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Faculty Evaluation System

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Abstract

An automatic system to analyze the textual feedbacks of faculty members teaching in any institute is proposed. The proposed system extracts all the important aspects from the feedbacks and then sentiment score of each aspect for each faculty is calculated using machine learning algorithms. The proposed system is flexible and versatile than the existing feedback evaluation system of teachers where students evaluate the teachers on predefined aspects decided by experienced and senior faculty and administrators. Our system, Faculty Evaluation System (FES) identifies strengths and weaknesses of teachers on all those aspects which are important to students. This information may also be used by higher authorities of the institute to form appropriate teams of faculty members for different academic and administrative activities of the institute.

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Keywords: Feature Extraction, Aspect Based Sentiment Analysis, Sentiment Evaluation, Sentiment Aggrigation, Natural Language Processing;

1. Introduction

Taking feedback of teachers from students in schools or colleges is an important activity of any educational institute. Traditionally teachers' feedback evaluation system is a questionnaire based system where a pre-designed questionnaire form is given to each student. The form may have 10 or more questions and students assign a grade to each question for every teacher according to the predefined measuring scale. On the basis of responses of all students, it is determined how much a teacher is able to contribute in his/her course. The main problem of questionnaire based system is that higher authorities identify the key points of a teacher and form question set on the

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basis of their personal experiences without taking into account students' view. Due to this, traditional questionnaire based system becomes very restricted as students can give their views for only those questions which are mentioned in the questionnaire.

A teacher despite having a good command over the subject may have some vital social merits/demerits which may affect the thinking of students either in a positive way or in a negative way. Every teacher has its own way of delivering lectures and students can easily identify the qualities/features of any teacher. For instance, the way a teacher introduces a new topic, his/her gesture in the class, writing skills, the method of answering questions, the knowledge of subject, etc may be more important to a student than the actual contents covered by the teacher to complete the course. Therefore, instead of taking pre-defined aspects, it will be more meaningful to extract the relevant features of a teacher from students' feedback.

To measure the effectiveness of a teacher to the satisfaction of every student, we are proposing an aspect based sentiment evaluation system. In the proposed system, we collect student feedback in the form of running text. Using linguistic features and machine learning techniques, in the first phase, important aspects of teachers are identified from the collected feedbacks and then for those aspects, the students' views are processed to find out the sentiments of students as either "good", "satisfactory" or "unsatisfactory" about every teacher for all the important aspects extracted from the data itself. This evaluation model overcomes the problems of traditional feedback system and it also allows the administration to make use of the information about each teacher on a variety of aspects for assigning important responsibilities to them. During the aspect identification process, the system chooses the vital aspects by grading each aspect on the basis of feedback of students. Aspect detection and evaluation of each aspect for every faculty allows an institute to use this information for effective utilization of its people leading to better growth. We divide our research paper in eight sections. Related works are discussed in section 2. Architecture of proposed system is given in section 3. Process of feature extraction is discussed in section 4. Feature sentiment evaluation is explained in section 5. Sentiment aggregation and report generation are discussed in section 6 and 7. Conclusion and future work are in section 8.

2. Related Work

Hu and Liu [1] proposed a method to perform aspect based sentiment analysis of products reviews. In this paper, authors assume that the product aspects are nouns and noun phrases. Nouns and noun phrases are extracted using association rule mining algorithm of data mining. Each sentence of review is considered as a transaction. This method is quite simple and has been used by many researchers with some modifications.

Popescu and Etzioni [2] used point wise mutual information gain (PMI) to check whether a noun or a noun phrase is a valid aspect or not. Authors computed PMI between candidate aspects and meronymy discriminators of product. Meronymy discriminators of product "camera" are 'of camera', 'camera has', 'camera comes with'. PMI (w1, w2) is the ratio of joint concurrences of word 'w1' and word 'w2' with respect to the individual occurrences of word 'w1' and 'w2'. Only those candidate aspects are considered valid aspects whose PMI score is greater than threshold value. Threshold value is determined experimentally.

Qiu et al. [3] proposed a double propagation algorithm to extract new aspects and sentiment expressions on the basis of syntactic structures of aspects and sentiment expressions. They use the bootstrapping technique where they start with some seed sentiment words and on the basis of known seed words new aspect are identified and vice versa.

Jin and Ho [4] consider aspect based sentiment analysis as a sequence labelling problem. Authors manually tag each word of reviews with appropriate labels and impose lexicalized Hidden Markov Model and from the tagged sentences, system learns patterns to identify aspects and sentiment expressions.

Jakob and Gurevych [5] extend the approach suggested by Jin and Ho [4] using Conditional Random Fields algorithm (CRF). CRF is learned in one domain and used to extract in other domain.

Mei et al.[6], proposed a topic model based approach which consists of an aspect model to determine aspects of the products and then positive and negative sentiment model determines the polarity of extracted aspects.

A. Kumar and R. Jain [7], proposed a system architecture to perform sentiment based analysis of teachers' feedback given by the students in textual form. Authors ignored objective sentences and identified the essential aspects of teacher by using conditional maximum entropy based approach with mutual information and TF-IDF of respective words in subjective sentences. Sentiment score is assigned to all identified aspects on the basis of point wise mutual information gain between identified aspects and sentiment words.

Ding, Liu and Yu [8], proposed a sentiment lexicon based method to determine sentiment polarity of aspects in sentences. Score +1 and -1 is assigned to all sentiment word belonging to positive and negative lexicons respectively. Sign of sentiment words are inverted if sentiment shifter is present near to sentiment words. Conjunctions of phrases are handled carefully to decide the sentiment of aspects. Finally a aggregation function is used to aggregate sentiment score of mentioned aspects.

Liu [9], proposed a formal grammar based system to decide sentiment polarity of simple and compound sentences. Formal grammar rules are expressed in form of BNF. Overall sentiment is computed on the constitutional words and syntactic structure with other words. Formal grammar is in generalized form, it can be used in any domain with some modifications.

N. Magesh et al. [10] proposed a machine learning based Decision Tree algorithm to prepare annual appraisal report for yearly increment and career advancement. WEKA is used for data preparation and system implementation. Major inputs to the system are employee attendance, no of paper presented in conferences, number of attended seminars and workshops etc..

Nabeela Altrabsheh et al. [11] proposed a machine learning based system to capture students sentiment on class room problems. Authors have experimented with Naive Bayes, Complement Naive Bayes, Maximum Entropy and Support Vector Machine algorithms and found that Support Vector Machine is the best performer with average accuracy 94%.

Mohammad Aman Ullah [12], proposed a system to perform sentiment analysis on students feedbacks collected from Facebook pages and groups to evaluate instructor performance using several supervised machine learning approaches.

3. Architecture of Proposed Faculty Evaluation System

The proposed feedback analysis system takes as input the collection of feedbacks in the form of running text for all the teachers of an institute. Faculty Evaluation System (FES) is divided into four components: ***Feature Extraction***, ***Feature Sentiment Evaluation***, ***Sentiment Aggregation*** *and* ***Report Generation***. Each component consists of different modules. First component of FES processes the raw input and then extracts essential features of faculty members on the basis of frequency, contextual information and linguistic information from all the possible features mentioned in the feedback. Second component evaluates sentiments of each essential feature using the sentiment orientation of surrounding text. Sentiment Aggregation part estimates aggregate sentiment score of each essential feature with respect to each teacher. Overall sentiment score is also assigned to each teacher by considering their sentiment scores for all essential features. Report generation part generates different reports to measure overall effectiveness of teachers. Generated reports are also helpful in academic and administrative decisions. Details of all components and their modules are given in next sections. The basic four tire architecture of ***Faculty Evaluation System*** is given below in Figure 1.

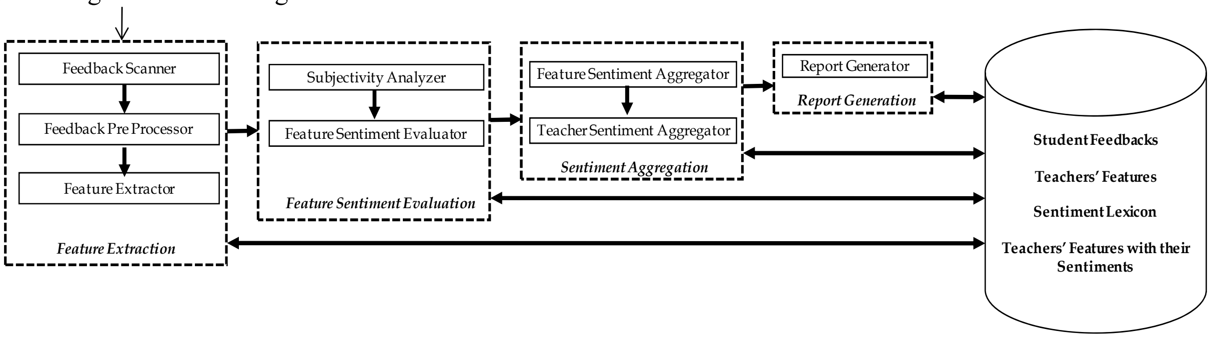

Figure 1: Architecture of Proposed Faculty Evaluation System

4. Feature Extraction

This Component consists of *Feedback Scanner*, *Feedback Pre Processor* and *Feature Extractor* modules**.** Major responsibilities of this component are to collect and combine the students' feedback from different sources, pre-process the collected feedbacks and identify all essential features (important features)for teachers (liked or disliked by the students). The three sub modules used in Feature Extraction are explained below.

4.1. Feedback Scanner

This It is a web crawler which automatically collects feedback of teachers from the specified sources and stores the data in a database. With the help of this module, we have collected feedback from two online platforms i.e. source1 [13] and source2 [14]. Different templates are required to collect feedbacks from different sources because each source has different patterns to store students' feedback. Input to this module is the address of remote source and template in which feedback has been stored. We also collected the textual feedbacks of 20 teachers of our college from 120 students of engineering stream.

4.2. Feedback Pre Processor

This module is responsible for removal of unwanted characters, irrelevant text, hyperlinks, HTML tags, images etc. Correction of misspelled words and text normalization are also done by this module. We have implemented this module using standard libraries of Python and NLTK.

4.3. Feedback Extractor

This is the main module of Feature Extraction component. Input to this module is pre processed feedbacks and output of this module is a list of important (essential) features. This module work in two phases, in the first phase all possible features for teacher are identified by extracting nouns and adjectives of each sentence and in the second phase irrelevant features is removed on the basis of their association with the sentiment words and the occurrence probability. We have used a semi supervised approach to implement Feature Extractor module.

This module is based on the approach proposed by Hu and Liu [1]. As mentioned in [1], we assume that the possible teachers' features are nouns, noun phrases, compound nouns and in addition to that we have also observed that not only nouns and compound nouns but other syntactic categories like adjectives, adverb may play an important role in providing features for sentiment analysis of professionals/ individuals. Therefore, we also include some adjectives and adverbs like *knowledgeable, conceptual, strong, friendly, encouragi*ng etc which are not sentiment bearing adjectives. So, in the first phase, we find all possible features (nouns, noun phrases, compound nouns and adjectives, adverb) from the collected feedbacks. This phase tries to dig all the main features of teachers observed by the students but during the processing it may contain many irrelevant words/phrases.

Inappropriate features are removed in the second phase using semi supervised approach combined with bootstrapping. Few well known features known as seed features are taken initially and with the help of this more features are added to the final list. It is assumed that valid features have similar context, or we can say features are paradigmatically related words. We iteratively increase the final list of features by choosing contextually related features which occur very frequently along with neighbouring sentiment words. This process is continued until all possible new features are added to the final list of features. In our experiment, we assume that those features are essential (important) features which are mentioned in at least 10% feedbacks. Steps of our proposed system are given below.

Algorithm for Feature Extraction:
Input: Pre Processed Feedbacks.
Output: List of essential (important) features for teachers'.

Step 1: *Extract all nouns, noun phrases and compound nouns from all feedbacks and add to the possible_features_list.*
Step 2: *Add selected modifiers (adjectives and adverbs)of 'teacher', 'institute' and 'subjects' (leaving usual modifiers like good, bad, awesome, worst etc) to the possible_feature_list.*
Step 3: *Add few well known features of teachers to the final_features_list as seed features.*
Step 4: *Compute the contextual information of all words /phrases present in final_features_list.*
Step 5: *Compute the contextual information of all words /phrases present in possible_features_list.*
Step 6: *Convert contextual information of words / phrases presented in possible_features_list and final_features_list in the form of vectors.*
Step 7: *Measure contextual similarity of each word/ phrase in possible_features_list to the words/phrases infinal_features_list.*

Step 8: *Add highly contextually similar words of possible_features_list to final_features_list if words frequently associated with sentiment words.*
Step 9: *Repeat step 2 to 8 until new words/ phrase are added to the existing final_features_list.*
Step 10: *Remove all words final_features_list whose frequency is less than threshold value. Frequency threshold value is decided experimentally.*
Step 11: *Remove invalid features (words / phrases) from final_features_list using linguistic and domain knowledge. Remaining words / phrases in final_features_list are the essential features for the teachers.*

5. Features Sentiment Evaluation

Feature Sentiment Evaluation component processes teacher wise feedback. System reads all the feedbacks of one teacher and stores the relevant information in a row. This way for all teachers a two dimensional table is generated. A row and a column represent a teacher and an essential feature. Cell (i,j) of table denotes sentiment score of feature 'j' for teacher 'i'. All objective sentences are ignored and for subjective sentences, sentiment biasness is computed on the basis of sentiment orientation and linguistic information of words present in the sentence. *Subjectivity Analyzer* and *Feature Sentiment Evaluator* modules are used to estimate sentiment scores of all essential features.

5.1. Subjectivity Analyzer

There are two types of sentences in the feedbacks: subjective sentences and objective sentences. Objective sentences have some factual information, in these types of sentences; students do not highlight any feature. For example: 'He is the Head of the Department', 'She is teaching us Computer Network.' In subjective sentences, students remark on their likes or dislikes about that teacher. Our system processes only subjective sentences and ignores objective sentences. To identify subjective sentences, we have used naïve based approach taking it as a two class classification problem. Input to the system is a training set. In training set, all the sentences are labeled with appropriate label i.e. subjective or objective. On the basis of input examples, Naïve Bayes algorithm generates probabilistic distribution of words for each class. On the basis of probabilities of words in different classes, it is determined whether the sentence is subjective or objective. Subjective analyzer forwards subjective sentences to next module for further processing and ignores objective sentences.

5.2. Feature Sentiment Evaluator

This module considers feedback student-wise at a time and tries to gather information for each essential feature from that feedback. While processing three possibilities may arise:

1. Essential features are present in the feedback and have positive orientation and such features are assigned above average score with the help of label 'good'.
2. Essential features are present in the feedback and have negative orientation and such features are assigned below average score with the help of label 'unsatisfactory'.
3. Essential features not present in the feedback are assigned a pre-defined average score with the help of label 'satisfactory'. Here it is assumed that students mention only those features in their feedback for which they feel strongly positive or negative. They do not explicitly specify about those features which are of average level. Therefore, a label 'satisfactory' is assigned to such features.

To compute sentiment scores of features, we need to classify the words as positive or negative according to the semantic weightage in the sentence. Many lexicons in open domain are available which provide sentiment scores but to get more domain dependent sentiment scores, we have developed domain specific teacher sentiment lexicon to get better sentiment scores for the features using bootstrapping technique. The algorithm to evaluate sentiment score for every feature of a teacher is given below.

Algorithm for Features Sentiment Evaluation
Input: Feedbacks given by the all students for a teacher, List of Features provided by Features Extraction module (essential / important features), Teacher Sentiment Lexicon.
Output: Assign a sentiment score to each feature for a teacher

Step **1**: *Select a feedback.*

Step 2: *Read the next sentence from the selected feedback.*
Step 3: *Pass the sentence to Subjectivity Analyzer module to determine whether the sentence is subjective or objective.*
Step 4: *If the sentence is objective then ignore it and go to the step 2, otherwise go to the step 5.*
Step 5: *Look for the features in the sentence and match it with the list provided by the Features Extraction module. If features match with the list provided by the Features Extraction module then go to step 6 otherwise go to step 2.*
Step 6: *If the part of speech of the identified feature is adjective or adverb, then sentiment label 'good' or 'unsatisfactory' is assigned by looking at the sentiment lexicon and sentiment shifter.*
Step 7: *If the part of speech of identified feature is noun or noun phrase, nearby qualifiers are extracted to estimate the sentiment value. If extracted qualifier is present in the positive lexicon then sentiment label 'good' is assigned otherwise 'unsatisfactory' is assigned. If any sentiment shifter present, sentiment shifter function is called.*
Step 8: *Go to the step 2 until all sentences of a feedback are processed.*
Step 9: *Average sentiment label 'satisfactory' is assigned to all other features not mentioned by the student in his / her feedback.*
Step 10: *Go to step 1 until all feedbacks are processed.*

6. Sentiment aggregation

Sentiment aggregation component is implemented through two modules: *Feature Sentiment Aggregator* and *Teacher Sentiment Aggregator*. Feature Sentiment Aggregator is responsible to estimate aggregate sentiment score of each essential features and Teacher Sentiment Aggregator estimates overall sentiment of each teacher by considering their all features sentiment scores.

6.1. Feature Sentiment Aggregator

Feature Sentiment Aggregator module is used to estimate comparative and aggregate sentiment scores of all essential features with respect to a teacher. Comparative sentiment score of an essential aspect for a teacher represents biasness of 'good'/ 'satisfactory' / 'unsatisfactory' with respect to total number of feedbacks. Comparative 'good' biasness of an essential aspect 'a' for a particular teacher 't' (good_pers (a, t)) is computed as.

$$\text{good\_pers (a, t)} = \frac{\text{Number of times feature 'a' is labeled as 'good' in all feedbacks of teacher 't'}}{\text{Total number of feedbacks of teacher 't'}} * 100 \quad (1)$$

In the above formula the variable 'a' may represent the feature 'Presentation' and variable 't' may represent a teacher named 'Aakash Verma' (fictitious name). Comparative biasness of 'satisfactory' and 'unsatisfactory' are computed in same way.
Aggregate sentiment score of an essential feature for a teacher is computed by considering all sentiments for that aspect. Aggregate sentiment score of an essential feature 'a' for a teacher (feature_aggregate_score (a, t)) is calculated using the formula given below. In this aggregation, we assign '+1' and '-1' sentiment score to each good and unsatisfactory feedbacks and sentiment score of satisfactory feedback is computed by fractional biasness of positivity and negativity for a particular feature 'a' for teacher 't'.
Let P,N and Neut is number of good, unsatisfactory and satisfactory feedbacks of a particular teacher 't' for a specific feature 'a'.

$$\text{feature\_aggregate\_score (a, t)} = \frac{P * (+1) + N * (-1) + \log\left(\frac{P+1}{N+1}\right) * Neut * (+1)}{P + N + \left|\log\left(\frac{P+1}{N+1}\right)\right| * Neut} \quad (2)$$

Value of feature_aggregate_score (a, t) is always between +1 and -1. This aggregation helps us, to estimate overall sentiment score of a feature. Aggregate score and Sentiment orientation of all essential aspects for teacher 'T1' is shown below in figure 2.

6.2. Teacher Sentiment Aggregator

This module assigns an effective sentiment score to each teacher. Effective sentiment score of a teacher represents the overall sentiment with respect to all essential features and all feedbacks. It is calculated by taking weighted average of feature aggregate score of all essential features of the teacher. Effective sentiment score of a teacher 't' (effective_senti_score(t)) is computed as.

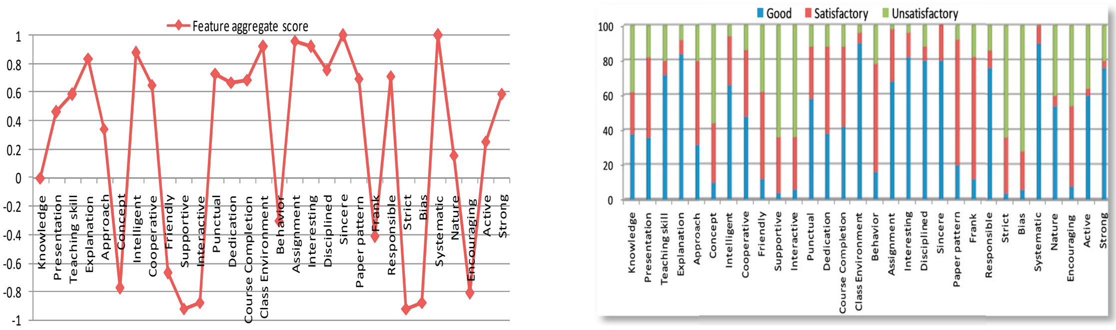

Figure 2: Aggregate score and Sentiment orientation of all essential aspects for teacher ‘T1’

$$\text{effective\_senti\_score(t)} = \frac{\sum_{a \in aspects} \text{feature\_aggregate\_score (a,t)} * weight(a,t)}{Total\ number\ of\ feedbacks for\ techer\ 't'} \tag{3}$$

$$\text{weight (a, t)} = \frac{\text{Number of feedbacks for techer 't' in which feature techer 'a' is mentioned}}{\text{Total number of feedbacks for techer 't'}} \tag{4}$$

In equation (3), feature_aggregate_score (a, t) and weight (a, t) are the aggregate sentiment score and weight of a feature ‘a’ for a teacher ‘t’ as computed in equation (2) and (4). Weight of a feature represents degree of inclusion of feature in the feedbacks. Effective sentiment score of teacher ‘T1’ is 0.1076.

7. Report Generation

Our proposed system can generate different kind of reports. Generated reports will be helpful for academic and administrative purposes. Some important reports are mentioned below with their utility.

7.1. Individual Teacher Report

Our system can generate a report for an individual teacher to display their effectiveness on all or selective features, this report will be helpful for teachers to identify their strong and weak features. Overall effectiveness of a teacher can be estimated by effective sentiment score. Individual Teacher Report of a teacher ‘T1’ is shown below in figure 3(a). From figure 4, we can conclude that teaching skill and explanation of teacher ‘T1’ is of above average level while he/she is not friendly and supportive.

7.2. Teachers Comparative Report

Proposed FES allows us to compare overall effectiveness of two or more teachers. We can compare two or more teachers with respect to selected or all essential features as shown in figure 3(a). Comparison of three teachers with respect to selected essential features is shown in figure 3(b). Figure demonstrates that ‘Teacher-3’ is better than ‘Teacher-1’ and ‘Teacher-2’ in most of the selected features.

7.3. Feature Grading Report

With the help of this report, we can grade essential features. Feature grade is a degree of remark mentioned in the feedbacks, as it shows the importance of a feature that how important it could be for a teacher. Grade of an essential feature is an overall weight and it is computed by similar formula used in equation (4). This report will be helpful during the selection of faculty members to evaluate his or her performance by considering the grading of features. From our experiment, we have found five important features which are knowledge, presentation, teaching skill, explanation and approach figure 4.

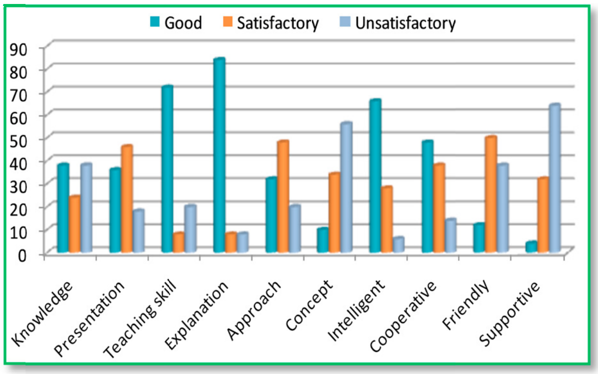

Figure 3(a): Individual Teacher Report of teacher 'T1'

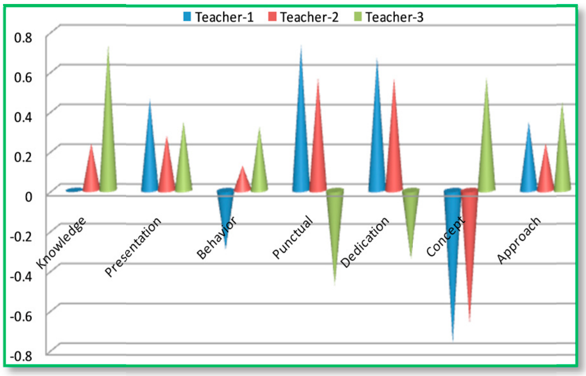

Figure 3(b): Teachers Comparative Report

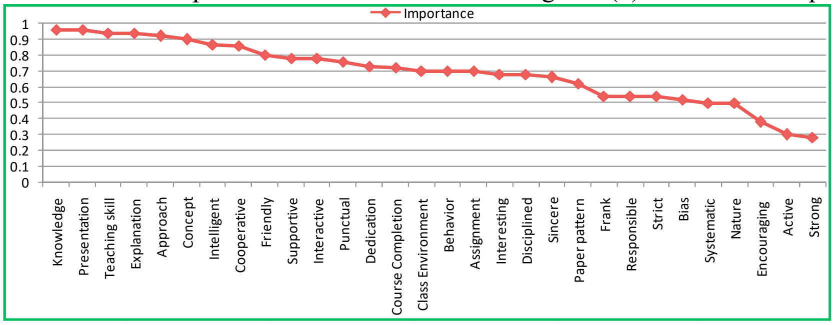

Figure 4: Feature Grading (Importance) Report

7.4. Committee Member Identification Report

A number of committees/ Cells are needed to fulfil the requirement of an institute or department. Each committee/cell is responsible for some specific task, to accomplish task successfully some compatible faculty (have specific qualities) members are required. For example in student counselling cell, faculty members have to be interactive, friendly, supportive and responsible etc. Our system helps in finding suitable faculty members for any committee/cell.

Our system is also able to perform gender and age base analysis of essential features. Impact of training, research and other administrative assignment on essential features can be captured with our proposed system. Such analysis will be helpful for the institute administration to take effective and quick decisions.

8. Result and Conclusion

Proposed Faculty Evaluation System (FES) is able to perform aspect based sentiment analysis of textual feedbacks collected from the students. Proposed FES is more versatile and useful than traditional questionnaire based system. Traditional questionnaire based system is very restricted; students can give their opinion (in form of marks or grade) only on those features which are mentioned in questionnaire. All features mentioned in questionnaire are decided by the institute administration and each feature has equal weigh while our proposed FES provides freedom to the students to express their opinion/review on any feature of the teacher. Essential features and their weights (importance) are computed statistically from the collected feedback as we have explained in Sentiment Aggregation section. We have experimented with 3235 feedbacks of sixty teachers collected from three different sources i.e. source1 [10], source2 [11] and source3 [12]. Main computational modules of FES are Feature Extractor, Sentiment Analyzer and Feature Sentiment Evaluator. To evaluate performance of our system, we have divided collected set into training and test sets. Average accuracies of main computational modules on different test sets are given below in table 1.

In the implementation of FES, we have evaluated sentiment score of each feature at scale of three i.e. 'good', 'satisfactory' and 'unsatisfactory'. To perform more grained sentiment analysis, our future plan is to use five scale sentiment score i.e. 'excellent', 'good', 'average', 'below average' and 'unsatisfactory' and make use of domain dependent linguistic knowledge to enhance accuracy of FES.

Table 1: Average accuracies of system FES Modules

Module	Average Accuracy in percentage		
	Source-1	Source-2	Source-3
Feature Extractor	85.46	86.67	87.49
Sentiment Analyzer	79.78	82.35	81.49
Feature Sentiment Evaluator	82.85	83.13	82.36

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