

# A Taste of Sentiment Analysis

Rob Zinkov

May 26th, 2011

# Outline

- 1 Introduction
- 2 Basics of NLP
- 3 Basic Techniques for Sentiment Analysis
- 4 Advanced Techniques for Sentiment Analysis
- 5 Further Questions

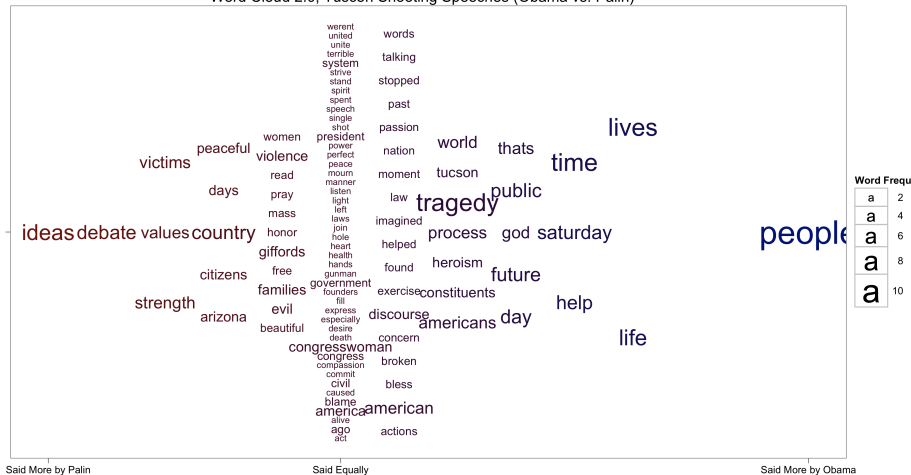
# What is Sentiment Analysis?

Sentiment Analysis is a subfield of Computational Linguistics concerned with extracting emotions from text

# Applications

# Applications - Political Blogs

Word Cloud 2.0, Tuscon Shooting Speeches (Obama vs. Palin)



# Applications - Political Blogs

- Tracking opinions on issues
- Tracking which issues are held emotionally
- Tracking subjectivity of bloggers

# Political Blogs - Challenges

- Identifying opinion holder
- Associating opinions with issue
- Identifying public figures and legislation

## Applications - Product Reviews

7 of 7 people found the following review helpful:

★★★★★ **This Milk Changed My Life**, August 8, 2010

By **Robert D. Queen "itcbob"** (Springfield, VA) - [See all my reviews](#)

REAL NAME™

**This review is from:** Tuscan Whole Milk, 1 Gallon, 128 fl oz (Misc.)

The Tuscan whole milk is the most amazing drink I have ever had. I used to be an alcoholic, but after one drink of this amazing milk, alcohol has never touched my lips again. Why drink bourbon when this amazing milk from the hills of Tuscany is now available to us all. Nothing short of the Second Coming compares to the sight of Tuscan Milk. Less than \$100 per gallon is a steal. Don't miss out on the amazing opportunity to experience Tuscany as its finest.

Help other customers find the most helpful reviews

Was this review helpful to you?

[Report abuse](#) | [Permalink](#)

 [Comment](#)

14 of 19 people found the following review helpful:

★☆☆☆☆ **No Protection at All**, August 8, 2007

By [J. McArthur](#)  - [See all my reviews](#)

REAL NAME™

**This review is from:** JL421 Badonkadonk Land Cruiser/Tank

My wife and kids were playing in my JL421, and I thought I would give them a bit of a scare as a joke, so I shot a few rounds at the side with a rather large gun that I have and the bullets penetrated right through and killed them all! I am so disappointed with the quality of this land cruiser. I called the manufacturer and they said it wouldn't be covered under warranty because I did it intentionally. I'm never buying from this company again.

Help other customers find the most helpful reviews

Was this review helpful to you?

[Report abuse](#) | [Permalink](#)

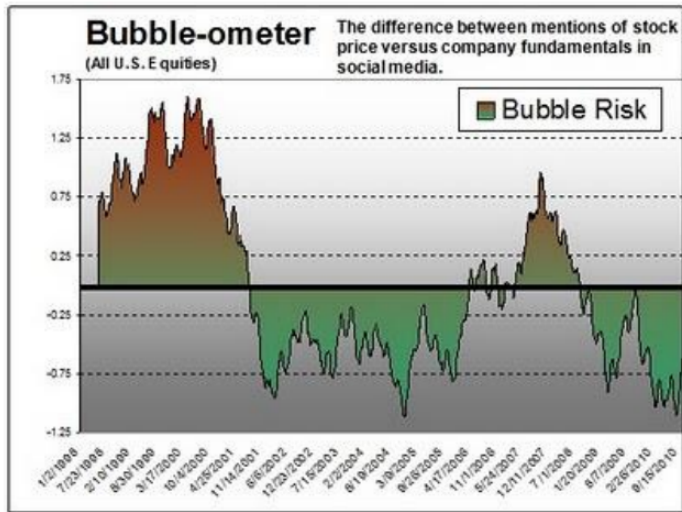
 [Comment](#)



# Product Reviews - Challenges

- Identifying aspects of product
- Associating opinions with aspects of product
- Identifying Fake Reviews
- No canonical form

# Applications - Financial News



# Financial News - Challenges

- Identifying the equity in the article (think commodities)
- Associating entities with market symbols
- Specialized financial terms with distinct sentiment
- Articles rarely only about one equity

## Applications - Brand Tracking



# Brand Tracking - Challenges

- Text likely to be unstructured
- Identifying Brand
- Identifying Opinion Holder/Demographic

# Goals

- Give a broad overview of the field
- Showcase the best current tools and approaches

# Caveats

- There are no good R code/libraries to do this (yet)
- This talk is biased towards my domains
- No one in this area really knows what they are doing

# History



# History

- Grew out of Web integration Field
- Started as extension of knowledge extraction
- This is why field sometimes called Opinion Mining
- Also why papers as likely to occur in ACL as in WWW
- Many early algorithms are extraction patterns
- Field was still largely academic

# Then something happened

## Twitter mood predicts the stock market

Johan Bollen, Huina Mao, Xiao-Jun Zeng

(Submitted on 14 Oct 2010)

Behavioral economics tells us that emotions can profoundly affect individual behavior and decision-making. Does this also apply to societies at large, i.e., can societies experience mood states that affect their collective decision making? By extension is the public mood correlated or even predictive of economic indicators? Here we investigate whether measurements of collective mood states derived from large-scale Twitter feeds are correlated to the value of the Dow Jones Industrial Average (DJIA) over time. We analyze the text content of daily Twitter feeds by two mood tracking tools, namely OpinionFinder that measures positive vs. negative mood and Google-Profile of Mood States (GPOMS) that measures mood in terms of 6 dimensions (Calm, Alert, Sure, Vital, Kind, and Happy). We cross-validate the resulting mood time series by comparing their ability to detect the public's response to the presidential election and Thanksgiving day in 2008. A Granger causality analysis and a Self-Organizing Fuzzy Neural Network are then used to investigate the hypothesis that public mood states, as measured by the OpinionFinder and GPOMS mood time series, are predictive of changes in DJIA closing values. Our results indicate that the accuracy of DJIA predictions can be significantly improved by the inclusion of specific public mood dimensions but not others. We find an accuracy of 87.6% in predicting the daily up and down changes in the closing values of the DJIA and a reduction of the Mean Average Percentage Error by more than 6%.

Subjects: **Computational Engineering, Finance, and Science (cs.CE)**; Computation and Language (cs.CL); Social and Information Networks (cs.SI); Physics and Society (physics.soc-ph)

Journal reference: Journal of Computational Science, 2(1), March 2011, Pages 1-8

DOI: [10.1016/j.jocs.2010.12.007](https://doi.org/10.1016/j.jocs.2010.12.007)

Cite as: [arXiv:1010.3003v1 \[cs.CE\]](https://arxiv.org/abs/1010.3003v1)

# Unique Challenges in Sentiment Analysis

# Opinions are not Facts

# Order Matters

- Sentences at end of article have stronger influence on sentiment
- Sentences at beginning of article have stronger influence on sentiment
- Irrelevant sentences influence sentiment of document.

# Order Matters - Valience Shifts

The camera is reasonable, but there are far better ones at this price  
The meal could have been better, though still tasty.

# Sentiment Orientation

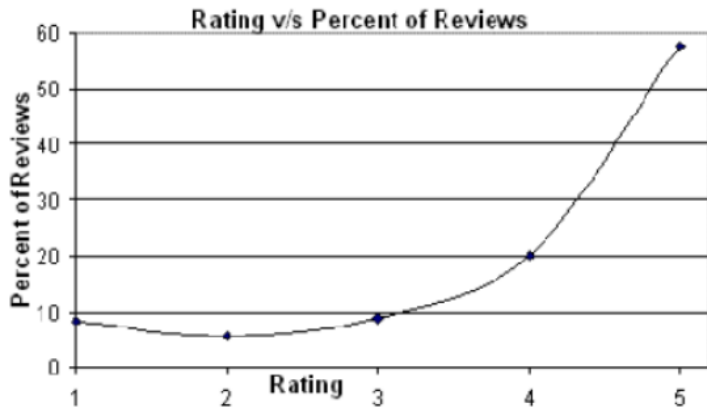
- shifts in sentiment noted by special words
- special words usually have no sentiment of their own
- sentiment though consistent in each phrase

# Sentiment Orientation - continued

- Naive method misses these shifts
- Bag of Words model fails here



# Opinions polarize



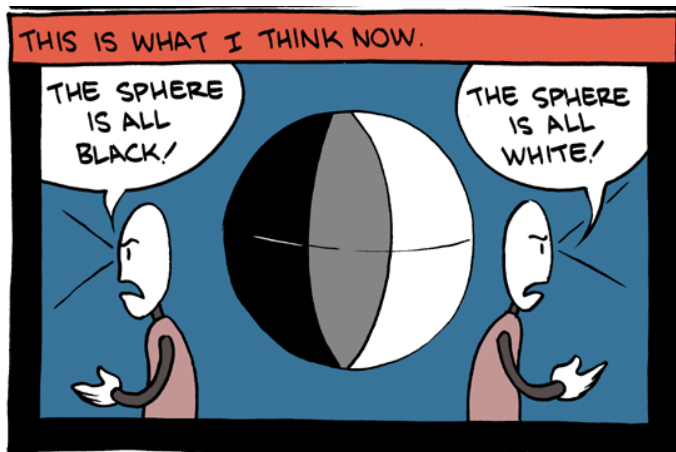
# Opinions have context

Small screen

Small carbon footprint

Opinions need to be normalized

# People disagree on what words mean



# Basics of Natural Language Processing

# Introduction to NLP

- Computational Linguistics is centered in Frequency Counts
- Frequency Counts become statistic through which we reason
- This statistic has flaws but still useful

# Stemming

It is useful to combine words with a common root.

When counting terms this groups words that denote the same term

This is done by dropping the end

|          |   |       |
|----------|---|-------|
| sleeping | } | sleep |
| sleeper  |   |       |
| sleeps   |   |       |



# Stopwords

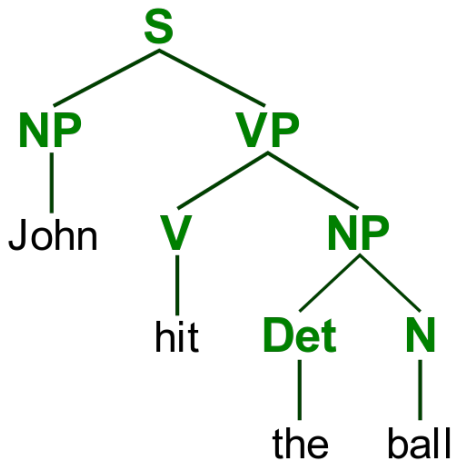
It is important to remove common words as they dominate all counts  
Common words in English:

a, the, an, is, be, could, there

Most NLP libraries packaged with a list of stopwords

Sometimes words will need to more finely processed  
The following tools exist in most NLP packages  
I prefer the Stanford NLP software suite  
<http://nlp.stanford.edu/software/index.shtml>

# Parsing



# Parsing

- Structure also derivable by parsing sentences
- Treat text like programming language
- Algorithms can then convert text into Tree
- Algorithms exist to learn grammar
- Very Heavyweight

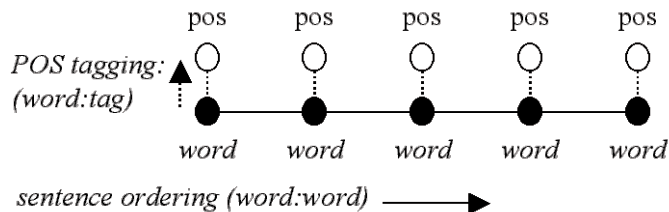
# Shallow Parsing

|        | COL:0   | COL:1 | TAG  |
|--------|---------|-------|------|
| POS:-4 | He      | PRP   | B-NP |
| POS:-3 | reckons | VBZ   | B-VP |
| POS:-2 | the     | DT    | B-NP |
| POS:-1 | current | JJ    | I-NP |
| POS: 0 | deficit | NN    | I-NP |
| POS:+1 | will    | MD    | B-VP |
| POS:+2 | narrow  | VB    | I-NP |
| POS:+3 | to      | TO    | B-PP |

# Shallow Parsing

- Less heavy to use than a full parser
- Processes words into phrases
- Training Chunking parser significantly easier/faster
- Requires having words tagged with their part of speech

# Part of Speech tagging

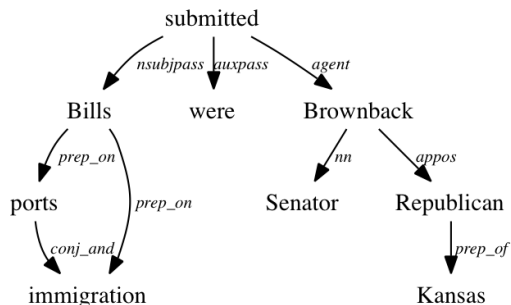


# POS tagging

- Simplest operation to perform on words
- All NLP libraries support this operation
- Provides lightweight metadata
- Very common word feature
- Used by nearly all more complex NLP techniques



# Dependency Parsing



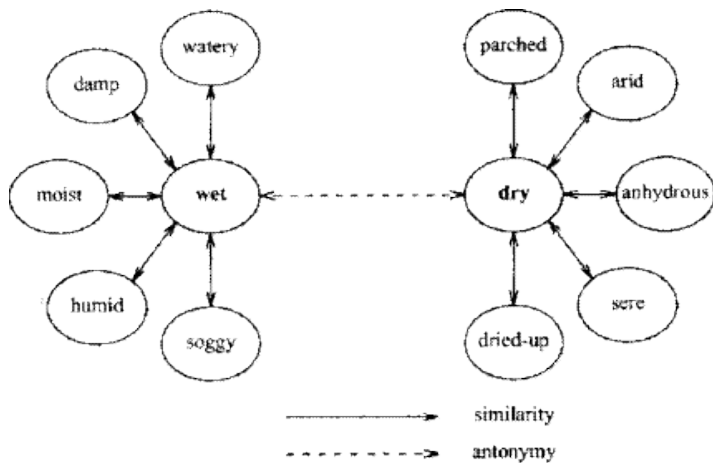
# Dependency Parsing

- Traditional Treebank Parsing is a bit bureaucratic
- Hides relations words have with each in sentence
- Dependency Parsing provides a lightweight alternative
- Alternative has looser representation, more language agnostic
- More readily captures which words modify each other

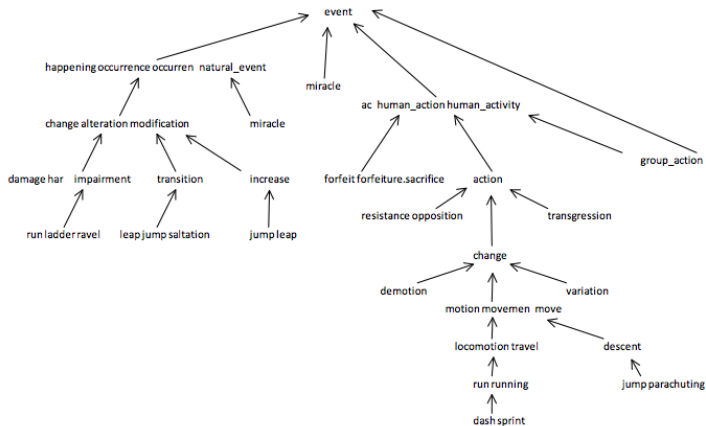
# Wordnet

- Words can be related by how similar they are
- Words are similar if they mean similar things
- Words are similar if they are a type of another word
- Words can have many meanings
- Wordnet is a hand curated ontology that annotates these relations

# Wordnet synsets



# Wordnet concept network

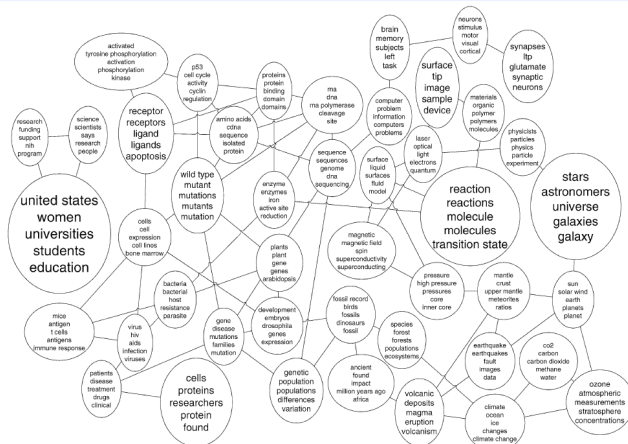


# Topic Modeling

Topic Modeling is a way to group and categorize documents  
Usually unsupervised approach

|                                                               |                                                                          |                                                                    |                                                                  |                                                             |
|---------------------------------------------------------------|--------------------------------------------------------------------------|--------------------------------------------------------------------|------------------------------------------------------------------|-------------------------------------------------------------|
| 217<br>INSECT<br>MYB<br>PHEROMONE<br>LENS<br>LARVAE           | 274<br>SPECIES<br>PHYLOGENETIC<br>EVOLUTION<br>EVOLUTIONARY<br>SEQUENCES | 126<br>GENE<br>VECTOR<br>VECTORS<br>EXPRESSION<br>TRANSFER         | 63<br>STRUCTURE<br>ANGSTROM<br>CRYSTAL<br>RESIDUES<br>STRUCTURES | 200<br>FOLDING<br>NATIVE<br>PROTEIN<br>STATE<br>ENERGY      |
| 42<br>NEURAL<br>DEVELOPMENT<br>DORSAL<br>EMBRYOS<br>VENTRAL   | 2<br>SPECIES<br>GLOBAL<br>CLIMATE<br>CO2<br>WATER                        | 280<br>SPECIES<br>SELECTION<br>EVOLUTION<br>GENETIC<br>POPULATIONS | 15<br>CHROMOSOME<br>REGION<br>CHROMOSOMES<br>KB<br>MAP           | 64<br>CELLS<br>CELL<br>ANTIGEN<br>LYMPHOCYTES<br>CD4        |
| 112<br>HOST<br>BACTERIAL<br>BACTERIA<br>STRAINS<br>SALMONELLA | 210<br>SYNAPTIC<br>NEURONS<br>POSTSYNAPTIC<br>HIPPOCAMPAL<br>SYNAPSES    | 201<br>RESISTANCE<br>RESISTANT<br>DRUG<br>DRUGS<br>SENSITIVE       | 165<br>CHANNEL<br>CHANNELS<br>VOLTAGE<br>CURRENT<br>CURRENTS     | 142<br>PLANTS<br>PLANT<br>ARABIDOPSIS<br>TOBACCO<br>LEAVES  |
| 39<br>THEORY<br>TIME<br>SPACE<br>GIVEN<br>PROBLEM             | 105<br>HAIR<br>MECHANICAL<br>MB<br>SENSORY<br>EAR                        | 221<br>LARGE<br>SCALE<br>DENSITY<br>OBSERVED<br>OBSERVATIONS       | 270<br>TIME<br>SPECTROSCOPY<br>NMR<br>SPECTRA<br>TRANSFER        | 55<br>FORCE<br>SURFACE<br>MOLECULES<br>SOLUTION<br>SURFACES |

# CTM - Coorelated Topic Models



# CTM - Coorelated Topic Models

- CTMs model the underlying topics within a document
- They differ from earlier approaches in capturing correlations between topics
- Give superior performance compared to other unsupervised models
- Available for use as an R package in CRAN (topicmodels)



# Named Entity Recognition

The purpose of NER is to extract out and label phrases in a sentence

Bill Clinton arrived at the United Nations Building in Manhattan.

# Sentiment Definitions

# Opinion

A vector denoting representing an opinion  
with values positive, negative, or neutral gradings

# Opinion Holder

The agent an opinion belongs to.  
This mostly relevant in political blogs

# Item Features

Facets of the object that are readily available

# Sentiment Features

Facets of the object that an opinion may be subscribed.  
These are usually hard to tease out of the text

# 1. Gather a Seed set

# Opinion corpora available at:

- Wiebe's corpora <http://www.cs.pitt.edu/mpqa/>
- Sentiwordnet: <http://sentiwordnet.isti.cnr.it/>
- Personal dictionaries (available on request)



# Gathering initial seed words

- Wiebe's work comes with subjectivity scores in addition to sentiment
- Sentiwordnet was autogenerated, quality could be better
- Personal dictionaries hand generated, small but good quality

## 2. Learn sentiment of unknown words

# Learn sentiment - Supervised

# Learn sentiment - Supervised

- Get a large collection of them labeled
- Use this collection as is

# Learn sentiment - Unsupervised - Turney

- Use Turney's Method
- Calculate Pointwise Mutual Information between every word and the seed words 'excellent' 'poor'

$$SO(w) = \lg\left(\frac{hits(w \text{ NEAR } excellent)hits(excellent)}{hits(w \text{ NEAR } poor)hits(poor)}\right)$$

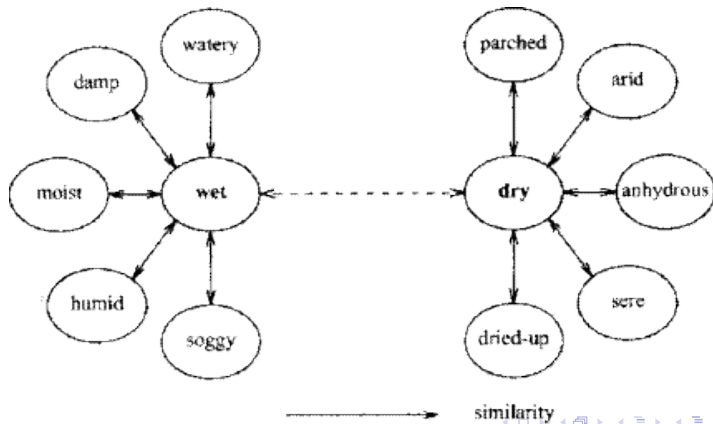
where  $hits(w \text{ NEAR } y)$  = number of times  $w$  is within 10 words of the  $y$

# Learn sentiment - Unsupervised - Twitter

- Use Turney's Method with Twitter
- Calculate Pointwise Mutual Information between every word and whenever it appears with ☹ or ☺ within a tweet
- This method has the advantage of being multilingual, other kinds of smiles aside

# Learn sentiment - Unsupervised - Wordnet

- Use wordnet to walk random paths from start word until arriving at a seed word
- Average across sentiments of all seed words arrived at
- This method is the fastest and most accurate



### 3. Apply rules to simplify document



- Rules make words more independent
- Rewrites make it less likely to misclassify a phrase

### Manually Discovered VS Patterns:

not(be )?(a)? disappoint(ed)ment)? → notdisappoint

not [article] (problem|complaint|issue) → noproblem

not (be|been|have|had) (a|any) (problem|complaint|issue|trouble|hassle)

not a (good|great|bad|very \_\_\_\_ ) → not(good|great|bad|very \_\_\_\_ )

not as \_\_\_\_ as → not\_\_\_\_ compared to

not as \_\_\_\_ → not\_\_\_\_

not the best → notgood

not the most \_\_\_\_ → not\_\_\_\_

not [augmenter] [adj] → not[adj]

not [adj] → not[adj]

no \_\_\_\_ (problem|complaint|issue|trouble|hassle) → noproblem

no (problem|complaint|issue|trouble|hassle) → noproblem

## 4. Identify opinion phrases

- Shallow Parse the document into chunks
- Remove chunks with mostly neutral words

Alternatively, extract with some rules

**Table 1.** Patterns of POS tags for extracting two-word phrases

|    | First word      | Second word          | Third word<br>(Not Extracted) |
|----|-----------------|----------------------|-------------------------------|
| 1. | JJ              | NN or NNS            | anything                      |
| 2. | RB, RBR, or RBS | JJ                   | not NN nor NNS                |
| 3. | JJ              | JJ                   | not NN nor NNS                |
| 4. | NN or NNS       | JJ                   | not NN nor NNS                |
| 5. | RB, RBR, or RBS | VB, VBD, VBN, or VBG | anything                      |

## 5. Extend sentiment to phrases and sentences

- Ultimately, sentiment is for phrases and sentences
- Use sentiment on individual words as priors
- Sentiment is based on joint probability across words in phrase
- Use Naive Bayes or a Markov Model as needed

## 6. Aggregate sentiments for display

Group phrases based on what you want the sentiment

- Entities
- Topics
- Sentiment Features
- Item Features
- Users



## 8. Generating Summary

# Generating Summary

- Largely only relevant when you returning text
- Rate all sentences based on readability
- Return snippet of text for each group with sentiment vector attached

# Summary

- 1 Gather a seed set
- 2 Learn sentiment of unknown words
- 3 Apply rules to simplify document
- 4 Identify opinion phrases
- 5 Extend sentiment to phrases and document
- 6 Aggregate sentiments for display
- 7 Generate summary

# Anaphora Resolution

- Many articles refer entities by their name only a few times
- Opinions will usually co-occur with an anaphora of the entity

His father, Nick Begich, won an election  
 posthumously, only they didn't know for sure that it  
 was posthumous because his plane just disappeared.  
 It still hasn't turned up. It's why locators are now  
 required in all US planes.

# Anaphora Resolution

- Simplest solution, replace all anaphora with their referent
- Trickier solution, aggregate all opinions associated with anaphora later
- Other options?

# Sentiment Analysis is fundamentally a Discriminative Learning Task

# Conditional Random Fields

- Sentiment is clearly affected by its surrounding context
- Sentiment is also affected by orientation shifting words
- Why not make these connections explicit in our model?
- Conditional Random Fields (CRFs) are a flexible way of representing these connections.

# Conditional Random Fields

In a CRF, we represent posterior probability of a set of sentiments given the underlying text.  $A$  is a collection of cliques in the graph of connections.

$$p(y|x) = \frac{1}{Z} \prod_A \psi_A(x_A, y_A)$$

$$\psi_A(x_A, y_A) = \exp \left\{ \sum_k \theta_{Ak} f_{Ak}(x_A, y_A) \right\}$$

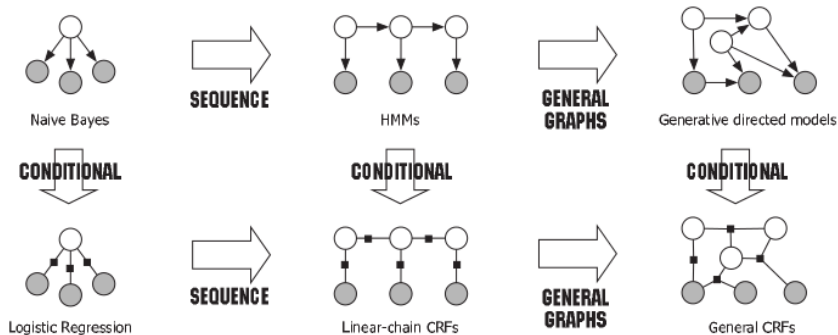


# Linear Chain CRFs

If we assume the sentiment of any given word only depends on the previous, the formula simplifies to

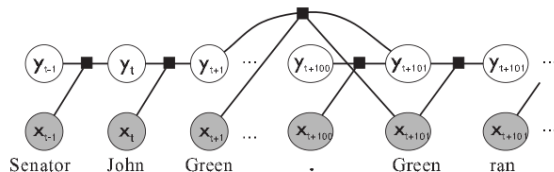
$$p(y|x) = \frac{1}{Z} \prod_t \exp \left\{ \sum_k \theta_k f_k(x_t, y_t, y_{t-1}) \right\}$$

# Linear Chain CRFs are best understood as a discriminative version of Hidden Markov Models



# Skip-chain CRFs

But we can assume sentiment depends on words much further away



We can now connect entities to each other and connect phrases explicitly separated by a sentiment shifting word.

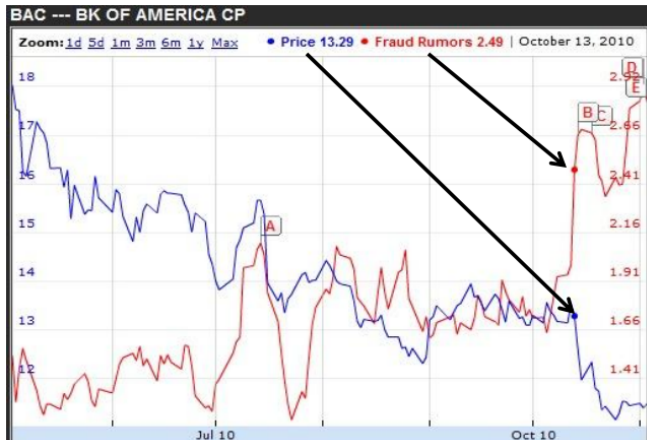
# CRFs - Conclusions

- CRFs allow us to add context to opinion
- Properly used they can handle the connections between sentiments on phrases as well as words
- CRFs allow us to link arbitrary features of words and labels to each other

# Extensions

# Extensions - Time Series

Just order your documents in time, and can plot changes in sentiment



# Extensions - Time Series

- This one tends to get used with financial data and monitoring brands
- Requires having access to lots of articles to make sense
- There can be sparsity issues so apply proper shrinkage

# Beyond Positive and Negative

We can be more subtle





# Sarcasm

If you deal with Product Review this is helpful

## ICWSM – A Great Catchy Name: Semi-Supervised Recognition of Sarcastic Sentences in Online Product Reviews

**Oren Tsur**

Institute of Computer Science  
The Hebrew University  
Jerusalem, Israel  
oren@cs.huji.ac.il

**Dmitry Davidov**

ICNC  
The Hebrew University  
Jerusalem, Israel  
dmitry@alice.nc.huji.ac.il

**Ari Rappoport**

Institute of Computer Science  
The Hebrew University  
Jerusalem, Israel  
www.cs.huji.ac.il/~arir

Sarcasm is best detected through punctuation and capitalization features

# Detecting Fake Reviews

- Fake Reviews are best treated as a classification task
- Collect enough and use frequency counts for features
- This is useful in production deployments and simple to implement

# Multilingual Sentiment Analysis

- Sentiment does not translate well
- Words that mean the same thing can not correspond wrt sentiment
- Retrain for each new language you wish to support

# Word-sense disambiguation

- This is largely not worth the effort
- Using the first sense of the word gives comparable performance to more sophisticated approaches
- Exception: domain specific corpus where word is unlikely to be the first sense. Use specialized dictionaries for this case

# Comparisons

- Sometimes opinions are stated relevant two separate entities
- Superlatives are a special case of this
- Treat these as a ranking problem and handle as a separate problem
- Merge sentiments during aggregation

R is much better than SPSS

# Lingering Questions

What keeps me from doing this in R?



## Further Questions - Large Data

- Text analysis is hard to do in R
- R has memory limits
- Using Hadoop or BigMemory usually means giving up many libraries
- `tm.plugins.distributed` helps a bit
- `snow` and `OpenMPI` gives mixed results

## Further Questions - Metadata

Is there a lightweight metadata format?

| Index | Offset | Property  | Value    |
|-------|--------|-----------|----------|
| 2     | 10     | POS       | NP       |
| 35    | 5      | Sentiment | Positive |
| 17    | 7      | POS       | JJ       |
| 51    | 20     | Chunk     | NULL     |
| 20    | 8      | Entity    | Person   |
| 2     | 45     | Sentence  | NULL     |

## Further Questions - Model Files

- Not enough of the tools take model files
- Model files are needed for tokenization, sentence splitting, pos tagging, chunking
- Without easy support for model files, multilingual support is difficult
- Without easy support, impossible to train better models as data becomes available

## Further Questions - Rule Files

- No standard on preprocessing rules
- DSL required for them
- Is this something we need to provide?
- Until better techniques come around, essential for any performance

# Theoretical Formulation

- Can these techniques be made less hacky?
- Dependency Parses provide much of the structure for tracking sentiment orientation
- Can structure be handled in a more unsupervised manner?

# References

Best starting point:

Sentiment Analysis and Subjectivity by Bing Liu

<http://www.cs.uic.edu/liub/FBS/NLP-handbook-sentiment-analysis.pdf>

# References (More)

- Joint Extraction of Entities and Relations for Opinion Recognition (Choi 2006)
- Mining Opinion Features in Customer Reviews (Liu 2004)
- A Holistic Lexicon-Based Approach to Opinion Mining (Deng 2008)
- I Cant Recommend This Paper Highly Enough (Dillard thesis)
- Entity Discovery and Assignment for Opinion Mining Applications (Deng 2009)
- Extracting Product Features and Opinions from Reviews (Popescu 2005)

# Conclusions

- Sentiment Analysis is a relatively young area
- Still plenty of ideas to be explored
- Widely applicable
- Really fun



# Questions?