UNIVERSITY OF SAN FRANCISCO
CHANGE THE WORLD FROM HERE

AI – Sentiment Analysis

Cindi Thompson

Follow-ups from Thursday

- TF-IDF versus Naïve Bayes
  - Naïve Bayes not so good for supporting IR
    - Why?
  - Would TF-IDF work for classification?
  - Given a new document, how to put it in a class bucket?
  - TF-IDF ignores class labels
  - But has been used as a pre-processor for NB

Follow-ups from Thursday

Learning algorithm complexity: train versus test time

- C - # of classes
- N - # of examples
- A - # of attributes
- AV - # of values (splits) of an attribute

Algorithm	Training time	Classification time
Decision trees	O(AN)+ $\sum^{AV} build(A - \{best\}, AV * A - AV\{best\})$ =O(A^2N)	O(A) (max depth of tree)
K-NN	O(1)	O(AN)
Naïve Bayes	O(N)+O(A*AV*C*N)	O(C^2A)

Follow-ups from Exam

- Bigram reminder

$$P(w_i|w_{i-1}) = \frac{c(w_{i-1},w_i)}{c(w_{i-1})}$$

```
<s> I am Sam </s>
<s> Sam I am </s>
<s> I do not like green eggs and ham </s>
```

P(I | <s>) = 2/3 = 0.67   P(Sam | <s>) = 1/3 = 0.33

P(am | I) = 2/3 = 0.67   P(</s> | Sam) = 1/2 = 0.5

P(Sam | am) = 1/2 = .5   P(do | I) = 1/3 =.33

Follow-ups from Exam

- Exercise in pairs
- How would you extend this to trigrams?
- What are some problems with a simple approach
- Will post an EC timed quiz on this in Canvas, to add to your midterm grade

Decision trees

- Entropy
- Attribute selection

Today's Roadmap

What is sentiment analysis?

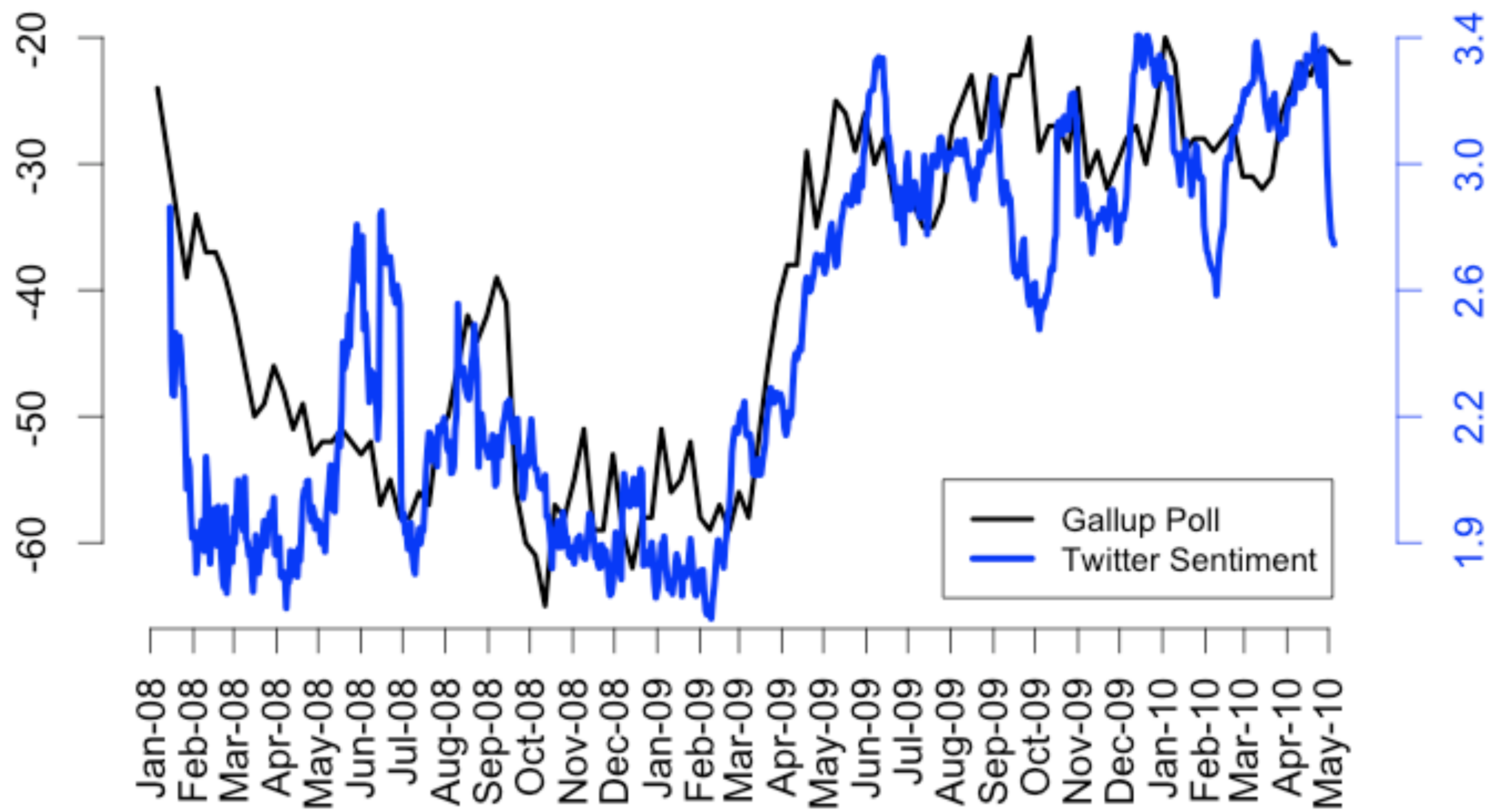
A baseline algorithm

Sentiment lexicons & learning them

Associated reading: http://sentiment.christopherpotts.net/

(Sections 1-5; the rest covers many more details than we will cover today)

Can Twitter sentiment replace surveys?



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

Social Media and its impact

- Ashton Kutcher tweets a complaint about firing of Penn State Coach before knowing it was due to a scandal
- Domino’s Pizza employees post disgusting videos on YouTube, went viral before Domino’s reacted
- Student bullying

Positive or negative movie review?

-  unbelievably disappointing
-  Full of zany characters and richly applied satire, and some great plot twists
-  this is the greatest screwball comedy ever filmed
-  It was pathetic. The worst part about it was the boxing scenes.

Some of the following slides were adapted from a Coursera NLP class!

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)

Other applications

- *Movie*: is this review positive or negative?
- *Products*: what do people think about the new iPhone?
- *Public sentiment*: how is consumer confidence? Is despair increasing?
- *Politics*: what do people think about this candidate or issue?
- *Prediction*: predict election outcomes or market trends from sentiment

A definition of sentiment analysis

- Sentiment analysis is the detection of **attitudes**

  "enduring, affectively colored beliefs, dispositions towards objects or persons"

  1. **Holder (source)** of attitude
  2. **Target (aspect)** of attitude
  3. **Type** of attitude
     - From a set of types
       - *Like, love, hate, value, desire,* etc.
     - Or (more commonly) simple weighted **polarity**:
       - *positive, negative, neutral,* together with *strength*
  4. **Text** containing the attitude
     - Sentence or entire document

Other names for similar / same task

- Opinion extraction
- Opinion mining
- Sentiment mining
- Subjectivity analysis
- Polarity classification

Levels of sentiment analysis

- Simplest task
  - Is the attitude of this text positive or negative?
- More complex
  - Rank the attitude of this text from 1 to 5
- Advanced
  - Detect the target, source, or complex attitude type

Examples

- *It’s great to finally have a phone with predictable battery life!*
- *The latest Bond movie has a flat, predictable plot*
- *If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut*

Examples

✅ *It's great to finally have a phone with predictable battery life!*

❌ *The latest Bond movie has a flat, predictable plot*

❌ *If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut*

How can a machine understand sentiment?

Approaches

- Machine learning from labeled data
- Use a sentiment lexicon
- Combine these two!

Today’s Roadmap

What is sentiment analysis?

A baseline algorithm

Sentiment lexicons & learning them

How can a machine understand sentiment?

Machine learning for sentiment analysis

- Provide examples of text with labeled sentiment
  - ✅ *It's great to finally have a phone with <u>predictable</u> battery life!*
  - ❌ *The latest Bond movie has a flat, <u>predictable</u> plot*
  - ❌ *If you are reading this because it is your <u>darling</u> fragrance, please wear it at home exclusively, and tape the windows shut*

How can a machine understand sentiment?

Machine learning for sentiment analysis

- Provide examples of text with labeled sentiment
- Break sentences into words and other “features”
  - Just adjectives? All words?
    - Bad, sweet, good
    - Love, image, film
  - Treat negation separately
  - Phrases?
    - “really like” or
    - “really” and “like”

How can a machine understand sentiment?

Machine learning for sentiment analysis

- Provide examples of text with labeled sentiment
- Break sentences into words and other “features”
- Apply a learning algorithm that decides which features associate with positive or negative sentiment
  - Any of the algorithms we’ve discussed in class, plus many other options!

Example: movie reviews

- Polarity detection: is a movie review positive or negative?

when _star wars_ came out some twenty years ago , the image of traveling throughout the stars has become a commonplace image . [...]

when han solo goes light speed , the stars change to bright lines , going towards the viewer in lines that converge at an invisible point .

cool .

october sky offers a much simpler image–that of a single white dot , traveling horizontally across the night sky . [. . .]

" snake eyes " is the most aggravating kind of movie : the kind that shows so much potential then becomes unbelievably disappointing .

it's not just because this is a brian depalma film , and since he's a great director and one who's films are always greeted with at least some fanfare .

and it's not even because this was a film starring nicolas cage and since he gives a brauvara performance , this film is hardly worth his talents .

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.
Bo Pang and Lillian Lee. 2004. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. ACL, 271-278

Tokenization – familiar theme!

- Deal with HTML and XML markup
- Twitter mark-up (names, hash tags)
- Capitalization (preserve for words in all caps)
- Phone numbers, dates
- Emoticons

```
[<>]?                          # optional hat/brow
[:;=8]                         # eyes
[\-o\*\']?                     # optional nose
[\)\]\(\[dDpP/\:\}\{@\|\\]     # mouth
|                              #### reverse orientation
[\)\]\(\[dDpP/\:\}\{@\|\\]     # mouth
[\-o\*\']?                     # optional nose
[:;=8]                         # eyes
[<>]?                          # optional hat/brow
```

- Some publicly available tokenizers
  - Christopher Potts
  - Brendan O'Connor – twitter oriented

Dealing with negation

Add NOT_ to every word between negation and following punctuation:

didn't like this movie , but I

didn't NOT_like NOT_this NOT_movie but I

Das, Sanjiv and Mike Chen. 2001. Yahoo! for Amazon: Extracting market sentiment from stock message boards. In Proceedings of the Asia Pacific Finance Association Annual Conference (APFA).
Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.

The learning part…

(Reminder on Naïve Bayes):

$$v_{NB} = \operatorname*{argmax}_{v_j \in V} P(v_j) \prod_i P(w_i \mid v_j)$$

Alternative smoothing approach to m-estimate of last time:

$$\hat{P}(w \mid c) = \frac{count(w,c)+1}{count(c)+|V|}$$

Cross validation

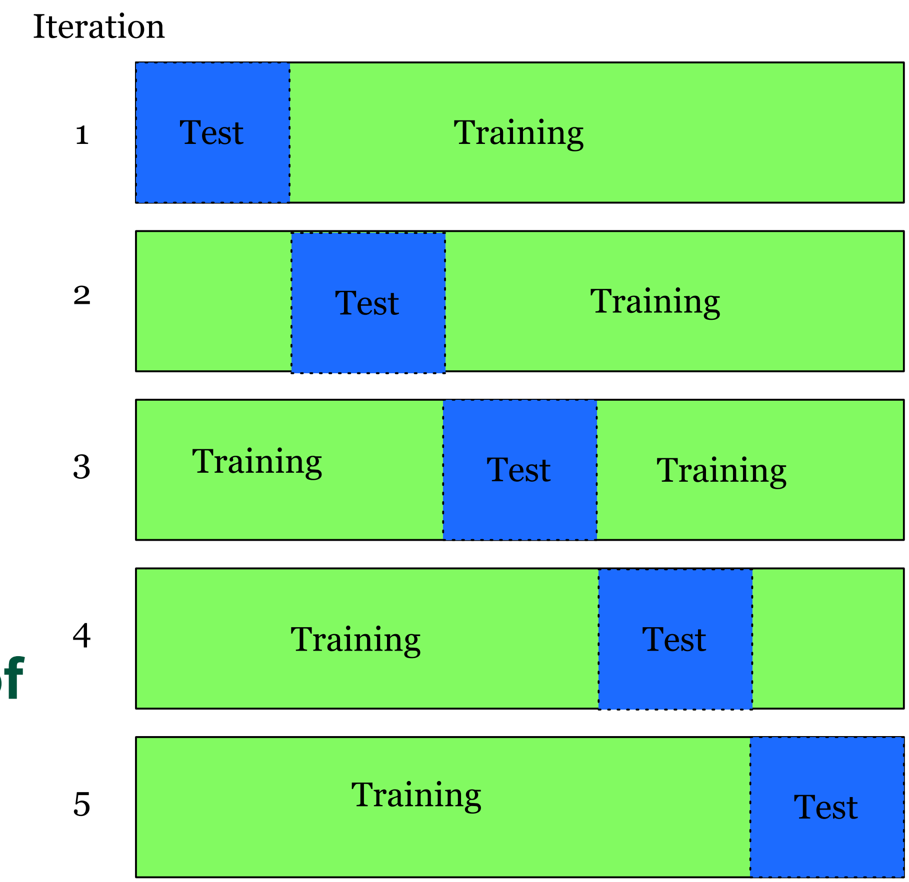
Break up data into N folds

(Equal positive and negative inside each fold?)

For each fold

- Choose the fold as a temporary test set
- Train on N-1 folds, compute performance on the test fold

Report average performance of the N runs



State of the art

Still lots of challenges!

- This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it **can't hold up**.
- Well as usual Keanu Reeves is nothing special, but surprisingly, the very talented Laurence Fishbourne is **not so good** either, I was surprised.

Many companies offer….

Demo!

(http://www.sentiment140.com/

And

http://socialmention.com/)

Today's Roadmap

What is sentiment analysis?

A baseline algorithm

Sentiment lexicons & learning them

Sentiment lexicons

Negative sentiment

- Bad, weird, hate, problem, tough

Positive sentiment

- Love, nice, sweet

Influencers

- No, never, didn't
- Few, many
- Maybe, perhaps, guess

$$\sum_{w \in text} sentiment\_score(w)$$

Where do we get a sentiment lexicon?

- Some smart people have created several which are available (more on that later)
- But could machine learning be used here, too?

Semi-supervised lexicon learning

Use a small amount of information

A few labeled examples

A few hand-built patterns

To bootstrap a lexicon

Identifying sentiment polarity of a word

Adjectives conjoined by "*and*" have same polarity

Fair **and** legitimate, corrupt **and** brutal

*fair **and** brutal, *corrupt **and** legitimate

Adjectives conjoined by "*but*" do not

fair **but** brutal

Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

Hatzivassiloglou & McKeown 1997
Step 1

Label seed set of 1336 adjectives (all >20 in 21 million word WSJ corpus)

657 positive

- adequate central clever famous intelligent remarkable reputed sensitive slender thriving…

679 negative

- contagious drunken ignorant lanky listless primitive strident troublesome unresolved unsuspecting…

Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

Hatzivassiloglou & McKeown 1997
Step 2

Expand seed set to conjoined adjectives

Google "was nice and"

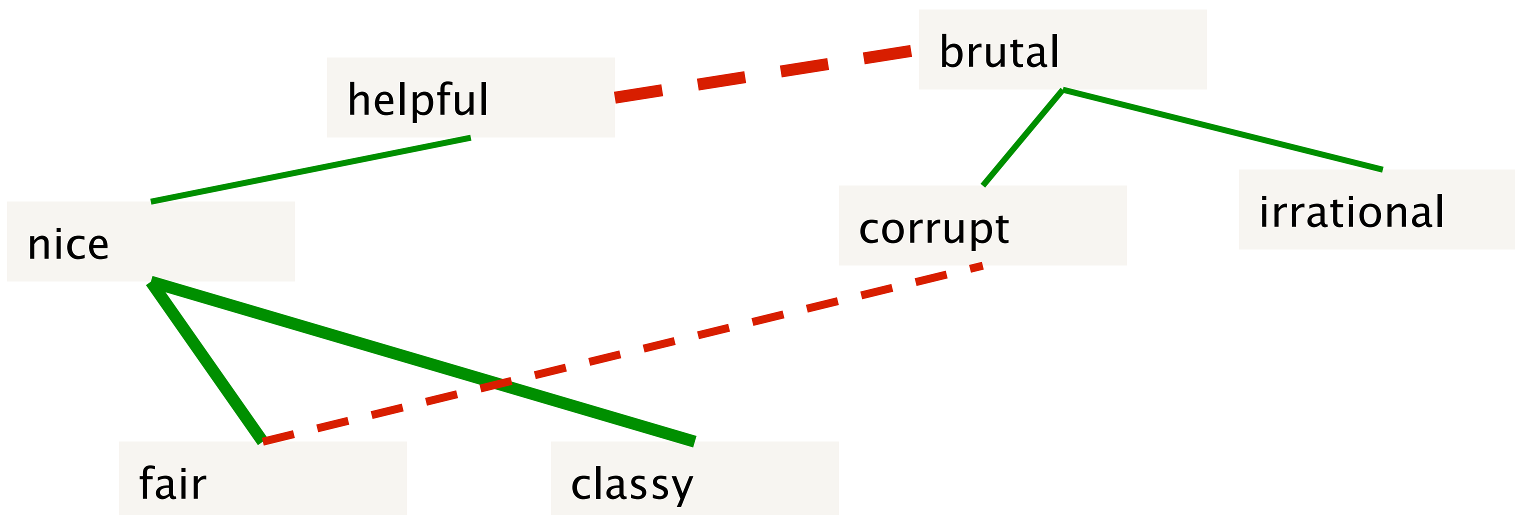
[Nice location in Porto and the front desk staff **was nice and** helpful ...]
www.tripadvisor.com/ShowUserReviews-g189180-d206904-r12068... +1
Mercure Porto Centro: Nice location in Porto and the front desk staff **was nice and** helpful - See traveler reviews, 77 candid photos, and great deals for Porto, ...

[If a girl **was nice and** classy, but had some vibrant purple dye in ...]
answers.yahoo.com › Home › All Categories › Beauty & Style › Hair +1
4 answers - Sep 21
Question: Your personal opinion or what you think other people's opinions might ...
Top answer: I think she would be cool and confident like katy perry :)

Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

Hatzivassiloglou & McKeown 1997
Step 3

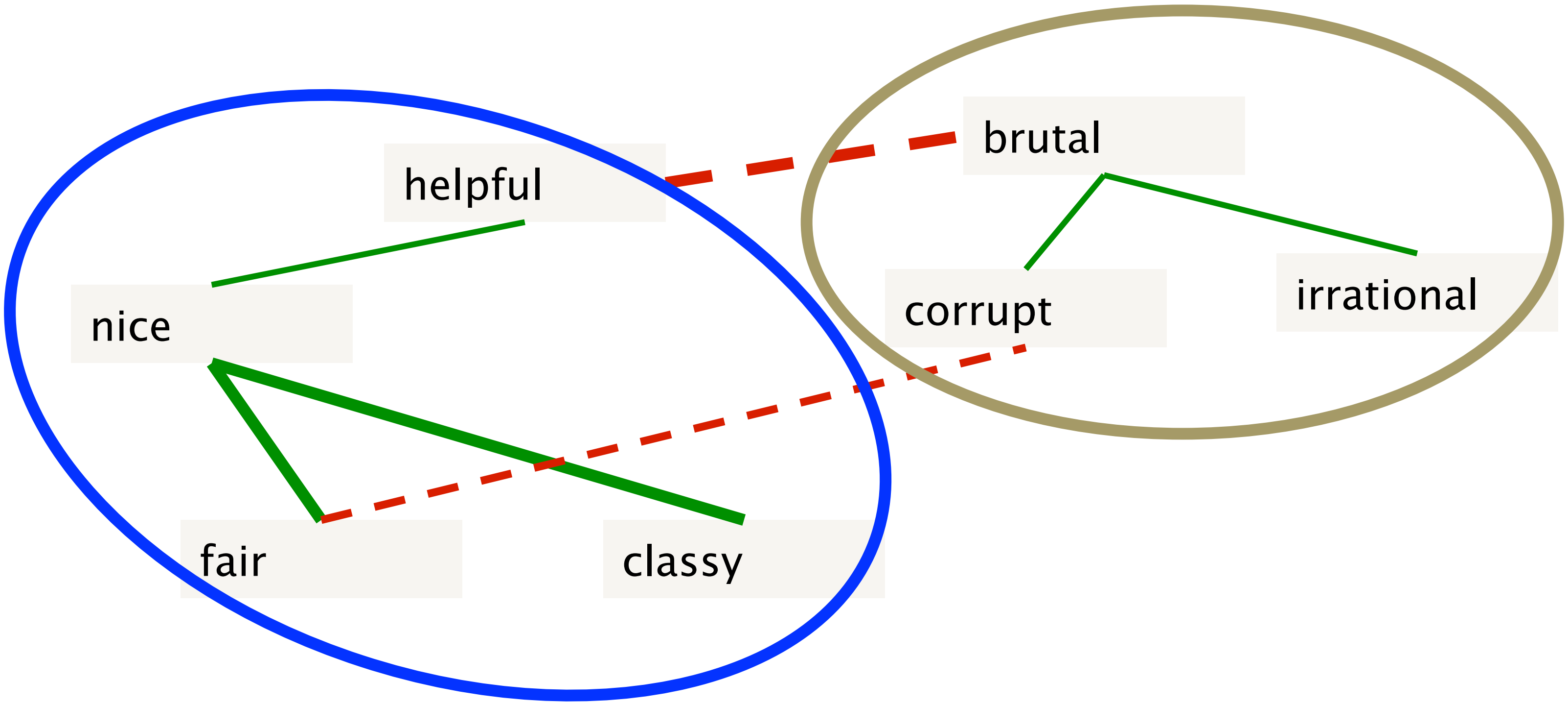
Apply machine learning: is a given word pair of the same or different polarity?



Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

Hatzivassiloglou & McKeown 1997
Step 4

Clustering: what is the best way to partition the graph into two?



Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

Learned Polarity lexicon

Positive

bold decisive **disturbing** generous good honest important large mature patient peaceful positive proud sound stimulating straightforward **strange** talented vigorous witty…

Negative

ambiguous **cautious** cynical evasive harmful hypocritical inefficient insecure irrational irresponsible minor **outspoken** **pleasant** reckless risky selfish tedious unsupported vulnerable wasteful…

Learned versus hand-built Polarity lexicons

Advantages:

Can be domain-specific

Can be more robust (more words)

Intuition

Start with a seed set of words (‘good’, ‘poor’)

Find other words that have similar polarity:

- Using “and” and “but”

Other approaches not discussed:

- Using words that occur nearby in the same document
- Using WordNet synonyms and antonyms

General Inquirer Lexicon

- 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:
  - Positiv (1915 words) and Negativ (2291 words)
  - Strong vs Weak, Active vs Passive, Overstated versus Understated
  - Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc
- Free for Research Use

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

LIWC (Linguistic Inquiry and Word Count)

- 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

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

MPQA Subjectivity Cues Lexicon

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

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.

LIWC (Linguistic Inquiry and Word Count)

type=weaksubj word1=abandon pos1=verb priorpolarity=negative

type=strongsubj word1=abase pos1=verb priorpolarity=negative

type=strongsubj word1=abash pos1=verb priorpolarity=negative

type=strongsubj word1=abhor pos1=anypos priorpolarity=negative

type=strongsubj word1=abhor pos1=verb priorpolarity=negative

type=strongsubj word1=abide pos1=anypos priorpolarity=positive

type=weaksubj word1=ability pos1=noun priorpolarity=positive

type=weaksubj word1=abnormal pos1=adj priorpolarity=negative

type=weaksubj word1=abolish pos1=verb priorpolarity=negative

type=weaksubj word1=above-average pos1=adj priorpolarity=positive

type=weaksubj word1=abound pos1=verb priorpolarity=positive

type=weaksubj len=1 word1=abrade pos1=verb stemmed1=y priorpolarity=negative

SentiWordNet

- 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
```

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

Why so many different lexicons?

- Different domains
- Different tasks
- Evolving understanding
- Different opinions!!

Sentiment analysis summary

Generally modeled as classification or regression task

predict a binary or ordinal (rating) label

Features:

Negation is important

Using all words (in Naïve Bayes) works well for some tasks

Finding subsets of words may help in other tasks

- Hand-built polarity lexicons
- Use seeds and semi-supervised learning to induce lexicons

Extra slide: Scherer Typology of Affective States

- **Emotion**: brief organically synchronized … evaluation of a major event
  - *angry, sad, joyful, fearful, ashamed, proud, elated*
- **Mood**: diffuse non-caused low-intensity long-duration change in subjective feeling
  - *cheerful, gloomy, irritable, listless, depressed, buoyant*
- **Interpersonal stances**: affective stance toward another person in a specific interaction
  - *friendly, flirtatious, distant, cold, warm, supportive, contemptuous*
- **Attitudes**: enduring, affectively colored beliefs, dispositions towards objects or persons
  - *liking, loving, hating, valuing, desiring*
- **Personality traits**: stable personality dispositions and typical behavior tendencies
  - *nervous, anxious, reckless, morose, hostile, jealous*

Extra slide: work on other affective states

Emotion:
Detecting annoyed callers to dialogue system
Detecting confused/frustrated versus confident students

Mood:
Finding traumatized or depressed writers

Interpersonal stances:
Detection of flirtation or friendliness in conversations

Personality traits:
Detection of extroverts

Extra slide: Detection of Friendliness

Friendly speakers use collaborative conversational style

Laughter

Less use of negative emotional words

More sympathy

- `That's too bad     I'm sorry to hear that`

More agreement

- `I think so too`

Less hedges

- `kind of    sort of    a little …`

Ranganath, Jurafsky, McFarland