

Assignment 2

CPSC 488: NATURAL LANGUAGE PROCESSING

10/14/2024

DR. CHRISTOPHER RYU

CALIFORNIA STATE UNIVERSITY, FULLERTON (CSUF)

Assignment Information

OPTIONAL: This assignment can be completed individually or by a team with up to 5 members.

Total score: 60

Due date: 12/09/2024 11:59PM

Members: Hammad Sheikh, Matthew Do, Ryan Avancena

Work distribution: Equal

Abstract - Machine learning (ML) and Artificial Intelligence (AI) worlds are experiences tremendous growth. Their applications are uncountable. One realm of applications for ML and AI is Natural Language Processing (NLP). In this aspect, there are various classification models that assist with text classification and processing. Our goal for this assignment is to utilize NLP techniques in analyzing news data for ETF FNGU to build a ML model that would maximize our investment returns. The stock data can be obtained via the Python libraries that Dr. Ryu [1] defined. News articles will be scraped from the web.

Keywords - Stock Trading, ETF, FNGU, Natural Language Processing, Machine Learning

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1 Introduction

There is a lot of stock data available in the world. All the stocks are impacted by the environment and the economical status of the world. This information is shared via news articles, which are in text format. We need to be able to analyze news data, identify patterns and sentiment, and utilize it to predict impact on stocks. However, due to the sheer size of data available and the amount of convolution, it is not an easy task for a human. If we can utilize the computing power and technology available in computers, we may be able to make an impact. This may not have been possible a few decades ago. However, with the expansion of ML and AI technologies, numerous applications become available. With the use of NLP, we can perform text classification and sentiment analysis.

Without generalizing too much, let us look at an ETF, ticker FNGU, with the goal of applying existing text classification and sentiment analysis algorithms on news and stock data, and analyzing their results for performance and accuracy to maximize our investment returns.

2 Approach

The generalized approach is shown below in Figure 1. (Data Acquisition \rightarrow Data Pre-Processing \rightarrow Sentiment Analysis and Model Development \leftrightarrow Model Evaluation.) Further details will be discussed in the following sections.

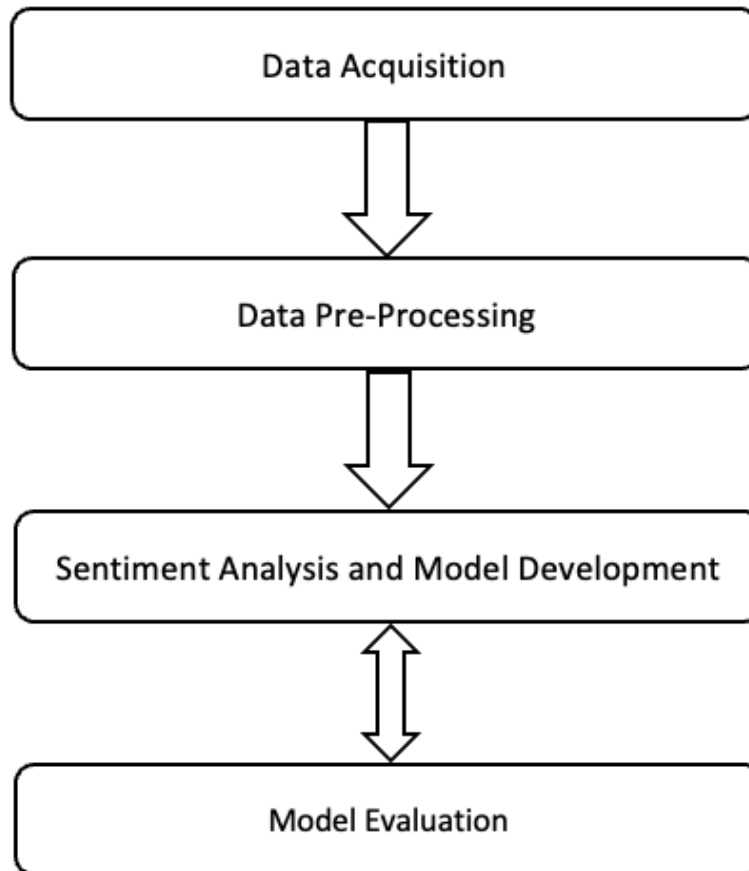


Figure 1: Generalized Approach

We will be relying on existing libraries as much as possible. This will help to focus on the classification and sentiment analysis task instead of building code from scratch for things that already exist. For example, `train_test_split` from `sklearn.model.selection` [2] will be utilized to split the data into training and testing datasets. We also tried different methodologies in order to test and assist each other. There are two main methodologies; one primarily developed by Matthew Do, that will now be referenced as “Method A” [3], and one primarily developed by Ryan Avancena, that will now be referenced as “Method B” [4].

2.1 Data Acquisition

The first step in data processing, regardless of whether it is for our assignment or any other project, is data acquisition. We need to have a dataset that can be used to train need based models.

Our assignment needs two main datasets; one for stock information and one for news articles. For the ETF information, we utilized Python library `yfinance` [5] to download the data and stored it locally in JSON files. For the news articles, we utilized `get_news()` function of the `yfinance` library [5] to grab the URLs and then grabbed the articles text and information via HTML parser, modified from Dr. Ryu’s [1] code. All the information grabbed is stored in appropriate JSON files to be utilized in model development. This enables us to have a defined set of data, which we can preprocess and utilize in our model development of sentiment analysis and investment returns.

Figure 2 shows a sample snapshot of FNGU market data acquired from `yfinance` [5], and Figure 3 shows a sample snapshot of news data scraped from the web via our HTML scraper.

Bulk data tickers info: Price		AAPL	AMZN	Adj Close	AVGO	CRWD	GOOG	META	MSFT	NFLX	...	AVGO	CRWD	...	Volume	META	MSFT	NFLX	NOW	NVDA
Ticker	Date														GOOG					
2013-01-02	00:00:00+00:00	16.705698	12.865500	2.395675		Nan	17.969599	27.915949	22.451811	13.144286	...	36716000		Nan	102033017	69846400	52899300	19431300	1525500	478836000
2013-01-03	00:00:00+00:00	16.494843	12.924000	2.408191		Nan	17.980036	27.686640	22.151047	13.798571	...	23295000		Nan	93075567	63140600	48294400	27912500	863100	298880000
2013-01-04	00:00:00+00:00	16.035383	12.957500	2.392730		Nan	18.335327	28.673666	21.736479	13.711429	...	27113000		Nan	110954331	72715400	52521100	17761100	1034400	524968000
2013-01-07	00:00:00+00:00	15.941059	13.423000	2.379478		Nan	18.255327	29.331686	21.695829	14.171429	...	16022000		Nan	66476239	63781800	37110400	45550400	2517000	618732000
2013-01-08	00:00:00+00:00	15.983952	13.319000	2.363281		Nan	18.219299	28.972767	21.582024	13.880000	...	20969000		Nan	67295297	45871300	44703100	24714900	2826800	466424000
...
2024-10-28	00:00:00+00:00	233.399994	188.389999	172.020004	301.320007	168.339996	578.159973	426.589996	749.119995
2024-10-29	00:00:00+00:00	233.669998	190.830002	179.240005	310.940002	171.139999	593.280029	431.950012	759.440002
2024-10-30	00:00:00+00:00	230.100006	192.729994	176.639999	307.450012	176.139999	591.799988	432.529999	753.739990
2024-10-31	00:00:00+00:00	225.910004	186.399994	169.770004	296.869995	172.690002	567.580017	406.350006	756.030029
2024-11-01	00:00:00+00:00	222.910004	197.929993	168.919998	303.130005	172.649994	567.159973	410.369995	756.099976

Figure 2: Sample snapshot of FNGU market data

<pre> { "0": { "ticker": "META", "date_published": "2024-11-02", "title": "Opinion: The 3 Best Tech Stocks to Own Ahead of 2025", "summary": "Don't sleep on these 3 stocks heading into 2025.", "link": "https://finance.yahoo.com/news/meta-platforms-third-quarter-2024-133838526.html?tsrc=rss", "first_p": "Revenue: US\$40.6b (up 19% from 3Q 2023).", "last_p": "Revenue of the American Interactive Media and Services industry.", "whole_article": "Meta Platforms (NASDAQ:META) Third Quarter 2024 Results\nKey Financial Results\nReve in line with analyst estimates. Earnings per share (EPS) surpassed analyst estimates by 14%\nLooking warning sign for Meta Platforms that you need to be mindful of.\nHave feedback on this article? Conce any stock, and does not take account of your objectives, or your financial situation. We aim to bring } }, { "1": { "ticker": "META", "date_published": "2024-11-02", "title": "Opinion: The 3 Best Tech Stocks to Own Ahead of 2025", "summary": "Don't sleep on these 3 stocks heading into 2025.", "link": "https://finance.yahoo.com/news/tech-earnings-fail-fire-traders-113001142.html?tsrc=rss", "first_p": "(Bloomberg) — Investors had hoped earnings from five of the world'su2019s biggest companie Hike, Breaking Campaign Vow\nInstead, in many cases they were left wanting.\nWhile Microsoft Corp., Ap Alphabet and Amazon ending the week in the green. The S&P 500 fell 1.4%, weighed down by the big-tech September, which would beat the estimate of 18% at the start of earnings season, according to data co intelligence dominated Magnificent Seven earnings this season. Amazon, Microsoft, Alphabet and Meta pu related demand is picking up steam, the message from management teams was that investors will need to significant costs. Microsoft\u2019s commercial cloud margin will narrow in the current quarter as capi told, technology, media and telecom stocks collectively saw the largest net selling in five weeks, acc course. Amazon, which has been dogged by concerns about pressure on margins from big spending, soothe to see,\u201du201d he said in an interview. \u201cThe AI winners will continue to perform.\u201d\nHowever, cheaper S&P 500 sectors that have outperformed big-tech stocks since July.\n\u201cThe story is still t Inflation Even Worse\nHow to End the Backlog of Asylum Cases? Take Them Out of the Courts\nHow Elon Mu } } </pre>	
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Figure 3: Sample snapshot of scraped News data

2.2 Data Pre-Processing

2.2.1 Method A [3]

In this method, we started with utilizing word2vec [6] for embedding the articles' text. However, this did not work for us. That is, the model trained really poorly. We believe the reason to be that we are giving every word (or word \rightarrow vec, which is deterministic) the same value across an article, which would freak out the training and converge everything to 0. This is not helpful.

We changed our direction after experimenting with word2vec [6]. We passed the scraped articles as input, while padding and truncating them at 580 characters. We pass this input set through bert-large-uncased tokenizer [7]. This allowed us to process the data and utilize it with existing functionalities of Bert [7] to develop a sentiment analyst model via bert-large-uncase [7]. More on this will be discussed in Section 2.3.

2.2.2 Method B [4]

2.3 Sentiment Analysis and Model Development

2.3.1 Method A [3]

In Section 2.2 we had tokenized our news articles (input data) via bert-large-uncased tokenizer [7].

2.3.2 Method B [4]

2.4 Model Evaluation

2.4.1 Method A [3]

2.4.2 Method B [4]

3 Conclusion and Future Work

For this assignment, it took us quite a bit of time to gather data. Additionally, it took us time to understand what technology and tools to utilize to process the data and develop a model that could provide us sentiment analysis. Though we were able to develop a model, it is not deployment ready. Our future work is to utilize the data, that we spent a lot of time to gather, and the existing development to better analyze news data in real-time. This work could then be further enhanced with the trends data and models that stock market analysts use in real-time to forecast market trends. Having such a model would provide tremendous value in better understanding and staying up-to-date with market trends.

4 Acknowledgements

I would like to acknowledge Dr. Jin [8] for ML, classification and probability distribution concepts, Professor Avery [9] for MLP concepts,

References

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