Sentiment Analysis and Opinion Mining

Dr. Furu Wei

Associated Researcher

Natural Language Computing Group,

Microsoft Research Asia

fuwei@microsoft.com

Sentiment Analysis Tutorials

- Sentiment Analysis in Practice Tutorial by Yongzheng Zhang et al. (ebay research lab | ICMD | 2011)
- Sentiment Symposium Tutorial by Christopher Potts (Stanford Linguistics | 2011)
- Sentiment Analysis Tutorial by Bing Liu (University of Illinois at Chicago | AAAI | 2011)
- Opinion Mining and Sentiment Analysis: NLP Meets Social Sciences by Bing Liu (University of Illinois at Chicago | 2010)
- Opinion Mining and Summarization by Bing Liu (University of Illinois at Chicago | WWW| 2008)
- Sentiment analysis and opinion mining (survey) by Bo Pang and Lillian Lee (Cornell University | 2008)

Lecture Agenda

- Introduction
- Twitter sentiment analysis
- Multilingual sentiment analysis
- Q&A

Outline

- Sentiment analysis
  - Introduction
    - Definition, application, components
  - Subtasks
    - Holder detection
    - Target detection
    - Polarity classification

Sentiment Analysis

- Also known as **opinion mining**: to understand the attitude of a speaker or a writer with respect to some topic
  - The attitude may be their judgment or evaluation, their affective state or the intended emotional communication
  - Most popular classification of sentiment: positive or negative

- For example
  - *<u>The pictures</u> are very clear.*
  - *In his recent State of the Union address, **US President Bush** quite unexpectedly labeled <u>Iran, Iraq, and the DPRK</u> as an "axis of evil".*

Applications of Sentiment Analysis

- Business intelligence system
- Purchase planning
- Public opinion management
- Web advertising

Google Product Search

HP Officejet 6500A Plus e-All-in-One Color Ink-jet - Fax / copier / printer / scanner
$89 online, **$100** nearby ★★★★☆ 377 reviews
September 2010 - Printer - HP - Inkjet - Office - Copier - Color - Scanner - Fax - 250 sh

Reviews

Summary - Based on 377 reviews

1 star	2	3	4 stars	5 stars

What people are saying

ease of use	"This was very easy to setup to four computers."
value	"Appreciate good quality at a fair price."
setup	"Overall pretty easy setup."
customer service	"I DO like honest tech support people."
size	"Pretty Paper weight."
mode	"Photos were fair on the high quality mode."
colors	"Full color prints came out with great quality."

Bing Shopping

HP Officejet 6500A E710N Multifunction Printer

Product summary Find best price **Customer reviews** Specifications Related items

$121.53 - $242.39 (14 stores)

☐ Compare

Average rating ★★★½☆ (144)

★★★★★	(55)
★★★★☆	(54)
★★★☆☆	(10)
★★☆☆☆	(6)
★☆☆☆☆	(23)
☆☆☆☆☆	(0)

Most mentioned

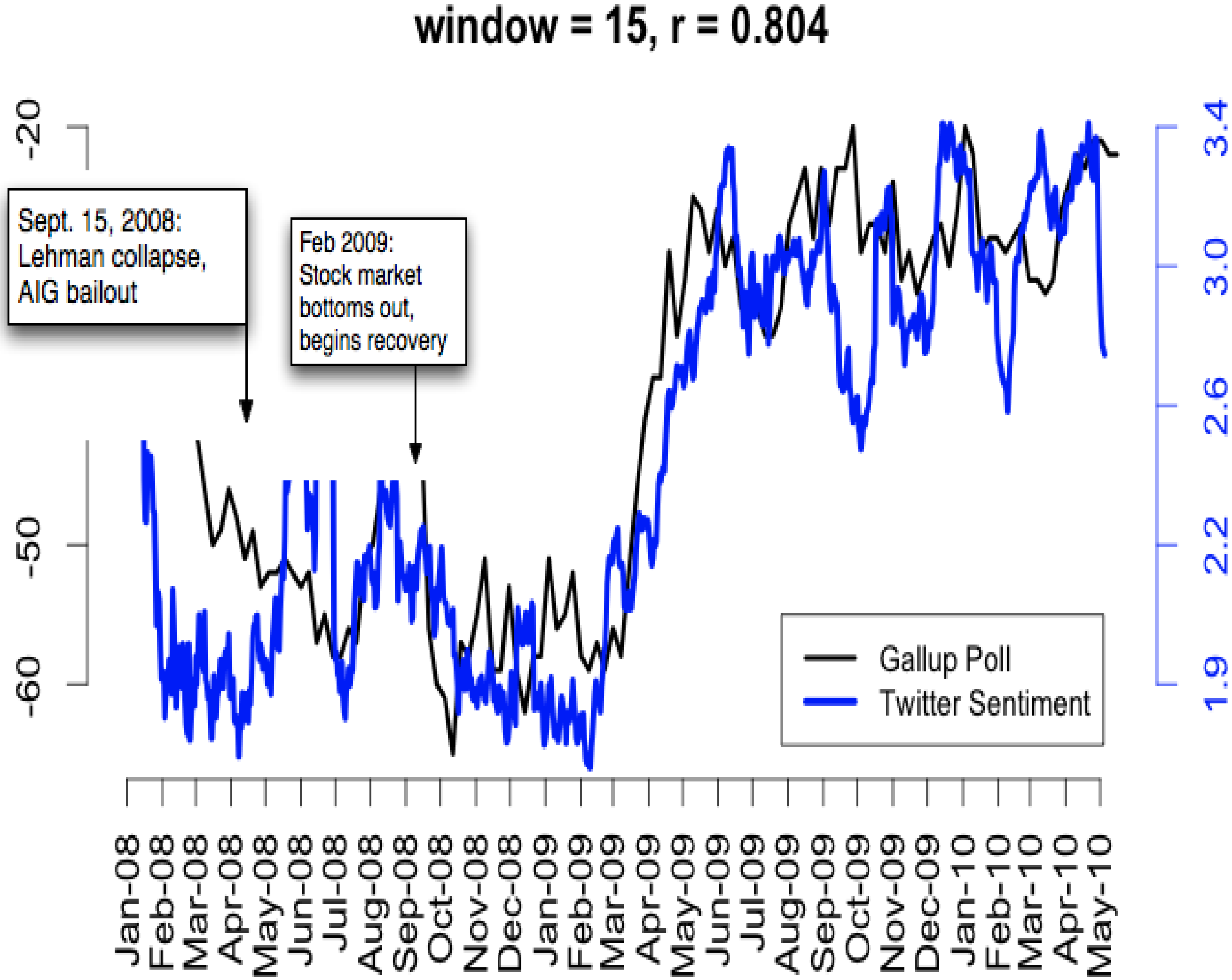
Performance	(57)
Ease of Use	(43)
Print Speed	(39)
Connectivity	(31)

More ▼

Show reviews by source

Best Buy (140)
CNET (5)
Amazon.com (3)

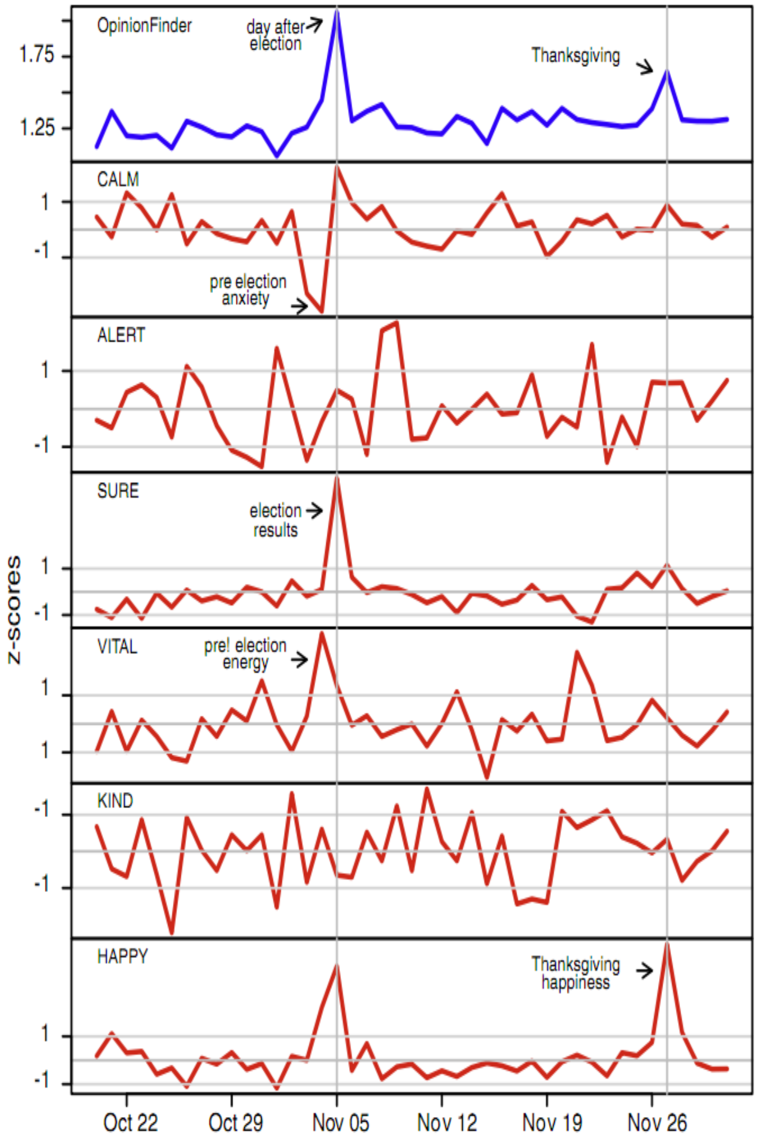
Twitter sentiment versus Gallup Poll of Consumer Confidence



Brendan O'Connor, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. 2010. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In ICWSM-2010

Twitter sentiment

Johan Bollen, Huina Mao, Xiaojun Zeng. 2011. Twitter mood predicts the stock market,
Journal of Computational Science 2:1, 1-8. 10.1016/j.jocs.2010.12.007.



Sentiment

- Sentiment = Holder + Polarity + Target
  - **Holder:** who expresses the sentiment
  - Target: what/whom the sentiment is expressed to
  - Polarity: the nature of the sentiment (e.g., positive or negative)

Sentiment

- Sentiment = Holder + Polarity + Target
  - **Holder:** who expresses the sentiment
  - Target: what/whom the sentiment is expressed to
  - Polarity: the nature of the sentiment (e.g., positive/negative)

- *In his recent State of the Union address,* **US President Bush** *quite unexpectedly labeled Iran, Iraq, and the DPRK as an "axis of evil".*

Negative

Sentiment

- The games in iPhone 4s are pretty funny!

Feature/Aspect

Target

Positive

Polarity

Holder = the user/reviewer

Sentiment

- Strength
  - Differentiate the intensity
- Confidence
  - Measure the reliability of the sentiment
- Summary
  - Explain the reason inducing the sentiment
- Time

Different Levels of SA

- Document level
  - E.g., product/movie review
- Sentence level
  - E.g., news sentence
- Expression level
  - E.g., word/phrase

Outline

- Sentiment analysis
  - Introduction
    - Definition, application, components
  - Subtasks
    - Holder detection
    - Target detection
    - Polarity classification

Holder Detection

- Identifying Sources of Opinions with Conditional Random Fields and Extraction Patterns
  - (Choi et al., HLT/EMNLP-05)

  International officers believe that the EU will prevail.
  International officers said US officials want the EU to prevail.

- View *source identification as an* information extraction task and tackle the problem using sequence tagging and pattern matching techniques simultaneously
  - *Linear-chain CRF model* to identify opinion sources
  - Patterns incorporated as features

CRF for Holder Detection

- Given a sentence X, to seek for a label sequence Y that maximizes

$$P(y|x) = \frac{1}{Z_x} \exp\left(\sum_{i,k} \lambda_k \, f_k(y_{i-1}, y_i, x) + \sum_{i,k} \lambda'_k \, f'_k(y_i, x) \right)$$

  – Y_i belongs to {'S', 'T', '-'}
  – λ_k and λ'_k are parameters, f_k and f'_k are feature functions
  – Z_x is the normalization factor

International	officers	believe	that	the	EU	will	prevail
S	T	-	-	-	-	-	-

Basic Features

- **Capitalization features:** all-capital, initial-capital
- **Part-of-speech features ([-2,+2]):** noun, verb, adverb, wh-word, determiner, punctuation, etc
- **Opinion lexicon features: [-1,+1]** whether or not the word is in the *opinion lexicon*
- **Dependency tree features**
  - the grammatical role of its chunk
  - the grammatical role of xi-1’s chunk
  - whether the parent chunk includes an opinion word
  - whether xi’s chunk is in an argument position with respect to the parent chunk
  - whether xi represents a constituent boundary
- **Semantic class features:** the semantic class of each word: authority, government, human, media, organization or company, proper name, and other

Extraction Pattern Learning

- Looking at the context surrounding each answer and proposes a lexico-syntactic pattern
  - *[They]$_h$ complained about the deficiencies of the benefits given to them.*
  - *<subj> complained*

- Compute the probability that the pattern will extract an opinion source

$$P(\text{source} \mid \text{pattern}_i) = \frac{\text{correct sources}}{\text{correct sources} + \text{incorrect sources}}$$

Extraction Pattern Features

- Four IE pattern-based features for each token xi
  - SourcePatt-Freq, SourcePatt-Prob,
  - SourceExtr-Freq, SourceExtr-Prob

  - Where
    - SourcePatt indicates whether a word activates any source extraction pattern. E.g., “complained” activates the pattern “<subj> complained”
    - SourceExtr indicates whether a word is extracted by any source pattern. E.g., “They” would be extracted by the *“<subj> complained”*

Experimental Results

- MPQA data
  - In total, 535 documents where targets are annotated by human
  - 135 as development set and feature engineering, and the remaining 400 for evaluation, performing 10-fold cross validation

- 3 measures: overlap match (OL), head match (HM), and exact match (EM)

		Recall	Prec	F1
Extraction Patterns	OL	48.5	81.3	60.8
	HM	46.9	78.5	58.7
	EM	41.9	70.2	52.5
CRF: basic features	OL	56.1	81.0	66.3
	HM	55.1	79.2	65.0
	EM	50.0	72.4	59.2
CRF: basic + IE pattern features	OL	59.1	82.4	68.9
	HM	58.1	80.5	67.5
	EM	52.5	73.3	61.2

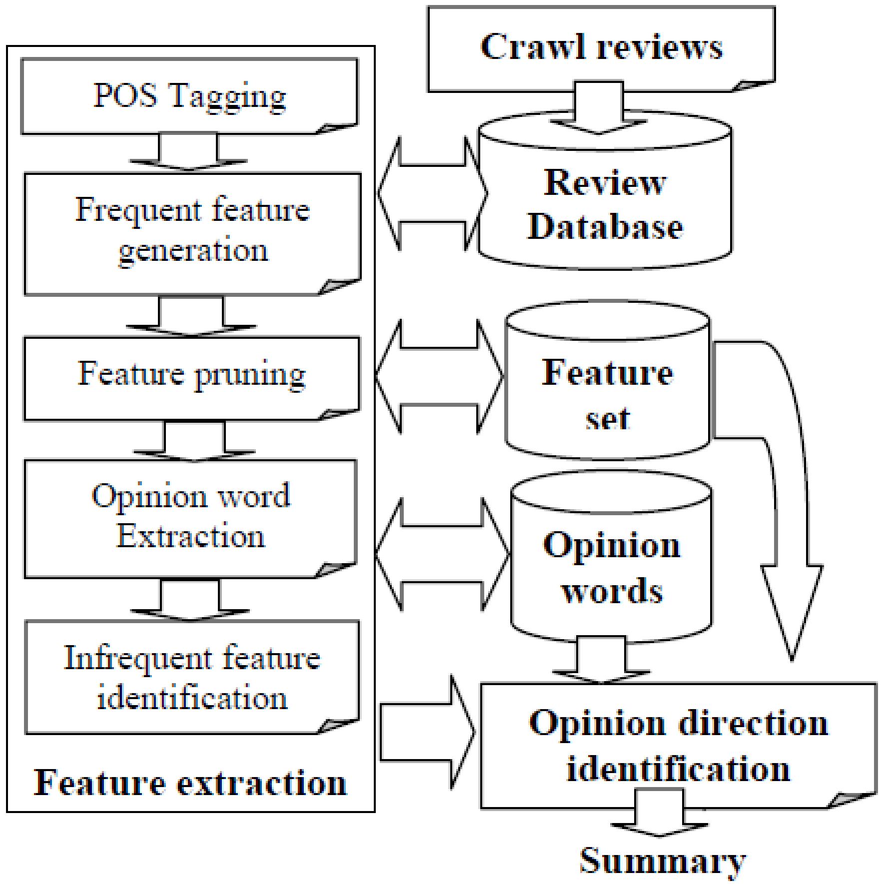
Outline

- Sentiment analysis
  - Introduction
    - Definition, application, components
  - Subtasks
    - Holder detection
    - Target detection
    - Polarity classification

Target Detection

- Mining Opinion Features in Customer Reviews
  - (Minqing Hu and Bing Liu, AAAI 2004)
    - *Explicit feature*
      - *The pictures are very clear.*
    - *Implicit feature*
      - *While light, it will not easily fit in pockets. (size)*
- Task definition
  - Given a product name and all the reviews of the product, to find the features of the product that appear explicitly as nouns or noun phrases in the reviews

Approach Overview



Frequent Features Detection

- Association rule mining
  - Find frequent features with three words or fewer
  - Appears in more than 1% of the review sentences (minimum support)

- Feature Pruning
  - Compactness: compact in at least 2 *sentences*
  - *p-support (pure support):* a p-support lower than the minimum p-support (3)

Infrequent Feature Detection

- People use the same adjective words to describe different subjects

  - *"Red eye is very easy to correct."*
  - *"The camera comes with an excellent easy to install software"*

  - *"The pictures are absolutely amazing"*
  - *"The software that comes with it is amazing"*

Infrequent Feature Detection

- Opinion word identification
  - For each sentence in the review database, if it contains any frequent feature, extract the nearby *adjective as* opinion word

- Infrequent feature detection
  - For each sentence in the review database, if it contains no frequent feature but one or more opinion words, find the *nearest noun/noun phrase of the opinion word* as an infrequent feature

Experimental Results

- Data: customer reviews of five electronics products from Amazon.com

Product name	No. of manual Features	Frequent features (association mining)		Compactness pruning		P-support pruning		Infrequent feature identification	
		Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Digital camera1	79	0.671	0.552	0.658	0.634	0.658	0.825	0.822	0.747
Digital camera2	96	0.594	0.594	0.594	0.679	0.594	0.781	0.792	0.710
Cellular phone	67	0.731	0.563	0.716	0.676	0.716	0.828	0.761	0.718
Mp3 player	57	0.652	0.573	0.652	0.683	0.652	0.754	0.818	0.692
DVD player	49	0.754	0.531	0.754	0.634	0.754	0.765	0.797	0.743
Average	**69**	**0.68**	**0.56**	**0.67**	**0.66**	**0.67**	**0.79**	**0.80**	**0.72**

Outline

- Sentiment analysis
  - Introduction
    - Definition, application, components
  - Subtasks
    - Holder detection
    - Target detection
    - Polarity classification

Lexicon Based Polarity Classification

- Mining and Summarizing Customer Reviews
  - (Hu and Liu, KDD-2004)

- Basic idea
  - Use the dominant orientation of the opinion words in the sentence to determine the orientation of the sentence.
  - That is, if positive/negative opinion prevails, the opinion sentence is regarded as a positive/negative one.

The General Inquirer

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls
- Categories:
  - Positive (1915 words) and Negative (2291 words)
  - Strong vs Weak, Active vs Passive, Overstated versus Understated
  - Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc
- Free for Research Use

LIWC (Linguistic Inquiry and Word Count)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007.

- Home page: http://www.liwc.net/
- 2300 words, >70 classes
- **Affective Processes**
  - negative emotion (*bad, weird, hate, problem, tough*)
  - positive emotion (*love, nice, sweet*)
- **Cognitive Processes**
  - Tentative (*maybe, perhaps, guess*), Inhibition (*block, constraint*)
- **Pronouns, Negation** (*no, never*), **Quantifiers** (*few, many*)
- $30 or $90 fee

MPQA Subjectivity Cues Lexicon

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.
Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

- Home page: http://www.cs.pitt.edu/mpqa/subj_lexicon.html
- 6885 words from 8221 lemmas
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL

Bing Liu Opinion Lexicon

Minqing Hu and Bing Liu. Mining and Summarizing Customer Reviews. ACM SIGKDD-2004.

- Bing Liu's Page on Opinion Mining
- http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar

- 6786 words
  - 2006 positive
  - 4783 negative

SentiWordNet

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010 SENTIWORDNET 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. LREC-2010

- Home page: http://sentiwordnet.isti.cnr.it/
- All WordNet synsets automatically annotated for degrees of positivity, negativity, and neutrality/objectiveness
- [estimable(J,3)] “may be computed or estimated”
- Pos 0 Neg 0 Obj 1
- [estimable(J,1)] “deserving of respect or high regard”
- Pos .75 Neg 0 Obj .25

Disagreements between polarity lexicons

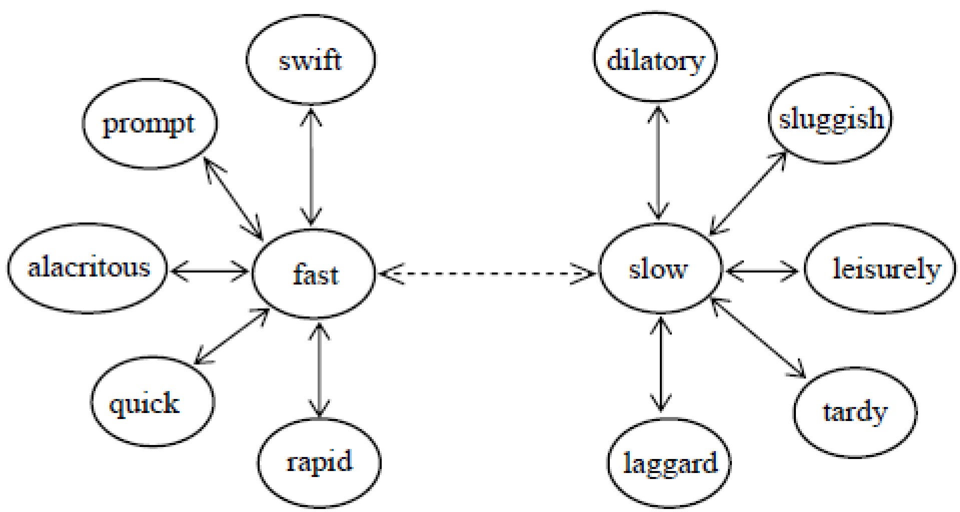
Christopher Potts, Sentiment Tutorial, 2011

	Opinion Lexicon	General Inquirer	SentiWordNet	LIWC
MPQA	33/5402 **(0.6%)**	49/2867 **(2%)**	1127/4214 **(27%)**	12/363 **(3%)**
Opinion Lexicon		32/2411 **(1%)**	1004/3994 **(25%)**	9/403 **(2%)**
General Inquirer			520/2306 **(23%)**	1/204 **(0.5%)**
SentiWordNet				174/694 **(25%)**
LIWC				

Lexicon Building

(Hu and Liu, KDD-2004)

- Utilize the adjective synonym set and antonym set in WordNet to predict the semantic orientations of adjectives
  - Adjectives share the same orientation as their synonyms and opposite orientations as their antonyms.
- Start with several seeds, iteratively expand to cover most opinion words



Hatzivassiloglou and McKeown (1997)

- Predicting the Semantic Orientation of Adjectives
  – (Hatzivassiloglou and McKeown, ACL-97)

- Assumption: adjectives connected by “and”/”but” tend to have same/opposite polarities

The tax proposal was

1. simple and well-received
2. simplistic but well-received
3. *simplistic and well-received

by the public.

Machine Learning based Approaches for Polarity Classification

- Thumbs up? Sentiment Classification using Machine Learning Techniques
  - (Pang et al., 2002)
- Basic idea
  - Treat sentiment classification simply as a special case of topic-based categorization
    - With the two “topics” being positive sentiment and negative sentiment
    - Use three standard algorithms: Naive Bayes classification, maximum entropy classification, and support vector machines

Approach Details

- Document representation
  - *Each* document *d is represented by a feature vector ~d:= $(n_1(d), n_2(d), \ldots, n_m(d))$*
  - *$n_i(d)$ could indicate presence, term frequency*

- Classification algorithms
  - Naive Bayes, Maximum Entropy, SVM

Data

- Movie reviews
  - From Internet Movie Database (IMDb)
    - http://www.cs.cornell.edu/people/pabo/movie-review-data/
    - http://reviews.imdb.com/Reviews/
  - 700 positive / 700 negative
- Experiment setting for ML classifiers
  - 3-fold cross validation
  - Treating punctuation as separate lexical items
  - No stemming or stoplists were used

Experimental Results

- Baseline: use a few words written by human to classify

	Proposed word lists	Accuracy
Human 1	positive: *dazzling, brilliant, phenomenal, excellent, fantastic* negative: *suck, terrible, awful, unwatchable, hideous*	58%
Human 2	positive: *gripping, mesmerizing, riveting, spectacular, cool, awesome, thrilling, badass, excellent, moving, exciting* negative: *bad, cliched, sucks, boring, stupid, slow*	64%

- ML-based methods

	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	”	pres.	81.0	80.4	**82.9**
(3)	unigrams+bigrams	32330	pres.	80.6	80.8	**82.7**
(4)	bigrams	16165	pres.	77.3	**77.4**	77.1
(5)	unigrams+POS	16695	pres.	81.5	80.4	**81.9**
(6)	adjectives	2633	pres.	77.0	**77.7**	75.1
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**
(8)	unigrams+position	22430	pres.	81.0	80.1	**81.6**

Compositional Sentiment Classification

- Sentiment composition on parsing tree
  – Sentiment composition rules on the parsing tree
  – Manually created linguistic patterns (~100)

ADJ	NOUN	→	NP	Example
NEG	POS	→	NEG	disappointed hope
NEG	NEG	→	NEG	a horrible liar
POS	POS	→	POS	a good friend
POS	NEG	→	NEG	a perfect misery
POS	NEU	→	POS	a perfect meal
NEG	NEU	→	NEG	a horrible meal

Fig. 1: *NP composition*

Klenner, Manfred, Stefanos Petrakis, and Angela Fahrni. 2009. Robust compositional polarity classification. Proc. RANLP, pp 180–184.

Translation based Sentiment Analysis

- Translation based sentiment analysis [Hiroshi et al. 2004]
  - Sentiment patterns as translation patterns
  - Sentiment clues as translation dictionary
  - Re-use the translation framework and implementation

Hiroshi, Kanayama, Nasukawa Tetsuya, andWatanabe Hideo. 2004. **Deeper sentiment analysis using machine translation technology**. Proc. COLING.

Translation based Sentiment Analysis

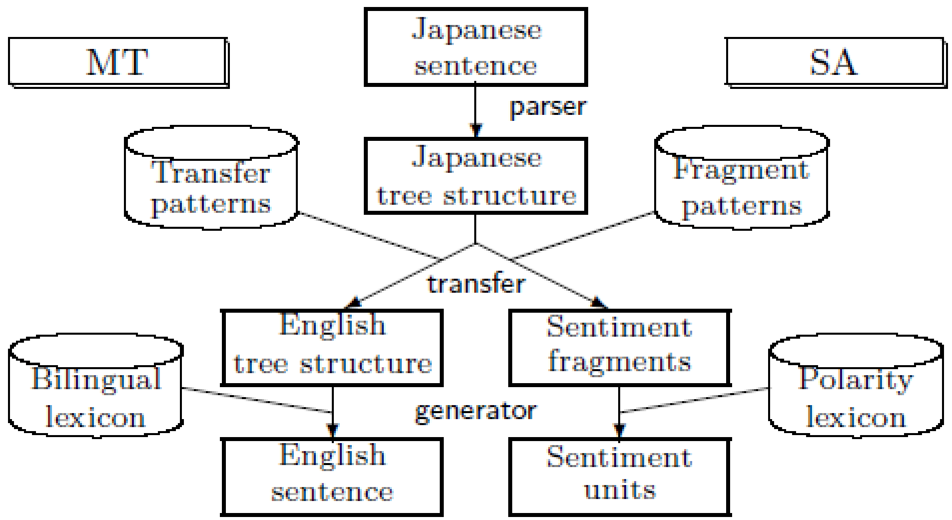


Figure 2: The concept of the machine translation engine and the sentiment analyzer. Some components are shared between them. Also other components are similar between MT and SA.

Other Related Approaches

- Topic sentiment mixture
  - Mei et al., 2007
- Semi-supervised approach
  - Li et al., 2010
- Domain Adaptation
  - Blizter et al., 2007

Summary

- Sentiment analysis refers to a set of subtasks
  - Holder, target, polarity

- Sentiment analysis is a challenging task and more difficult than traditional topic-based classification
  - Understanding of the semantics is often needed
    - How could anyone sit through this movie?

  - Same word/phrase may have different polarities in different domains
    - An unpredictable movie (positive)
    - An unpredictable politician (negative)

Twitter Sentiment Analysis

Twitter sentiment classification

- The objective
  - From a cluster of tweets, find positive and negative tweets on a given topic
  - Extended work: opinion summary
- Sentiment classification task
  - Holder: the author who publishes the tweet
  - Target: normally it is the given topic (query)
  - Polarity: to be decided
- Example
  - For a target: Windows7 (as a query)
  - Get a tweet "*Windows 7 is much better than Vista!*"
  - Output: positive

Challenges of tweet sentiment classification

- Sentence level rather than document level
- Short and incomplete sentences
- Full of ambiguous words, abbreviation words
- Informal and unedited texts
  - *"another part of me by Micheal Jackson is soo nicee! Loooveeeeee itttttttttt!"*
- Not enough annotated data readily available

Progress of the existing research

- Two step approach
  - Barbosa and Feng, 2010: Two-step approach to classify the sentiments of tweets using SVM classifiers
- Using hashtags, smileys, emoticons to collect training data
  - Davidiv et al., 2010 : Classify tweets into multiple sentiment types using hashtags and smileys as labels
  - Go et al., 2009: SVM classifier + collect training data using emoticons

Existing Systems

- Lexicon-based method
  - Based on the balance of # of positive words and # of negative words
  - Twittratr
- Rule-based
  - Based on syntactic rules, e.g., [query] is pos-adj
  - Tweetfeel
- Machine learning based
  - Based on the classifier built on a training data
  - Twitter sentiment

http://twitrratr.com/search/Microsoft

Favorites | Microsoft | twitrratr

Page ▾ Safety ▾ Tools ▾

twitrratr

TRACKING OPINIONS ON TWITTER

SEARCH

SEARCHED TERM	POSITIVE TWEETS	NEUTRAL TWEETS	NEGATIVE TWEETS	TOTAL TWEETS
Microsoft	**619**	**9470**	**317**	**10406**

5.95% POSITIVE

at a columbia engineering job fair. ny state dot is here. the city of portland. nyc dot. real networks. microsoft. great fee stuff (view)

i love how unhelpful microsoft help articles are (view)

new microsoft blog: the windows 7 blog for developers http://is.gd/4isg i think this blog could also interesting for admins. (view)

microsoft gemini is what you always wanted excel to be. its an excellent step forward to bi for the masses. (view)

microsoft gemini is what you always wanted excel to be. its an excellent step forward to bi for the masses. (view)

@zik actually, i know people @ msnbc.com and already knew that... still, i don't think microsoft is happy with nbc making them look dumb. (view)

@zik actually, i know people @ msnbc.com and already knew that... still, i don't think microsoft is happy with nbc making them look dumb. (view)

91.01% NEUTRAL

Reading Harvard Business columnist Stew Friedman that says Microsoft could learn from Neil Young. Hhmm.. OK. (view)

Just ordered Microsoft Office 2007 Professional for $66 and change after shipping. Much better than the $390 that Amazon wants. (view)

@bryansimpson I have been hearing that a lot over the past month. Maybe them and Microsoft need to get together. (view)

Microsoft Ad Business Strong, But Display Ads Threatened: Among Microsoft's diverse revenue streams, its d.. http://bit.ly/2owGq0 (view)

Got myself a Microsoft Natural 4000 keyboard amd wireless optical mouse. Need a USB hub methinks (view)

[PCWorld] Microsoft Taps Telefonica to Deliver Live Messenger VOIP http://tinyurl.com/5g57pj (view)

Found this: meta name="GENERATOR" content="Microsoft FrontPage 4.0". I think I just threw up in my mouth a little. (view)

3.05% NEGATIVE

why microsoft develop ie ? it sucks grrrrrr (view)

why microsoft develop ie ? it sucks grrrrrr (view)

why microsoft develop ie ? it sucks grrrrrr (view)

why microsoft develop ie ? it sucks grrrrrr (view)

why microsoft develop ie ? it sucks grrrrrr (view)

f*ck you internet explorer!! microsoft, you should be utterly ashamed of yourselves. (view)

f*ck you internet explorer!! microsoft, you should be utterly ashamed of yourselves. (view)

f*ck you internet explorer!! microsoft, you should be utterly ashamed of yourselves. (view)

f*ck you internet explorer!! microsoft, you should be utterly ashamed of yourselves. (view)

f*ck you internet explorer!! microsoft, you should be utterly


http://www.tweetfeel.com/#microsoft
Bing
Favorites
What do tweeple think about microsoft? Check o...
Page Safety Tools
Tweetfeel Biz | FAQ | Contact Us | Biz Login
A New Level of Tweetfeel Biz
tweetfeel
microsoft
Search
Try some Twitter trends: Bondan Prakoso Scott Pilgrim Ramadan Inception Meteor Shower iOS Poulsen
60
89
= 60%
LOL RT @gmilh: RT @BillGayts I love microsoft prodott. I li prend and me li ficc in my ass.
@leighpenny1 Is it OK that I love microsoft Excel and would marry it if I could figure out have to have sex with it?
I love microsoft Office 2010....Yeah i kno im a nerd at heart!
RearType? Expliquenme el prototipo de Table que desarrolla microsoft #fail TOTAL
RT @BillGayts I love microsoft prodott. I li prend and me li ficc in my ass.
@dancerlindsey nope PS3...microsoft sucks
Read our FAQ Subscribe to our API Legal Stuff 100% Guarantee Share
Follow us
Email us
Brought to you by conversition
Powered by twitter
Done, but with errors on page.
Internet | Protected Mode: On
100%

Twitter Sentiment - Windows Internet Explorer

http://twittersentiment.appspot.com/search?query=Microsoft

Favorites | Twitter Sentiment

Page ▾ Safety ▾ Tools ▾

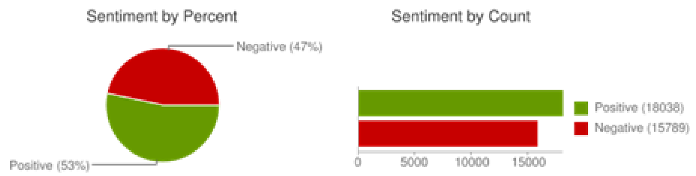
Sign in | Help

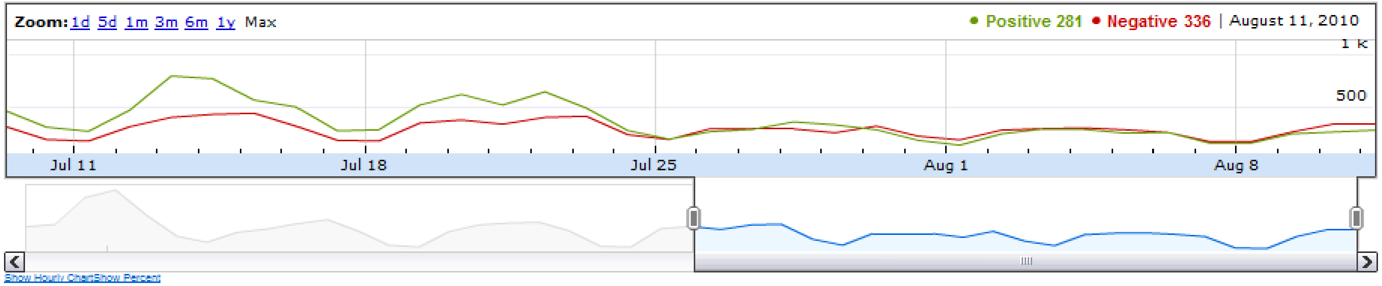
Twitter Sentiment

Type in a word and we'll highlight the good and the bad

microsoft [Search] Save this search

Sentiment analysis for microsoft





Show Hourly ChartShow Percent

Tweets about: microsoft

Choose a date range: [ ] to [ ] [Update] Note: We can only remember as far back as November 26, 2009

abbykutiwa: @iamtomwah the creator of apple or **microsoft** didn't go to college, can't remember who...
Posted 20 minutes ago
Reclassify the sentiment as: [Negative ○ ○ ○ Positive]

SivadYar: @Catawampus25 the joys of working at **Microsoft** eh? :P
Posted 23 minutes ago
Reclassify the sentiment as: [Negative ○ ○ ○ Positive]

tomarbuthnot: @sevanjaniyan lol, that's your answer to all **Microsoft** related problems! :-)
Posted 28 minutes ago
Reclassify the sentiment as: [Negative ○ ○ ○ Positive]

mamotokyo: Internet Explorer 7 of **Microsoft** is SUCK.
Posted 39 minutes ago
Reclassify the sentiment as: [Negative ○ ○ ○ Positive]

BrianaThaBombb: @ClickClackAG I have a xbox 360 assshole! But my uncle works fer **Microsoft** thas why lol
Posted 40 minutes ago
Reclassify the sentiment as: [Negative ○ ○ ○ Positive]

comparelaptops: Fury as users locked out of Hotmail: **Microsoft** says users should switch to ChromeUsers have hit back at **Microsoft** ... http://bit.ly/b5d73C

Issues (1)

- Most current research or systems do not consider the target when classifying the sentiment
- Example
  - Input a target “google”
  - *“Here's a great article about Monte Veronese cheese. It's in Italian so just put the url into Google translate and enjoy http://ow.ly/3oQ77”*
  - Sentiment classification: positive , however actually it is not towards to the target that user inputs

Issues (2)

- Most current research and systems treat a tweet independently with its context
- However, there is severe shortage of the information in a single tweet as it is short and often uncompleted

Observation

- There is strong association between the polarities of connected tweets
  - An user tends to have same polarities towards some celebrities with a fixed length of time
  - The user who retweets a tweet normally has the same opinions with the original tweet

Target-dependent twitter sentiment analysis (ACL 2011)

Our approach on tweet sentiment classification (1)

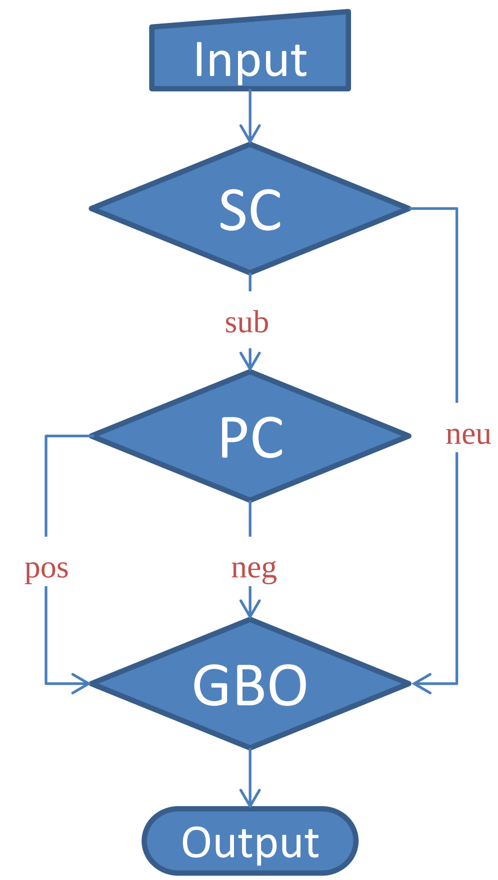
- Consider dependency relation between the target and the sentiment word
  - *E.g., Windows 7 is much better than Vista!*
    - *Output positive if target is Windows 7, and output negative if target is Vista*
  - *People everywhere love Windows & vista. Bill Gates*
    - *Output positive if target is Windows & vista, and output neutral if target is Bill Gates (If we don't consider the relation between Windows & Vista and Bill Gates)*

Our approach on tweet sentiment classification (2)

- Consider the context of the tweet
  - *E.g., "First game: Lakers!"*
  - *It is too short to decide the polarity, but when we consider the tweets in its context, we will make a better judgment*

Overview of our approach

- Task definition
  - Input
    - a collection of tweets containing the target (or query)
  - Output
    - labels assigned to each of the tweets
- Three steps
  - Subjectivity classification (SC)
  - Polarity classification (PC)
  - Graph-based optimization (GBO)



Preprocessing

- Tweet normalization
  – A simple rule-based model
  – “gooood” to “good”, “luve” to “love”
- POS tagging
  – OpenNLP POS tagger
- Word stemming
  – A word stem mapping table (about 20,000 entries)
- Syntactic parsing
  – A Maximum Spanning Tree dependency parser (McDonald et al., 2005)

Classification of subjectivity and polarity

- Binary SVM classifiers with linear kernel
  - Target-independent features
    - Content features
      - Words, punctuations, emoticons, and hashtags
    - Sentiment lexicon features
      - The number of positive or negative words in the tweet according to a sentiment lexicon (General Inquirer)
  - Target-dependent features(see next page)

Target-dependent features (1)

- Templates for generating target-dependent features
  - *Subject/object of* a transitive verb wi
    - wi _arg2, e.g., “I love iPhone”, => “love_arg2”
    - wi_arg1, e.g., “Obama reaffirms ..” => reaffirm_arg1
  - *Subject of* a intransitive verb
    - Wi_it_arg1
  - *Head of* an adjective or noun
    - Wi_arg1
  - Connected by a copula (verb “to be”) with an adjective or noun
    - Wi_cp_arg1
  - ….

Target-dependent features (2)

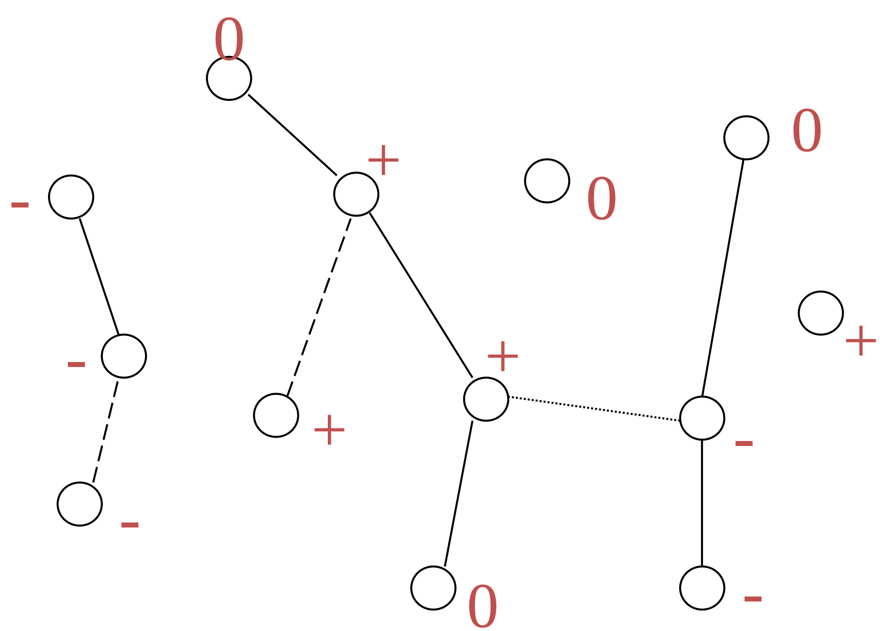
- Handle negations by adding "*neg-*"
  - "*iPhone does not work better with the CellBand*" *=> neg-work_arg1*
- *Seven negations are used including not, n't, neither, seldom, hardly, etc.*

Target expansion

- Sometimes, sentiments are not expressed exactly towards the target
  - *"I am passionate about Microsoft technologies especially Silverlight."*
  - *Microsoft (input target) vs. Microsoft technologies(actual appearance)*
- Extended targets are viewed equally as target
  - All noun phrases including the target
  - Mentions co-referring to the target
  - Top K nouns with strong association with the target
- Note: we don't use ontology now

Graph-based sentiment optimization

- Relation types among the input tweets
  - Retweeting
  - Being published by the same person
  - Replying



Graph-based sentiment optimization

$$p(c \mid \tau) \longrightarrow \text{Relaxation Labeling (Angelova and Weikum, 2006)} \longrightarrow p(c \mid \tau, G)$$

The output score by SC and PC to calculate p(c| τ)

Iteratively optimize p(c| τ,G)

$$p(c \mid \tau, G) = p(c \mid \tau) \sum_{N(d)} p(c \mid N(d)) \, p(N(d))$$

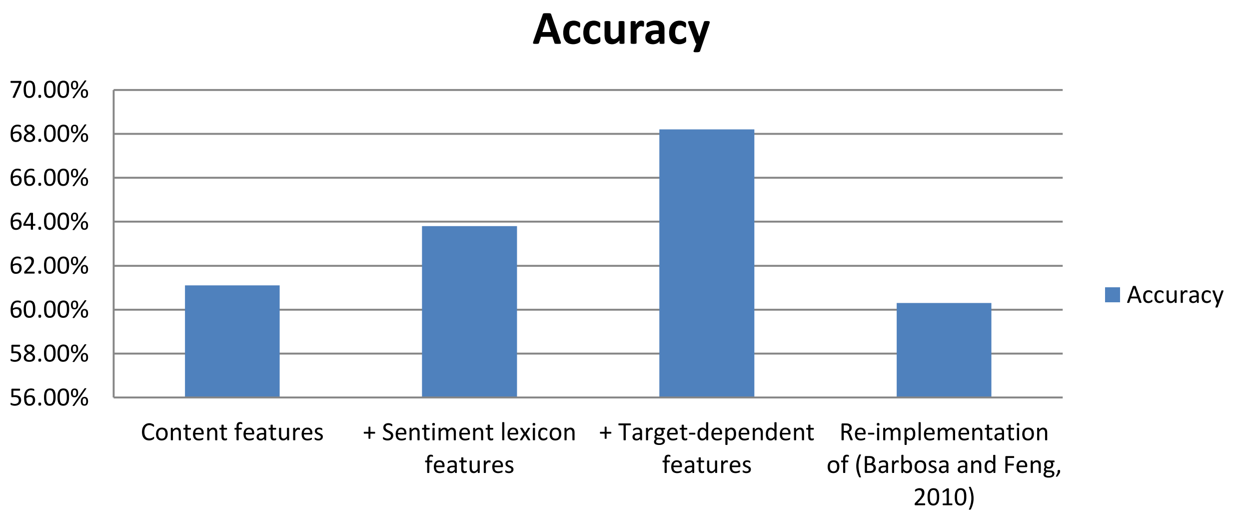
- *c* is the sentiment label of a tweet, which belongs to {positive, negative, neutral}
- *G* is the tweet graph
- *N(d)* is a specific assignment of sentiment labels to all immediate neighbors of the tweet
- τ is the content of the tweet

Experimental setting

- Raw data
  - 5 queries: *Obama, Google, iPad, Lakers, Lady Gaga*
  - 400 English tweets downloaded for each from Twitter
- Annotation
  - 2 human annotators
  - 3 labels: positive, negative or neutral
  - 459 positive, 268 negative and 1,212 neutral tweets
- Inter-annotator study
  - For 86% of tweets, two annotators give identical labels
  - For 13%, neutral-subjective disagreement
  - For 1%, positive-negative disagreement

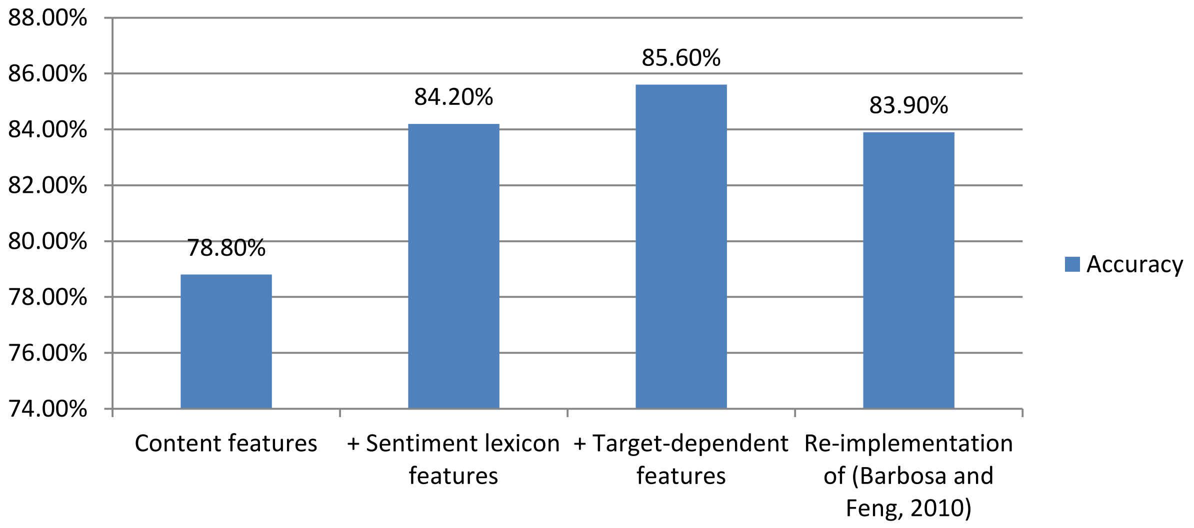
Subjectivity classification evaluation

- Data
  - 727 subjective (positive + negative) tweets and 1212 neutral tweets
  - 5 fold cross validation



Polarity classification evaluation

- Data
  - 268 negative and 459 positive tweets
  - 5 fold cross validation



Evaluation of graph-based optimization

- Data
  - 459 positive, 268 negative and 1,212 neutral tweets

System	Accuracy(%)	F1-score (%)		
		pos	neu	neg
Target-dependent sentiment classifier	66.0	57.5	70.1	66.1
+Graph-based optimization	68.3	63.5	71.0	68.5

Summary of our approaches

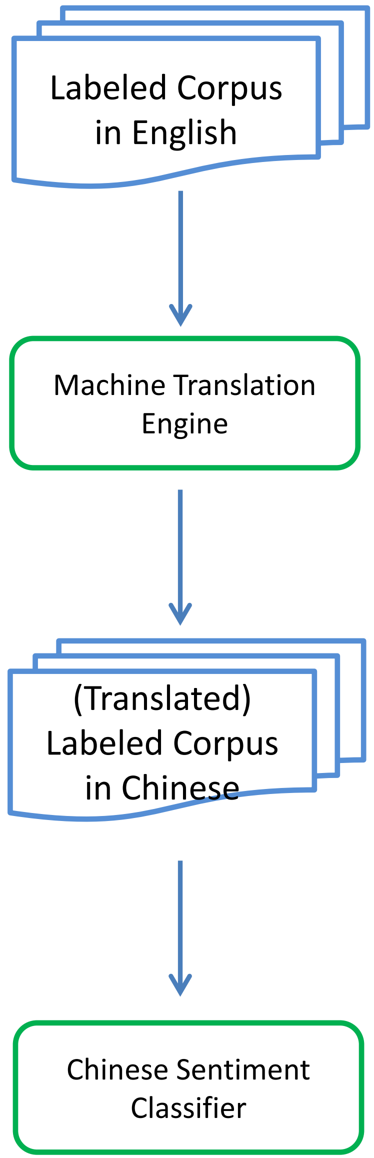
- Target-dependent features are used using dependency relation
- Targets are extended by various tricks to cover more appearances of targets
- A simple graph-model is used to take the context into consideration by relaxation labeling process

Multilingual Sentiment Analysis

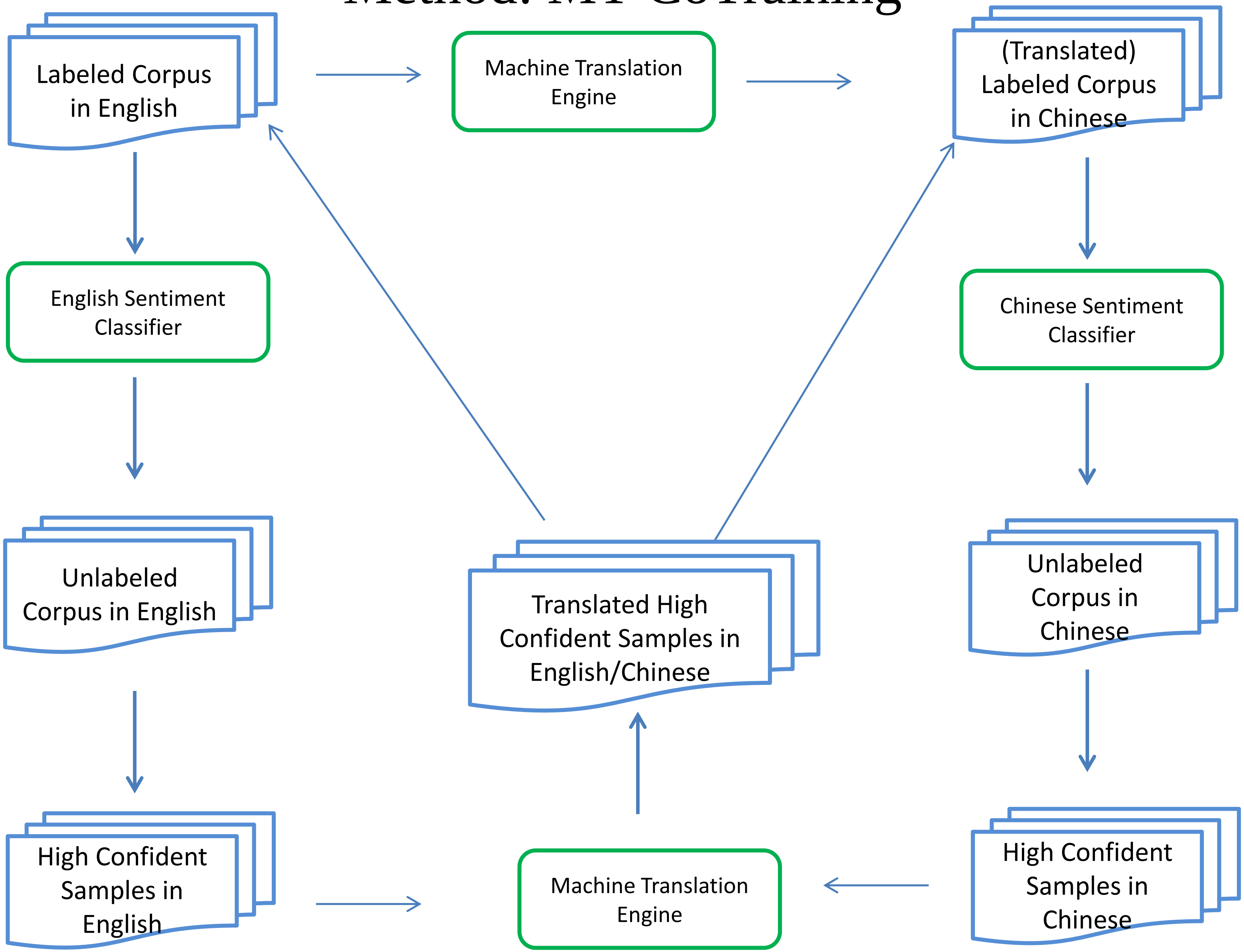
Task

- Train a sentiment classifier for a foreign language with labeled data on English and unlabeled parallel data on both languages
- Input
  - Labeled English data L_e
  - Unlabeled parallel data U_{ef}
  - Labeled foreign language data L_f (optional)
- Output
  - Sentiment classifier on the foreign language C_f

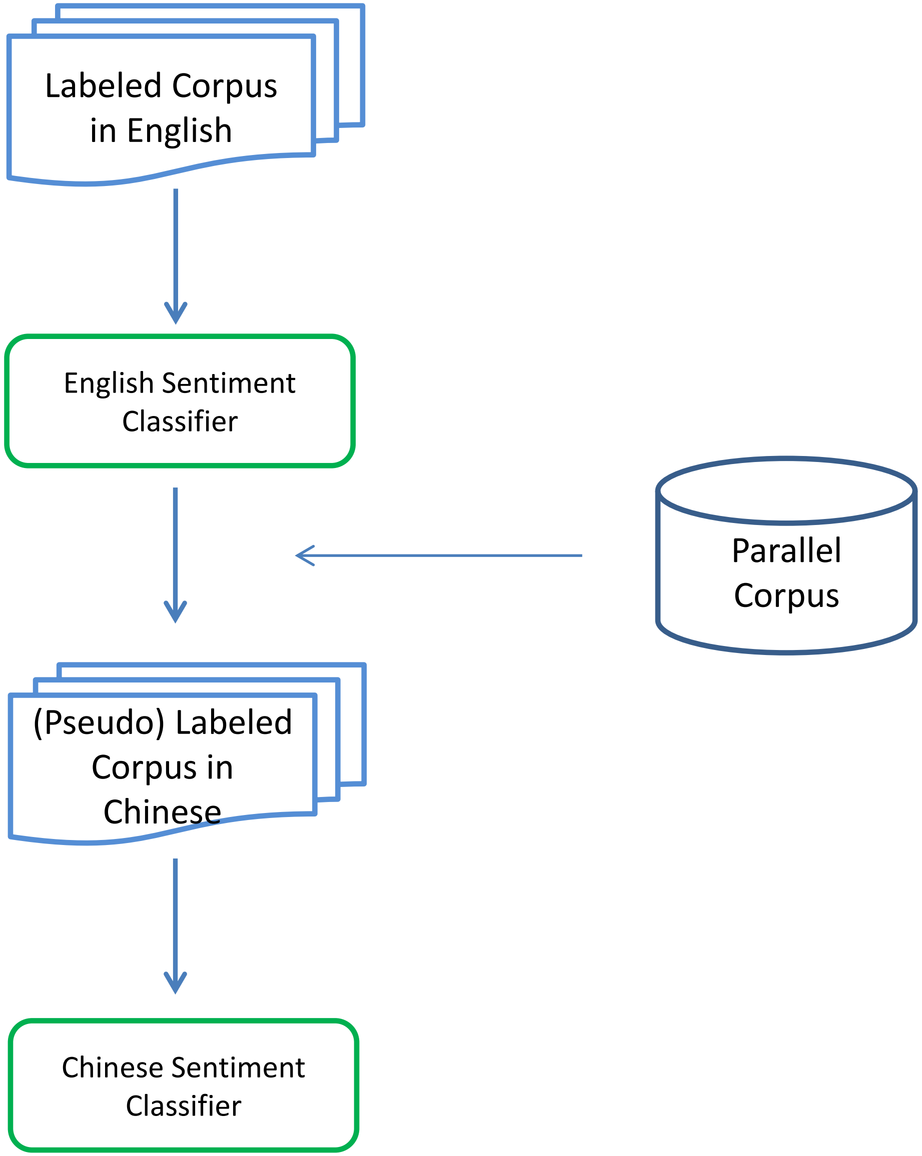
Method: MT-SVM



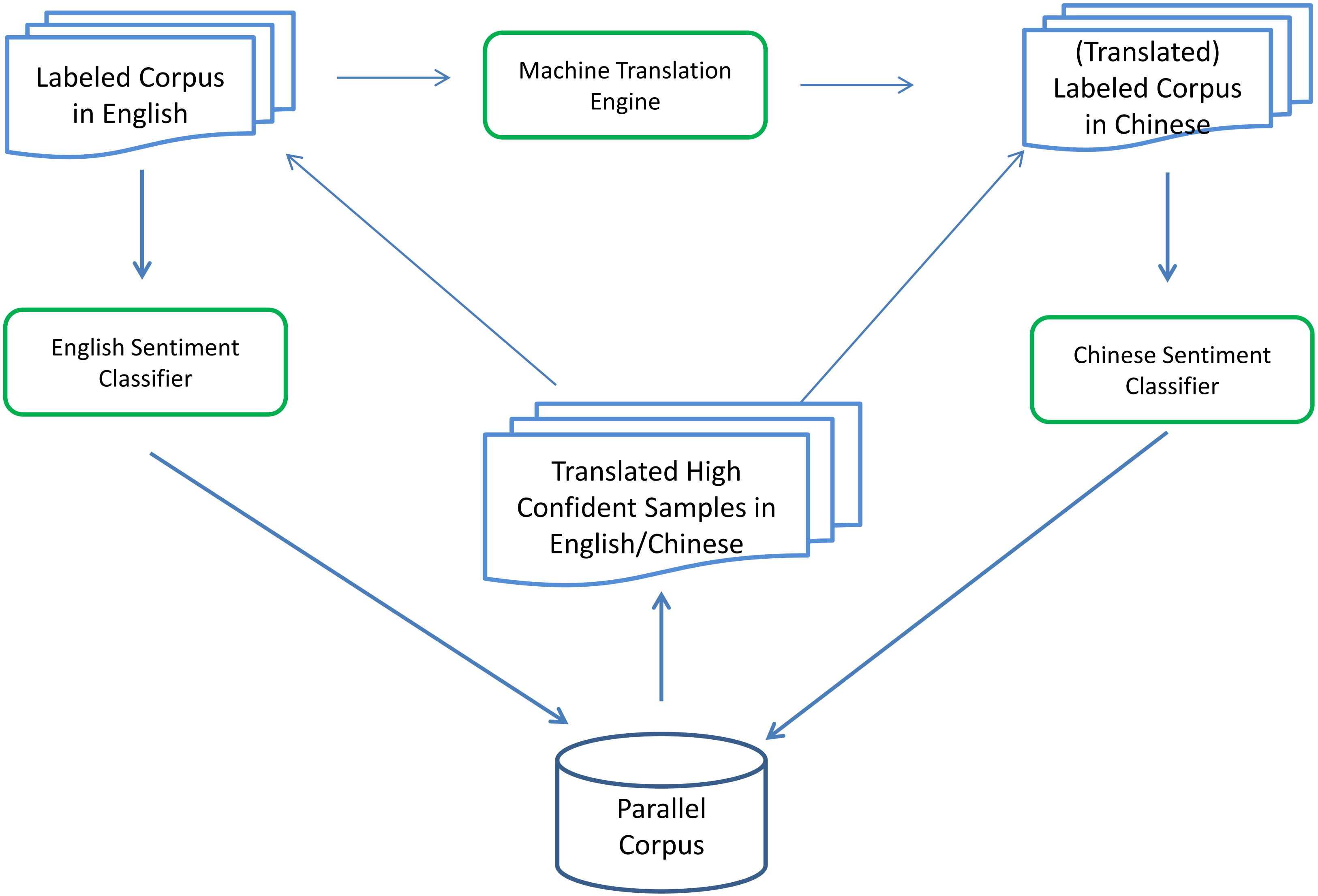
Method: MT-CoTraining



Method: Para-SVM



Method: Para-CoTraining



Cross-Lingual Mixture Model for Sentiment Classification (ACL 2012)

Existing Work

- (Wan 2009) uses machine translated text as training data
- (Prettenhofer 2010) projects both languages into the same space with bilingual words mapping and learn classifiers on this space
- (Lu 2011) improves bilingual sentiment classification by enforcing label consistency on parallel corpus

Challenges

- Problems and challenges
  - Machine translation engine
    - Feature/vocabulary coverage
    - Polysemy
  - Language projection with bilingual words mapping
    - Polysemy
  - Label consistency on parallel corpus
    - Label consistency is only determined by sentence alignment probability

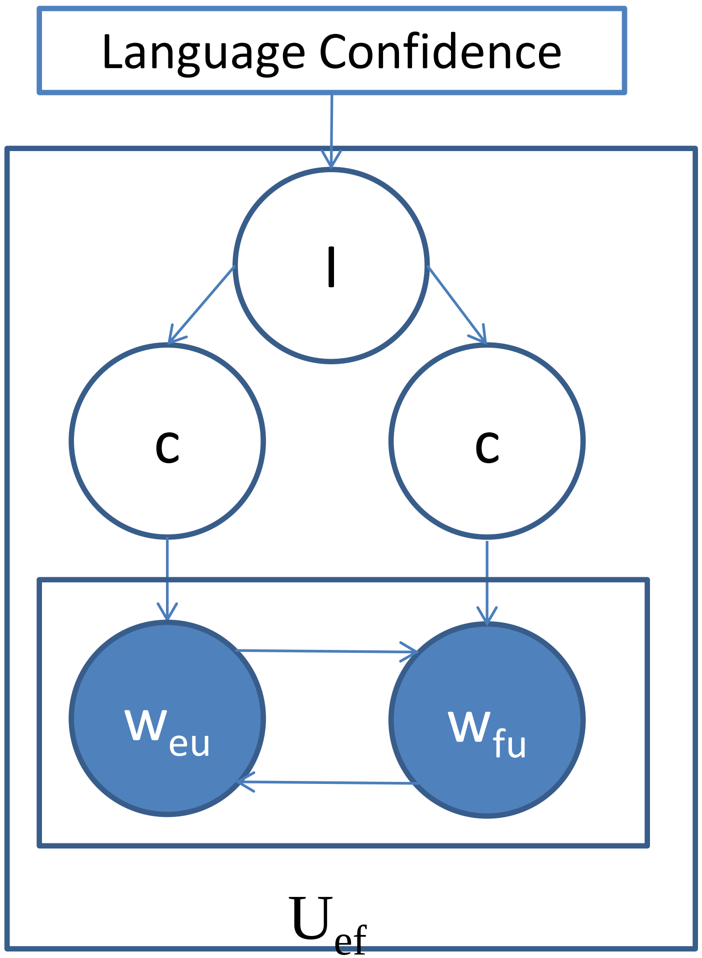
Answers to Challenges

- Improve feature/vocabulary coverage with parallel corpus
- Use word alignment in parallel corpus to choose mapping for polysemy
- Determine label consistency in parallel corpus with word alignment

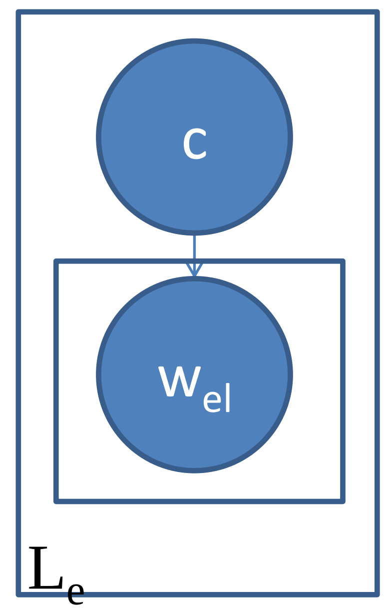
Cross-Language Mixture Model

- Word level assumption in parallel sentences
  - The aligned words between English and Chinese have the same functions for determining the sentiment polarity for sentences
- Generative model
  - The process of sentence generation:
    - Select a polarity label wrt. prior distribution
    - Select words
      - Generate a Chinese word according to the polarity label
      - Generate a Chinese word by projecting an English word with the same polarity
  - Train the parameters by maximizing the likelihood of the large unlabeled parallel corpus and the labeled monolingual data (English with/without Chinese)

Cross-Language Mixture Model



×



$P(U_{ef} | \theta_1, \theta_2)$ × $P(L_{ef} | Ce, \theta_1, \theta_2)$

Unlabeled Parallel data

Labeled English data

Parameter Estimation

$$argmax_\theta \; L(\theta|D_t, D_s, U) = L(\theta|D_s) + L(\theta|D_t) + L(\theta|U)$$

$$L(\theta|D_s) = \sum_{i=1}^{|D_s|}\sum_{j=1}^{|C|}\sum_{s=1}^{|V_s|} N_{si} \log P(w_s|c_j)\delta_{ij}$$

$$L(\theta|D_t) = \sum_{i=1}^{|D_t|}\sum_{j=1}^{|C|}\sum_{t=1}^{|V_t|} N_{ti} \log P(w_t|c_j)\delta_{ij}$$

Generating a Chinese word according to a polarity

$$L(\theta|U) = \sum_{i=1}^{|U_t|}\sum_{j=1}^{|C|}\sum_{t=1}^{|V_t|} [N_{ti} \log \left(\underline{P(w_t|c_j)} + \underline{P(w_t|w_s)P(w_s|c_j)}\right)$$

$$+ \sum_{i=1}^{|U_s|}\sum_{j=1}^{|C|}\sum_{s=1}^{|V_s|} [N_{si} \log \left(P(w_s|c_j) + P(w_s|w_t)P(w_t|c_j)\right)]$$

Generating a Chinese word by projectingan English word with same polarity

Parameter Estimation

$$argmax_{\theta} \; L(\theta|D_t, D_s, U) = L(\theta|D_s) + L(\theta|D_t) + L(\theta|U)$$

$$L(\theta|D_s) = \sum_{i=1}^{|D_s|}\sum_{j=1}^{|C|}\sum_{s=1}^{|V_s|} N_{si} \log \underline{P(w_s|c_j)}\delta_{ij}$$

$$L(\theta|D_t) = \sum_{i=1}^{|D_t|}\sum_{j=1}^{|C|}\sum_{t=1}^{|V_t|} N_{ti} \log \underline{P(w_t|c_j)}\delta_{ij}$$

$$L(\theta|U) = \sum_{i=1}^{|U_t|}\sum_{j=1}^{|C|}\sum_{t=1}^{|V_t|} [N_{ti} \log (\underline{P(w_t|c_j)} + \boxed{P(w_t|w_s)}\underline{P(w_s|c_j)})$$

$$+ \sum_{i=1}^{|U_s|}\sum_{j=1}^{|C|}\sum_{s=1}^{|V_s|} [N_{si} \log (\underline{P(w_s|c_j)} + \boxed{P(w_s|w_t)}\underline{P(w_t|c_j)})]$$

Probability of generating a word *w* for polarity *c* *estimated by EM*

Projection probability estimated by word alignment probability

EM

$$P(c_j|u_{si}) = Z(c_{u_{si}} = c_j) = \frac{\prod_{w_s \in u_{si}} [P(w_s|c_j) + \sum_{P(w_s|w_t)>0} P(w_s|w_t)P(w_t|c_j)]}{\sum_{c_j} \prod_{w_s \in u_{si}} [P(w_s|c_j) + \sum_{P(w_s|w_t)>0} P(w_s|w_t)P(w_t|c_j)]} \tag{5}$$

$$P(c_j|u_{ti}) = Z(c_{u_{ti}} = c_j) = \frac{\prod_{w_t \in u_{ti}} [P(w_t|c_j) + \sum_{P(w_t|w_s)>0} P(w_t|w_s)P(w_s|c_j)]}{\sum_{c_j} \prod_{w_t \in u_{ti}} [P(w_t|c_j) + \sum_{P(w_t|w_s)>0} P(w_t|w_s)P(w_s|c_j)]} \tag{6}$$

E-Step

M-Step

$$P(w_s|c_j) = \frac{1 + \sum_{i=1}^{|D_s|} \Lambda_s(i) N_{si} P(c_j|d_i)}{|V| + \sum_{s=1}^{|V_s|} \Lambda(i) N_{si} P(c_j|d_i)}$$

$$P(w_t|c_j) = \frac{1 + \sum_{i=1}^{|D_t|} \Lambda_t(i) N_{ti} P(c_j|d_i)}{|V| + \sum_{t=1}^{|V_t|} \Lambda(i) N_{ti} P(c_j|d_i)}$$

Experiments

Methods	NTCIR-EN NTCIR-CH	MPQA-EN NTCIR-CH
MT-SVM	62.34	54.33
Para-SVM	N/A	N/A
MT-CoTrain	65.13	59.11
Para-CoTrain	67.21	60.71
CLMM	70.96	71.52

Classification Result using Only English Labeled Data

Note:

- # of parallel sentences: 20,000
- MT engine: Microsoft translator
- NTCIR-EN (English labeled corpus): 4,294
- NTCIT-CH (Chinese labeled corpus): 1,739
- MPQA-EN (English labeled corpus): 4,598

Experiments

Methods	NTCIR-EN NTCIR-CH	MPQA-EN NTCIR-CH
SVM	80.58	80.58
MT-CoTrain	82.28	80.93
Para-CoTrain	82.35	82.18
CLMM	82.73	83.02

Classification Result using English and Chinese Labeled Data

Revisit Sentiment Analysis Future Work (I)

- Sentiment vs. topic classification
  - Single word can determine the class
    - Subjective vs. objective
    - Positive vs. negative
  - Invertible (negation)
  - Contextual
    - Local and long distance context
  - Compositional
  - Target dependent
  - Topic (domain) dependent
  - Annotation and adaption (language, domain, topic)
  - Imbalance classification

Future Work (II)

- Understand the user (sentiment holder)
- Sentiment insight mining
- Implicit sentiment (semantic context of sentiment)
  - Sarcasm, Irony, Metaphor, Polysemous

Questions?

THANKS