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Extracting Features and Sentiment Words from Feedbacks of Learners in Academic Environments

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Abstract. The aim of this paper is to describe a natural language processing methodology in order to identify opinions that are expressed in the text and populate those opinionated words in a domain-driven opinion lexicon. As part of our recent research in opinion mining, our system aggregates students' feedbacks from several faculties and derives meaningful comments that are expressed by them about courses, teaching, evaluation, infrastructure and many others. In this paper, we employ a rule-based approach to extract features, capture sentiment words from those comments and build opinion vocabulary, based on a corpus of academic feedback reviews.

Keywords: Text analytics, Sentiment classification, Opinion mining, Academic feedbacks

1. Introduction

People are talking about an educational institution and its business everyday. For instance, students are talking about the institution directly face to face and behind its back. Students are saying how much they like the institution and how much they dislike the institution. They often express what they wish the institution could do for them. Students write a feedback to the institution every year or every semester, post blogs about the institution, discuss about the institution endlessly in public forums and in emails.

The employees of an institution are also talking about it. Employees produce greater ideas that are languishing for lack of right context to apply them. Similarly, parents and public who are related to the institution are also passing serious and meaningful comments on the institution positively and negatively [1]. They talk about the institution over telephone, public forums, chat rooms and emails that will enable the institution to become the leader among its peers, if listened carefully.

Students provide valuable feedback every year as they go out of the institution after their graduation or progress themselves to next year of their academic study. The information they supply about their course, facilities and others are highly unstructured in their own language. But, these unstructured data can be much useful for the institute to shape up the curriculum, teaching methods, faculty improvements, infrastructure, its vision statement, students' facilities and so on. However, the unstructured nature of the feedback is relatively complex and large volume of feedback data requires automated analysis [2].

Imagine 10000 or more of these meaningful comments and opinions in databases. In the database, they can be indexed and sorted based on year. But this large collection of comments cannot answer even this simple query, *what are the curriculum related problems reported by the students in this year?*. If the data could be leveraged to do this analysis, then attention or focus can be given to those courses that require intense revision, thus significantly improve the quality of the curriculum.

Unstructured information related to students, employees, parents and public could teach us many things about our views and excellence towards them. For example,

- What are the most common issues that our students have?
- What are the most common issues that our faculty and employees have?
- Where are the areas of dissatisfaction of our students?
- Where are the areas of dissatisfaction of our faculty and employees?
- Who are the faculty doing good job?
- What are the areas where the cost can be reduced?
- What are the expectations of parents of students from the institution?

Apart from these generic objectives of teaching, learning, facilities and infrastructure, we have further applied Blooms approach that refers to a classification of the different objectives that educators set for students (learning objectives). Bloom's Taxonomy divides educational objectives into three "domains": Cognitive, Affective, and Psychomotor (sometimes loosely described as *knowing/head*, *feeling/heart* and *doing/hands* respectively). Bloom's Taxonomy is considered to be a foundational and essential element within the education community. Further, our feedback aggregating system will have to be enhanced with the metrics to evaluate adaptive learning and personalization outcomes.

Besides unstructured information, students are expected to provide structured information of their details and academic performance to make their feedback reliable. Collection feedbacks from students and their evaluation of teachers has become integral part of learning though there are several perspectives of evaluation process. The evaluation process is viewed such as testing teaching materials, teaching methods and teaching effectiveness. Others view them as a means of improving current practices. Hence the purpose of evaluation will be to get quality assurance and quality enhancement in terms of accountability, appraisal and development of curriculum, infrastructure, teaching and so on [3-5].

This paper focuses on automatic textual analysis of students' feedbacks that are gathered through our Feedback and Opinion Aggregator system. The system has been designed for a set of feedback parameters based on the guidelines of NAAC–UGC, India. It also allows us to study both quantitative feedback features through numerical ratings as well as qualitative features through natural language free texts. These natural language free texts are important sources of information for sentiment analysis which is a popular problem in Opinion mining that has attracted presently a great deal of attention from researchers.

The rest of the paper is organized as follows: Section 2 and 3gives overview of academic feedbacks and their importance. Section 4 discusses explicit feature and sentiment words extraction in the context of academic feedbacks, while section 5 illustrates the experiments and results. Finally section 6 concludes the paper.

2. Overview of Academic Feedbacks

We make use of real student feedbacks collected through our system. Our feedback and opinion aggregator has been designed to collect feedbacks and opinions from students of various departments of our institution. The set of features of feedbacks are based on feedback guidelines suggested by National Accreditation and Assessment Council (NAAC), University Grants Commission (UGC), India. NAAC is the central body that widely evaluates universities and academic institutions to sustain quality in curriculum, teaching methods and teacher qualities.

There are 3 sections in the feedback form namely, sectionA, sectionB and sectionC. Section-A contains a set of evaluation parameters for which every student should give their feedbacks through nominal value from 0 to 5 for the corresponding rating of very poor, poor, average, good and excellent. The set of questions in section-B are multiple choice type questions, there by students will offer feedbacks with either YES, NO or NO COMMENTS responses. Finally, section-C provides some short descriptive questions so that students can describe the strengths and weaknesses of their teaching faculty members. Furthermore, '*Any other comments'* question is of generic interest type where students can give their informal opinions about virtually anything about their life, environment and so on. Fig. 1 depicts the screen shot of our feedback aggregator to gather feedbacks from academic stakeholders.

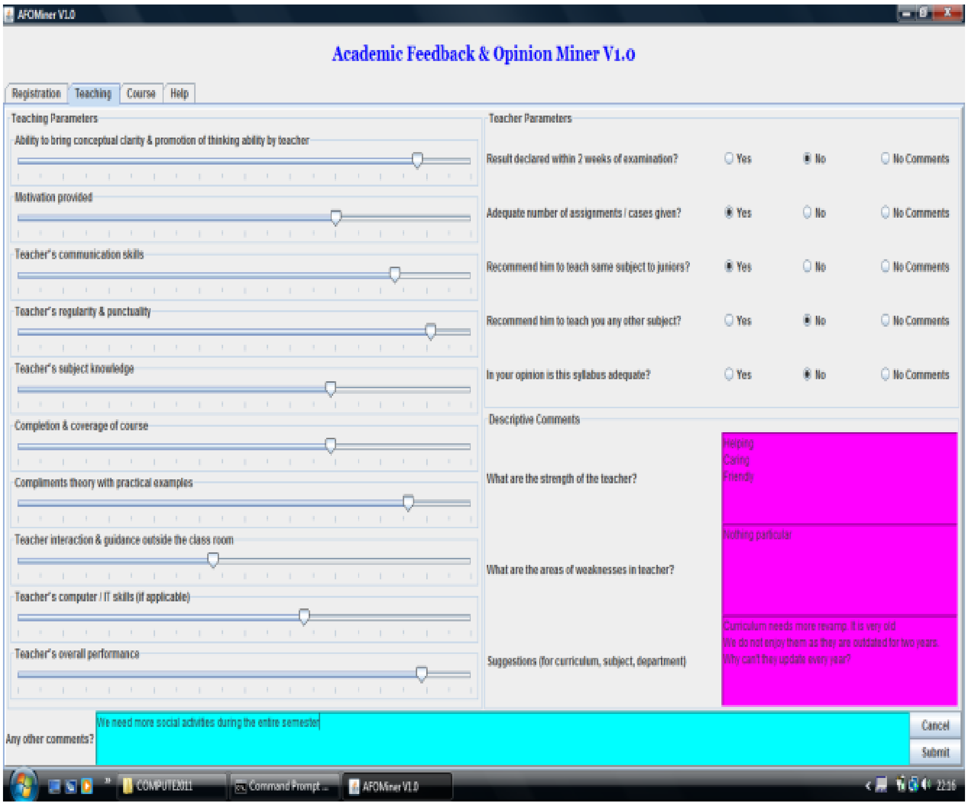

Fig. 1: Screen shot of feedback and opinion aggregator system. This teacher and teaching evaluation tab allows students to rate their feedback through sliders and radio buttons. They can give opinions through free text in the text areas.

The aim of collecting and data mining feedbacks and opinions from the students of an institution is two-fold:

- With the help of the feedbacks obtained from the students through the feedback parameters, teachers, faculties and institution in general can review their current status of the courses, teaching standards, teaching methodologies, expectations of students from the institution during their course of study.
- Understanding feedbacks help not only the current trend of courses, teaching and facilities, but also future requirements, expectations, and visions for the institute

For each feedback, the system gathers values in numerical ratings (1 – 10) for sectionA, Yes-No-No-comments for sectionB and short descriptions for sectionC review questions. Finally, our system collects informal opinion about anything related to their programme as a free-text.

3. Importance of Free Text Feedbacks from Learners

Free text associated with *any other comments* section of the feedback parameters is an important source of information for the institution. It naturally provides them important things of the environment such as infrastructure, facilities, ICT, and others. It tells us very specific opinion of aspects students honestly liked or disliked.

More importantly, these free texts are the means for understanding how honest their feedback was, particularly the numerical ratings given by the students. The set of features discussed in the *any other comments* section will have direct impact and justify some of the high, low numerical ratings. The free text may also give suggestions for understanding the numerical ratings of the overall performance (OP) feature that allows students to provide a collective rating without any mathematical justification.

However, the problem is that natural language comments or free text comments are difficult to understand automatically by the computer [6-9]. Machine understanding of free text suffers from serious problems such as grammar of the text, associated semantics, aggregation, ambiguity of words, multiple semantics in the same sentence, contradicting semantics, fuzziness and so on. Furthermore, human beings are more fun of using abbreviations and culture-specific terms while expressing their opinions.

4. Extracting Features and Sentiment Words from Feedbacks

In most of the opinion mining or sentiment analysis applications, the sentiment dictionary plays a key role. Although an universal sentiment dictionary is desirable, domain specific sentiment dictionary or lexicon becomes highly practical. Sentiment words are words that convey positive or negative sentiment polarities. It is also well known that many such words are domain dependent.

4.1 Explicit and Implicit Features

Our proposed opinion mining system classifies features into two categories: explicit features and implicit features. Explicit features are those features that are explicitly mentioned in the feedback or opinion. For example, consider an example of a feedback

The infrastructure in my classroom is simply superb

In this feedback, a student is highly satisfied with the classroom infrastructure. Here infrastructure is the feature that the student talks about. While the feature of the classroom is explicitly mentioned about, some other features are implicit and hard to predict, as shown in the following example.

Though often revised, the knowledge gained by students remain less

In this example, a student is talking about the syllabus of a course, even though the word, syllabus appears nowhere. In this paper, we focus on predicting explicit features from the feedbacks supplied by students.

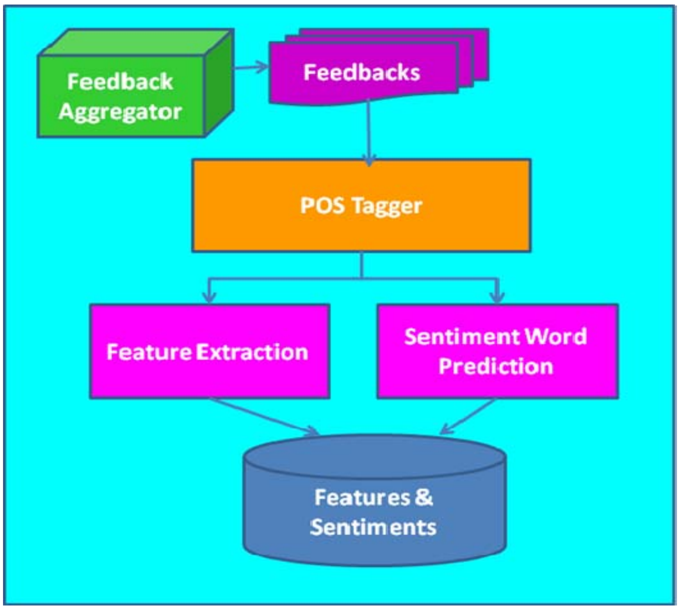

Fig. 2: Our Proposed Architecture

4.2 The Architecture

Figure2 gives the architectural overview of our proposed feedback mining system. Feedback aggregator collects feedbacks and opinions from students, including free text comments. We call these natural language free text comments as feedbacks for simplicity. These thousands of free text comments will be the corpus of feedbacks that provide ample scope for text analysis. The POS tagger performs natural language text analysis by name part-of-speech tagging, from which explicit feature will be extracted as well as sentiment words will be predicted. These explicit features and sentiment words will become our dataset for further feedback mining.

4.3 Part of Speech Tagging

Student feedback features are basically nouns and noun phrases in their free text comment sentences. We have applied Stanford POS tagger in order to parse each feedback so as to split text into series of sentences and to produce part-of-speech tag for each word. As a result, the word will be identified as a noun, verb, noun phrase, adjective and so on.

4.4 Feature Identification and Extraction

Feature identification and extraction task involves identifying feedback features on which several students have expressed their opinions in a free text format. In this paper, we focus on identifying explicit features that are to be populated in the feature and sentiment words database. Some descriptions of explicit features are discussed in the previous section. In this research, we assume explicit features are those features that appear as nouns and noun phrases in the feedback which are gathered from academic learners.

```
extractFeatures(Sentence S)
POSTags P <- POSTagger(S)
N <- nouns(P)
NP <- nounPhrases(P)
if (N not Empty OR NP not Empty)
    F <- F U N U NP
return F
```

Fig. 3: Algorithm for feature extraction

```
sentimentWordExtractor(Sentence S)
Feature F <- extractFeatures(S)
if (F not Empty)
  for (each f in F)
      SW <- SW U adjacentAdjective of f
return SW
```

Fig. 4: Algorithm for sentiment word extractor

Figure3 depicts the algorithm for feature extraction module. The algorithm takes the given sentence as input and returns all features that are present in the sentence. It returns all nouns and noun phrases as features after segmenting it into series of POS tags.

4.5 Sentiment Word Extraction

After finding explicit features from a set of feedbacks, the next task for our system is to identify sentiment words or opinion words. Sentiment words express opinions about the subject, on contrast to the object. Subjective opinions are those opinions that discuss the subject. This is different from objective opinions which usually describe the factual information of the object. The adjective that is present in the given student feedback is used to predict the subjectivity of the feedback. So, our proposed system uses adjectives as sentiment words. Instead of predicting sentiment words in every sentence of the feedback, we consider only those sentences that contain a explicit feature.

Figure4 depicts the algorithm to extract all sentiment words from the given sentence if it contains at least one feature. If there is a feature present in the sentence, then the algorithm retrieves the adjacent adjective of the feature and returns all sentiment words which are aggregated in each iteration.

5. Experiments and Results

The services for feature extraction and sentiment word prediction have been integrated with our feedback aggregator service as part of our Academic Feedback and Opinion Miner project. This section presents our experimental results. We use the student feedback collections that are obtained through our feedback aggregator service. The collection contains 4 feedback data sets, each for Computer Science (DS1), Computer Applications (DS2), Information Technology (DS3) and Bio Informatics (DS4) programme. On average, each dataset contains 250 sentences and 50 feedbacks (we assume natural language free text to be our feedback, setting apart other numerical rated responses) based on our class size of 50.

We employed 50 of our bachelors students from Computer Science department for our experiments. The team has been well trained with NLP basics including features and sentiment words. The members of the team carried out the experiment to manually label all features and their corresponding set of sentiment words and their predictions are documented. The precision and recall measures of feature extraction service and sentiment words prediction service for all four datasets are reported in Table 1.

Observing the table for feature extraction, it is easy to understand the our simplified approach results into a reasonable precision in extracting explicit features, except for the datasets DS3 and DS4. The precision for these two datasets are somewhat below because of the large number of rare features which lowers the precision.

Regarding sentiment word extraction from the table, one can easily understand that the proposed approach is effective with better precision in extracting correct sentiment words for the datasets DS1, DS3 and DS4. However, precision for DS2 is relatively low. The reason behind this little low precision is because of the inherent difficulty in distinguishing ordinary adjectives from sentiment ones.

Considering the recall values for both feature extraction and sentiment words extraction tasks, our straight forward approach brings reasonably better recall values in which the features and sentiment words extracted could cover more than 70% of the whole features and sentiment words set.

Dataset	Feature Extraction		Sentiment Words Extraction	
	Precision	Recall	Precision	Recall
DS1	65	80	60	70
DS2	60	75	55	75
DS3	55	70	60	75
DS4	55	85	65	68

Table 1: Precision and Recall values for Feature and Sentiment Words Extraction

6. Conclusion

This paper has proposed straight forward rule based techniques to extract explicit features and sentiment words from academic feedbacks that are provided by student learners based on natural language processing methods. Our experimental results indicate our simplified approach for feature extraction and sentiment words extraction is very promising in performing the tasks. The objective is to build a lexicon of terms that are features and sentiment words. This lexicon will be an important repository with which further information retrieval tasks will be performed. The lexicon will be the key to find polarity of sentiment words that will help us predicting overall sentiments of the learners on various aspects related to academics and others. One can also predict the trend that is prevalent among students.

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