Impact of Earning Calls on Stock Price

Proposal for TD

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Agenda

- Point of Departure
- Objective, Project Approach and Methodologies
- Data Preprocessing
- Model Implementation and Findings
- Conclusion

Key take aways

Highlight key phrases in an earnings report that have a strong market reaction to non-savy individuals

word	score
exposed generation	0.638304
fēnix	0.517008
selonsertib	0.390604
goodwill impairment	0.389783
active passive	0.339420
decommissioning trust	0.296758
airsolutions	-0.311048
women	-0.362432
device tax	-0.503936
port neal	-0.567010
appliances	-0.743718
clarence	-1.222472

Approach:

- Created a **relation of phrases** and their **associated negative or positive reactions** they have on the market following the earnings report.
- Created a **automated** pipeline to produce which **phrases** would provide **meaningful change** to the stock on **any earnings report**.

Why should TD care?

Major Possible Applications

Employee Training → Enterprise → Help employees **identify** what **language** to focus on during an earnings call

Decision Justification → Traders → Give a **quantifiable** justification for trading **decisions** and **identify** pre-exisiting **bias'**

Consumer Insights → Commercial → Feeding **positive / negative portions** of earning reports to the consumer to **help** stock **purchase decisions**

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Objective

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Develop a machine learning model to predict change in stock prices after a quarterly earnings call

Key Activities

1. **Data Preprocessing**
2. **Sentiment Analysis deriving sentiment scores**
3. **Develop the best machine learning model for predicting return of stock price after calls**

Key Performance Index:

Return on stock price

Scope of Analysis:

464 frims: S&P 500+ TD from 2012 to 2019

Introduction and Summary of Methodologies

Major Methods

Sentiment Analysis:

1. ***TextBlob***
   - Python library based on **Naive Bayes**
   - Determines the **polarity of phrases** ranging from negative to positive
2. **TF-IDF & Custom Dictionary**
   - Converting **text** data **into vectors**
   - Counts the **frequency of words** to determine **sentiment** of word (frequency within and across document)
   - Used training data to create our own dictionary of sentiment scores

Predictive Models:

1. **XGBoost**
   - Decision-tree-based ensemble **Machine Learning** Algorithm
2. **KNN Regression**
   - Calculate the average of the numerical target of the K nearest target

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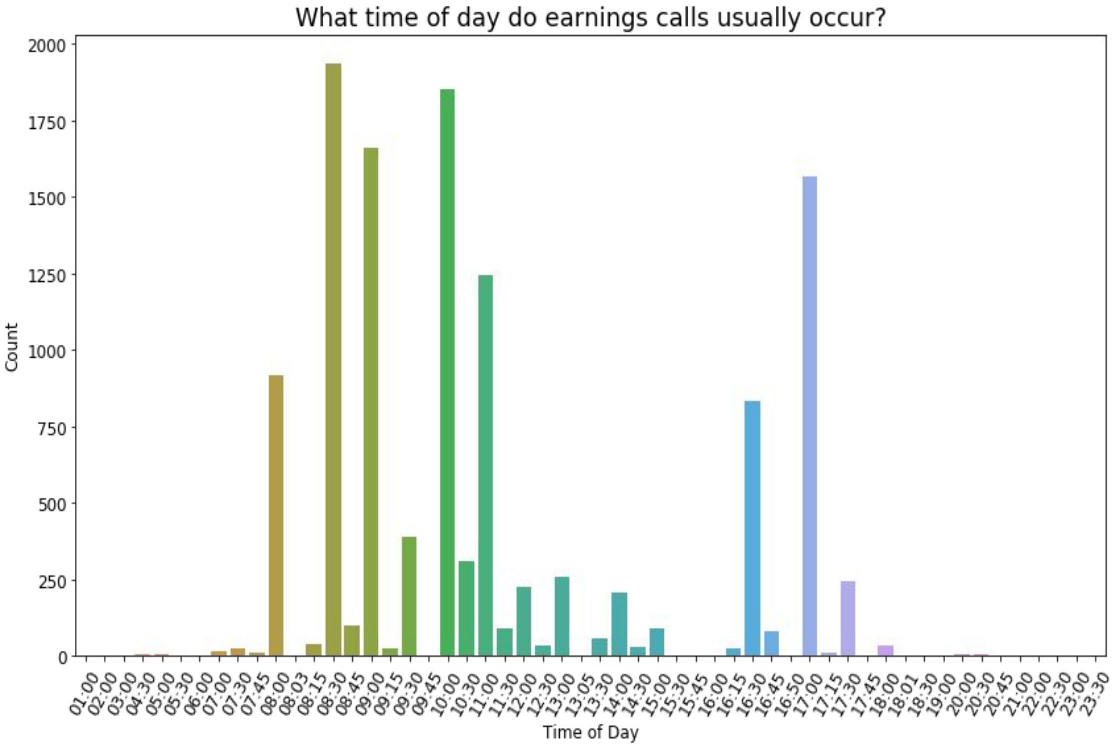
Data Preprocessing



Cutoff Time Determination:

1. Before 4 PM: return = return on current day
   After 4 PM: return = return on next business day

2. More calls happen within regular Trading Hours (9:30 AM – 4:00 PM)

3. Market is very sensitive and react quickly to factors that may affect the stock

Additional Processing:
1. Remove stop words
2. Remove paragraphs with fewer than 20 words

Sentiment Analysis Deriving Sentiment Score

Sentiment score for each word → **Four sentiment level** → **Features**

word	score
exposed generation	0.63830359
ffinix	0.51700819
selonsertib	0.39060405
goodwill impairment	0.38978335
active passive	0.33942026
decommissioning trust	0.29675753
conocophillips	0.28174528
barry	0.27157012
…	…
airsolutions	-0.3110483
women	-0.3624323
device tax	-0.5039356
port neal	-0.5670098
appliances	-0.7437176
clarence	-1.2224719

word	score	Level
exposed generation	0.63830359	4
ffinix	0.51700819	4
selonsertib	0.39060405	4
goodwill impairment	0.38978335	4
active passive	0.33942026	4
decommissioning trust	0.29675753	4
conocophillips	0.28174528	4
barry	0.27157012	4
…	…	…
airsolutions	-0.3110483	1
women	-0.3624323	1
device tax	-0.5039356	1
port neal	-0.5670098	1
appliances	-0.7437176	1
clarence	-1.2224719	1

id	level 1	level 2	level 3	level 4
124	0.3923289	0.13888193	0.1724743	0.29631487
126	0.37374013	0.13211659	0.19068374	0.30345955
127	0.36927536	0.15826087	0.16521739	0.30724638
128	0.37535891	0.13469068	0.17306186	0.31688854
129	0.40026333	0.13846829	0.16875137	0.29251701
224	0.37413518	0.16205428	0.16418308	0.29962746
391	0.3555889	0.16054014	0.17504376	0.30882721
392	0.339254	0.169627	0.17969213	0.31142688
393	0.36102868	0.15751731	0.17284866	0.30860534
394	0.36409102	0.16254064	0.16604151	0.30732683
395	0.36246527	0.1636777	0.16923466	0.30462238

Preparing the Analytical File – ADV

id	level 1	level 2	level 3	level 4	word_count	return
124	0.3923289	0.13888193	0.1724743	0.29631487	10936	0.02362205
126	0.37374013	0.13211659	0.19068374	0.30345955	9656	-0.0236453
127	0.36927536	0.15826087	0.16521739	0.30724638	9215	0.03479702
128	0.37535891	0.13469068	0.17306186	0.31688854	10661	0.03645463
129	0.40026333	0.13846829	0.16875137	0.29251701	11622	0.03922647
224	0.37413518	0.16205428	0.16418308	0.29962746	10225	-0.0278293
391	0.3555889	0.16054014	0.17504376	0.30882721	10054	-0.0130023
392	0.339254	0.169627	0.17969213	0.31142688	8454	0.01890701
...	...	...	...	...	...	...

- Target variable: return (percentage increase/decrease)
- Features: word_count, sentiment score (levels 1 to 4)

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Model Comparision

Data Type	Accuracy Score (MSE)	
	KNN	XGBoost
Validation Dataset	0.000774	0.001384

Why KNN?

- Lower MSE
- Interpretable, no complex hyperparameters tuning

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Further Investigation

- **NLP:**

  1. Increase the sample size to enrich the dictionary

  2. Apply the model to related industries

- **Prediction model:**

  1. Require additional data for inputs into more advanced models such as LSTM

  2. Combine with a time series model may increase the prediction power.

Thank you!