

EXPLORATION OF DIFFERENT AI METHODS FOR STOCK MOVEMENT AND VALUE PREDICTION VIDEO URL FOR LINGFEL:

VIDEO URL FOR SOPHIA (ZHI): https://drive.google.com/open?id=1BhnMoQoJmWzC7knQcqNDbwCVRnYXZ4e

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VIDEO URL FOR LINGFEI:

https://drive.google.com/open? id=0B44mHCW9kp5rUHU4MIdOOEpzQUVxVW1SVnRGejNmX3IINIRR

INTRODUCTION

- Stock market behavior is most interesting during earnings season due to spikes in volatility and stock volume.
- ► We study stock value and movement prediction during earnings season.



DATA ACQUISITION: PART I

- ▶ Data obtained from the CRSP database. Our stock universe includes NYSE, AMEX, and NASDAQ from 1996 to 2018.
- ► Portfolio sorted into quintiles using 3-day cumulative returns from pre-announcement period.
- ► Long-short portfolio formed by buying (selling) firms in the lowest (highest) quantile.
- ► Each stock for every period within the portfolio is equally-weighted.

DATA ACQUISITION: PART II

- ► Earnings conference call transcripts taken from relevant company websites, and 10-K reports gathered from SEC.
- ► Data treated using Stopwords corpus and lemmatized using Wordnet corpus.
- ► For the earnings transcripts, feature extraction was done via n-grams model for various values of n.
- ► Labels were denoted "+1" or "-1" depending on whether the stock price increased or decreased between $\pm d$ days of the earnings call day.
- ► Feature extraction was done via Loughran and McDonald sentiment word master dictionary for the 10-K reports.

IMPLEMENTATION

Long-short Portfolio

▶ Jensen's alpha and beta were first estimated when the model was exposed to basic CAPM

$$R_t - R_f = \alpha + \beta_{mkt}(Mkt_t - R_f) + \epsilon_t$$

and 3-Factor Fama & French (FFM):

EXPERIMENTAL RESULTS

$$R_t - R_f = \alpha + \beta_{mkt} (Mkt_t - R_f) + \beta_{smb} SMB_t + \beta_{hml} HML_t + \epsilon_t$$

Long-short Portfolio

Figure 1: Correlation Heatmap

NLP

- ► For the call transcripts, n-grams model was used with minimization of hinge loss via stochastic gra-
- sessed for neighboring bag of words of 10-Ks.

$$J(U,V) = \frac{|U \cap V|}{|U \cup V|}, \quad C(U,V) = \frac{|U * V|}{|U| * |V|}.$$

▶ Define (non-) changers by quintile of J/C. Return and Sharpe ratio were assessed by word list.

- dient descent.
- ▶ Jaccard similarity (J) and cos similarity (C) were as-

$$J(U,V) = \frac{|U \cap V|}{|U \cup V|}, \quad C(U,V) = \frac{|U * V|}{|U| * |V|}.$$

Sentiment Analysis with 10-K Reports

Table 3: Sharpe Ratio (SR) by Word List Category

Sentiment	SR (size = 5)	SR (size = 10)
negative	-3.08	-1.95
positive	3.04	-0.52
uncertainty	0.57	-3.11
litigious	1.64	5.98
constraining	-2.38	-4.31
interesting	-2.34	-4.4 1

Table 1: 3-day Cumulative Excess Return

Mean	0.02
Standard Deviation	0.076
3-Day Sharpe Ratio	0.158

Table 2: Regression on CAPM and Fama-French 3-Factor

CAPM	Estimate	Std. Error	t-value	P(> t)
$\overline{-lpha_{Mkt}}$	0.00374	0.000633	5.89	$1.03 \cdot 10^{-8}$
β_{Mkt}	0.0342	0.054092	0.71	0.48
F-F 3-F	Estimate	Std. Error	t-value	P(> t)
$\overline{\alpha_{total}}$	0.00385	0.000667	5.61	$1.16 \cdot 10^{-8}$
eta_{Mkt}	0.0371	0.04821	0.85	0.45
eta_{SMB}	0.0860	0.08912	0.93	0.35
β_{HML}	0.0579	0.08457	0.66	0.51

Figure 2: Average Announcement-Window Return

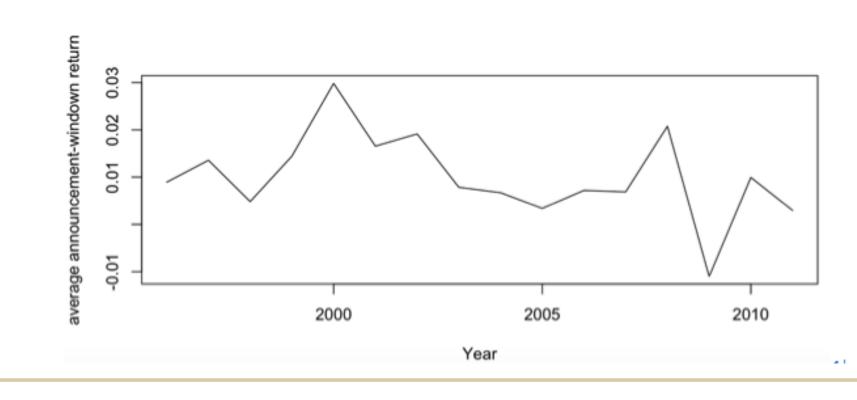


Figure 3: Cumulative Return by Word List Category over Year

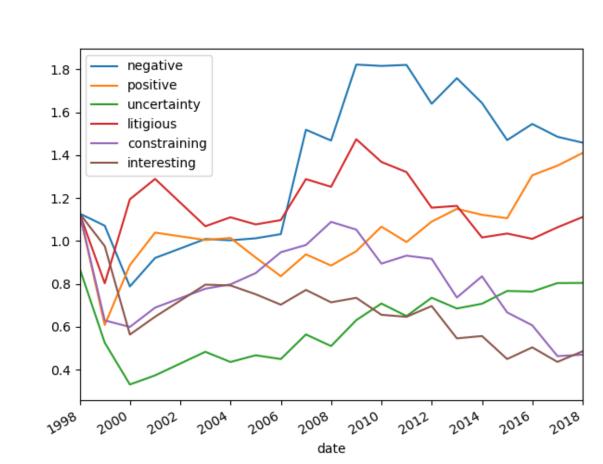
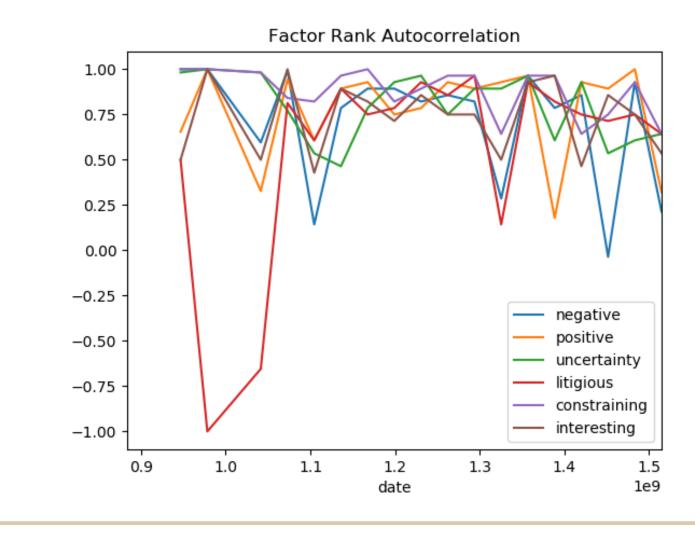


Figure 4: Factor Rank Autocorrelation to measure stability



EXPERIMENTAL RESULTS, CONTD.

Machine Learning with Call Transcripts

Figure 5: Linear Classifier Accuracy for Varying N-Gram Feature Extraction

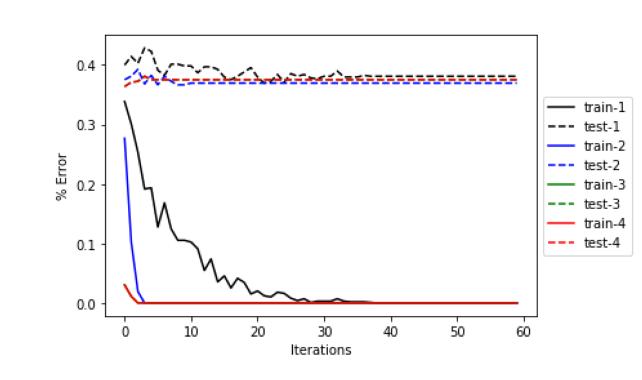
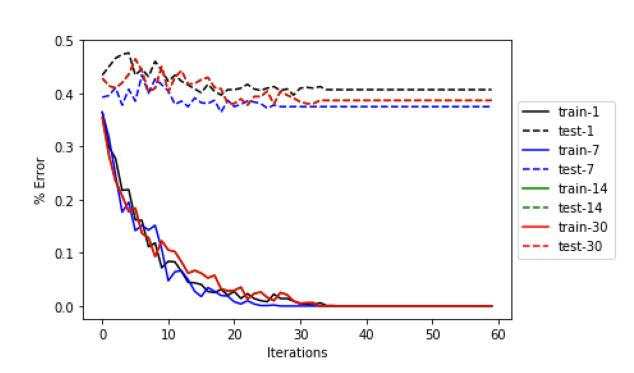


Figure 6: Linear Classifier Accuracy for Varying Days before and After Earnings Call



Conclusions

- ► Short term reversals around earnings announcements is a viable trading strategy. Abnormal returns over the CAPM model and FAMA French Three-factor model are observed in this strategy.
- ► Including more consecutive words in the feature space did not improve the classifier's accuracy by much, hinting at the possible non-linear nature of the feature space.
- ► Significant change in "litigious" and "negative" generated earning surprises, while "constraining" and "interesting" gave the opposite. It is unclear for "positive" and "uncertainty".

FUTURE WORK

- ► Adding alpha factors explored in NLP on call transcripts and 10-Ks such as changer in "litigious" to the CAPM or FFM during earnings announcements to verify higher stock movement prediction.
- Expanding the scope of data by including, e.g., 10-Qs, news reports, etc. would enhance the model stability and accuracy.
- ► Moreover, non-linear classifiers such as neural networks can be utilized to improve stock movement prediction, along with the increase in data points.