

EN.601.666 INFORMATION RETRIEVAL AND WEB
AGENTS
Project Writeup

**CLASSIFICATION OF 1-DAY RETURN
BASED ON EARNING CALL**

May 17, 2022

URL: https://github.com/g-1f/irwa_project

Yifei Gu

ygu52@jh.edu

1 Overview

This project aims use earnings calls for stocks to classify 1 day return after the earning call. The assumption is that the earning call for each individual stock contributes to the volatility and return of the stock within a short time period. In this project, some features are extracted from the prepared remarks part of earning call transcript as predictors for classifying 1 day return.

2 Instructions

To run the code:

- `python scrape.py`
The script scrapes earning call presentation transcript for the desired listing of stocks, and generate a meta-data data frame that include `stocks`, `earnings_url`, `date`, `path` etc...
- `python meta_data.py`
The script generate additional meta data include `trailing eps`, `trailing pe`, `forward pe`, `market cap` and `target`.

Feature extraction includes:

- `python sentiment_analysis.py` generates sentiment features.
- `python readability_score.py` generates readability features.
- `python svd.py` generates svd matrix.

For building data set and model:

- `python preprocessing.py` pre-process the above features for model.
- `model.ipynb` jupyter-notebook for building classifier.

3 About this project

The scraping script scrapes `prepared remarks` for each earning call from The Motley Fool. Additionally, it scrapes `tickers` and their `sectors` from **Nasdaq-100** and **SP-500** Urls. Namely:

- It provides an accessible and easy way to scrape earning calls. Note that <https://seekingalpha.com/> was previously the go-to option before banning web scrappers.
- It can scrape earning calls based on desired input tickers.

The features extracted consists of follows: sentiment analysis, SVD for document-term matrix, and readability, specifically:

- pre-process earning call transcript with bag-of-words model and filter irrelevant words based on frequency, then find sentiment score:
 - use VADER and TextBlob to find polarity scores and sentiment score for pre-processed transcript.
 - Loughran McDonald-SA-2020 sentiment word list specialize word sentiment in financial reports. Sentiments score includes Litigious, Positive, Negative, Constraining, Uncertainty, StrongModal, WeakModal are calculated with bag-of-words model.

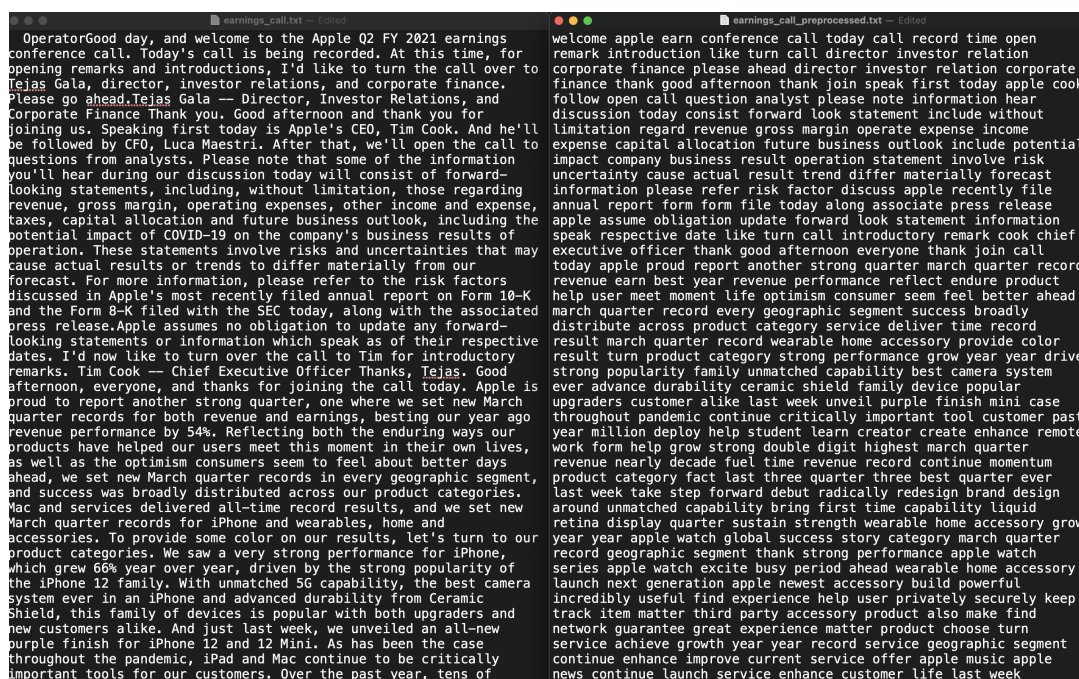


Figure 1: original transcript vs pre-processed

- Dimension reduction with SVD:
 - calculate Tf-idf document term matrix
 - get first 4 dimensions of term representation for all earning call documents.

Path	svd_1	svd_2	svd_3	svd_4
/Users/gyf/Desktop/earning call analysis/CTAS/2022/Q1/	0.02294622101477207	-0.006085854424916311	-0.010238358068644517	0.002366072187086217
/Users/gyf/Desktop/earning call analysis/CTAS/2022/Q2/	0.02639244296472701	-0.007086554000573436	-0.0201888972141872	0.00041388349949480634
/Users/gyf/Desktop/earning call analysis/CTAS/2021/Q4/	0.02226903627485426	-0.013167334330072942	-0.013014858963548712	-0.008472851225689857
/Users/gyf/Desktop/earning call analysis/WELL/2022/Q1/	0.024724563381259505	0.0036650555395668825	0.008087858157894154	-0.017491698898400816
/Users/gyf/Desktop/earning call analysis/WELL/2021/Q1/	0.02252081753848908	0.020919541472658072	0.010943298884167653	-0.01148572156035765
/Users/gyf/Desktop/earning call analysis/WELL/2021/Q2/	0.022914525232205173	0.023081347778520698	0.004621070597237323	-0.013607580161141981
/Users/gyf/Desktop/earning call analysis/WELL/2021/Q4/	0.025712780297647297	0.010495126761064085	-0.005772120660678381	-0.011291433904716508
/Users/gyf/Desktop/earning call analysis/WELL/2021/Q3/	0.023984268955591248	0.011132899240735898	0.005480514097485518	-0.014943784121480006
/Users/gyf/Desktop/earning call analysis/VZ/2021/Q1/	0.028470793637884923	-9.400704056429323e-05	-0.007253442604846614	-0.01330362633826202
/Users/gyf/Desktop/earning call analysis/VZ/2021/Q2/	0.027109857451502135	0.0002017223948817806	-0.012030946938085733	-0.015054920561068727
/Users/gyf/Desktop/earning call analysis/VZ/2021/Q3/	0.025629365201837343	-0.01872816197960082	-0.01288586738144202	-0.014124457073074805
/Users/gyf/Desktop/earning call analysis/AMZN/2022/Q1/	0.024693543577156276	-0.010465286384873302	0.008942525247202572	-0.012104213374343649
/Users/gyf/Desktop/earning call analysis/AMZN/2021/Q1/	0.02185810716281909	-0.01999815973434758	0.005315836958206393	-0.02166827490877166
/Users/gyf/Desktop/earning call analysis/AMZN/2021/Q2/	0.019047389012951287	-0.03282012022386174	-0.0006276875297257448	-0.017787465119081976
/Users/gyf/Desktop/earning call analysis/AMZN/2021/Q4/	0.02149037932892842	-0.01822544664246636	0.0035222676854189225	-0.022652988504201582
/Users/gyf/Desktop/earning call analysis/AMZN/2021/Q3/	0.018560174522906994	-0.037425243933493044	0.017806703954004983	-0.02574700129428252
/Users/gyf/Desktop/earning call analysis/DXC/2022/Q1/	0.029924860868662837	-0.008624185175184087	-0.004984072763775243	-0.02241074796859939
/Users/gyf/Desktop/earning call analysis/DXC/2022/Q2/	0.02889501894828952	-0.011847035900338306	0.0037711696624677105	-0.022609371587081616
/Users/gyf/Desktop/earning call analysis/DXC/2022/Q3/	0.028451076657210302	-0.014629849111143232	-0.004265290098509432	-0.02357316544304251
/Users/gyf/Desktop/earning call analysis/DXC/2021/Q4/	0.028877965907042915	-0.018635602077321272	-0.0031963671951644955	-0.025190926577998863
/Users/gyf/Desktop/earning call analysis/CNP/2021/Q1/	0.02019853291408187	0.019456537905516828	0.05464099074617022	-0.004680968953919976
/Users/gyf/Desktop/earning call analysis/CNP/2021/Q2/	0.021631261706554585	0.010720581155711874	0.04917769150886834	-0.010424344891378097
/Users/gyf/Desktop/earning call analysis/CNP/2021/Q3/	0.021706163870583866	0.020489717469437153	0.04595380844674584	-0.00784180788884129

Figure 2: SVD demo

- Readability score:
 - Various readability metrics were used for feature generation, includes:
 - * Flesch-Kincaid Reading Ease
 - * Dale Chall Readability
 - * Gunning Fog
 - * SPACHE

In short, the project:

- **calculate sentiment** of earning calls with bag-of-words models
- **reduce dimension** of earning calls with tf-idf weighting.
- **calculate readability** of earning calls.
- **predict** whether to **hold, buy, sell** a stock given earning call. (more on evaluation part)

4 Limitations

There are multiple limitations of this project, namely:

- It only uses earning call features as predictors, in the real world, earning call & earnings is only one component of that moves the market. There are thousands of other things that could move the market for example: for the exact same earning call under different interest rates, the return could be significantly different. Thus, a lot of other features could potentially be added.
- The target is the categorized 1 day return. The stock market is highly volatile under different market conditions and thus irrational. The 1 day return suffers from noise significantly, some better metrics like 3-day, 1-week returns could be used as well. (I tried 5 days and the performance was not good).
- I only used bad-of-words model for sentiment analysis. A more comprehensive, n-gram model that tokenize financial term well should be used to improve the accuracy of sentiment scores. This is the same case for SVD.
- During this project, I noticed difficulty of getting some financial data, for example, it is very hard to get estimate eps, actual eps for every stock on the earning date, which is one of the most important features that sadly I could not scrape. So lack of data is also one aspect.

5 Evaluation

The target is the 1-day return of stock categorized as follows:

- 0 Hold: between -3% and +3%,
- 1 Buy: above +3%,
- -1 Sell: fall below -3%,

Multiple models are compared, including LGBM, KNN and decision tree. The model recommended is Light GBM classifier. Light GBM splits the tree leaf-wise with the best fit whereas other boosting algorithms split the tree depth-wise or level-wise rather than leaf-wise. With decision tree as a baseline, the performance is as follows: And feature importance are as follows:

Decision Tree accuracy score: 0.6794871794871795
KNN accuracy score: 0.764102564102564
LightGBM Model accuracy score: 0.7743589743589744

Figure 3: baseline Decision Tree vs KNN vs LGBM

	cols	fea_imp
9	svd_3	498
8	svd_2	485
18	sent_TB	479
10	svd_4	473
16	neu_vader	445
7	svd_1	440
24	Negative	436
13	d_c	432
25	Constraining	432
6	Market_cap	403
22	Uncertainty	397
15	neg_vader	386
19	Litigious	385
20	Positive	363
4	Trailing_pe	361
3	Forward_pe	342
11	f_k	330
17	pos_vader	306
12	g_f	301
5	Trailing_eps	275
14	spache	275
23	StrongModal	210
21	WeakModal	165
2	Quarter	148
0	Sector	142
1	Year	91

Figure 4: Feature importance

6 Conclusion

From the feature importance , one can observe that some dimensions in svd serves important role in the model, and neutral sentiment score from **VADER**, and negative words, constraining words from Loughran McDonald-SA-2020 sentiment word list also affect the classification.

Overall, this project demonstrates that some alternative data could be used as features for all kinds of different areas.