Sentiment Analysis in Twitter with Lightweight Discourse Analysis

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ABSTRACT

We propose a lightweight method for using discourse relations for polarity detection of tweets. This method is targeted towards the web-based applications that deal with noisy, unstructured text, like the tweets, and cannot afford to use heavy linguistic resources like parsing due to frequent failure of the parsers to handle noisy data. Most of the works in micro-blogs, like Twitter, use a bag-of-words model that ignores the discourse particles like but, since, although etc. In this work, we show how the discourse relations like the connectives and conditionals can be used to incorporate discourse information in any bag-of-words model, to improve sentiment classification accuracy. We also probe the influence of the semantic operators like modals and negations on the discourse relations that affect the sentiment of a sentence. Discourse relations and corresponding rules are identified with minimal processing - just a list look up. We first give a linguistic description of the various discourse relations which leads to conditions in rules and features in SVM. We show that our discourse-based bag-of-words model performs well in a noisy medium (Twitter), where it performs better than an existing Twitter-based application. Furthermore, we show that our approach is beneficial to structured reviews as well, where we achieve a better accuracy than a state-of-the-art system in the travel review domain. Our system compares favorably with the state-of-the-art systems and has the additional attractiveness of being less resource intensive.

KEYWORDS: Sentiment Analysis, Discourse, Twitter, Connectives, Micro-blogs
1 INTRODUCTION

An essential phenomenon in natural language processing is the use of discourse relations to establish a coherent relation, linking phrases and clauses in a text. The presence of linguistic constructs like connectives, modals, conditionals and negation can alter sentiment at the sentence level as well as the clausal or phrasal level. Consider the example, “@user share 'em! i'm quite excited about Tintin, despite not really liking original comics. Probably because Joe Cornish had a hand in.” The overall sentiment of this example is positive, although there is equal number of positive and negative words. This is due to the connective despite which gives more weight to the previous discourse segment. Any bag-of-words model would be unable to classify this sentence without considering the discourse marker. Consider another example, “Think i'll stay with the whole 'sci-fi' shit, but this time...a classic movie.” The overall sentiment is again positive due to the connective but, which gives more weight to the following discourse segment. Thus it is of utmost importance to capture all these phenomena in a computational model.

Traditional works in discourse analysis use a discourse parser (Marcu 2000; Zirn et al., 2011, Wellner et al.; 2007; Pitler et al., 2009; Elwell et al., 2008) or a dependency parser (Vincent et al., 2006). Many of these works and some other works in discourse (Taboada et al., 2008; Zhou et al., 2011) build on the Rhetorical Structure Theory (RTS) proposed by Mann et al. (1988) which tries to identify the relations between the nucleus and satellite in the sentence. Most of these theories are well-founded for structured text, and structured discourse annotated corpora are available to train the models. However, using these methods for micro-blog discourse analysis pose some fundamental difficulties:

1. Micro-blogs, like Twitter, do not have any restriction on the form and content of the user posts. Users do not use formal language to communicate in the micro-blogs. As a result, there are abundant spelling mistakes, abbreviations, slangs, discontinuities and grammatical errors. This can be observed in the given examples from real-life tweets. The errors cause natural language processing tools like parsers and taggers to fail frequently (Dey et al., 2009). As the tools are generally trained on structured text, they are unable to handle the noisy and unstructured text in this medium. Hence most of the discourse-based methods, based on RST or parsing of some form, will be unable to perform very well in micro-blog data.

2. The web-based applications require a fast response time. Using a heavy linguistic resource like parsing increases the processing time and slows down the application.

Most of the works in micro-blogs, like Twitter, (Alec et al., 2009; Read et al., 2005; Pak et al., 2010; Gonzalez et al., 2011) use a bag-of-words model with features like part-of-speech information, unigrams, bigrams etc. along with other domain-specific, specialized features like emoticons, hashtags etc. In most of these works, the connectives, modals and conditionals are simply ignored as stop words during feature vector creation. Hence, the discourse information that can be harnessed from these elements is completely discarded. In this work, we show how
the connectives, modals, conditionals and negation based discourse information can be incorporated in a bag-of-words model to give better sentiment classification accuracy.

The roadmap for the rest of the paper is as follows: Related work is presented in Section 2. Section 3 presents a comprehensive view of the different discourse relations. Section 4 studies the effect of these relations on sentiment analysis and identifies the critical ones. Section 5 discusses the influence of some semantic operators on discourse relations for sentiment analysis. We develop techniques for using the discourse relations to create feature vectors in Section 6. Lexicon based classification and supervised classification systems are presented in Section 7 to classify the feature vectors. Experimental results are presented in Section 8, where we use three different datasets, from the Twitter and Travel review domain, to validate our claim. The results are discussed in Section 9, followed by conclusions.

2 RELATED WORK

2.1 Discourse Based Works

Maru (2000) discussed probabilistic models for identifying elementary discourse units at clausal level and generating trees at the sentence level, using lexical and syntactic information from discourse-annotated corpus of RST. Wellner et al. (2007) considers the problem of automatically identifying arguments of discourse connectives in the PDTB. They model the problem as a predicate-argument identification where the predicates are discourse connectives and arguments serve as anchors for discourse segments. Wolf et al. (2005) presents a set of discourse structure relations and ways to code or represent them. The relations were based on Hobbs (1985). They report a method for annotating discourse coherent structures and found different kinds of crossed dependencies.

In the work, Contextual Valence Shifters (Polanyi et al., 2004), the authors investigate the effect of intensifiers, negatives, modals and connectors that changes the prior polarity or valence of the words and brings out a new meaning or perspective. They also talk about pre-suppositional items and irony and present a simple weighting scheme to deal with them.

Somasundaran et al. (2009) and Asher et al. (2008) discuss some discourse-based supervised and unsupervised approaches to opinion analysis. Zhou et al. (2011) present an approach to identify discourse relations as identified by RST. Instead of depending on cue-phrase based methods to identify discourse relations, they leverage it to adopt an unsupervised approach that would generate semantic sequential representations (SSRs) without cue phrases.

Taboada et al. (2008) leverage discourse to identify relevant sentences in the text for sentiment analysis. However, they narrow their focus to adjectives alone in the relevant portions of the text while ignoring the remaining parts of speech of the text.

Most of these discourse based works make use of a discourse parser or a dependency parser to identify the scope of the discourse relations and the opinion frames. As said before, the parsers fare poorly in the presence of noisy text like ungrammatical sentences and spelling mistakes (Dey et al., 2009). In addition, the use of parsing slows down any real-time interactive system due to
increased processing time. For this reason, the micro-blog applications mostly build on a bag-of-words model.

### 2.2 Twitter Based Works

Twitter is a micro-blogging website and ranks second amongst the present social media websites (Prelovac, 2010). A micro-blog allows users to exchange small elements of content such as short sentences, individual pages, or video links. Alec et al. (2009) provide one of the first studies on sentiment analysis on micro-blogging websites. Barbosa et al. (2010) and Bermingham et al. (2010) both cite noisy data as one of the biggest hurdles in analyzing text in such media.

Alec et al. (2009) describe a distant supervision-based approach for sentiment classification. They use hashtags in tweets to create training data and implement a multi-class classifier with topic-dependent clusters. “The # symbol, called a hashtag, is used to mark keywords or topics in a Tweet. It was created organically by Twitter users as a way to categorize messages”\(^1\).

Barbosa et al. (2010) propose an approach to sentiment analysis in Twitter using POS-tagged n-gram features and some Twitter specific features like hashtags. Joshi et al. (2011) propose a rule-based system, C-Feel-It, which classifies a tweet as positive or negative based on the opinion words present in it. It uses sentiment lexicons for classification and twitter-specific features like emoticons, slangs, hashtags etc. Use of emoticons is common in social media and microblogging sites, where the users express their sentiment in the form of accepted symbols. Example: ☺ (happy), 😞 (sad).

Read et al., (2005) and Pak et al. (2010) propose a method to automatically create a training corpus using micro-blog specific features like emoticons, which is subsequently used to train a classifier. Gonzalez et al. (2011) discuss an approach to identify sarcasm in tweets. To create a corpus of sarcastic, positive and negative tweets, they rely on the user provided information in the form of hashtags. They claim that the author is the best judge for determining whether the tweet is sarcastic or not, which is indicated by the hashtags used by the author in the post.

Our work builds on the discourse-related works of Polanyi et al. (2004), Wolf et al. (2005) and Taboada et al. (2008) and carries the idea further in the sentiment analysis of micro-blogs. We exploit the various features discussed in the Twitter specific works to develop a bag-of-words model, in which the discourse features are incorporated to give better sentiment classification accuracy.

We evaluate our system on three datasets using lexicon-based classification as well as a supervised classifier (SVM). We use a manually labeled tweet set of 8,507 tweets and an automatically annotated set of 15,204 tweets using hashtags, to establish our claim. We, further, use a dataset from the travel review domain by Balamurali et al. (2011) to show that our method is beneficial to structured reviews as well, which is indicated by the improved classification accuracy over the compared work.

\(^1\)https://support.twitter.com/articles/49309
3 CATEGORIZATION OF DISCOURSE RELATIONS

“An important component of language comprehension in most natural language contexts involves connecting clauses and phrases together in order to establish a coherent discourse” (Wolf et al., 2004). A coherently structured discourse is a collection of sentences having some relation with each other. A coherent relation reflects how different discourse segments interact (Hobbs 1985; Marcu 2000; Webber et al., 1999). Discourse segments are non-overlapping spans of text. The interaction relations between discourse segments may be of various forms as listed in Table 1.

| Coherence Relations       | Conjunctions                                      |
|---------------------------|---------------------------------------------------|
| Cause-effect              | because; and so                                   |
| Violated Expectations     | although; but; while                               |
| Condition                 | if…(then); as long as; while                      |
| Similarity                | and; (and) similarly                               |
| Contrast                  | by contrast; but                                  |
| Temporal Sequence         | (and) then; first, second, … before; after; while |
| Attribution               | according to …; …said; claim that …; maintain that …; stated |
| Example                   | for example; for instance                         |
| Elaboration               | also; furthermore; in addition; note (furthermore) that; (for, in, with) which; who; (for, in, on, against, with) whom |
| Generalization            | in general                                        |

Table 1: Contentful Conjunctions used to illustrate Coherence Relations (Wolf et al. 2005)

Our work, almost entirely, rests on this platform, where we identify the relations from Table 1, which can affect the analysis of opinions most in a discourse segment. Table 2 provides some examples, taken from Twitter, to illustrate the effect of conjunctions in discourse analysis. These examples are similar to the ones in Polanyi et al. (2004) and Taboada et al. (2008). The words in bold connect the discourse segment in brackets. The relations are broadly classified in ten categories in Table 2.

4 DISCOURSE RELATIONS CRITICAL FOR SENTIMENT ANALYSIS

Not all of the discourse relations are significant from the point of view of sentiment analysis. This section examines the role of the critical ones in SA.

1. Violated Expectations and Contrast - A simple bag-of-words model will classify Example 2 (Table 2) as neutral. This is because it has one positive term excited and one negative phrase not
really liking. However, it represents a positive emotion of the opinion holder, due to the segment after the connective despite. In Example 5, brightened is positive and poorly is negative. Hence the overall polarity is un-decided. But it should have been positive, since the segment following but gives the overall impression of the opinion-holder which is positive.

Violating expectation conjunctions oppose or refute the neighboring discourse segment. We further categorize them into the following two sub-categories: Conj_Fol and Conj_Prev.

Conj_Fol is the set of conjunctions that give more importance to the discourse segment that follows them. Conj_Prev is the set of conjunctions that give more importance to the previous discourse segment.

Thus, in Example 5 of Table 2, the discourse segment following but should be given more weight. In Example 2, the discourse segment preceding despite should be given more weight.

| 1. | Cause-effect: (YES! I hope she goes with Chris) so (I can freak out like I did with Emmy Awards.) |
| 2. | Violated Expectations: (i’m quite excited about Tintin), despite (not really liking original comics.) |
| 3. | Condition: If (MicroMax improved its battery life), (it wud hv been a gr8 product). |
| 4. | Similarity: (I lyk Nokia) and (Samsung as well). |
| 5. | Contrast: (my daughter is off school very poorly), but (brightened up when we saw you on gmtv today). |
| 6. | Temporal Sequence: (The film got boring) after a while. |
| 7. | Attribution: (Parliament is a sausage-machine: the world) according to (Kenneth Clarke). |
| 8. | Example: (Dhoni made so many mistakes…) for instance, (he shud’ve let Ishant bowl wn he was peaking). |
| 9. | Elaboration: In addition (to the worthless direction), (the story lacked depth too). |
| 10. | Generalization: In general, (movies made under the RGV banner) (are not worth a penny). |

Table 2: Examples of Discourse Coherent Relations

2. Conclusive or Inferential Conjunctions - These are the set of conjunctions, Conj_infer, that tend to draw a conclusion or inference. Hence, the discourse segment following them (subsequently in Example 11) should be given more weight.

Example 11: @User I was nt much satisfied with ur so-called gud phone and subsequently decided to reject it.
3. **Conditionals** - In Example 3 (Table 2), both improve and gr8 represent a high degree of positive sentiment. But the presence of if tones down the final polarity as it introduces a hypothetical situation in the context. The if...then...else constructs depict situations which may or may not happen subject to certain conditions.

In our work, the polarity of the discourse segment in a conditional statement is toned down, in lexicon-based classification. In supervised classifiers, the conditionals are marked as features. Such statements are not completely ignored as objective, as they bear some sentiment polarity.

4. **Other Discourse Relations** - Sentences under Cause-Effect, Similarity, Temporal Sequence, Attribution, Example, Generalization and Elaboration, provide no contrasting, conflicting or hypothetical information. They can be handled by taking a simple majority valence of the individual terms, as in a bag-of-words model.

*Table 3* lists all the essential discourse relations discussed in this section. The relations have been compiled from Hobbs (1985), Polanyi *et al.* (2004) and Taboada *et al.* (2008).

5 **SEMANTIC OPERATORS INFLUENCING DISCOURSE RELATIONS**

There are some semantic operators that influence the discourse relations connecting the phrases. In the sentence You may like the movie despite the bad reviews, the connective despite gives more weightage to the discourse segment preceding it and hence, like is weighed up. But the uncertainty resulting from may that pulls down the weightage is completely ignored. Similarly, in the sentence He put a lot of effort for the finals, but still it was not good enough to win the match, the connective but upweights good and win ignoring the negation operator not. In this section, we consider the semantic operators like the modals and negation, ignoring which results in an incorrect interpretation of the sentiment.

| Relations   | Attributes                                      |
|-------------|-------------------------------------------------|
| Conj_Fol    | but, however, nevertheless, otherwise, yet,     |
|             | still, nonetheless                              |
| Conj_Prev   | till, until, despite, in spite, though, although|
| Conj_Infer  | therefore, furthermore, consequently, thus, as  |
|             | a result, subsequently, eventually, hence       |
| Conditionals| If                                              |
| Strong_Mod  | might, could, can, would, may                   |
| Weak_Mod    | should, ought to, need not, shall, will, must   |
| Neg         | not, neither, never, no, nor                    |

*Table 3*: Discourse Relations and Semantic Operators Essential for Sentiment Analysis

1. **Modals** - Events that have happened, events that are happening or events that are certain to occur are called realis events. Events that have possibly occurred or have some probability to occur in the distant future are called irrealis events. Thus, it is important to distinguish between
real situations and hypothetical ones. The modals (might, may, could, should, would etc.) depict irrealis events. Example 3 (Table 2) does not necessarily talk of MicroMax being great, but talks of its possibility of being great subject to certain conditions (its battery life). These constructs cannot be handled by taking a simple majority valence of terms.

We further divide the modals into two sub-categories: Strong_Mod and Weak_Mod.

Strong_Mod is the set of modals that express a higher degree of uncertainty in any situation.

Weak_Mod is the set of modals that express lesser degree of uncertainty and more emphasis on certain events or situations.

In our work, the polarity of the discourse segment neighboring a strong modal is toned down in lexicon-based classification, similar to the conditionals, as it expresses a higher degree of uncertainty. In supervised classifiers, the modals are marked as features.

Example 12 (Strong Modals): Unless I missed the announcement their God is now featured on postage stamps, it might be a hard sell.

He may be a rising star.

Example 13 (Weak Modals): G.E 12 must be the most deadly General Election for politicians ever.

Our civil service should work without TD interference.

2. Negation - The negation operator (Example: not, neither, nor, nothing etc.) inverts the sentiment of the word following it. The usual way of handling negation in SA is to consider a window of size n (typically 3-5) and reverse the polarity of all the words in the window. In Example 14, negating all the words in a window of size 5 reverses the polarity of “like” for Samsung as well; this is undesirable. We consider a negation window of size 5 and reverse all the words in the window, till either the window size exceeds or a violating expectation (or a contrast) conjunction is encountered. Hence, the scope of reversing polarity is limited to the appearance of but in the given example.

Example 14 (Negation): I do not like Nokia but I like Samsung.

6 ALGORITHM TO HARNESS DISCOURSE INFORMATION

The discourse relations and the semantic operators (identified in Section 4 and Section 5) are used to create a feature vector, according to the following algorithm.

Let a user post $R$ consist of ‘m’ sentences $s_i$ ($i=1...m$), where each $s_i$ consist of $n_i$ words $w_{ij}$ ($i=1...m$, $j=1...n_i$). Let $f_{ij}$ be the weight of the word $w_{ij}$ in sentence $s_i$, initialized to 1. Let $A$ be the set of all discourse relations in Table 3. Let $flip_{ij}$ be a variable which indicates whether the polarity of $w_{ij}$ should be flipped or not. Let $hyp_{ij}$ be a variable which indicates the presence of a conditional or a strong modal in $s_i$. 

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for $i=1 \ldots m$
  for $j=1 \ldots n_i$
    $f_{ij}=1$;
    $hyp_{ij}=0$;
 1.   if $w_{ij} \in \text{Conditionals or } w_{ij} \in \text{Strong}\_\text{Mod}$
      $hyp_{ij}=1$;
  end if
  end for

  for $j=1 \ldots n_i$
    $flip_{ij}=1$;
    2.   if $w_{ij} \in Conj\_\text{Fol or } w_{ij} \in Conj\_\text{Infer}$
      for $k=j+1 \ldots n_i$ and $w_{ij} \notin A$
        $f_{ik}+=1$;
      end for
    end if
  3. else if $w_{ij} \in Conj\_\text{Prev}$
    for $k=1 \ldots j-1$ & $w_{ij} \notin A$
      $f_{ik}+=1$;
    end for
  end if
  4. else if $w_{ij} \in Neg$
    for $k=1 \ldots \text{Neg}\_\text{Window}$ and $w_{ik} \notin Conj\_\text{Prev}$ and $w_{ik} \notin Conj\_\text{Fol}$
      $flip_{ij+k}=-1$;
    end for
  end if
end for

**Input:** Review $R$

**Output:** $w_{ij}, f_{ij}, flip_{ij}, hyp_{ij}$

**Algorithm 1:** Using the Discourse Relations to Create the Feature Vector

In *Step 1*, we mark all the *conditionals* and *strong modals* which are handled separately by the lexicon-based classifier and the supervised classifier.

In *Step 2* and *Step 3*, the weight of any word appearing before *Conj\_Prev* and after *Conj\_Fol* or *Conj\_Infer* is incremented by 1.
In Step 4, the polarity of all the words appearing within a window (Neg_Window is taken as 5), from the occurrence of a negation operator and before the occurrence of a violating expectation conjunction, are reversed.

Finally, we get the feature vector \{w_{ij}, f_{ij}, flip_{ij} and hyp_{ij}\} for all the words in the review.

Here, the assumption is that the effect of any conjunction is restricted to continuous spans of text till another conjunction or the sentence boundary.

7 FEATURE VECTOR CLASSIFICATION

We devised a lexicon based system as well as a supervised system for feature vector classification.

7.1 Lexicon Based Classification

The Bing Liu sentiment lexicon (Hu et al., 2004) is used to find the polarity \( \text{pol}(w_{ij}) \) of a word \( w_{ij} \). It contains around 6800 words which are manually polarity labeled. The polarity of the review (pos or neg) is given by,

\[
\text{pos} = \frac{\sum_{i=1}^{\text{m}} \sum_{j=1}^{\text{n}} f_{ij} \times \text{flip}_{ij} \times \text{p}(w_{ij})}{\text{m} \times \text{n}^{(\text{hyp}_{ij} = 0)}}
\]

\[
\text{neg} = \frac{\sum_{i=1}^{\text{m}} \sum_{j=1}^{\text{n}} f_{ij} \times \text{flip}_{ij} \times \text{p}(w_{ij})}{\text{m} \times \text{n}^{(\text{hyp}_{ij} = 1)}}
\]

Equation 1 finds the weighted, signed polarity of a review. The polarity of each word, \( \text{pol}(w_{ij}) \) being +1 or -1, is multiplied with its discourse-weight \( f_{ij} \) (assigned by Algorithm 1), and all the weighted polarities are added. \( \text{flip}_{ij} \) indicates if the polarity of \( w_{ij} \) is to be negated.

In case there is any conditional or strong modal in the sentence (indicated by \( \text{hyp}_{ij} = 1 \)), then the polarity of every word in the sentence is toned down, by considering half of its assigned polarity (\( \frac{+1}{2} \) or \( \frac{-1}{2} \)).

Thus, if good occurs in the user post twice, it will contribute a polarity of \( +1 \times 2 = +2 \) to the overall review polarity, if \( \text{hyp}_{ij} = 0 \). In the presence of a strong modal or conditional, it will contribute a polarity of \( \frac{+1}{2} \times 2 = +1 \).

All the stop words, discourse connectives and modals are ignored during the classification phase, as they have a zero polarity in the lexicon.

7.2 Supervised Classification

The Support Vector Machines have been found to outperform other classifiers, like Naïve Bayes and Maximum Entropy, in sentiment classification (Pang et al., 2002). Hence, in our work, SVM’s are used to classify the set of feature vectors \{flip_{ij}, w_{ij}, f_{ij} and hyp_{ij}\}.
Features used in the Support Vector Machines:

N-grams – *Unigrams* along with *Bigrams* are used.

Stop Words – All the stop words (like *a*, *an*, *the*, *is* etc.) and discourse connectives are discarded.

Feature Weight – In the *baseline bag-of-words* model, the feature weight has been taken as the feature frequency i.e. the number of times the unigram or bigram appears in the text. In the *discourse-based bag-of-words* model, the *discourse-weighted frequency* of a word is considered. *Algorithm 1* assigns a weight $f_{ij}$ to every occurrence of a word $w_{ij}$ in the post. If the same word occurs multiple times, the weights from its multiple occurrences will be added and used as a feature weight for the word.

Modal and Conditional Indicator – This is a Boolean variable which indicates the presence of a strong modal or conditional in the sentence (i.e. $hyp_{ij}$).

Stemming – All the words are stemmed in the text so that “acting” and “action” have a single entry corresponding to “act”.

Negation – A Boolean variable ($flip_{ij}$) is appended to each word ($w_{ij}$) to indicate whether it is to be negated or not (i.e. $flip_{ij} = 1$ or $flip_{ij} = 0$).

Emoticons – An emoticon dictionary is used to map each emoticon to a *positive* or *negative* class. Subsequently, the emoticon class information is used in place of the emoticon.

Part-of-Speech Information – The part-of-speech information is also used with a word.

Feature Space - In the *lexeme feature space* individual words are used as features; whereas in the *sense space*, the sense of the word (synset-id) is used in place of the word. A synset is a set of synonyms that collectively disambiguate each other to give a unique sense to the set, identifiable by the *synset-id*. This is beneficial in distinguishing between the various senses of a word.

For example, the word *bank* has 18 senses (10 Noun senses and 8 Verb Senses). Consider the two senses of a *bank* – 1) *Bank* in the sense of “a financial institution”, identifiable by the synset “depository financial institution, bank, banking concern, banking company”, and 2) *Bank* in the sense of relying, identifiable by the synset “trust, swear, rely, bank”. Now, the first sense has an objective polarity whereas the second sense has a positive polarity. This distinction cannot be made in the lexeme feature space, where we consider only the *first* sense of the word.

8 EVALUATION

8.1 Dataset

We performed experiments on three different datasets to validate our approach:

**Dataset 1**: Twitter is crawled using a Twitter API and 8507 tweets are collected based on a total of around 2000 different entities from 20 different domains. The following domains are used for crawling data: *Movie*, *Restaurant*, *Television*, *Politics*, *Sports*, *Education*, *Philosophy*, *Travel*, *Books Technology*, *Banking & Finance*, *Business*, *Music*, *Environment*, *Computers*, *Automobiles*. 

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Cosmetics brands, Amusement parks and Eatables and History. These are manually annotated by 4 annotators into four classes - positive, negative, objective-not-spam and objective-spam. The objective-not-spam category contains tweets which are objective in nature but are not spams. The objective-spam category contains spam tweets which are subsequently ignored during evaluation.

**Dataset 2:** Following the works of Read et al. (2005), Alec et al. (2009), Pak et al. (2010) and Gonzalez et al. (2011) we create an artificial dataset using hashtags. The Twitter API is used to collect another set of 15,214 tweets based on hashtags. Hashtags #positive, #joy, #excited, #happy etc. are used to collect tweets bearing positive sentiment, whereas hashtags like #negative, #sad, #depressed, #gloomy, #disappointed etc. are used to collect negative tweets. Hashtag keywords are subsequently removed from the tweets.

**Dataset 3:** Travel Review Dataset in Balamurali et al. (2011) contains 595 polarity-tagged documents for each of the positive and negative classes. All the words in the travel review documents are automatically tagged with their corresponding synset-id’s using Iterative Word Sense Disambiguation algorithm (Khapra et al., 2010).

### 8.2 Evaluation on the Twitter Dataset 1 and 2

The crawled tweets are pre-processed before evaluation. All the links (urls) in the tweets are replaced by #link. All the user id’s in the tweets are replaced by #user.

| Manually Annotated Dataset 1 |  |
|-------------------------------|--|
| #Positive | #Negative | #Objective Not Spam | #Objective Spam | Total |
| 2548 | 1209 | 2757 | 1993 | 8507 |

| Auto Annotated Dataset 2 |  |
|----------------------------|--|
| #Positive | #Negative | Total |
| 7348 | 7866 | 15214 |

**Table 4:** Twitter Datasets 1 and 2 Statistics

Evaluations are performed in Dataset 1 and 2 under a 2-class and a 3-class classification setting. In the 2-class setting, only positive and negative tweets are considered; whereas in the 3-class setting positive, negative and objective-not-spam tweets are considered. All the experiments in these two datasets are performed in the lexeme feature space using lexicon-based classification as well as supervised classification.

The baseline system, for this part of the evaluation, is taken as C-Feel-It (Joshi et al., 2011). It is a rule-based system which implements a bag-of-words model using lexicon-based classification. The accuracy comparisons between C-Feel-It and the discourse system are performed under identical settings. The only difference between the two systems is the handling of connectives, modals, conditionals and negation, as indicated by Algorithm 1.

Graph 1 shows the accuracy comparison between C-Feel-It and the discourse system, in Datasets 1 and 2, using lexicon-based classification under a 2-class and a 3-class setting. Graph 2 shows
the accuracy comparison between baseline SVM and SVM integrated with discourse features, in Datasets 1 and 2, under a 2-class and a 3-class setting. All the SVM features discussed in Section 7.2, except the discourse features arising out of the incorporation of discourse weighting, modal and conditional indicator and negation, are used in the baseline SVM model. A linear kernel, with default parameters, is used in the SVM (Chang et al., 2011) with 10-fold cross-validation.

Graph 1: Accuracy Comparison between C-Feel-It and Discourse System using Lexicon in Datasets 1 and 2

Graph 2: Accuracy Comparison between Baseline SVM and SVM with Discourse in Datasets 1 and 2

8.3 Evaluation on the Travel Review Dataset 3

The travel review dataset (Balamurali et al., 2011) is used to determine whether our discourse-based approach performs well for structured text as well. This evaluation is done under a 2-class classification setting in the lexeme space as well as the sense space. Table 5 shows the accuracy comparison between the baseline bag-of-words model and bag-of-words model integrated with discourse features using lexicon-based classification, in dataset 3, under a 2-class setting.

| Sentiment Evaluation Criterion                  | Accuracy |
|------------------------------------------------|----------|
| Baseline Bag-of-Words Model                     | 69.62    |
| Bag-of-Words Model + Discourse                  | 71.78    |

Table 5: Accuracy Comparison between Bag-of-Words and Discourse System using Lexicon in Dataset 3
An automatic word sense disambiguation algorithm, Iterative Word Sense Disambiguation (Khapra et al., 2010), has been used to autoannotate the words in the review with their corresponding synset-id’s. The same dataset is used in this work. A linear kernel, with default parameters, is used in the SVM with 5-fold cross-validation, similar to the compared system (Balamurali et al., 2011). Table 6 shows the performance of the discourse system along with the compared system using different features, on Dataset 3, using supervised classification. The features used in the SVM, for this part of the evaluation, include stop word removal, no stemming, part-of-speech information and unigrams. These features are used in all the systems in Table 6, including the discourse one. Table 6 shows the system accuracy under four scenarios:

1. When only unigrams are used
2. When only sense of unigrams are used
3. When unigrams are used along with their senses (synset-id’s)
4. When unigrams are used with senses and discourse features

9 DISCUSSIONS

Accuracy improvements over the baseline and the compared systems in all the datasets clearly signify the effectiveness of incorporating discourse information for sentiment classification. The bag-of-words model integrated with discourse information outperforms the bag-of-words model, without this information, under all the settings; although, the performance improvements vary in different settings. Statistical tests have been performed and all the accuracy improvements have been found to be statistically significant with 99% level of confidence.

| Systems                                             | Accuracy (%) |
|-----------------------------------------------------|--------------|
| Only Unigrams                                       | 84.90        |
| Only IWSD Sense of Unigrams [26]                    | 85.48        |
| Unigrams + IWSD Sense of Unigrams [26]              | 86.08        |
| Unigrams + IWSD Sense of Unigrams + Discourse Features | **88.13**    |

Table 6: Accuracy Comparisons in Travel Review Dataset 3

9.1 Accuracy Comparison between C-Feel-It and Discourse System

These comparisons are performed under a 2-class and a 3-class classification setting, using lexicon-based classification, in the lexeme space under identical settings - the only difference being the incorporation of discourse features. In Dataset 1, there is an accuracy improvement of around 4% over C-Feel-It for both 2-class and 3-class classification. The discourse system accuracy at 72.81% for 2-class classification is higher than that of the 3-class classification accuracy of 61.31%. This shows that 3-class classification of tweets is much more difficult than 2-class classification.
9.2 Accuracy Comparison between Baseline SVM and Discourse System

These comparisons are performed under a 2-class and a 3-class classification setting, using supervised classification, in the lexeme space. A similar feature set, except the discourse features, is used for both the systems. In Dataset 1, there is an accuracy improvement of 1% in both the 2-class and 3-class classification, which has been found to be statistically significant. In Dataset 2, there is an accuracy improvement of 2% over baseline SVM for 2-class classification. It is observed that in the 2-class setting, the discourse system performs better in the lexicon-based classification with an accuracy of 72.81% compared to the supervised classification accuracy of 70.75%. This is contrary to the common scenario in text classification, where the supervised classification system always performs much better than the lexicon-based classification. This may be due to the very sparse feature space, owing to the length limit of tweets (140 characters).

9.3 Accuracy Comparison in Dataset 3

In the Travel review dataset, lexicon-based classification yielded an accuracy improvement of 2% for the discourse model over simple bag-of-words model, in the lexeme space. In the SVM classification, in the sense space, under a 2-class setting, the discourse system achieved an accuracy of 88% compared to 86% accuracy of Balamurali et al. (2011). A similar feature set has been used in both the models, which indicates that the performance improvement is due to the incorporation of discourse features in SVM.

9.4 Drawbacks

The lexicon-based classification suffers from the usage of a generic lexicon in the lexeme space, where it cannot distinguish between the various senses of a word. The lexicons do not have entries for the interjections like wow, duh etc. which are strong indicators of sentiment. The frequent spelling mistakes, abbreviations and slangs used in the tweets do not have entry in the lexicons. For example, love and great are frequently written as luv and gr8 respectively, which will not be detected. A spell-checker may help the system in this regard.

The supervised system suffers from a sparse feature space due to very short contexts. A concept expansion approach, to expand the feature vectors, may prove to be useful. This is due to the extensive world knowledge embedded in the tweets. For example, the tweet “He is a Frankenstein” is tagged as objective. The knowledge that Frankenstein is a negative concept is not present in the lexicon. The IWSD algorithm for automatic sense annotation has an F-Score of 70%, which means many of the word-senses were wrongly tagged. In case a better WSD algorithm is used, higher system accuracy can be achieved in the travel review dataset.

In the absence of parsing and tagging information, due to the noisy nature of the tweets, the scope of the discourse marker has been heuristically taken till the sentence boundary or till the next discourse marker. Consider the sentence, “I wanted to follow my dreams and ambitions despite all the obstacles, but I did not succeed.” Here want and ambition will get the polarity +2 each, as they appear before despite; obstacle will get a polarity -1 and not succeed will get a polarity -2. Thus the overall polarity is +1, whereas the overall sentiment should be negative.
This is because we do not consider the positional importance of a discourse marker in the sentence and consider all the discourse markers to be equally important. A better method is to give a ranking to the discourse markers based on their positional and pragmatic importance.

10 FUTURE WORKS AND CONCLUSIONS

In this work, we showed that the incorporation of discourse markers in a bag-of-words model improves the sentiment classification accuracy by 2 - 4%. This approach is particularly beneficial for - 1) applications dealing with noisy text where parsing and tagging do not perform very well, and 2) applications, requiring a fast response time, where employing a heavy linguistic tool like parsing will be detrimental to its performance due to the increased processing time.

Most of the works in micro-blogs, like Twitter, build on a bag-of-words model that ignores the discourse markers. We demonstrated an approach to incorporate discourse information to improve their performance, retaining the simplicity of the bag-of-words model. We validated this claim on two different datasets (manually and automatically annotated) from Twitter, where we achieved an accuracy improvement of 4% for lexicon-based classification over an existing application (Joshi et al., 2011), and 2% for supervised classification over the baseline SVM with advanced features. We also showed that our method fares well for structured reviews as well, where we achieved similar accuracy improvements over Balamurali et al., 2011.

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