Supervised Categorization of Open Response Feedback in Higher Education

Ville Kivimäki[1], Thomas Bergström[2], Jiri Lallimo[3], Alexander Jung[4]

[1]IT Services, Aalto University, P.O. Box 14100, FI-00076 Aalto, Finland, ville.kivimaki@aalto.fi
[2]IT Services, Aalto University, P.O. Box 11100, FI-00076 Aalto, Finland, thomas.bergstrom@aalto.fi
[3]Learning Services, Aalto University, P.O. Box 11100, FI-00076 Aalto, Finland, jiri.lallimo@aalto.fi
[4]Department of Computer Science, Aalto University, P.O Box 15400, FI-00076 Aalto, Finland, alex.jung@aalto.fi

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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 deimensional 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.

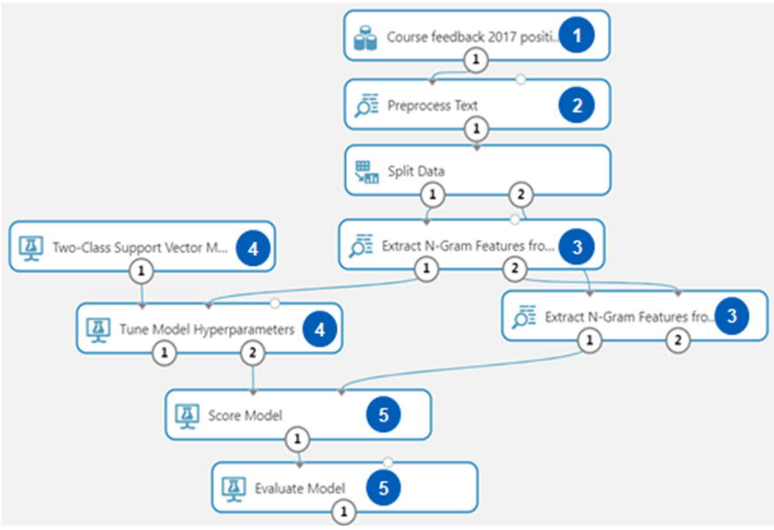

Figure 1 Data processing model used in Azure Machine Learning Studio

4. RESULTS AND CONCLUSIONS

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

Table 1: Model accuracy, precision and recall for the different feedback categories

Feedback category	Accuracy	Precision	Recall
Positive: Lectures	93%	92%	78%
Positive: Assignment	92%	81%	73%
Positive: Project	95%	91%	85%
Positive: Content	84%	75%	69%
Positive: Staff	95%	70%	70%
Negative: Assignment	83%	72%	60%
Negative: Peer Grading	95%	82%	64%
Negative: Lectures	97%	79%	92%

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

Chang, Y.-W., & Lin, C.-J. (2008). Feature ranking using linear SVM. In Causation and Prediction Challenge (pp.53–64). Retrieved from http://www.jmlr.org/proceedings/papers/v3_old/chang08a/chang08a.pdf

Denson, N., Loveday, T., & Dalton, H. (2010). Student evaluation of courses: what predicts satisfaction? *Higher Education Research & Development*, *29*(4), 339–356. https://doi.org/10.1080/07294360903394466

Hemminki, M., Leppänen, M., & Valovirta, T. (2013). *Get inspired! A guide for successful teaching* (Vol. 16). Aalto University. Retrieved from https://aaltodoc.aalto.fi/bitstream/handle/123456789/11990/isbn9789526054865.pdf

Joachims, T. (1998). Text categorization with Support Vector Machines: Learning with many relevant features. In C. Nédellec & C. Rouveirol (Eds.), *Machine Learning: ECML-98* (Vol. 1398, pp. 137–142). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/BFb0026683

Pawar, P. Y., & Gawande, S. H. (2012). A Comparative Study on Different Types of Approaches to Text Categorization. *International Journal of Machine Learning and Computing*, 423–426. https://doi.org/10.7763/IJMLC.2012.V2.158

Stupans, I., McGuren, T., & Babey, A. M. (2016). Student Evaluation of Teaching: A Study Exploring Student Rating Instrument Free-form Text Comments. *Innovative Higher Education*, *41*(1), 33–42. https://doi.org/10.1007/s10755-015-9328-5

6. AUTHORS' BIOGRAPHIES

Ville A. Kivimäki is a project manager at the Aalto University School of Engineering in Finland. He graduated as Master of Arts from the University of Tampere in 2007. He has later deepened his academic background through university pedagogical studies and programming and he is currently working towards his Ph.D. He is currently teaching a personal development course in Aalto University and working as an educator at the University of Tampere in service design and productisation. He has organised workshops on student success, service design, personal development and learning analytics. He currently serves as a project manager for two projects (Dynamic Course and Programme Level Feedback System, T4: Teach, Thousand, Track, Target) aiming to enhance student-teacher relation and to advance students' academic achievements. LinkedIN: www.linkedin.com/in/ville-kivimaki

Thomas A. Bergström is an IT solution architect at the Aalto University IT department in Finland. He graduated as Master of Science (Tech.) from Helsinki University of Technology in 2008. He has worked in IT industry both within software development and in management consultation since 2005. Thomas is responsible for Solution consultation service in Aalto IT and helps clients turn their needs into solutions. Thomas is involved in various machine learning activities in Aalto and coordinates some machine learning projects in Aalto IT. LinkedIN: linkedin.com/in/thomas-bergström-52644826

Jiri A. Lallimo works as a project manager at the Aalto University for the project AnalytiikkaÄly (~AnalyticsAI). He graduated as MA (education) In University of Helsinki, Finland in 2001. His forthcoming doctoral dissertation is titled 'Distributed expertise and learning in multiprofessional work'. He has worked as a researcher at the Center of Networked Learning and Knowledge Building,at the Center of Research on Activity, Development and Learning, University of Helsinki, Finland and as a senior researcher focusing on digital learning at University of Turku, Department of Teacher Education. His research has focused on learning in education settings and professional networks by combining psychology of learning, theories of collective expertise and sociomaterial view of the learning tools. The current research focuses on development and use of learning analytics in higher education. LInkedIN: https://www.linkedin.com/in/jiri-lallimo-7a3739/

Alexander Jung is Assistant Professor at the department of Computer Science of Aalto University. He obtained the Master of Science (Tech.) and Phd in Electrical Engineering and Computer Science from TU Vienna in 2008 and 2012, respectively. After a Post-Doc stay at ETH Zurich and TU Vienna, he joined Aalto in 2015 where he is leading the group "Machine Learning for Big Data". His research revolves around fundamental limits and efficient algorithms for large-scale data analysis (big data). He is teaching the main courses on machine learning and artificial intelligence at Aalto university and has been elected as Teacher of the Year 2018 at the computer science department.