Daily Frequency Stock Trading Strategy

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1 Introduction

In this report, we show that, with appropriate choice of features, CNN models could help with discovering and implementing the trading strategy for a single name stock. There will be five sections in this report including Stock Selection, Feature Selection, CNN Model Accuracy, Trading Signal accuracy in terms of portfolio performance and Future Works.

2 Stock Selection

The stock selection and feature selection are complementary to each other. The optimal way to approach this is to find a stock with stable growth and not much impacted by the events. Since based on the public information, there does not exist a high frequency indicator for the prediction of events such as Merger and Acquisition or Regulatory risk. For instance, the fintech companies in China like Ant Financial and 360 DigiTech Inc(QFIN) are facing high regulatory risk nowadays since this is a new sector in China that are booming and regulation is tending to deleverage their ABS and consumer loan business by providing more equity in case they are too big to fail.
Fundamentally, the stock market should be the market consensus of the future revenue cash flow discount back. In this report, we choose Apple as the target firm for the following reasons:

- Business that has been performing well in a good sector and have competitive advantages
- Least driven by turnaround stories
- Obvious high incremental value added to the society
- Risk control from underlying business
- Potential large growth supported by the industry development trend

3 Feature Selection

The goal of this project is to build a firm-wide model for daily stock return prediction. For a chosen stock, we need to identify the informative variables and build the corresponding model for forecasting. Hence, what factors we utilize to train the model is critical for the effectiveness and accuracy of the prediction.

We'll use CNN for the modelling section, which itself is equipped with feature selection capability. Thus, we'll try to collect as many informative variables as we could. The first group of features we collected are the ones that have the same underlying company but in different instruments from equity. To collect indicators from CDS market, Derivative market. We choose the following factors:

- Option Market — 30-day Implied Volatility for in the money options
- CDS Market — 1-year default probability and 1-yr distance to default
- Stock Market — Historical return, RSI, high-low, volume, etc
- Financial Report — P/S and P/EBITDA
- Google Trend — Popularity of "Apple" online
- Global Market — Foreign exchange rate and ETF index in major sales countries for Apple

For the indicators from CDS and Option market, We choose 30-day in the money implied volatility for Option market is dynamic and there is no one parameter that could describe all. Option in natural is a forward-looking market and contains the market sentiments. Implied Volatility shows market expectation and we focus on in-the-money options for they are the most active ones trading. The price-to-sales ratio utilizes a company's market capitalization and revenue to determine whether the stock is valued properly. Price-to-EBITDA also known as price multiple which is used to measure the current share price relative to earnings before interest, tax, amortization and depreciation. Fundamentally, a quarterly event that could affect the stock price is if the revenue and net sales beat market consensus. For subscription business, they would also see if the amount of subscribers are increasing as expected or not. For Apple, they also have a subscription business in the App store as well as how welcomed the products are in the market. Google Trend is a good indicator of whether the brand and services are popular in the current market.

From the financial report, we take Price to Sales and Price to EBITDA ratios here since it is updated on a daily basis for the high frequency nature of price change.

As shown in the chart the revenue of Apple not only depends on how well the economy in the US is doing, but also the purchasing power in Europe,

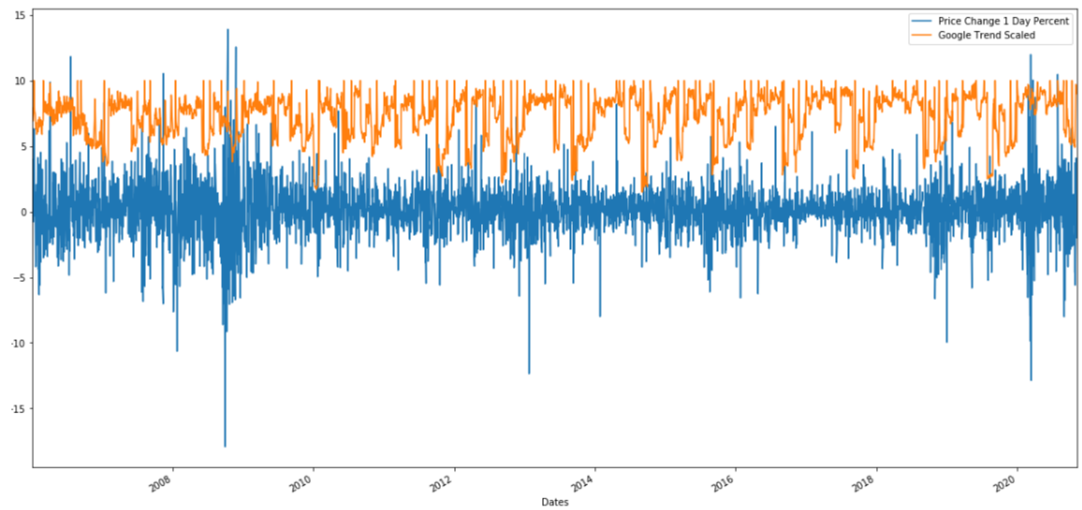


Figure 1: Google Trend vs Stock Return

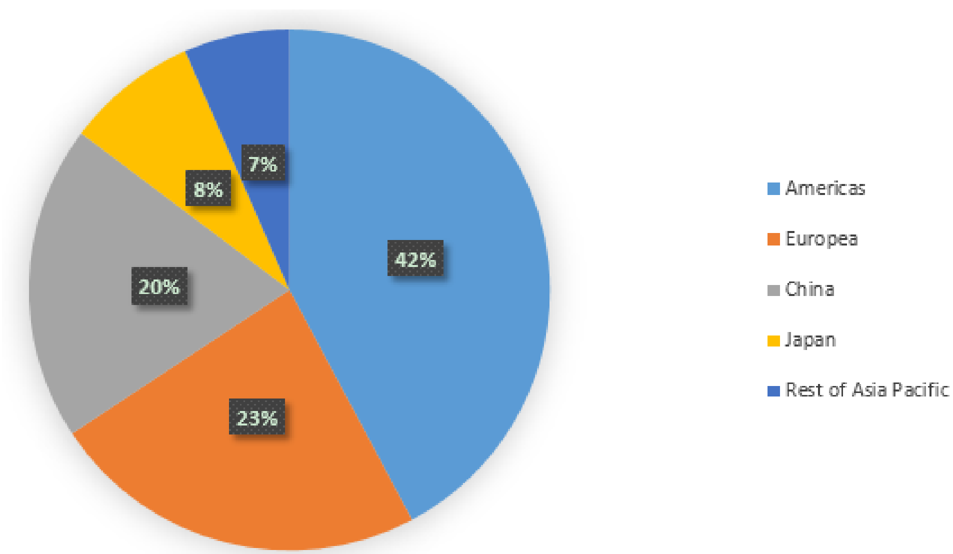


Figure 2: Net Sales Worldwide Allocation in 2018

China and Japan etc. Hence, the changes of foreign exchange rate between yen, CNY, Euro and British Pound against USD also affect the purchasing power and operating cost globally. Other than the value of the currency, we track the index of the specific country to show the condition of the overall economy. The earnings growth is sensitive to the state of the economy. The stock market is fluctuating since the earnings and expectations are fluctuating since the economy is fluctuating. Thus, we include FTSE index, SP 500, Nasdaq etc. in our model input.

4 CNN Model Construction

4.1 Data Processing

For the data part, we firstly used rolling windows to make 90 days data as a unit. And the basic idea is that we use passed 90 days data as an input to predict the 91st y value.

4.2 Categorize Y values

Bisection split:
For y value, we transformed y values into 2 categories.

- Transformed y values which are greater than 0 to 1
- Transformed y values which are less than 0 to 2

Trisection split:
For y value, we transformed y values into 3 categories based on the principle that the threshold we picked could make data balance.

- Transformed y values which are greater than 1 to 1
- Transformed y values which are less than -0.6 to 2
- Transformed y values which are between -0.6 and 1 to 0

4.3 Model structure

In our work, we built 4 CNN models with different layers. The structures of the 4 CNN models became more and more complicated with the increasing number of layers.

- CNN with 1 layers
- CNN with 2 layers
- CNN with 3 layers
- CNN with 4 layers

4.4 Models performances of Bisection in different time ranges

- Case 1:10/23/2009 - 12/31/2010
- Case 2:10/19/2017 - 12/28/2018
- Case 3:09/04/2019 - 11/09/2020

4.4.1 Time Range: 01/03/2006 - 12/31/2010

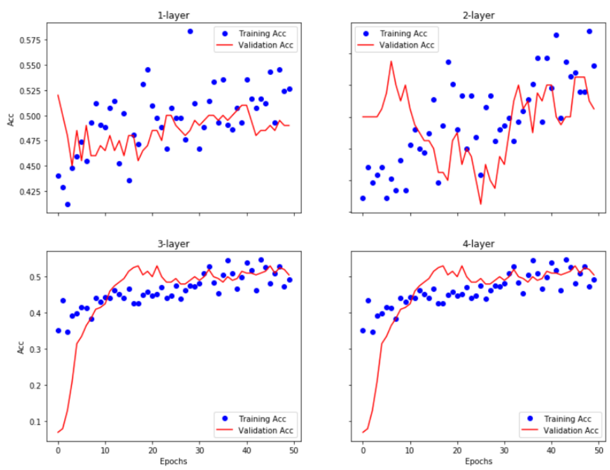


Figure 3: Case 1

Training: 01/03/2006 - 10/23/2009

1-layer	2-layer	3-layer	4-layer
55.33%	53.67%	53.67%	52.33%

4.4.2 Time Range: 01/03/2006 - 09/04/2019

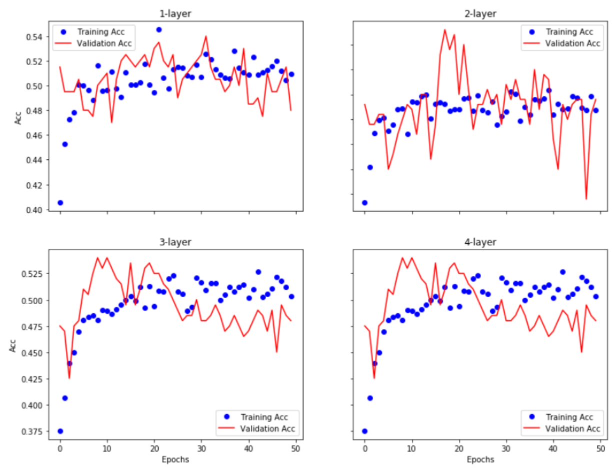


Figure 4: Case 2

Training: 01/03/2006 - 10/19/2017

1-layer	2-layer	3-layer	4-layer
50.33%	46.33%	52.00%	52.33%

4.4.3 Time Range: 01/03/2006 - 11/09/2020

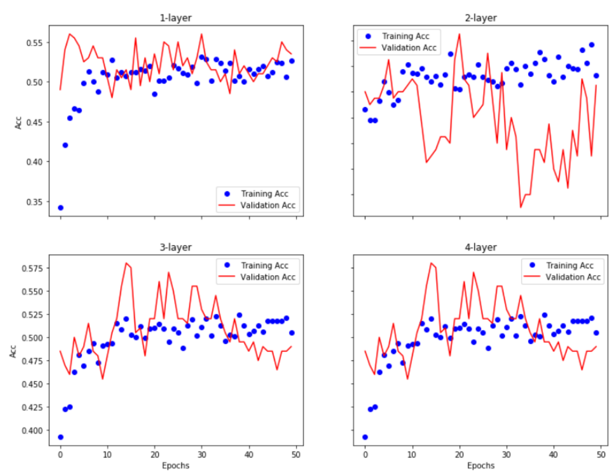


Figure 5: Case 3

Training: 01/03/2006 - 09/04/2019

1-layer	2-layer	3-layer	4-layer
45.00%	57.00%	56.67%	55.67%

Among three time ranges, we can see that models trained on 2006-2019 have the highest accuracy and normally models with higher complexity would have higher accuracy. And one interesting finding is that models trained on 2006-2017(11 years) have lower accuracy than models trained on 2006-2009(3 years) which violates our common understanding that models trained on more data would have better performance. The other finding is that models have the best performance on predicting 2020 which is not a normal year. We still need to try other stocks to see if the two findings are occasional or there is some valuable information we need to dig in.

4.5 Models performances of trisection in different time ranges

4.5.1 Time Range: 01/03/2006 - 12/31/2010

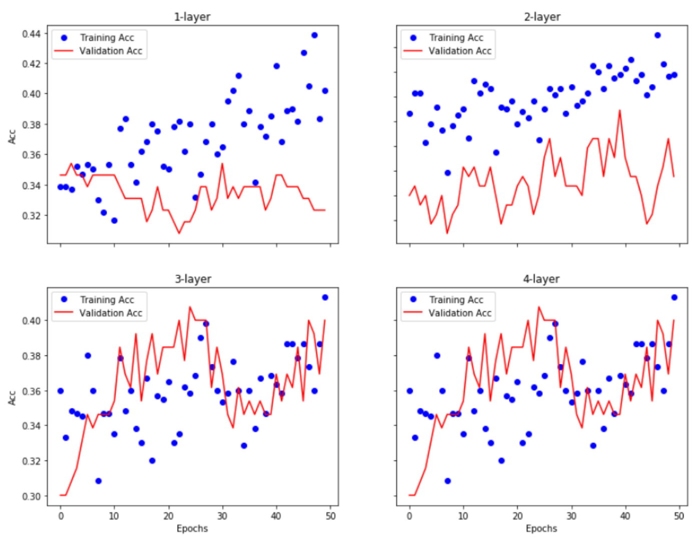


Figure 6: Case 1

Training: 01/03/2006 - 10/23/2009

1-layer	2-layer	3-layer	4-layer
31.33%	29.00%	30.33%	28.00%

4.5.2 Time Range: 01/03/2006 - 09/04/2019

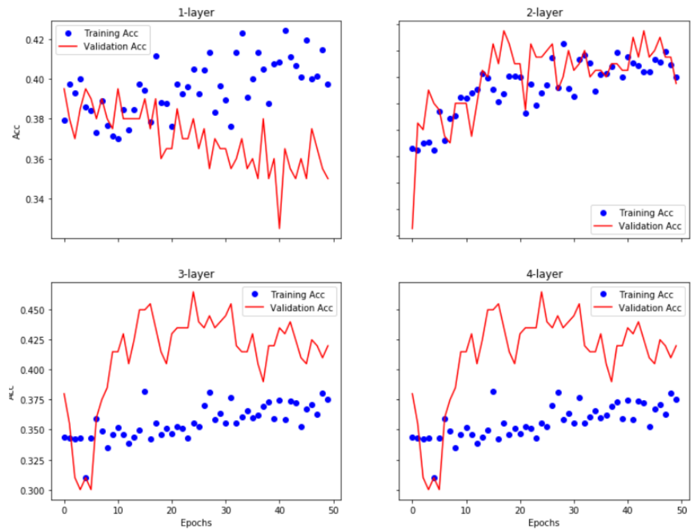


Figure 7: Case 2

Training: 01/03/2006 - 10/19/2017

1-layer	2-layer	3-layer	4-layer
30.00%	30.67%	31.00%	30.67%

4.5.3 Time Range: 01/03/2006 - 11/09/2020

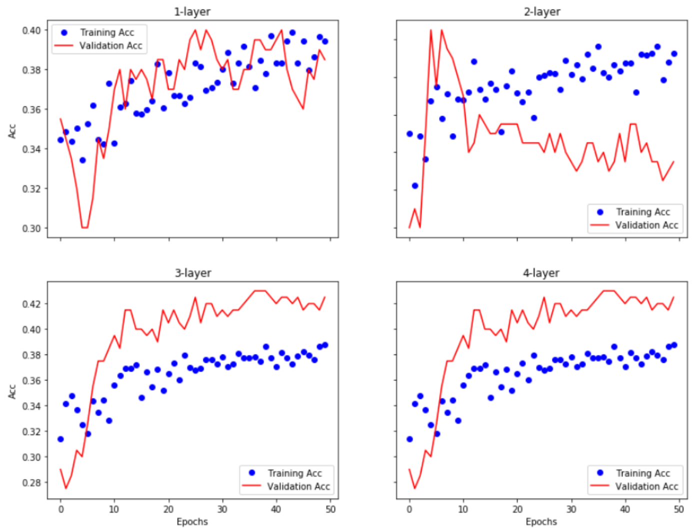


Figure 8: Case 3

Training: 01/03/2006 - 09/04/2019

1-layer	2-layer	3-layer	4-layer
28.67%	28.33%	28.33%	28.00%

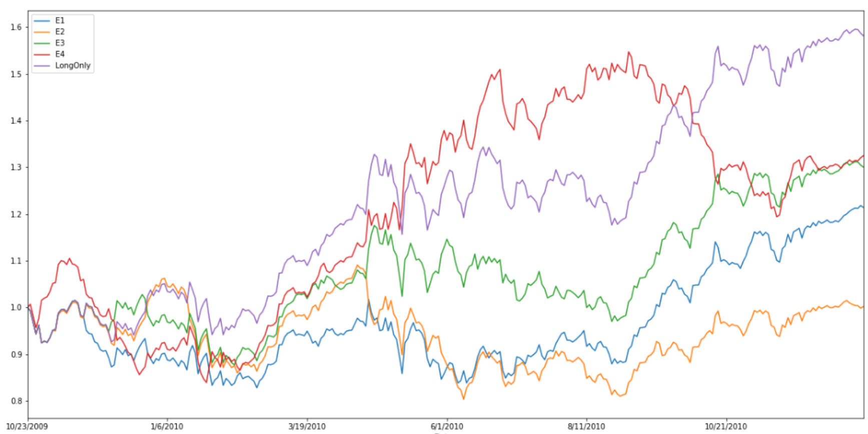
For trisection split conditions, we can see that there is no strong relationship between model's complexity and model's performance which is different from what we found in bisection conditions. And among three time ranges, models trained on 2006-2017 have the best performance. However models trained on 2006-2019 to predict 2020 have worst performance which is also different from bisection conditions. All in all, trisection models have better performance when they trained on more data however have worst performance when predicting abnormal year.

5 Trading Performance

The strategy is straightforward and purely based on the daily signal. At the beginning we will have one unit of wealth to invest in and the model will give us the signal of long or short the stock. Three period were selected to stress test the accuracy of this model and the performance is as following:

5.1 Bisection Split

5.1.1 Testing: 10/23/2009 - 12/31/2010

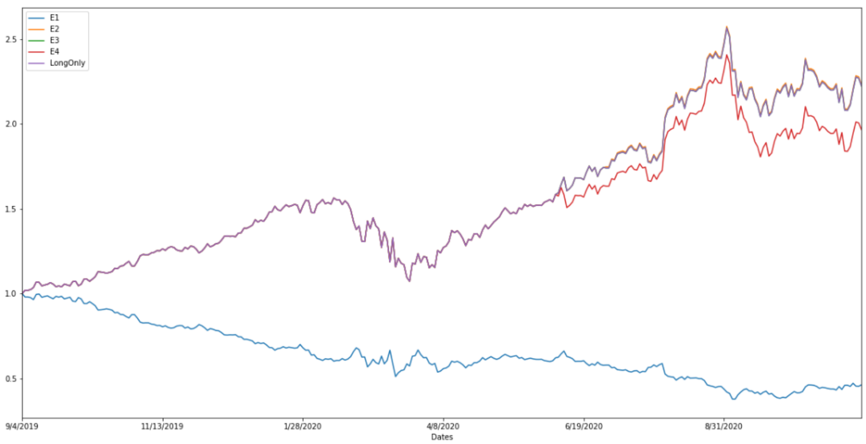


Case 1

5.1.2 Testing: 10/19/2017 - 12/28/2018

Case 2

5.1.3 Testing: 9/04/2019 - 11/09/2020



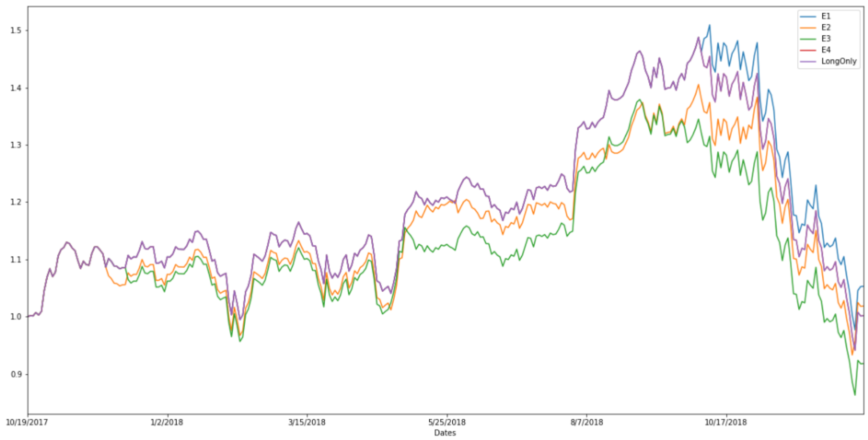
Case 3

5.2 Trisection Split

5.2.1 Testing: 10/23/2009 - 12/31/2010

Case 1

5.2.2 Testing: 10/19/2017 - 12/28/2018



Case 2

5.2.3 Testing: 9/04/2019 - 11/09/2020

Case 3

As shown in these charts, we bench marked signals performance with the long-only strategy. The purple line stands for the Long Only strategy which means that we enter the position at t_0 and hold it till the end. E_1, E_2, E_3, E_4 refers to the models with different complexity. The subscript tells how many layers the model has. The trisection model, E_1 always yield a better result than the others, which makes sense since more model complexity would bring overfitting issue.

In general, trisection split has a better performance than bisection split. Among models in Bisection split, the higher complexity model performs better which aligns with the intuition.

The reason why we choose Long Only strategy as the benchmark is that this strategy itself is a realistic strategy. Value investors tend to hold the stocks without actively trading it because a stock with strong growth potential has no need for sale. We did not choose SP500 either since this is not a basket of portfolios yet. From this perspective, the step of stock selection is critical since in a longer horizon, the stock should goes up. If we could capture some of the accurate short timing, that is a win because Type I error has more punishments than Type II error for a good stock short timing identification. The reason why Trisection split is better than bisection split has the same intuition. Once we set the threshold as up zero and below zero, we require high accuracy of the signals. Yet, for Trisection model, after we convert all holding signals to long, we increase the tolerance of blurry short timing identification.

6 Future Work

The future plan is to expand the basket by working on more stocks and after testing the effectiveness of each model, we could have a portfolio and investigate on the right combination to benchmark the performance with the index. When the portfolio is matured and diversified including stocks from multiple sectors, we could gauge the performance with SP500 index.