Effects of Discussion Strategies and Learner Interactions on Performance in Online Mathematics Courses: An Application of Learning Analytics

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Introduction
Problem Statement & Possible Solution

Problem

• High failure rates in college math courses; higher in online math courses

What we know

• In mathematics learning contexts, a few studies found that the use of online discussions helped in
  - decreasing math anxiety
  - increasing achievement outcomes
• Learners performed better in “effectively designed and structured online discussions”

Challenges in Practice & Research

• Instructors seldom design/implement structured online discussions
• Prior studies tended to focus on students’ discussion behaviors rather than instructor involvement
• Little research in mathematics learning contexts
Question: What discussion design works best in online math courses?
Research Purposes

For online introductory mathematics courses:

01 Exploring instructors’ use of discussion strategies that enhance meaningful learner interactions and performance

02 Investigating learner behaviors and interaction patterns that lead to better performance
**RESEARCH QUESTIONS**

**Presage**
- **Student Characteristics**
- **Teaching Context** (Instructors’ use of discussion strategies)
  - Discussion Design
    - Grouping
    - Types of prompts
    - Types of setting
  - Monitoring & Facilitation
    - Instructor participation
    - Types of Feedback
  - Assessment
    - Use of grades

**Process**
- Students’ Approaches to Learning (Learner Interactions)
  - Participatory behaviors
    - Online speaking behaviors
    - Online listening behaviors (Wise et al., 2014)
- Quality of Students’ Interactions
  - Knowledge construction
  - Social interaction
  - Self-Regulated processes (Ke & Xie, 2009)

**Product**
- Performance (Final grades)

RQ1 [Course-level analysis] What design strategies for online discussions are associated with positive student performance?

RQ2 [Course-level analysis] How do different design strategies in online discussions impact the kinds of learner interactions?

RQ3 [Student-level analysis] What types of learner interactions are associated with positive student performance?

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*Adopted from Biggs’s 3P (Presage-Process-Product) model of teaching and learning*
### Canvas Learning Management System (LMS)

Canvas Learning Management System (LMS) used at a public university located in the western U.S.

- **Fully online introductory (0 and 1000 levels) math/statistics courses** offered between 2011 fall and 2015 summer
- **Courses that used online discussions**

### Methods

#### Research Context & Sample

<table>
<thead>
<tr>
<th>Courses</th>
<th># of courses</th>
<th>N = 72</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># of instructors</td>
<td>N = 11</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Students</th>
<th># of students</th>
<th>N = 2,869</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unique #</td>
<td>N = 2,404</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Activities (Discussion topics)</th>
<th>(N = 703)</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Events/Actions (Discussion messages)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instructors: 1,284 messages</td>
</tr>
<tr>
<td>Students: 20,884 messages</td>
</tr>
</tbody>
</table>
METHODS
Workflow & Data Analysis Methods

Knowledge Discovery in Databases (KDD) Process

Selection → Pre-processing (Data cleaning) → Transformation → Data mining → Interpretation/Evaluation

Canvas LMS

Clickstream data → Text Mining → Instructors’ Use of Discussion Strategies

Registration system Data → Text Mining → Learner Interactions

Textual data → Text Mining → Course Performance

RQ1: Classification and Regression Tree

RQ2: Kruskal-Wallis H Test

RQ3: Hierarchical Linear Modeling
### METHODS

**Measurement**

#### Instructor’ Use of Discussion Strategies

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Variables</th>
<th>Data sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discussion design</td>
<td>Grouping</td>
<td>Log Data</td>
</tr>
<tr>
<td></td>
<td>Types of setting</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Types of Discussion prompts</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Monitoring</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Types of Feedback (Kleij et al., 2015)</td>
<td></td>
</tr>
<tr>
<td>Monitoring &amp; Facilitation</td>
<td>Use of grades</td>
<td>Textual Data</td>
</tr>
<tr>
<td>Assessment</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
METHODS

Data Pre-processing (Text mining)

1. Hand-coded 10% of messages
   • IRR: .908 ($p = .00$)

2. Imported the training into LightSIDE
   • Unigrams + Bigrams + Trigrams

3. Four built-in algorithms
   : Naïve Bayes classifier, Logistic regression, Support Vector Machines (SVM), Decision trees

4. 10-fold cross-validation
   • Confusion matrix
   • Accuracy, Kappa values

5. Hand-coded 50% of messages

6. Applied the developed model to the rest of the dataset (50% of the discussion messages)
PRELIMINARY RESULTS

Semi-automated Content Analysis

<table>
<thead>
<tr>
<th>Prediction Models</th>
<th>Initial (hand-coding: 10% of discussion messages)</th>
<th>Final (hand-coding: 50% of discussion messages)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve Bayes</td>
<td>0.58, 0.29</td>
<td>0.66, 0.49</td>
</tr>
<tr>
<td>Logistic regression</td>
<td>0.63, 0.33</td>
<td>0.75, 0.60</td>
</tr>
<tr>
<td>SVM</td>
<td>0.61, 0.37</td>
<td>0.73, 0.57</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.48, 0.16</td>
<td>0.56, 0.30</td>
</tr>
</tbody>
</table>

**Prediction accuracy**

- Naïve Bayes: 0.58, 0.66
- Logistic Regression: 0.63, 0.75
- SVM: 0.61, 0.73
- Decision Tree: 0.48, 0.56

**Cohen’s kappa (κ)**

- Naïve Bayes: 0.29, 0.49
- Logistic Regression: 0.33, 0.60
- SVM: 0.37, 0.57
- Decision Tree: 0.16, 0.30
PRELIMINARY RESULTS

Correlation analysis

- “Instructors’ posts” showed the strongest positive correlation with the students’ average final grades ($r = .72$, $p < .05$).

- The ratio of “open-ended prompts” ($r = .69$, $p < .05$) and the ratio of “elaborated feedback” ($r = .57$, $p < .05$) showed the significant and positive correlations with the average final grades.

- The ratio of “other prompts” ($r = -.69$, $p < .05$) and the ratio of “operational feedback” ($r = -.58$, $p < .05$) showed the significant and negative correlations with the average final grades.

*Included continuous variables only*
PRELIMINARY RESULTS

RQ1: Classification and Regression Tree (CART)

*N = Number of Courses

Avg. final grade = 2.02

n = 72 (100%)

Open-ended prompts < 69.0%

n = 31 (43.1%)
Avg. final grade = 2.64

Open-ended prompts ≥ 69.0%

n = 41 (56.9%)
Avg. final grade = 1.55

Threaded discussions only

n = 25 (34.7%)
Avg. final grade = 1.48

Elaborated Feedback < 16.8%

n = 18 (25.0%)
Avg. final grade = 1.40

Elaborated Feedback ≥ 16.8%

n = 7 (9.7%)
Avg. final grade = 1.68

Side Comments, or Mixed settings

n = 16 (22.2%)
Avg. final grade = 1.66

Grading = No or Partially

n = 13 (18.1%)
Avg. final grade = 2.28

Grading = Yes

n = 18 (25.0%)
Avg. final grade = 2.89
Lessons Learned & Future Work

• Text mining (semi-automated analysis)
  - Importance of the amount of hand-coding
  - Logistic regression outperformed other algorithms
  - Use of unigram, bigrams, trigrams altogether

• Use of open-ended discussion prompts and grading students’ messages will lead to better student performance in online mathematics courses.

Future Work

• Validation of the CART analysis results
• RQ2: Statistical Analyses (Kruskal-Wallis H Test)
• RQ3: Hierarchical Linear Modeling (HLM)
  - Interpretation and evaluation of the results
Thank you

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