Supervised Categorization of Open Response Feedback in Higher Education

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1. SUMMARY
Efficient use of student feedback is mandatory for the continuous development of curricula and teaching skills. Student feedback can be collected in various ways such as using Likert scale questions or open responses to particular questions. While Likert-type data is rather easy to process using standard analytic tools, open response feedback is more challenging. However, studies suggest that open response items written in natural language provide qualitative and situated insights for practical course development. In large-scale courses, processing open responses through human labour becomes unfeasible in volume, too complex by content and might lead to serious bias. In an age of quality assurance, tenure track systems and large-scale courses on digital platforms, teachers need new tools to process natural language data collected on their courses. In this paper, we study the application of machine learning methods for classifying open response student feedback data in a higher education institution (HEI) context to support course development based on summative course feedback. We develop a model for data processing and apply it in Microsoft Azure Machine Learning Studio (AMLS). For model validation, we use human-processed training data consisting of 1580 feedback items. We end up suggesting semi-structured formulation for collecting open response items as a part of summative course feedback, based on our findings and related literature.

2. INTRODUCTION
Course development hinges to a large extend on the efficient use of student feedback (Hemminki, Leppänen, & Valovirta, 2013). Based on the EUA Trends 2018 report, 98% of higher education institutions report using student feedback to assess teaching. Typically this is summative feedback that is collected after a course. Most frequently these questionnaires consist of statistically valid Likert scale questions and open response items (Denson, Loveday, & Dalton, 2010). While Likert data helps in focusing program level development, free text items provide insights into what students perceive as most important (Stupans, McGuren, & Babey, 2016).

In this paper, we apply machine learning tools to automatically process and organize open response student feedback. The paper focuses on data processing phases that are applied to data after course feedback has been collected. Our aim is not to analyse the learning behavior of students. Rather, this paper develops a method for categorizing the student feedback in order to simplify the evaluation of the feedback by the course staff (see Section 4).

The aim of this paper is to develop a method for categorizing the student feedback in order to simplify the evaluation of the feedback by the course staff (see Section 4). For the clarity, our aim is not to analyse the learning behavior of students, the knowledge students possess, or the students’ peerceptions on learning.

The paper makes the following contributions:
• We propose a novel model for categorizing (classifying) student feedback data.
• We apply this model to a natural language dataset collected on a large-scale course.
• We suggest practical guidelines for applying this model in HEI context.

3. MACHINE LEARNING MODEL

The feedback classifier has been implemented using AMLS, which is Platform-as-a-Service-type machine learning tool that provides capabilities for building and operationalizing machine learning models. In particular, AMLS offers ready-made modules for text data, which can be used to preprocess and featurize text into numerical vectors in order to feed the data into machine learning models. From many available models we selected the support vector machine (SVM) that has been extensively and successfully used in text classification tasks (Pawar & Gawande, 2012).

SVMs are suitable for text classification due to their ability to generalize well in high dimensional feature spaces, thus eliminating the need for feature selection (Joachims, 1998). As a linear classification model, the SVM offers interpretability of the learned model (Chang & Lin 2008).

The course feedback data was extracted from the learning management system Moodle. In Figure 1 we go through the process of handling this course feedback dataset. This process starts with data preparation (phases 1–3), continues with model creation validation (4–5), after which the model was deployed.

![Figure 1 Data processing model used in Azure Machine Learning Studio](image_url)

4. RESULTS AND CONCLUSIONS

The proposed student feedback classifier was evaluated by using accuracy, precision and recall metrics (Table 1). Results were encouraging for all tested categories.

<table>
<thead>
<tr>
<th>Feedback category</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive: Lectures</td>
<td>93%</td>
<td>92%</td>
<td>78%</td>
</tr>
<tr>
<td>Positive: Assignment</td>
<td>92%</td>
<td>81%</td>
<td>73%</td>
</tr>
<tr>
<td>Positive: Project</td>
<td>95%</td>
<td>91%</td>
<td>85%</td>
</tr>
<tr>
<td>Positive: Content</td>
<td>84%</td>
<td>75%</td>
<td>69%</td>
</tr>
<tr>
<td>Positive: Staff</td>
<td>95%</td>
<td>70%</td>
<td>70%</td>
</tr>
<tr>
<td>Negative: Assignment</td>
<td>83%</td>
<td>72%</td>
<td>60%</td>
</tr>
<tr>
<td>Negative: Peer Grading</td>
<td>95%</td>
<td>82%</td>
<td>64%</td>
</tr>
<tr>
<td>Negative: Lectures</td>
<td>97%</td>
<td>79%</td>
<td>92%</td>
</tr>
</tbody>
</table>
Based on our experience, machine learning can be used to categorize textual course feedback especially if the text documents are relatively short and there is enough training data available. Pre-processing of the text is mandatory and greatly improves the accuracy of the model. Some feedback categories, such as lecture, project and assignment contain specific keywords and are thus easier to categorize, while some categories such as content and grading are more difficult as they do not contain similar keywords.

Our findings contribute to develop new teacher tools for assessing open response data through categorization. The model we used provides possibilities for, e.g. most representative feedback items per category and quantity of items per category.

5. REFERENCES


6. AUTHORS’ BIOGRAPHIES

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