Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

Stock market is one of the most competitive financial markets. Traders need to compute the financial workloads with low latency and high throughput. In the past, people were using the traditional store and process method to calculate the heavy financial workloads efficiently. However to achieve low latency and high throughput, data-centers were forced to be physically located close to the data sources, instead of other more economically beneficial locations. This is the main reason, the data-streaming model was developed and it can process large amount of data more efficiently. It was shown in studies that using data streaming we can solve the options pricing and risk assessment problems using traditional methods, for example Japanese candlesticks, Monte-Carlo models, Binomial models, with low latency and high throughput. However instead of using those traditional methods, we approached the problems using machine learning techniques. We tried to revolutionize the way people address data processing problems in stock market by predicting the behaviour of the stocks. In fact, if we can predict how the stock will behave in the short-term future we can queue up our transactions earlier and be faster than everyone else. In theory, this allows us to maximize our profit without having the need to be physically located close to the data sources.

We examined two models.

Model 1 - We used a complete random model using a random number genertor. If the generated number is greater than `.7` (inclusive), we buy a stock and if it is less than `.3` (inclusive) we sell. We do nothing if the generated number is between `.3` (exclusive) and `.7` (exclusive). We close our position just before the exchange closes for the day.

Model 2 - In this model, we use multiple machine learning algorithms to get the final decision. For example, we will use classification techniques to classify stocks into different buckets (For us, it is three). Then we train three neural networks for these three buckets and take position in the market based on which cluster takes the dominance and what the cluster represents. Each of those models are applied on real stock market data and checked whether it could return profit.

Problem Statement

For the concept of this thesis we tried to predict the price of the stock in the short term future and decide whether it is better to buy, sell our stocks or do nothing(no trading). There is no strict definition of short term future. It can be any interval from nanoseconds until a few days. We decided that we will use 1-day interval as our prediction time. As the stock price depends on the time, time interval is a parameter that had to be decided. We think that 1-day can be a good representation of short term future. Also using a constant time interval simplifies the problem significantly. The main objective is to maximize the profit by trying to increase the capital. We tried to come up with an optimal trading strategy to maximize the potential profit. The main idea is to model a stock trading into 1-day intervals and using historical information of the stock, we tried to predict if we should avoid trading or take a position which would either end above or below our entry price in the stock. We tried to train and test our model on historical stock data collected during the period of November 2010 to June 2019.

Metrics

Our metrics is completely based on number of successful trades. While building the model, we considered a threshold of 40% change as minimum difference for opening a position. For example, model is going to predict BUY if it thinks that the change is going to be 40% higher than the opening price. Similarly, it will predict SELL if the prediction is 40% lower than the opening price. Anything in between will be considered no trading day. Finally, based on how many of the above trades are closed successfully, our model will be evaluated for accuracy. More details on model evalution is here

Economist believe that stock market follows Random Walk theory. The theory suggests that changes in stock prices have the same distribution and are independent of each other. Therefore, it assumes the past movement or trend of a stock price or market cannot be used to predict its future movement. In short, random walk theory proclaims that stocks take a random and unpredictable path that makes all methods of predicting stock prices futile in the long run. Considering that theory, we believe that a random number generator would be best fit for bench mark evaluation. A benchmark model is described here. If our model performs better than random walk based on accuracy as defined above, we would consider our approach as a successful one.

II. Analysis

Data Exploration

There are two types of data we have to download from external sources, the list of stocks we want to analyze and prices for each stock in the given time period. DataHub provides API to download list of tickers.

Symbol	Description
A	Agilent Technologies, Inc. Common Stock
AA	Alcoa Inc. Common Stock
AA$B	Alcoa Inc. Depository Shares Representing 1/10th Preferred Convertilble Class B Series 1
AAC	AAC Holdings, Inc. Common Stock
AAN	Aaron's, Inc. Common Stock
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ZPIN	Zhaopin Limited American Depositary Shares, each reprenting two Ordinary Shares
ZQK	Quiksilver, Inc. Common Stock
ZTR	Zweig Total Return Fund, Inc. (The) Common Stock
ZTS	Zoetis Inc. Class A Common Stock
ZX	China Zenix Auto International Limited American Depositary Shares, each representing four ordinary shares.

Shape: (3298, 2)

As we see, there are 3298 tickers. Let's download last traded volume for all the tickers. It is possible that either yahoo do not have data for all of them or we might be throttled for downloading large amount of data in this short period of time. However for the purpose of this paper, we could just focus on whatever data we could download.

Symbol	Description	Last Volume
A	Agilent Technologies, Inc. Common Stock	1712146.0

Symbol	Description	Last Volume
AA	Alcoa Inc. Common Stock	4695503.0
AAP	Advance Auto Parts Inc Advance Auto Parts Inc W/I	1065904.0
AAT	American Assets Trust, Inc. Common Stock	275667.0
ABB	ABB Ltd Common Stock	1777283.0
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WGO	Winnebago Industries, Inc. Common Stock	635929.0
WHG	Westwood Holdings Group Inc Common Stock	35491.0
WHR	Whirlpool Corporation Common Stock	912040.0
WIA	Western Asset/Claymore Inflation	42550.0
WIT	Wipro Limited Common Stock	989588.0

Shape: (1511, 3)

Looks like we were able to download data for 1511 tickers. Let's filter our tickers which has less than 1,000,000 volume. We want to trade stocks which have good liquidity.

Symbol	Description	Last Volume
A	Agilent Technologies, Inc. Common Stock	1712146.0
AA	Alcoa Inc. Common Stock	4695503.0
AAP	Advance Auto Parts Inc Advance Auto Parts Inc W/I	1065904.0
ABB	ABB Ltd Common Stock	1777283.0
ABBV	AbbVie Inc. Common Stock	8004485.0
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W	Wayfair Inc. Class A Common Stock	2126930.0
WAB	Westinghouse Air Brake Technologies Corporation Common Stock	1239700.0
WDAY	Workday, Inc. Common Stock	1872762.0
WEC	Wisconsin Energy Corporation Common Stock	1465017.0
WES	Western Gas Partners, LP Limited Partner Interests	1672866.0

Shape: (455, 3)

This leaves us with 455 tickers to deal with. Yahoo finance provides free stock price data. We are going to use pandas_datareader package to download Yahoo finance data for all these tickers. The dataset will provide us Open, High, Low, Close, Adj. Close and Volume data.

We used following script to find out if there are any missing information in our dataset.

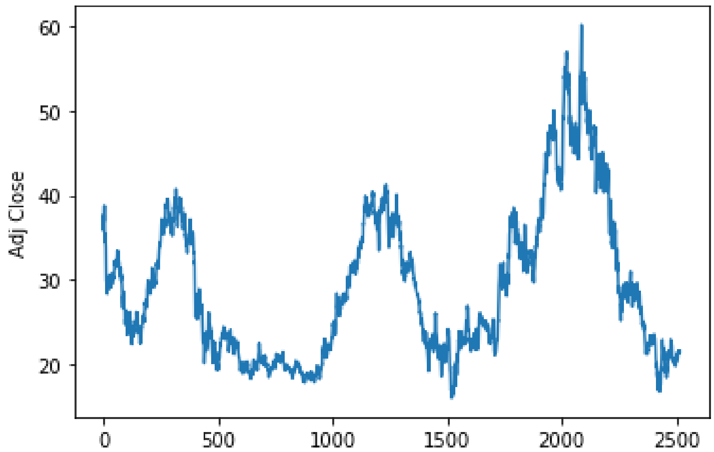
```
for ticker in tickers:
df = pd.read_csv('./data/' + ticker + ".csv")
if (df[df.isna()].dropna().shape[0] > 0):
    print('Ticker ', ticker, ' has NA data')
```

`./data` folder have all the ticker information. The stock information for each ticker is stored in .csv file.

The above script returned no output, indicating there are no dataset with missing information.

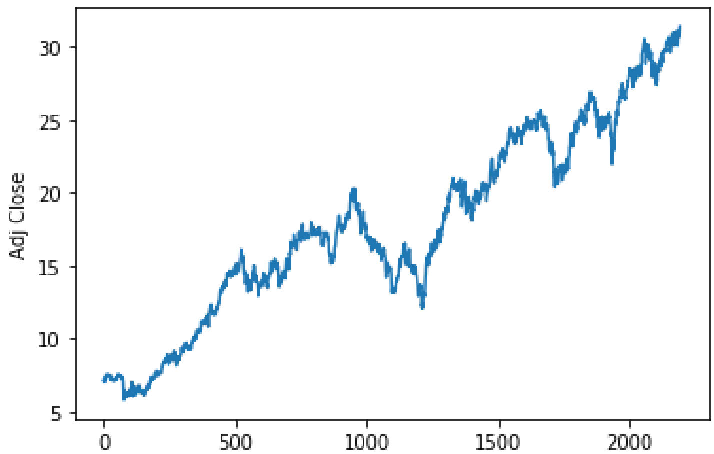
Exploratory Visualization

Let's look into some of the data downloaded to get an idea if there are any specific pattern that our model could learn. Let's start with ticker AA. Following is the price chart.



You could see there are areas where the ticker is trading sideways. Sideways behaviors are hard to learn using simple Neural Networks and so, there is higher probability that our strategy might not work well in this ticker.

Let's now look into data that we could learn easily. STAG is one of the ticker with such data.



Majority of the data is either trending high or trending low. When we use stratified sample for training, it is possible to get higher accuracy in model prediction.

Algorithms and Techniques

After normaizing our data and splitting them into 33% test and rest for training, we reach our end result in two steps.

Step 1 - We removed the label column from train data and used all the normalized features and passed through KMeans classification with k=3, indicating BUY, SELL and NONE. In order to select which cluster is going to represent BUY, SELL or NONE, we first cluster the data and then calculate total count of BUY, SELL and NONE in each clusters. The final cluster table might look like this

	BUY	SELL	NONE
cluster0_pred	104	96	376
cluster1_pred	146	121	210
cluster2_pred	154	101	354

From the above table, we see that cluster2 represents highest number for BUY, then cluster1 for SELL and cluster0 for NONE. It is possible that same cluster might be highest for more than one trade direction. In those cases, we will just discard those tickers.

Step 2 - Once data has been categoried, we are going to run three neural networks for the three clusters. We are going to use following features -

```
- open
- high
- low
- close
- adj. close
- volumne
- Triangular Moving Average
- SAR
- MACD
- RSI
- STOCH
- AD
- ATR
- N  - x (change of price between current and the day selected by x)
```

During prediction, data will be passed to all the three networks. Based on which NN prediction has the highest value, we would take the trade in that direction. In the above example, if cluster2's NN has the highest output, we would take BUY position.

Once the models are built, we will test the model with the train data again to calculate the accuracy. Tickers with accuracy more than 70% will be considered for final evaluation.

Benchmark

Trading is a probability game. Our first model is using a random number generator to generate a number between `0` and `1` and taking position based on the value. The goal is to prove that a systemic approach (in this case using machine learning models) yields higher returns as compared to taking position randomly.

If the value of random number generator is less `.3` (inclusive), we will short the stock and close the position before market closes for the day. Similarly, if the generated number is greater than `.7` (inclusive), we will buy the the stock. Any value between `.3` and `.7` will be excluded and no position in market would be taken. The success of this approach is going to be based on how many trades were closed with profit. This data is going to be our benchmark to compare with our model.

III. Methodology

Data Preprocessing

Our data in data frame is listed as ascending order based on date. The features mentioned above are going to be generated using ta-lib. Different types of technical indicators are used. One of each technical indicator category from Volume, Moving Average, Osscilator, etc are used so that we get a diversified representation of our price data.

We also calculated changes upto past 10 days from current price.

`Label` is calculated as

```
Label = Current price - previous day price
      = N - 1
```

`direction` is calculated as (Using normalized Label data)

```
direction = Label >= .4, then BUY
          = Label <= -.4, then SELL
          = NONE
```

Implementation

As mentioned above, there are 455 tickers that we have to process. It is not practical to process each of them individually. So we first developed script to process one ticker and then wrapped it inside a for loop to process all the tickers. It took 2 days to complete processing all the tickers.

- Download ticker list
- Get last traded volume for each ticker
- Filter our tickers with less than 1,000,000 volume
- Download open, high, low, close, Adj Close, volume data for the filtered list
- Calculate N-1,N-2,N-2,N-4,N-5,N-6,N-7,N-8,N-9,N-10 changes for price, where N is the current day. So N-1 would be change for current price from previous day
- Calculate Label = N-1
- Calculate TRIMA, SAR, MACD, RSI, STOCH, AD, ATR indicators
- Save the information in .pkl file
- At this stage, we should have 455 pkl file with the data we need for our clustering and neural network modeling

We created few utility methods to help us with processing. The process method in `./helpers/utils.py` takes a ticker name and does following

- Read pkl file
- Create Label column as described above
- Use MinMaxScaler to normalize data
- Split the data into train and test, with test size as 33%

- Open a training job in AWS for KMeans
- Deploy the model in AWS
- Label the train and test data using the new cluster information
- Delete the KMeans predictor
- Filter train data into 3 dataset based on 3 clusters
- Open 3 training jobs in AWS for PyTorch NN model
- Deploy the models in AWS
- Predict the train and test data using the 3 new NN
- Categorize cluster0, cluster1, cluster2 as BUY, SELL and NONE appropriately
- Generate a random prediction for train and test data
- Calculate accuracy
- Save the accuracy in accuracy.csv file

The above method is looped through all the 455 tickers we filtered before. The accuracy.csv contains details of all the accuracies for different tickers.

Refinement

Since we were processing and building models for large number of tickers, a generalized epoch value for neural networks for all tickers would be ideal. We started with 100 first and kept changing the value until we saw little to no change in BCELoss. The final value that we selected was 200.

We followed similar process for selecting a value for hidden nodes for neural network.

IV. Results

Model Evaluation and Validation

It is necessary to understand that the models we selected depend on finding a pattern. If there are no patterns to learn from, the models are not going to perform well. Keeping this in mind, we decided to filter out tickers where our model perfored could not perform well in training data.

```
accuracy_df = pd.read_csv("./data/accuracy.csv").drop(
  columns=["benchmark_test_accuracy", "benchmark_train_accuracy"])
accuracy_df = accuracy_df[accuracy_df['train_accuracy'] > .7]
print(accuracy_df.head())
print("Shape:", accuracy_df.shape)
```

ticker	test_accuracy	train_accuracy
ABEV	0.8151515151515152	0.7828746177370031
AEG	0.9945945945945946	0.9974811083123426
AMC	0.7333333333333333	0.7443181818181818
ALSN	0.6890595009596929	0.7204502814258912
AMX	0.8870588235294118	0.87115165336374
------	------------------	------------------
GLW	0.8709677419354839	0.912280701754386

ticker	test_accuracy	train_accuracy
PBI	0.9121951219512195	0.904040404040404
RES	0.7526881720430108	0.7062146892655368
SHO	0.981012658227848	0.949404761904762
STAG	0.7460317460317459	0.7651888341543513

Shape: (64, 3)

As the above code shows, we filtered out all tickers where model's success rate is less than 70%. Out of 455 tickers, we now have 64 tickers where our model performed really well on training data. If we look closely, test accuracy is also near by train accuracy for these 64 tickers. Accuracy of 70% means, 7 out of 10 trades would be winning trade as per our prediction and each day prediction would reseult in minimum of 40% return from opening price. If we are able to enter the market at opening of session and close the trade by end of day, we would hypothetically have 40% return per day. As of Feb 2020, most of the major stock brokers do not charge commission. Considering that fact, this approach seems to be a promising strategy for building portfolio.

Trading 64 tickers per day might not be a feasible strategy for most of the retail traders. It might be good idea for them to filter the data donw with threshold of 90%, meaning tickers where the model has 90% success rate.

ticker	test_accuracy	train_accuracy
AEG	0.9945945945945946	0.9974811083123426
BRX	0.8921933085501859	0.9012567324955116
VVR	1.0	1.0
BSX	0.9607843137254902	0.9730941704035876
DRH	0.9792207792207792	0.9816625916870416
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GCI	0.9170854271356784	0.9154664996869128
GE	0.9186046511627908	0.9017160686427456
GLW	0.8709677419354839	0.912280701754386
PBI	0.9121951219512195	0.904040404040404
SHO	0.981012658227848	0.949404761904762

Shape: (21, 3)

This filter brings the ticker list to 21.

Justification

As mentioned in the beginning of this report, economist believe stock market is a random walk. Let's have a quick look into our accuracy table which has accuracy from both our model and ramdom strategy.

ticker	test_accuracy	benchmark_test_accuracy	train_accuracy	benchmark_train_accuracy
ABEV	0.8151515151515152	0.4272727272727273	0.7828746177370031	0.4189602446483181

ticker	test_accuracy	benchmark_test_accuracy	train_accuracy	benchmark_train_accuracy
AEG	0.9945945945945946	0.4594594594594595	0.9974811083123426	0.4508816120906801
AMC	0.7333333333333333	0.3586206896551724	0.7443181818181818	0.3522727272727273
ALSN	0.6890595009596929	0.3570057581573896	0.7204502814258912	0.3696060037523452
AMX	0.8870588235294118	0.3694117647058823	0.87115165336374	0.3899657924743444
------	------------------	-----------------------	------------------	------------------------
GLW	0.8709677419354839	0.41935483870967744	0.912280701754386	0.456140350877193
PBI	0.9121951219512195	0.37560975609756103	0.904040404040404	0.3939393939393939
RES	0.7526881720430108	0.3870967741935484	0.7062146892655368	0.3220338983050847
SHO	0.981012658227848	0.3987341772151899	0.949404761904762	0.3928571428571429
STAG	0.7460317460317459	0.3968253968253968	0.7651888341543513	0.36617405582922813

Shape: (64, 5)

Let's analyze ABEV. We start with train infomration. Our model accuracy is 78% whereas benchmark is 41%. Similary, benchmark is around 42% in test data, whereas out model accuracy is 81%. If we continue analyzing other tickers, it clearly shows that our model performed extremly well as compared to taking position completely randomly.

V. Conclusion

Free-Form Visualization

We were able to build a trading strategy based on historical data and have been able to train machine learning models to trade the market. Not only that, we were able to combine multiple machine learning model to learn patterns in historical data. The reason we used historical data and not real time data for testing was time efficiency but also the ability to compare models and trading strategies using the same testing data.

We treated our historical data as real time data. We can use the same methods and be able to predict the stock price in real time. One of the goals of this thesis was that we should be able to utilize the stock market on real time and all the simulations were done in way that would make it easy to transition from historical to real time data.

As an investment it can be characterized as really profitable. However the neural network cannot predict sudden changes in the price that happen during the time that the stock market is closed. An example is when a company or their direct competitors announce their term results. Those kinds of events can skyrocket the stock price or make it lose considerable value.

Reflection

The area we struggled at the beginning was to find out a reasonable value of hyperparameters to start with. Spinning AWS instance for every test we were trying, was time consuming because bootstraping AWS instances take time.

Once we knew what we would like use in our models, the next challenge was to figure out how we could expedite the process of building models for all the tickers. It is also necessary to ensure that when modeling is complete, we faithfully clean out all AWS resources to avoid recurring charges. On the bright side, having GPU for training these models was the benefit we got from AWS. It took almost 2 days to generate all the models.

Improvement

We used one set of model for each ticker. Thereby, we created almost 455 set of models, each set consisting of 4 models. Although at the end, we filtered everything down to 64 tickers, we could look into each discarded models and fine tune parameters to come up with better results.

It is also possible that we might be able to combine all these models and create one generalized model which works on all the tickers. This will reduce deployment cost when this strategy is used in real time trading. Combining all the models might make this approach more realistic approximation system.

Our Neural Network layers are Linear Layers. We could try LSTM which has been proven theoritically to produce better results in time series analysis. We could also try XGBoost where learning is faster than traditional neural network models. The point being, we could try different machine learning models and see which one performs better than others.

Lastly, the strategy that we followed in this paper could further be fine tuned using sentiment analysis. Stock markets react to news and adding that factor in trading model could produce even better results.

References

1 Stock Market prediction using Artificial Neural Networks, Rafael Konstantinou

2 Predicting Stocks with Machine Learning, Magnus Olden

3 Random Walk Theory

4 Yahoo Finance

5 DataHub