2022 MCM Problem C: Trading Strategies

Alyssa Lung, Megan Ma, Kevin Tang, Ryan Kawamura, Zayne Kratz

Summary:

The most basic way to decide what action to take (buy, sell, hold) is to determine whether the asset is predicted to incline or decline. If the asset value is expected to increase, you should hold. If the value is expected to decrease, you should sell. Additionally, the decision to hold or sell depends on the time frame of which you are predicting the asset value. For example, if the value of the asset is predicted to decline slightly the next day, and then incline rapidly over the next year, it would be better to hold than to sell. Therefore, there should be a set of criteria which will be able to determine action based on the prediction of future asset prices.

Therefore, we decided that our model should have 2 main parts: first, a predictive portion where the price of an asset can be predicted for the future, based on the previous prices up to that day. Second, a trading portion which decides what action to take based on the aforementioned prediction. Each day, the predictive model will predict tomorrow's asset price using the previous day's asset prices, and the criteria will be rechecked for which actions should be taken that specific day. This will model the best possible actions to be taken over the course of the investment period so that the profit made off the investment can be maximized.

Utilizing an initial state of $1,000 cash, we created six variations of the model to determine the optimal selling and buying conditions for an asset. We find the best model incorporates four parameters. The first is a 2% threshold for gold that represents the difference between the day's actual value and the moving average. This threshold accounts for when the value of gold is lower than expected or higher than expected by 2%. Similarly, we chose a 20% threshold for bitcoin. The next parameter was an initial investment of $500 into gold and $500 into bitcoin, doing this allowed the investment to increase from the beginning and was motivated by the assumption that the stock market always trends upwards. Lastly, during each transaction, only 20% of the available cash was utilized to buy and 20% of the asset's value was sold when the criteria was met.

After running the model, we see the final portfolio value on 9/10/2021 was $41,538, or an increase in $40,538. The success of the portfolio was largely due to Bitcoin's success over the course of the model. The model's predictions and thresholds when buying or selling capitalized on Bitcoin's immense success by diverting funds into the stock when it was at a low.

Contents:

1. Problem statement and background

Many people see trading as an opportunity. Whether they make simple investments into the S&P 500 or buy shares of a company, there are a multitude of opportunities to make money through trading.

In this project, our team attempts to create a model that could maximize a trader's profits based only on the information from the value of an asset in the previous days.

We start with $1000 to invest, and create a model that helps traders maximize their profits by indicating when to buy, sell, and hold the assets of gold and bitcoin.

We will approach this project by using the concept of a moving average and buying and selling assets depending on how much an asset deviates from the previous day's moving average. The idea is that the moving average represents what the asset "should" be and any deviations will likely return to a similar price. Thus we should be able to take advantage of these deviations to "buy low and sell high."

2. Initial Assumptions

- Our model's only knowledge is the previous value of an asset. We have no access to news, world events, economic developments, etc.
- Since gold is only traded on days the market is open (6 PM Sunday to 5 PM Friday and closed on holidays), we assumed that the value of gold on the days it was not traded is the same as the value of gold the previous day it was able to be traded. Thus, we can make one model which trades both gold and bitcoin that will behave the same as if gold wasn't able to be traded on specific days.
- We assume that we trade exactly right after the market opens each day, since we only know the previous day's closing price.
- There is a trading commission for the purchasing and selling which costs a set percentage of the amount traded.
    - The transaction costs for gold is 1%
    - The transaction cost for bitcoin is 2%
- There is no cost to hold an asset
- We are starting with $1000 on 9/11/2016 and will be trying to increase the value of our portfolio as much as possible by 9/10/2021.

3. Price Prediction Model

3.1 Asset Predictions - Stochastic Baseline

We first constructed a stochastic model that uses the distribution of gold's daily percent change from all years before 9/11/2016 in order to simulate the conditions of the future market based on previous gold trends. Here is the dataset we were looking at:

Date	Price	Open	High	Low	Vol.	Change %
Jun 10, 2022	1,842.60	1,849.80	1,850.95	1,841.75	-	-0.55%
Jun 09, 2022	1,852.80	1,855.10	1,857.80	1,841.90	131.29K	-0.20%
Jun 08, 2022	1,856.50	1,855.00	1,862.40	1,846.60	114.14K	0.24%
Jun 07, 2022	1,852.10	1,843.50	1,858.20	1,838.50	119.21K	0.46%
Jun 06, 2022	1,843.70	1,853.70	1,861.20	1,843.00	103.18K	-0.35%
Jun 03, 2022	1,850.20	1,872.60	1,878.60	1,849.70	115.34K	-1.13%

We are focusing on the % daily change, which is the percentage that the stock increased/decreased compared to the previous day. We made a distribution of all the daily percent changes up to 9/11/2016, which is when our simulation of future prices start:

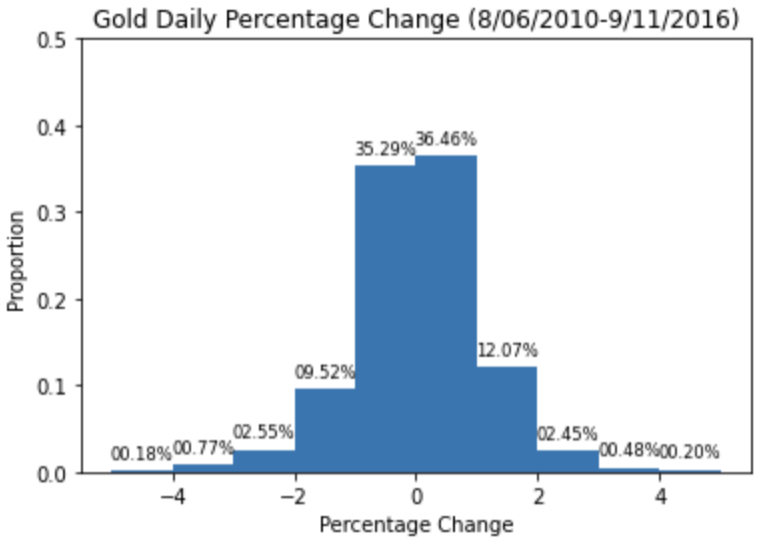


Figure 3.1.1:Distribution of gold's daily percent change.

Although this distribution looks normal, it is not perfectly normal. Therefore, we decided to utilize a random number chosen from a uniform distribution from 0 to 1 to simulate this distribution. We split up this uniform distribution proportional to the area of the daily percent change distribution. If the variable fell into a certain portion of the uniform distribution, the asset price would be adjusted according to its corresponding percent change, starting with the actual asset price on the day of 9/11/2016. Here is the simulation:

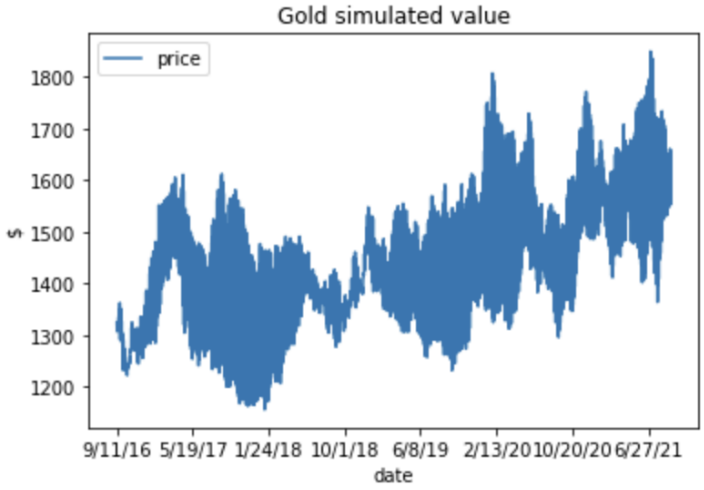


Figure 3.1.2: Gold's simulated value

Note that this visualization shows the price fluctuating with a random component every day, so the lines are very close together and therefore are hard to distinguish and looks like an area even though it is one distinct line. As you can see above, gold's simulated final value at 9/10/21 is $1588.82. Compare this to gold's actual final value, which was $1794.60.

We also constructed a similar daily percentage change distribution for bitcoin, however since bitcoin was created in 2009, historical data is only widely available starting in 2010. Our bitcoin stochastic model uses the distribution of its daily percent change from 2010 to 9/11/2016 in order to simulate the conditions of the cryptocurrency market based on previous trends.

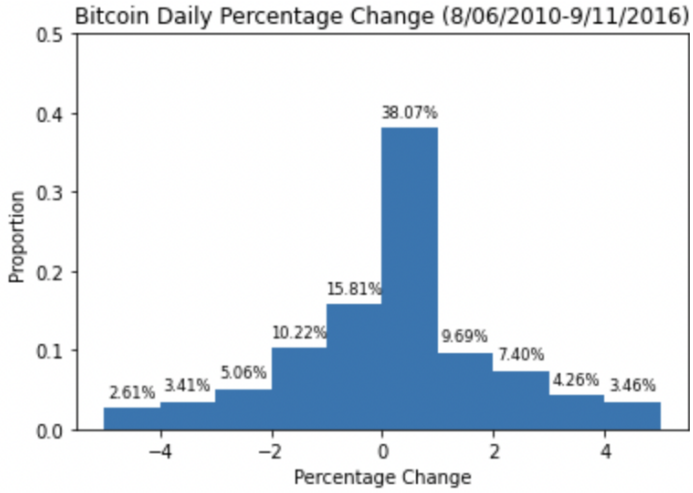


Figure 3.1.3 Distribution of bitcoin's daily percent change Source: "Bitcoin Historical Data." *Investing.com*

Here is the simulated value of bitcoin according to this distribution:

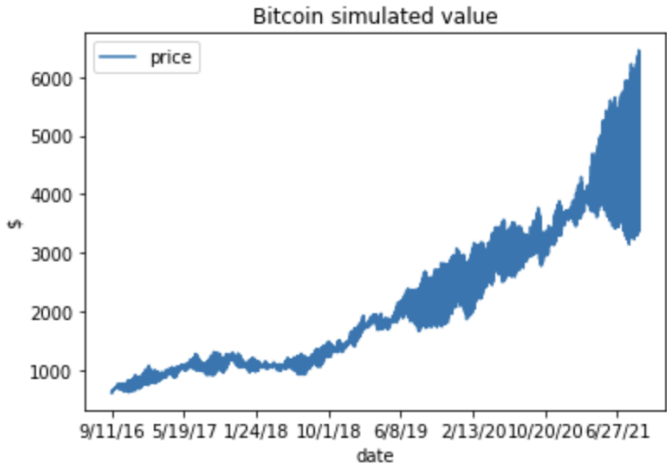


Figure 3.1.4 Bitcoin's simulated value. Source: "Gold Futures Historical Prices." *Investing.com*

As you can see, bitcoin's simulated final value is $3.367.052970, while bitcoin's actual final value is $46,368.69. We can see that the final simulated value of bitcoin is higher than the final simulated value of gold, which makes sense because we used different daily change distributions for each asset depending on previous prices of the asset. However, this model has a flaw which is that it does not take in new data on the prices of bitcoin.

Bitcoin as with the entire cryptocurrency market has been extremely volatile in recent years and does not follow a very predictable pattern of behavior. This is especially true since we built this stochastic model using data only up to 2016 in order to simulate the price from 9/11/2016 to 9/10/2021. Thus **this model is not as good a predictor for bitcoin as it is for gold**.

After constructing stochastic models to simulate future asset prices, we see that **using randomness to simulate changes in bitcoin does not lead to very accurate simulations of the actual asset prices**.

There may be a way to combine predicting future values using stochasticity with predicting future values using past values that are updated every day which would make the simulation more accurate. However, we felt like we did not have the resources available to reevaluate the model many times to update it to include each day's prices. Additionally, random changes to the asset prices can be attributed to different economic and world events that affect the probability of an increase/decrease. Therefore we decided to look into other ways to approach the problem.

Thus we decided to use a deterministic approach since a good trading model should make the same decisions if it's given the same exact set of data in order to reliably be profitable, otherwise the end value of our portfolio could vary greatly simply by chance. After researching stock trading techniques, we decided on using a moving average to determine whether to buy, sell, or hold.

3.2 Moving Average

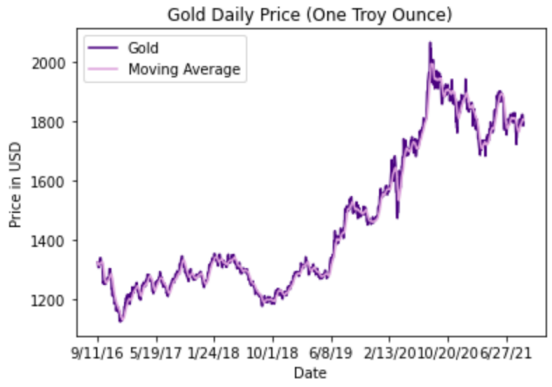
We decided to use the concept of a moving average in our initial model because it is a tool that is used in real life by stock traders that only requires knowledge of previous stock/asset prices. A moving average is used to estimate the trend of the value of the assets over a specified window of days. The moving average for each day is calculated by taking the average price of an asset from the previous k days.

Theoretically, the moving average would represent the trend that the stock should follow so if there are any significant variations in price then a correction in the opposite direction should also follow soon. This model allows us to take advantage of variations in the market in order to make money by buying when an asset suddenly drops below its predicted price, then selling it when the market corrects and increases again to what it should be.

For the model, we chose a window of fourteen days to calculate the moving average because we think that fourteen days can show an asset's trends relatively well. Thus, to mathematically calculate the moving average on the nth day — represented by MA_n — we calculated the sum of the actual values of the assets on each day — represented by x_k — 14 days prior to nth day and divided the sum by 14.

$$MA_n = \frac{1}{14} \sum_{k=n-14}^{n} x_k$$

Then, to create the plot of the moving average, for every day k, we plot the coordinates of (k, MA_k). We used a python function, rolling, to implement this formula and find the moving average of the asset prices up to a certain day.



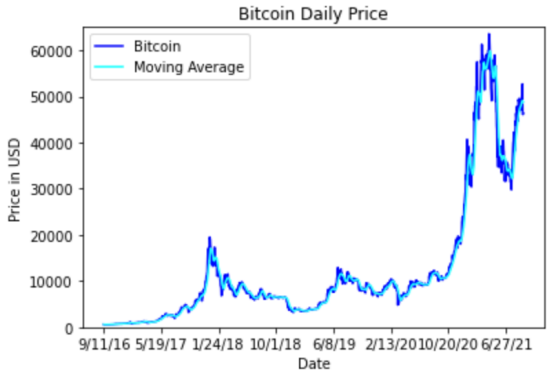


Figure 3.2.1: Gold daily price and moving average.
Figure 3.2.2: Bitcoin daily price and moving average.

As you can see from the figures, the gold moving average is very close to the actual gold prices, and same for bitcoin. Compared to our simulation of future gold and bitcoin prices, the moving average is a much better estimator of the stock prices. Therefore, we decided to utilize the moving average instead of predicting future prices in order to determine what action to take for that day. Because we are only allowed to use prices up to a certain day, each day we will reevaluate which actions to take based on the moving average prices up to that day. It should also be noted that despite both Figure 3.2.1 and Figure 3.2.2 having vast fluctuations, bitcoin is many times more volatile of an asset than gold.

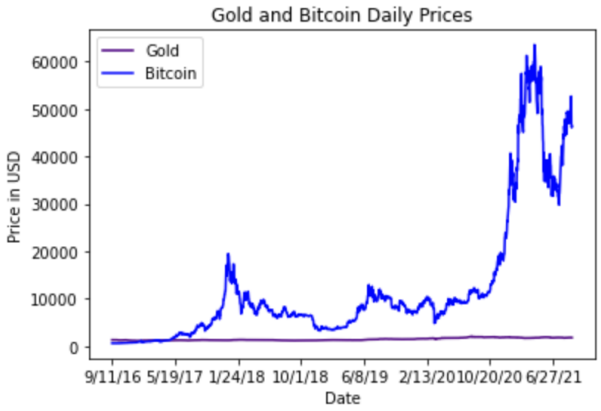


Figure 3.2.3: Bitcoin daily prices, U.S. dollars per bitcoin.

4. Update Assumptions

We first must update our model's assumptions after deciding to implement the moving average method. Thus we add the following assumption:

- Our moving average uses a window of 14 so that it examines the price of the previous 14 days in its calculations.

We then constructed a model and continued to refine and update it through several iterations by modifying our procedures for buying and selling the assets.

Trading Model 1: Initial buy/sell procedures.

In order for our model to be able to execute trades, we needed to implement thresholds that, if met, will have our model execute a transaction. We also needed to determine the transaction amounts for how much we would buy and sell. We first used static dollar amounts as the thresholds for both gold and bitcoin. We also set our purchase amount to use 50% of available cash and we set our sell amount to sell 100% of the asset.

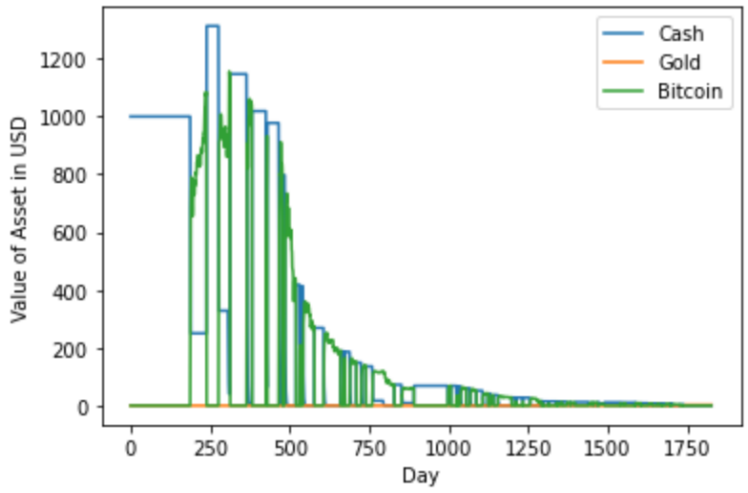
The procedures to buy/sell for this model are as follows:

- If the price of gold is less than its moving average by $75 or more, then we will use 50% of our available cash to purchase more gold.

- If the price of gold is more than its moving average by $75 or more, then we will sell all of the gold we are holding.
- If the price of bitcoin is less than its moving average by $200 or more, then we use 50% of available cash to purchase more bitcoin.
- If the price of bitcoin is greater than its moving average by $200 or more, then we sell all bitcoin we are holding.

Using the five number summary of the differences between the actual value and the moving average, we chose $75 and $200 thresholds as they were in the third quartile of each respective sample. The value of each asset was high enough that it would initiate enough transactions to allow us to visualize the effect of choosing a threshold.

We chose to use 50% of our available cash to buy a specific asset in order to allow our portfolio to still have remaining cash to both buy the other respective asset on the same day or continue to buy more assets in the future. We chose to sell 100% if selling an asset in order to maximize profits.



Trading Model 1: Initial buy/sell procedures

Model 1 Analysis:

Final Portfolio Value: $2.94
Number of Transactions: 1,113

This is not a good model, it lost almost all of its value during this time period. We believe this is due to the fact that we used fixed dollar amounts as the thresholds for when we would buy and sell. As a result, the same static value would represent different percentage differences and thus have different probabilities of happening at different price points.

Trading Model 2: Use percent differences for thresholds

We quickly realized that using a static number would lead to very poor trading decisions because of price changes in assets. Thus based on our analysis of Trading Model 1, we decided to refine our model to use percentage differences for the thresholds and keeping the other procedures the same.

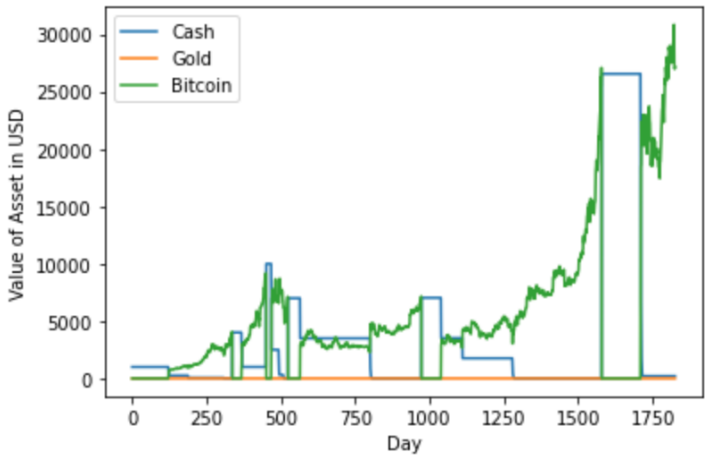
To calculate the percentage difference between the value of the asset at the specific day with the moving average up until then, we define T_n as this value. We took the actual price of the asset on that day, P_n, subtracted by the moving average, MA_n, and divided the difference value by actual price of the asset, P_n.

$$T_n = \frac{P_n - MA_n}{P_n}$$

The procedures to buy/sell for this model are as follows:

- Buy thresholds: Percent difference <= **-20%** for both gold and bitcoin
- Sell thresholds: Percent difference >= **20%** for both gold and bitcoin
- Buy amounts: Use 50% of available cash to buy the respective asset
- Sell Amounts: Sell 100% of the respective asset

We made our threshold change to be set at 20% to represent significant deviations that the asset's price had from the moving average.



Trading Model 2: Percent Differences for thresholds

Model 2 Analysis:

Final Portfolio Value: $27,344.13
Number of Transactions: 63

We see that this model performs magnitudes better than model one, not only does it increase the portfolio value, we see an increase in value of over 2700%. We see that there are much fewer

transactions when compared to Model 1 (63 transactions instead of 1113), thus we think that this means our model may be becoming refined enough to pick out the most profitable trades to execute.

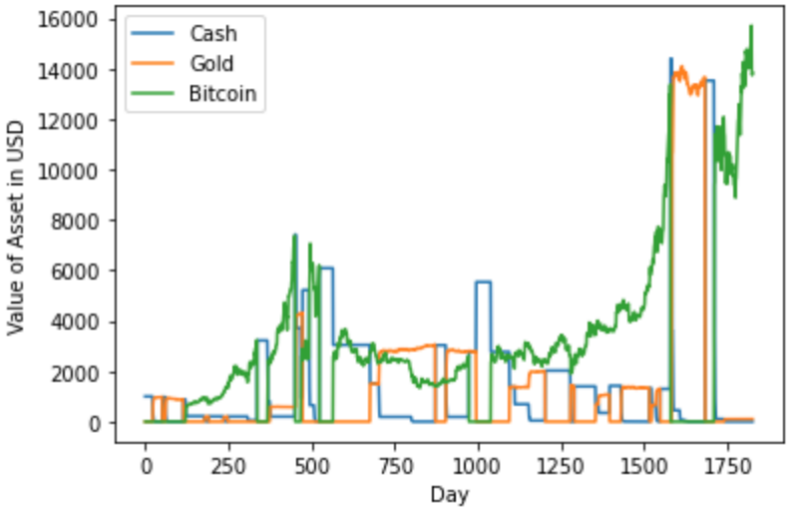
Trading Model 3: Changing threshold for gold

We noticed in Model 2 it did not have any transactions for gold. Indeed, referring to the distribution of daily percent changes, we see gold fluctuates a maximum of 5% above or below the moving average. Thus we decided to see how our model may improve by varying the gold threshold between 2% and 4%.

Model 3.1:

The procedures to buy/sell for this model are as follows:

- Buy thresholds: **-4%** for gold and -20% for bitcoin
- Sell thresholds: **4%** for gold and 20% for bitcoin
- Buy amounts: Use 50% of available cash to buy the respective asset
- Sell Amounts: Sell 100% of the respective asset



Trading Mode 3.1: Gold 4% thresholds

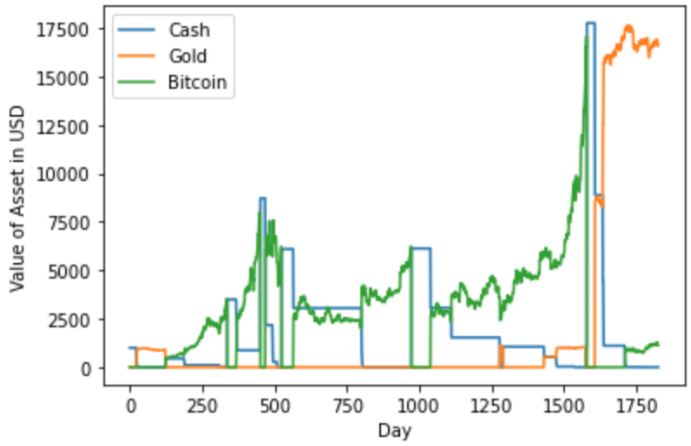
Final Portfolio Value: $13,931.00

Number of Transactions: 311

Model 3.2:

The procedures to buy/sell for this model are as follows:

- Buy thresholds: **-3%** for gold and -20% for bitcoin
- Sell thresholds: **3%** for gold and 20% for bitcoin
- Buy amounts: Use 50% of available cash to buy the respective asset
- Sell Amounts: Sell 100% of the respective asset



Trading Mode 3.2: Gold 3% threshold

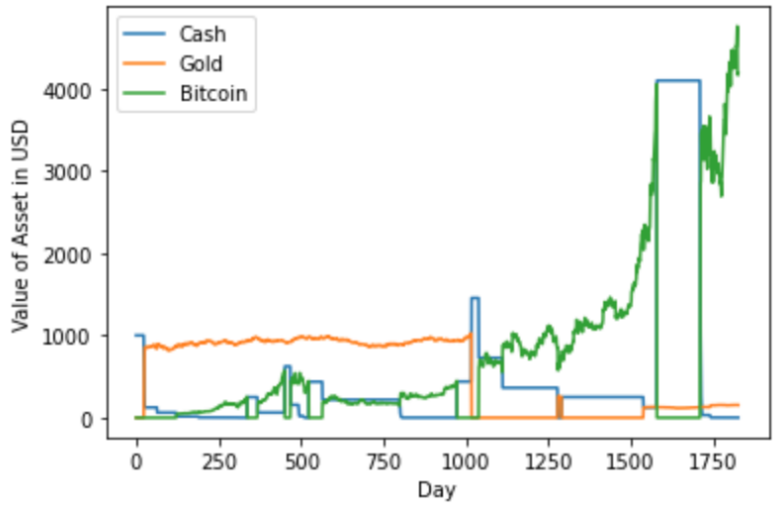
Final Portfolio Value: $17,770.20

Number of Transactions: 152

Model 3.3:

The procedures to buy/sell for this model are as follows:

- Buy thresholds: **-4%** for gold and -20% for bitcoin
- Sell thresholds: **4%** for gold and 20% for bitcoin
- Buy amounts: Use 50% of available cash to buy the respective asset
- Sell Amounts: Sell 100% of the respective asset



Trading Mode 3.3: Gold 4% Threshold

Final Portfolio Value: $4,321.69

Number of Transactions: 100

Model 3 Analysis:

The best iteration of Model 3 was Model 3.2, which changed the threshold of gold to 3% and had a **final portfolio value of $17770.20 with 152 transactions**. We will continue to use 3% for future gold thresholds as a result.

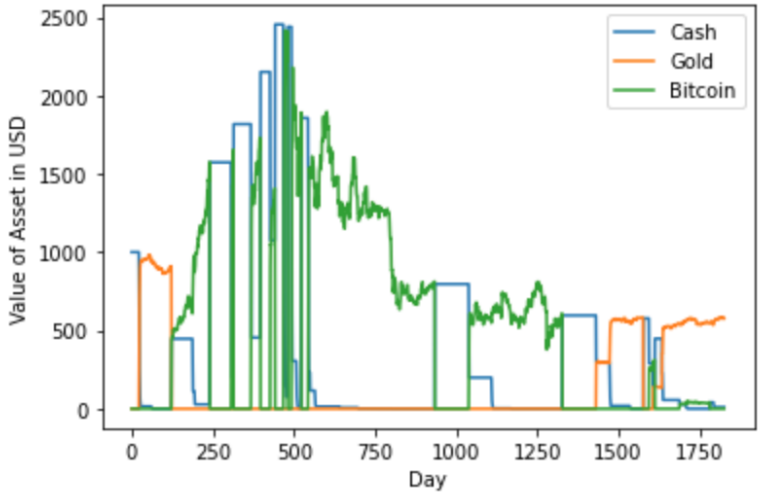
Trading Model 4: Changing the threshold for bitcoin

After finding an optimal threshold for gold, we decided to try further refine our model by adjusting the threshold for bitcoin too. We previously examined thresholds for bitcoin of 20%, thus we will examine thresholds of 15% and 25% in Model 4.

Model 4.1:

The procedures to buy/sell for this model are as follows:

- Buy thresholds: -3% for gold and **-15%** for bitcoin
- Sell thresholds: 3% for gold and **15%** for bitcoin
- Buy amounts: Use 50% of available cash to buy the respective asset
- Sell Amounts: Sell 100% of the respective asset

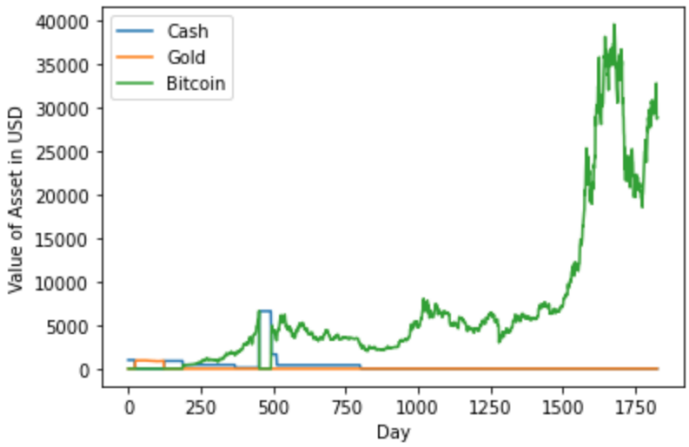


Trading Mode 4.1: Bitcoin 15% threshold

Final Portfolio Value: $586.57
Number of Transactions: 242

Model 4.2:

- Buy thresholds: -3% for gold and **-25%** for bitcoin
- Sell thresholds: 3% for gold and **25%** for bitcoin
- Buy amounts: Use 50% of available cash to buy the respective asset
- Sell Amounts: Sell 100% of the respective asset



Trading Mode 4.2: Bitcoin 25% threshold

Final Portfolio Value: $28,847.89

Number of Transactions: 115

Model 4 Analysis:

We see that changing the bitcoin threshold to 15% or 25% did not result in better model performance. Neither Model 4.1 nor Model 4.2 had outperformed what we saw with using the 20% threshold in Model 2 which had a **final portfolio value of $27,344.13 with 63 trades.**. Thus we will continue to use 20% as the threshold for bitcoin in future models.

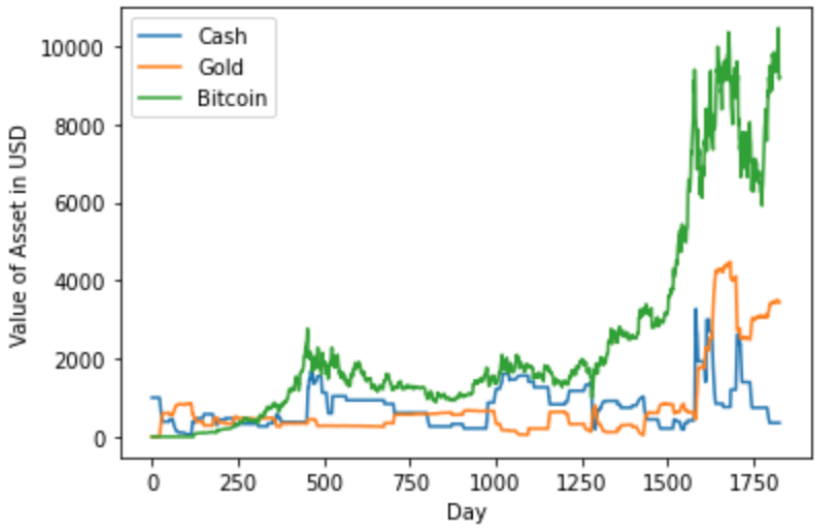
Trading Model 5: Increasing trading frequency

After finding optimal thresholds, we decided to increase the frequency of our trades by reducing our thresholds and simultaneously reducing the amounts that we bought/sold in each transaction. **We decreased the gold threshold from 3% to 2%. We also decreased the bitcoin threshold from this previously best performing model from 25% to 20%.** And since we're increasing the frequency of trading, we thought instead of buying with 50% of our cash and selling 100% of an asset, we could **examine the results of using buy/sell amounts of 10%, 20%, and 50%.**

Model 5.1:

The procedures to buy/sell for this model are as follows:

- Buy thresholds: **-2%** for gold and **-20%** for bitcoin
- Sell thresholds: **2%** for gold and **20%** for bitcoin
- Buy amounts: **Use 10% of available cash to buy the respective asset**
- Sell Amounts: **Sell 10% of the respective asset**



Trading Mode 5.1: Buy/Sell amounts are 10%

Final Portfolio Value: $13,005.39

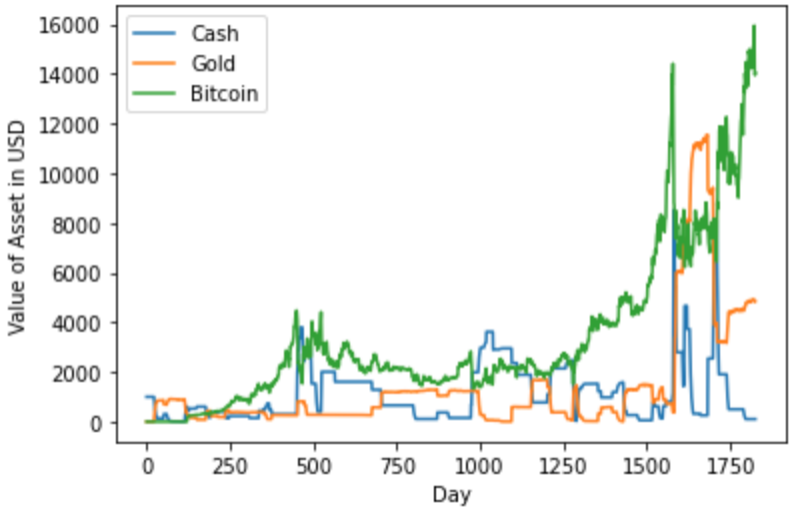
Number of Transactions: 311

Model 5.2:

The procedures to buy/sell for this model are as follows:

The procedures to buy/sell for this model are as follows:

- Buy thresholds: **-2%** for gold and **-20%** for bitcoin
- Sell thresholds: **2%** for gold and **20%** for bitcoin
- Buy amounts: **Use 20% of available cash to buy the respective asset**
- Sell Amounts: **Sell 20% of the respective asset**



Trading Mode 5.2: Buy/sell amounts are 20%

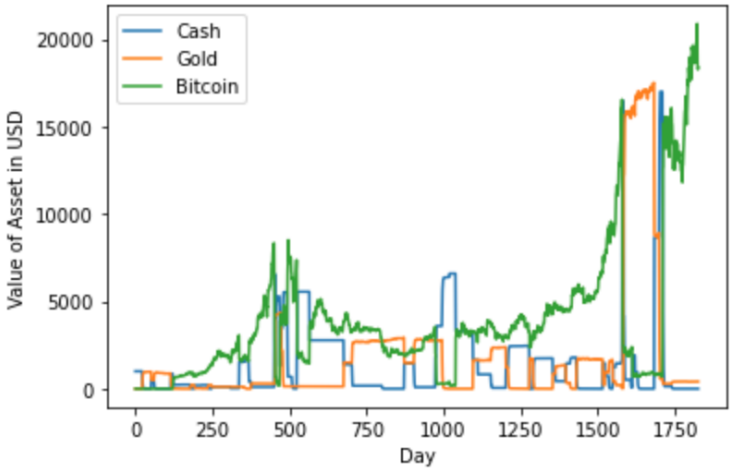
Final Portfolio Value: $18,988.26

Number of Transactions: 311

Model 5.3:

The procedures to buy/sell for this model are as follows:

- Buy thresholds: **-2%** for gold and **-20%** for bitcoin
- Sell thresholds: **2%** for gold and **20%** for bitcoin
- Buy amounts: **Use 50% of available cash to buy the respective asset**
- Sell Amounts: **Sell 50% of the respective asset**



Trading Mode 5.3: Buy/Sell Amounts are 50%
Final Portfolio Value: $18,793.73
Number of Transactions: 311

Model 5 Analysis:

The best iteration of Model 5 was Model 5.2. We kept the same thresholds from earlier and increased our transaction amounts to using 20% when buying and selling 20% of an asset in the event of a sale. Of all iterations in Model 5, we saw a that Model 5.2 had the **best final portfolio value of $18988.26 with 311 trades.** Thus we will use this transaction amount for future models too.

Trading Model 6: Initial Diversification

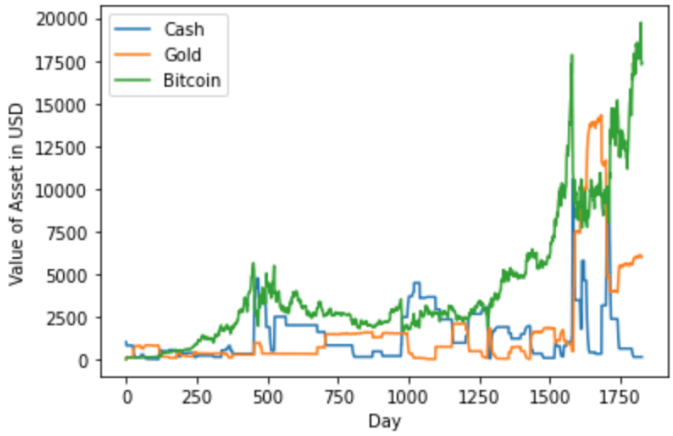
We noted that since the value of cash stays static, it may be beneficial to initially invest our portfolio into gold and bitcoin so that we can also benefit more from days in which we don't make trades and the value of gold or bitcoin rises. Having an initial investment in both will allow us to examine whether keeping an asset for longer improves or hinders our end result.

Model 6.1:

The procedures to buy/sell for this model are as follows:

- **We buy $100 worth of gold and $100 worth of bitcoin on the first day to diversify.**
- Buy thresholds: -2% for gold and -20% for bitcoin

- Sell thresholds: 2% for gold and 20% for bitcoin
- Buy amounts: Use 20% of available cash to buy the respective asset
- Sell Amounts: Sell 20% of the respective asset



Trading Mode 6.1: Initial Diversification, $100 in each asset.

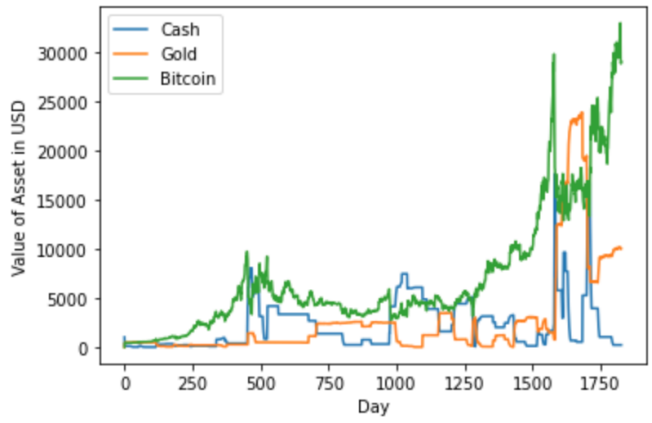
Final Portfolio Value: $23,498.22

Number of Transactions: 311

Model 6.2:

The procedures to buy/sell for this model are as follows:

- **We buy $450 worth of gold and $450 worth of bitcoin on the first day to diversify.**
- Buy thresholds: -2% for gold and -20% for bitcoin
- Sell thresholds: 2% for gold and 20% for bitcoin
- Buy amounts: Use 20% of available cash to buy the respective asset
- Sell Amounts: Sell 20% of the respective asset



Trading Mode 6.2: Initial Diversification, $450 in each asset.

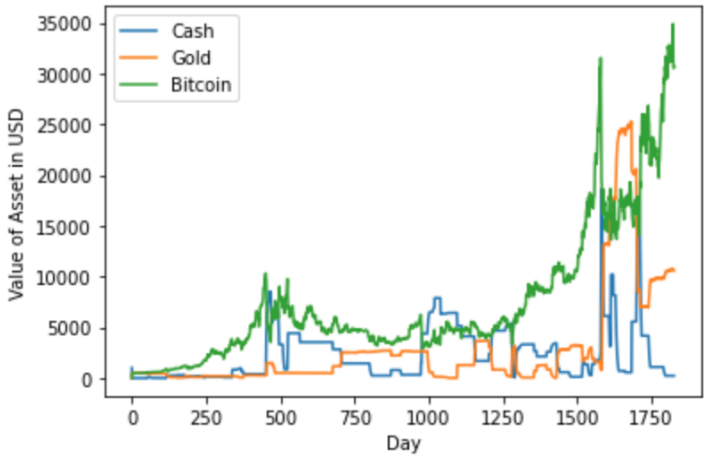
Final Portfolio Value: $39,283.12

Number of Transactions: 311

Model 6.3:

The procedures to buy/sell for this model are as follows:

- **We buy $500 worth of gold and $500 worth of bitcoin on the first day to diversify.**
- Buy thresholds: -2% for gold and -20% for bitcoin
- Sell thresholds: 2% for gold and 20% for bitcoin
- Buy amounts: Use 20% of available cash to buy the respective asset
- Sell Amounts: Sell 20% of the respective asset



Trading Mode 6.3: Initial Diversification, $500 in each asset.

Final Portfolio Value: $41,538.10

Number of Transactions: 311

Model 6 Analysis:

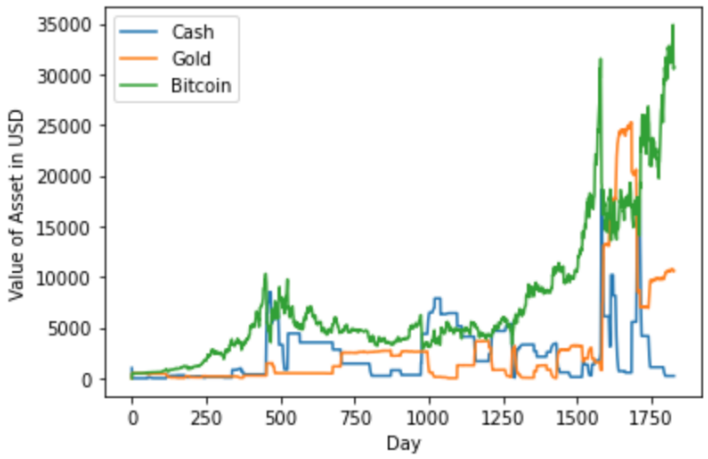
The best iteration of Model 6 was Model 6.3. We kept all the same parameters from earlier in Model 5.2 and additionally invested $500 in gold and $500 in bitcoin on day 1.

Of all iterations in Model 6, we saw that Model 6.3 had the **best final portfolio value of $41,538.10 with 311 trades.** This is the best performing model we have yet to create and will be our final model.

Final Model:

Our final model was most successful. At the very end our model had the following conditions:

- We buy $500 worth of gold and $500 worth of bitcoin on the first day to diversify.
- Buy thresholds: -2% for gold and -20% for bitcoin
- Sell thresholds: 2% for gold and 20% for bitcoin
- Buy amounts: Use 20% of available cash to buy the respective asset
- Sell Amounts: Sell 20% of the respective asset



Trading Mode 6.3: Initial Diversification, $500 in each asset.

Final Portfolio Value: $41,538

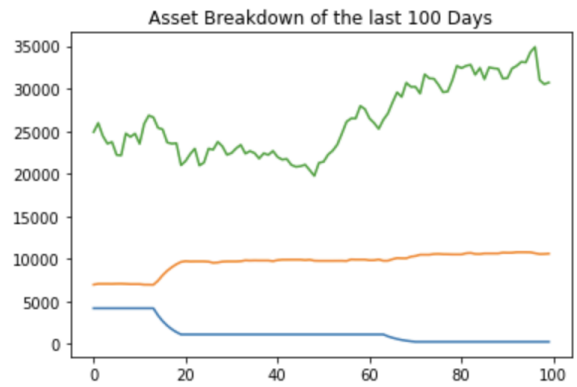
Number of Transactions: 311

Analysis of Model's Performance

Examining our final model, we see that on 9/10/21, we are predicted to have $41,538, which is over forty times the value we started with. Though most individual portfolios don't grow at this extremely successful rate, a large part of the model's success was identifying the potential of bitcoin. Over the last decade, bitcoin has grown at exponential rates and accounts for a large proportion of the final valuation. These results are realistic as the value of bitcoin increased from $1 a share in 2011 to $1,000 in 2017[1]. Using a combination of multiple factors also reflects reality as stock traders buy/sell at different rates, create thresholds at which to take action, and initially invest a set amount of money into a potentially successful stock. Diversifying by investing half of the liquid funds into gold and the other half into bitcoin resembles the strategy of investing in an asset that has slow growth but is likely to go up (gold) and a new asset to the market that offers immense potential to do well (bitcoin).

Since all computations were completed in Python, we can assume the calculations are correct.

[1] (DeMatteo)



This figure highlights the asset breakdown of the last 100 days leading up to the final day of 9/10/21. Here we can see the smaller changes as the value change is reflected in our state list. This highlights how our model follows the day to day value of each asset and makes a decision to buy, sell, or hold. In the last 100 days, we see bitcoin fluctuating much more rapidly and leading to significant growth whereas the value of gold slightly increases over the 100 day window, which was the motivation behind choosing the percent difference threshold levels.

We also looked at the stability of our model by seeing how it was affected by changes in the transaction fees, which was defined to be constant in the problem set. The purpose of testing this with different values was to check the sensitivity of our model, and to make sure that there was no unforeseen reliance on the transaction fees being constant. To achieve this, we tested two different transaction fees, one that was 4 times larger than those given in the problem, so a gold transaction fee of 4% and a bitcoin transaction fee of 8%, and another where there were no transaction fees. Changing the transaction fee did not change the number of transactions we made or their distribution, but it did change the amount of money that each transaction made.

Even though changing the transaction fees did have a somewhat significant effect on the total profit that our model made, with the increased transaction fees leading to an ending value of $28,591.22, a loss of $12,946.88, and a removal of the transaction fees leading to an ending value of $47,073.06, an increase of $5,534.96, this still proves that our model was successful. Through Training Model 5, we tried to increase the amount of trades that were made, and we were successful in doing so, but that also means that transaction fees had a larger effect on the outcome of our model, which was shown in the results of changing these fees.

5. Future Improvements

Moving forward, there are various ways to improve the model to better predict when to buy, sell, or hold. One way would be when buying or selling; rather than using 20% of funds to buy or selling 20% of the asset, selling or buying proportionally to the rate at which difference increased or decreased would help to capitalize on the occurrences when there were extreme peaks or

valleys. For example, if the percent difference of the moving average and the value was greater than 30%, we could sell a bigger proportion in comparison to if the percent difference was 15%.

Another improvement to the model would be to implement the acceleration of an asset's change in price. If we saw that bitcoin was accelerating down, we could assume the price would drop soon and thus sell. Analyzing when an asset's change in price was either accelerating upwards or downwards would allow the model to more accurately buy, sell, or hold right at the bottom of the peaks and valleys.

Furthermore, we could have added an element which accounted for significant drops, such as those caused by overall stock market crashes. We could have done this by implementing a counter that takes into account the number of days that a stock is increasing or decreasing, and using this value to cap the amount that we would buy and sell based on those changes.

6. Conclusion:

We started trying to create a stochastic model in order to predict what will happen with the stock market, but it ended up producing inaccurate day-to-day results. Because of this, we started using and eventually settled on a deterministic model which is based on moving averages, and yielded more accurate results.

From this, we were able to make an initial trading model. This model was still flawed, so we began editing the thresholds for when to buy and sell gold and bitcoin to create a more successful model. The first change looked at the transaction differences in percentages as opposed to absolute values. From this, we found that gold should have a lower threshold, since it's less volatile, so that we were still making transactions with gold. From here, we created a model which lowered the overall thresholds for trading, so that we were making more frequent trades, which we found to be more profitable. Finally, we created a model to test with an initial diversification, starting with different initial values. We know that the stock market will increase in the long term, so by starting with initial values invested in both Gold and Bitcoin, we are taking advantage of this, ensuring that we are making a long term profit in addition to the short term, day-to-day trades that also made profit. Once we had our final model, we looked at the effect of different transaction fees to make sure that they had a reasonable effect on our model, which they did. From our final model, with the initial condition of having $1000, we ended with $41,538 at the last day, resulting in a profit of $40,538, which is a successful margin, proving the success and validity of our model.

6.1 Report of Contributions:

Stochastic price prediction model - Megan
Deterministic price prediction model and moving averages - Ryan

Initial trading model and models with changed gold threshold - Alyssa
Model with percent differences, models with changed bitcoin threshold, and models with more frequent trading - Kevin
Diversified model and testing of the final model - Zayne

7. Memorandum:

To: Traders
From: Kevin Tang, Megan Ma, Zayne Kratz, Ryan Kawamura, Alyssa Lung
Date: June 10, 2008
Subject: Trading Strategies

Utilizing only the past stream of daily prices to date, we have created a model to predict the future prices of gold and bitcoin, and decide whether to buy, sell, or hold. Our strategy is to hold if the asset value is expected to increase, sell when the value is expected to increase, and buy when the value is low but expected to increase. To accomplish this we generated a set of criteria to take action upon.

Our model:

1. Predictive - using previous prices to predict the price of an asset in the future.
2. Trading - using criteria and the predicted value, we decide whether to buy, sell, or hold.

We first used a stochastic model to represent the fluctuations of an asset from day to day. Percent changes from the last twenty years were examined to create a distribution representative of the random fluctuation. However, we discovered that while stochasticity was somewhat successful for predicting gold, it was not successful for predicting bitcoin mainly due to the fact that bitcoin is newer to the market and thus has less data to examine.

Next we use a moving average to predict future values. Using a 14 day window, we concluded that the moving average was a strong predictor of future values as it followed the same patterns and fluctuations of the actual data.

To construct our model, we decided upon criteria to determine when to sell or buy each asset. Moreover, we decided to use the percent difference between the moving average and the actual value on that day. We varied the percent difference thresholds for bitcoin and gold to determine which value was ideal. Next, we evaluated how changing the proportion of asset or cash value we sold or bought at would affect the model. This means instead of selling 100% of an asset when the criteria to sell it was met, we only sell X%. The same goes for buying. Lastly, we looked at whether initially investing in each asset would affect our final portfolio value.

Therefore, we are suggesting that the best strategy for you to use in order to maximize your profit by the end of the trading window is to follow the thresholds and buying actions as detailed in our final model 6.3. You should diversify your portfolio by investing $500 in gold and $500 in bitcoin at the start of the period of which you are looking to trade. By following the buy and sell thresholds, and buy and sell amounts as detailed in our model, you will be able to maximize

profit. We have optimized these thresholds through multiple iterations of testing in order to result in the best return on your investment.

After running the final model, our final portfolio value on 9/10/21 was $41,538 and the total number of transactions was 311. Analyzing our results in comparison to changes in gold and bitcoin until the end date, we see the results are relatively similar to the growth and decline of each asset.

Additionally, analyzing the transaction rates (1% for gold and 2% for bitcoin), we see that increasing the rates to 4% for gold and 8% for bitcoin, our end value was $28,591.22, a loss of $12,946.88. Changing the rates to 0, the end value was $47,073.06, an increase of $5,534.96.

One area of suggested improvement is selling or buying proportionally to the rate at which difference increased or decreased would help to capitalize on the occurrences when there were extreme peaks or valleys. Another improvement for the future is to consider the acceleration of stock prices to see when a decrease or increase was slowing down, this would allow the model to purchase at the lowest valleys and highest peaks. Furthermore, we could have added an element which accounted for significant drops, such as those caused by overall stock market crashes.

From our final model, with the initial condition of having $1000, we ended with $41,538 at the last day, resulting in a profit of $40,538, which is a successful margin, proving the success and validity of our model.

8. **Reference List:**

1. “Bitcoin Historical Data.” *Investing.com*, https://www.investing.com/crypto/bitcoin/historical-data. Accessed 10 June 2022.
2. DeMatteo, Megan. “Bitcoin Price History 2009-2022 | NextAdvisor with TIME.” *TIME*, https://time.com/nextadvisor/investing/cryptocurrency/bitcoin-price-history/. Accessed 10 June 2022.
3. “Gold Futures Historical Prices.” *Investing.com*, https://www.investing.com/commodities/gold-historical-data. Accessed 10 June 2022.
4. “6.2 Moving averages | Forecasting: Principles and Practice (2nd ed).” *OTexts*, https://otexts.com/fpp2/moving-averages.html. Accessed 10 June 2022.