On the Importance of Text Analysis for Stock Price Prediction

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Motivation

- Many people are interested in the financial market
- A vast amount of text information online
- Hard to monitor in real time for individual investors

Financial reports list events that impact company performance

- "**8-K**" financial reports for companies
- US companies required to file an 8-K upon events like layoffs, mergers, officer changes

On November 15, 2011, ***the Board of Directors (the "Board") of Apple Inc. (the "Company") appointed*** *Robert A. Iger to the Board. Mr. Iger will serve on the Audit and Finance Committee of the Board.*

The problem

- Can we predict stock price movement after the 8-K report is released?
  - Since 8-K generally released after market close, can we predict what happens when market opens?
- Modeled as a three-class classification problem:

  UP: $\Delta > +1\%$,

  DOWN: $\Delta < -1\%$,

  STAY: $-1\% < \Delta < +1\%$
- Various controls and normalizations (normalize by change in S&P 500 index)

Our question: How is the text of 8-K reports linked with stock movements?

- Does language in 8-K reports offer additional information?
  - What kind of information?
- How long does the effect persist in the marketplace?

Related Work

- Xie et al. (2013): Tree representations of information in news
- Bollen et al. (2010): Twitter mood for market movement
- Bar-Haim et al. (2011): Identifying better expert investors
- Leinweber and Sisk (2011): Effect of news and the time needed to process the news in event-driven trading
- Kogan et al. (2009): A method that predicts risk based on financial reports
- Engelberg (2008): Linguistic information has more long-term predictability

- Only few previous results show improvements from textual information on predicting the impact of financial events on top of quantitative features

Corpus

- 8-K financial reports for S&P 500 companies
  - Between 2002-2012 (2009-2010 dev, 2011-2012 test)
  - 13,671 documents, 28M words
  - 8-K reports are mostly released before the market open or after the market closed
- Financial Annotations:
  - Daily history of stock prices
    - The (normalized) difference in the company's stock price before and after the report is released
  - Earnings Per Share (EPS)
    - Reported EPS (from 8-K reports)
    - Consensus EPS (the estimation of analysts)

Baseline Financial Features

Earnings surprise	The gap between the actual and expected earnings per share
Recent stock price changes	1 week, 1 month, 1 quarter, 1 year
Volatility S&P 500 index	roughly represents the expected movement of S&P 500 index over the following 30 days
Event category features	Event types in 8-K reports (merger, bankruptcy, …)

Linguistic Features

- Unigram features

. . . On a GAAP basis, the Company reported a net loss of $356 million . . . We remain intensely focused on helping …

{loss:1, basis:1, remain:2 … }

Linguistic Features

- Unigrams are too sparse!

  {loss:1, basis:1, remain:2, dimension:0, clandestine:0, … }

- Projected textual features into a smaller-dimension latent space by non-negative matrix factorization
  - Unigrams are projected into 50, 100, 200 dimension vectors
  - Benefits: captures latent meaning, faster training

Linguistic Features

loss

{1, 0, 0, …}

{0.11, -0.23, 1.76, …} $\in R^n$

basis

{0, 1, 0, …}

{-0.34, 0.61, -0.7, … } $\in R^n$

{loss:1, basis: 1, remain:2 … }

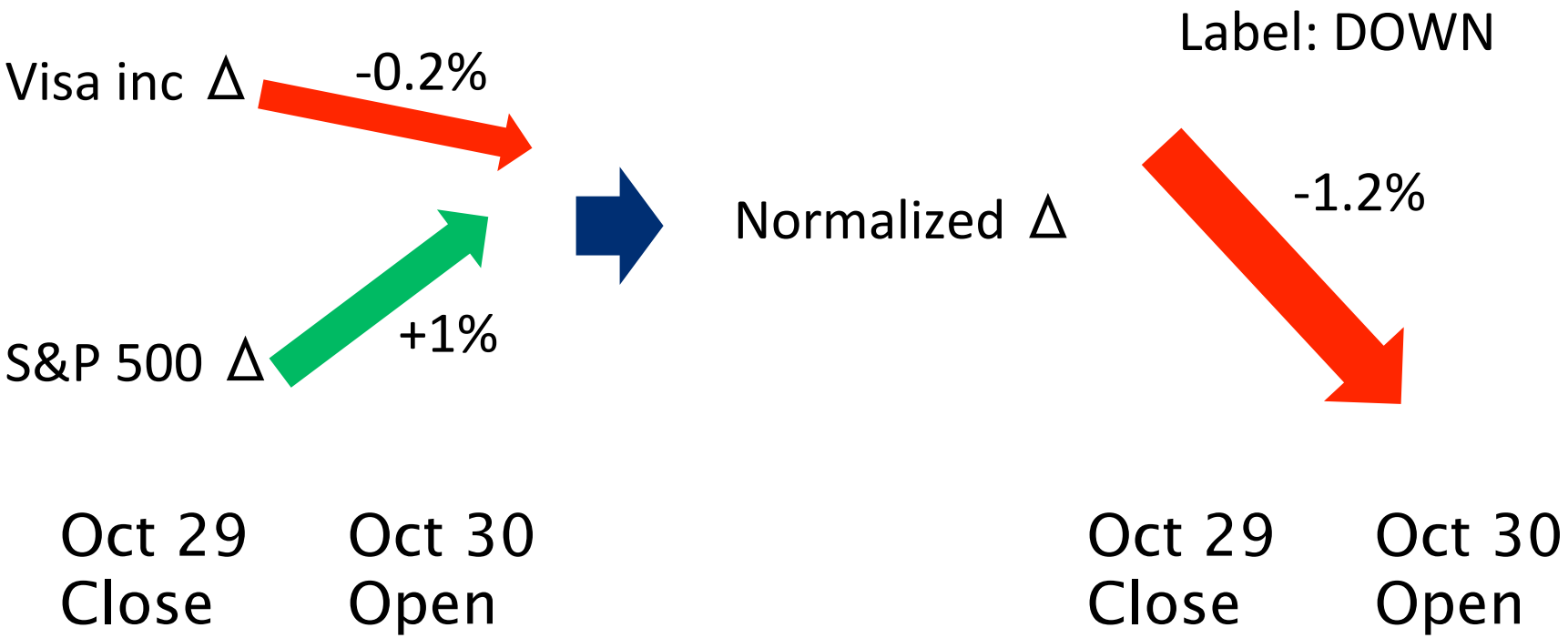
{1, 1, 2, …}

{0.2391, 0.7293, -1.2301, … } $\in R^n$

n=50, 100, 200

Example

Visa inc 8-K report released after Oct 29 market close



Example

- **Earnings surprise** = (0.58-0.56)/0.56*100 = 3.57%
- **Event type**: Results of Operations and Financial Condition

From 8-K report

. . . On a GAAP basis, the Company reported a net loss of $356 million . . . We remain intensely focused on helping …

- **Unigrams**: {loss: 1, basis: 1, …}
- **NMF vectorized**: {0.2391, 0.7293, -1.2301, … }

Classifier

- Random forest with 2000 trees
- Tuned on the development set (The size of random subset of features when training)
- PMI based feature selection
  - Among top 5000 features, keep features occurred at least 10 times throughout the training data -> 2319 unigram features

Five Models

Financial baseline 2

Financial baseline 1

Explicit text

Text projected into latent space

Everything (ensemble)

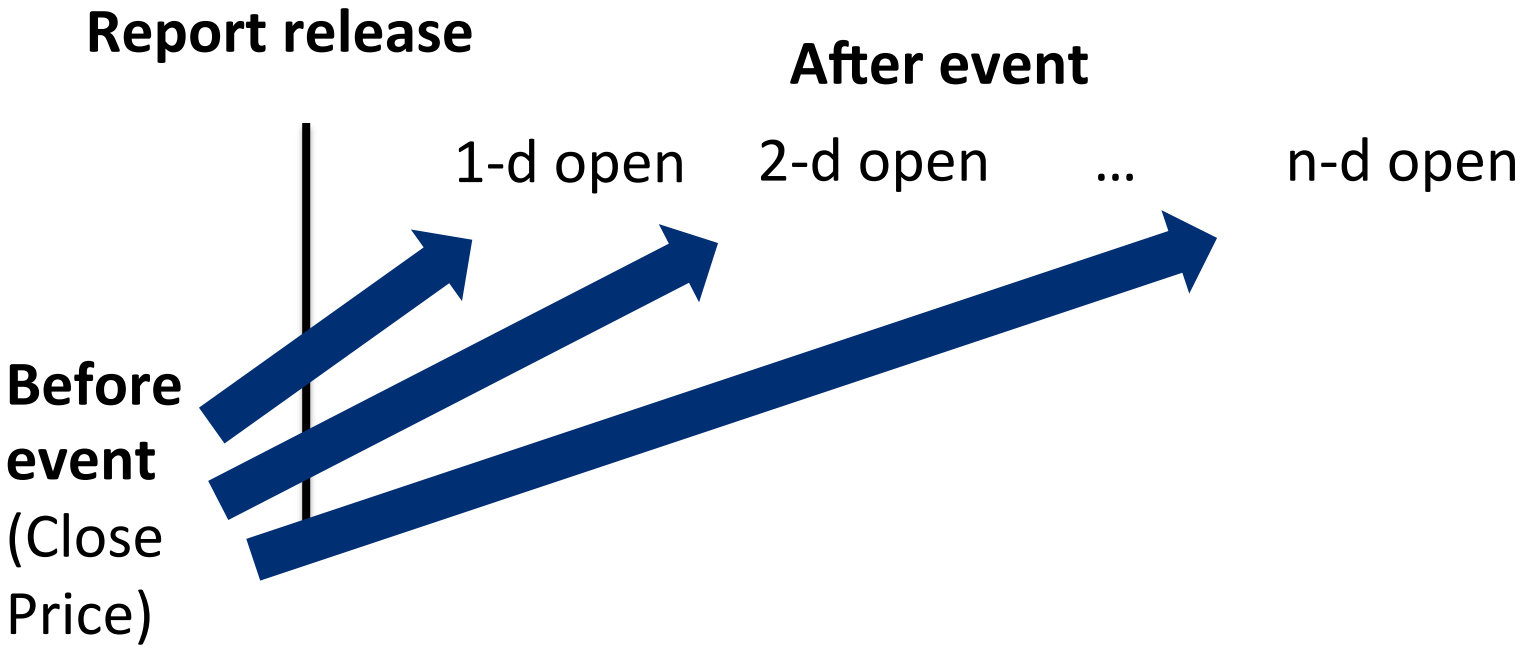
Feature	B1	B2	Uni	NMF	E
Earnings surprise	√	√	√	√	√
Recent movements		√	√	√	√
Volatility index		√	√	√	√
Event category		√	√	√	√
Unigrams			√		√
NMF vector				√	√

Results

System	Accuracy
Random guess	33.3
Majority class	34.9
Baseline1	49.4
Baseline2	50.1
Unigram model	54.4
NMF 50	54.7
NMF 100	55.4
NMF 200	55.3
Ensemble	55.5

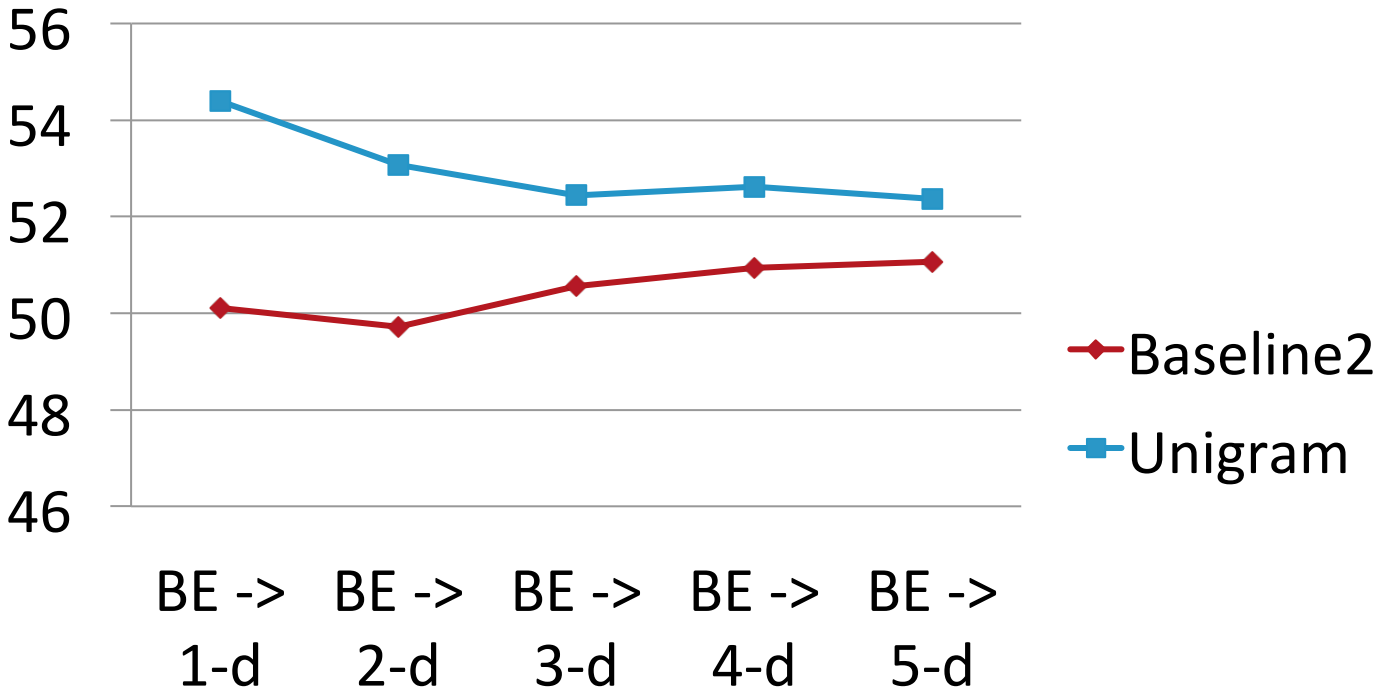
- Financial baseline 1: using only earnings surprise
- Financial baseline 2: using numeric & event category features to see financial baseline
- Ensemble: combined unigram and 3 NMF models

Temporal Aspect Model



- Investigates the predictive power of text as we move farther away from the event
- Same as before, it predicts UP/DOWN/STAY

Results: Temporal Aspect Model



* BE: before event

- The effect of linguistic features diminishes quickly

Results: Temporal Aspect Model

- Engelberg's (2008):
  - Soft information (textual information) requires a higher processing cost and takes longer to affect the market

Results: Temporal Aspect Model

- Why the opposite result?

- Our data: company report (short term)
- Their data: news article (longer term)

- News articles reflect not only new information, but also the perspectives and opinions of third parties
- Hypothesis: the market is highly sensitive to company reports in the short term, but more sensitive to third party perspectives in the longer term

Positive & Negative words from Unigrams

Positive: Increase, growth, new, strong, forward, well, grow, product, future, we

Negative: charge, loss, lower, decline, reduce, down, adjust, regulation, offset, reduction, while

Error Analysis

- **Correct label**: DOWN
- **Unigram**: DOWN, **baseline2**: UP

*… despite **lower** than expected growth, the more rapid **decline** in demand for FedEx Express services, particularly from Asia, outpaced our ability to **reduce** operating costs.*
…

- lower, decline, and reduce are in our top features

Error Analysis (2)

- **Correct label**: DOWN
- **Unigram**: STAY, **baseline2**: DOWN

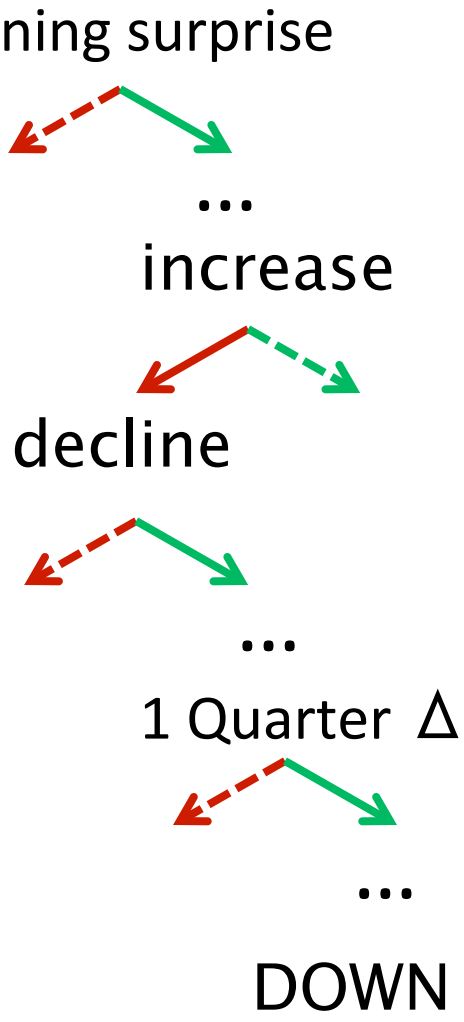
*"We are very **pleased** with our fourth quarter and full year results, as well as …*

- Unigram model incorrectly predicts STAY even though the company has unsatisfactory earnings per share

Example Decision Path

- Abbott Laboratories
- Apr 15, 2009 report
- True label: DOWN
- Decision: DOWN

*… This resulted in a $230 million **decline** in Depakote sales in the first quarter …*



Negative Results

- Sentiment features
  - SentiWordNet: domain difference. e.g., ***growth*** is objective (or slightly negative)
  - Sentiment lexicons from Jegadeesh and Wu (2013): The list is small and 77% of lexicons are already in our feature set.
- Bigrams and Word clustering features
- Other classifiers (logistic regression or multilayer perceptron)

Limitations

- Do not trade using this yet ☺
- Predicts movement but not magnitude (how big the change will be)
- It ignores several important real-world factors:
  - **Transaction costs**: bid-ask spreads
  - **Slippage**: the tendency of large trading programs to move the market
  - **Borrowing costs** for short positions
- Does not parse numbers and their meaning

Conclusions

- New corpus of 8-K financial reports, annotated with financial metrics
  - http://nlp.stanford.edu/pubs/stock-event.html
- Text helps to predict stock price movement,
  - short-term movement is sensitive to events in company reports
  - longer-term movement may be sensitive to third-party perspectives in news
- Domain is important when using sentiment lexicons
  - Using all unigrams was better than using published lexicons
- Methodology
  - Dimensionality reduction of word vectors helps
  - Random forests worked well to combine lexical and numeric features