Association between Twitter Sentiment and the S&P 500 Index



Jinyu Xia Advisor: Professor Bret Hanlon. Department of Statistics, University of Wisconsin-Madison

Motivation

Behavioral economics believe that in the real-world situations, people's decision-making process is affected by their emotions. Therefore, studying and quantifying people's emotions would add to methods currently available to predict economic trend such as the stock index.

Introduction

We study the association between Twitter sentiment and the stock index by exploring several aspects:

- Generate Twitter Sentiment
- Detect Twitter sentiment anomalies that correspond with the S&P 500's fierce daily fluctuation.
- Predict stock market daily trend from Twitter sentiment.

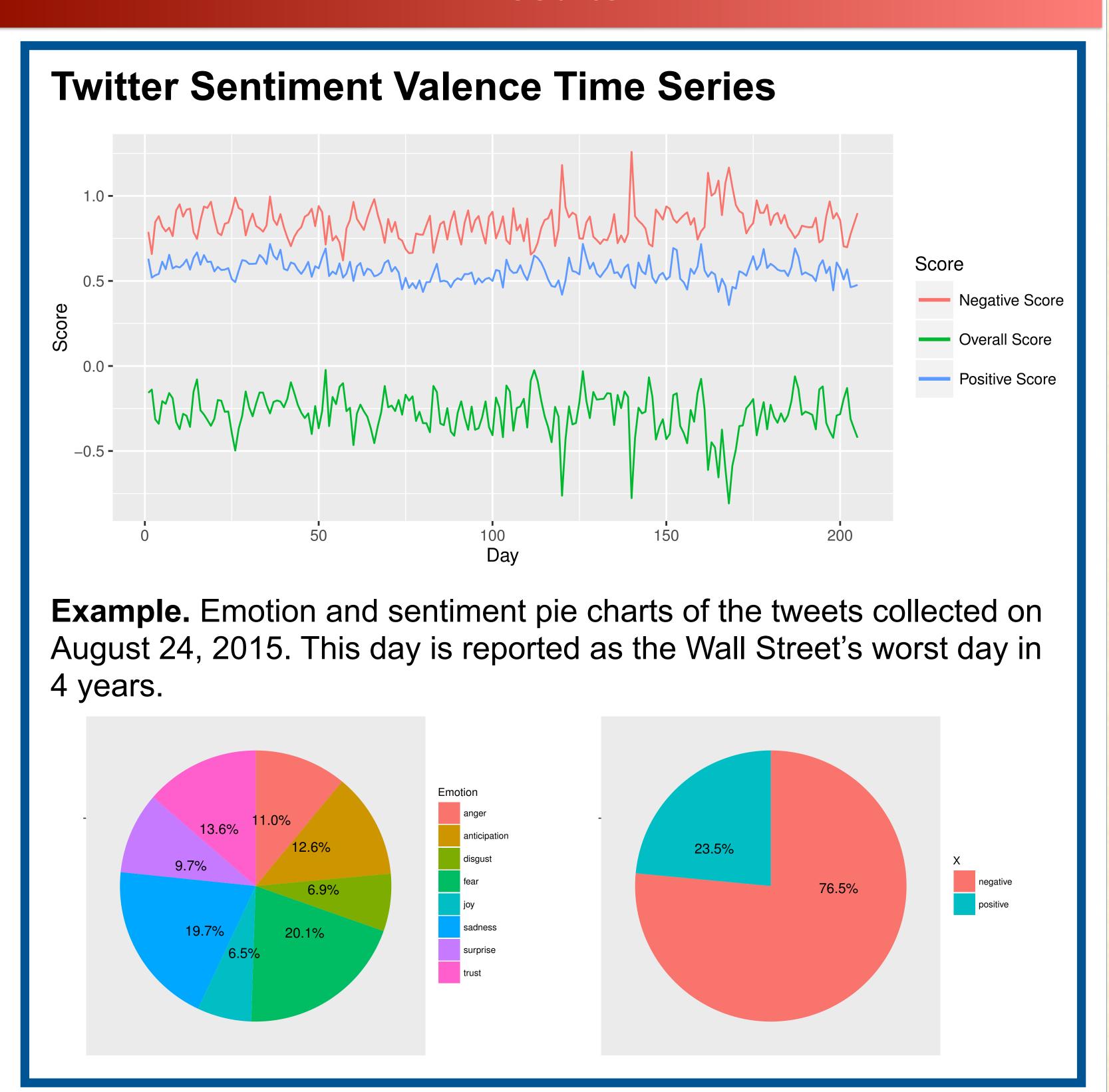
Methods

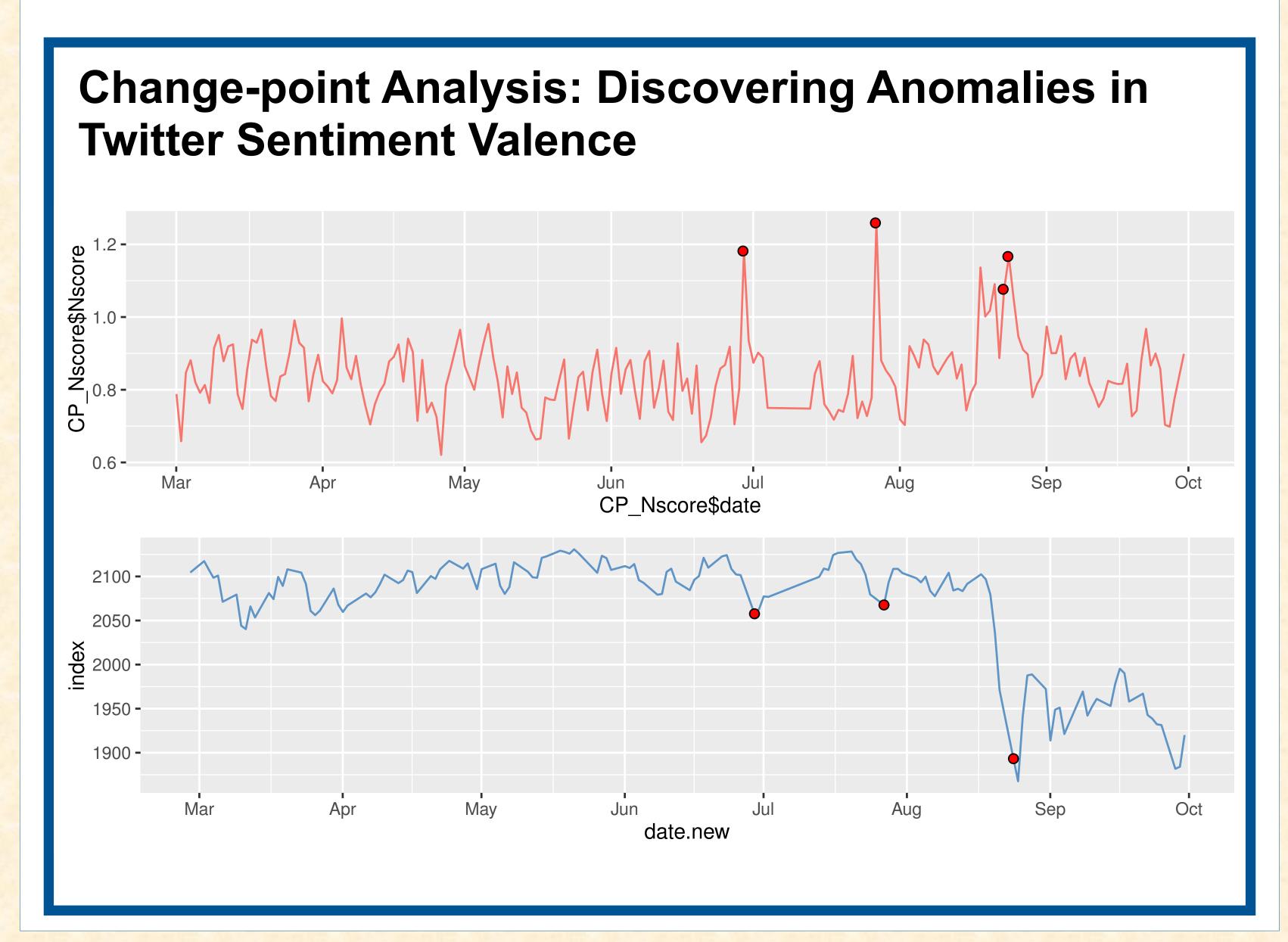
Sentiment Generation. We collected tweets from the Twitter streaming API from March 2015 to September 2015. After the raw data process, we obtain the positive/negative sentiment valence of each tweet by applying voter algorithm based on NRC Emotion Lexicon.

Anomalies Detection. We detect anomalies in the S&P 500 by using Seasonal Hybrid Extreme Studentized Deviate test. Then we check the Twitter sentiment valence anomalies are connected with the stock market crashes.

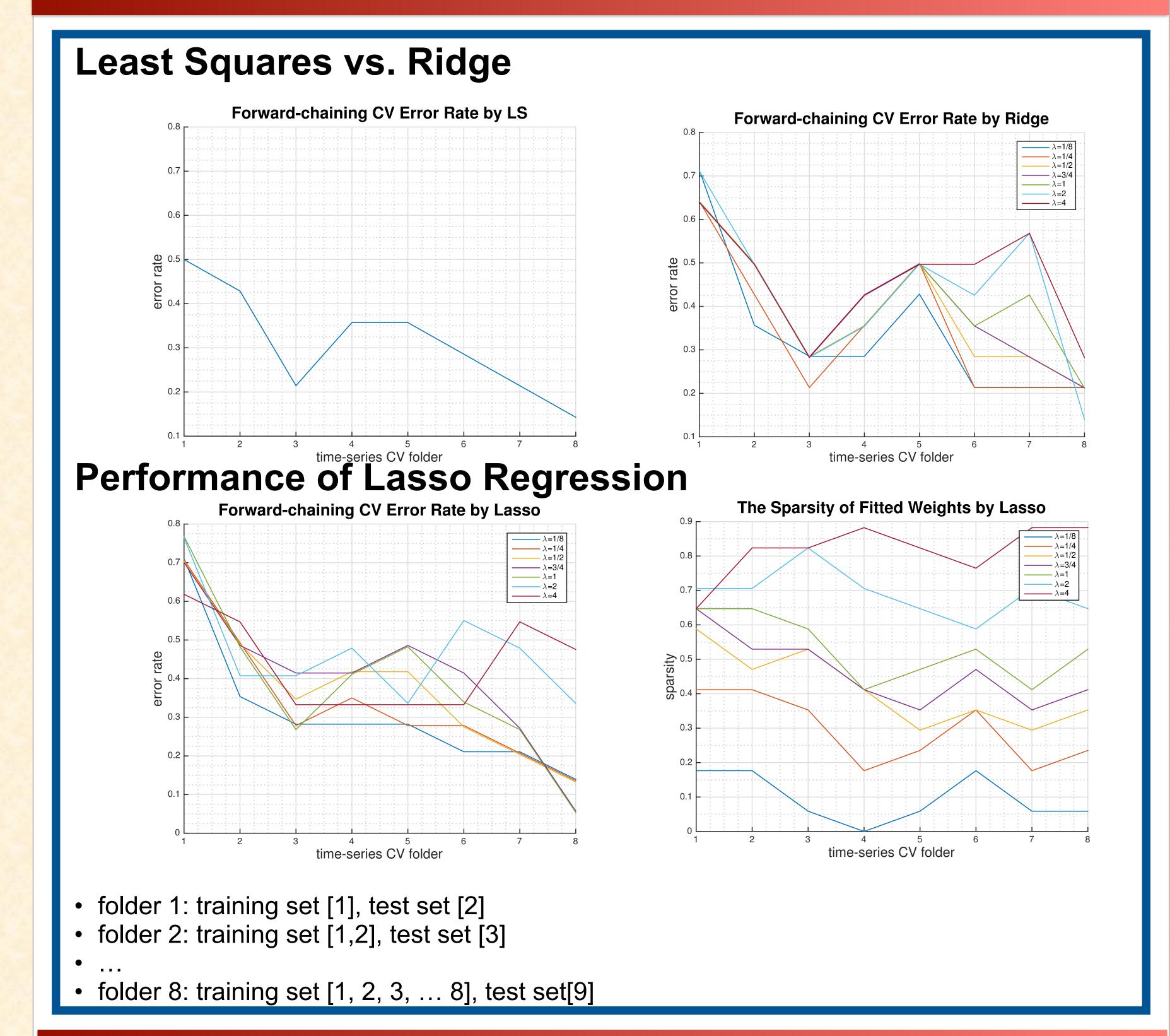
Prediction. To predict the daily trend of the S&P 500 index from Twitter sentiment, we applied LS binary classification, the Lasso, Ridged, and logistic regression. For each of the machine learning techniques, we use forward-chaining method to estimate its performance.

Results





Results



Summary&Conclusions

- The anomalies detection shows that, from March 2015, to September, all of the days on which the Twitter Sentiment outlier are detected are followed by stock market crash.
- For LS binary classification, the lowest error rate are achieved when we include all of the previous 8 folders as training set, and the left one as test set. The error rate is 0.1429.
- For Regularized LS regression,
- Ridge. When $\lambda = 2$, Ridge can achieve the same performance as LS.
- **Lasso.** When λ is 3/4 and 1, the best error rate is 0.0714 (i.e. There is only 1 misclassification in the test set). The Lasso with $\lambda = 1$ or 3/4 select only half of the original features. Hence, in our problem, Lasso help improving the generalization of our model and avoid overfitting.

Reference

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