Faculty of computer science

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Analysis of Earnings Call Impact on Stock Prices

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Introduction

Earnings Call – An earnings call is a conference call or webcast conducted by a company's management team to discuss its financial performance and provide updates to shareholders and investors.

GitHub

In this research, we investigate the impact of earnings call on stock prices and abnormal returns and develop a binary classifier that predicts the rise or fall of the share price in 30 days based on earnings call transcripts.

Relevance and Novelty

- A lot of researches about applying Text data in Stock Price Prediction in recent years.
- Stock prices affects by multiple factors and Text data can be helpful in finding new patterns in prediction with a combination with financial data

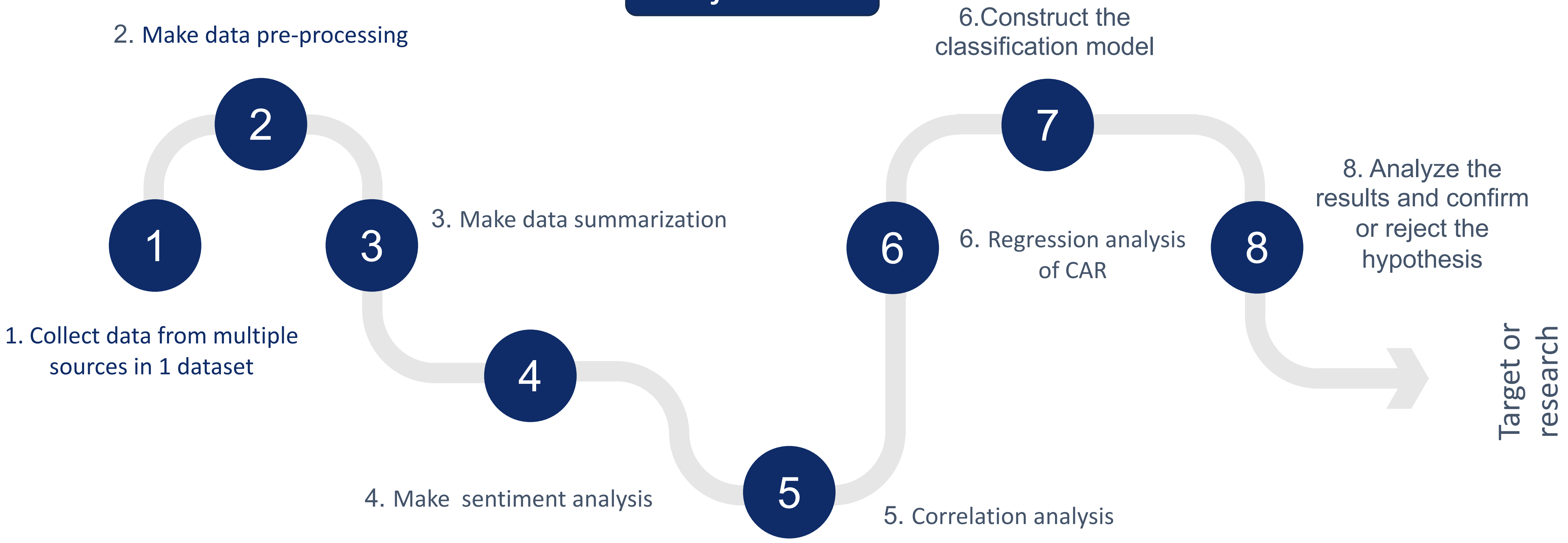
The novelty of this study lies in the thorough examination of data related to companies that have large capitalization in S&P100 index. Additionally, the impact of distinct parameter sets, including text, tone, and company sector, was evaluated for price growth prediction within 30-day period.

Article	Years	Methods	Metrics & Results	Key Fundings
Towards Earnings Call and Stock Price Movement	2020	Embeddings & Transformers	• MCC and Accuracy • Accuracy - 52.45% • MCC - 0.0445	• Deep learning model outperforms traditional baseline models • Information given in earnings calls relates to stock price fluctuations and can be beneficial in relevant forecasting tasks.
Short-term stock trends prediction based on sentiment analysis and machine learning	2022	SVM & KNN & Boosting	• Accuracy & F1 • Accuracy - 62% • F1 – 0.67	• The adjusted sentiment index has the potential to enhance the precision of stock trend • Incorporating the weight of individual reviews has a noteworthy impact on the precision of predictions
The influence of conference calls' semantic characteristics on the company market performance: Text analysis	2019	Panel Regression analysis	• $R^2 - 0.2$	• Significant impact of textual features of the conference call and tone on the abnormal stock returns (for 3, 14, 30 days) • the financial market affects the direction and importance of text information used by management
An Exploratory Study of Stock Price Movements from Earnings Calls	2022	LSTM & GNN	• Accuracy, Precision, Recall • Recall – 0.61 • Accuracy – 60% • Precision - 0.609	• Weak correlation with the stock price fluctuations after the earnings call • Features of earnings calls can predict stock price movements

Target

The main goal of the work is to find a dependencies between text data and prices and construct a binary classification model for stock price prediction.

Objectives



Hypothesis

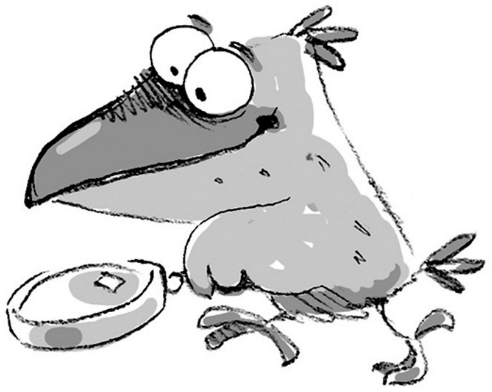
•The transcripts of earnings call can influence companies return.

•There is a positive correlation between transcripts of earnings call and stock prices.

•There is a correlation between the tone of earnings call and fundamental indicator – Price/Sales Ratio.

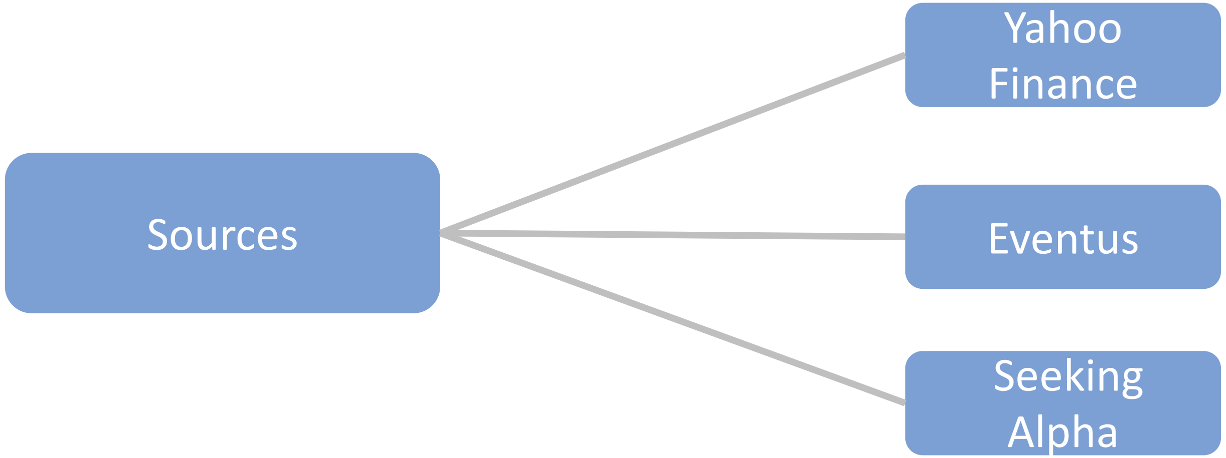
•The tone of earnings call affects stock prices.

•Is it possible to make a portfolio based on sentiment analysis of earnings calls and predict stock price movements



100 Companies from S&P100 list

3,5 years ~ 1200 transcripts



- Adj Close
- Volume
- Price/Sales

- CAR with 5 windows : (0,+1), (0,+5), (0,+30), (-1,+1), (-2,+2).

- Transcripts of Earnings Calls

- The numeric data was Scaled before prediction
- The Text data was cleaned from stop words and char symbols, lemmatized and embedded using TF-IDF approach.
- The Text data was summarized using Extractive summarization approach by BertSum model.

Dataset Overview

Earnings Call & Financial Data

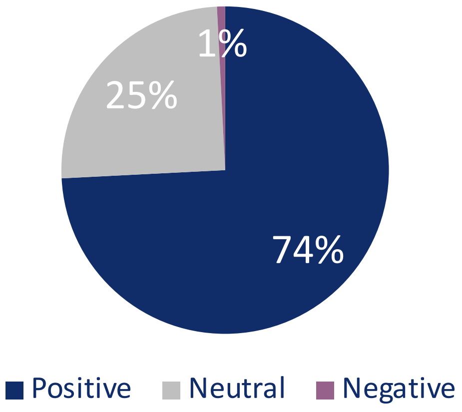
	CC ID	Script ID	Participant	Speech	Tickers	Fiscal Quarter	Date	Sector	Cusip	Adj Close	Adj Close_lag_30	Volume	Price_bool	Price/Sales
11	13	26	[Operator, Tejas Gala, Tim Cook, Luca Maestri]	Good day, everyone. Welcome Apple Incorporated...	AAPL	Q1 2020	2020-01-28	Information Technology	037833100	77.689812	73.449394	162234000.0	0	5.205189
10	12	24	[Operator, Tejas Gala, Tim Cook, Luca Maestri]	Good day everyone. Welcome Apple Incorporated ...	AAPL	Q2 2020	2020-04-30	Information Technology	037833100	72.018120	60.465324	183064000.0	0	4.757222
9	11	22	[Operator, Tejas Gala, Tim Cook, Luca Maestri]	Good day, everyone. Welcome Apple Incorporated...	AAPL	Q3 2020	2020-07-30	Information Technology	037833100	94.570129	86.417282	158130000.0	0	6.781509

Eventus Dataset

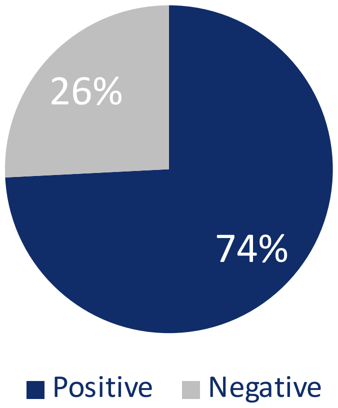
Name	...	SCAR3	CAR_WLS_Weight3	N_ar4	CAR_Window_4	SCAR4	CAR_WLS_Weight4	N_ar5	CAR_Window_5
APPLE INC	...	-1.579770	247.761567	3	0.007342	0.391060	2836.709522	5	-0.005790
APPLE INC	...	-0.656044	248.829138	3	0.005413	0.285165	2775.123916	5	0.005872
APPLE INC	...	-1.005295	235.277717	3	0.016497	0.858405	2707.554675	5	0.007294
APPLE INC	...	0.133853	190.522044	3	0.052240	2.446188	2192.700476	5	0.054539
APPLE INC	...	2.077923	124.628278	3	-0.001879	-0.071004	1428.414443	5	-0.009932

Sentiment Analysis

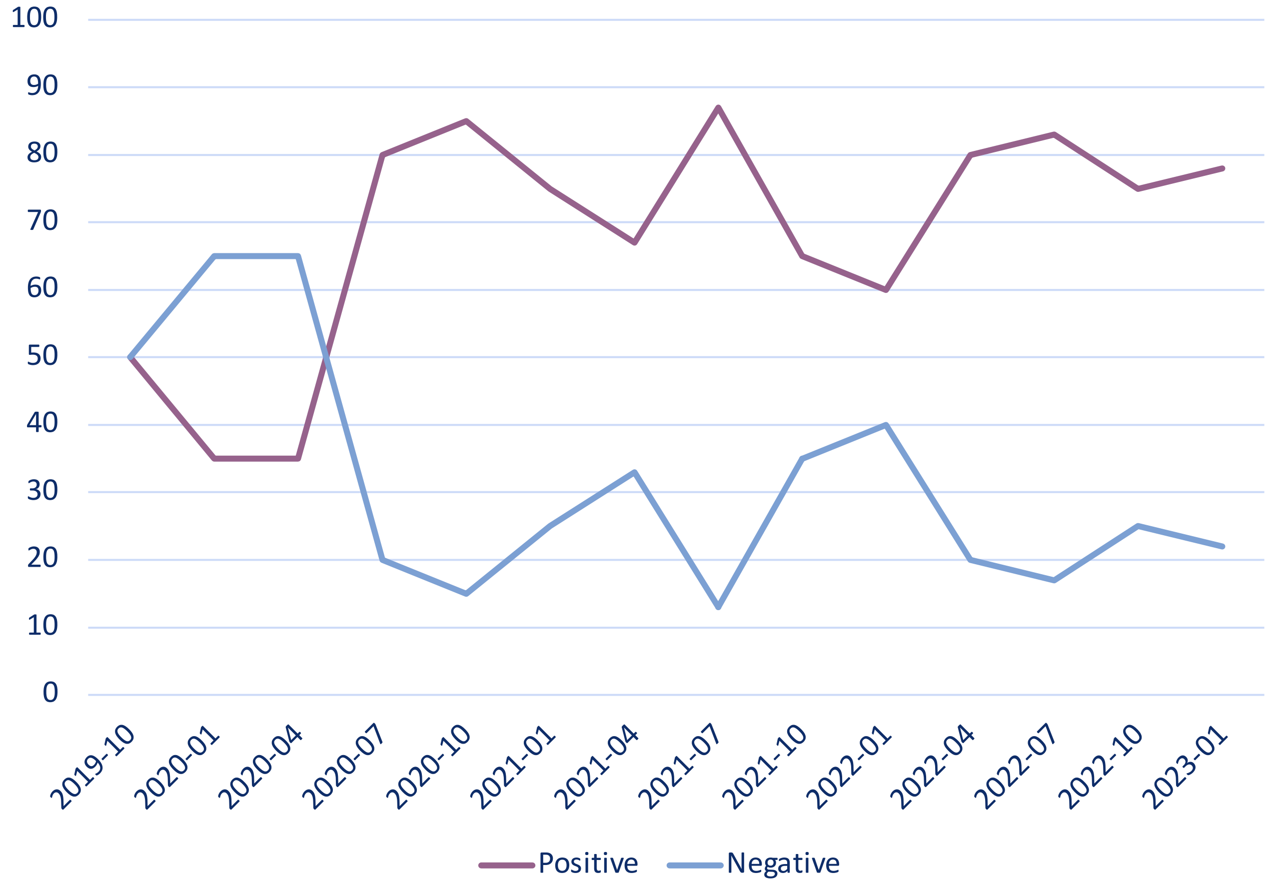
Distribution of Tone Regular



Distribution of Tone Changed



Frequency of Conference's Tone by Years



Fixed-Effect Regression with CAR

$$Y_{it} = \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \gamma_1 D_{1i} + \cdots + \gamma_1 D_{ni} + u_i$$

Point-biserial correlation coefficient of correlation

$$r_{pb} = \frac{M_1 - M_0}{s_n} \sqrt{\frac{n_1 n_0}{n^2}}$$

Eventus metodology

$$CAR_{T_{1i},T_{2i}} = \sum_{t=T_{1i}}^{T_{2i}} A_{it}$$

where: T_{1i} – start date of the period ;

T_{2i} –end date of the period;

A_{it} – abnormal market returns : $A_{it} = R_{it} - R_{mt}$

$$z_t = \frac{TSAR_t}{N^{0.5}(s_{SAR_t})},$$

$$s_{SAR_t} = \frac{1}{N-1} \sum_{i=1}^{N} (SAR_{it} - \frac{1}{N} \sum_{j=1}^{N} SAR_{jt}),$$

where:

SAR_{it} – standardized abnormal return and

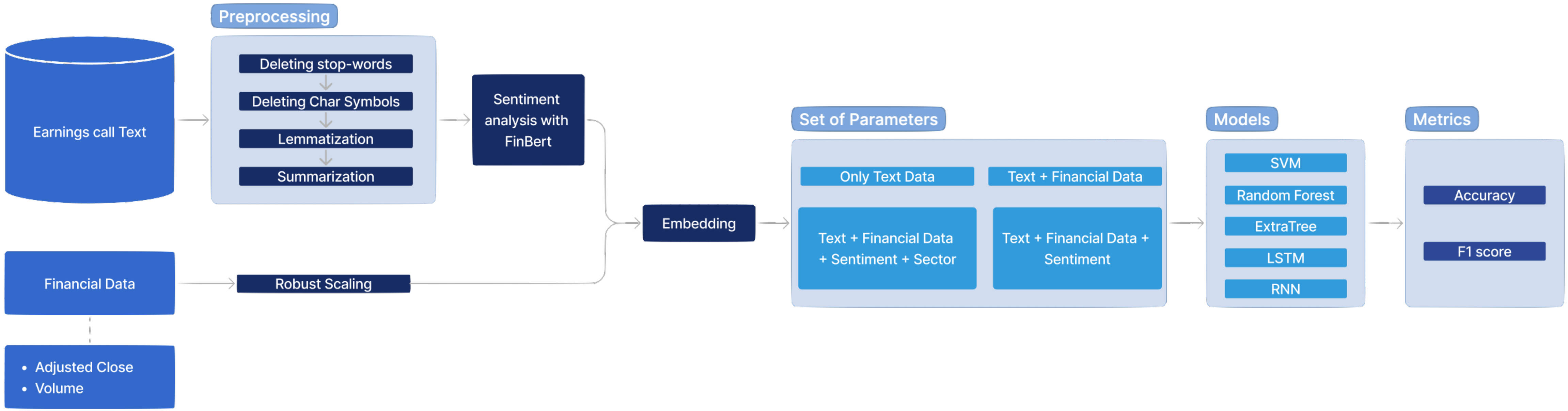
$$TSAR_t = \sum_{i=1}^{N} SAR_{it}$$

Binary Classification model

$$f(x) = \begin{cases} 1, & Stock\ price_{30\ days} > Stock\ price_{day\ of\ conference} \\ 0, & Stock\ price_{30\ days} \leq Stock\ price_{day\ of\ conference} \end{cases}$$

Classification Metrics

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN},\ F1\ score = \frac{TP}{TP+0.5(FP+FN)}$$



Results

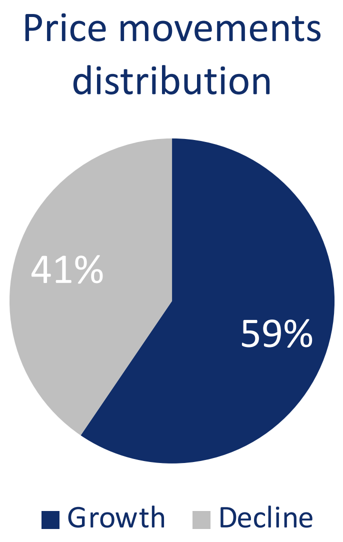
Correlation Analysis

Correlation between Price/Sales ratio and conference tone

- Statistically significant correlation of 0.186 with p-value 0.007 at a 5% significance level
- Confirms the hypothesis regarding the interaction of price and conference tonality

Correlation between Price Increase and conference tone

- No statistically significant relationship found between conference tone and price growth over one month.
- Unable to support the theory that tone has an impact on short-term price growth



Car Regression Analysis output

Market Model Abnormal Returns, Value Weighted Index

Days	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	StdCsect Z	Generalized Sign Z
(0,+1)	224	0.01%	0.01%	127:97>	0.017	2.259*
(0,+5)	224	0.64%	0.58%	127:97>	1.511$	2.259*
(0,+30)	224	0.71%	0.45%	120:104)	0.780	1.323$
(-1,+1)	224	-0.03%	-0.04%	125:99>	-0.105	1.992*
(-2,+2)	224	0.05%	0.04%	118:106	0.114	1.056

The symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a generic one-tail test. The symbols (,< or),> etc. correspond to $,* and show the direction and significance of a generic one-tail generalized sign test.

Eventus (R) Software from Cowan Research, L.C.

```
Call:
   felm(formula = CAR_Window_3 ~ df$tone + df$Volume + df$Adj.Close |      CUSIP

Residuals:
      Min        1Q    Median        3Q       Max
-0.235370 -0.047995  0.001162  0.047713  0.216275

Coefficients:
                  Estimate Cluster s.e. t value Pr(>|t|)
df$toneNegative -1.974e-01    1.576e-02  12.523 1.91e-13 ***
df$tonePositive  1.873e-01    2.474e-03  75.697  < 2e-16 ***
df$Volume        1.598e-11    5.337e-10   0.030  0.97631
df$Adj.Close    -2.178e-04    6.877e-05  -3.167  0.00353 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08702 on 1082 degrees of freedom
  (7 observations deleted due to missingness)
Multiple R-squared(full model): 0.2161   Adjusted R-squared: 0.06969
Multiple R-squared(proj model): 0.04118   Adjusted R-squared: -0.1379
F-statistic(full model, *iid*):1.476 on 34 and 1082 DF, p-value: 0.05543
F-statistic(proj model):  2398 on 4 and 30 DF, p-value: < 2.2e-16
```

Statistically significant windows of cumulative abnormal returns (CAR) related to company conferences dates dates :

- (0,+1), (0,+5), and (-1,+1) windows have 5% significance level.
- (0,+30) window has 10% significance level.

Regression analysis on CAR(0,+30) window:

- Regression analysis shows statistically significant results for the impact of tonality and earnings calls (0,+30) window.
- Confirms the hypothesis regarding the effect of conference tone and stock financial data on abnormal firm returns over the month.

Overall, we find a significant impact of tonality and earnings calls on CAR with different windows.

The Results of model performance with different feature combination.

Model \ Features	Text and Financial Data	Text, Tonality and Financial Data	Text, Tonality, Sector and Financial Data
SVM	Accuracy: 0.37 F1: 0.29	Accuracy: 0.37 F1: 0.20	Accuracy: 0.52 F1: 0.27
Random Forest	Accuracy: 0.51 F1: 0.61	Accuracy: 0.41 F1: 0.52	Accuracy: 0.55 F1: 0.34
Gradient Boosting	Accuracy: **0.60** F1: **0.71**	Accuracy: 0.48 F1: 0.57	Accuracy: 0.55 F1: 0.5
ExtraTree	Accuracy: 0.46 F1: 0.51	Accuracy: 0.44 F1: 0.53	Accuracy: **0.67** F1: **0.41**
LSTM	Accuracy: **0.68** F1: **0.55**	Accuracy: 0.53 F1: 0.33	Accuracy: 0.55 F1: 0.38
RNN	Accuracy: 0.4 F1: 0.51	Accuracy: 0.39 F1: 0.58	Accuracy: 0.5 F1: 0.4

Best model is the **Gradient Boosting** model, the results show that the model has an accuracy of **60%** and an f1 score of **71%** . **LSTM** model had the highest prediction accuracy results and can be better with larger datasets.

The baseline SVM :

- Only text : Accuracy – 0.48; F1 – 0.38
- Only Fin. Data : Accuracy – 0.59; F1 – 0.17

Key outcomes:

- Significantly improved prediction accuracy compared to using financial measures alone and text alone.

- Adding tonality to the prediction reduced the model's quality metrics.

- Incorporating the categorical variable of company sector improved accuracy for most models but decreased the F1 score.

Summary:

The results have a good predictive power. The quality scores of the Gradient Boosting and LSTM models are higher than in the benchmark models from previous research.

Limitations of the research

- Small amount of data were analyzed.
- Focus on companies listed on the S&P100 index, which represents established and large companies.
- Analysis primarily considers the influence of large corporations.

Further research suggestions

Incorporate the findings into the process of building a long-term portfolio, particularly using in portfolio rebalancing.

Explore the impact of earnings conferences by aggregating information from news and social media.

Analyze the influence of Federal Reserve system meetings on stock prices.

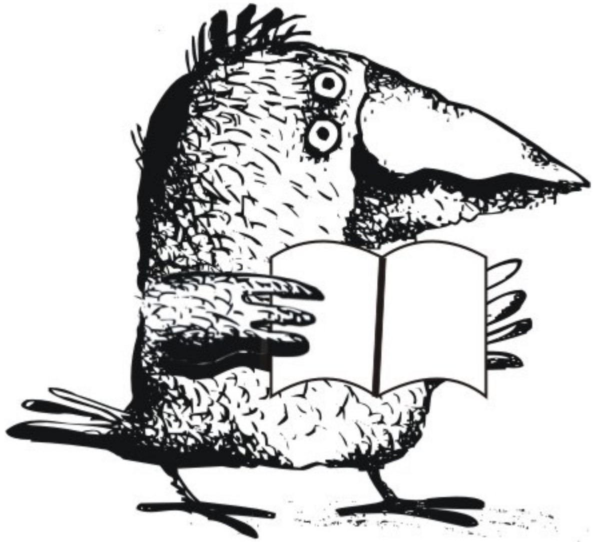
Utilize entity recognition models to assess the impact of specific entities on value growth and incorporate them into classification models.

Work overview

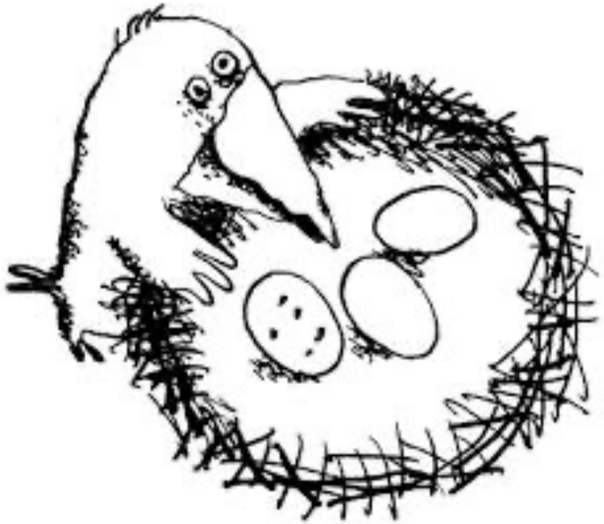
- The necessary data for the analysis were collected and pre-processed.
- A correlation analysis of the tone of the text and Price/Sales ratio was performed.
- Regression analysis of the influence of conferences on abnormal returns was performed.
- A binary classifier predicting stock price movements was constructed.

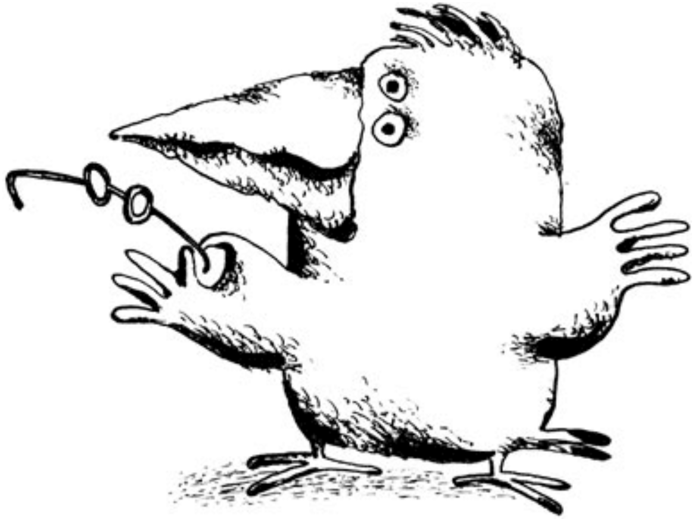
Key results

- Finding a weak correlation between the fundamental indicator and the tone of the transcript.
- Finding a statistically significant relationship between the cumulative abnormal return and the call.
- Construction of a binary classifier with the best values of Accuracy : 0.60, F1 : 0.71, which exceeds the value of Benchmarks.



Thank you for attention!





References

- Araci, D. (2019) Finbert: Financial sentiment analysis with pre-trained language models, arXiv.org. Available at: https://arxiv.org/abs/1908.10063
- Caporale, G.M. and Plastun, A. (2022) Abnormal returns and stock price movements: Some evidence from developed and Emerging Markets - Journal of Investment Strategies, Risk.net. Available at: https://www.risk.net/journal-of-investment-strategies/7943491/abnormal-returns-and-stock-price-movements-some-evidence-from-developed-and-emerging-markets (Accessed: 30 May 2023).
- Chen, J. (2021) Earnings call, Investopedia. Investopedia. Available at: https://www.investopedia.com/terms/e/earnings-call.asp
- Christoph Hanck, M.A. (2020) Introduction to econometrics with R, 10.3 Fixed Effects Regression. https://www.econometrics-with-r.org/10-3-fixed-effects-regression.html
- Cowan, A.R. (2007) Eventus User's Guide, Eventus ® Software for Event Studies and CRSP database usage. Available at: http://www.eventstudy.com/Eventus-Guide-8-Public.pdf (Accessed: 27 May 2023).
- Davis, A.K. et al. (2014) The effect of manager-specific optimism on the tone of earnings conference calls - review of accounting studies, SpringerLink. Springer US. Available at: https://link.springer.com/article/10.1007/s11142-014-9309-4
- Doran, J.S., Peterson, D.R. and Price, S.M.K. (2010) Earnings conference call content and stock price: The case of reits - The Journal of Real Estate Finance and Economics, SpringerLink. Springer US. Available at: https://link.springer.com/article/10.1007/s11146-010-9266-z
- FATALIYEV, K. et al. (2021) Text-based Stock Market Analysis: A review - arxiv.org, arxiv.org. Available at: https://arxiv.org/pdf/2106.12985
- Fink, J. (2020) A review of the post-earnings-announcement drift, Journal of Behavioral and Experimental Finance. Available at: https://www.sciencedirect.com/science/article/pii/S2214635020303750
- Fu, X., Wu, X. and Zhang, Z. (2019) The information role of earnings conference call tone: Evidence from stock price crash risk - journal of business ethics, SpringerLink. Springer Netherlands. Available at: https://link.springer.com/article/10.1007/s10551-019-04326-1#:~:text=We find strong evidence that,up to various robustness checks.
- Fyodorova, E. et al. (2019) The influence of conference calls' semantic characteristics on the ..., Russian Journal of Economics. Available at:https://pdfs.semanticscholar.org/4467/32321b7b99e01ab3902159a330754c93227a.pdf
- Guo, L., Shi, F. and Tu, J. (2017) Textual analysis and machine leaning: Crack unstructured data in finance and accounting, The Journal of Finance and Data Science. Available at: https://www.sciencedirect.com/science/article/pii/S2405918816300496
- Haddi, E., Liu, X. and Shi, Y. (2013) The role of text pre-processing in sentiment analysis, Procedia Computer Science. Elsevier. Available at: https://www.sciencedirect.com/science/article/pii/S1877050913001385
- Korstanje, J. (2021) The F1 score, Medium. Available at: https://towardsdatascience.com/the-f1-score-bec2bbc38aa6
- Ma, Z. et al. (2020) Towards earnings call and stock price movement , arxiv. Available at: https://arxiv.org/pdf/2009.01317.pdf
- Medya, S. et al. (2022) An exploratory study of stock price movements from earnings calls, arxiv.org. Available at: https://arxiv.org/pdf/2203.12460v1
- Peterson, D.R. (2011) Earnings conference calls and stock returns: The incremental informativeness of textual tone, Journal of Banking & Finance. North-Holland. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0378426611002901
- Point-biserial correlation coefficient (2023) Wikipedia. Available at: https://en.wikipedia.org/wiki/Point-biserial_correlation_coefficient
- Qiu, Y., Song, Z. and Chen, Z. (2022) Short-term stock trends prediction based on sentiment analysis and machine learning - soft computing, SpringerLink. Available at: https://link.springer.com/article/10.1007/s00500-021-06602-7
- Shen, X., Wang, G. and Wang, Y. (2021) The influence of research reports on stock returns: The mediating effect of machine-learning-based investor sentiment, Discrete Dynamics in Nature and Society. Available at: https://www.hindawi.com/journals/ddns/2021/5049179/