Sentiment Analysis of Movie Reviews

A new Feature-based Heuristic for Aspect-level Sentiment Classification

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***Abstract*—This paper presents our experimental work on a new kind of domain specific feature-based heuristic for aspect-level sentiment analysis of movie reviews. We have devised an aspect oriented scheme that analyses the textual reviews of a movie and assign it a sentiment label on each aspect. The scores on each aspect from multiple reviews are then aggregated and a net sentiment profile of the movie is generated on all parameters. We have used a SentiWordNet based scheme with two different linguistic feature selections comprising of adjectives, adverbs and verbs and n-gram feature extraction. We have also used our SentiWordNet scheme to compute the document-level sentiment for each movie reviewed and compared the results with results obtained using Alchemy API. The sentiment profile of a movie is also compared with the document-level sentiment result. The results obtained show that our scheme produces a more accurate and focused sentiment profile than the simple document-level sentiment analysis.**

Keywords: Sentiment Analysis, SentiWordNet, Aspect Oriented Sentiment Analysis, Movie Review Mining.

I. INTRODUCTION

Sentiment analysis is language processing task that uses a computational approach to identify opinionated content and categorize it as positive or negative. The unstructured textual data on the Web often carries expression of opinions of users. Sentiment analysis tries to identify the expressions of opinion and mood of writers. A simple sentiment analysis algorithm attempts to classify a document as 'positive' or 'negative', based on the opinion expressed in it. The document-level sentiment analysis problem is essentially as follows: Given a set of documents D, a sentiment analysis algorithm classifies each document $d \in D$ into one of the two classes, *positive* and *negative*. Positive label denotes that the document *d* expresses a positive opinion and negative label means that *d* expresses a negative opinion of the user. More sophisticated algorithms try to identify the sentiment at sentence-level, feature-level or entity-level.

There are broadly three types of approaches for sentiment classification of texts: (a) using a machine learning based text classifier -such as Naïve Bayes, SVM or kNN- with suitable feature selection scheme; (b) using the unsupervised semantic orientation scheme of extracting relevant n-grams of the text and then labeling them either as positive or negative and consequentially the document; and (c) using the SentiWordNet based publicly available library that provides positive, negative and neutral scores for words. Some of the relevant past works on sentiment classification can be found in [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11] and [12].

The new user-centric Web hosts a large volume of data created by various users. Users are now co-creators of web content, rather than being passive consumers. The social media is now a major part of the Web. The statistics shows that every four out of five users on the Internet use some form of social media. The user contributions to social media range from blog posts, tweets, reviews and photo/ video uploads etc. A large amount of the data on the Web is unstructured text. Opinions expressed in social media in form of reviews or posts constitute an important and interesting area worth exploration and exploitation. With increase in accessibility of opinion resource such as movie reviews, product reviews, blog reviews, social network tweets, the new challenging task is to mine large volume of texts and devise suitable algorithms to understand the opinion of others. This information is of immense potential to companies which try to know the feedback about their products or services. This feedback helps them in taking informed decisions. In addition to be useful for companies, the reviews and opinion mined from them, is helpful for users as well. For example, reviews about hotels in a city may help a user visiting that city locating a good hotel. Similarly, movie reviews help other users in deciding whether the movie is worth watch or not.

In this paper we have attempted to explore a new SentiWordNet based scheme for both document-level and aspect-level sentiment classification. The document-level classification involves use of different linguistic features (ranging from Adverb+Adjective combination to Adverb+Adjective+Verb combination). We have also devised a new domain specific heuristic for aspect-level sentiment classification of movie reviews. This scheme locates the opinionated text around the desired aspect/ feature in a review and computes its sentiment orientation. For a movie, this is done for all the reviews. The sentiment scores on a particular aspect from all the reviews are then aggregated. This process is carried out

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for all aspects under consideration. Finally a summarized sentiment profile of the movie on all aspects is presented in an easy to visualize and understandable pictorial form. The rest of the paper is organized as follows. Section II describes the basic approach of the SentiWordNet formulation for sentiment classification, along details of our implementation. Section III describes the dataset used and performance metrics computed. Section IV presents the results and the paper concludes with key observations in Section V.

II. Algorithmic Formulation

We have based our computational method on the publicly available library SentiWordNet [13]. The SentiWordNet approach involves obtaining sentiment score for each selected opinion containing term of the text by a lookup in its library. In this lexical resource each term *t* occurring in WordNet is associated to three numerical scores obj(t), pos(t) and neg(t), describing the objective, positive and negative polarities of the term, respectively. These three scores are computed by combining the results produced by eight ternary classifiers. To make use of SentiWordNet we need to first extract relevant opinionated terms and then lookup for their scores in the SentiWordNet. Use of SentiWordNet requires a lot of decisions to be taken regarding the linguistic features to be used, deciding how much weight is to be given to each linguistic feature, and the aggregation method for consolidating sentiment scores. We have implemented the SentiWordNet based algorithmic formulation for both document-level and aspect-level sentiment classification.

A. Document-level Sentiment Classification

The document-level sentiment classification attempts to classify the entire document (such as one review) into 'positive' or 'negative' class. The approaches based on SentiWordNet targets the term profile of the review document and extract terms having desired POS label (such as adjectives, adverbs or verbs). This clearly shows that before applying the SentiWordNet based formulation; the review text should be applied to a POS tagger which tags each term occurring in the review text. Then some selected terms (with desired POS tag) are extracted and the sentiment score of each extracted term is obtained from the SentiWordNet library. The scores for all extracted terms in a review are then aggregated using some weightage and aggregation scheme. Thus two key issues are to decide (a) which POS tags should be extracted, and (b) how to decide the weightage of scores of different POS tags extracted while computing the aggregate score.

We have explored with different linguistic features and scoring schemes. Computational Linguists suggest that adjectives are good markers of opinions. For example, if a review sentence says "The movie was excellent", then use of adjective 'excellent' tells us that the movie was liked by the reviewer and possibly he had a wonderful experience watching it. Sometimes, Adverbs further modify the opinion expressed in review sentences. For example, the sentence "The movie was extremely good" expresses a more positive opinion about the movie than the sentence "the movie was good". A related previous work [14] has also concluded that 'Adverb+Adjective' combine produces better results than using adjectives alone. Hence we preferred the 'adverb+adjective' combine over extracting 'adjective' alone. The adverbs are usually used as complements or modifiers. Few more examples of adverb usage are: *he ran quickly, only adults, very dangerous trip, very nicely, rarely bad, rarely good etc*. In all these examples adverbs modify the adjectives. Though adverbs are of various kinds, but for sentiment classification only adjectives of degree seem useful.

Some previous works have suggested exploiting the 'verb' POS tags in addition to 'adjective' for sentiment classification. Here, we have explored with two linguistic feature selection schemes. In one we only extract 'adjectives' and any 'adverbs' preceding the selected adjective. In the other one we extract both 'adjectives' and 'verbs', along with any 'adverbs' preceding them. Since, adverbs are modifying the scores of succeeding terms, it needs to be decided as to what proportion the sentiment score of an 'adverb' should modify the succeeding 'adjective' or 'verb' sentiment score, to achieve higher accuracy. We have taken the modifying weightage (scaling factor) of adverb score as 0.35, based on the conclusions reported in [14] and [11]. The other main issue that remains to be addressed is how should the sentiment scores of extracted 'adverb+adjective' and 'adverb+verb' combines be aggregated. For this we have tried different weight factors ranging from 10% to 100%, i.e. the 'adverb+verb' scores are added to 'adverb+adjective' scores in a weighted manner.

In the first scheme of using only 'adverb+adjective' combine, we have chosen a scaling factor sf = 0.35. This is equivalent to giving only 35% weight to adverb scores. The modifications in adjective scores are thus in a fixed proportion to adverb scores. Since we chose a value of scaling factor sf = 0.35, the adjective scores will get a higher priority in the combined score. The indicative pseudo-code of key steps for this scheme i.e. SentiWordNet (AAC) is illustrated below. Here AAC refers to Adverb+Adjective Combine.

```
For each sentence, extract adv+adj combines.
For each extracted adv+adj combine do:
 • If adj score=0, ignore it.
 • If adv is affirmative, then
   o If score(adj)>0
     ▪ fsAAC (adv,adj)= min(1,score(adj)+sf*score(adv))
   o If score(adj)<0
     ▪ fsAAC (adv,adj)= min(1,score(adj)-sf*score(adv))
 • If adv is negative, then
   o If score(adj)>0
     ▪ fsAAC(adv,adj)= max(-1,score(adj)+sf*score(adv))
   o If score(adj)<0
     ▪ fsAAC(adv,adj)= max(-1,score(adj)-sf*score(adv))
```

Here, adj refers to adjectives and adv refers to adverbs. The final sentiment values (fs_{AAC}) are scaled form of adverb and adjective SentiWordNet scores, where the adverb score is given 35% weightage. The presence of 'Not' is handled by negating the obtained scores. First of all we extract sentence boundaries of a review and then we process all the sentences. For each sentence we extract the adv+adj combines and then compute their sentiment scores as per the scheme described in the pseudo-code. The final document sentiment score is an aggregation of sentiment scores for all sentences occurring in it. The score value determines the polarity of the review.

The second implementation that we attempted combines both 'adverb+adjective' and 'adverb+verb' sentiment scores. It is similar to the previous scheme in its way of combining adverbs with adjectives or verbs, but differs in the sense that it counts both adjectives and verbs for deciding the overall sentiment score. We have tried with different aggregation weights for adjective and verb scores and concluded that 30% weight for verb score produces best accuracy levels. The occurrence of 'not' has been handled in a similar manner as in previous scheme. The indicative pseudo-code of key steps for this scheme, i.e., SentiWordNet (AAAVC) is illustrated below. Here AAAVC refers to Adverb+Adjective and Adverv+Verb Combine.

```
For each sentence, extract adv+adj and
adv+verb combines.
1. For each extracted adv+adj combine do:
 •  If adj score=0, ignore it.
 •  If adv is affirmative, then
    o  If score(adj)>0
       ▪  f(adv,adj)=
          min(1,score(adj)+sf*score(adv))
    o  If score(adj)<0
       ▪  f(adv,adj)= min(1,score(adj)-
          sf*score(adv))
 •  If adv is negative, then
    o  If score(adj)>0
       ▪  f(adv,adj)= max(-
          1,score(adj)+sf*score(adv))
    o  If score(adj)<0
    o  f(adv,adj)= max(-1,score(adj)-
       sf*score(adv))
2. For each extracted adv+verb combine do:
       ▪  If verb score=0, ignore it.
       ▪  If adv is affirmative, then
          •  If score(verb)>0
             o  f(adv,verb)=
                min(1,score(verb)+sf*score(a
                dv))
          •  If score(verb)<0
             o  f(adv,verb)=
                min(1,score(verb)-
                sf*score(adv))
       ▪  If adv is negative, then
          •  If score(verb)>0
             o  f(adv,verb)= max(-
                1,score(verb)+sf*score(adv))
          •  If score(verb)<0
             o  f(adv,verb)= max(-
                1,score(verb)-sf*score(adv))
3. f_AAAVC(sentence)=f(adv,adj)+
 0.3*f(adv,verb)
```

In this scheme, we compute sentiment score for all 'adverb+adjective' and 'adverb+verb' combines in a sentence and aggregate them together. This is done for all sentences and the document-level sentiment polarity value is determined based on the aggregated sentiment score of the review document.

B. Aspect-level Sentiment Analysis

The document-level sentiment classification is a reasonable measure of positivity or negativity expressed in a review. However, in selected domains it may be a good idea to explore the sentiment of the reviewer about various aspects of the item in that domain, expressed in that review. Moreover, practically most of the reviews have mixture of positive and negative sentiment about different aspects of the item and it may be difficult and inappropriate to insist on an overall document-level sentiment polarity expressed in a review for the item. Thus, the document-level sentiment classification is not a complete, suitable and comprehensive measure for detailed analysis of positive and negative aspects of the item under review. The aspect-level sentiment analysis allows us to analyze the positive and negative aspects of an item. However, this kind of analysis is often domain specific. The aspect-level sentiment analysis involves the following: (a) identifying which aspects are to be analyzed, (b) locating the opinionated content about that aspect in the review, and (c) determining the sentiment polarity of views expressed about an aspect.

Since we are restricted to movie reviews, a focused domain, we tried to explore the aspect-level sentiment analysis of the movie reviews. The first step was to identify which aspects are worth considering in movie domain. We made an extensive search for identifying the aspects in different film awards, movie review sites and film magazines and worked out a list of aspects. Since a particular aspect is expressed by different words (such as screenplay, screen presence, acting) by users, we created an aspect-vector for all aspects under consideration. Another example is use of words like songs, audio, singer, sound track or lyrics, while referring to music and song component of a movie. After creating aspect vectors, we parse a review sentence-by-sentence. For each sentence, we look for presence of opinion about an aspect. If there is one, we use the SentiWordNet based approach to determine its sentiment polarity. This is done for all the sentences in a review and subsequently for all reviews of a movie. The scores for a particular aspect from all the reviews of a movie are aggregated to obtain an opinionated analysis of that aspect.

The sentiment analysis around aspects thus first locates an opinionated content about an aspect in a review and then uses the SentiWordNet based approach to compute its sentiment polarity. We used the SentiWordNet (AAC) scheme for this purpose. When an aspect indicating term (those terms that belong to the aspect vector created in the beginning) is located, we first lookup up to 5-gram backward for occurrence of adjectives or adverb+adjective combines. If no such term is found, we search up to 5-gram forward for their occurrence. In both cases the lookup terminates at 5-gram or sentence boundary whichever is encountered first. Then the sentiment polarity for these terms is computed using the SentiWordNet based formulation for AAC, described earlier.

III. DATASET AND PERFORMANCE MEASURES

We have performed our experimental evaluation on a moderate sized dataset collected on our own. In order to evaluate the performance of our algorithmic formulations, we have computed standard Information retrieval performance measures, described ahead.

A. Collecting Datasets

We have collected 10 reviews each for 100 Hindi movies from the popular movie review database website *www.imdb.com*[15].We have labeled all these reviews manually to evaluate performance of our algorithmic formulations. Out of 1000 movie reviews collected, 760 are labeled positive and 240 are labeled as negative reviews.

B. Performance Evaluation

In order to evaluate the accuracy and performance of our algorithmic formulations, we computed the standard performance metrics of Accuracy, Precision, Recall and F-measure. The measure of Accuracy *A* used by us is:

$$A = \frac{Number\ of\ Correctly\ Classified\ Documents}{Total\ Number\ of\ Documents} \quad \textbf{(1)}$$

The equation for F-Measure *F*used by us is as follows:

$$Precision\ (l,c) = n_{lc}/n_c \quad \textbf{(2)}$$

$$Recall\ (l,c) = n_{lc}/n_l \quad \textbf{(3)}$$

$$F(l,c) = \frac{2*Recall(l,c)*Precision(l,c)}{Precision(l,c)+Recall(l,c)} \quad \textbf{(4)}$$

$$Overall\ F = \sum_i \frac{n_i}{n} \max\left(F(i,c)\right) \quad \textbf{(5)}$$

where n_{lc} is number of documents with original label *l* in classified label *c*;n_c is number of documents classified as *c* and n_l is number of documents in original class with label *l*. The equation for Entropy *E* used by us is following:

$$E_c = -\sum_l P(l,c) * \log\left(P(l,c)\right) \quad \textbf{(6)}$$

$$Overall\ E = \sum_c \frac{n_c * E_c}{n} \quad \textbf{(7)}$$

where, $P(l,c)$ is the probability of documents of classified class with label c belongs to original class with label l, and *n* is total number of documents. As we can see from the equations above, accuracy is measured in percentage, whereas Precision, Recall and F-measure metric values range from 0 – 1. A smaller value for entropy metric is an indicator of good performance of the algorithm. We have also evaluated sentiment results of our data using the Alchemy API [16], to compare the performance of our algorithms.

IV. RESULTS

We have explored different linguistic feature selection, weighing and aggregation schemes. For document-level sentiment classification, we used the SWN (AAC) and SWN (AAAVC) schemes. We obtained result of document level sentiment classification of the data collected using both these schemes and also using Alchemy API. Table I presents the values of performance metrics obtained for our own implementations and Alchemy API.

TABLE I. PERFORMANCE VALUES ON MOVIE REVIEW DATASET

Method	*Performance measure*	*Value*
SWN (AAC)	Accuracy	77.6%
	F-measure	0.7642532
	Entropy	0.21800485
SWN (AAAVC)	Accuracy	78.7%
	F-measure	0.77374506
	Entropy	0.21472746
Alchemy API	Accuracy	77.4%
	F-measure	0.7778397
	Entropy	0.2068102

The table II presents a comparison of the sentiment label assignments by our algorithmic formulations and the Alchemy API with manually labeled data. We can see that out of total number of 760 actual positive reviews, SWN (AAC) labels 678 as positive, SWN (AAAVC) labels 688 and Alchemy API labels 634 as positive. Similarly out of 240 actual negative reviews, the three algorithmic formulations label negative 98, 99 and 140 reviews, respectively. The table III presents the percentage wise sentiment label assignment statistics by the three algorithmic formulations. As we can see from the table, out of 1000 total reviews, the SWN (AAC) labels 82% as positive, SWN (AAAVC) labels 82.9% as positive and Alchemy API labels 73.4% as positive. Similarly out of total 1000 reviews, the three algorithmic formulations label negative 18%, 17.1% and 26.6% reviews, respectively. Figure 1 and 2 present a pictorial view of the results shown in table II.

TABLE II. COMPARISON OF SENTIWORDNET SCHEMES AND ALCHEMY API WITH MANUALLY DECIDED SENTIMENT LABELS

Method	*Actual*		*Observed (in comparison to Actual)*	
		Number		*Number*
SWN (AAC)	Positive	760	Positive	678
	Negative	240	Negative	98
SWN (AAAVC)	Positive	760	Positive	688
	Negative	240	Negative	99
Alchemy API	Positive	760	Positive	634
	Negative	240	Negative	140

TABLE III. TOTAL PERCENTAGE OF 'POSITIVE' AND 'NEGATIVE' LABELS ASSIGNED BY THREE METHODS

Method	*Movie Review Dataset*	
SWN (AAC)	POS	82%
	NEG	18%
SWN (AAAVC)	POS	82.9%
	NEG	17.1%
Alchemy API	POS	73.4%
	NEG	26.6%

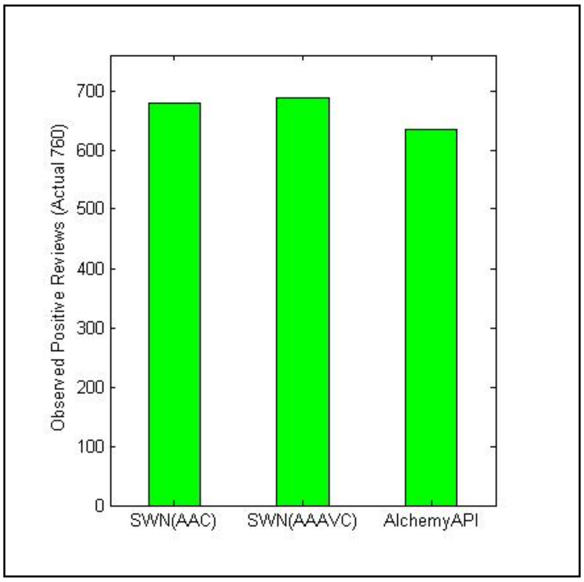

Fig. 1 Correctly Classified Positive Reviews by the three methods

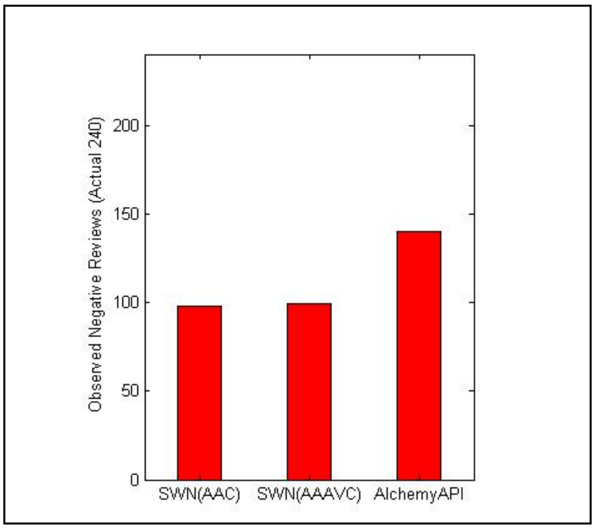

Fig. 2 Correctly classified negative reviews by the three methods

As described earlier, we have explored using different weightage factors for adding the 'adverb+verb' sentiment scores to 'adverb+adjective' sentiment scores. We tried with different values for weightage factors for 'adverb+verb' combine from 10% to 100%. The figures 3 and 4 below demonstrate the F-measure and Entropy values obtained in SWN (AAAVC) method with variation of weightage factors from 10% to 100%.

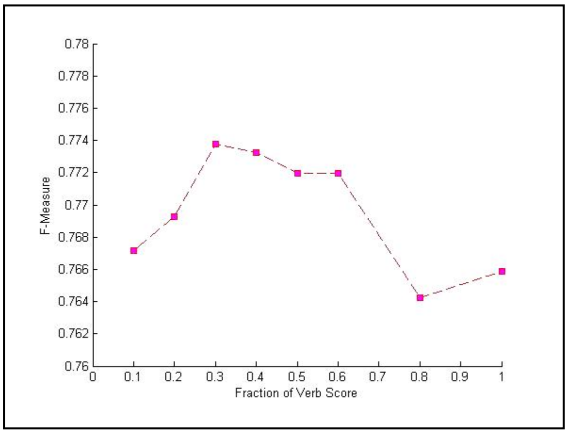

Fig. 3 Variation of F-measure value with different weightage factors

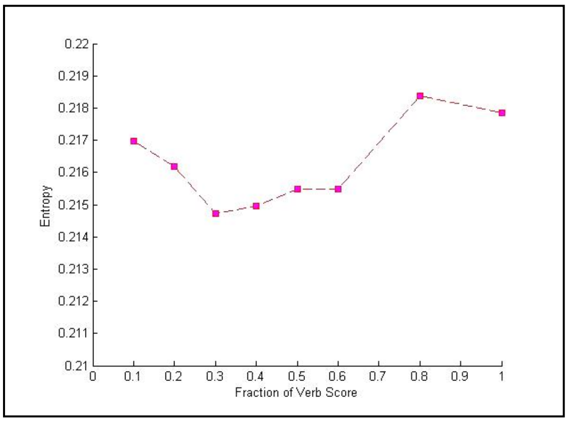

Fig. 4 Variation of Entropy value with different weightage factors

The document-level sentiment classification results obtained by our algorithmic formulation are not only reasonable accurate as compared to actual manual sentiment labels, but are also comparable to the results obtained by the Alchemy API. Among the three methods, SWN (AAAVC) produces the most accurate results with verb score weightage factor of 30%. The SWN (AAC) method is close to the performance level of SWN (AAAVC), but it's the later method which has a marginal edge over it.

The aspect-level sentiment analysis is the second and main contribution of our experimental formulation. In this part, we have obtained sentiment score of a particular movie on its different aspects. All the 10 reviews of the movie are scanned for these aspects and then sentiment scores about an aspect from all the reviews are combined. The figures 5 and 6 present two example results of the aspect-level sentiment analysis. As clearly visible in these figures, the movie 'Guru' is rated positive on almost all major aspects. Its document-level sentiment classification result also has a positive majority. The movie 'no problem' on the other hand is rated negative on all major aspects and its document-level sentiment classification also has a negative majority. We can use our method to automatically and quickly present the sentiment profile on different aspects of a movie from a large number of user reviews about it. The results are presented in pictorial, easy to visualize and understandable form.

V. OBSERVATIONS AND CONCLUSION

Our experimental work makes two important contributions. First, it explores the use of 'Adverb+Verb' combine with 'Adverb+Adjective' combine for document-level sentiment classification of a review. Second, it proposes a new feature-based heuristic scheme for aspect-level sentiment classification of a movie. The aspect level sentiment classification produces an accurate and easy to understand sentiment profile of a movie on various aspects of interest. Interestingly, the aspect-level sentiment profile result is congruent to the document-level sentiment classification of reviews of a movie. Though, the aspect-level sentiment profile produces a more focused and accurate sentiment summary of a particular movie and is more useful for the users.

The document-level schemes implemented by us include use of 'Adverb+Adjective' combine only, and use of 'Adverb+Verb' combine with the 'Adverb+Adjective' combine. This is done to explore the opinionated value of different linguistic features of a review and finding a way As a result, many of the sentiment calculation were highly influenced by the tacit assumption is that a review describes about only best aggregate all the opinionated information in a review together to produce a document-level sentiment summary. The results demonstrate that adding the sentiment score of 'Adverb+Verb' combines to the commonly used 'Adverb+Adjective' combine further improves the accuracy of sentiment classification. The best weightage factor for verb scores obtained through multiple experimental runs is 30%.

The aspect-level sentiment analysis algorithmic formulation designed by us is a novel and unique way of obtaining a complete sentiment profile of a movie from multiple reviews on different aspects of evaluation. The resultant sentiment profile is informative, easy to understand, and extremely useful for users. Moreover, the algorithmic formulation used for aspect-level sentiment profile is very simple, quick to implement, fast in producing results and does not require any previous training. It can be used on the run and produces very useful and detailed sentiment profile of a movie on different aspects of interest. This part of the implementation can also be used as an add-on step in movie recommendation systems that use content-filtering, collaborative-filtering or hybrid approaches. The sentiment profile can be used as an additional filtering step for designing appropriate movie recommender systems as explored earlier in [17] and [18]. This aspect-level sentiment profiling is a valuable form of sentiment analysis and subsequent exploitation of information expressed by a large number of users about a particular movie. The only restriction with this aspect-level implementation is that it is domain specific. However, only little changes (in aspect vectors) would be required to use this algorithmic formulation in a different domain.

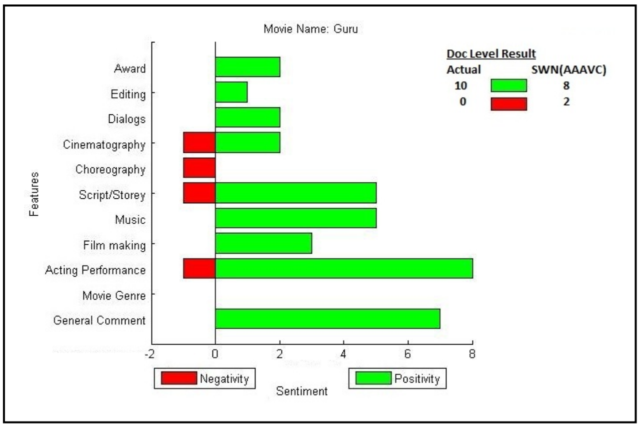

Fig. 5 Sentiment Profile of a positively rated movie. The actual and observed document-level sentiment scores are also shown.

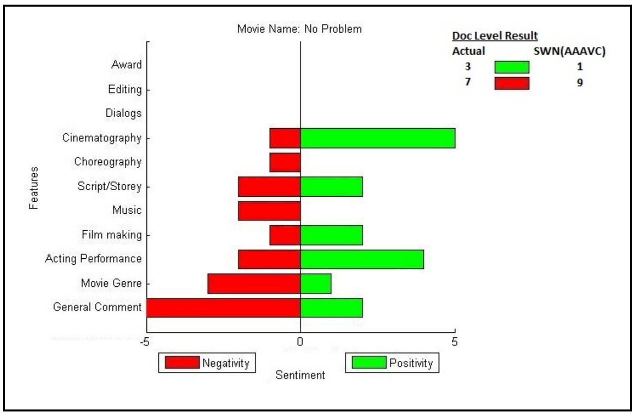

Fig. 6 Sentiment Profile of a negatively rated movie. The actual and observed document-level sentiment scores are also shown.

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