Sentiment Analysis in Twitter with Lightweight Discourse Analysis

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Discourse

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- Presence of a discourse marker can alter the overall sentiment of a sentence

  In most of the bag-of-words models, the discourse markers are ignored as stop words during feature vector creation

Motivation

- *i'm quite excited about Tintin,* ***despite*** *not really liking original comics - probably because Joe Cornish had a hand in*

- *Think i'll stay with the whole 'sci-fi' shit* **but** *this time...a classic movie.*

Motivation Contd…

- Traditional works in *discourse analysis* use parsing of some form like a discourse parser or a dependency parser
- 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

Motivation Contd…

- 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*
- The errors cause natural language processing tools like *parsers* and *taggers* to fail frequently
- Increased processing time adds an overhead to real-time applications

Discourse Relation

- A coherently structured discourse is a collection of sentences having some relation with each other
- A coherent relation reflects how different discourse segments interact
- Discourse segments are non-overlapping spans of text

Discourse Coherent Relations

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*

Contentful Conjunctions used to illustrate Coherence Relations (Wolf *et al.* 2005)

Discourse Coherent Relations Examples

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).*

Discourse Relations and Sentiment Analysis

- Not all discourse relations are significant for sentiment analysis

- Discourse relation essential for Sentiment Analysis
  - That connects segments having contrasting information
    - Violated Expectations
  - That places higher importance to certain discourse segments
    - Inferential Conjunctions
  - That incorporates hypothetical situation in the context
    - Conditionals

- Semantic Operators influencing discourse relations in Sentiment Analysis
  - That incorporates hypothetical situation in the context
    - Modals
  - That negates the information in the discourse segment
    - Negation

Violated Expectations and Contrast

- *Violating expectation* conjunctions oppose or refute the neighboring discourse segment

- We categorize them into *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

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(i'm quite excited about Tintin), **despite** *(not really liking original comics.)*
(my daughter is off school very poorly), **but** *(brightened up when we saw you on gmtv today).*

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@User *I was not much satisfied with ur so-called good phone and* **subsequently** *decided to reject it.*

Conditionals

- Conditionals introduce 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

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.* Modals depict irrealis events

- We 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*

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(Strong Modals): *Unless I missed the announcement their God is now featured on postage stamps, it* **might** *be a hard sell.*
(Weak Modals): *G.E 12* **must** *be the* most *deadly General Election for politicians ever.*

Negation

- The negation operator 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

- **(Negation):** *I do not like Nokia* **but** *I like Samsung*

- 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

Features

Discourse 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*

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- Words after them are given more weightage
- Frequency count of those words is incremented by 1

- *The movie looked promising^{+1}, but it failed^{-2} to make an impact in the box-office*

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> - A window of 5 is considered
> - Polarity of all words in the window are reversed till another violating expectation conjunction is encountered
> - The polarity reversals are specially marked
> - *I do not like*$^{-1}$ *Nokia* **but** *I like*$^{+2}$ *Samsung.*

Algorithm Contd…

- 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
- The weight of a word w_{ij} is adjusted according to the presence of a discourse marker or a semantic operator
- 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.
- **Input**: Review R
- **Output**: w_{ij}, f_{ij} , $flip_{ij}$, hyp_{ij}

Lexical Classification

Bing Liu sentiment lexicon (Hu *et al.*, 2004) is used to find the polarity *pol(wij)* of a word w_{ij}

$$sign\left(\sum_{i=1}^{m}\sum_{j=1}^{n_i} f_{ij} \times flip_{ij} \times p(w_{ij})\right)$$

$$\begin{aligned} where\ p(w_{ij}) &= pol(w_{ij})\ \ if\ hyp_{ij} = 0 \\ &= \frac{pol(w_{ij})}{2}\ \ \ if\ hyp_{ij} = 1 \end{aligned}$$

Supervised Classification

- Support Vector Machines are used with the following features:
  - N-grams (N=1,2)
  - Stop Word Removal (except discourse markers)
  - Discourse Weight of Features - f_{ij}
  - Modal and Conditional Indicators - hyp_{ij}
  - Stemming
  - Negation - $flip_{ij}$
  - Emoticons
  - Part-of-Speech Information
  - Feature Space
    - Lexeme - w_{ij}
    - *Sense-Space – Synset-id*(w_{ij})

Datasets

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  - 8507 tweets over 2000 entities from 20 domains
  - Annotated by 4 annotators into positive, negative and objective classes

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- Dataset 2 (Twitter – Auto Annotated)
  - 15,214 tweets collected and annotated based on hashtags
  - Positive hashtags - #positive, #joy, #excited, #happy
  - Negative hashtags - *#negative, #sad, #depressed, #gloomy,#disappointed*

Datasets Contd…

Manually Annotated Dataset				
#Positive	#Negative	#Objective Not Spam	#Objective Spam	Total
2548	1209	2757	1993	8507
Auto Annotated Dataset				
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7348	7866			15214

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- Dataset 3 (Travel Domain - Balamurali *et al.*, EMNLP 2011)
  - Each word is manually tagged with its disambiguated WordNet sense
  - Contains 595 polarity tagged documents of each

Dataset Domains

Movie, Restaurant, Television, Politics, Sports, Education, Philosophy, Travel, Books, Technology, Banking & Finance, Business, Music, Environment, Computers, Automobiles, Cosmetics brands, Amusement parks, Eatables, History

Baselines

- Twitter
  - C-Feel-It (Joshi *et al.*, 2011, ACL)

- Travel Reviews
  - Balamurali *et al.*, 2011, EMNLP
  - Iterative Word-Sense Disambiguation Algorithm (Khapra *et al.*, 2010, GWC) is used to auto sense-annotate the words

Features

- Let a user post *R* consist of *m* sentences s_i $(i=1 \ldots m)$, where each s_i consist of n_i words w_{ij} $(i=1 \ldots m, j=1 \ldots n_i)$

- Let f_{ij} be the weight of the word w_{ij} in sentence s_i, initialized to 1

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- **Input**: Review *R*
- **Output**: w_{ij}, f_{ij} , $flip_{ij}$, hyp_{ij}

Classification Results in Twitter (Datasets 1 and 2)

Comparison with C-Feel-It (Joshi *et al.*, ACL 2011)

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Lexicon-based Classification

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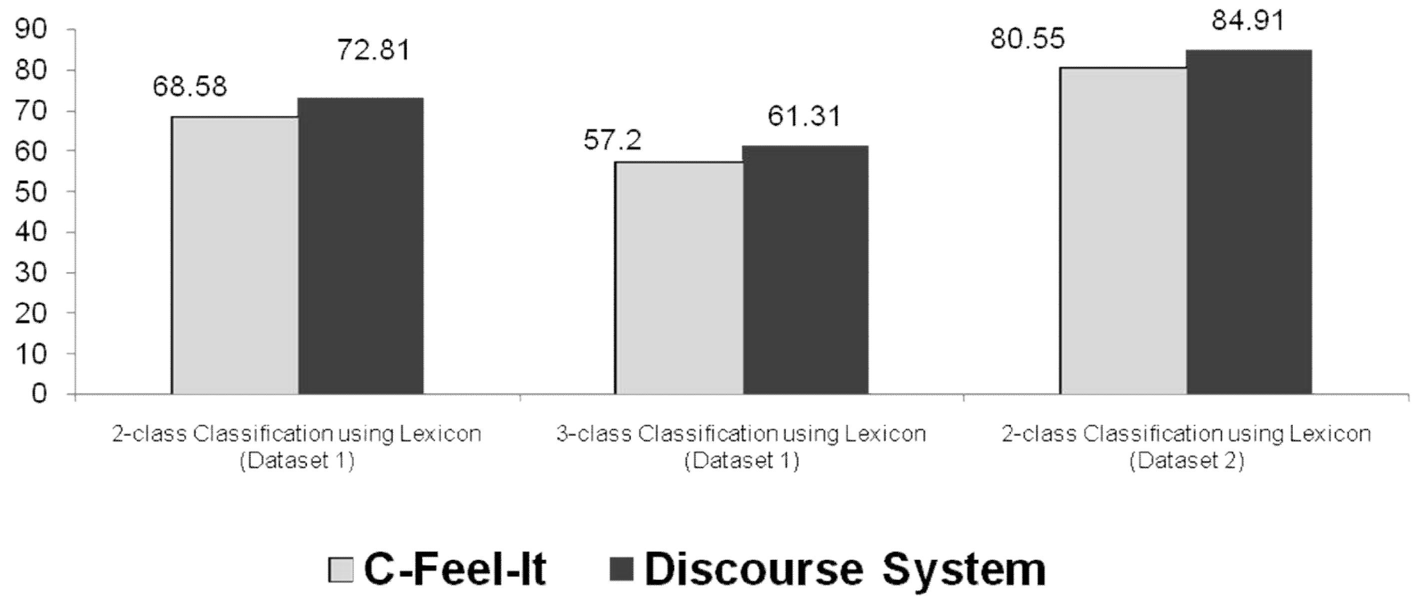
Lexicon-based Classification



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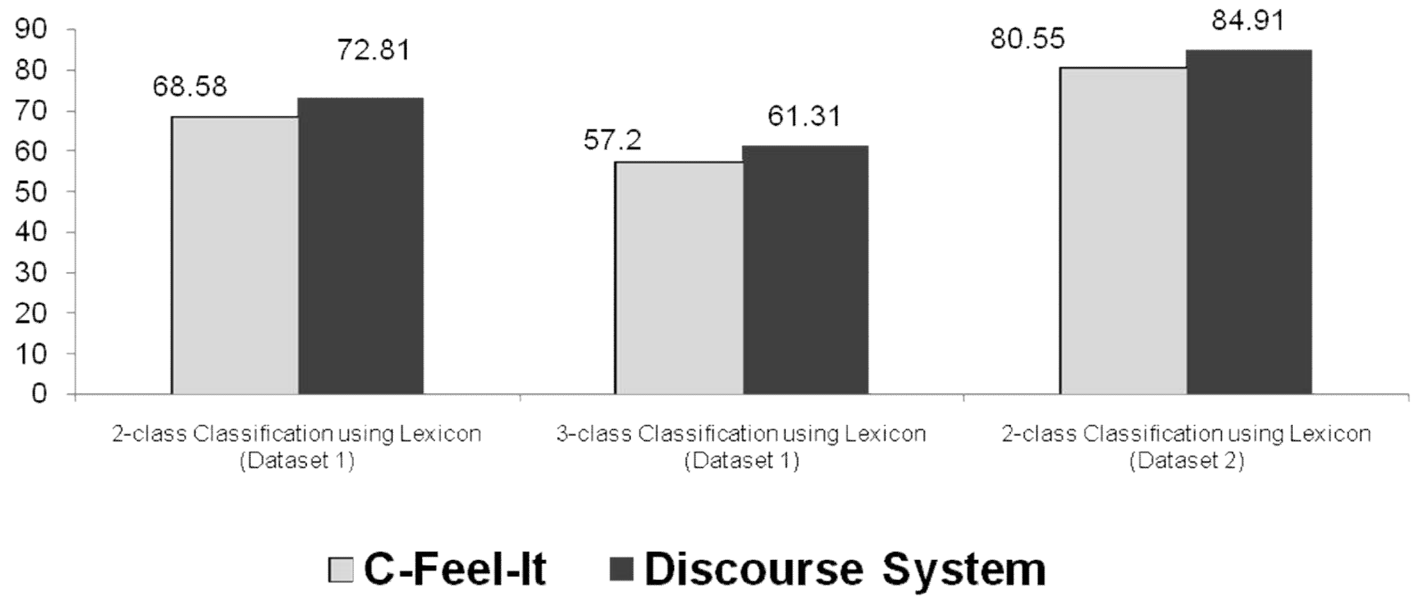

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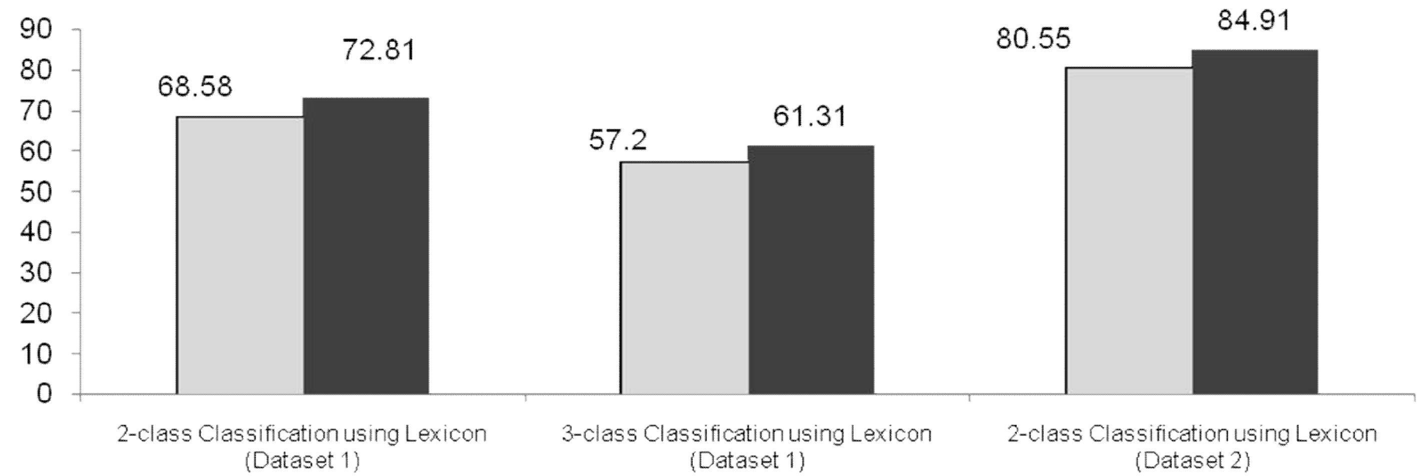

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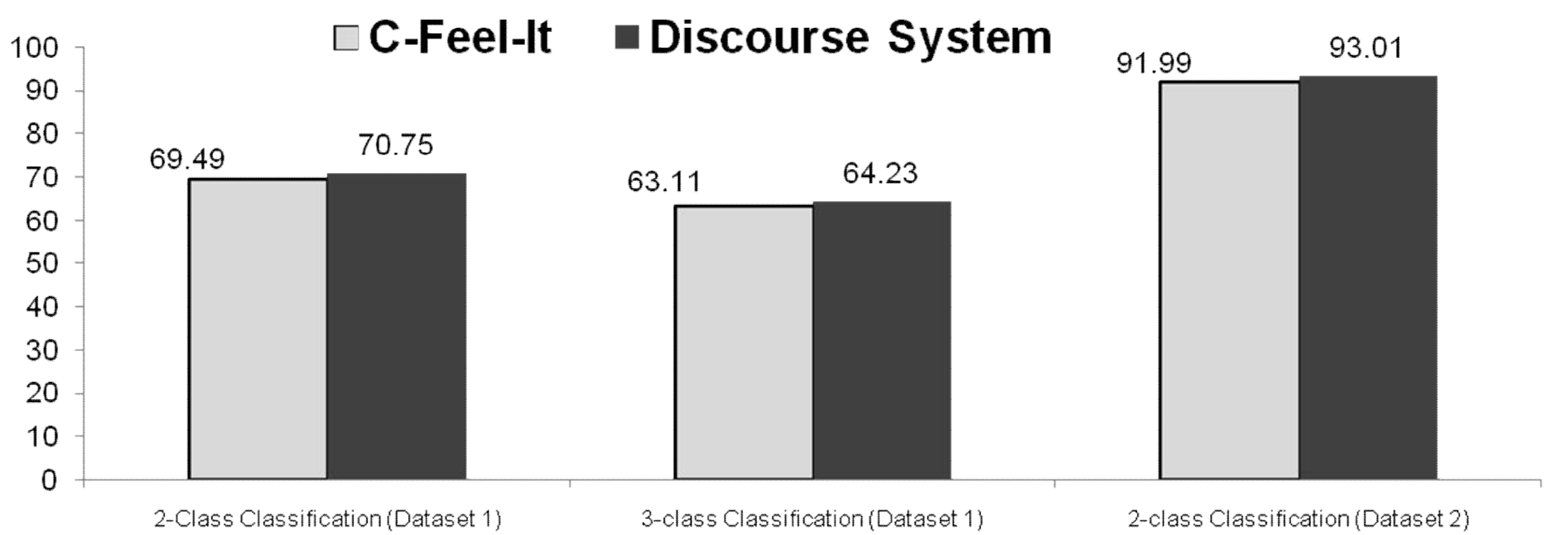

Classification Results in Travel Reviews (Dataset 3) Comparison with Balamurali *et al.*, EMNLP 2011)

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Lexicon-based Classification

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

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Baseline Bag-of-Words Model	69.62
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Supervised Classification

Systems	Accuracy (%)
Baseline Accuracy (Only Unigrams)	84.90
Balamurali *et al.*, 2011 (Only IWSD Sense of Unigrams)	85.48
Balamurali *et al.*, 2011 (Unigrams+IWSD Sense of Unigrams)	86.08
Unigrams + IWSD Sense of Unigrams+Discourse Features	**88.13**

Drawbacks

- Usage of a generic lexicon in lexeme feature space
- Lexicons do not have entries for interjections like *wow*, *duh etc*. which are strong indicators of sentiment
- Noisy Text (*luv, gr8, spams, …)*
- Sparse feature space (140 chars) for supervised classification
- 70% accuracy of IWSD in sense space for travel review classification

Drawbacks Contd…

- *I wanted^{+2} to follow my dreams and ambitions^{+2} **despite** all the obstacles^{-1}, **but** I did not succeed^{-2}.*

- *want* and *ambition* will get polarity *+2 each*, as they appear before *despite, obstacle* will get polarity *-1* and *not succeed* will get a polarity *-2 as they appear after but*

- Overall polarity is *+1,* whereas the overall sentiment should be *negative*

- We do not consider *positional importance* of a discourse marker in the sentence and consider all markers equally important

- Better give a ranking to the discourse markers based on their *positional* importance

- Thank You
- Questions ?