

Customers Sentiment on Banks

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ABSTRACT

Social media has revolutionized the new-age customer's decision making through the myriads of sources available to them like online feedback or reviews, forum discussions, blogs and Twitter on the web. There is no need for them to depend on their peers any longer. When more convenient and efficient sources like user reviews are readily available to them over the internet. Vast and authentic information about all possible products ranges and services are at a click away. Even for commercial organization the task of gathering public opinion has been rendered tremendously easy, for the same reason that taking opinion polls and conducting surveys are now much simpler due to the abundance of information on the web. However, finding and monitoring opinion sites on the Web and filtering the information contained in them according to our need remains a difficult task because of the rapid increase in the number of distinct sites. Each site usually contains a huge volume of opinionated text which is difficult for any individual to go through. The average human reader will have difficulty identifying relevant sites and extracting and summarizing the opinions in them. Automated sentiment analysis systems are thus needed. This paper focuses on extracting the features from bank reviews taken from mouthshut.com and myBankTracker.com sites given by reviewers to state their opinions. This is done at aspect level of analysis using ontology. Then it determines whether they are positive or negative. Output of such analysis is then summarized.

General Terms

Natural Language Processing, Opinion Mining

Keywords

Sentiment Analysis, Opinion Mining, Ontology, Bank.

1. INTRODUCTION

In this era of internet one is surrounded by digital world with lot of information on the web. Now getting the opinions or sentiments about a topic such as reviews on software, product, films, music, and books etc are quite easy. Each site typically contains a huge volume of opinion text that is not always easily deciphered in long blogs and forum postings. Automated sentiment analysis systems are thus needed to separate the factual statements and opinionated statements. *Opinion mining*, a sub discipline within data mining and computational linguistics, refers to the computational techniques for extracting, classifying, understanding, and assessing the opinions expressed in various online news sources, social media comments, and other user-generated content. Sentiment analysis is often used in opinion mining to identify sentiment, affect, subjectivity, and other emotional states in online texts [1].

In this paper, we present an ontology based feature extraction of a bank review and analyze the sentiment of the review for

financial domain. The proposed methodology takes the bank review from mouthshut.com and myBankTracker.com site. The reviews are read manually and ontology is built based on the features in the bank domain supported by natural language processing method. This in turn is useful to the users to view the interpretation of the reviews without actually reading it. The system takes the review in the form of a text file and processes it; it is then passed to the parser where each word in the sentence is tagged. Based on the particular tag given to each word, nouns are sent to the Ontology where the feature determining word is found. Later Sentence with the feature carrying word is processed and filtered using type dependencies and then passed to mining algorithm to obtain the result. SentiWordNet and S-Word list are used to determine the scores of the sentiment carrying word. The result so obtained at document level obtained is aggregated and converged to a particular bank.

The rest of the paper is organized as follows. Some relevant related works are shown in Section 2. Section 3 presents the architecture of system design to describe the way the system works. Section 4 shows the experimental results for the system. Finally, some conclusions and future work are put forward in Section 5 and Section 6.

2. RELATED WORK

The early research work of sentiment analysis is done on different levels like document, sentence and feature level. In *document level* the opinion is on single entity or the document as a whole. In *sentence level* the opinion analysis is done on each sentence to determine opinion polarity. *Feature Level or Aspect level* is used to analyze the sentiment of a statement at a lower level and directly looks at the sentiment itself [2].

Feature based sentiment classification done in previous research work [3, 4] was based on feature selection and extraction which was done by finding the sentiment words in the document and also the feature to which they refer. When it comes to feature extraction the sentence on which opinion is given has some target which needs to be extracted. The research work for feature level sentiment analysis is done for movies, hotels and products. The feature can be expressed *explicitly* in the sentence or can be *implicit* (hidden) within the sentence.

Example: (1) The internet banking of ABC bank is extremely pathetic.

(2) I bet if you don't fail 3 out of 10 times in online transactions.

The above two are the sentiment examples on the aspect "*internet banking*" but the first one is explicit and the second one is implicit.

2.1 Feature extraction

It is a task of extracting the aspects or feature. For example, "The customer service of XYZ bank is frustrating" the feature is "customer service" of the entity "XYZ bank". In the above

example the opinion “frustrating” is not about the “bank” but about the “customer service”.

The explicit feature can be extracted as:

- Depending on frequency of nouns and noun phrases
- Based on the relations between Opinion and Target.

2.1.1 Feature Extraction depending on frequency of nouns and noun phrases

The method proposed by Hu and Liu (2004) was to read a number of reviews and extract nouns and noun phrases identified by part-of-speech (POS) tagger from it. The threshold value was set and compared with the extracted frequently occurring words. Only if the word count was greater than the threshold the word was identified as a feature. The method proposed by (Blair-Goldenson et.al, 2005) improved the previous method by considering the frequent occurring noun phrases that are present only in the sentiment statements. The candidate aspects are collapsed at the word stem level and are manually weighted according to their frequency.

2.1.2 Feature extraction based on the relations between Opinion and Target.

The opinions and targets are often related to each other and so using the sentiment words which are already known the target features can be extracted. If the feature is not so important than nobody will express any opinion about it.

(Hu and Liu, 2004) proposed the method for extracting the infrequent aspects using the “nearest” function to find the dependency relation between the sentiment word and nearest noun or noun phrase that it modifies. For example “*ABC bank is the best.*”, if we know “best” is the sentiment word in this example then “bank” is extracted as a feature.

The method proposed by (Zhuang, Jing and Zhu, 2006) extracted the aspects based on dependency relations by using a dependency parser.

(Qiu et al.; 2011) proposed a double propagation method using dependency relationship for extraction of both sentiment words and aspects.

Instead of using a normal dependency parser a phrase dependency parser was used in (Wu et al.; 2009) for extraction of noun phrases and verb phrases, which can be more suitable for aspect extraction [2].

2.2 Ontology

It is designed to provide domain related knowledge that can be understandable by the system and the user. It is a conceptualization of a domain (Gruber 1993) which consists of concepts and their relationship. We used the domain ontology to get the domain related features. Our approach is driven by Lizhen Liu [5], which proposed a Fuzzy Domain Sentiment Ontology Tree (FDSOT) for Sentiment Analysis of product reviews. The FDSOT was designed to contain the product attributes and their positive and negative sentiment words. But in our approach we have created the ontology to contain only the Bank Features and not the sentiment words. As in bank domain the same sentiment words may belong to more than one feature.

2.3 Type Dependency and Relation

Stanford dependency representation allows each word to have multiple governors. The parsers may generate a different number of dependencies for each sentence. The dependency

parsers require that the data is part-of-speech tagged. The Stanford typed dependencies representation was designed to provide a simple description of the grammatical relationships in a sentence that can easily be understood and used by people without linguistic expertise who want to extract textual relations [6]. Mukherjee and Bhattacharyya [7] used dependency parser to find the association between opinion expression and features.

3. ONTOLOGY DRIVEN SENTIMENT ANALYSIS FOR BANKING SERVICES (ODSAFBS)

3.1 Architecture

The architecture of ODSAFBS is illustrated in Figure 1. The architecture is divided into data collection, pre-processing, ontology building, review classification, summary generation as shown in the (Figure 1). An ODSAFBS is aimed at generating a summary classification from multiple reviews of banks.

The objective of the work is to perform sentiment analysis by extracting the features from bank reviews given by reviewers to state their opinions. In the ODSAFBS architecture the set of reviews were collected from mouthshut.com and myBankTracker.com sites. Each text review contained number of sentences with or without sentiment. The preprocessing was performed by splitting each review into sentences, removing the stop words and repeated characters. The preprocessed sentences were parsed using Stanford Parser for assigning part of speech tags to each word. The nouns were extracted from each sentence and compared with the predesigned bank feature ontology. If bank feature was present in the sentence then the required type dependencies were found and based on that the sentiment word was extracted for that feature. Finally the polarity value was found using SentiWordNet3 [8] and S-Word list for a sentence. The same process was repeated for the complete review to determine whether the review was positive or negative. The work focused at the feature level of analysis. Output of such analysis was then summarized and aggregated which was easily understood by the customer.

Algorithm Steps:

For each review:

- I. Select a sentence from the review.
- II. Parse the sentence using Stanford Parser.
- III. Find features (target words) using ontology within that sentence.
- IV. If the feature is found then using type dependencies extract the sentiment carrying words.
- V. For extracting the sentiment carrying word use sentiment extraction algorithm.
- VI. Check SWord List to find sentiment carrying word.
- VII. Extract polarity using SentiWordNet3.
- VIII. Assign net polarity to target sentiment word.
- IX. Classify and aggregate result.

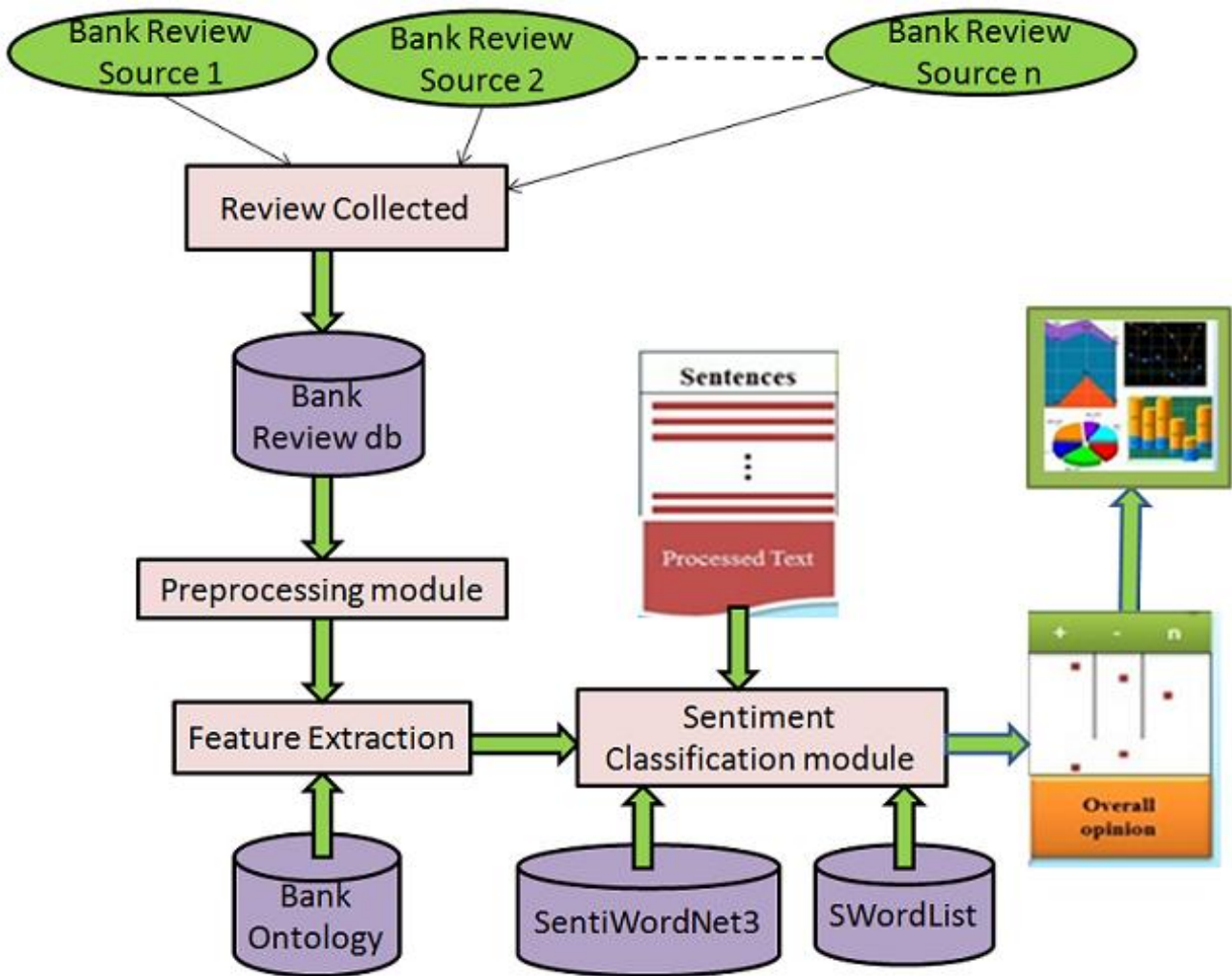


Fig 1: Architecture for “Ontology Driven Sentiment Analysis for Banking Services (ODSAFBS)”

3.2 Bank Ontology Design for Feature Extraction

The design process of bank ontology started with the top down approach. The features related to the bank domain were extracted based on the frequency count of nouns in the set of bank reviews collected from mouthshut.com site. The features were cross verified by manually going through the reviews. The graphical representation of the part of bank ontology created for bank features is illustrated in Figure 2.

The ontology starts with bank as the root node. Customers generally give feedback on customer care, net banking and charges imposed. So these are the main features under bank domain. These main features will still have some sub features for example; net banking as a root node will have sub features as availability, security and many more as can be seen in the Figure 2. Apart from these 3 main features the remaining features of bank domain were kept under miscellaneous.

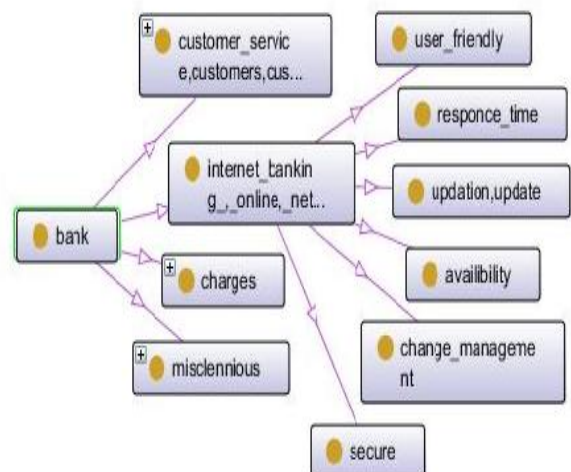


Fig 2: A part of Bank Feature Ontology (FO)

3.3 Sentiment Extraction Algorithm

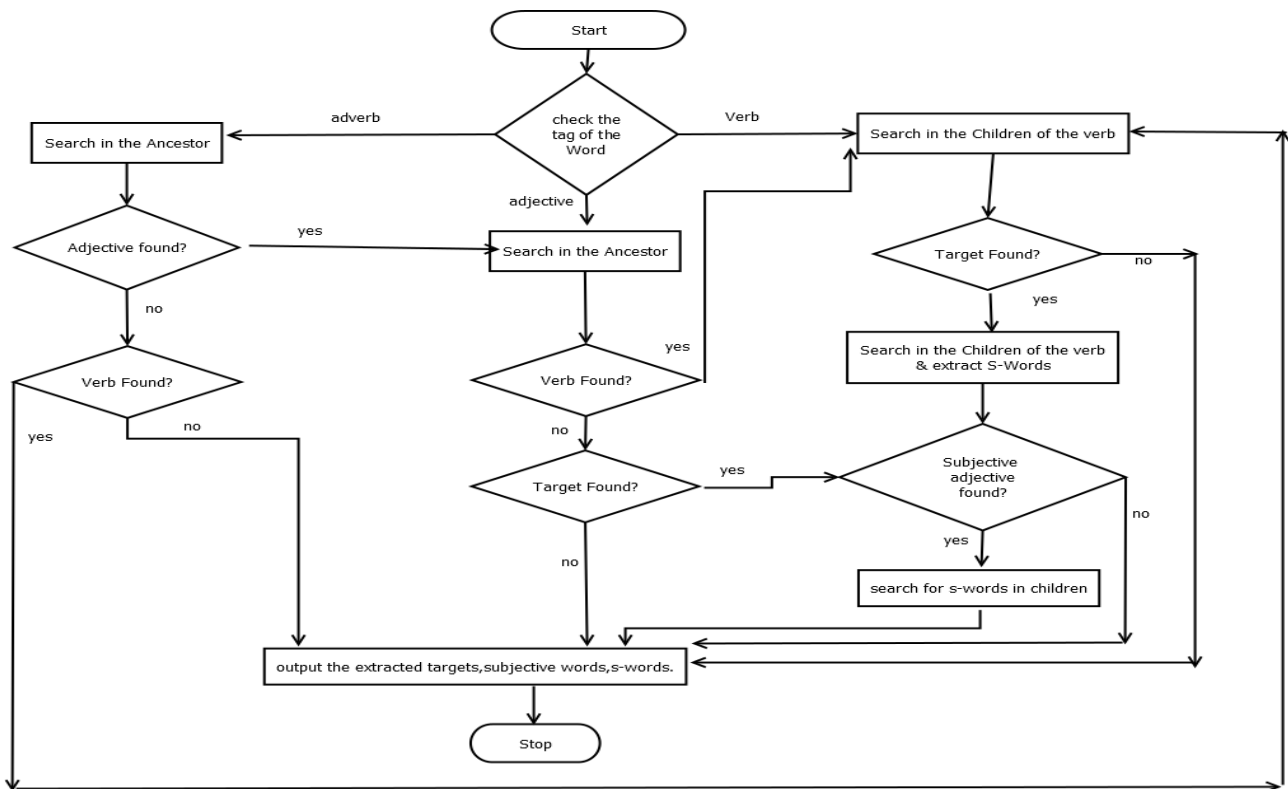


Fig 3: Sentiment Extraction Algorithm Flowchart

In the previous step using bank ontology, if the feature is present in the sentence of the review, then that sentence is passed into the sentiment extraction algorithm to get the sentiment about that feature using the dependency relation. The algorithm steps are shown in the form of flowchart in Figure 3.

The type dependencies used in the experiment are **nsubj, prep, dobj, agent, advmod, amod, nn, neg, prep_of, acomp, xcomp, appos**

For example, in a sentence from axis bank review text file:
“World Worst Bank, slow Internet banking, not good customer service Axis bank “.

The sentence of the axis bank review along with POS tagging is stored in the table 1 after preprocessing.

Table 1. Snapshot of Review Sentence

| Sentence | Tagging | Words |
|---|---|--|
| world worst bank , slow internet_banking , not go... | NN JJS NN NNP JJ NN NNPRB JJ NN NN NNP | world worst bank , slow internet_banking , not go... |

In the review sentence of the example there are three features bank, internet banking and customer service along with positive and negative sentiment words worst, slow, good and a negation word not which change the polarity.

Table 2 contains the details about the relation type dependencies parent, child their position and POS tags in sentence. These positions are required to get the nearest sentiment of the extracted feature.

Table 2. Snapshot of Review Type Dependency

| Relation Type | parent | child | pWord No | cWord No | pTag | cTag |
|---------------|------------------|------------------|----------|----------|------|------|
| nsubj | customer service | world | 10 | 1 | NN | NN |
| amod | bank | worst | 3 | 2 | NN | JJS |
| dep | world | bank | 1 | 3 | NN | NN |
| amod | world | slow | 1 | 5 | NN | JJ |
| dep | slow | internet banking | 5 | 6 | JJ | NN |
| neg | good | not | 9 | 8 | JJ | RB |
| amod | world | good | 1 | 9 | NN | JJ |
| dobj | customer service | bank | 10 | 11 | NN | NN |

The sentiment word can be directly obtained from above table

1. if(feature obtained from ontology is same as parent word).
2. if(child tag starts With ("JJ") || ("NN") || ("VB") || ("RB"))
3. If child word is present in the SentiWordNet or S-word list

For example, in row number 2 of table 2 the feature “bank” of ontology is same as the parent word “bank”. The child tag is JJS which starts with JJ and the child word “worst” is present in the sentiment word list and the polarity is assigned using SentiWordList and S-word list as shown in table 3.

Table 3. Snapshot of Feature Sentiment Pair and Score

| Feature | Sentim | SwordScore | Sword |
|------------------|----------|----------------------|-------|
| bank | worst | -0.5 | -3 |
| internet_banking | slow | -0.08843537414965988 | -2 |
| customer_service | not good | -0.6337632198238539 | -2 |

But many times the sentiment words for the feature cannot be directly obtained and for that the indirect method of sentiment extraction algorithm is used as shown in Figure 3.

3.4 Polarity Assignment to Sentiment Word

After extracting sentiment word for the feature the polarity is assigned to the sentiment word using two lists: *SentiWordNet3* and *S-word*.

3.4.1 SentiWordNet

ODSAFBS uses the SentiWordNet to retrieve the scores of the sentiment words. SentiWordNet is a ‘lexical resource’, where each WordNet Synset(set of synonyms) is associated to positive and negative scores which are represented in the snapshot of SentiWordNet3 in Table 4, describing positivity and negativity of the terms present in the Synsets. The range of the scores for each Synset is between ‘0.0 to 1.0’. The same sentiment word can have different score based on the POS tag in the sentence [8].

Table 4. Snapshot of SentiWordNet3

| #POS | ID | PosScore | NegScore | SynsetTerms |
|------|--------|----------|----------|-------------|
| a | 229630 | 0.25 | 0.75 | Worst#1 |
| n | 127672 | 0 | 0.875 | Worst#3 |

3.4.2 S-word list

S-word list is a combination of domain specific words carrying sentiments and the Emotion Look-Up Table of the SentiStrength database. S-Word list is used in ODSA FBS to get the positive and negative scores. ‘The SentiStrength is a lexicon of 2310 sentiment words and word stems obtained from the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker, Mehl, & Niederhoffer, 2003), the General Inquirer list of sentiment terms (Stone, Dunphy, Smith, & Ogilvie, 1966) and ad-hoc additions made during testing, particularly for new CMC words.’ For each text, SentiStrength outputs a positive sentiment score from 1 to 5 and a negative score from -1 to -5. SentiStrength also provides a Booster word list which radically changes the polarity level of sentiment word. Negation words are certain words, which invert the polarity of the sentiment score in the sentence [9].

Table 5. Snapshot of S-Word list

| S-word | Score |
|----------|-------|
| response | 1 |
| worst | -3 |
| slow | -2 |
| good | 2 |

4. EXPERIMENTAL RESULTS

The system is based upon two aspects. One being that the user does not have to read a number of reviews to make a judgment toward a bank. Instead of that the user can go through the analysis result, which is indeed based upon the sentiment analysis of the reviews for a particular bank. Another aspect being that the user can enter their review and its scoring can dynamically be generated and displayed respectively. The experiment was performed on bank reviews collected manually and stored in the database. Not all the sentences in each review contained sentiment. The sentences containing features were extracted from a review for finding the corresponding sentiment, if any. The extracted feature and sentiment word along with the sentiment score for each pair in the sentence were stored in the database as shown in table 3. The aggregated positive and negative score for each review was calculated (using table 3) for all the features like bank

(bpos and bneg), charge (chargepos and chargeneg), customer care (custpos and custneg), internet banking (ibpos and ibneg) and miscellaneous (mispos and misneg) and stored in database. The total count of positive and negative sentiment pairs along with the net positive and net negative scores were stored in database as shown in table 6 for S-word list and SentiWordNet.

Table 6. Experiment Result

| Snapshot of Review Scores using S-word list | | | | | | | | | | | | | | |
|---|----------|----------|-----------|-----------|----------|----------|----------|----------|--------|--------|----------|----------|----------|----------|
| review | bpos | bneg | chargepos | chargeneg | custpos | custneg | ibpos | ibneg | mispos | misneg | countpos | countneg | netpos | netneg |
| hdfc9 | 1.33339 | -1 | 0 | 0 | 3.676334 | 0 | 0 | 0 | 0 | 0 | 5 | 2 | 15.53035 | -1.1 |
| hdfc15 | 0.329545 | -1.13636 | 0 | -0.5 | 0 | -0.11826 | 0 | 0 | 0 | 0 | 1 | 4 | 0.329545 | -2.26998 |
| icici7 | 0 | -0.64773 | 0 | 0 | -0.25993 | 0 | 0 | 0 | 0 | 0 | 1 | 3 | 0 | -0.90356 |
| axis5 | 0 | 0 | 0 | 0 | -1.13636 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | -2.63636 |
| icici11 | 0 | 0 | 0 | 0 | 0.99099 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0.784091 | 0 |
| hdfc1 | 0 | -0.11826 | 0 | 0 | 0.361408 | 0 | 0.361408 | -0.11826 | 0 | 0 | 2 | 3 | 0.722816 | -0.23653 |
| axis17 | 0 | 0 | 0 | -0.61382 | 0.09121 | -2.42459 | 0.375 | -0.97523 | 0 | 0 | 5 | 10 | 0.492364 | -12.2982 |
| sbi45 | 0 | 0 | 0 | -0.30682 | 0.809056 | -0.7062 | 0 | 0 | 0 | 0 | 4 | 3 | 1.912342 | -1.51302 |
| axis46 | 0 | 0 | 0 | -0.3 | 0.526875 | -0.35479 | 0 | -0.61826 | 0 | 0 | 2 | 0 | 0.542386 | -3.23785 |

| Snapshot of Review Scores using SentiWordNet | | | | | | | | | | | | | | |
|--|------|------|-----------|-----------|---------|---------|-------|-------|--------|--------|----------|----------|--------|--------|
| review | bpos | bneg | chargepos | chargeneg | custpos | custneg | ibpos | ibneg | mispos | misneg | countpos | countneg | netpos | netneg |
| hdfc9 | 7 | 4 | 0 | -0 | 88 | 0 | 0 | 0 | 0 | 0 | 11 | 2 | 89 | -9 |
| hdfc15 | 3 | -5 | 0 | -3 | 1 | 0 | 0 | 0 | 0 | 0 | 2 | 3 | 4 | -30 |
| icici7 | 0 | -1 | 0 | -2 | 2 | -3 | 0 | 0 | 0 | 0 | 1 | 4 | 2 | -7 |
| axis5 | 0 | 0 | 0 | 0 | 3 | -4 | 0 | 0 | 0 | 0 | 2 | 2 | 4 | -6 |
| icici11 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 2 | 2 | 0 | 4 |
| hdfc1 | 1 | 0 | 0 | 0 | 2 | -1 | 1 | -1 | 0 | 0 | 3 | 2 | 4 | -2 |
| axis17 | 0 | 0 | 0 | 0 | 0 | -2 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | -2 |
| sbi45 | 0 | 0 | 0 | -3 | 4 | -6 | 0 | 0 | 0 | 0 | 2 | 3 | 7 | -32 |
| axis46 | 0 | 0 | 0 | -3 | 4 | -2 | 1 | -3 | 0 | 0 | 4 | 3 | 0 | -8 |

The aggregated score of all the four banks were calculated based on table 6 as shown in table 7 and table 8 and the graphical representation of the same is shown in figure 4 and figure 5.

Table 7: Aggregated score for Banks using S-word list

| Banks | countPos Pairs | NetPos Score | NetPos Score / countPos Pairs | countNeg Pairs | NetNeg Score | NetNeg Score / countNeg Pairs |
|-------|----------------|--------------|-------------------------------|----------------|--------------|-------------------------------|
| axis | 42 | 133 | 3.166667 | 68 | -361 | -5.30882 |
| hdfc | 44 | 177 | 4.022727 | 48 | -239 | -4.97917 |
| icici | 33 | 87 | 2.636364 | 32 | -98 | -3.0625 |
| sbi | 51 | 155 | 3.039216 | 49 | -203 | -4.14286 |

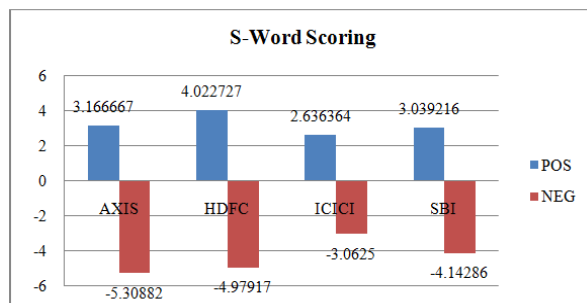


Fig 4: Analysis Result Using SentiWordNet Scoring

Table 8: Aggregated score for Banks using SentiWordNet

| Banks | countPos Pairs | NetPos Score | NetPos Score / countPos Pairs | countNeg Pairs | NetNeg Score | NetNeg Score / countNeg Pairs |
|-------|----------------|--------------|-------------------------------|----------------|--------------|-------------------------------|
| axis | 34 | 10.16776 | 0.299052 | 66 | -41.8269 | -0.63374 |
| hdfc | 40 | 24.77252 | 0.619313 | 38 | -22.4371 | -0.59045 |
| icici | 21 | 10.48259 | 0.499171 | 32 | -11.1587 | -0.34871 |
| sbi | 46 | 23.31279 | 0.5068 | 39 | -16.7909 | -0.43054 |

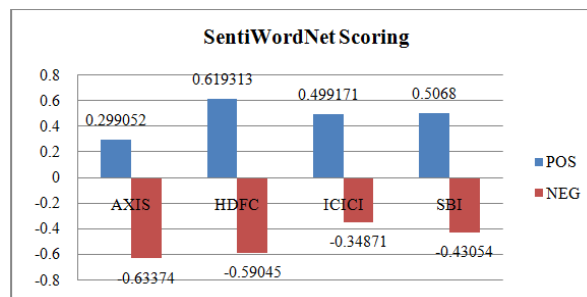


Fig 5: Analysis Result Using SentiWordNet Scoring

In the set of 100 reviews 279 feature sentiment pairs were extracted from which 75 were true positive sentiment feature pairs and 129 were true negative sentiment feature pairs. The remaining 75 pairs were falsely predicted. The sentiment feature pair prediction for bank reviews is shown in table 9.

Table 9. Sentiment Feature Pair Prediction

| Actual class | Predicted Class | |
|--------------------|--------------------|--------------------|
| | Positive Sentiment | Negative Sentiment |
| Positive Sentiment | 75(TP) | 21(FN) |
| Negative Sentiment | 54(FP) | 129(TN) |

Accuracy: It provides the accuracy of the system with respect to correctly identified positive and negative sentiment and their feature.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (eq. 1)$$

True Positive (TP): No of correctly identified positive sentiment feature pairs.

True Negative (TN): No of correctly identified negative sentiment feature pairs.

False Positive (FP): No of negative sentiment feature pairs identified as positive.

False Negative (FN): No of positive sentiment feature pairs identified as negative.

The accuracy for bank review is calculated using the formula in (eq. 1).

$$Accuracy = \frac{(75+129)*100}{(75+21+54+129)} = 73.11828 \quad (eq. 2)$$

The graphical representation of analysis of bank reviews is shown in figure 6.

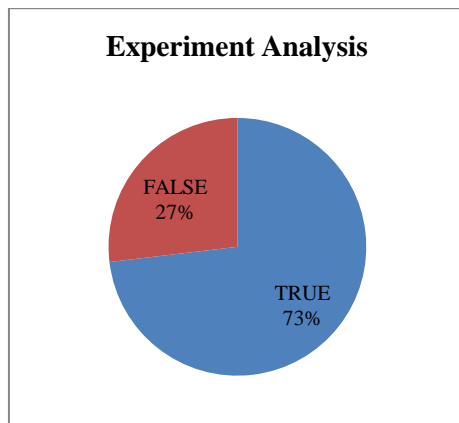


Fig 6: Bank Review Detection Analysis

5. CONCLUSION

ODSAFBS address the Sentiment Analysis problem from the end user’s perspective. With hundreds of reviews about a single entity, it is practically not feasible to go through all the reviews so as to get useful information. The research uses a combination approach of domain ontology and Stanford dependency relation which intends to enhance the sentiment classification. By using this approach one can view the strength or the weakness of the features of a particular bank in more detail.

6. FUTURE WORK

There is a further scope of an analysis for comparative type of review where two or more banks could be compared.

7. ACKNOWLEDGMENTS

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8. REFERENCES

- [1] Chen, H., Zimbra, D, “AI and opinion mining. Intelligent Systems”, IEEE. 25(3), pp. 74-80 (2010).
- [2] Bing Liu, “Sentiment Analysis and Opinion Mining”, Morgan & Claypool Publishers, May 2012.
- [3] Tushar Ghorpade, ”Feature based Sentiment Classification for Hotel Reviews using NLP and Bayesian Classification”, Proceedings of 2012 International Conference on Communication, Information & Computing Technology (ICCICT), Oct. 19-20, Mumbai, India.
- [4] Vipin Kumar, Sonajharia Minz, “Mood Classification of Lyrics using SentiWordNet”, 2013 International Conference on Computer Communication and Informatics (ICCCI -2013), Jan. 04 – 06, 2013, Coimbatore, INDIA.
- [5] Lizhen Liu, Xinhui Nie, Hanshi Wang, “Towards a Fuzzy Domain Sentiment Ontology Tree for Sentiment Analysis”, Proceeding of International Conference on Image and Signal Processing (CISP), IEEE, 2012.
- [6] “Stanford typed dependencies manual”, Marie-Catherine de Marne_e and Christopher D. Manning, September 2008.
- [7] Subhabrata Mukherjee and Pushpak Bhattacharyya, “Feature Specific Sentiment Analysis for Product Reviews”, Department of Computer Science and Engineering, IIT Bombay.
- [8] Andrea Esuli, “SENTIWORDNET: A Publicly Available Lexical Resource for Opinion Mining”, fifth international conference on Language Resources and Evaluation, LREC 2006.
- [9] Mike Thelwall, “Heart and Soul: Sentiment Strength Detection in the Social Web with SentiStrength”.