'} \) is to the right of \( l_j \) in \( C_3 \). Thus, it holds that \( d(j, C_3) \leq d(m', C_3) \). We have proved above that \( d(m', C_3) \leq \delta_{opt} \). Hence, we also obtain \( d(j, C_3) \leq \delta_{opt} \).

This proves that \( C_3 \) is an optimal configuration. As discussed above, the lemma follows.

Lemma 6.6.2. Suppose \( L_1 \) and \( L_2 \) are two lists of \( \mathcal{L} \) whose last indices are the same. Then, if \( \delta(C_{L_1}) \leq \delta(C_{L_2}) \) and \( x(C_{L_1}) \leq x(C_{L_2}) \), then \( L_1 \) dominates \( L_2 \).

Proof. Assume \( L_2 \) is a canonical list of \( \mathcal{I}[1, i] \). Our goal is prove that \( L_1 \) is also a canonical list of \( \mathcal{I}[1, i] \). To this end, it is sufficient to construct an optimal configuration in which the order the intervals of \( \mathcal{I}[1, i] \) is \( L_1 \). The proof techniques are similar to (but simpler than) that for Lemma 6.6.1.

Let \( m \) be the last index of \( L_1 \) and \( L_2 \). Let \( h \) (resp., \( g \)) be the left neighboring index of \( m \) in \( L_1 \) (resp., \( L_2 \)).

Since \( L_2 \) is a canonical list, there is an optimal list \( Q \) that is consistent with \( L_2 \). By the definition of \( g \), all indices (if any) strictly between \( g \) and \( m \) in \( Q \) are from \( \mathcal{I}[i+1, n] \). Let \( S \) denote the set of indices of \( \mathcal{I}[i+1, n] \) before \( g \) in \( Q \). We consider the general case where \( S \neq \emptyset \).
\[ Q_1 : \ldots g, S, m, \ldots \]
\[ Q_2 : \ldots h, S, m, \ldots \]

Figure 6.14. Illustrating the two lists \( Q_1 \) and \( Q_2 \). In \( Q_1 \) (resp., \( Q_2 \)), the indices strictly before \( S \) are exactly those in \( T[1, i] \setminus \{ m \} \).

As in the proof of Lemma 6.6.1, we can obtain an optimal list \( Q_1 \) that is the same as \( Q \) except that all indices of \( S \) are now right after \( g \) in \( Q_1 \) (i.e., all indices of \( Q \) before \( g \) except those in \( S \) are still before \( g \) in \( Q_1 \) with the same relative order, and all indices of \( Q \) after \( g \) are now after indices of \( S \) in \( Q_1 \) with the same relative order; e.g., see Fig. 6.14). Therefore, in \( Q_1 \), the indices before and including \( g \) are exactly those in \( T[1, i] \setminus \{ m \} \).

Let \( Q_2 \) be another list that is the same as \( Q_1 \) except the following (e.g., see Fig. 6.14): We re-arrange the indices before and including \( g \) such that they follow exactly the same order as in \( L_1 \). Note that \( L_1 \) is consistent with \( Q_2 \). In the following, we show that \( Q_2 \) is an optimal list, which will prove the lemma.

Since \( Q_1 \) is an optimal list, there is an optimal configuration \( C_1 \) whose interval order is the same as \( Q_1 \). Consider the configuration \( C_2 \) that is the same as \( C_1 \) except the following: For each interval \( k \) before and including \( g \), we set the position of \( I_k \) the same as its position in \( C_{L_1} \). Hence, the interval order of \( C_2 \) is the same as \( Q_2 \). In the following, we show that \( C_2 \) is an optimal configuration, which will prove that \( Q_2 \) is an optimal list.

We first show that \( C_2 \) is feasible. For each interval \( k \) before and including \( h \), its position in \( C_2 \) is the same as that in \( C_{L_1} \), and thus interval \( k \) is still valid in \( C_2 \). Other intervals are also valid since they do not change their positions from \( C_1 \) to \( C_2 \). In the following, we show that no two intervals overlap in \( C_2 \). Based on our way of constructing \( C_2 \), it is sufficient to show that \( x^r_h(C_2) \leq x^l_t(C_2) \), where \( t \) is the right neighboring index of \( h \) in \( Q_2 \). Note that \( x^r_h(C_2) = x^r_h(C_{L_1}) \) and \( x^l_t(C_2) = x^l_t(C_1) \). In the following, we prove that \( x^r_h(C_{L_1}) \leq x^l_t(C_1) \). Depending on whether \( x^r_h(C_{L_1}) \leq x^r_g(C_{L_2}) \), there are two cases.

1. If \( x^r_h(C_{L_1}) \leq x^r_g(C_{L_2}) \), then since \( L_2 \) is consistent with \( Q_1 \) and \( C_{L_2} \) is constructed based on the left-possible placement strategy, we have \( x^r_g(C_{L_2}) \leq x^r_g(C_1) \), and thus, \( x^r_h(C_{L_1}) \leq x^r_g(C_1) \).
Lemma 6.6.3. \( E \) guarantees the following property on algorithm given in Section 6.6.2.

Proof. We prove the lemma by induction. Initially, after \( I_1 \) is processed, \( \mathcal{L} \) consists of the only list \( L = \{1\} \). Therefore, \( E(\mathcal{L}) = \{1\} \) and the lemma trivially holds.

We assume that the lemma holds after interval \( I_{t-1} \) is processed. Let \( \mathcal{L} \) be the set after \( I_i \) is processed. For differentiation, we let \( \mathcal{L}' \) denote the set \( \mathcal{L} \) before \( I_i \) is processed.

Depending on whether the size of \( E(\mathcal{L}') \) is 1 or 2, there are two cases.
The case $|E(L')| = 1$. Let $m$ be the only index of $E(L')$. Hence, for each list $L \in L'$, $m$ is the last index of $L$. Depending on whether $x_m^r \leq x_i^r$, there are two subcases.

1. If $x_m^r \leq x_i^r$, then according to our preliminary algorithm, Case I of the algorithm happens on every list $L \in L'$, and $i$ is appended at the end of $L$ for each $L \in L'$. Therefore, the last indices of all lists of $L$ are $i$, and the lemma statement holds for $E(L)$.

2. If $x_m^r > x_i^r$, then note that $I_i \subseteq I_m$ in the input. Consider any list $L \in L'$. According to our preliminary algorithm, if $x_i^l \leq x_m^l(C_L)$, then $i$ is inserted into $L$ right before $m$; otherwise, $i$ is appended at the end of $L$, and further, a new list $L^*$ is produced in which $m$ is at the end.

Therefore, in this case, $E(L)$ has either one index or two indices. If $|E(L)| = 2$, then $E(L) = \{i, m\}$. Since $I_i \subseteq I_m$ in the input, the lemma statement holds on $E(L)$.

The case $|E(L')| = 2$. By induction hypothesis, one interval of $E(L')$ contains the other one in the input. Let $m$ and $m'$ be the two indices of $E(L')$, respectively, such that $I_{m'} \subseteq I_m$ in the input. Hence, we have $m < m'$ and $x_{m'}^r \leq x_m^r$.

Depending on the $x$-coordinates of right endpoints of $I_i$, $I_m$, and $I_{m'}$ in the input, there are three subcases: $x_m^r \leq x_i^r$, $x_{m'}^r \leq x_i^r < x_m^r$, and $x_i^r < x_{m'}^r$.

1. If $x_m^r \leq x_i^r$, then for each list $L \in L'$, Case I of the algorithm happens, and $i$ is appended at the end of $L$. Therefore, the last indices of all lists of $L$ are $i$, and the lemma statement holds for $E(L)$.

2. If $x_{m'}^r \leq x_i^r < x_m^r$, then consider any list $L \in L'$. If $m'$ is at the end of $L$, then Case I happens and $i$ is appended at the end of $L$. If $m$ is at the end of $L$, then either Case II or Case III of the algorithm happens. Hence, either $i$ or $m$ will be the last index of $L$; if a new list $L^*$ is produced in Case III, then its last index is $m$. 

Therefore, after every list of $L'$ is processed, the last index of each list of $L$ is either $m$ or $i$, i.e., $E(L) = \{m, i\}$. Note that $I_i$ is contained in $I_m$ in the input. Hence, the lemma statement holds for $E(L)$.

3. If $x^r_i < x^r_{m'}$, then $I_i$ is contained in both $I_m$ and $I_{m'}$ in the input. Consider any list $L \in L'$. Regardless of whether the last index is $m$ or $m'$, Case I does not happen. We claim that Case III does not happen either. We prove the claim only for the case where the last index of $L$ is $m$ (the other case can be proved similarly). Indeed, in the configuration $C_L$, it holds that $x^r_{m'} \leq x^r_m(C_L)$. Since $m$ is the last index of $L$, we have $x^r_m(C_L) \leq x^l_m(C_L)$. Since $x^r_i < x^r_{m'}$, we obtain $x^l_i \leq x^r_i < x^r_{m'} \leq x^r_m(C_L) \leq x^l_m(C_L)$. This implies that Case III of the algorithm cannot happen.

Hence, Case II happens, and $i$ is inserted into $L$ right before the last index. Therefore, the last indices of all lists of $L$ are either $m$ or $m'$. The lemma statement holds for $E(L)$.

This proves the lemma. 

6.6.2 A Pruning Procedure

Based on Lemmas 6.6.1 and 6.6.2, we present an algorithm that prunes redundant lists from $L$ after each step for processing an interval $I_i$. In the following, we describe the algorithm, whose implementation is discussed in Section 6.6.3.

By Lemma 6.6.3, $E(L)$ has at most two indices. If $E(L)$ has two indices, we let $m$ and $m'$ denote the two indices, respectively, such that $I_{m'} \subseteq I_m$ in the input. If $E(L)$ has only one index, let $m$ denote it and $m'$ is undefined. Let $L_1$ (resp., $L_2$) denote the set of lists of $L$ whose last indices are $m'$ (resp., $m$), and $L_1 = \emptyset$ if and only if $m'$ is undefined.

Our algorithm maintains several invariants regarding certain monotonicity properties, as follows, which are crucial to our efficient implementation.

1. $L$ contains a canonical list of $I[1, i]$.

2. For any two lists $L_1$ and $L_2$ of $L$, $x(C_{L_1}) \neq x(C_{L_2})$ and $\delta(C_{L_1}) \neq \delta(C_{L_2})$. 

3. If $\mathcal{L}_1 \neq \emptyset$, then for any lists $L_1 \in \mathcal{L}_1$ and $L_2 \in \mathcal{L}_2$, $x(C_{L_1}) < x(C_{L_2})$.

4. For any two lists $L_1$ and $L_2$ of $\mathcal{L}$, $x(C_{L_1}) < x(C_{L_2})$ if and only if $\delta(C_{L_1}) > \delta(C_{L_2})$.

In other words, if we order the lists $L$ of $\mathcal{L}$ increasingly by the values $x(C_L)$, then the values $\delta(C_L)$ are sorted decreasingly.

After $I_n$ is processed, by the algorithm invariants, if $L$ is the list of $\mathcal{L}$ with minimum $\delta(C_L)$, then $L$ is an optimal list and $\delta_{opt} = \delta(C_L)$.

Initially after the first interval $I_1$ is processed, $\mathcal{L}$ has only one list $L = \{1\}$, and thus, all algorithm invariants trivially hold. In general, suppose the first $i - 1$ intervals have been processed and all algorithm invariants hold on $\mathcal{L}$. In the following, we discuss the general step for processing interval $I_i$.

For differentiation, we let $\mathcal{L}'$ refer to the original set $\mathcal{L}$ before interval $i$ is processed. Similarly, we use $\mathcal{L}'_1$ and $\mathcal{L}'_2$ to refer to $\mathcal{L}_1$ and $\mathcal{L}_2$, respectively. Let $L'_1, L'_2, \ldots, L'_a$ be the lists of $\mathcal{L}'$ sorted with $x(C_{L'_1}) < x(C_{L'_2}) < \cdots < x(C_{L'_a})$, where $a = |\mathcal{L}'|$. By the fourth invariant, we have $\delta(C_{L'_1}) > \delta(C_{L'_2}) > \cdots > \delta(C_{L'_a})$. If $\mathcal{L}'_1 = \emptyset$, let $b = 0$; otherwise, let $b$ be the largest index such that $L'_b \in \mathcal{L}'_1$, and by the third algorithm invariant, $\mathcal{L}'_1 = \{L'_1, \ldots, L'_b\}$ and $\mathcal{L}'_2 = \{L'_{b+1}, \ldots, L_a\}$. Depending on whether $\mathcal{L}'_1 = \emptyset$, there are two main cases.

The Case $\mathcal{L}'_1 = \emptyset$

In this case, for each list $L' \in \mathcal{L}'$, its last index is $m$. Depending on whether $x^r_m \leq x^r_i$, there are two subcases.

The first subcase $x^r_m \leq x^r_i$. In this case, according to the preliminary algorithm, for each list $L'_j \in \mathcal{L}'$, Case I happens and $i$ is appended at the end of $L'_j$, and we use $L_j$ to refer to the updated list of $L'_j$ with $i$. According to our left-possible placement strategy, $x^1_i(C_{L_j}) = \max\{x(C_{L'_j}), x^1_i\}$. Thus, $x(C_{L_j}) = x^1_i(C_{L_j}) + |I_i|$ and $d(i, C_{L_j}) = x^1_i(C_{L_j}) - x^1_i$.

As the index $j$ increases from 1 to $a$, since the value $x(C_{L'_j})$ strictly increases, $x^1_i(C_{L_j})$ (and thus $x(C_{L_j})$ and $d(i, C_{L_j})$) is monotonically increasing (it may first be constant and then strictly increases after some index, say, $a_1$). Formally, we define $a_1$ as follows. If $x(C_{L'_j}) > x^1_i$, then let $a_1 = 0$; otherwise, define $a_1$ to be the largest index $j \in [1, a]$ such that $x(C_{L'_j}) \leq x^1_i$ (e.g., see Fig. 6.15). In the following, we first assume $a_1 \neq 0$. As
Lemma 6.6.4.

1. If the red segment shows the interval $i$, the configurations $C_j$ increases on $j$. Illustrated in Figure 6.15.

Formally, let $a$ be the largest index after some index, say, $a$. Thus, $L^j, a$ exists, then let $a_2 = a$. The following lemma is proved based on Lemma 6.6.2.

Lemma 6.6.4. 1. If $a_1 > 1$, then for each $j \in [1, a_1 - 1]$, $L_{a_1}$ dominates $L_j$.

2. If $a_2 < a$, then for each $j \in [a_2 + 1, a]$, $L_{a_2}$ dominates $L_j$.

Proof. 1. Let $k = a_1$ and assume $k > 1$. Consider any $j \in [1, k - 1]$. By the definition of $a_1$, $x^j_i(C_{L_j}) = x^j_i(C_{L_k}) = x^j_i$. Therefore, $x(C_{L_j}) = x(C_{L_k}) = x^j_i + |I_i|$. Since $d(i, C_{L_j}) = d(i, C_{L_k}) = 0$, we have $\delta(C_{L_j}) = \delta(C_{L_k})$. Since $j < k$, $\delta(C_{L_j}) > \delta(C_{L_k})$. Thus, we obtain $\delta(C_{L_j}) > \delta(C_{L_k})$.

Since $x(C_{L_j}) = x(C_{L_k})$, $\delta(C_{L_j}) > \delta(C_{L_k})$, and the last indices of $L_j$ and $L_k$ are both $i$, by Lemma 6.6.2, $L_k$ dominates $L_j$.

2. Let $k = a_2$ and assume $k < a$. Consider any $j \in [k + 1, a]$. As discussed before, $x(C_{L_j})$ is monotonically increasing on $j \in [1, a]$. Therefore, $x(C_{L_k}) \leq x(C_{L_j})$. By the definition of $a_2$ and since $\delta(C_{L_j})$ is a unimodal function on $j \in [1, a]$, it holds that $\delta(C_{L_k}) \leq \delta(C_{L_j})$. By Lemma 6.6.2, $L_k$ dominates $L_j$.

This proves the lemma.
By Lemma 6.6.4, we let \( \mathcal{L} = \{ L_j \mid a_1 \leq j \leq a_2 \} \). The above is for the general case where \( a_1 \neq 0 \). If \( a_1 = 0 \), then we let \( \mathcal{L} = \{ L_j \mid 1 \leq j \leq a_2 \} \).

**Observation 6.6.5.** All algorithm invariants hold for \( \mathcal{L} \).

**Proof.** By Lemma 6.6.4, the lists that have been removed are redundant. Hence, \( \mathcal{L} \) contains a canonical list of \( I[1, i] \) and the first algorithm invariant holds.

By our definitions of \( a_1 \) and \( a_2 \), when \( j \) increases in \([a_1, a_2]\), \( x(C_{L_j}) \) strictly increases and \( \delta(C_{L_j}) \) strictly decreases. Therefore, the last three algorithm invariants hold. \( \square \)

The following lemma will be quite useful for the algorithm implementation given later in Section 6.6.3.

**Lemma 6.6.6.** If \( a_1 < a_2 \), then for each \( j \in [a_1 + 1, a_2] \), \( x(C_{L_j}) = x(C_{L_j'}) + |I_i| \). For each list \( L_j \in \mathcal{L} \) with \( j \neq a_2 \), \( \delta(C_{L_j}) = \delta(C_{L_j'}) \).

**Proof.** By the definition of \( a_1 \), for any \( j \in [a_1 + 1, a_2] \), it always holds that \( x(C_{L_j}) = x(C_{L_j'}) + |I_i| \). This proves the first lemma statement.

Recall that \( \delta(C_{L_j}) = \max\{\delta(C_{L_j'}), d(i, C_{L_j})\} \) for each \( j \in [1, a] \).

Consider any list \( L_j \) with \( j \neq a_2 \). Assume to the contrary that \( \delta(C_{L_j}) \neq \delta(C_{L_j'}) \). Then, \( \delta(C_{L_j}) = d(i, C_{L_j}) \). Since \( \delta(C_{L_j}) = d(i, C_{L_j}) < d(i, C_{L_{a_2}}) \), we obtain \( \delta(C_{L_j}) \leq \delta(C_{L_{a_2}}) \), which contradicts with \( \delta(C_{L_j}) > \delta(C_{L_{a_2}}) \). \( \square \)

The second subcase \( x_i^r > x_i^r \). In this case, for each list \( L_j' \in \mathcal{L}' \), according to our preliminary algorithm, depending on whether \( x_i^l \leq x_i^l(C_{L_j'}) \), either Case II or Case III can happen. If \( x_i^l \leq x_i^l(C_{L_j'}) \), then let \( c = 0 \); otherwise, let \( c \) be the largest index \( j \) such that \( x_i^l > x_i^l(C_{L_j'}) \) (e.g., see Fig. 6.16). In the following, we first consider the general case where \( 1 \leq c < a \).

For each \( j \in [1, c] \), observe that \( x_i^l(C_{L_j'}) = x(C_{L_j'}) - |I_m| \leq x(C_{L_j'}) - |I_m| = x_i^l(C_{L_j'}) < x_i^l \). According to our preliminary algorithm, Case III happens, and thus \( L_j' \) will produce two lists: the list \( L_j \) by appending \( i \) at the end of \( L_j' \), and the new list \( L_j^* \) by inserting \( i \) in front of \( m \) in \( L_j' \). Further, according to our left-possible placement strategy, \( x_i^l(C_{L_j}) = x(C_{L_j}) \) in \( C_{L_j} \), and \( x_i^l(C_{L_j'}) = x_i^l \) and \( x_i^l(C_{L_j'}) = x_i^r \) in \( C_{L_j} \). By Observation 6.4.5, \( \delta(C_{L_j}) = \max\{\delta(C_{L_j}), d(i, C_{L_j})\} \) and \( \delta(C_{L_j'}) = \max\{\delta(C_{L_j'}), d(m, C_{L_j'})\} \).
Observation 6.6.7. $\delta(C_L \delta) \leq \delta(C_L')$ for any $j \in [1, c]$.

Proof. For any $j \in [1, c]$, note that $d(m, C_L \delta) = x_m^j(C_L \delta) - x_m^j = x_m^m - x_m^m$. Therefore, $d(m, C_L \delta)$ is the same for all $j \in [1, c]$. On the other hand, we have $\delta(C_L') \geq \delta(C_L \delta)$. Thus, $\delta(C_L \delta) \leq \delta(C_L')$. $\square$

By the above observation and Lemma 6.4.7, among the new lists $L^*_j$ with $j = 1, 2, \ldots, c$, only $L^*_c$ needs to be kept.

For each $j \in [1, c]$, note that $x(C_{L_j}) = x(C_{L_j'}) + |L_j|$. Since $x(C_{L_j'})$ is strictly increasing on $j \in [1, c]$, $x(C_{L_j})$ is also strictly increasing on $j \in [1, c]$. Since $d(i, C_{L_j}) = x_i^j(C_{L_j}) - x_i^j = x(C_{L_j'}) - x_i^j$ for any $j \in [1, c]$, $d(i, C_{L_j})$ also strictly increases on $j \in [1, c]$. Further, since $\delta(C_{L_j'})$ strictly decreases on $j \in [1, c]$, $\delta(C_{L_j})$, which is equal to max{$\delta(C_{L_j'}), d(i, C_{L_j})$}, is a unimodal function (i.e., it first strictly decreases and then strictly increases). Let $c_1$ be the smallest index $j \in [1, c - 1]$ such that $\delta(C_{L_j}) \leq \delta(C_{L_{j+1}})$, and if such an index $j$ does not exist, then let $c_1 = c$.

Lemma 6.6.8. If $c_1 < c$, then $L_{c_1}$ dominates $L_j$ for any $j \in [c_1 + 1, c]$.

Proof. Consider any $j \in [c_1 + 1, c]$. Since $\delta(C_{L_j})$ is a unimodal function on $j \in [1, c]$, by the definition of $c_1$, $\delta(C_{L_{c_1}}) \leq \delta(C_{L_j})$. Recall that $x(C_{L_{c_1}}) \leq x(C_{L_j})$. Since the last indices of $L_{c_1}$ and $L_j$ are both $i$, by Lemma 6.6.2, $L_{c_1}$ dominates $L_j$. $\square$

By the preceding lemma, if $c_1 < c$, then we do not have to keep the lists $L_{c_1+1}, \ldots, L_c$ in $L$. Let $S_1 = \{L_1, \ldots, L_{c_1}\}$.

Consider any index $j \in [c + 1, a]$. By the definition of $c$ and also due to that $x(C_{L_j})$ is strictly increasing on $k \in [1, a]$, it holds that $x_m^j(C_{L_j}) \geq x_m^j$, and thus Case II of the preliminary algorithm happens on $L_j$ and $L_j$ is obtained by inserting $i$ right
Lemma 6.6.10. 1. If $S$ is the subsequence of the lists of $L_j$ and $x_\ast_m(C_{L_j}) = x(C_{L_j})$. As $j$ increases in $[c+1,a]$, since $x(C_{L_j})$ strictly increases, both $x(C_{L_j})$ and $d(m,C_{L_j})$ strictly increase. Since $\delta(C_{L_j})$ is strictly decreasing on $j \in [c+1,a]$, we obtain that $\delta(C_{L_j})$ is a unimodal function on $j \in [c+1,a]$ (i.e., it first strictly decreases and then strictly increases).

Let $S = \{L_1, \ldots, L_c, L_c^\ast, L_{c+1}, \ldots, L_a\}$. For convenience, we use $L_{c+0.5}$ to refer to $L_c^\ast$ (and $L_{c+0.5}^\ast$ refers to $L_c'$); in this way, the indices of the ordered lists of $S$ are sorted. Consider the subsequence of the lists of $S$ from $L_{c+0.5}$ to the end (including $L_{c+0.5}$). Define $c_2$ to be the index of the first list $L_j$ such that $\delta(C_{L_j}) \leq \delta(C_L)$, where $L$ is the right neighboring list of $L_j$ in $S$; if such a list $L_j$ does not exist, then we let $c_2 = a$.

Observation 6.6.9. As $j$ increases in $[1,a]$, $x(C_{L_j})$ is strictly increasing except that $x(C_{L_{c+0.5}}) = x(C_{L_{c+1}})$ may be possible.

Proof. Recall that $x(C_{L_j})$ is strictly increasing on $j \in [1,c]$ and $j \in [c+1,a]$, respectively. Let $l = |I_1| + |I_m|$. Note that $x(C_{L_c}) = x_1(C_{L_c}) + l$, $x(C_{L_{c+1}}) = x_1(C_{L_{c+1}}) + l$.

By our definition of $c$, $x_1(C_{L_c}) < x_1(C_{L_{c+1}})$. Thus, $x(C_{L_c}) < x(C_{L_{c+1}})$ and $x(C_{L_{c+1}})$. This shows that $x(C_{L_j})$ is strictly increasing on $j \in [1,a]$ except that $x(C_{L_{c+1}}) = x(C_{L_{c+1}})$ may be possible.

Lemma 6.6.10. 1. If $c_2 < a$, then $L_{c_2}$ dominates $L_j$ for any $L_j \in S$ with $j > c_2$.

2. If $c_2 \geq c + 1$ and $x(C_{L_{c+0.5}}) = x(C_{L_{c+1}})$, then $L_{c+1}$ dominates $L_{c+0.5}$.

Proof. We first show that $\delta(C_{L_j})$ is a unimodal function on $j \in [c+0.5,a]$.

Recall that for each $j \in [c+1,a]$, $\delta(C_{L_j}) = \max\{\delta(C_{L_j}), d(m,C_{L_j})\}$, and $\delta(C_{L_j}) = \max\{\delta(C_{L_j}), d(m,C_{L_j})\}$. For each $j \in [c+0.5,a]$, since $m$ is the last index of $L_j$, we have $d(m,C_{L_j}) = x(C_{L_j}) - x_\ast_m$. By Observation 6.6.9, $d(m,C_{L_j})$ is strictly increasing on $[c+0.5,a]$ except that $d(m,C_{L_{c+0.5}}) = d(m,C_{L_{c+1}})$ may be possible. Since $\delta(C_{L_j})$ on $j \in [1,a]$ is strictly decreasing, $\delta(C_{L_j})$ is a unimodal function on $j \in [c+0.5,a]$.

By the definition of $c_2$, $\delta(C_{L_j})$ is strictly decreasing on $[c+0.5,c_2]$ and monotonically increasing on $[c_2,a]$. 

Lemma 6.6.11. If \( L \) is not the first list of both \( L_{c_2} \) and \( L_j \), and \( x(L_{c_2}) \leq x(L_j) \). Since the last indices of both \( L_{c_2} \) and \( L_j \) are \( m \), by Lemma 6.6.2, \( L_{c_2} \) dominates \( L_j \).

If \( c_2 \geq c+1 \) and \( x(L_{c_2}) = x(L_{c+1}) \), by the definition of \( c_2 \), \( \delta(L_{c_2}) > \delta(L_{c+1}) \). Since the last indices of both \( L_{c+0.5} \) and \( L_{c+1} \) are \( m \), by Lemma 6.6.2, \( L_{c+1} \) dominates \( L_{c+0.5} \). The lemma thus follows. \( \Box \)

Let \( S_2 = \{ L_{c_0+0.5}, L_{c+1}, \ldots, L_{c_2} \} \) and we remove \( L_{c+0.5} \) from \( S_2 \) if \( c_2 \geq c+1 \) and \( x(L_{c+0.5}) = x(L_{c+1}) \). In the following, we combine \( S_1 \) and \( S_2 \) to obtain the set \( L \). We consider the lists of \( S_2 \) in order. Define \( c' \) to be the index \( j \) of the first list \( L_j \) such that \( \delta(L_{c_1}) > \delta(L_j) \), and if no such list \( L_j \) exists, then let \( c' = c_2 + 1 \).

Lemma 6.6.11. If \( L_{c'} \) is not the first list of \( S_2 \) or \( c' = c_2 + 1 \), then for each list \( L_j \) of \( S_2 \) with \( j < c' \), \( L_{c_1} \) dominates \( L_j \).

**Proof.** We assume that \( L_{c'} \) is not the first list of \( S_2 \) or \( c' = c_2 + 1 \).

Note that we have proved in the proof of Lemma 6.6.10 that \( \delta(L_j) \) on \( j \in [c+0.5, c] \) is strictly decreasing. By the definition of \( c' \), it holds that \( \delta(L_{c_1}) \leq \delta(L_j) \) for any \( L_j \in S_2 \) with \( j < c' \).

Consider any list \( L_j \) of \( S_2 \) with \( j < c' \).

Recall that \( \delta(L_{c_1}) = \max\{ \delta(L_{c_1}'), d(m, C_{L_{c_1}}) \} \). We claim that \( \delta(L_{c_1}) = d(m, C_{L_{c_1}}) \).

Indeed, note that \( \delta(L_{c_1}') \leq \delta(L_{c_1}) \leq \delta(L_{c_1}) \). Since \( \delta(L_{c_1}) \leq \delta(L_j) \), we obtain \( \delta(L_{c_1}') \leq \delta(L_j) \), and thus, \( \delta(L_j) = d(m, C_{L_j}) \).

Consequently, we have \( \delta(L_{c_1}) \leq d(m, C_{L_{c_1}}) \) and \( x(L_{c_1}) \leq x(L_j) \) (by Observation 6.6.9). Further, the last index of \( L_{c_1} \) is \( i \) and the last index of \( L_j \) is \( m \), with \( x_i^* \leq x_m^* \). By Lemma 6.6.1, \( L_{c_1} \) dominates \( L_j \).

The lemma thus follows. \( \Box \)

We remove from \( S_2 \) all lists \( L_j \) with \( j < c' \), and let \( L = S_1 \cup S_2 \). In general, if \( c' \neq c_2 + 1 \), then \( L = \{ L_1, \ldots, L_{c_1}, L_{c'}, \ldots, L_{c_2} \} \); otherwise, \( L = \{ L_1, \ldots, L_{c_1} \} \).

The above discussion is for the general case where \( 1 \leq c < a \). If \( c = 0 \), then \( L_{c_1}, c_1 \) and \( c' \) are all undefined, and we have \( L = \{ L_1, \ldots, L_{c_1} \} \). If \( c = a \), then \( L = \{ L_1, \ldots, L_{c_1} \} \) if \( \delta(L_{c_1}) \leq \delta(L_{c_1}) \) and \( L = \{ L_1, \ldots, L_{c_1}, L_{c_1} \} \) otherwise.
Observation 6.6.12. All algorithm invariants hold on \( L \).

Proof. We only consider the most general case where \( 1 \leq c < a \) and \( c' \neq c_2 + 1 \), since other cases can be proved in a similar but easier way.

By Lemmas 6.6.8, 6.6.10, and 6.6.11, all pruned lists are redundant and thus \( L \) contains a canonical list of \( I[1, i] \). The first algorithm invariant holds.

If \( x(C_{L_{c+0.5}}) = x(C_{L_{c+1}}) \), then \( L_{c+0.5} \) and \( L_{c+1} \) cannot be both in \( L \) by Lemma 6.6.10(2). Thus, by Observation 6.6.9, \( x(C_{L_j}) \) strictly increases in \([1, a] \). Recall that for any list \( L_j \in L \), the last index of \( L_j \) is \( i \) if \( j \leq c_1 \) and \( m \) otherwise. Recall that \( I_i \) is contained in \( I_m \) in the input. Thus, the fourth algorithm invariant holds.

Further, our definitions of \( c_1 \), \( c' \), and \( c_2 \) guarantee that \( \delta(C_L) \) on all lists \( L \) following their order in \( L \) is strictly decreasing. Therefore, the other two algorithm invariants also hold.

The following lemma will be useful for the algorithm implementation.

Lemma 6.6.13. For each list \( L_j \in L \), if \( L_j \neq L_{c_1} \), then \( x(C_{L_j}) = x(C_{L'_j}) + |I_i| \); if \( L_j \notin \{ L_{c_1}, L_{c_1}, L_{c_2} \} \), then \( \delta(C_{L_j}) = \delta(C_{L'_j}) \).

Proof. If \( L_j \neq L_{c_1} \), then we have discussed before that \( x(C_{L_j}) = x(C_{L'_j}) + |I_i| \) always holds regardless of whether the last index of \( L_j \) is \( i \) or \( m \).

If \( L_j \notin \{ L_{c_1}, L_{c_1}, L_{c_2} \} \), assume to the contrary that \( \delta(C_{L_j}) \neq \delta(C_{L'_j}) \). Then, since \( \delta(C_{L_j}) = \max \{ \delta(C_{L'_j}), d(k, C_{L_j}) \} \), we obtain that \( \delta(C_{L_j}) = d(k, C_{L_j}) \), where \( k \) is the last index of \( C_{L_j} \) (\( k \) is \( i \) if \( j < c \) and \( m \) otherwise). Note that \( j \) is either in \([1, c_1] \) or \([c', c_2] \). We discuss the two cases below.

1. If \( j \in [1, c_1] \), then the last index of \( L_j \) is \( i \). Since \( L_j \neq L_{c_1} \), \( j < c_1 \) holds. We have discussed before that \( d(i, C_{L_j}) \leq d(i, C_{L_{c_1}}) \). Thus, we can deduce \( \delta(C_{L_j}) = d(i, C_{L_j}) \leq d(i, C_{L_{c_1}}) \leq \delta(C_{L_{c_1}}) \). However, we have already proved that \( \delta(C_{L_j}) > \delta(C_{L_{c_1}}) \). Thus, we obtain contradiction.

2. If \( j \in [c', c_2] \), the analysis is similar. In this case the last index of \( L_j \) is \( m \) and \( j < c_2 \). Since \( j < c_2 \), we have discussed before that \( d(m, C_{L_j}) \leq d(m, C_{L_{c_2}}) \). Thus, we can deduce \( \delta(C_{L_j}) = d(m, C_{L_j}) \leq d(m, C_{L_{c_2}}) \leq \delta(C_{L_{c_2}}) \). However, we have already proved that \( \delta(C_{L_j}) > \delta(C_{L_{c_2}}) \). Thus, we obtain contradiction.
The lemma thus follows.

The Case $\mathcal{L}_1' \neq \emptyset$

We then consider the case where $\mathcal{L}_1' \neq \emptyset$. In this case, recall that $\mathcal{L}_1' = \{L_1', \ldots, L_b\}$ and $\mathcal{L}_2' = \{L_{b+1}', \ldots, L_a\}$. For each $L_j' \in \mathcal{L}'$, the last index of $L_j'$ is $m'$ if $j \leq b$ and $m$ otherwise. Recall that $I_m \subseteq I_m$ in the input. As in the proof of Lemma 6.6.3, there are three subcases: $x_i^r \geq x_{m'}^r$, $x_{m'}^r \leq x_i^r < x_m^r$, and $x_i^r < x_{m'}^r$.

The first subcase $x_i^r \geq x_{m'}^r$. In this case, for each $L_j' \in \mathcal{L}'$, Case I of the preliminary algorithm happens and $L_j$ is obtained by appending $i$ at the end of $L_j'$. Our pruning procedure for this subcase is similar to the first subcase in Section 6.6.2, and we briefly discuss it below.

First, for each $L_j' \in \mathcal{L}'$, $x_i^l(C_{L_j}) = \max\{x(C_{L_j}), x_i^l\}$ and $\delta(C_{L_j}) = \max\{\delta(C_{L_j}), d(i, C_{L_j})\}$. We define $a_1$ and $a_2$ in exactly the same way as in the first subcase of Section 6.6.2, and further, Lemma 6.6.4 still holds. Similarly, we let $\mathcal{L}$ consist of only those lists $L_j$ with $j \in [a_1, a_2]$. By the similar analysis, Observation 6.6.5 and Lemma 6.6.6 still hold. We omit the details.

The second subcase $x_{m'}^r \leq x_i^r < x_{m'}^r$. In this case, we first apply the similar pruning procedure for the first (resp., second) subcase of Section 6.6.2 to set $\mathcal{L}_1'$ (resp., $\mathcal{L}_2'$), and then we combine the results. The details are given below.

For set $\mathcal{L}_1'$, the last indices of all lists of $\mathcal{L}_1'$ are $m'$. Since $x_{m'}^r \leq x_i^r$, for each $L_j' \in \mathcal{L}_1'$, Case I of the preliminary algorithm happens and $L_j$ is obtained by appending $i$ at the end of $L_j'$. We define $a_1$ and $a_2$ in the similar way as in the first subcase of Section 6.6.2 but with respect to the indices in $[1, b]$. In fact, since $x_i^r < x_{m'}^r$, it holds that $x_i^l \leq x_i^r < x_m^r \leq x(C_{L_j})$, and consequently, $a_1 = 0$. Similarly, Lemma 6.6.4 also holds with respect to the indices of $[1, b]$. Further, as $j$ increases in $[1, a_2]$, $x(C_{L_j})$ is strictly increasing and $\delta(C_{L_j})$ is strictly decreasing. Let $S_1' = \{L_1, L_2, \ldots, L_{a_2}\}$.

For set $\mathcal{L}_2'$, the last indices of all its lists are $m$. Since $x_i^r < x_{m'}^r$, for each list $L_j' \in \mathcal{L}_2$, either Case II or Case III of the algorithm happens. We define $c$ in the similar way as in the second subcase of Section 6.6.2 but with respect to the indices of $[b + 1, a]$. Specifically, if $x_i^l \leq x_i^l(C_{L_{b+1}})$, then let $c = b$; otherwise, let $c$ be the largest
index $j \in [b + 1, a]$ such that $x'_i > x'_m(C'_{L_j})$. We consider the most general case where $b + 1 \leq c < a$ (other cases are similar but easier).

For each $j \in [b + 1, c]$, there is also a new list $L_j^*$. Similar to Observation 6.6.7, $\delta(C_{L_j^*}) \leq \delta(C_{L_j})$ for any $j \in [b + 1, c]$. Hence, among the new lists $L_j^*$ with $j = b + 1, \ldots, c$, only $L_c^*$ needs to be kept. Let $S' = \{L_{b+1}, \ldots, L_c, L_c^*, L_{c+1}, \ldots, L_a\}$. We also use $L_{c+0.5}$ to refer to $L_c^*$. We define the three indices $c_1, c_2$, and $c'$ in the similar way as in the second subcase of Section 6.6.2 but with respect to the ordered lists in $S'$. Similarly, Observation 6.6.9, Lemmas 6.6.8, 6.6.10, and 6.6.11 all hold with respect to the lists in $S'$. Let $S'_2 = \{L_{b+1}, \ldots, L_{c_1}, L_{c'}, \ldots, L_{c_2}\}$.

Finally, we combine the lists of the two sets $S'_1$ and $S'_2$ to obtain $L$, as follows. Recall that $L_{a2}$ is the last list of $S'_1$. We consider the lists of $S'_2$ in order. Define $b'$ to be the index $j$ of the first list $L_j$ of $S'_2$ such that $\delta(C_{L_{a2}}) > \delta(C_{L_j})$, and if no such list $L_j$ exists, then let $b' = c_2 + 1$.

Lemma 6.6.14. 1. $x(C_{L_{a2}}) < x(C_{L_{b+1}})$.

2. If $b' > b + 1$, then $L_{a2}$ dominates $L_j$ for any list $L_j \in S'_2$ with $j < b'$.

Proof. For $L_{a2}$, since $a_1 = 0$, we have $x(C_{L_{a2}}) = x(C_{L_{a2}}) + |I_i|$. For $L_{b+1}$, it holds that $x(C_{L_{b+1}}) = x(C_{L_{b+1}}') + |I_i|$. Since $x(C_{L_{a2}}) < x(C_{L_{b+1}})$, we have $x(C_{L_{a2}}) < x(C_{L_{b+1}})$. This proves the first statement of the lemma.

Next we prove the second lemma statement. Assume $b' > b + 1$. Consider any list $L_j \in S'_2$ with $j < b'$. In the following, we show that $L_{a2}$ dominates $L_j$.

Recall that the values $\delta(L)$ of the lists $L$ of $S'_2$ are strictly decreasing following their order in $S'_2$. By the definition of $b'$, $\delta(C_{L_{a2}}) \leq \delta(C_{L_j})$. Note that the last index of $L_j$ can be either $i$ or $m$, and the last index of $L_{a2}$ is $i$.

If the last index of $L_j$ is $i$, then since $\delta(C_{L_{a2}}) \leq \delta(C_{L_i})$ and $x(C_{L_{a2}}) < x(C_{L_{b+1}}) \leq x(C_{L_i})$, by Lemma 6.6.2, $L_{a2}$ dominates $L_j$.

If the last index of $L_j$ is $m$, then $\delta(C_{L_j}) = \max\{\delta(C_{L_j'}), d(m, C_{L_j})\}$. Recall that $\delta(C_{L_{a2}}) = \max\{\delta(C_{L_{a2}}'), d(i, C_{L_{a2}})\}$ and $\delta(C_{L_{a2}}') > \delta(C_{L_j})$. Due to $\delta(C_{L_{a2}}) \leq \delta(C_{L_j})$, we can deduce $\delta(C_{L_j'}) < \delta(C_{L_{a2}}') \leq \delta(C_{L_{a2}}) \leq \delta(C_{L_j})$. Therefore, $\delta(C_{L_{a2}}) \leq \delta(C_{L_j}) = d(m, C_{L_j})$. Again, $x(C_{L_{a2}}) < x(C_{L_{b+1}}) \leq x(C_{L_j})$. Since the last index of $L_{a2}$ is $i$ and that of $L_j$ is $m$, with $I_i \subseteq I_m$ in the input, by Lemma 6.6.1, $L_{a2}$ dominates $L_j$. □
By Lemma 6.6.14, we let $\mathcal{L}$ be the union of the lists of $S'_1$ and the lists of $S'_2$ after and including $b'$ (if $b' = c_2 + 1$, then $\mathcal{L} = S'_1$).

Observation 6.6.15. All algorithm invariants hold on $\mathcal{L}$.

Proof. As the analysis in Section 6.6.2, $S'_1 \cup S'_2$ must contain a canonical list of $\mathcal{I}[1, i]$. In light of Lemma 6.6.14(2), $\mathcal{L}$ also contains a canonical list.

Also, the values of $x(C_L)$ for all lists $L$ of $S'_1$ (resp., $S'_2$) are strictly increasing. By Lemma 6.6.14(1), the values of $x(C_L)$ for all lists $L$ of $\mathcal{L}$ are also strictly increasing. On the other hand, the values of $\delta(C_L)$ for all lists $L$ of $S'_1$ (resp., $S'_2$) are strictly decreasing. The definition of $b'$ makes sure that the values of $\delta(C_L)$ for all lists $L$ of $\mathcal{L}$ must be strictly decreasing. Also, note that the lists of $\mathcal{L}$ whose last indices are $i$ are all before the lists whose last indices are $m$.

Hence, all algorithm invariants hold on $\mathcal{L}$. □

The following lemma will be useful for the algorithm implementation.

Lemma 6.6.16. For each list $L_j \in \mathcal{L}$, if $L_j \neq L^*_c$, then $x(C_{L_j}) = x(C_{L'_j}) + |I_i|$; if $L_j \notin \{L_{a2}, L^*_c, L_{c1}, L_{c2}\}$, then $\delta(C_{L_j}) = \delta(C_{L'_j})$.

Proof. Consider any list $L_j \in \mathcal{L}$.

If $L_j \neq L^*_c$, then since $a_1 = 0$, $x(C_{L_j}) = x(C_{L'_j}) + |I_i|$ always holds regardless whether the last index of $L_j$ is $i$ or $m$.

Assume $L_j \notin \{L_{a2}, L^*_c, L_{c1}, L_{c2}\}$. To prove that $\delta(C_{L_j}) = \delta(C_{L'_j})$, if $j \leq b$, then we can apply the analysis in the proof of Lemma 6.6.6; otherwise, we can apply the analysis in the proof of Lemma 6.6.13. We omit the details. □

The third subcase $x'_i < x'_{m'}$. In this case, for each list $L'_j \in \mathcal{L}'$, as analyzed in the proof of Lemma 6.6.3, only Case II of our preliminary algorithm happens, and thus $L_j$ is obtained from $L'_j$ by inserting $i$ into $L'_j$ right before the last index. Further, it holds that $x(C_{L_j}) = x(C_{L'_j}) + |I_i|$ regardless of whether the last index of $L'_j$ is $m$ or $m'$. Since $x(C_{L'_j})$ is strictly increasing on $j \in [1, a]$, $x(C_{L_j})$ is also strictly increasing on $j \in [1, a]$.

Consider any list $L'_j \in \mathcal{L}'$ with $j \leq b$. Recall that the last index of $L'_j$ is $m'$. By Observation 6.4.3, $\delta(C_{L_j}) = \max\{\delta(C_{L'_j}), d(m', C_{L_j})\}$, and $d(m', C_{L_j}) = x_{m'}(C_{L_j}) - x'_{m'} = x(C_{L_j}) - x'_{m'}$. Thus, $d(m', C_{L_j})$ strictly increases on $j \in [1, b]$. Since $\delta(C_{L'_j})$ strictly
Lemma 6.6.17. If \( e_1 < b \), then \( L_{e_1} \) dominates \( L_j \) for any \( j \in [e_1 + 1, b] \).

Proof. Assume \( e_1 < b \) and let \( j \) be any index in \([e_1 + 1, b]\). By our definition of \( e_1 \) and since \( \delta(C_{L_{e_1}}) \) is unimodal on \([1, b]\), it holds that \( \delta(C_{L_{e_1}}) \leq \delta(C_{L_j}) \). Recall that \( x(C_{L_{e_1}}) < x(C_{L_j}) \). Since the last indices of both \( L_{e_1} \) and \( L_j \) are \( m' \), by Lemma 6.6.2, \( L_{e_1} \) dominates \( L_j \).

Due to Lemma 6.6.17, let \( S_1 = \{L_1, L_2, \ldots, L_{e_1}\} \).

Consider any list \( L'_j \in \mathcal{L}' \) with \( j > b \). Recall that the last index of \( L'_j \) is \( m \).

Similarly as above, \( \delta(C_{L'_j}) = \max\{\delta(C_{L'_j}), d(m, C_{L'_j})\} \) and \( d(m, C_{L'_j}) = x(C_{L'_j}) - x^r_m \).

Similarly, \( \delta(C_{L_j}) \) is a unimodal function on \( j \in [b + 1, a] \). If \( \delta(C_{L_{b+1}}) \leq \delta(C_{L_{b+2}}) \), then we let \( e_2 = b + 1 \); otherwise, define \( e_2 \) to be the largest index \( j \in [b + 1, e_2] \) such that \( \delta(C_{L_{j-1}}) > \delta(C_{L_{j+1}}) \). Hence, \( \delta(C_{L'_j}) \) is strictly decreasing on \( j \in [b + 1, e_2] \). By a similar proof as Lemma 6.6.17, we can show that if \( e_2 < a \), then \( L_{e_2} \) dominates \( L_j \) for any \( j \in [e_2 + 1, a] \). Let \( S_2 = \{L_{b+1}, L_{b+2}, \ldots, L_{e_2}\} \).

We finally combine \( S_1 \) and \( S_2 \) to obtain \( \mathcal{L} \) as follows. Define \( b' \) to be the smallest index \( j \) of \([b + 1, e_2]\) such that \( \delta(C_{L_{e_1}}) > \delta(C_{L_j}) \), and if no such index exists, then let \( b' = e_2 + 1 \).

Lemma 6.6.18. If \( b' > b + 1 \), then \( L_{e_1} \) dominates \( L_j \) of \( S_2 \) for any \( j \in [b + 1, b' - 1] \).

Proof. Assume \( b' > b + 1 \) and let \( j \) be any index in \([b + 1, b' - 1] \). Since \( \delta(C_{L_j}) \) is strictly decreasing on \( j \in [b + 1, e_2] \), by the definition of \( b' \), \( \delta(C_{L_{e_1}}) \leq \delta(C_{L_j}) \).

Recall that \( \delta(C_{L_{e_1}}) = \max\{\delta(C_{L_{e_1}}'), d(m, C_{L_{e_1}})\} \), \( \delta(C_{L_{e_1}}') = \max\{\delta(C_{L_{e_1}}'), d(m', C_{L_{e_1}})\} \), and \( \delta(C_{L_{e_1}}) < \delta(C_{L_{e_1}}') \). Hence, we obtain \( \delta(C_{L_j}) < \delta(C_{L_{j+1}}) \leq \delta(C_{L_j}) \), and thus \( \delta(C_{L_j}) = d(m, C_{L_j}) \). Since \( \delta(C_{L_{e_1}}) \leq \delta(C_{L_{j+1}}) \), \( \delta(C_{L_{j+1}}) \leq d(m, C_{L_j}) \). Further, recall that \( x(C_{L_{e_1}}) < x(C_{L_j}) \). Then, Lemma 6.6.1 applies since the last index of \( L_{e_1} \) is \( m' \) and that of \( L_j \) is \( m \), with \( x^r_m \leq x^r_{m'} \). By Lemma 6.6.1, \( L_{e_1} \) dominates \( L_j \). \( \square \)
In light of Lemma 6.6.18, we let \( L = S_1 \cup \{ L_1, \ldots, L_{e_2} \} \) if \( b' \neq e_2 + 1 \) and \( L = S_1 \) otherwise. By similar analysis as before, we can show that all algorithm invariants hold on \( L \), and we omit the details. The following lemma will be useful for the algorithm implementation.

Lemma 6.6.19. For each list \( L_j \in \mathcal{L} \), \( x(C_{L_j}) = x(C_{L'_j}) + |I_i| \); if \( L_j \notin \{ L_{e_1}, L_{e_2} \} \), then \( \delta(C_{L_j}) = \delta(C_{L'_j}) \).

Proof. We have shown that \( x(C_{L_j}) = x(C_{L'_j}) + |I_i| \) for any \( j \in [1, a] \).

Consider any list \( L_j \in \mathcal{L} \) and \( j \notin \{ e_1, e_2 \} \). By the similar analysis as in Lemma 6.6.13, we can show that \( \delta(C_{L_j}) = \delta(C_{L'_j}) \). The details are omitted. \( \square \)

6.6.3 The Algorithm Implementation

In this section, we implement our pruning algorithm described in Section 6.6.2 in \( O(n \log n) \) time and \( O(n) \) space. We first show how to compute the optimal value \( \delta_{opt} \) and then show how to construct an optimal list \( L_{opt} \) in Section 6.6.4.

Since \( \mathcal{L} \) may have \( \Theta(n) \) lists and each list may have \( \Theta(n) \) intervals, to avoid \( \Omega(n^2) \) time, the key idea is to maintain the lists of \( \mathcal{L} \) implicitly. We show that it is sufficient to maintain the “\( x \)-values” \( x(C_L) \) and the “\( \delta \)-values” \( \delta(C_L) \) for all lists \( L \) of \( \mathcal{L} \), as well as the list index \( b \) and the interval indices \( m' \) and \( m \). To this end, and in particular, to update the \( x \)-values and the \( \delta \)-values after each interval \( I_i \) is processed, our implementation heavily relies on Lemmas 6.6.6, 6.6.13, 6.6.16, and 6.6.19. Intuitively, these lemmas guarantee that although the \( x \)-values of all lists of \( \mathcal{L} \) need to change, all but a constant number of them increase by the same amount, which can be updated implicitly in constant time; similarly, only a constant number of \( \delta \)-values need to be updated. The details are given below.

Let \( \mathcal{L} = \{ L_1, L_2, \ldots, L_a \} \) such that \( x(C_{L_j}) \) strictly increases on \( j \in [1, a] \), and thus, \( \delta(C_{L_j}) \) strictly decreases on \( j \in [1, a] \) by the algorithm invariants.

We maintain a balanced binary search tree \( T \) whose leaves from left to right correspond to the ordered lists of \( \mathcal{L} \). Let \( v_1, \ldots, v_a \) be the leaves of \( T \) from left to right, and thus, \( v_j \) corresponds to \( L_j \) for each \( j \in [1, a] \). For each \( j \in [1, a] \), \( v_j \) stores a \( \delta \)-value \( \delta(v_j) \)
that is equal to \( \delta(C_{\ell_j}) \), and \( v_j \) stores another \( x \)-value \( x(v_j) \) that is equal to \( x(C_{\ell_j}) - R \), where \( R \) is a \textit{global shift} value maintained by the algorithm.

In addition, we maintain a pointer \( p_b \) pointing to the leaf \( v(b) \) of \( T \) if \( b \neq 0 \) and \( p_b = \text{null} \) if \( b = 0 \). We also maintain the interval indices \( m \) and \( m' \). Again, if \( p_b = \text{null} \), then \( m' \) is undefined.

Initially, after \( I_1 \) is processed, \( L \) consists of the single list \( L = \{1\} \). We set \( R = 0 \), \( m = 1 \), and \( p_b = \text{null} \). The tree \( T \) consists of only one leaf \( v_1 \) with \( \delta(v_1) = 0 \) and \( x(v_1) = x_1^r \).

In general, we assume \( I_{i-1} \) has been processed and \( T, m, m', p_b, \) and \( R \) have been correctly maintained. In the following, we show how to update them for processing \( I_i \).

In particular, we show that processing \( I_i \) takes \( O((k + 1) \log n) \) time, where \( k \) is the number of lists removed from \( L \) during processing \( I_i \). Since our algorithm will generate at most \( n \) new lists for \( L \) and each list will be removed from \( L \) at most once, the total time of the algorithm is \( O(n \log n) \).

As in Section 6.6.2, we let \( L' = \{L'_1, L'_2, \ldots, L'_a\} \) denote the original set \( L \) before \( I_i \) is processed. Again, if \( b \neq 0 \), then \( L'_1 = \{L'_1, \ldots, L'_b\} \) and \( L'_2 = \{L'_{b+1}, \ldots, L'_a\} \). We consider the five subcases discussed in Section 6.6.2.

The Case \( L'_1 = \emptyset \)

In this case, the last indices of all lists of \( L' \) are \( m \).

The first subcase \( x^*_m \leq x^*_i \). In this case, in general we have \( L = \{L_j \mid a_1 \leq j \leq a_2\} \).

We first find \( a_1 \) and remove the lists \( L_1, \ldots, L_{a_1-1} \) if \( a_1 > 1 \) as follows.

Starting from the leftmost leaf \( v_1 \) of \( T \), if \( x(v_1) + R \) (which is equal to \( x(C_{\ell_1}) \)) is larger than \( x^*_i \), then \( a_1 = 0 \) and we are done. Otherwise, we consider the next leaf \( v_2 \).

In general, suppose we are considering leaf \( v_j \). If \( x(v_j) + R > x^*_i \), then we stop with \( a_1 = j - 1 \). Otherwise, we remove leaf \( v_{j-1} \) (not \( v_j \)) from \( T \) and continue to consider the next leaf \( v_{j+1} \) if \( j \neq 1 \) (if \( j = a \), then we stop with \( a_1 = a \)).

If \( a_1 \neq 0 \), then the above has found the leaf \( v_{a_1} \). In addition, we update \( x(v_{a_1}) = x^*_i - R - |I_i| \) (we have minus \( |I_i| \) here because later we will increase \( R \) by \( |I_i| \)).

Next we find \( a_2 \) and remove the lists \( L_{a_2+1}, \ldots, L_a \) (by removing the corresponding leaves from \( T \)) if \( a_2 < a \), as follows. Recall that for each \( j \in [a_1+1, a] \), \( \delta(C_{\ell_j}) = x(v_{a_1}) \).
max{\(\delta(C_{L_j'})\), \(d(i,C_{L_j})\)}, with \(\delta(C_{L_j'}) = \delta(v_j)\) and \(d(i,C_{L_j}) = x'_i(C_{L_j}) - x'_i = x(C_{L_j'}) - x'_i = x(v_j) + R - x'_i\). Hence, we have \(\delta(C_{L_j}) = \max\{\delta(v_j), x(v_j) + R - x'_i\}\).

If \(a_1 = a\), then we have \(a_2 = a_1\) and we are done. Otherwise we do the following. Starting from the rightmost leaf \(v_a\) of \(T\), we check whether \(\max\{\delta(v_{a-1}), x(v_{a-1}) + R - x'_i\} \leq \max\{\delta(v_a), x(v_a) + R - x'_i\}\). If yes, we remove \(v_a\) from \(T\) and continue to consider \(v_{a-1}\). In general, suppose we are considering \(v_j\). If \(j = a_1\), then we stop with \(a_2 = a_1\). Otherwise, we check whether \(\max\{\delta(v_{j-1}), x(v_{j-1}) + R - x'_i\} \leq \max\{\delta(v_j), x(v_j) + R - x'_i\}\). If yes, we remove \(v_j\) from \(T\) and proceed on \(v_{j-1}\). Otherwise, we stop with \(a_2 = j\).

Suppose the above procedure finds leaf \(v_j\) with \(a_2 = j\). We further update \(\delta(v_j) = \max\{\delta(v_j), x(v_j) + R - x'_i\}\). By Lemma 6.6.6, we do not need to update other \(\delta\)-values.

The above has updated the tree \(T\). In addition, we update \(R = R + |I_i|\), which actually implicitly updates all \(x\)-values by Lemma 6.6.6. Finally, we update \(m = i\) since the last indices of all updated lists of \(L\) are now \(i\).

This finishes our algorithm for processing \(I_i\). Clearly, the total time is \(O((k + 1) \log n)\) since removing each leaf of \(T\) takes \(O(\log n)\) time, where \(k\) is the number of leaves that have been removed from \(T\).

The second subcase \(x'_m > x'_i\). In this case, roughly speaking, we should compute the set \(L = \{L_1, \ldots, L_{c_1}, L_{c_1'}, L_{c_1'+1}, \ldots, L_{c_2}\}\).

We first compute the index \(c\), i.e., find the leaf \(v_c\) of \(T\). This can be done by searching \(T\) in \(O(\log n)\) time as follows. Note that for a list \(L'_j\), to check whether \(x'_i > x'_m(C_{L'_j})\), since \(x'_m(C_{L'_j}) = x(C_{L'_j}) - |I_m| = x(v_j) + R - |I_m|\), it is equivalent to checking whether \(x'_i > x(v_j) + R - |I_m|\), which is equivalent to \(x'_i - R + |I_m| > x(v_j)\). Consequently, \(v_c\) is the rightmost leaf \(v\) of \(T\) such that \(x'_i - R + |I_m| > x(v)\), and thus \(v_c\) can be found by searching \(T\) in \(O(\log n)\) time.

Next, we find \(c_1\), and remove the leaves \(v_j\) with \(j \in [c_1 + 1, c]\) if \(c_1 < c\), as follows (note that if the above step finds \(c = 0\), then we skip this step).

Recall that for each \(j \in [1, c]\), \(\delta(C_{L_j}) = \max\{\delta(C_{L'_j}), d(i,C_{L_j})\}\), with \(\delta(C_{L'_j}) = \delta(v_j)\) and \(d(i,C_{L_j}) = x'_i(C_{L_j}) - x'_i = x(C_{L'_j}) - x'_i = x(v_j) + R - x'_i\). Hence, we have \(\delta(C_{L_j}) = \max\{\delta(v_j), x(v_j) + R - x'_i\}\).

Starting from \(v_c\), we first check whether \(\delta(C_{L_{c-1}}) > \delta(C_{L_c})\), by computing \(\delta(C_{L_{c-1}})\) and \(\delta(C_{L_c})\) as above. If yes, then \(c_1 = c\) and we stop. Otherwise, we remove \(v_c\) and
This procedure continues until either \( \delta(C_{L_{j-1}}) \geq \delta(C_{L_j}) \). If yes, then \( c_1 = j \); otherwise, we remove \( v_j \) and proceed on \( v_{j-1} \).

In addition, after \( v_{c_1} \) is found as above, we update \( \delta(v_{c_1}) = \max\{\delta(v_{c_1}), x(v_{c_1}) + R - x'_i\} \).

Next, consider the new list \( L^*_c \), which is \( L_{c+0.5}^* \). We have the following \( \delta(C_{L^*_c}) = \max\{\delta(C_{L_{c}^*}) \), \( d(m, C_{L^*_c})\} = \max\{\delta(C_{L_{c}^*}), x'_m(C_{L^*_c}) - x'_m\} \). Due to that \( \delta(C_{L^*_c}) = \delta(v_c) \) and \( x'_m(C_{L^*_c}) = x'_r \), we have \( \delta(C_{L^*_c}) = \max\{\delta(v_c), x'_r - x'_m\} \) (if the above has removed \( v_c \), then we temporarily keep the value \( \delta(v_c) \) before \( v_c \) is removed). Also, recall that \( x(C_{L^*_c}) = x'_r + |I_m| \). Therefore, we can compute both \( \delta(C_{L^*_c}) \) and \( x(C_{L^*_c}) \) in constant time. We insert a new leaf \( v_{c+0.5} \) to \( T \) corresponding to \( L^*_c \), with \( \delta(v_{c+0.5}) = \delta(C_{L^*_c}) \) and \( x(v_{c+0.5}) = x(C_{L^*_c}) - R - |I_i| \) (the minus \( |I_i| \) is due to that later we will increase \( R \) by \( |I_i| \)).

Next, we determine \( c_2 \), and remove the leaves \( v_j \) with \( j \in [c_2 + 1, a] \) if \( c_2 < a \), as follows. Recall that for each \( j \in [c + 1, a] \), \( \delta(C_{L_j}) = \max\{\delta(C_{L_j}), d(m, C_{L_j})\} \), with \( \delta(C_{L_j}) = \delta(v_j) \) and \( d(m, C_{L_j}) = x'_m(C_{L_j}) - x'_m = x(C_{L_j}) + |I_i| - x'_m = x(v_j) + R + |I_i| - x'_m \). Hence, we have \( \delta(C_{L_j}) = \max\{\delta(v_j), x(v_j) + R + |I_i| - x'_m\} \), which can be computed in constant time once we access the leaf \( v_j \).

Starting from the rightmost leaf \( v_n \), in general, suppose we are considering a leaf \( v_j \). If \( j = c + 0.5 \), then we stop with \( c_2 = c + 0.5 \). Otherwise, let \( v_h \) be the left neighboring leaf of \( v_j \) (so \( h \) is either \( j - 1 \) or \( j - 0.5 \)). We check whether \( \delta(C_{L_h}) > \delta(C_{L_j}) \) (the two values can be computed as above). If yes, we stop with \( c_2 = j \); otherwise, we remove \( v_j \) from \( T \) and proceed on considering \( v_h \).

If the above procedure returns \( c_2 \geq c + 1 \), then we further check whether \( x(C_{L^*_c}) = x(C_{L_{c+1}}) \). If yes, then we remove the leaf \( v_{c+0.5} \) from \( T \). If \( c_2 \geq c + 1 \), we also need to update \( \delta(v_{c_2}) = \max\{\delta(v_{c_2}), x(v_{c_2}) + R + |I_i| - x'_m\} \).

Finally, we determine \( c' \) and remove all leaves strictly between \( v_{c_1} \) and \( v_{c'} \), as follows. Recall that given any leaf \( v_j \) of \( T \), we can compute \( \delta(C_{L_j}) \) in constant time. Starting from the right neighboring leaf of \( v_{c_1} \), in general, suppose we are considering a leaf \( v_j \). If \( \delta(C_{L_{c_1}}) \leq \delta(C_{L_j}) \), then we remove \( v_j \) and proceed on the right neighboring leaf of \( v_j \). This procedure continues until either \( \delta(C_{L_{c_1}}) > \delta(C_{L_j}) \) or \( v_j \) is the rightmost leaf and
has been removed. 

In addition, we update \( R = R + |I_i| \). In light of Lemma 6.6.13 and by our way of setting the value \( x(v_{c+0.5}) \), this updates all \( x \)-values. Also, the above has “manually” set the values \( \delta(v_{c_1}), \delta(v_{c_2}), \) and \( \delta(v_{c+0.5}) \), by Lemma 6.6.13, all \( \delta \)-values have been updated. Finally, we update \( m, m', \) and \( p_b \) as follows.

In the general case where \( 1 \leq c < a \) and \( c' \neq c_2 + 1 \), we set \( m' = i \) and \( p_b \) to the leaf \( v_{c_1} \). If \( c' = c_2 + 1 \), then the last indices of all lists of \( \mathcal{L} \) are \( i \), and thus we set \( m = i \) and \( p_b = \text{null} \). If \( c = 0 \), then the last indices of all lists of \( \mathcal{L} \) are \( m \), then we do not need to update anything. If \( c = a \), then if \( L_c^* \notin \mathcal{L} \), then the last indices of all lists of \( \mathcal{L} \) are \( i \) and we set \( m = i \) and \( p_b = \text{null} \), and if \( L_c^* \in \mathcal{L} \), then we set \( m' = i \) and \( p_b \) to \( v_{c_1} \).

This finishes processing \( I_i \). The total time is again as claimed before.

The Case \( \mathcal{L}_1' \neq \emptyset \)

In this case, \( \mathcal{L}_1' = \{L_1', \ldots, L_b'\} \) and \( \mathcal{L}_2' = \{L_{b+1}', \ldots, L_a'\} \). The last indices of all lists of \( \mathcal{L}_1' \) (resp., \( \mathcal{L}_2' \)) are \( m' \) (resp., \( m \)). Note that the pointer \( p_b \) points to the leaf \( v_b \).

The first subcase \( x_i^r \geq x_{m'}^r \). In this case, the implementation is similar to the first subcase of Section 6.6.3, so we omit the details.

The second subcase \( x_{m'}^r \leq x_i^r < x_{m'}^r \). As our algorithm description in Section 6.6.2, we first apply the similar implementation as the first subcase of Section 6.6.3 on the leaves from \( v_1 \) to \( v_b \), and then apply the similar implementation as the second subcase of Section 6.6.3 on the leaves from \( v_{b+1} \) to \( v_a \). So the leaves of the current tree corresponding to the lists in \( S_1' \cup S_2', \) i.e., \( \{L_1, \ldots, L_{a_2}, L_{b+1}, \ldots, L_{c_1}, L_{c'}, \ldots, L_{c_2}\} \), as defined in the second subcase of Section 6.6.2.

Next, we determine \( b' \) and remove all leaves from \( T \) strictly between \( v_{a_2} \) and \( v_{b'} \). Starting from the right neighboring leaf of \( v_{a_2} \), in general, suppose we are considering a leaf \( v_j \). If \( \delta(C_{L_{a_2}}) \leq \delta(C_{L_j}) \) (as before, these two values can be computed in constant time once we have access to \( v_{a_2} \) and \( v_j \)), then we remove \( v_j \) and proceed on the right neighboring leaf of \( v_j \). This procedure continues until either \( \delta(C_{L_{a_2}}) > \delta(C_{L_j}) \) or \( v_j \) is the rightmost leaf and has been removed.

Finally, we update \( R = R + |I_i| \). To update \( p_b \), \( m \), and \( m' \), depending on the values \( c, c' \) and \( b' \), there are various cases. In the general case where \( b + 1 \leq c < a, c' \neq c_2 + 1 \),
and \( b' \neq c_2 + 1 \), we update \( p_b = v_{c_1} \) and \( m' = i \). We omit the discussions for other special cases.

The third subcase \( x'^*_i < x'^*_{m'} \). In this case, starting from \( v_b \), we first remove all leaves from \( v_{c_1 + 1} \) to \( v_b \). The algorithm is very similar as before and we omit the details. Then, starting from \( v_{a'} \), we remove all leaves from \( v_{e_2 + 1} \) to \( v_{a} \). Finally, starting from \( v_{e_1} \), we remove all leaves strictly between \( v_{e_1} \) to \( v_{b'} \). In addition, we update \( R = R + |I_i| \).

In the general case where \( b' \neq e_2 + 1 \), we set \( p_b \) pointing to leaf \( v_{e_1} \); otherwise, we set \( m = m' \) and \( p_b = \text{null} \).

This finishes processing \( I_i \) for all five subcases. The algorithm finishes once \( I_n \) is processed, after which \( \delta_{opt} = \delta(v) \), where \( v \) is the rightmost leaf of \( T \) (as \( \delta(v) \) is the smallest among all leaves of \( T \)). Again, the total time of the algorithm is \( O(n \log n) \). Clearly, the space used by our algorithm is \( O(n) \).

### 6.6.4 Computing an Optimal List

As discussed above, after \( I_n \) is processed, the list (denoted by \( L_{opt} \)) corresponding to the rightmost leaf (denoted by \( v_{opt} \)) of \( T \) is an optimal list, and \( \delta_{opt} = \delta(v_{opt}) \). However, since our algorithm does not maintain the list \( L_{opt} \) explicitly, \( L_{opt} \) is not available after the algorithm finishes. In this section, we give a way (without changing the complexity asymptotically) to maintain more information during the algorithm such that after it finishes, we can reconstruct \( L_{opt} \) in additional \( O(n) \) time.

We first discuss some intuition. Consider a list \( L \in \mathcal{L} \) before interval \( I_i \) is processed. During processing \( I_i \) for \( L \), observe that the position of \( i \) in the updated list \( L \) is uniquely determined by the input position of the last interval \( I_m \) of \( L \) (i.e., depending on whether \( x'^*_i \geq x'^*_m \)). However, uncertainty happens when \( L \) generates another “new” list \( L^* \). More specifically, suppose \( L \) is a canonical list of \( \mathcal{I}[1, i-1] \). If there is no new list \( L^* \), then by our observations (i.e., Lemmas 6.4.2 and 6.4.4), the updated \( L \) is a canonical list of \( \mathcal{I}[1, i] \). Otherwise, we know (by Lemma 6.4.6) that one of \( L \) and \( L^* \) is a canonical list of \( \mathcal{I}[1, i] \), but we do not know exactly which one is. This is where the uncertainty happens and indeed this is why we need to keep both \( L \) and \( L^* \) (thanks to Lemma 6.4.7, we only need to keep one such new list). Therefore, in order to reconstruct \( L_{opt} \), if processing \( I_i \) generates a new list \( L^* \) in \( \mathcal{L} \), then we need to keep the relevant information about \( L^* \).
The details are given below.

Specifically, we maintain an additional binary tree $T'$ (not a search tree). As in $T$, the leaves of $T'$ from left to right correspond to the ordered lists of $L$. Consider a leaf $v$ of $T'$ that corresponds to a list $L \in L$. Suppose after processing $I_i$, $L$ generates a new list $L^*$ in $L$. Let $m$ be the last index of the original $L$ (before $I_i$ is processed). According to our algorithm, we know that the last two indices of the updated $L$ are $m$ and $i$ with $i$ as the last index and the last two indices of $L^*$ are $i$ and $m$ with $m$ as the last index. Correspondingly, we update the tree $T'$ as follows. First, we store $i$ at $v$, e.g., by setting $A(v) = i$, which means that there are two choices for processing $I_i$. Second, we create two children $v_1$ and $v_2$ for $v$ and they correspond to the lists $L$ and $L^*$, respectively. Thus, $v$ now becomes an internal node. Third, on the new edge $(v, v_1)$, we store an ordered pair $(m, i)$, meaning that $m$ is before $i$ in $L$; similarly, on the edge $(v, v_2)$, we store the pair $(i, m)$. In this way, each internal node of $T'$ stores an interval index and each edge of $T'$ stores an ordered pair.

After the algorithm finishes, we reconstruct the list $L_{opt}$ in the following way. Let $\pi$ be the path from the root to the rightmost leaf $v_{opt}$ of $T'$. We will construct $L_{opt}$ by considering all intervals from $I_1$ to $I_n$ and simultaneously considering the nodes in $\pi$. Initially, let $L_{opt} = \{1\}$. Then, we consider $I_2$ and the first node of $\pi$ (i.e., the root of $T'$). In general, suppose we are considering $I_i$ and a node $v$ of $\pi$. We first assume that $v$ is an internal node (i.e., $v \neq v_{opt}$).

If $i < A(v)$, then only Case I or Case II of our preliminary algorithm happens, and we insert $i$ into $L_{opt}$ based on whether $x^r_i \geq x^r_m$ (specifically, if $x^r_i \geq x^r_m$, then we append $i$ at the end of $L_{opt}$; otherwise, we insert $i$ right before the last index of $L_{opt}$) and then proceed on $I_{i+1}$.

If $i \geq A(v)$ (in fact, $i$ must be equal to $A(v)$), then we insert $i$ into $L_{opt}$ based on the ordered pair of the next edge of $v$ in $\pi$ (specifically, if $i$ is at the second position of the pair, then $i$ is appended at the end of $L_{opt}$; otherwise, $i$ is inserted right before the last index of $L_{opt}$) and then proceed on the next node of $\pi$ and $I_{i+1}$.

If $v = v_{opt}$, then we insert $i$ into $L_{opt}$ based on whether $x^r_i \geq x^r_m$ as above, and then proceed on $I_{i+1}$. The algorithm finishes once $I_n$ is processed, after which $L_{opt}$ is constructed. It is easy to see that the algorithm runs in $O(n)$ time and $O(n)$ space.
Once $L_{opt}$ is computed, we can apply the left-possible placement strategy to compute an optimal configuration in additional $O(n)$ time.

Theorem 6.6.20. Given a set of $n$ intervals on a line, the interval separation problem is solvable in $O(n \log n)$ time and $O(n)$ space.

6.7 The Lower Bound

By a linear-time reduction from the integer element distinctness problem [72,73], we can obtain an $\Omega(n \log n)$ time lower bound for the problem under the algebraic decision tree model, which implies the optimality of our algorithm.

Given a set of $n$ integers $A = \{a_1, a_2, \ldots, a_n\}$, the element distinctness problem is to ask whether there are two elements of $A$ that are equal. The problem has an $\Omega(n \log n)$ time lower bound under the algebraic decision tree model [72,73]. We create a set $\mathcal{I}$ of $n$ intervals as an instance of our interval separation problem as follows. For each $a_i \in A$, we create an interval $I_i$ centered at $a_i$ with length 0.1. Let $\mathcal{I}$ be the set of all intervals.

Since all elements of $A$ are integers, it is easy to see that no two elements of $A$ are equal if and only if no two intervals of $\mathcal{I}$ intersect. On the other hand, no two intervals of $\mathcal{I}$ intersect if and only if the optimal value $\delta_{opt}$ in our interval separation problem on $\mathcal{I}$ is equal to zero. This completes the reduction. This reduction actually shows that even if all intervals have the same length, the interval separation problem still has an $\Omega(n \log n)$ time lower bound.
CHAPTER 7

Future Work

We discuss some future work that are natural extensions of the problems we studied before.

1. The Cycle Version of Multiple Barrier Coverage Problem

   In Chapter 5, we solved the line version of multiple barrier coverage problem. One natural extension is the cycle version of this problem. In the cycle version, there is a cycle $C$ and each barrier becomes an arc on $C$. Each sensor is still a point on $C$ but now can cover an arc of $C$ centered at the sensor. In addition, in the cycle version, the distance of any two points on $C$ is defined as the length of the shortest path between the two points on $C$.

   If there is only one barrier, i.e., $m = 1$, the problem has already been studied and a linear time algorithm is known [33] after the sensors are sorted on $C$. For the general value $m$, however, the problem has not been considered before. We propose to study this problem and try to extend our algorithm for the line version in Chapter 5.

2. The Min-Sum Version of the Multiple Barrier Coverage Problem

   In Chapter 5, we studied the min-max version of multiple barrier coverage problem. A closely related problem is the min-sum version, defined as follows. Given $m$ barriers and $n$ sensors on a line $L$, the goal is to move sensors so that the union of the covering intervals of all sensors covers all barriers and the total sum of the movements of all sensors is minimized.

   If $m = 1$, i.e., there is only one barrier, the problem has been studied before and the previously best algorithm runs in $O(n \log n)$ time [63]. To our best knowledge, the general case has not been considered before. We plan to study this problem. One possible direction is to see whether the algorithm in [63] can somehow be extended.
It may also be interesting to consider the cycle version of the problem.

3. Separating Overlapped Intervals on a Cycle

We solve the separating overlapped intervals problem on a line in Chapter 6. It might also be interesting to consider the cycle version of the problem. Let $\mathcal{I}$ be a set of $n$ intervals on a closed cycle $C$. We say that two intervals overlap if their intersection contains more than one point. The problem is to move the intervals of $\mathcal{I}$ along the cycle $C$ such that no two intervals overlap and the maximum moving distance of these intervals is minimized.

If all intervals of $\mathcal{I}$ have the same length, then the problem is essentially the same as the problem of spreading points on a cycle that we studied in Chapter 3, and thus, by using our algorithm in Chapter 3, after the left endpoints of the intervals are sorted, the problem can be solved in $O(n)$ time. For the general problem where intervals may have different lengths, to the best of our knowledge, the problem has not been studied before.
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