A High-dividend Stock Classification Technique based on Multi-Layer Perceptron Model

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***Abstract*—This paper is using Multi-Layer Perceptron (MLP) to find stocks that pay high dividends to investors consistently per year. It is another way to get profits without trying to find the best time to sell the stocks when the prices are higher than the prices investors bought. The data resource for the model contains annual dividends, the average stock prices, and several fundamental indicators for the companies we are gathering. The indicators are basically to examine if the companies run their business well from an accounting standpoint. That also means the companies we select will closely fit the situations we want which are profitable and consistent for years. We try to make the indicators simple for every investor so that they would have a better way to put their money in a safer target.**

Another key point is that we want to consider the annual percentage rate (APR) from bank saving accounts. Then we expect the APRs of stocks we choose will be a little higher than the rates of bank saving accounts which are generally considered as low-risk targets. So, we try to find a risk-return tradeoff since the higher the risk, the higher the potential reward.

Keywords—MLP, deep learning, data mining, classification, stock market, stock dividend, fundamental analysis, APR.

I. INTRODUCTION

We are providing a technique that can help investors to find reliable and profitable companies to invest, which means the prices of the stocks we pick are not volatile for several years and pay profit out of their reserves to the shareholders regularly. Therefore, the investors are still able to earn profits passively from the dividends repeatedly in the long term. Dividends are a way in which association share the profit generated from running the business. The way they are paid are usually a cash payment which are often from earnings, paid to the shareholders of a company. These are mostly paid on a quarterly, or sometimes, a yearly basis. Choosing to invest in dividend stocks is a favorable adjustment between putting the money in savings accounts and investing in the stock market. The idea of getting stock dividends as main profits is safer because we do not want to consider our investment as playing gambling. That is one reason that we need to examine the dividends from the previous years as the performance of how the company runs the business. Companies can be affected by several aspects. There are various kinds of factors to influence the market, such as global pandemic, war, government policy changes, interest rates, inflation, technological change, and corporate performance. They are all able to lead the market to go up and down. So, we only use recent 5 years of data to train our model which is better than 10 years of data or more.

The reason we do not adopt technical analysis is because it is not reliable enough. If only using technical analysis to predict stock price in the markets, it is not a healthy way even risky to invest. Most of the technical indicators provide probable entry and exit points to buy and sell. But the truth is the forecasting accuracy is not 100% because stock markets are changing extremely fast and hard to predict. It is the idea of only looking at the prices being fluctuated and knowing nothing about the companies. This process is so-called speculation, not what investment is. Although all stock trading has certain speculation, speculative trades have a notably high effect in financial markets. The existing solutions of forecasting in the stock markets are generally using a common strategy that buy low and sell high. The solutions only work in a limited stocks or in a short period of time, but it ends up being not adaptive or robust for a long term investment. The paper brings out a safer and long-term scheme. Investing a stock with its dividend can be a better strategy to invest. Dividend stocks have factual outperformed most stocks in the markets with less volatility. It is because dividend stocks give two ways of return which are regular capital appreciation and income from dividend payments of the its stock price. If investors do dividend investing appropriately, they can earn many benefits in the similar way that compounding interest offers in this kinds of investments. When investors re-invest dividends benefit back into the stocks, buying more shares with dividends gained, that wealth increases exponentially over time.

On a basis of MLP, it consists of three kinds of layers—the input layer, hidden layer and output layer. We take the four fundamental indicators as our input layers. Since the model allows for probability-based classification or predictions of input layers into multiple labels. We consider the labels as four levels of dividend rates. So, we will choose the annual dividend–price ratio from the stock companies as the output layer. In an artificial neural network, the layer is the last layer of neurons which generates given outputs for the program. This ratio can later be compared to the Annual percentage rate (APR) of common banks since the average bank interest rates for saving accounts in the us are less than 0.7%. The hidden layers in MLP are layers in between input layers and output ones, where artificial neurons take in a set of several weighted input data and generate a result through an activation function. In this paper, we will also compare the accuracy by using one-hidden-layer and two-hidden-layer with different sizes so that we are able to optimize the number of hidden layers and the size of the layers between the input layer and the output layer. The diagram of our MLP model is as follows.

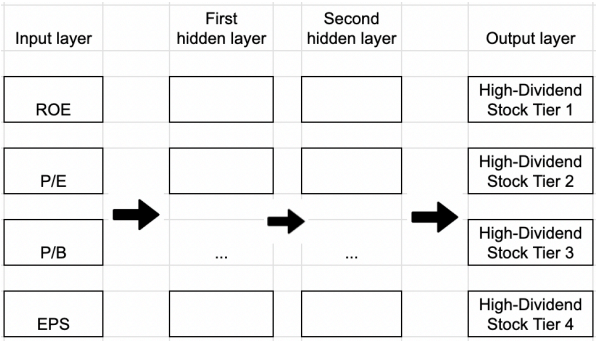


Figure 1. Layers of the MLP model

After we optimize the hidden layers and train the model, we will be able to use the trained model to understand the range of high prices and low prices for the certain stocks. We then can use this model to forecast by the latest financial statement if the companies will share similar portion of dividends as usual to their shareholders and also if the stock prices are reasonable to re-invest money in. Therefore, the goal of this model is to narrow down companies that are fundamentally robust, support reasonable, sustainable, carry low debt, and growing dividend yields, and also trade at relatively low or reasonable prices. It is commonly known that earning dividends from stocks is one of the popular ways for investors to create passive income. Technically it is simple, but not easy to earn the dividends permanently. That is the key reason the scheme conducts a way that can keep focusing on dividend persistency and need to keep tracking the trend by training the past five years of fundamental indicators.

II. RELATED WORKS

Before data science becoming popular, most stock analyzers used technical analysis. Analyzing technical indicators is a traditional trading method utilized to assess investments and diagnose trading options by analyzing statistical trends collected from trading activities, such as price movement and price volume.

Nowadays, most stock price forecasting methods which use data science techniques are mostly focusing on the prices in time series format. This section will simply introduce four models which are commonly used for stock prediction.

A. Moving Average technique

Moving Average (MA) technique is the most common technical indicator which is an average price calculation of a stock over a set period of time. Moving Average are commonly adopted for pointing out the price of a stock over a specified period of time. How we calculate moving averages is to identify the trend direction of a stock or to decide its support and resistance levels. It is a way to follow certain trends because it is established on past prices. The longer the time period we adopt for the moving average, the greater the trend we can see. Some common uses are 5-day Moving Average, 50-day Moving Average, and 200-day Moving Average. Take one example of moving average to predict the times to buy and sell. Through getting a 50-day and 200-day moving average on a technical chart, a buy signal occurs when the 50-day crosses above the 200-day. A sell signal occurs once the 50-day drops below the 200-day.

B. Moving Average Convergence Divergence

There is another technique which is similar to Moving Average technique but with two additional features Convergence and Divergence. It is known as Moving Average Convergence Divergence(MACD). It also uses a trend-following momentum signals that indicates the connection between two moving averages of a security's price. Stockbrokers or traders use the MACD to recognize when bullish or bearish market is coming. Basically bullish signal means the price is going to go up, and bearish signal means the price will go down.

C. Relative Strength Index

The relative strength index (RSI) is a momentum signal used in stock volume analysis that determines the magnitude of previous price changes to identify overbought or oversold situations in the price of a stock. For instance, RSI usually provides short-term buy and sell signals. RSI level below 30 is considered as a buy signals. RSI level above 70 generate sell signals. It is a prominent indicator and is commonly used by technical analysts over the world.

D. Long Short-Term Memory

Long Short-Term Memory (LSTM) is widely used for sequence prediction models which can store past crucial information and neglect the information that is not important to the prediction accuracy. It amplifies the memory of repeated neural networks. Repetitive neural networks carry short term memory in that they allow earlier determining information to be adopted in the present neural networks. The model allows us to pass a great range of parameters such as learning rates, and input and output biases. Therefore, there is no need for a lot of fine tune.

E. AutoRegressive Integrated Moving Average

The method is also called ARIMA. It shows that the time series is regressed on its own recent data in terms of two polynomials. The first one of these polynomials is for autoregression, the second is for the moving average. The model implicitly assumes that the future will resemble the past. The Autocorrelation part means the relationship between one day's stock price and yesterday's stock price. Partial autocorrelation connects one day's stock price and the price which was from a week before. The model is considered to be reliable, effective, and capable of predicting short-term stock market changes.

F. Recurrent Neural Network

Recurrent neural network (RNN) is a kind of artificial neural network that handles time series data or sequential data. The model typically allows previous outputs to be used as input data while having several hidden states. It works on the concept of storing the future stock price of a particular layer and feeding this back to the previous stock prices in order to forecast the output of the layer. It is a progressive form of models that has inner memory that makes RNN capable of calculating long sequences. This scheme allows RNN very appropriate for stock price forecasting. Thus, it always has a tendency to involve long historical data.

G. Support Vector Machines

Support vector machines (SVMs) are a group of supervised learning models used for regression, noise detection and classification. The model uses the support vectors and maximize the bound of the classifier. The good points of SVMs are efficient in high dimensional data set. And it is also suitable in cases where the number of samples is less than the number of dimensions. SVM model has a

relatively good performance in short term. One of the biggest problems for stock prediction is the volatility of the stock prices. Thus, it is not very robust in the long term because of the stock price outliers.

III. PROPOSED WORK

First of all, we need to define the main point of how we get the APR. Most stocks have 4 dividends of a year which are consider DIV1, DIV2, DIV3, and DIV4. We consider AD as our Annual Dividend and the other term AVGP as the average closing stock price of one single year. So, the formulas we use are as follows.

AD = (DIV1 + DIV2 + DIV3 + DIV4)

AVGP = (Σ Daily Stock Price) / Days of a Year

APR (%) = AD * 100 / AVGP

The code in Python is as follows:

```
import yahoo_fin.stock_info as si
def get_APR(symbol):
    data = []
    years = ['2020', '2019', '2018', '2017', '2016']
    for year in years:
        t1, t2 = '01/01/'+year, '12/31/'+year
        p_data = si.get_data(symbol, start_date = t1, end_date = t2)
        avg_price = round(p_data['close'].mean(), 2)
        d = si.get_dividends(symbol, start_date = t1 , end_date = t2)
        apr = round(d['dividend'].sum() / avg_price * 100, 0)
        data.append(apr)

    return data
```

We use a Python API from Yahoo Finance to get the dividend data of stocks. The period of data set we gather are from year 2016 to 2020 which are the recent 5 years. The Daily Price contains four kinds of prices that are Opening, Closing, High, and Low. And we want the final price of a day, so the price we grab is the Closing Price.

By using the formulas and implemented Python function, we are able to calculate each stock APR per year which is also considered one output data for a year. The 4 categories of APRs are from 1% to 4 %. Then we use the categories with hidden layers and input data to train our model. As we mentioned, we can optimize the hidden layers to classify 4 groups of high-dividend stocks from the data we have. Since our model is based on MLP, the input data is the source we feed into the model. We have to gather our fundamental indicators as the input layer of the model. For the following parts, we will describe what the 4 indicators mean in a more detailed way.

A. Return on Equity Ratio (ROE)

ROE is a financial ratio to show the performance of a company. Basically it means how good the company is in generating returns on the investment it received from its shareholders. It is calculated by dividing net income by shareholders' equity. The formula is as follows.

ROE = Average Shareholders / Equity Net Income

Take this financial numbers as an example. If a company has a net income of $2,000 and shareholders' equity of $10,000. Use the ROE equation to calculate the company's return on equity for the period: ROE = $2,000 / $10,000. The ROE is 20%. Generally, ROE could be from 5% to 60% and it depends on various industries because every business has different business model that makes different amounts of profit. Here is a dataset example of 3M's ROE.

Date	Net Income	Equity	ROE
2020-12-31	$5.45B	$12.93B	47.38%
2020-09-30	$4.96B	$11.94B	45.93%
2020-06-30	$5.11B	$10.92B	48.68%
2020-03-31	$4.93B	$10.21B	47.86%

B. Earnings Per Share (EPS)

In a Nutshell, EPS shows how much money per share is generated by a company in a single financial year. The term is an important indicator of the financial performance of a company. It is calculated as a company's profit divided by the shares of its stock.

EPS = Total earnings / shares

Take one bank as an example, if the fiscal year 2017 net income for the bank is $18 billion. And its preferred stock dividends were $1.5 billion. The average outstanding common shares stood at 10 billion. So, the EPS will be

Earnings = 18 billion - 1.5 billion = 16.5 billion

EPS = 16.5 /10 billion = $1.65

For the following financial terms, we will also take 3M company as our dataset examples.

Year	Annual 3M EPS
2020	$9.36
2019	$7.72
2018	$8.89
2017	$7.93

C. Price-Earnings ratio (P/E)

The P/E ratio guides each investor decide the stock market value of a share that is compared to the organization's earnings. To put it simply, the P/E shows what the market is ready to pay at the present time for a stock based on its past or future revenue. A high P/E could convey that a stock's price is relatively high to earnings and very likely overvalued. This is one reason the P/E is often pointed out as the price multiple because it indicates how much money investors are willing to spend per dollar of earnings.

P/E = Stock Price / EPS

Let us have another example of this term, if the EPS of an enterprise is $20 and its stock price is currently $500, its PE ratio would be 500 divided by 20, which comes out to 25. One way to put it is that the stock is trading 25 times higher than the company's revenue, or 25x. The dataset of 3M looks like the following table.

Date	Stock Price	EPS	3M PE
2020-12-31	167.69	$9.25	18.13
2020-09-30	152.37	$8.53	17.86
2020-06-30	147.05	$8.82	16.67
2020-03-31	127.4	$8.52	14.95
2019-12-31	163.15	$7.81	20.89
2019-09-30	150.72	$8.42	17.9

D. Price-to-Book value (P/B)

The P/B ratio assesses a stock price against a company's book value which is its fundamental worth. Although every industry varies in different ways to run their business, the ratios under 1 often points out a stock is undervalued; over 3 may denote it is overvalued.

P/B = Market Price per share / Total Book value

As the previous terms, there is no exception for this one to be calculate by per share. The P/B ratio is the market price divided by the book value. Let us specify some financial numbers for a company with

- Assets: $325 million
- Liabilities: $75 million
- Outstanding shares: 10 million
- Stock price: $50 per share

To begin with, we have to calculate the company's book value and book value per share.

Book value = Assets + Liabilities

= $325 million - $75 million = $250 million

The book value per share = book value + shares

= $250 million / 10 million = $25

P/B ratio = stock price + book value per share

= $50 / $25 = 2

Date	Stock Price	Book Value	P/B
2020-12-31	167.69	$22.38	7.49
2020-09-30	152.37	$20.70	7.36
2020-06-30	147.05	$18.95	7.76
2020-03-31	127.4	$17.75	7.18
2019-12-31	163.15	$17.60	9.27
2019-09-30	150.72	$18.72	8.05
2019-06-30	157.47	$17.63	8.93

E. Hidden layers for MLP

As the previous part described, a hidden layer in an artificial neural network is in the middle of input and output layers. It allows users to model complex data thanks to the neurons. In this paper, we expect to compare one-hidden layer and two-hidden-layer. So, firstly we use a-hidden-layer with different sizes to train our MLP model and see what the best accuracy is. The sizes we are using are from size 1 to size 30. The accuracy is up to 70 % of correct. For the second phase, we select different combinations of sizes for the first hidden layer and the second one. And in this case we obtain a better result than one-hidden-layer which leads to about 82% at most. In fact, we also tried to train the model with 3-hidden-layer but it does not show a better result. Instead, there is a tendency to lead the training to be overfitting that can not perform accurately against unknown data. It seems that with a 3-hidden-layer model makes the layers learn too many details in the training data along with the outliers from the training data. As a consequence, the MLP with too many hidden layers has a poor performance on our stock test datasets. Therefore, the neural network is not successful to sum up patterns deliver in the training dataset.

F. Filtering the companies

When we tried to optimize the hidden layers and the accuracy, there is a critical difficulty we encountered. The problem is how to choose companies as our dataset. It means we can not randomly pick companies since many stocks in the stock markets are volatile and risky. If the stocks we choose are unstable, that also means we are based on a chaotic situation to train the model. The results of the method we propose would seem to conflict with random companies in the market. We organize two ways of filtering the stocks we want to gather.

The first one is to use standard deviation of daily stock price changes to determine if the prices over the period of time is stable. We know stock prices can going any ways in a 5 years period, such as a tendency of going up, going down, or fluctuating in a seasonal way. The last one trend is what we want. The seasonal stocks might be characterized by a demand at different times of the year. Their business is related to weather, events, or some specific holidays. They have their peak seasons and low seasons. For example, a retail company makes more money during Christmas time and new year. Or some business that specialize in sports T-shirts is probably not as active off sport season, but the revenue surges extremely in the season or throughout the finals.

We use correlation to find reliable companies if we already have one or two good ones. For example, if we consider certain stocks in the same industry or sector, such as real estate, banking or health care, are likely to have the same trend to go in the same direction and react to the market in the same way.

To sum up, in order to select the good stocks for our dataset, we begin by finding the average price for each stock. The time period we evaluate is 5 years, then add up each stock's daily price for the time period and divide by the amount of days in the period. This is how we get the average price. The next step is the way we describe to calculate a standard daily deviation for every stock.

IV. Experiments

The goal of our experiment is to find the accuracy of MLP model. Here are several steps we do our experiment.

A. Data Gathering

- The first data source is from Yahoo Finance API
- The other source is from https://www.marcotrend.net/
- Convert data to CSV files from HTML table
- Summarize all CSVs to a summary_dataset.csv

B. Companies Selecting

Dividend finding is a tested and proved scheme of wealth cumulation that provides inflation defense in a way that banking systems do not. But finding first-class dividend-paying companies is not easy. That is why we need to keep running these steps a few times. This method features the main factors investors can search for, in their search for worthy dividend-paying investment. Firstly we try to find dividend stocks with high APR for a couple of years, the APR would be from 1% and 6%, also consider the combinations of four fundamental indicators which are EPS, P/B, P/E, and ROE. Since it is the first step, we are not that strict so that we are not avoiding some companies that look not so good but might be with potentials.

C. Data Cleaning

Remove the additional prices we do not need that are opening price, high price, low price since we consider the closing price as the main price of a day. There are no missing values for the fundamental indicators but for EPS data, we can only access them based on a year not quarterly. For dividends data set, many companies distribute them annually and some ones do quarterly. In order to be in the same period of time, we convert them to yearly-based.

D. APR Calculating

Based on the formulas we present, we calculate each APR for one company for one single year. The APR is where we put them for the output layer. The APR ranges contains 4 tiers of categories, and the percentages of them are from 1% to 4 %. The format of the main dataset summary_dataset.csv is as follows:

Symbol	EPS	ROE	PE	PB	APR
AAPL	3.28	75.22	29.4	24.57	1.0
AAPL	2.97	54.35	18.3	10.45	1.0
AAPL	2.98	45.77	15.6	7.35	1.0
AAPL	2.3	36.04	15.95	5.47	2.0
AAPL	2.08	37.16	11.8	4.05	2.0
GLPI	2.3	20.66	15.7	3.12	7.0
GLPI	1.81	15.64	21.17	3.32	7.0
GLPI	1.58	15.4	15.72	2.42	7.0
GLPI	1.79	15.13	15.15	2.25	7.0

E. Data Training

We divide our dataset into two sets which are training set and test set. Training set contains 80% of the original data, and test set contains the other 20%.

The MLP library we import is from a third party Python Library called sklearn.neural_network. It applies to different areas of dataset. There are various parameter for fine tuning, such as

- activation
- max_iter
- solver
- alpha
- batch_size
- learning_rate_init
- warm_start

F. Hidden Layer Optimization

For single hidden-layer optimization, the sizes we are using are from size 1 to size 30, and the accuracy is from 30% going up to about 70 %. But it starts to go down when the size is 29, so we just stop at the size 30 for the single hidden layer.

For double hidden-layer optimization, we also adopt the sizes starting from 1, and the accuracy begins with 50%. Then the percentage fluctuates for a few sizes, it arrives at 82 % when the size is 15.

G. Plotting the result and Observing

This is not necessary a final step because we need to plot all the result and observe if there is a chance to progress or make some adjustments. If it does, we can go back to step B to re-choose the companies and keep observing if there are improvement this model can have.

We also use Python matplotlib to generate our visualizations. Visualizations are easier for humans to identify the trend or find some other ways to improve.

V. Comparisons

Our goal is mainly focusing on passive income and protect our money first. That is why we want to find reliable companies that run the business well for recent five years. The existing solutions are mostly focusing on predicting price and easy profit. The solutions work for some situations, but it is not a long-term investment.

Generally, the related solutions are based on technical analysis which is mostly analyzing stock prices in time series. Some of them add other factors, such as news, event, weather, pandemic, and holidays to forecast the future stock price. Most methods only work in certain stocks or only work in a short period of time. That is why we propose a more fundament way and calculate the APR based on stock dividends. If we identify the indicators we use are reliable, they are good signs of how the owner run their business and also how profitable they are. And the companies we are

finding are long-term trustworthy business for investors because they share dividends with their shareholders.

For the last layers, we classify 4 tiers of stocks. Since saving account in the banking system usually provide very low interest for their clients, the Return On Investment (ROI) needs to be better than the bank interest rate. Our goal is to find reliable stocks to earn regular dividends.

Among the dividend-paying stocks, we could use the model to apply the current financial indicators to know if the companies will share benefits as the previous five years. If we know the average dividends annually, we can use it to figure out when is the good price to hold on. For example, there is a company that pays $4 to their shareholders yearly. And when the stock price is $100, we can invest the money as our the capital to get a 4% APR by holding the stock.

Because we are focusing on dividend-paying stocks, it tends to be less volatile than non-dividend-paying stocks on average. In addition to a dividend stream, especially when investors re-invest to take advantage of the power of compounding, can help build gigantic wealth over time.

VI. CONCLUSION

We use APR as our main criterion to compare in the stock markets and banking systems. It is a general way to see how good the investments are. For example, the APRs of the stocks are better than interest rate of the banks all over the world. We also try to find higher dividend payout ratio, but the risk follows. Another point is filtering companies is more difficult than the process of MLP training.

There are a few of the benefits to invest cash in products such as stocks can have much higher returns than bank savings accounts and CDs. Although saving is certainly safer than investing in stocks, it is unlikely result in the most wealth accumulated over the long term. So, this method is trying to balance between risks and rewards a risk-return. We all know that the higher the potential reward, the higher the risk.

VII. FUTURE WORKS

The method is obviously not flawless. There are still works we can add to consider and it would be improved.

- Add more fundamental indicators as the input layer
- Consider more kinds of industries
- Combine one or more models to apply
- Fine tune the parameters of MLP
- Divide the output layer into more categories
- Lower the APR

VIII. OTHER INFORMATION

A. *Github URL:*

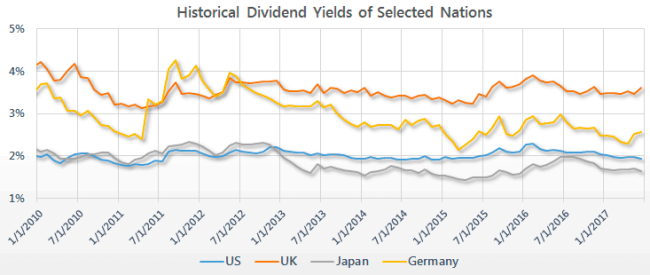
https://github.com/spadog777/MLP_Stocks

B. *Companies we gather*

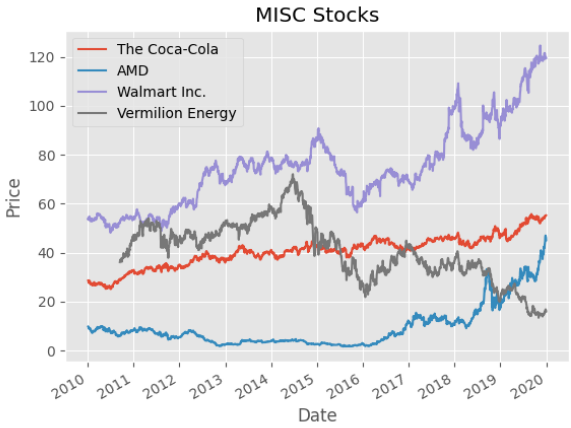
Stock Symbol	Company
AAPL	apple
GLPI	gaming-and-leisure-properties
OKE	oneok
UVV	universal
PM	philip-morris
VLO	valero-energy
PSX	phillips-66
EIX	edison
NWE	northwestern
ALE	allete
SR	spire
MMM	3M
LAMR	lamar-advertising
WEC	wec-energy
ES	eversource-energ
CMI	cummins

C. *Visualizations*

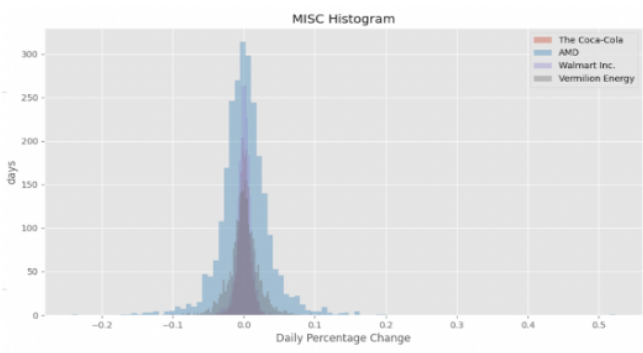
A. *APRs of Selected Nations*



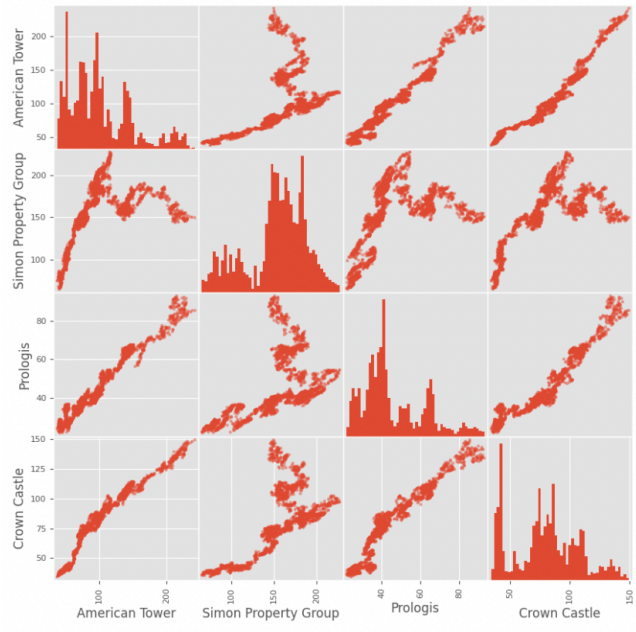
B. *Stock Prices Changes*



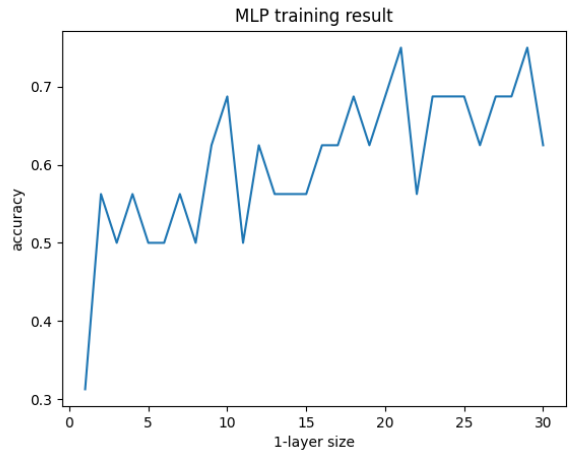
C. *Standard Deviation of Daily Percentage Price Change*



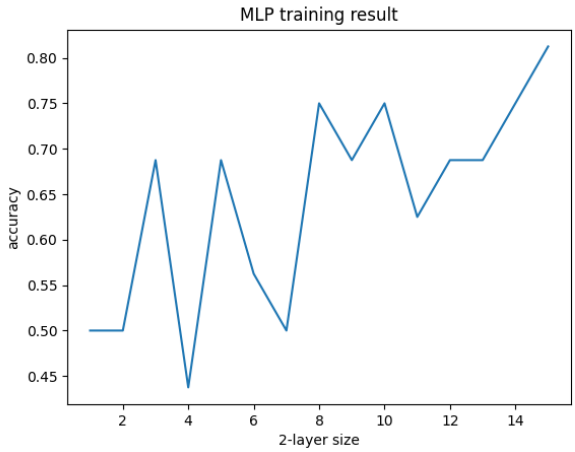
D. *Correlation between Companies in the same Industry*



E. *Optimization of Single Hidden Layer*



F. *Optimization of Double Hidden Layer*



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