# Sentiment Analysis

## What is Sentiment Analysis?

# 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.

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# 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."

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# Bing Shopping

## HP Officejet 6500A E710N Multifunction Printer

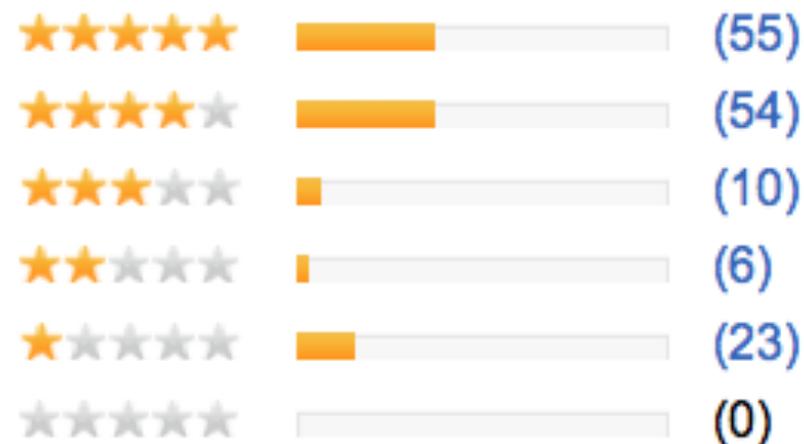
Product summary    Find best price    **Customer reviews**    Specifications    Related items

$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)

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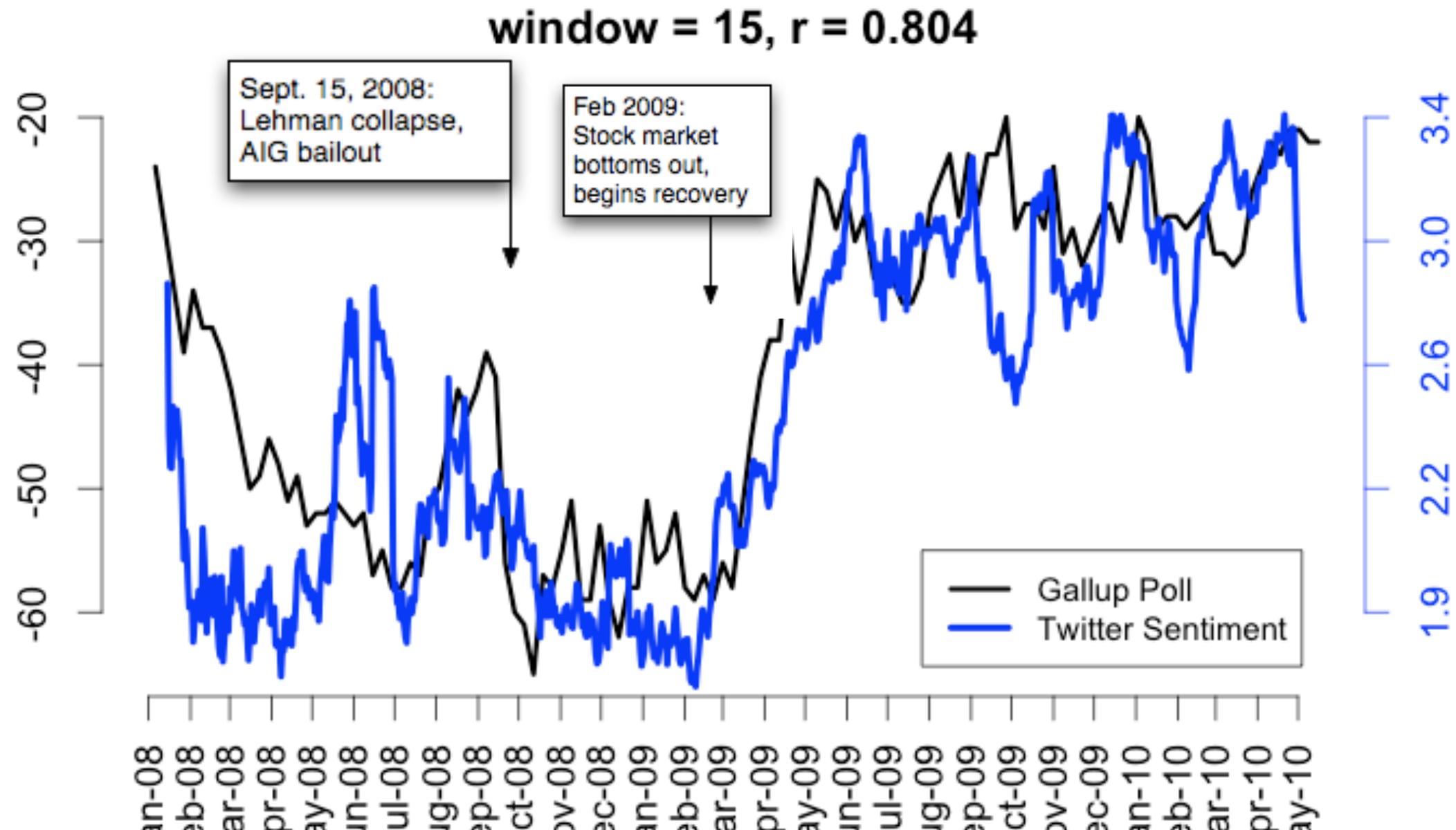
# Twitter sentiment versus Gallup Poll of Consumer Confidence

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.

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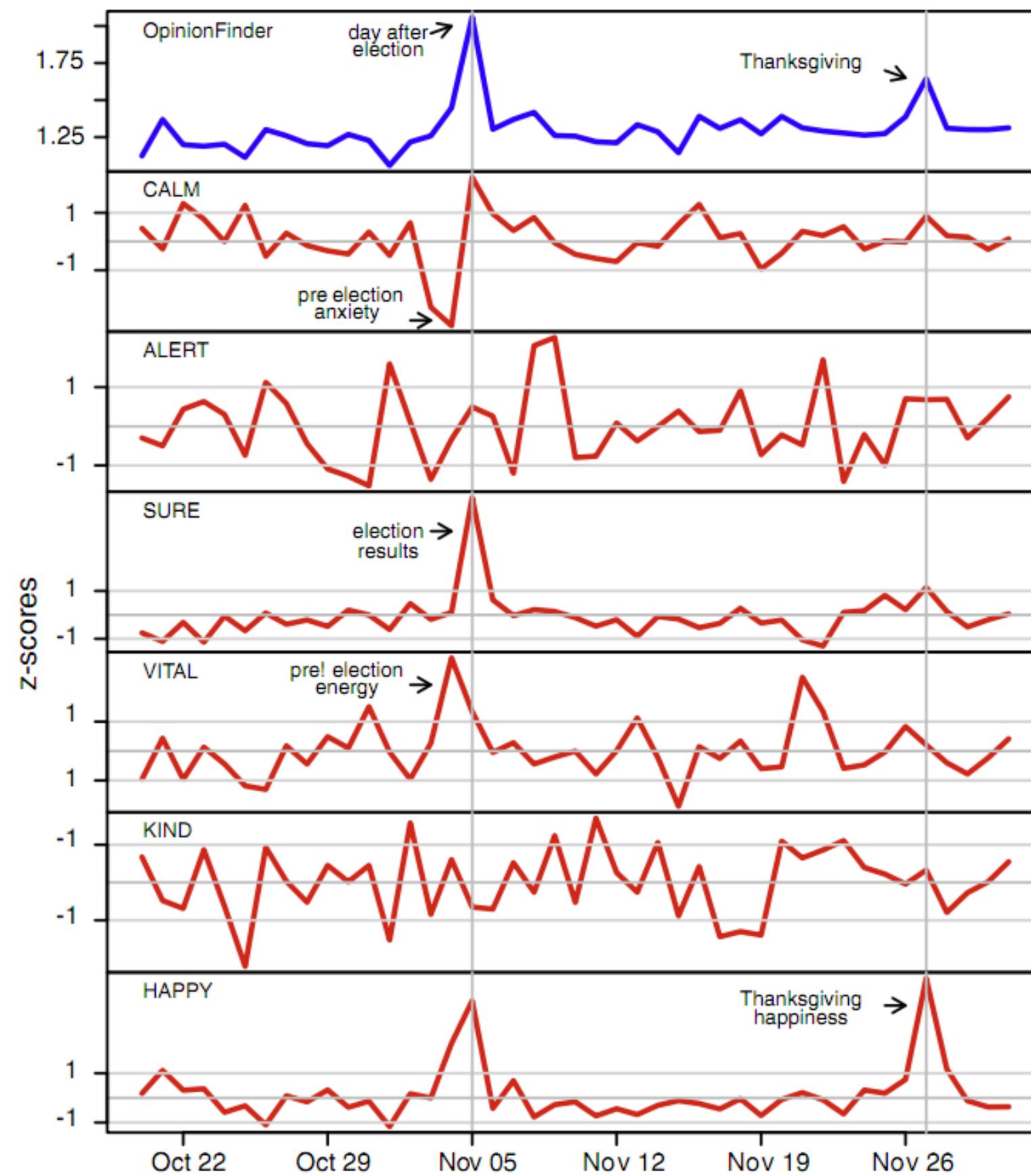
Bollen et al. (2011)

- CALM predicts DJIA 3 days later

- At least one current hedge fund uses this algorithm

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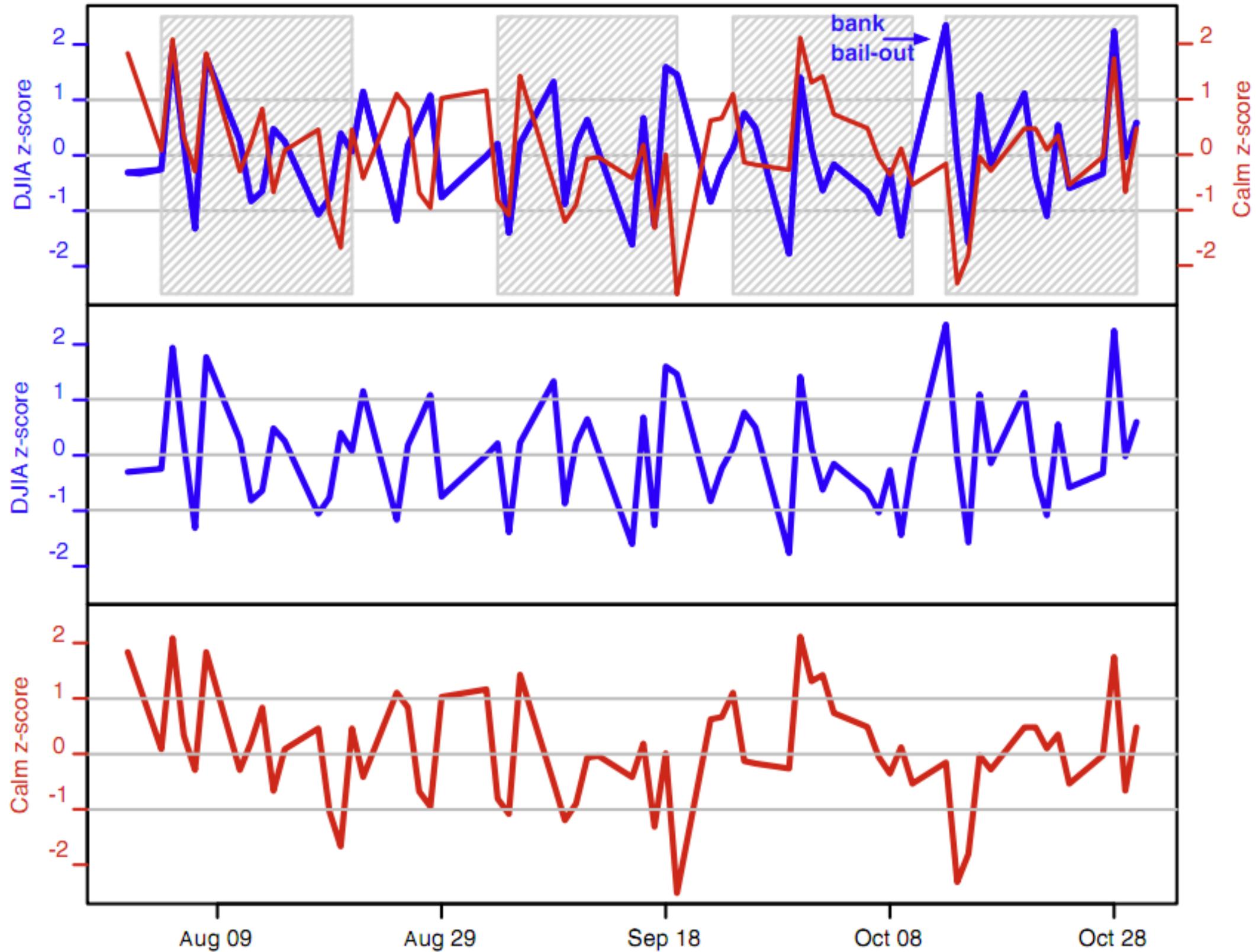

# Target Sentiment on Twitter

- ## Twitter Sentiment App

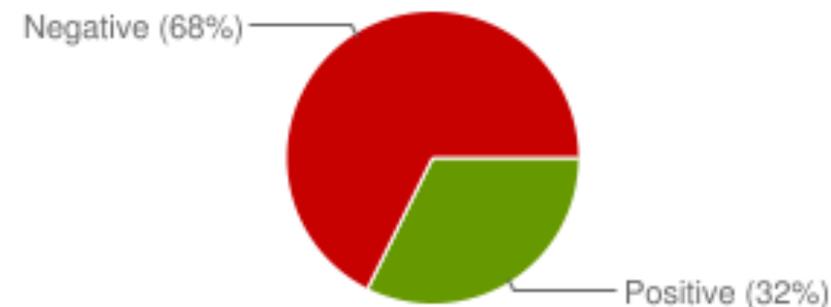
- Alec Go, Richa Bhayani, Lei Huang. 2009. Twitter Sentiment Classification using Distant Supervision

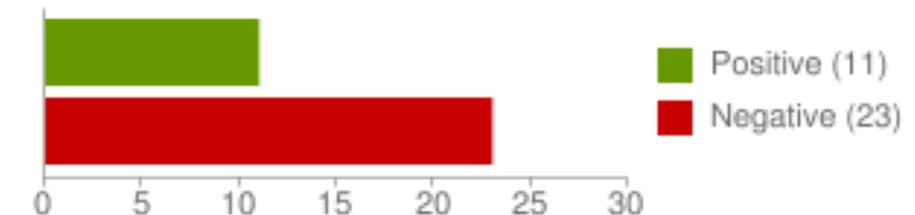
Type in a word and we'll highlight the good and the bad

| "united airlines" | Search | Save this search |

## Sentiment analysis for "united airlines"

Sentiment by Percent

Negative (68%)
Positive (32%)

Sentiment by Count

Positive (11)
Negative (23)

jljacobson: OMG... Could @**United airlines** have worse customer service? W8g now 15 minut
Posted 2 hours ago

12345clumsy6789: I hate **United Airlines** Ceiling!!! Fukn impossible to get my conduit in this d
Posted 2 hours ago

EMLandPRGbelgiu: EML/PRG fly with Q8 **united airlines** and 24seven to an exotic destination
Posted 2 hours ago

CountAdam: FANTASTIC customer service from **United Airlines** at XNA today. Is tweet more
Posted 4 hours ago

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# Sentiment analysis has many other names

- Opinion extraction
- Opinion mining
- Sentiment mining
- Subjectivity analysis

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# Why sentiment analysis?

- *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

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# 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*

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# 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

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# 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 types

# Sentiment Analysis

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# Sentiment Analysis

What is Sentiment Analysis?

# Sentiment Analysis

A Baseline Algorithm

# Sentiment Classification in Movie Reviews

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

- Polarity detection:
  - Is an IMDB movie review positive or negative?
- Data: *Polarity Data 2.0:*
  - http://www.cs.cornell.edu/people/pabo/movie-review-data

# IMDB data in the Pang and Lee database

✓

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 .

# Baseline Algorithm (adapted from Pang and Lee)

- Tokenization
- Feature Extraction
- Classification using different classifiers
  - Naïve Bayes
  - MaxEnt
  - SVM

# Sentiment Tokenization Issues

- Deal with HTML and XML markup

- Twitter mark-up (names, hash tags)

- Capitalization (preserve for
  words in all caps)

- Phone numbers, dates

- Emoticons

- Useful code:

  - Christopher Potts sentiment tokenizer

  - Brendan O'Connor twitter tokenizer

Potts emoticons

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

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# Extracting Features for Sentiment Classification

- How to handle negation
  - I **didn't** like this movie

    vs
  - I really like this movie
- Which words to use?
  - Only adjectives
  - All words
    - All words turns out to work better, at least on this data

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# Negation


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.


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

# Reminder: Naïve Bayes

$$c_{NB} = \underset{c_j \in C}{\mathrm{argmax}} \, P(c_j) \prod_{i \in positions} P(w_i \mid c_j)$$

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

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# Binarized (Boolean feature)  Multinomial Naïve Bayes

- Intuition:
  - For sentiment (and probably for other text classification domains)
  - Word occurrence may matter more than word frequency
    - The occurrence of the word *fantastic* tells us a lot
    - The fact that it occurs 5 times may not tell us much more.
  - Boolean Multinomial Naïve Bayes
    - Clips all the word counts in each document at 1

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# Boolean Multinomial Naïve Bayes: Learning

- From training corpus, extract *Vocabulary*

- Calculate $P(c_j)$ terms
  - For each $c_j$ in $C$ do
    $docs_j \leftarrow$ all docs with class $=c_j$

$$P(c_j) \leftarrow \frac{|docs_j|}{|\text{total \# documents}|}$$

- Calculate $P(w_k \mid c_j)$ terms
  - Remove duplicates in each doc:
  - $Text_j \leftarrow$ single doc containing all $docs_j$
    - For each word type $w$ in doc
    - For each word $w_k$ in *Vocabulary*
      - Retain only a single instance of $w$
      $n_k \leftarrow$ \# of occurrences of $w_k$ in $Text_j$

$$P(w_k \mid c_j) \leftarrow \frac{n_k + \alpha}{n + \alpha \mid Vocabulary \mid}$$

# Boolean Multinomial Naïve Bayes on a test document *d*

- First remove all duplicate words from *d*

- Then compute NB using the same equation:

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_{i \in positions} P(w_i \mid c_j)$$

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# Normal vs. Boolean Multinomial NB

| Normal | Doc | Words | Class |
|---|---|---|---|
| Training | 1 | Chinese Beijing Chinese | c |
| | 2 | Chinese Chinese Shanghai | c |
| | 3 | Chinese Macao | c |
| | 4 | Tokyo Japan Chinese | j |
| Test | 5 | Chinese Chinese Chinese Tokyo Japan | ? |

| Boolean | Doc | Words | Class |
|---|---|---|---|
| Training | 1 | Chinese Beijing | c |
| | 2 | Chinese Shanghai | c |
| | 3 | Chinese Macao | c |
| | 4 | Tokyo Japan Chinese | j |
| Test | 5 | Chinese Tokyo Japan | ? |

# Binarized (Boolean feature) Multinomial Naïve Bayes


B. Pang, L. Lee, and S. Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.
V. Metsis, I. Androutsopoulos, G. Paliouras. 2006. Spam Filtering with Naive Bayes – Which Naive Bayes? CEAS 2006 - Third Conference on Email and Anti-Spam.
K.-M. Schneider. 2004. On word frequency information and negative evidence in Naive Bayes text classification. ICANLP, 474-485.
JD Rennie, L Shih, J Teevan. 2003. Tackling the poor assumptions of naive bayes text classifiers. ICML 2003


- Binary seems to work better than full word counts
  - This is **not** the same as Multivariate Bernoulli Naïve Bayes
    - MBNB doesn't work well for sentiment or other text tasks
- Other possibility: log(freq($w$))

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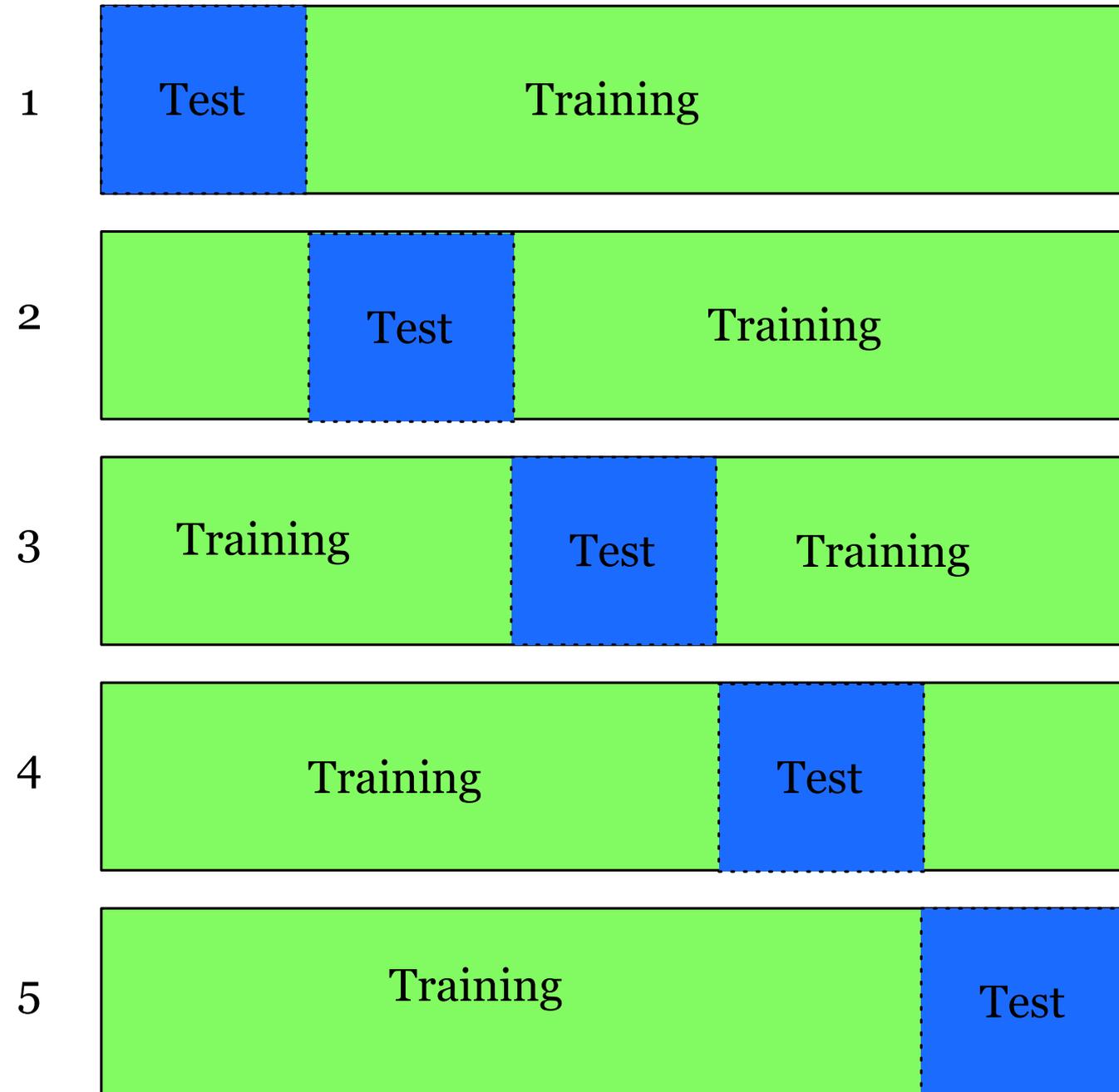
# Cross-Validation

- Break up data into 10 folds
  - (Equal positive and negative inside each fold?)
- For each fold
  - Choose the fold as a temporary test set
  - Train on 9 folds, compute performance on the test fold
- Report average performance of the 10 runs

Iteration

| | |
|---|---|
| 1 | Test / Training |
| 2 | Training / Test / Training |
| 3 | Training / Test / Training |
| 4 | Training / Test |
| 5 | Training / Test |

# Other issues in Classification

- MaxEnt and SVM tend to do better than Naïve Bayes

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# Problems:
# What makes reviews hard to classify?

- Subtlety:
  - Perfume review in *Perfumes: the Guide*:
    - "If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut."
  - Dorothy Parker on Katherine Hepburn
    - "She runs the gamut of emotions from A to B"

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# Thwarted Expectations and Ordering Effects

- "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.

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# Sentiment Analysis

## A Baseline Algorithm