Analyzing Sentiments from Student Feedback using open-ended questions and advanced text analytics

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Abstract—
Knowing the user sentiments are useful for various adaptation purposes where improving is more important than the statistical conclusions. In the process of teaching and learning knowledge about student sentiments and opinions can be used to address problems that affect student engagement and improve the quality of teaching process. Educational institutions highly focus on collecting and analyzing student's feedbacks to study their sentiments towards instructors, course content and ensure the quality and the performance of the instructors. When it comes to improving skills, nothing can be beat the constructive feedback. Though Likert scale surveys are great for statistical analysis they provide less solutions on what to be improved. There for adopting open-ended questions are great when analyzing student's true sentiments. CURIX is a new generation feedback tool replacing traditional surveys with Al-driven chatbot for student feedback analysis and learning sentiments of students that help instructors to improve their performance. CURIX is a combination of advanced text analytics with the power of Natural Language Processing and cloud processing cognitive service applications where student's sentiments can be analyzed with start, stop, continue-question set (SSC) approach. It will generate the insights for Instructors to enhance their performance by replacing classical feedback surveys with a state of art text analytics solution to mine the student sentiments for continuous improvement in educational domain. Further this solution can be extended in cooperative and business environments to gather insights and sentiments where improvement is essential with replacing traditional survey systems.

Keywords— Sentiment Analysis, feedback mining,
Natural language Processing, text analysis

1. INTRODUCTION
so where should teacher improvement come from, part of it come from pure experience and formal training. But the other most important factor of improving skills is receiving and acting on feedback. But the teachers receive significantly small amount of feedback over their careers. In almost every profession feedback is the main drive of improvement, from athletes to CXOs to authors. We all need feedback to become better. In 2009, the OECD (Organization for Economic Co-operation and
Development) investigation done by group of experts regarding what the effect feedback has with in the teaching profession. Feedback has a strong positive influence on tutors and their work, and it increases the job satisfaction. Having feedback will significantly increase teacher skill development and it highlights that many countries have a lacking in feedback systems. Most of the universities, schools and institutions teacher feedback is synonymous to teacher evaluation.

How feedback is collected in most of the situations are using survey questions students are being asked, approximately most of the 80% are closed ended Likert-scale questions. Although close ended questions are being used as a methodology for statistical analysis there is a huge lacking in providing useful data that can be used as evidence for improvement. For that we need open ended questions that helps to collect detailed and valuable information without limiting the users for a set of responses. When we come to teaching and learning process which is big complex can never be describe and evaluate using pre-set limited responses because often, we can learn about things, we did not expect all using a written feedback.

Also, evaluating those large set of feedback forms can be time consuming tedious task, but fortunately technology can be adopted to handle those situations with the advancement in modern software engineering trends and methodologies. The goal of the stems is to translate student comments into usable recommendations that can be adopted to improve teaching and learning process. When improvement is more important than statistical analysis, the focus must change from Likert-scale to open-ended questions when collecting teacher feedback. The issue with collecting open-ended feedback has always been the time-consuming task of categorizing and analysing comments. As classes continue to grow larger and most of the time they are having scalability issues therefore most of the institutions and universities just depend on quantitative feedback collection which are just Likert scale question set, due to this reason there is a trend that unfortunately been towards ignoring open-ended comments, simply because there's too much work related to extracting useful information. Today, the development of text analytics is moving forward at a much faster pace than ever before. With that comes the possibility of a
potentially revolving transformation of how teachers handle written student feedback. Text analytics could help to make it possible to take full advantage of written feedback without having to do any significant amount of manual effort. The teachers’ focus could be easily aimed at improvement instead of interpretation.

II. HISTORY

When researchers back in the late 1990’s started to tackle text analysis, by then it was called text mining, a text was still treated as a “bag of words” without any deeper perception of the semantics (the meaning) of the content. Subsequently, a few years later, the word cloud came into popular use in text analytics contexts. The next step in the analytical development is known as data mining and can find more complex patterns within written text-data. Techniques such as clustering, categorization, and link analysis are being used to dig deeper into a text. Identifying misspelled and related words are now possible by converting words into vectors (In the text analytics, these vectors are called Tensors) and comparing them by each other. As we now already have entered the era of machine learning and artificial intelligence, we can approach text analytics in a much more accurate way than ever before. Self-learning neural networks can be taught to analyse context around a word to decide what it refers to. For example, the word tank can, in different contexts, refer to an armoured vehicle, a water reservoir or a person’s name according to each context.

II. EXITING SYSTEMS

Sentiment Analysis has become a famous research area during past few years and those related work can be mainly classified in to three main approaches: (a) Lexicon based (b) machine learning based and (c) hybrid approach.

A. Lexicon Based Approach

The lexicon can be built manually or automatically and a lexicon or dictionary determine the polarity of a given text-based content, A lexicon is used to represent a list of words which are associated with the sentiment polarity.

Rajput and Haider have described the usage of lexicon to determine the sentiment polarity of student feedback. They have used a modified general-purpose sentiment dictionary to determine the polarity of onions and sentiments in academic domain. Their research shows that using a domain specific sentiment lexicon will help to achieve better results with compared to any general-purpose sentiment lexicon. Hu and Liu have used an online lexical resource WordNet to predict the semantic orientation of an opinion word. Taboada et al has suggested another lexicon-based approach which determine the polarity of a word with using dictionaries created. Also, there are numerous general purpose and domain specified lexicons such as MPQA opinion corpus,
Linguistic Inquiry and word count database, Harvard General Inquirer and many more.

B. Machine learning based Approach

Machine learning based approaches are commonly used in sentiment analysis process using a predictive model using an existing dataset. There it is evaluated the performance and accuracy of the learned model with the data set used for testing. This can be further classified in to supervised learning and unsupervised learning. Unsupervised learning approach does not need any data set to comment the exact sentiment labels. A Pointwise mutual information (PMI) based method was used to identify the polarity of a phrase by Turney. He suggested an unsupervised method of sentiment analysis where polarity of text content was identified by aggregating the polarities of phrases which consists with adverbs and adjectives. Fernandez et al suggested a method based on dependency parsing technique where unstructured text based data. Supervised machine learning approaches of sentiment analysis is consisting of training the classifiers using the linguistic features which are extracted from the text. Some of the linguistic feature that have been widely used include n-grams, word representations etc. those models were trained using Naïve Bayes, Maximum entropy and support vector machine (SVM) algorithms.

IV. IMPLEMENTATION

Today, text analytics is being applied and used in a wide range of areas from automated advertisement placement to advanced military trigger warning systems. In student feedback applications we are moving in a sub-domain of text analytics called sentiment analysis. Sentiment analysis is still early on its development, but already today it is being used commercially to extract emotions from large datasets. For example, it is used by hotels to find out what features customers appreciate and what needs improvement, most of the online sales system and service vendors use these techniques with the data that can be extracted from thousands of online reviews to identify points of strong concurrence. The result from a hotel review analysis could look something similar to this: For better understanding let’s consider this statement regarding a hotel service.

‘65% of guests are concerned with the room, most of them negative, and often mentions terms such as noisy and poorly cleaned.’

This is basically the exact same thing that we want from a text analytics system for student feedback comments.
A system like this, where open-ended data is as easy to collect and analyse as Likert-scale responses that can be applied in areas such as teacher evaluations or market research where respondent data is typically collected by surveys.

So, for the question, how far along has text analytics specifically for student feedback gotten? We can conclude that, as there’s no standard way of analysing text, every vendor is doing things in their own way with various degrees of success. Different systems range in complexity from simple word cloud representations of collected comments to in-depth technical analysis using neural networks and deep learning.

Proposed system is an integrated platform both for collecting, categorizing and analysing student feedback. Not only does this service replace the need for boring surveys by using a chatbot interface, it also contains a text analytics-system built around neural networks, deep-learning and sentiment recognition specifically designed for educational comments, with the help machine learning techniques and Azure cloud.

A. Data Collection

The proposed system is designed to collect student feedbacks with open-ended question sets with the ambition of qualitative data processing. To collect student feedbacks, it is used the ‘Stop, Start, continue’ (SSC) method is adapted. This is t widely used formative evaluation in higher education. Many of the universities around the world use SSC or similar methodologies. Apart from SSC there is a quick check mode as well where it generates quick insights for the tutors. The following questions used for the SSC approach

- What could the teacher stop doing, that would improve the course?
- What could the teacher start doing, that would improve the course?
- What is working well with the course, and should continue the way it is?
- What’s your overall experience of the course?
- Do you have any other comments?

Quick check approach questions are as follows.

- What’s your overall experience?
- What can be improved?
- What has been working well?
- Do you have any other comments?

Text mining approach is used in sentiment analysis process. The following methods are adopted in the process of extracting the keywords from student feedbacks

a) Tokenization
This is the methodology of breaking up the sequence strings into pieces of words, keywords, phrases and other elements which are known as tokens. A Token can be a single word, phrase or a whole sentence. During the process of tokenization some characters like punctuation marks special symbols are neglected.

b) Stop Word removal
Stop words are the words that filtered out before or after processing of natural language data, these words will be removed to extract only meaningful information from those data. Words such as ‘the, is, at, which, on, who, where, how, before, after’ etc. are falling into this category.

c) Clustering
The process of making a group of abstract objects into classes of similar object is known as clustering. A cluster of data objects can be treated as a single group. In this process the sets of data will be partitioned into the groups based on the data similarity and then assign the labels to those groups. This approach of clustering over classification will be the adaptability to changes and helps to separate useful features that help to identify different groups.

d) Classification
The process of organizing data into categories for the effective and efficient use. Proper classified system makes essential data easy to find and retrieve whenever necessary. This can be important for risk management.

e) Sentiment Analysis
Sentiment analysis is the use of natural language processing, text analysis, text mining and computational linguistics to identify and extract subjective information in source materials. Sentiment analysis is widely used modern web platforms and social media for variety of applications from marketing to customer service improvements. Sentiment analysis focus to determine the attitude of the user with respect to some topics or the context of the situation. This can be his or her emotional feeling, judgement or the effective state.

IV. Selected methodology
Many approaches of using natural-language processing were explored to gain a better understanding of the feedback data, such as sentence topic identification and clustering. Unfortunately, many of these methods were ineffective and unsuccessful due to the lack of data and the high variability of the topics in the written responses. The approach of using machine learning approaches to
augment the ability to measure the essence through
qualitative text feedbacks is focused on most machine learning models to have very large amounts of labelled data to create meaningful results from those raw data. For the implementation and experimenting of the proposed system Microsoft Azure Machine Learning Studio is used due to its operational simplicity. Microsoft has extensively trained algorithms, which eliminates the need to provide a training dataset with their researches. Additionally, this cloud software service is consisting with a graphical programming interface which allows for rapid prototyping and iterative development. Azure cloud uses data augmentation techniques such as Term Frequency Inverse-Document Frequency (TFIDF), tokenizing, word rooting, and sentence hashing due to the relatively small amount of data used. In Microsoft Azure data can be transferred into actionable insights using the best-in-class machine learning tools. This architecture allows us to combine any data at any scale, and to build and deploy custom machine learning models at scale.

Figure 1. Natural language processing (NLP) pipeline in Azure cloud
Source: docs.microsoft.com

1. Bring together all your structured, unstructured and semi-structured data using Azure Data Factory to Azure Blob Storage.
2. Use Azure Databricks to clean and transform the structureless datasets and combine them with structured data from operational databases or data warehouses.
3. Use scalable machine learning/deep learning techniques, to derive deeper insights from this data.
4. Leverage native connectors between Azure Databricks and Azure SQL Data Warehouse to access and move data at scale.
5. Power users take advantage of the inbuilt capabilities of Azure Databricks to perform root cause determination and raw data analysis.
6. Run ad hoc queries directly on data within Azure Databricks.
7. Take the insights from Azure Databricks to Cosmos DB to make them accessible through web and mobile apps.

Figure 2. Advanced Analytics Architecture of Microsoft Azure
Source: azure.microsoft.com

The proposed system is having two user parties who are students and tutors. Tutors will generate a feedback form base on the course modules, and it will be shared with the students with the help of smart mobile application. Students will get a push notification with related to the evaluation form sent by the tutor. Then a chatbot will collect the answers from the students which are open ended set of questions and those data will be sent to the Azure Cloud. The system is developed as modules and even the data can be sent to the IBM Watson cloud at the same time for the sentiment analysis and text analysis, but in this paper, it is focused how the Azure cloud is adopted.
for the system design due to availability of advanced data visualization tools and support with custom design of machine learning systems with advance integrated tools. The system architecture is as shown in the figure 3.

Microsoft Azure’s Sentiment Text Analytics is a machine learning classification algorithm which is used to generate a sentiment value between 0 and 1. If the Values closer to 1 they indicate positive sentiment, while values closer to 0 indicate negative sentiment. The model is well pretrained with an extensive body of text with sentiment associations. Therefore it is not necessary to provide training data set and The model uses a combination of techniques such as text analysis, text processing, word placement, and word associations. Sentiment analysis is performed on the entire sentence, instead of extracting sentiment for individual words in the text. Normally there will be a high accuracy when the sentences are short and contain common words.

IV. DISCUSSION
When it comes to improving the skills, constructive feedback plays an important role. Likert-scale surveys are great for statistical analysis, but they are unable to provide answers to what exactly need to be improved. Best actionable feedback can be gained through open ended questions and Start, Stop, continue (SSC) approach is great for this process. This smart application of student feedback handling is taking next steps with AI driven chatbot which collects feedback by a personal, fun chat conversation with modular design and architecture. With the power of Azure Machine learning tools and modelling it has possible to analyse and categorize students sentiments and generate insights for tutors to improve their teaching skills to the next level.

V. CONCLUSION
In this study, I have investigated how the student feedback evaluation can be taken to the next level with the personalized conversion and Azure machine learning could platform tools. This study will help to simplify the student feedback analysis process with more engagement of the students and leverage the power of open-ended questions in a way that is effortless with the modern sentiment analysis methods and Machine learning approaches. The platform will automatically categorize and analyse in the Azure cloud engine and the tutor will be presented with the specific points where improvement is possible.

References


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