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Extracting Implicit Suggestions from Students' Comments – A Text Analytics Approach

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Abstract: At the end of each course, students are required to give feedback on the course and instructor. This feedback includes quantitative rating using Likert scale and qualitative feedback as comments. Such qualitative feedback can provide valuable insights in helping the instructor enhance the course content and teaching delivery. However, the main challenge in analysing the qualitative feedback is the perceived increase in time and effort needed to manually process the textual comments. In this paper, we provide an automated solution for analysing comments, specifically extracting implicit suggestions from the students' qualitative feedback comments. The implemented solution leverages existing text mining and data visualization techniques and comprises three stages namely data pre-processing, implicit suggestions extraction and visualization. We evaluated our solution using student feedback comments from seven undergraduate core courses taught at the School of Information Systems, Singapore Management University. The experiments show that the proposed solution generated suggestions from the comments with the F-Score of 78.1%.

Keywords: student feedback, teaching evaluation, implicit suggestions, text analytics, text mining, classification techniques

1. Introduction

Student feedback on course and instructor provide a wealth of information about students' experiences in the course (Lizzio et al., 2002). Student evaluation systems help to counter anecdotal information about teaching behaviours and effectiveness. The evaluation systems provide a channel to systematically assess teaching and provide useful information about the effectiveness of teaching methods, instructor presentation, assignments, etc. (Moore & Kuol, 2005). This valuable feedback helps the instructor in improving the teaching and learning process (Murray, 1997; Elaine & Iain, 2005;Hounsell, 2003).

Education institutions conduct, analyse and disseminate the results of course evaluations either online, on paper, or through a combination of both methods. The student evaluation systems collect two types of evaluations; quantitative and qualitative. At the end of the course, the instructors will receive the evaluation reports for analysing their course delivery.

The quantitative evaluations are analysed, summarized and a table with statistics along with comparisons across the courses and faculty is generated for the instructors' perusal. The qualitative evaluation report comprises the students' feedback presented as a list of comments. The main challenge in analysing the qualitative feedback is the perceived increase in time and effort needed to assess written comments. For example, a single course, depending on the class size, can contain student comments that can range anywhere from 50 to 1000 sentences. Therefore, due to pragmatics, qualitative feedback from students is primarily conducted, evaluated and used for formative, rather than summative, purposes (Franklin, 2001; Lewis, 2001). Few research works explored how evaluations are used by several groups in the education such as instructors and administrators (Beran & Violato, 2007; Beran et al., 2005). The studies indicate that these groups rarely review written comments, and prefer use only what they perceive to be the more time-efficient, the quantitative ratings.

However, research undertaken by Harper and Kuh (2007) reveals that qualitative teaching evaluations can often bring to light issues that cannot emerge through conventional quantitative means. Beran et al. (2005) suggested that students, instructors and administrators ought to be offered training about the value of written comments and on techniques for, respectively, writing and analysing these comments effectively. However, manually analysing qualitative feedback of large data is painstaking and tiring process due the high volumes of data. Therefore, there is a need for automated tools to analyse the qualitative comments and extract useful information from the comments and present insights in a user friendly format.

In general, the students' comments can be categorized into three types; Objective comments, Opinions and Suggestions.

Objective comments: An objective comment is a sentence which is completely unbiased. It is generally a fact about entities or events and their properties. For example "The programming fundamentals are taught in the first three weeks of the course" is an objective comment (Liu, 2010).

Opinions: Unlike factual information, opinions are subjective expressions that describe people's sentiments and feelings towards entities or events (Beran et al., 2005). For example, "sometimes the instructor talks too fast for us to grasp the concept" is a sentiment towards the instructors' presentation skills. A polarity can be assigned to the opinions. A single opinion from a single opinion holder is usually not sufficient for action. In most instances, one needs to analyse opinions from a large number of people,

- A *positive opinion* is usually a positive sentiment or feeling or likes of an opinion holder. For example, "the instructor is very knowledgeable, patient and easy-going".

- A *negative opinion* is usually a negative sentiment or feeling or dislikes of an opinion holder. Negative opinions without context do not provide the details on the humans' dislikes. For example, "I don't like this course" is a negative comment and the aspects of what he or she dislikes is unclear. Negative opinions with context are more useful. For example, "The project in this course is very heavy", is a negative comment about the aspect, "project".

Suggestions: Suggestions are comments that can be used for the product or service improvements (Ramanand et al, 2010; Brun & Hagege, 2013; Jhamtani, 2015). A suggestive comment in product reviews by a customers, aims to provide a suggestive intent for possible improvement of the product or service aspect. Figure 1 shows types of suggestions along with examples.

- *Implicit suggestions*: Implicit suggestions are expressed as wishes or improvements.

- *Explicit suggestions*: These are similar to the negative opinions. User likes and dislikes are taken into account to make recommendations. In the given example, "Sometimes he went through the concepts a bit too fast for us to grasp", is a negative comments and one of the possible recommendation is that, "the instructor must slow his pace".

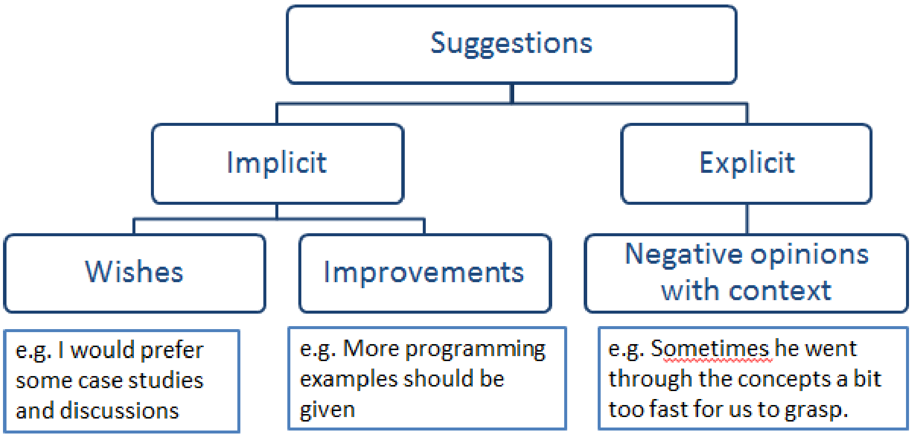

Figure 1. Types of suggestions from students' comments

In this paper we focus on extracting implicit suggestions from the students' qualitative feedback using text mining approaches. There are several benefits of suggestions extraction task.

Firstly, suggestions are useful to improve the teaching and learning process in the course. For example, the suggestion such as "more programming examples should be given" is useful for enhancing the learning process of the students in the programming course. Secondly, when combined with the quantitative feedback, the suggestions help the instructor to prioritize and target the required changes that need to be applied to the course. Usually, the instructor uses the quantitative feedback on questions related to course and accordingly amends the course for improvements. In addition to quantitative feedback, the instructor can use suggestions which most students talk about and amend the course with more informed evidences on the specific components of the course. For example, if students provided a low score to "course labs, project and assignment" and then added suggestions in the comment sections, the instructor can use the suggestions on the labs, project and assignments to focus on the main issue and make relevant amendments. Therefore, the instructor can analyse where the main concern lies, whether it is in labs or projects or assignments, and amend the course accordingly. Thirdly, suggestions are useful to help improve the instructor's performance. We observe that the junior students take senior students' advices in course bidding and selection. Hence, it is important for the instructor to improve his or her teaching and the course content. Through the course evaluation systems, the instructor has the opportunity to discover the gaps in the teaching delivery and course content. Applied in the effective manner, the instructor's overall performance can be improved. Lastly, the management, dean or associated dean, can use the suggestions, to make decisions on the providing the necessary training or support to the instructor, for improving teaching delivery and course content.

One of the main challenges with implicit suggestions extraction task is the textual nature of comments which are expressed in natural language. We explain the challenges in detail in Section 2. Furthermore, the suggestions are embedded within the text. Opinion mining, topic extraction and NLP techniques (Liu, 2010;Sarawagi, 2008) from the text mining and linguistics research are widely popular for mining users' comments in social media. Sentiment mining techniques are widely used for product review mining in consumer business world (Liu, 2010; Hu, 2004). We leverage these techniques for building the solution for implicit suggestion extraction task. Our solution applies data mining and text mining techniques on qualitative comments to extract suggestions from students' comments.

Our work is novel in a way it focuses on implicit suggestions extraction from students' comments. To the best of our knowledge there is no previous work that focuses on suggestions from students, using student qualitative feedback comments. We evaluated our solution using student feedback provided by the students for undergraduate core courses taught at the School of Information Systems, Singapore Management University collected over two semesters on seven different courses. Our experiments show that statistical classifier, decision tree C5.0 performs better than SVM with an overall F-Score of around 78.1% in extracting implicit suggestions task.

The paper will be structured as follows. Section 2 describes the implicit suggestion extraction task. Section 3 will be devoted to literature review on opinion mining research, suggestion extraction studies and student teaching evaluations research. Section 4 describes our implicit suggestion extraction solution overview and its details. In section 5, we focus on dataset, experiments, results and discussions. We conclude in Section 6 pointing some interesting future directions of our work.

2. Implicit Suggestion Extraction Task Definition

In this section, we explain the Implicit Suggestion Extraction task in detail. The input to the task is the list of student comments. Figure 2 shows sample inputs and outputs to our task.

Usually, the comments are short in nature but they may contain opinions as well as suggestions. For example, the first comment in Figure 2, contains an opinion as well as an implicit suggestion. "The course is good" is an opinion and "I do however feel that labs should be done in class to replace ICE" is an implicit suggestion. Also note that the fourth comment is a negative opinion with context and can be referred to as an explicit suggestion. In our work, we focus only on extracting the implicit suggestions from the students' comments. The aim of the extraction task is to extract the sentences that are suggestions and provide the visuals to the faculty for deeper analysis.

The main challenges in the task include data challenges, suggestion identification and visuals dashboard generation.

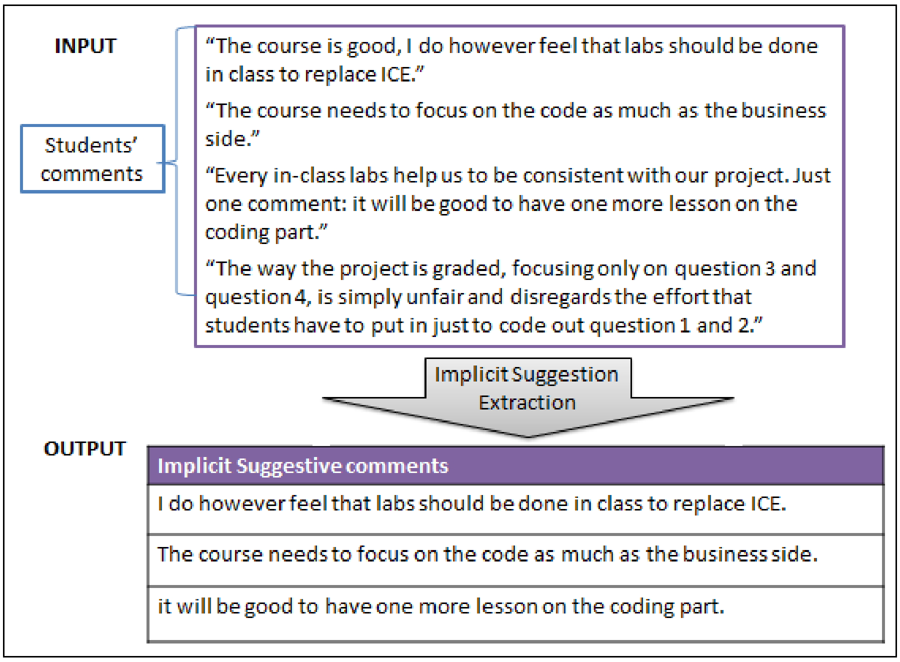

Figure 2. Sample inputs and outputs to implicit suggestion extraction task

In the next section, we provide some relevant literature review that provides the necessary background for our solution approach.

3. Literature Review

In this section, we provide some background on suggestion extraction and text mining algorithms. We rely on this background and leverage on some existing text mining techniques for designing our solution approach.

3.1 Opinion Mining

Opinion mining involves extracting sentiments and feeling from various sources like social media and online forum. Summarizing opinions helps government and businesses to adjust their governance policy and business strategy (Hu, 2004). Opinion mining has many real-life applications and several application-oriented research studies have been published (Liu, 2010;Sarawagi, 2008;Hu 2004). Opinion mining architecture takes users' comments as inputs to generate sentiment analysis visualizations as outputs that can aid the decision makers in decision making process. Analysing student feedback focusses on automatically extracting opinions of students on course and instructor from large number of qualitative comments. In this work we leverage on the opinion architecture devised by Liu (Liu, 2010).Liu's opinion architecture is built on text processing and text classification techniques.

3.2 Suggestion Extraction

Unlike opinion mining where we identify the like and dislikes or positive from negative comments. Extracting suggestions seeks to discover objective comments indicating what improvement an individual would like to see or have. Automatic discovery of suggestions from customer reviews or surveys is vital to understanding and addressing customer concerns. Equipped with this insight, businesses can channel their resources into improving their product or services. A previous study has employed rules based approach for identifying user wishes (Ramanand et al, 2010) through rule based method. There has been other research works in mining suggestion from sources like, tweets on mobile phone, electronics and hotel reviews (Sapna & Paul, 2015). Brun & Hagege developed a recommender system using customer profile and suggestions (Brun & Hagege, 2013). Yang et al. demonstrated that suggestion extraction can be applied in user recommendation based on user profile and geographical context (Yang & Fang, 2013). In our work, we study the implicit suggestion extraction from the students' course feedback. To our knowledge this is the first work in education data analytics research. We used classification based approaches for extracting implicit suggestions from qualitative comments.

3.3 Student Evaluations and Opinion Mining

Education institutions implement teaching evaluation surveys that enable comparisons to be made across the institution whilst allowing flexibility for individual course modules. These survey questions are the combination of "program-wide" questions and "module-specific" questions. Student surveys provide valuable feedback that helps course designers towards improving teaching style, course content and assessment design, and overall student learning (Murray,1997; Elaine & Iain, 2005). Hounsell suggested that the feedback must be analysed and interpreted with great care so that action, and ultimately improvement, can result from feedback process (Hounsell, 2013).

Altrabsheh concluded that Support Vector Machines and complement Naïve Bayes produced the most accurate results while learning sentiment (Altrabsheh, 2014). They developed a system to analyse sentiments in real time to provide real-time intervention in the classroom. To predict whether or not a student would retake the course, Hajizadeh experimented on student feedback to analyse the sentiments (Hajizadeh, 2014). To study the opinion words from student feedback, Rashid used generalized sequential pattern mining and association rule mining (Rashid et at., 2013). Gottipati and Venky provided a framework for the qualitative feedback analysis (Gottipati & Venky, 2017). In this framework, they mentioned the challenges of textual data. Nitin et al, suggested a text mining approach to study the sentiments and topics in students' comments (Nitin at al, 2015). However, the goal of all these previous works was to extract the sentiments and not the suggestions from the student feedback comments.

In our work, we are focusing on implicit suggestions extraction from students' comments. To the best of our knowledge there is no previous work that focuses on suggestions extraction from student qualitative feedback comments. In our work, we leverage on some of the approaches suggested by the earlier works. We apply classification techniques in extracting suggestions from student qualitative feedback.

4. Solution

In this section, we first present the overview of our solution and then the details of each component of the solution.

4.1 Solution Overview

Figure 3 shows the overview of our solution approach for implicit suggestion extraction. The solution approach consists of three main stages. In the first stage, raw input comments are pre-processed and prepared for suggestion extraction stage. The second stage is critical to our solution approach. This stage employs text mining algorithms for the extraction of suggestions from the processed comments. In the final stage, the extracted suggestions are aggregated for comprehensive reporting that can used by the instructors and administrators of improving the teaching and learning process.

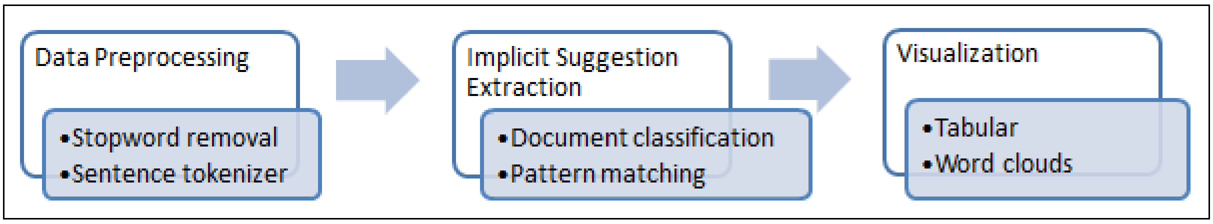

Figure 3. Solution approach for implicit suggestion extraction task

4.2 Solution Details

In the first stage, to pre-process the data, all sentences are extracted from input comments using sentence tokenizers (Kurt, 2016). Tokenization deals with the splitting of text into units during data pre-processing which is critical for the second stage algorithms. Text can be tokenized in to paragraphs, sentences, phrases and single words. We also adopt a vector space representation of a document where each comment is evaluated as document term frequency.

Second stage involves extracting implicit suggestions using text classification methods. In our experiments, we used four different classification algorithms.

- Decision tree C5.0 - C5.0 is a classification tree that is produced by algorithms that identify various ways of splitting data. It is used to predict outcome or class to which the data belongs. A data is one comment and the outcome is either “a suggestion” or “not a suggestion” [27].
- Conditional Inference Tree (cTree) - cTrees work much like C5.0 decision tree for classification tasks. However, it uses significance test procedures to select variable and maximizing information measures [23].
- Generalized Linear Models (GLM) - GLM works on a fundamental principle of linear regression, an approach to model a relationship between variables used for prediction analysis. Each predictor has a coefficient with an assign level of significance or correlation to a certain class. The class in this case is “suggestion” or “not a suggestion” [24].
- Support vector machine (SVM) – SVMs finds a hyperplane that categorize the comments by their features over a space. The goal is to maximize the distance between the planes and points that falls on the edge of the plane known as support vectors for better performance of the algorithm [25, 26].

In last stage, the goal is to provide user friendly summaries of the suggestions obtained from student comments. The visualization interfaces design goal is to be more user friendly for search, comparison and analysis (see Figure 4). Graphical representation of the text using word clouds for a quick view is the most commonly used visual model. Additionally, we also designed query based tables style suggestions for better usability. We depict sample screen from our dashboard in Section 5.3. Other designs include the bar chart comparisons of the number of suggestions for various aspects of the course. The frequency of the suggestions will also enable the instructor to prioritize the changes that need to be undertaken for the course content or course delivery improvements.

5. Experiments

In this section, we first explain our datasets followed by results and discussions. Our experiments are designed to evaluate the implicit suggestion extraction stage and the visualization stage.

5.1 Datasets and Data Preparation

The dataset is the qualitative teaching evaluation feedback submitted by students attending undergraduate core courses offered by the School of Information Systems at Singapore Management University for two terms in a year. Not all comments are useful for analysing. For example, comments such as “NA” and “Nil” are discarded as they introduce noise into the datasets. After clean up, we have a total of 5,342 comments for our experiments.

Data Preparation for Experiments: To evaluate various classification methods, we first randomly sampled a small dataset, then we manually labelled the comments that are suggestions and finally, tested various classification methods described in previous section. To compare the models, we used text evaluation measures; precision, recall and F-Score (Hu, 2004). Precision is the fraction of comments that are actually suggestions among the total number comments classified as suggestions. Recall is the fraction of actual suggestions that have been retrieved over total number of suggestions in all the student comments. F-Score is the harmonic mean of precision and recall.

We took a subset of 399 comments randomly, to perform training and testing. We first perform sentence tokenizing (Kurt, 2016) on each of the 399 comment, which produces 604 sentences.

For example, *"Enthusiastic and entertaining. Classes were never boring. More in class exercises would be good to have"* is tokenized into three sentences. We asked human judges to manually label these sentences as suggestions or not. We present the results in the next section and the visualizations of the tool in section 5.3.

5.2 Implicit Suggestion Classification Results

We evaluated four different statistical classifiers and the results are depicted in Table 1. We observe SVM and C5.0 give high precision and recall scores. C5.0 gives highest F-Score of 78.1% compared to other models.

Table 1: Evaluation results using different classification methods.

Classifier	Precision	Recall	F-Score
Generalized Linear Models (GLM)	0.676	0.650	0.658
Support Vector Machine (SVM)	0.755	0.719	0.735
Conditional Inference Tree (CTREE)	0.781	0.681	0.698
Decision Tree C5.0	0.802	0.775	0.781

We further manually analysed the results to study the misclassifications that lead to low F-Scores. Table 2 shows some example comments and the predicted values by C5.0 classifier. We observe that the misclassified comments are poor in grammatical structure. One possible way of improving the tool performance is combining the rule-based or pattern-based techniques which can be considered as future work to improve this tool.

Table 2: Sample comments from the dataset and the predictions by the tool as implicit suggestion or not.

Comment (Sentence Tokenized)	Actual	Predicted
"Prof could have given more leeway to teams seeking to enhance automation for clients."	Yes	Yes
"We should have more practices in class to allow us to learn more stuff."	Yes	Yes
"Lessons can be more engaging, by asking the students questions or trying out models."	Yes	Yes
"Course could have spent more time on app logger and less time on the rest of the stuff'	Yes	Yes
"He tries to make the lessons as structured as he can."	No	Yes
"Prior to this course, i never knew that Excel could be used to anaylse or project future sales."	No	Yes
Probably organize lab sessions once a week for students to clear their doubts when they are using excel.	Yes	No
Spends more time going through the examples as some students take more time to understand	No	No

5.3 Visualizations

For developing visual dashboard *Shiny*, a web application development tool is used [27]. A sample screen of the dashboard is depicted in Figure 4. Top of the screen provides keyword search functionality and a frequency bar to filter the suggestions. To the left of the screen, list of suggestions are presented in a tabular form and on the right is a word cloud. The word cloud gives an aerial perspective of the suggestion data, words that are of importance are highlighted by their size and colour. The instructor can use the word clouds as a reference to further refine their search and specify the frequency count for filtering the suggestions. For example, if the instructor would like to know what suggestions are given for the word *"assignment"* which is highlighted in pink, he or she can enter this term in the search entry box.

In this example, we observe that students provide suggestions relating to the word *"assignment"*. Some sample suggestions include "assignment to be done in groups", "provide clear objectives or direction" and "assignments to be in chuck size".

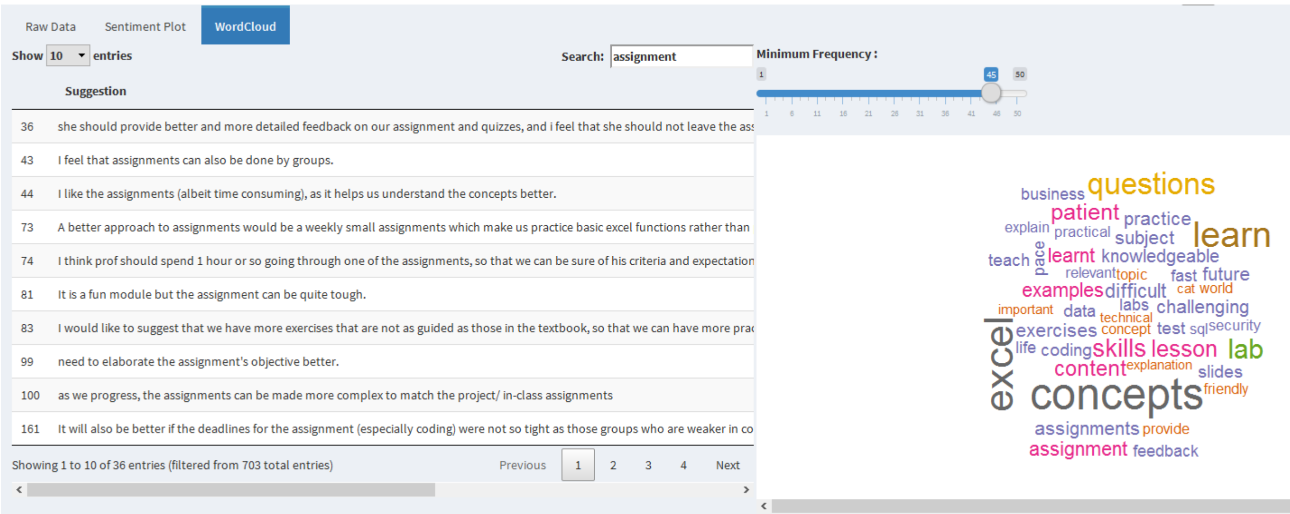

Figure 4. Visual dashboard for suggestions in a tabular form and word clouds. The tool enables to study a single course or compare across courses.

6. Conclusion

Student suggestions aid the teaching faculty in improving the teaching content and class delivery for improving the learning process. In this paper, we proposed a new task of extracting implicit suggestions from students' qualitative feedback comments. We adopted techniques based on text mining and opinion mining research. We observed that decision tree C5.0 classifier provides better performance with F-Score of 78.1%. Our future works includes detecting explicit suggestion where within a negative sentiment statement a suggestion is embedded. Future work will focus on extracting the topics within a suggestion, for example, instructor presentation, project work and exam. This would provide specific insight on what are the areas of improvement and highlights main concern within those suggestions. We are working on the further refining the visualization aspect of the dashboard based on feedback from instructors.

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References

Altrabsheh, N., Cocea, M., & Fallahkhair, S. (2014). Learning sentiment from students' feedback for real-time interventions in classrooms. In Adaptive and Intelligent Systems (pp. 40-49). Springer.

Beran, T., Violato, C., & Kline, D. (2007). What's the 'use' of student ratings of instruction for administrators? One university's experience. Canadian Journal of Higher Education,17(1), 27-43.

Beran, T., Violato, C., Kline, D., & Frideres, J. (2005). The utility of student ratings of instruction for students,faculty, and administrators: A "consequential validity" study. Canadian Journal of Higher Education, 35(2), 49-70.

C. Brun and C. Hagege (2013). Suggestion Mining: Detecting Suggestions for Improvements in Users Comments. Research in Computing Science, Vol. 70, pp. 199-209, 2013.

Chih-Chung Chang and Chih-Jen Lin. 2011. LIBSVM: A library for support vector machines. ACM Trans. Intell. Syst. Technol. 2, 3, Article 27 (May 2011), 27 pages. DOI=http://dx.doi.org/10.1145/1961189.1961199

Cortes, C. & Vapnik, V. (1995). Support-vector network. Machine Learning, 20, 1–25

Elaine Keane and Iain Mac Labhrainn (2005). "Obtaining Student Feedback onTeaching & Course Quality." Centre for Excellence in Learning & Teaching. Apr 2005

Franklin, J. (2001). Interpreting the numbers: Using a narrative to help others read student evaluations of your teaching accurately. In K.G. Lewis (Ed.), Techniques and strategies for interpreting student evaluations [Special issue]. New Directions for Teaching and Learning, 87, 85-100.

Hajizadeh, N., & Ahmadzadeh, M. (2014). Analysis of factors that affect students' academic performance-Data Mining Approach.

Harper, S. R., & Kuh, G. D. (2007). Myths and Misconceptions about Using Qualitative Methods in Assessment. New Directions for Institutional Research, 136, 5-14.

Hastie TJ, Pregibon D (1992) Generalized linear models. In: Chambers JM, Hastie TJ, editors, Statistical Models in S, Chapman & Hall/CRC, chapter 6.

Hounsell, D. (2003) The evaluation of teaching in H. Fry, S. Ketteridge, and S. Marshall. A handbook for teaching and learning in highereducation: enhancing academic practice London: KoganPage

Jhamtani H., Chhaya N., Karwa S., Varshney D., Kedia D., Gupta V. (2015) Identifying Suggestions for Improvement of Product Features from Online Product Reviews. In: Liu TY., Scollon C., Zhu W. (eds) Social Informatics. Lecture Notes in Computer Science, vol 9471. Springer, Cham

Kurt Hornik (2016). openNLP: Apache OpenNLP Tools Interface. R package version 0.2-6. https://CRAN.R-project.org/package=openNLP

Lewis, K.G. (2001). Using midsemester student feedback and responding to it. In K.G. Lewis (Ed.), Techniques and strategies for interpreting student evaluations [Special issue]. New Directions for Teaching and Learning, 87, 33-44.

Liu, Bing. (2010) Sentiment Analysis and Subjectivity, in Handbook of Natural Language Processing, Second Edition, N. Indurkhya and F.J. Damerau, Editors. 2010.

Lizzio, A., Wilson, K. & Simons, R. (2002) University students' perceptions of the learning environment and academic outcomes: implications for theory and practice, Studies in Higher Education, 27, 27–52

M. Hu and B. Liu. (2004) Mining Opinion Features in Customer Reviews. In 19th national conference on Artifical intelligence, AAAI'04.

Max Kuhn, Steve Weston, Nathan Coulter and Mark Culp.(2015) C code for C5.0 by R. Quinlan C50: C5.0 Decision Trees and Rule-Based Models. R package version 0.1.0-24. https://CRAN.R-project.org/package=C50

Moore, S., and N. Kuol (2005). A Punitive Tool or a Valuable Resource? Using Student Evaluations to Enhance Your Teaching, in O'Neill, G., Moore, S., McMulline B. (Eds). Emerging Issues in the Practice of University Learning and Teaching, Dublin: AISHE, 2005, 141-148

Murray, H. (1997). Does evaluation of teaching lead to improvement of teaching? International Journal for Academic Development, 2(1), 8-23

Nitin, Gokran Ila; Shankararaman, Venky; And Gottipati Swapna. (2015) Analyzing Educational Comments for Topics and Sentiments: A Text Analytics Approach. (2015). Frontiers in Education Conference 45th, October 2015, El Paso, Texas. 1-9. Research Collection School Of Information Systems

P. Yang and H. Fang (2013). Opinion-based user profile modeling for contextual suggestions. In ICTIR, page 18, 2013.

Ramanand, J., Bhavsar, K., Pedanekar, N. (2010) Wishful thinking: finding suggestions and'buy'wishes from product reviews. In: Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text, pp. 54–61. Association for Computational Linguistics (2010)

Rashid, A., Asif, S., Butt, N. A., & Ashraf, I. (2013). Feature Level Opinion Mining of Educational Student Feedback Data using Sequential Pattern Mining and Association Rule Mining. International Journal of Computer Applications,81(10), 31-38.

Sapna Negi and Paul Buitelaar. (2015). Curse or boon? presence of subjunctive mood in opinionated text. In Proceedings of the 11th International Conference on Computational Semantics, pages 101–106, London, UK, April. Association for Computational Linguistics.

Sarawagi, Sunita (2008). Information extraction. Foundations and Trends in Databases, 2008. 1(3): p. 261-377.

Swapna Gottipati, Venky Shankararaman. (2017) "A Conceptual Framework for Analyzing Students' Feedback". IEEE Frontiers in Education Conference (FIE) (FIE 2017),October, Indianapolis.

T. Hothorn, K. Hornik, A. Zeileis, (2016) "ctree: Conditional Inference Trees", cran.r_project, [online] Available: http://cran.r-project.org/web/packages/partykit/vignettes/ctree.pdf.

Winston Chang (2016). shinydashboard: Create Dashboards with 'Shiny'. R package version 0.5.3. https://CRAN.R-project.org/package=shinydashboard