Twitter Mood Predicts the Stock Market

Xiao-Jun Zeng

School of Computer Science

University of Manchester

x.zeng@manchester.ac.uk

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Introduction and Motivation

- Common sense often says that stock markets are driven by “fear and greed”—that is, by psychological as well as financial factors
- Behavioural finance and economics theory have established that investors’ behaviour can be shaped by whether they feel optimistic (bullish) or pessimistic (bearish) about future market values
- Psychological research tells us that human decisions (including financial decisions) are significantly driven by emotion and mood

=> Conclusion: Sentiment and mood has significant impact to investors’ behaviour and stock move

Introduction and Motivation

Available investment sentiment and mood information:

- **Confidence and sentiment Indexes such as**
  - Conference Board's Consumer Confidence Index
  - Michigan's Consumer Sentiment Index
  - Gallup's Economic Confidence Index
- **Investor sentiment polls such as**
  - Merrill Lynch Investor Sentiment
  - American Association of Individual Investors

=> Problem: Such indexes are expensive and so limited coverage. More importantly, often too slow and too late

Introduction and Motivation

- Recent research suggests that mining social media data (blogs, Twitter feeds, etc) can provide valuable information to predict changes in various economic and commercial sentiment indicators
- There are a number of social media mining tools having been developed

=> Motivation: Perhaps social media data such as Twitter can provide more comprehensive and real-time information about market sentiment and mood for stock price prediction.

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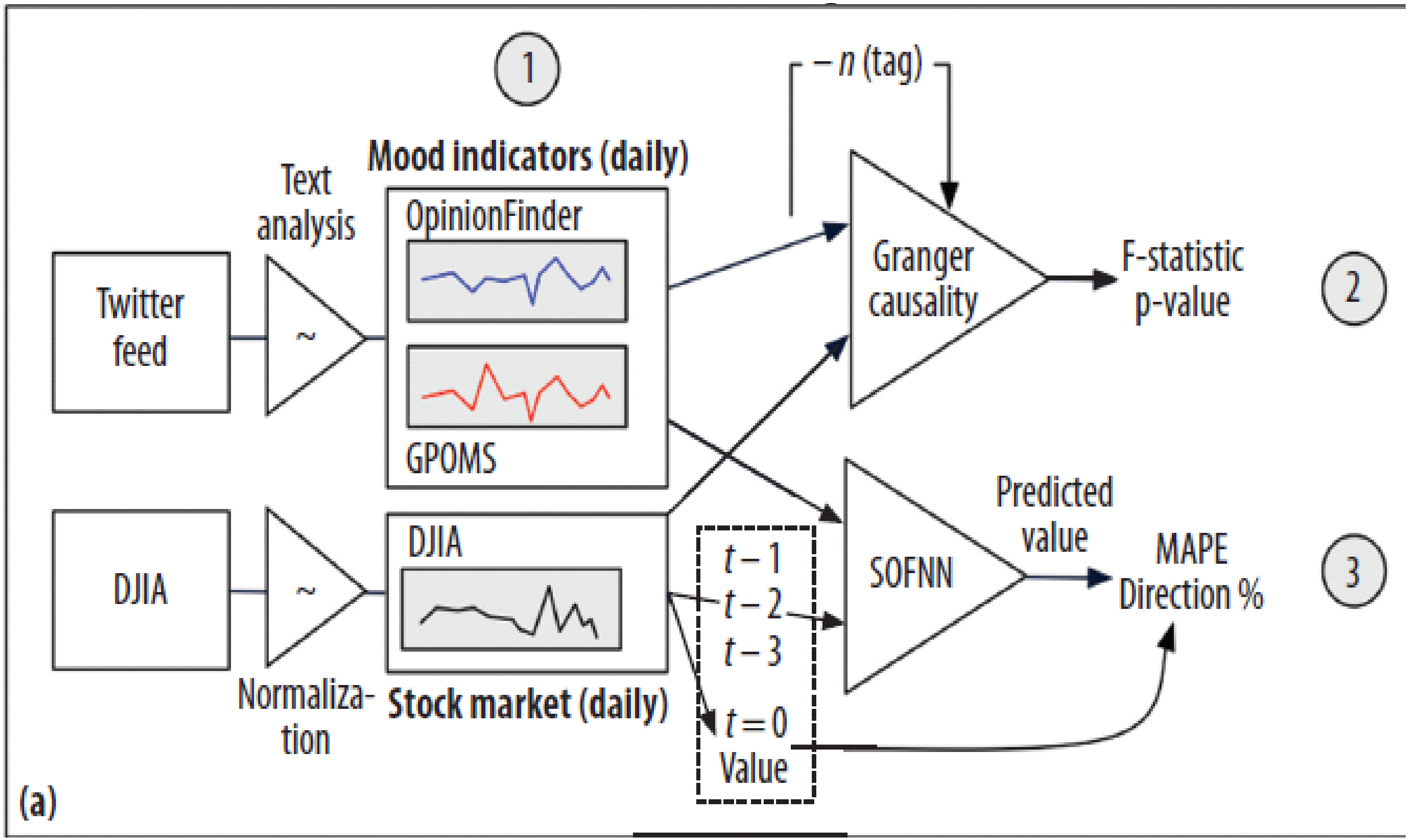
Approach – Framework: Methodology

3 phases of methodology



Twitter mood model and analysis

Twitter Mood Analysis Tools

- **OpinionFinder (OF):** a widely used sentiment-analysis tool that classifies texts in terms of their positive versus negative sentiment
  - Have been shown to correlate with the Consumer Confidence Index from Gallup and the Reuters/University of Michigan Surveys of Consumers
- **Google-Profile of Mood States (GPOMS):** a now proprietary tool that measures six different dimensions of mood often ignored by traditional sentiment-tracking methods—calm, alert, sure, vital, kind, and happy

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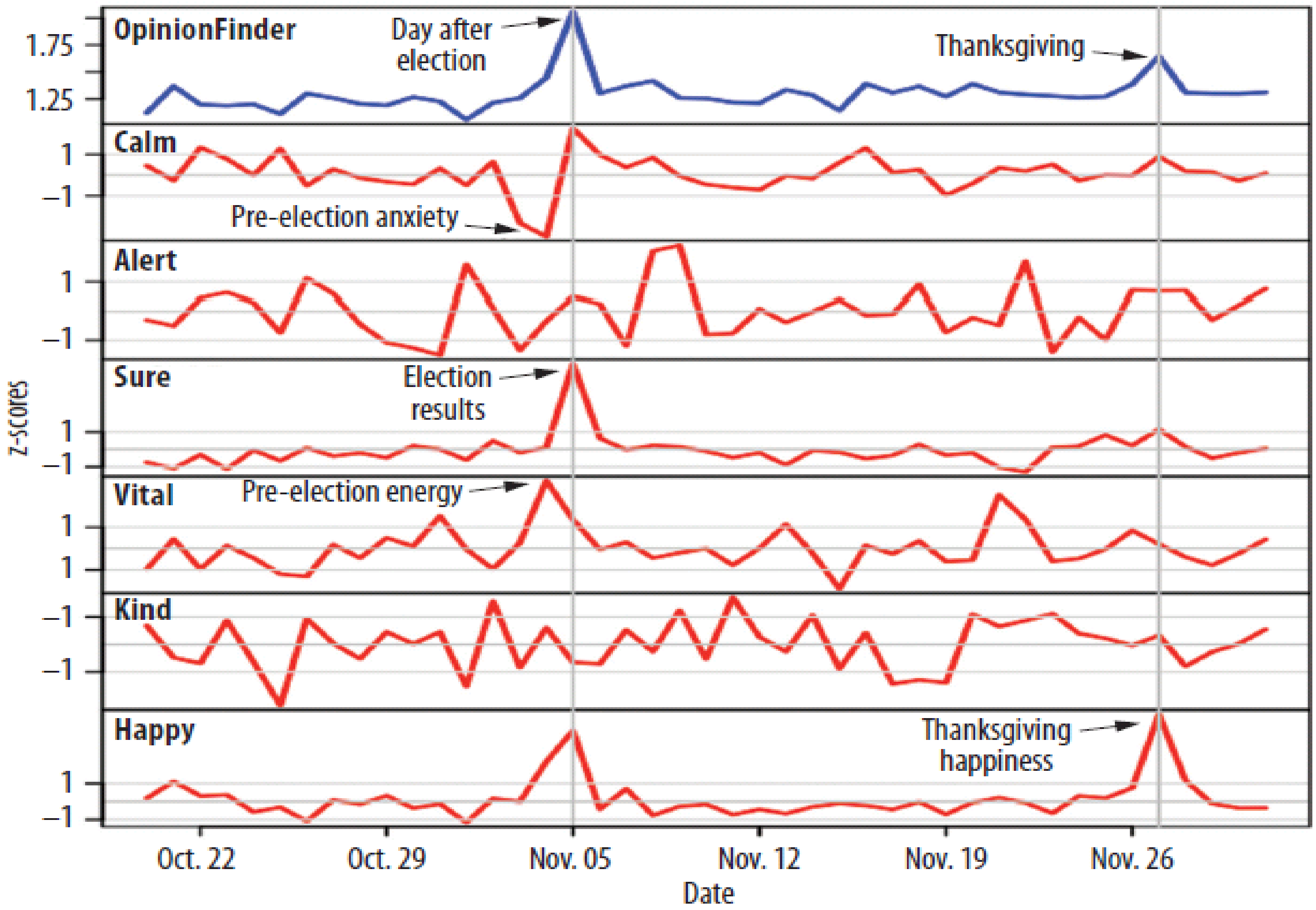
Twitter mood model and analysis

Outcome: Daily time series of public mood fluctuations



Causality analysis of mood vs. DJIA prices

Granger causality analysis of mood vs. DJIA prices

- A time series Xt is said to Granger-cause Yt if it can be shown, usually through a series of t-tests and F-tests on lagged values of Xt (and with lagged values of Yt also included), that those Xt values provide statistically significant information about future values of Yt.
- DJIA time series, denoted Yt= $D_t = DJIA_t - DJIA_{t-1}$ is the daily changes (between day t and t−1) in stock market value.

Causality analysis of mood vs. DJIA prices

Granger causality analysis of mood vs. DJIA prices

$$L_1: \quad D_t = \alpha + \sum_{i=1}^{n} \beta_i D_{t-i} + \varepsilon_t$$

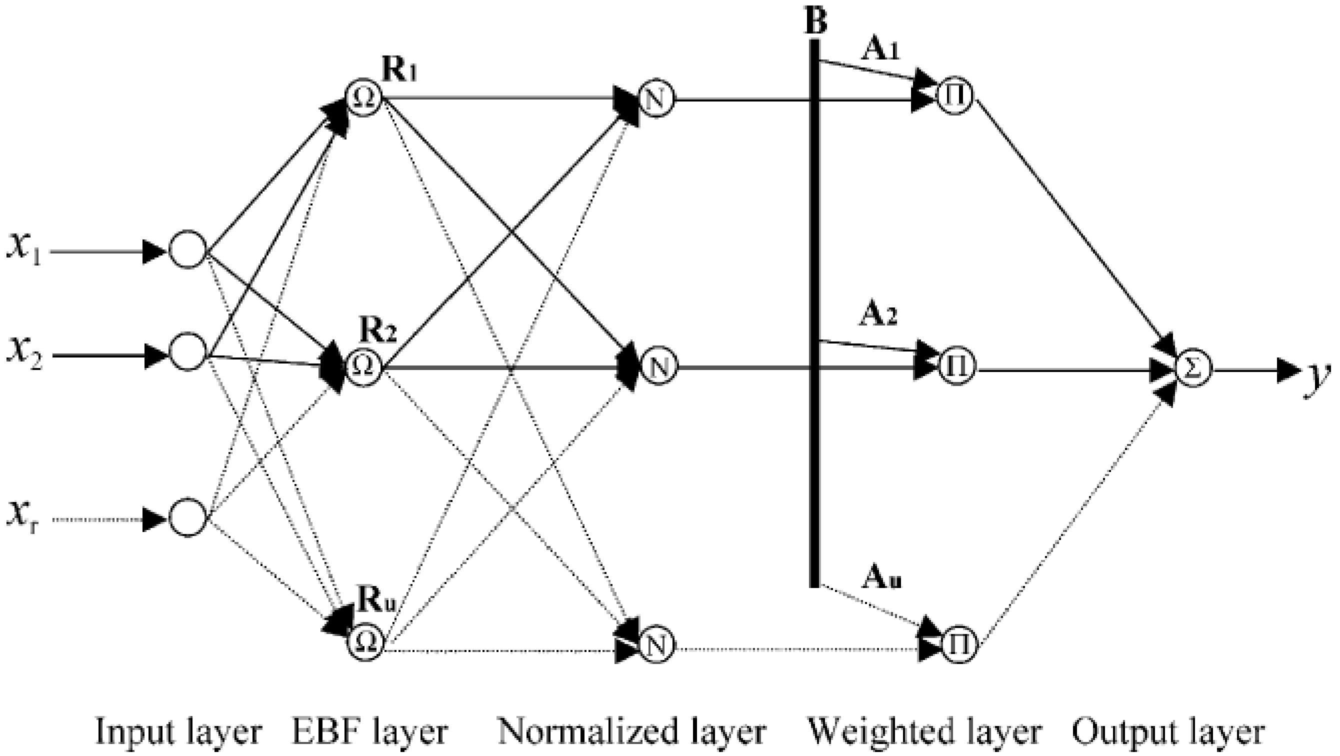
$$L_2: \quad D_t = \alpha + \sum_{i=1}^{n} \beta_i D_{t-i} + \sum_{i=1}^{n} \gamma_i X_{t-i} + \varepsilon_t$$

where X_{t-i} are mood time series

- **Outcome:** Mood has the highest Granger causality relation with DJIA for lags ranging from 2 to 6 days. This also determines how many lagged values need to be included in nonlinear modelling.

Nonlinear models for mood-based stock prediction

- Self-organizing fuzzy neural networks



Nonlinear models for mood-based stock prediction

- Self-organizing fuzzy neural networks

$$y(\mathbf{x}) = \sum_{j=1}^{u} f_j = \frac{\sum_{j=1}^{u} w_{2j} \exp\left[-\sum_{i=1}^{r} \frac{(x_i - c_{ij})^2}{2\sigma_{ij}^2}\right]}{\sum_{k=1}^{u} \exp\left[-\sum_{i=1}^{r} \frac{(x_i - c_{ik})^2}{2\sigma_{ik}^2}\right]}$$

- This can be regarded as the normalised radial basis function (RBF) networks but
  - No hole for the no training data areas
  - More transparent and interpretable

Nonlinear models for mood-based stock prediction

- Self-organizing learning algorithm:
  - An evolving learning algorithm which will automatically determine the number of neurons or basis functions and learn model parameters
  - Convergence to real systems has been proved if there are enough training data
  - High accuracy in comparing many other methods
  - Have been successfully applied to electrical load forecasting, exchange rate forecasting, and function approximation

Nonlinear models for mood-based stock prediction

- Self-organizing learning algorithm - Main Steps:
  - **Start from a network with one neuron**
  - **Adding a neural** (or basis function) when the existing model is not complicated enough to catch up the nonlinear behaviour
  - **Merger neurons** if they are highly similar to avoid overfitting
  - **Pruning a neuron** if it makes little contribution to the forecasting accuracy
  - Recursive least square parameter learning to catch the time varying factor

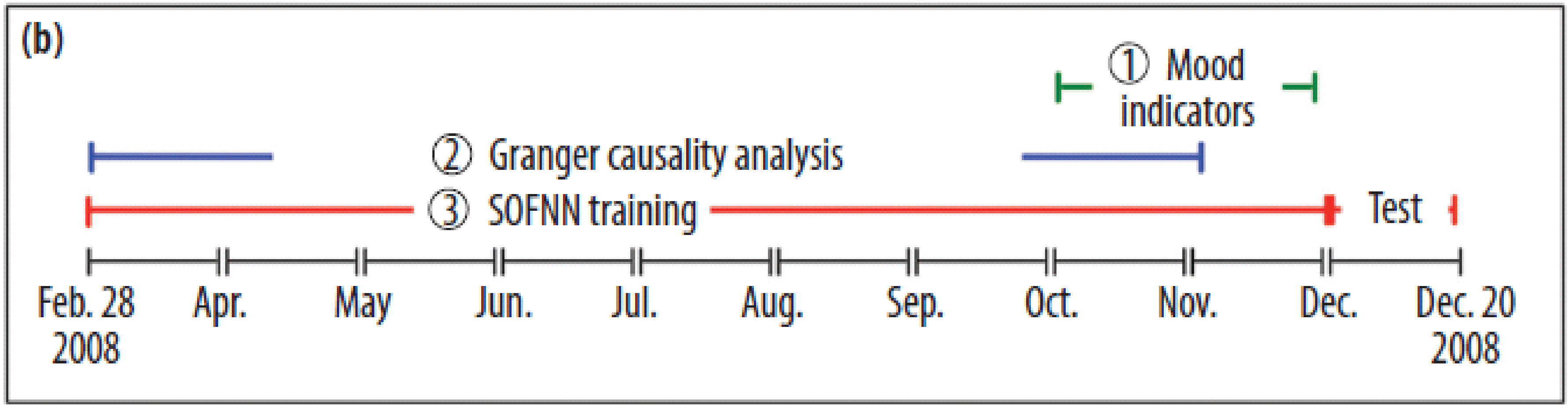
Experiment

Experiment Data

- Twitter Data:a collection of public tweets that was recorded from February 28 to December 19th, 2008 (9,853,498 tweets posted by approximately 2.7M users). For each tweet these records provide a tweet identifier, the date–time of the submission (GMT+0), its submission type, and the text content of the Tweet which is by design limited to 140 characters
- DJIA closing values between February 28 to December 19th, 2008

Experiment

Timeline



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Experiment

Experiment Setting

- Forecasting period – n=3 days ahead:
  - To predict the DJIA value on day t, the input attributes of our SOFNN include combinations of DJIA values and raw mood values of the past n days. We choose n−3 since the results from causal analysis indicate that past n−3 the Granger causal relation between Calm and DJIA decreases significantly
- Input variables:
  - Different combinations of six dimension Mood variables and DJIA values with the last 3 days
- Forecasting testing period:
  - December1 to December19, 2008

Experiment

Experiment Result

DJIA daily prediction using SOFNN.

Evaluation	I_{0F}	I_0	I_1	$I_{1,2}$	$I_{1,3}$	$I_{1,4}$	$I_{1,5}$	$I_{1,6}$
MAPE (%)	1.95	1.94	1.83	2.03	2.13	2.05	1.85	**1.79***
Direction (%)	73.3	73.3	**86.7**	60.0	46.7	60.0	73.3	80.0

Where the different input sets are

$$
\begin{aligned}
I_0 &= \{DJIA_{t-3,2,1}\} \\
I_1 &= \{DJIA_{t-3,2,1}, X_{1,t-3,2,1}\} \\
I_{1,2} &= \{DJIA_{t-3,2,1}, X_{1,t-3,2,1}, X_{2,t-3,2,1}\} \\
I_{1,3} &= \{DJIA_{t-3,2,1}, X_{1,t-3,2,1}, X_{3,t-3,2,1}\} \\
&\dots
\end{aligned}
$$

Conclusion and future research

Conclusion: Although more technical improvements are needed and much more experiments are required, our research and some following works suggest:

- Social media data (blogs, Twitter feeds, etc) include some useful mood and sentiment information related to stock market
- Including such mood and sentiment information can improve the accuracy of stock prediction

Conclusion and future research

Future work: More comprehensive prediction system combines:

- Online news mining from web data and social media data, as big news are often accumulated from many small news and such online mining will provide the early indicators for the current unpredictable news;
- Online social media data mining to get early mood and sentiment indicators
- Historical stock price data and fundamental financial data

to further improve the accuracy of stock forecasting.