Text-based Forecasting

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Text-based Forecasting

- So far, we’ve thought about text analysis to predict properties of the text or author:
    - topic (e.g., science- vs. sports-related)
    - opinion (e.g., positive vs. negative)
    - emotional state (e.g., happy vs. sad)
    - stance (e.g., pro-life vs. pro-choice)
    - political affiliation (e.g., liberal vs. conservative)
- Text analysis can also be used to detect on-going “real-world” events or to predict future events

Detecting on-going Events

- Detecting on-going “real-world” events
    - consumer confidence
    - candidate approval ratings
    - newsworthy events (e.g., natural disasters)
    - drug side-effects
    - demographic information
    - people’s habits and moods
    - consumer engagement with a product (viewers)
    - identifying influential “players”
    - traffic
    - ….

Detecting on-going Events

- There exist alternative methods for detecting on-going events (e.g., polls, surveys, hospital records, financial reports, ...)
- However, they have limitations
  - expensive
  - sparse/incomplete
  - delayed response
  - intrusive/disruptive
  - ....

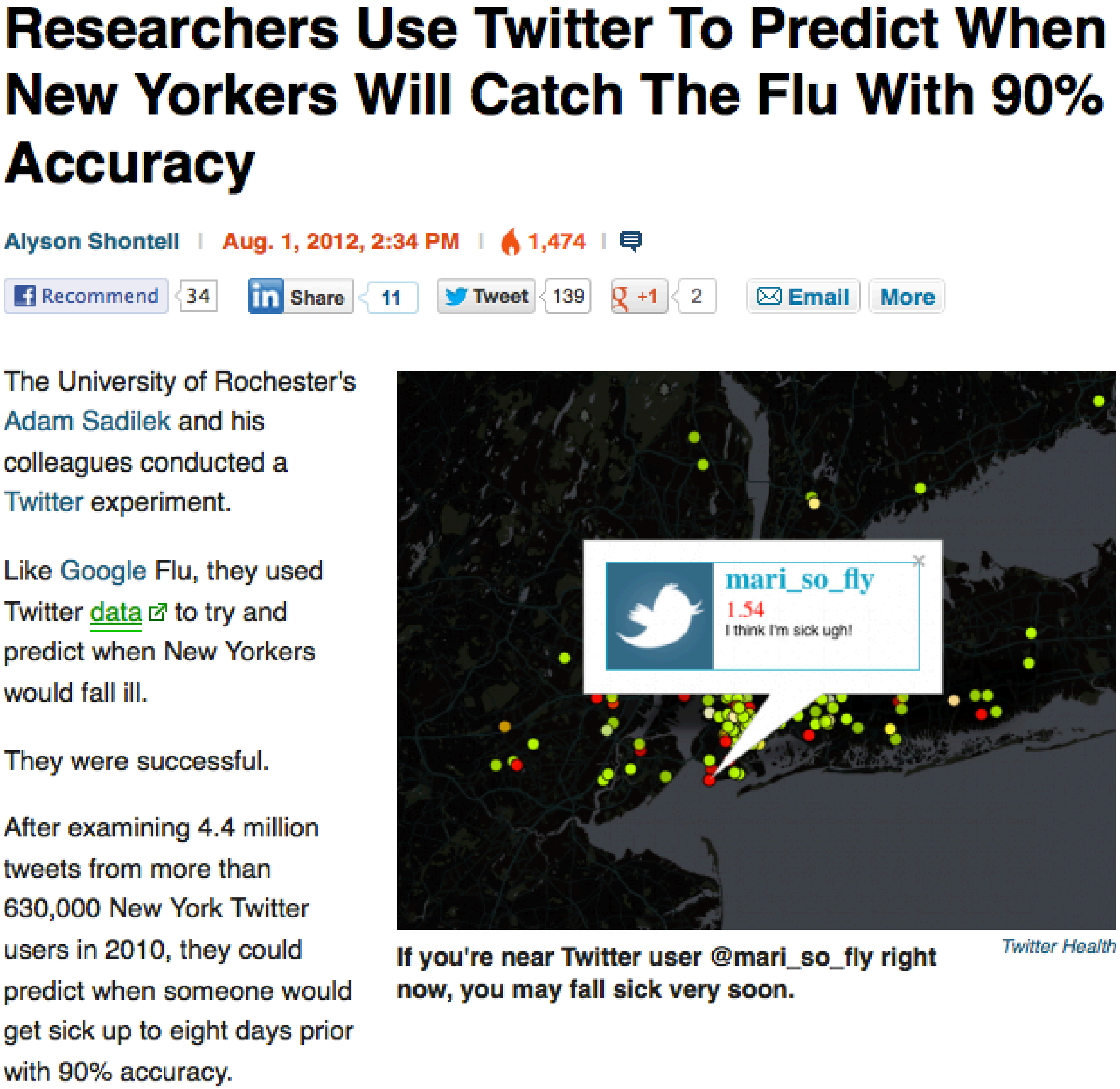
Predicting Future Events

- Predicting future events
  - stock price movements
  - election results
  - voter turnout
  - product sales or, more generally, product demand
  - consumer spending
  - socio-political unrest
  - ….

Sources of (Textual) Evidence

- Webpages
- News articles
- Blogs
- Tweets
- Search engine queries
- Facebook posts, comments, likes, connections, etc.
- Linked-in interactions (e.g., cross-company connections)
- Event transcriptions (e.g., http://www.fednews.com/)
- ....
- Discussion: how are these different and what are they good for?

Examples



Researchers Use Twitter To Predict When New Yorkers Will Catch The Flu With 90% Accuracy

Alyson Shontell | Aug. 1, 2012, 2:34 PM | 1,474 |

The University of Rochester's Adam Sadilek and his colleagues conducted a Twitter experiment.

Like Google Flu, they used Twitter data to try and predict when New Yorkers would fall ill.

They were successful.

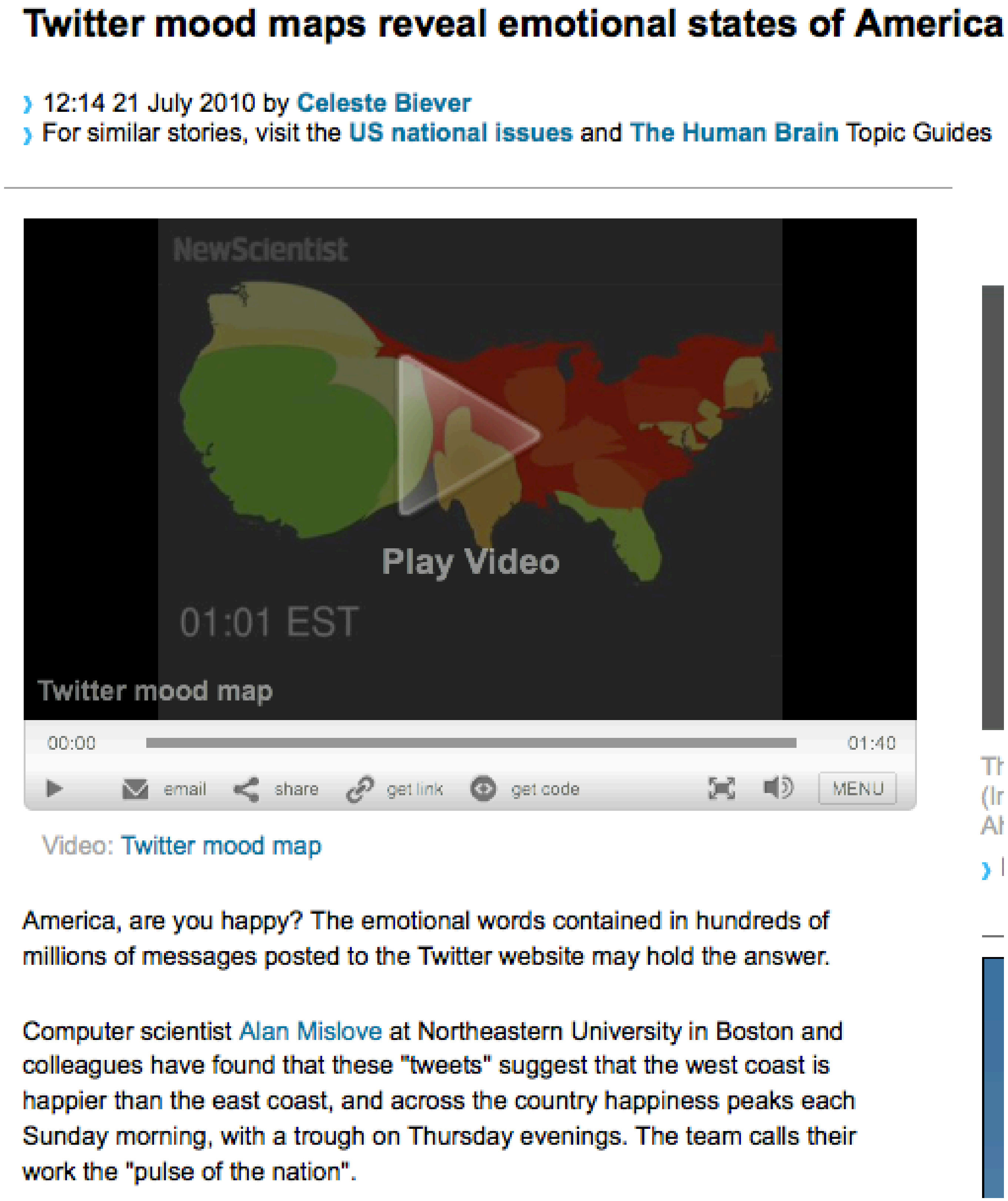
After examining 4.4 million tweets from more than 630,000 New York Twitter users in 2010, they could predict when someone would get sick up to eight days prior with 90% accuracy.

mari_so_fly
1.54
I think I'm sick ugh!

Twitter Health

If you're near Twitter user @mari_so_fly right now, you may fall sick very soon.

Examples



Twitter mood maps reveal emotional states of America

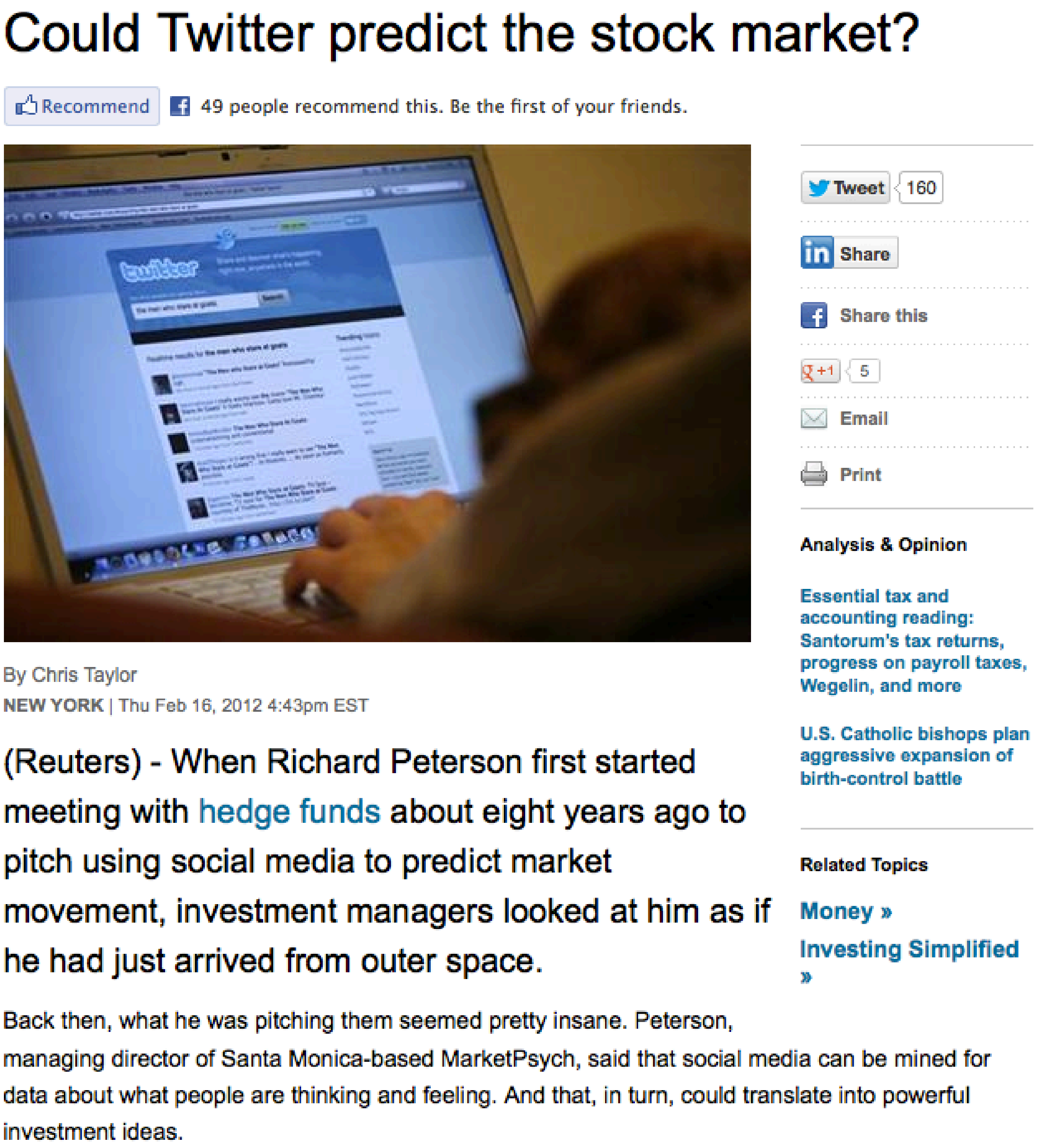
› 12:14 21 July 2010 by Celeste Biever
› For similar stories, visit the US national issues and The Human Brain Topic Guides

Video: Twitter mood map

America, are you happy? The emotional words contained in hundreds of millions of messages posted to the Twitter website may hold the answer.

Computer scientist Alan Mislove at Northeastern University in Boston and colleagues have found that these "tweets" suggest that the west coast is happier than the east coast, and across the country happiness peaks each Sunday morning, with a trough on Thursday evenings. The team calls their work the "pulse of the nation".

Examples



Could Twitter predict the stock market?

49 people recommend this. Be the first of your friends.

By Chris Taylor

NEW YORK | Thu Feb 16, 2012 4:43pm EST

(Reuters) - When Richard Peterson first started meeting with hedge funds about eight years ago to pitch using social media to predict market movement, investment managers looked at him as if he had just arrived from outer space.

Back then, what he was pitching them seemed pretty insane. Peterson, managing director of Santa Monica-based MarketPsych, said that social media can be mined for data about what people are thinking and feeling. And that, in turn, could translate into powerful investment ideas.

Analysis & Opinion

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U.S. Catholic bishops plan aggressive expansion of birth-control battle

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Basic Ingredients

- Stream of textual data + target signal
- Temporal window (depends on the task, on-going or future outcome)
- Method for identifying the ‘relevant’ elements
    - Can be tricky (e.g., predicting Facebook stock price using tweets)
- Sentiment and/or topic analysis of individual datapoints
- Data point aggregation
- Classification or regression algorithm

General Assumptions

- The text contains enough signal to predict the outcome
- Correlation, not causation
- Errors on data stream items do not necessarily translate to errors on target value
    - example: mood prediction

Reading the Markets

- K. Lerman, A. Gilder, Mark Dredze, and F. Pereira. Reading the Markets: Forecasting Public Opinion of Political Candidates by News Analysis. In *Coling '08*.

Reading the Markets

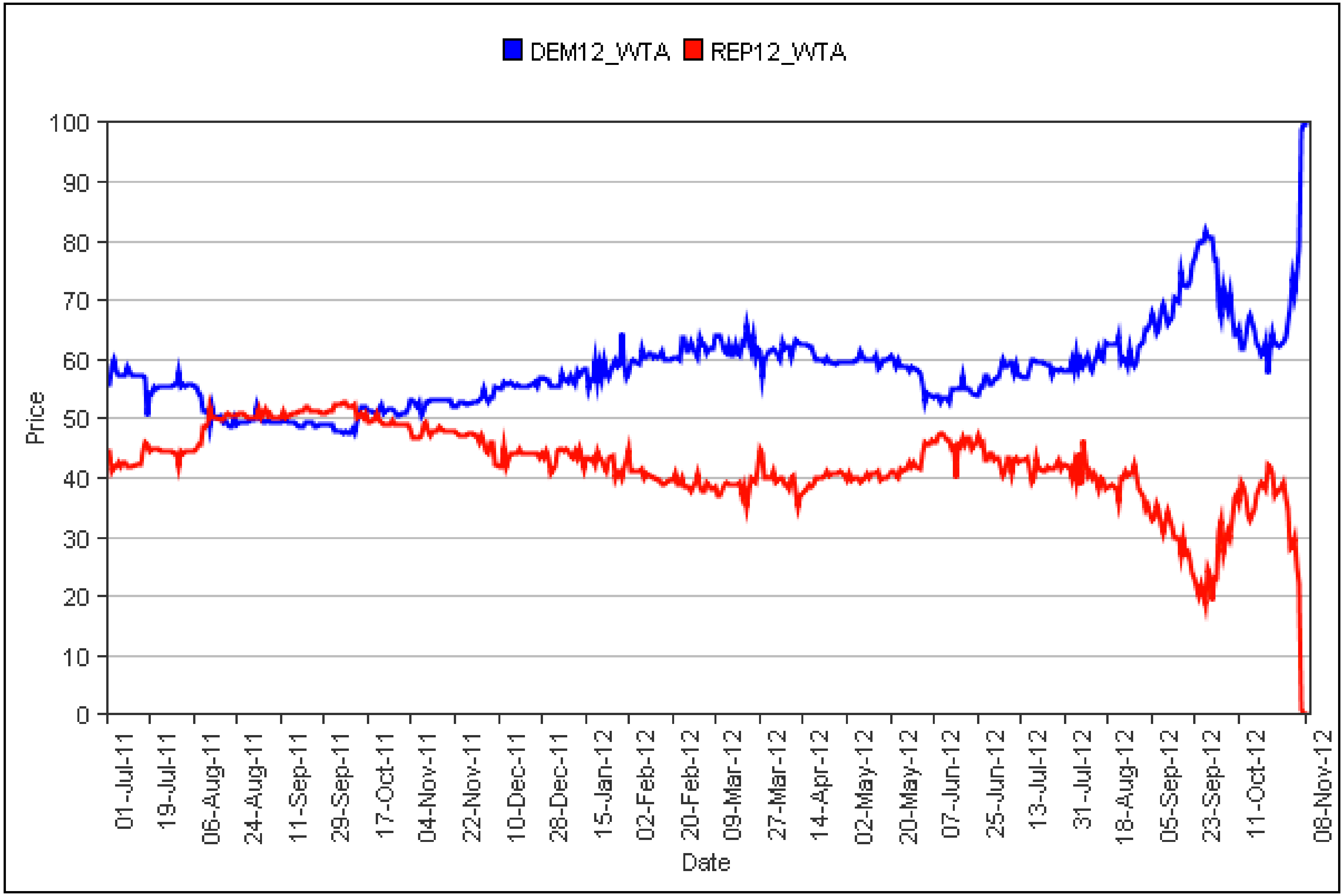
- Input: news articles
- Outcomes:
  - public opinion about presidential candidates in the 2004 election (e.g., Kerry, Bush)
  - public opinion surrogate: on-going “stock” price for a candidate ($1 awarded for every winning stock) in a prediction market
- Motivation: public opinion can be predicted based on the topics covered in the news (not just sentiment)

Prediction Markets

http://tippie.uiowa.edu/iem/markets/data_pres12.html

Pres12_WTA

2012 US Presidential Election Winner Takes All Market



Reading the Markets

- Input: news articles and market data up to today (early morning, before the market opens)
- Prediction: (average price today) - (average price yesterday)
- Action: buy/sell single stock vs. sell/buy single stock

Reading the Markets

(1) unigram features

- Motivation: public opinion may depend on the topics covered in the media
    - e.g., mentions of “iraq” are bad for Bush
- Method: term counts generated from all of the day’s news articles (big document)

Reading the Markets

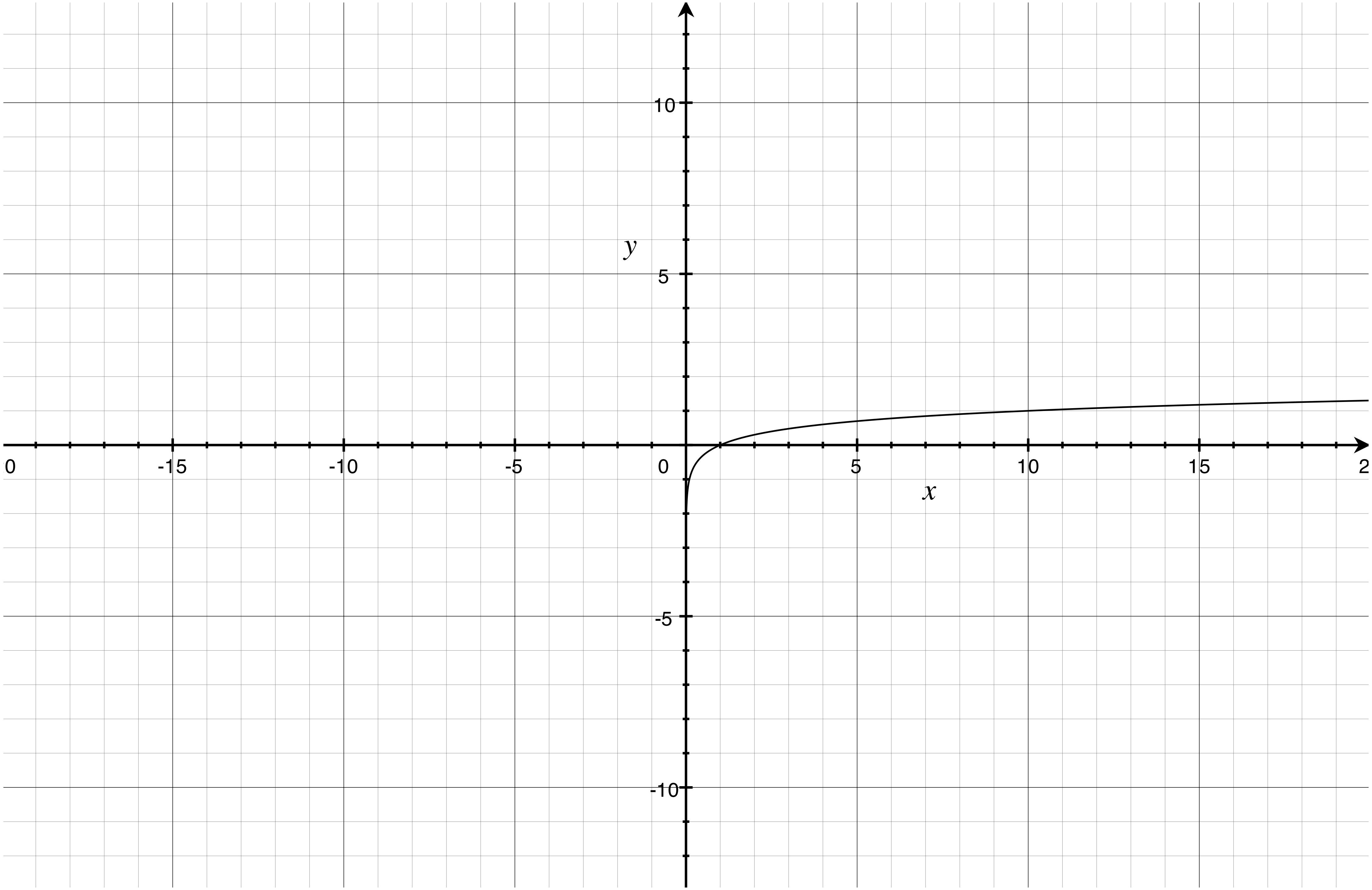
(2) news focus features

- Motivation: while the news may cover an event for several days, public opinion may not shift. Thus, it seems important to model shifts in news focus (term frequencies)
- Method: compare each term's frequency today with the average frequency in the past three days
- Values > 0 indicate increase in focus; values < 0 indicate decrease in focus

$$\Delta f_i^t = \log \left(\frac{f_i^t}{\frac{1}{3}(f_i^{t-1} + f_i^{t-2} + f_i^{t-3})} \right)$$

Reading the Markets

(2) news focus features



Reading the Markets

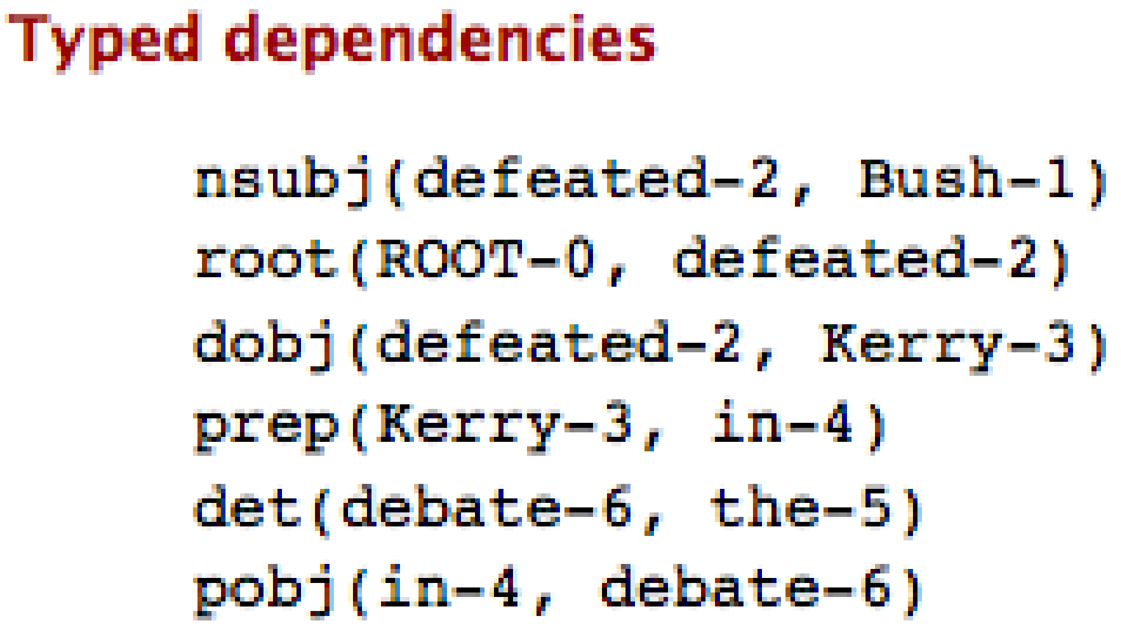
(3) entity features

- Motivation: public opinion may depend on the topics associated with a particular candidate
  - e.g., the term “scandal” may be bad for Bush, but only if it is associated with Bush (and not Kerry)
- Method: identify sentences that mention only one candidate (e.g., Bush) and construct features by combining the candidate with all content words in the sentence
- Example: “Bush is facing another scandal” would be associated with features **bush_facing** and **bush_scandal**

Reading the Markets

(4) dependency features

- Motivation: the previous feature representation cannot handle sentences that mention more than one entity
  - e.g., “Bush defeated Kerry in the debate”
- Method: generate features from a *dependency parse* of the sentence



Typed dependencies

```
nsubj(defeated-2, Bush-1)
root(ROOT-0, defeated-2)
dobj(defeated-2, Kerry-3)
prep(Kerry-3, in-4)
det(debate-6, the-5)
pobj(in-4, debate-6)
```

(output from stanford parser: http://nlp.stanford.edu:8080/parser/)

Reading the Markets

(5) market history feature

- Motivation: the market has a “natural” flow (independent of news).
  - e.g., a candidate who is doing well will continue doing well.
- Method: train a regression model to predict today’s change in market price based on the market price of the past few days and use this classifier’s prediction as a feature

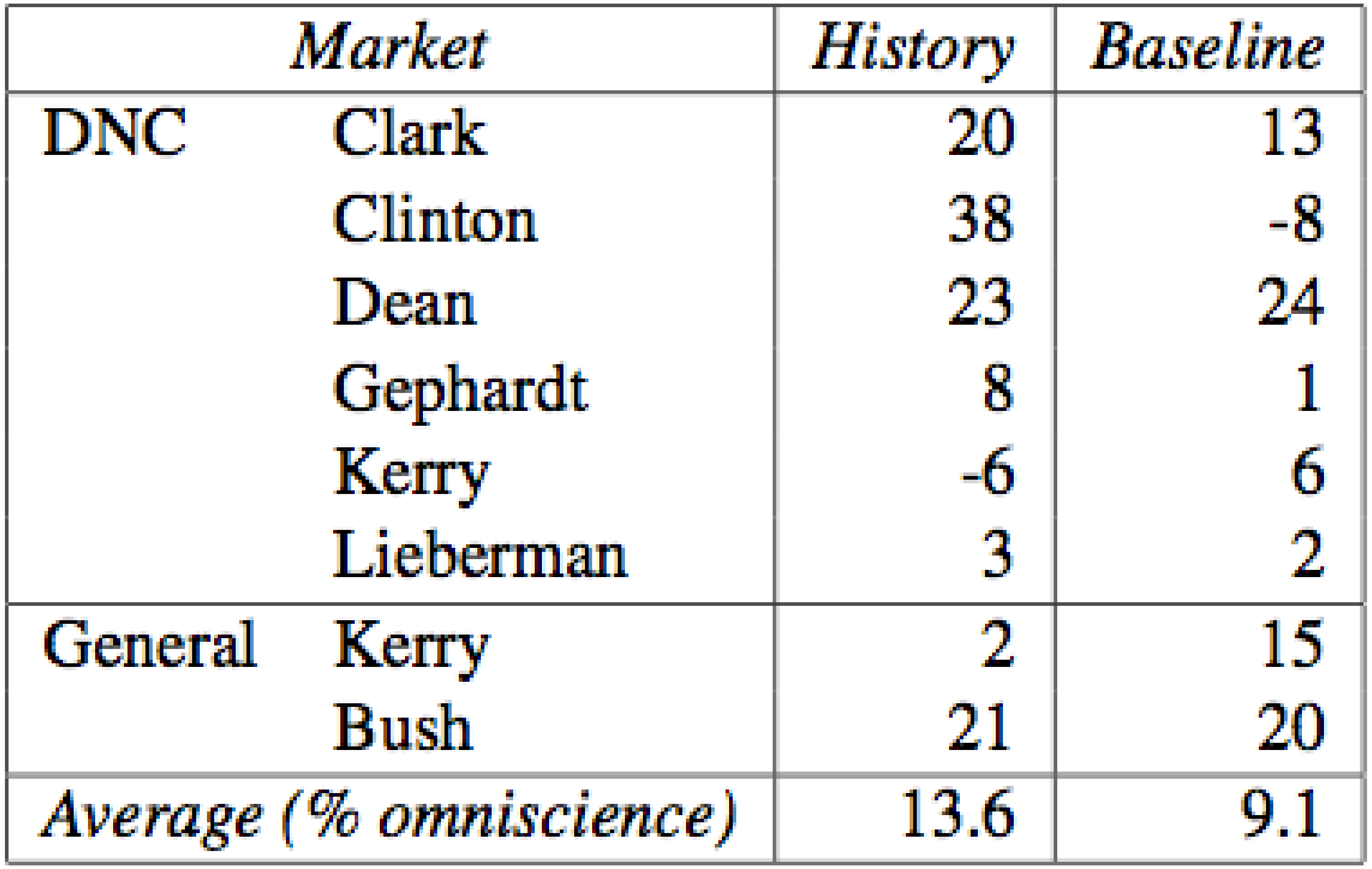
Evaluation Methodology

- Simulated “real-time” evaluation:
  - Given data up to SOD on day t…
  - Predict: (avg. price t) - (avg. price t-1)
  - Make observation at EOD t and retrain
  - Motive to day (t + 1)
- Metric: percentage of best possible profit. Takes into account direction and magnitude. In the range [0,1]

Reading the Markets

results

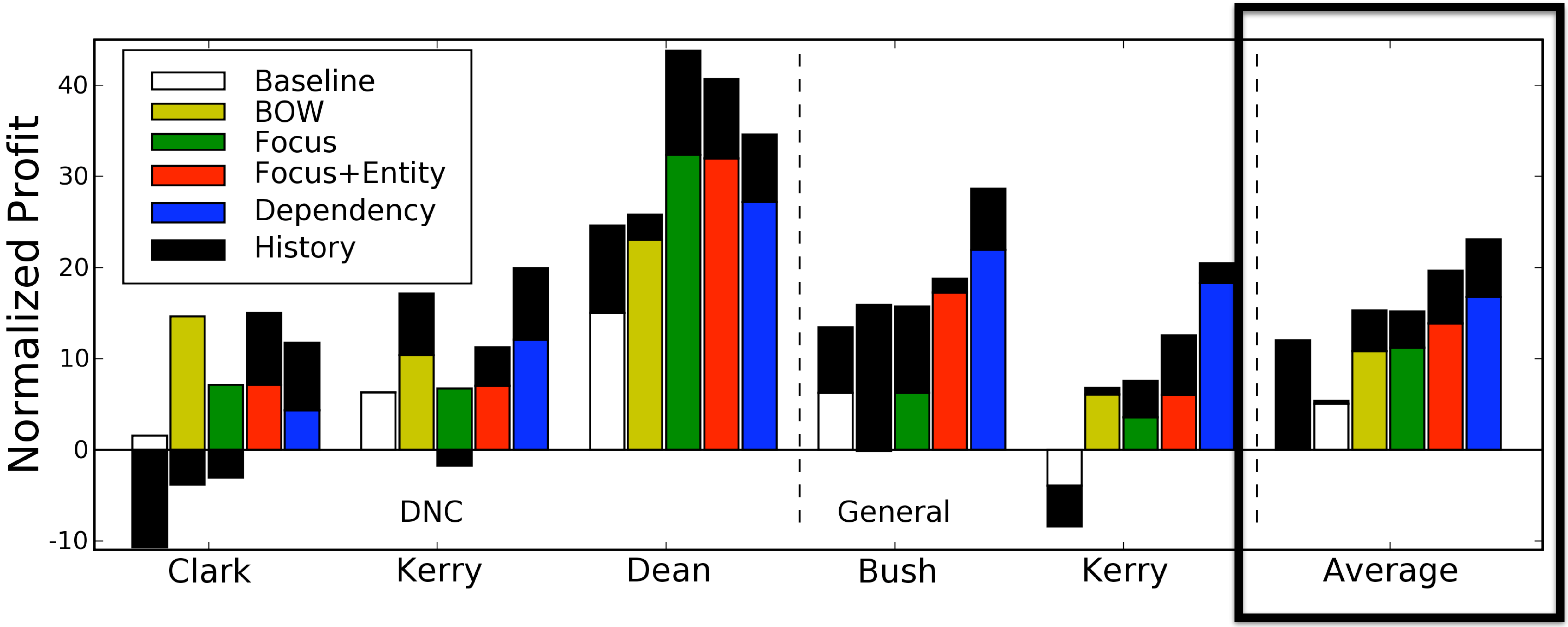
- History: prediction based on prior three days
- Baseline: # of mentions of each entity as features



Market		*History*	*Baseline*
DNC	Clark	20	13
	Clinton	38	-8
	Dean	23	24
	Gephardt	8	1
	Kerry	-6	6
	Lieberman	3	2
General	Kerry	2	15
	Bush	21	20
Average (% omniscience)		13.6	9.1

Reading the Markets

results


Normalized Profit
Baseline
BOW
Focus
Focus+Entity
Dependency
History
DNC
General
Clark
Kerry
Dean
Bush
Kerry
Average