



# Portfolio Python

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# Introduction

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- Select Stocks (2-4) @ current risk with 3 yr predicted Close
- Input Variable: Historical Close
- Target Variable: Predicted Close (3 yrs) (Reflecting Investor Retire date)
- Worked/Didn't work: Will Review by model
- Monte Carlo chosen as accurate historical predictor
- FB Prophet chosen as a well functioning predictor (separate and seasonality from data.)



# Cupcake, Birthday Cake and Wedding Cake

	Analyze Portfolio Cupcake	Optimization of Portfolio Birthday Cake	Portfolio Selection Wedding Cake
Models	Pandas	FB Prophet  Machine Learning sklearn Random Forest Monte Carlo	Regression Anal, Lin Regression, Neural Network- TensorFlow, Keras Dashboard
Data Source	CSV, ALPACA	ALPACA Yfinance,	API
Variables	Closing Price NASD, SPY DJIA	Closing Price, Returns  News Stock, Rumors	Closing Price, Returns
Code Structure	Stock,Pandas, PIP Install Functions	Stock Class LSTM Stk Pred Portfolio Class Functions	StreamSt StatsModel Time Series
Visualization	pathlib, plotlib	plot_plotly,	
Investments	ADP, BR, CDK, AAPL, GOOG, NFLIX, NVDA	AAPL, AMZN,GOOG, NVDA, NTFX, FB, PFE, (BIIB -Bio place holder ) 8 Stocks	BTC, ETH, SOL, ADA (C DOGE, AVAX (narrow



# FB Prophet (Model 1) Code Slide 1

```
In [1]: 1 import streamlit as st
        2 from path import Path
        3 from datetime import date
        4 import pandas as pd
```

```
In [2]: 1 import yfinance as yf
        2 from prophet import Prophet
        3 from fbprophet.plot import plot_plotly
        4 from plotly import graph_objs as go
        5 START = "2016-01-01"
        6 TODAY = date.today().strftime("%Y-%m-%d")
        7 st.title("Anthon Stock Predictor")
        8 stocks = ("AAPL", "AMZN", "GOOG", "NTEFX", "NTEFX", "ORCL", "TSLA", "FB", "PFE", "BIIB")
        9 selected_stocks = st.selectbox("Select dataset for prediction", stocks)
       10 n_years = st.slider("Years of Prediction:", 1, 4)
       11 period = n_years * 365
       12 #(venv) stock prediction code
       13 #(venv) stock prediction streamlit run main.py
       14 def load_data(ticker):
       15     data = yf.download(ticker, START, TODAY)
       16     data.reset_index(inplace=True)
       17     return data
       18
       19 ##Set stock to analyze
       20 selected_stock = "AMZN"
       21
       22 data_load_state = st.text("Load data...")
       23 data = load_data(selected_stock)
       24 data_load_state.text("Loading data...done!")
       25
       26 # Forecasting
       27 df_train = data[['Date', 'Close']]
       28 df_train = df_train.rename(columns= {"Date": "ds", "Close": "y"})
       29
       30 m=Prophet()
       31 m.fit(df_train)
       32 future = m.make_future_dataframe (periods=period)
       33 forecast = m.predict(future)
       34
       35 print("AMAZON:")
       36
       37 st.subheader ('Forecast data')
       38 st.write(forecast.tail())
       39 st.write('forecast data')
       40 #Fig1 = plot_plotly (m.forecast)
       41 st.write('forecast components')
       42 Fig2 = m.plot_components(forecast)
       43 st.write(Fig2)
```



## FB Prophet Code 2

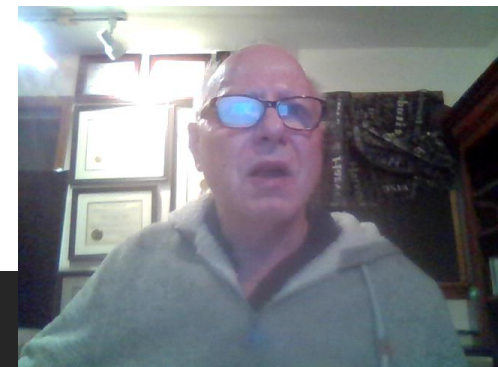
```
In [3]: 1  ##Set stock to analyze
        2  selected_stock = "GOOG"
        3
        4  data_load_state = st.text("Load data...")
        5  data = load_data(selected_stock)
        6  data_load_state.text("Loading data...done!")
        7
        8  # Forecasting
        9  df_train = data[['Date', 'Close']]
       10  df_train = df_train.rename(columns= {"Date": "ds", "Close": "y"})
       11
       12  m=Prophet()
       13  m.fit(df_train)
       14  future = m.make_future_dataframe (periods=period)
       15  forecast = m.predict(future)
       16
       17  print("GOOGLE:")
       18
       19  st.subheader ('Forecast data')
       20  st.write(forecast.tail())
       21  st.write('forecast data')
       22  #Fig1 = plot_plotly (m.forecast)
       23  st.write('forecast components')
       24  Fig2 = m.plot_components(forecast)
       25  st.write(Fig2)
```





## FB Prophet Code Slide 3

```
: 1  ##Set stock to analyze
2  selected_stock = "PFE"
3
4  data_load_state = st.text("Load data...")
5  data = load_data(selected_stock)
6  data_load_state.text("Loading data...done!")
7
8  # Forecasting
9  df_train = data[['Date', 'Close']]
10 df_train = df_train.rename(columns= {"Date":"ds", "Close":"y"})
11
12 m=Prophet()
13 m.fit(df_train)
14 future = m.make_future_dataframe (periods=period)
15 forecast = m.predict(future)
16
17 print("PFE:")
18
19 st.subheader ('Forecast data')
20 st.write(forecast.tail())
21 st.write('forecast data')
22 #Fig1 = plot_plotly (m.forecast)
23 st.write('forecast components')
24 Fig2 = m.plot_components(forecast)
25 st.write(Fig2)
```



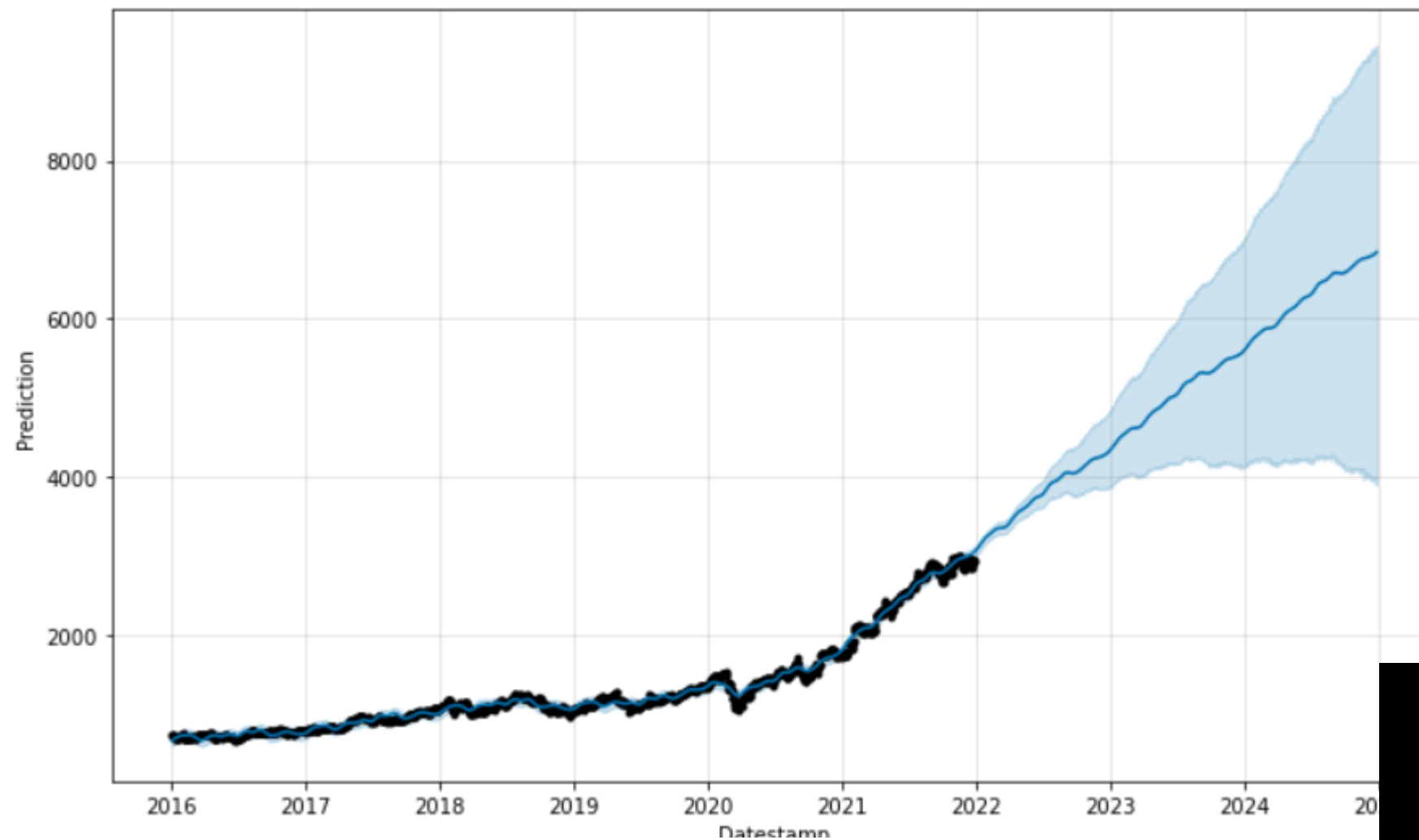
## FB Prophet Code 4

```
In [5]: 1  ##Set stock to analyze
        2  selected_stock = "NFLX"
        3
        4  data_load_state = st.text("Load data...")
        5  data = load_data(selected_stock)
        6  data_load_state.text("Loading data...done!")
        7
        8  # Forecasting
        9  df_train = data[['Date', 'Close']]
       10  df_train = df_train.rename(columns= {"Date":"ds", "Close":"y"})
       11
       12  m=Prophet()
       13  m.fit(df_train)
       14  future = m.make_future_dataframe (periods=period)
       15  forecast = m.predict(future)
       16
       17  print("NETFLIX:")
       18
       19  st.subheader ('Forecast data')
       20  st.write(forecast.tail())
       21  st.write('forecast data')
       22  #Fig1 = plot_plotly (m.forecast)
       23  st.write('forecast components')
       24  Fig2 = m.plot_components(forecast)
       25  st.write(Fig2)
```



# Googol Close Price Trend (USD)

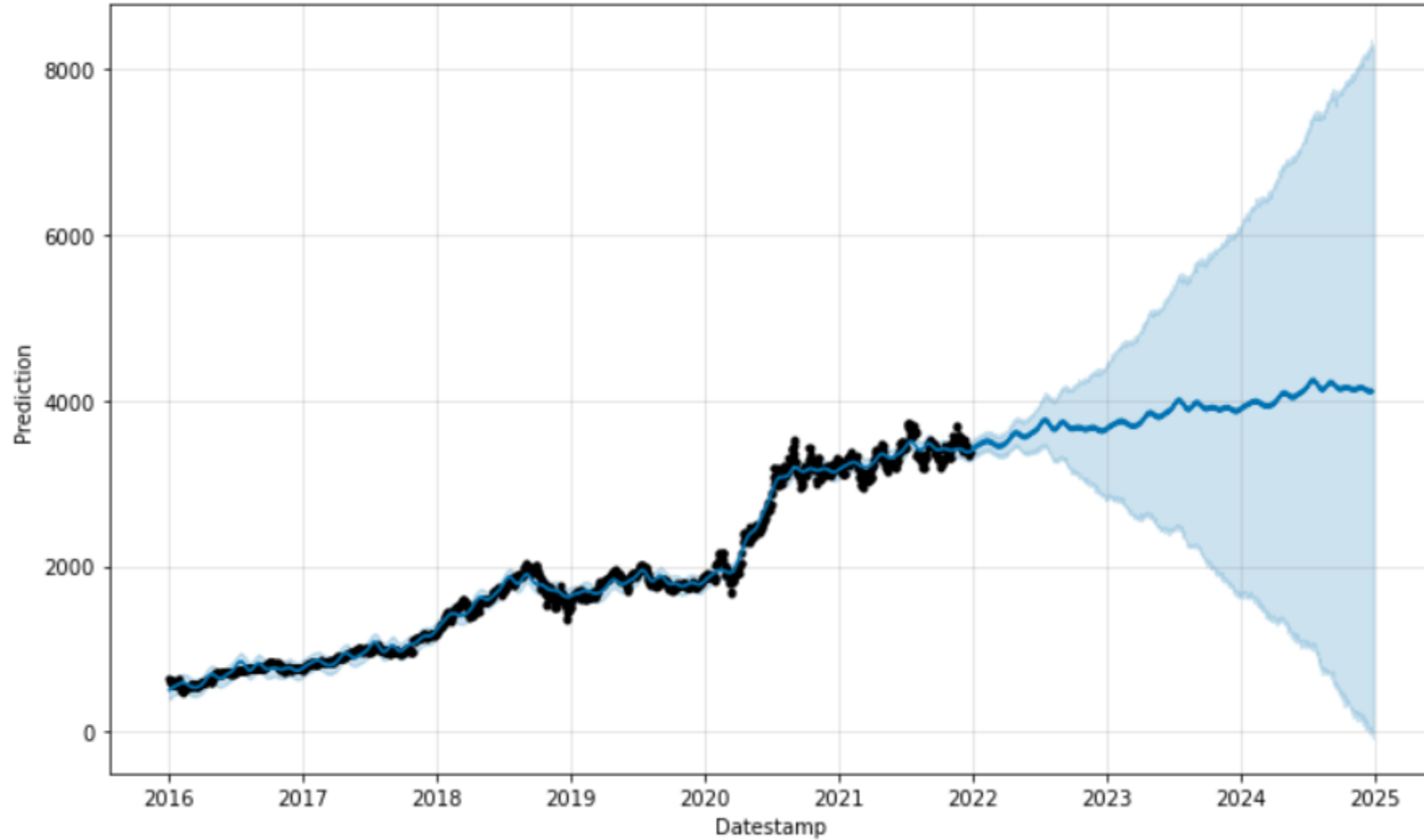
GOOG Daily plot:



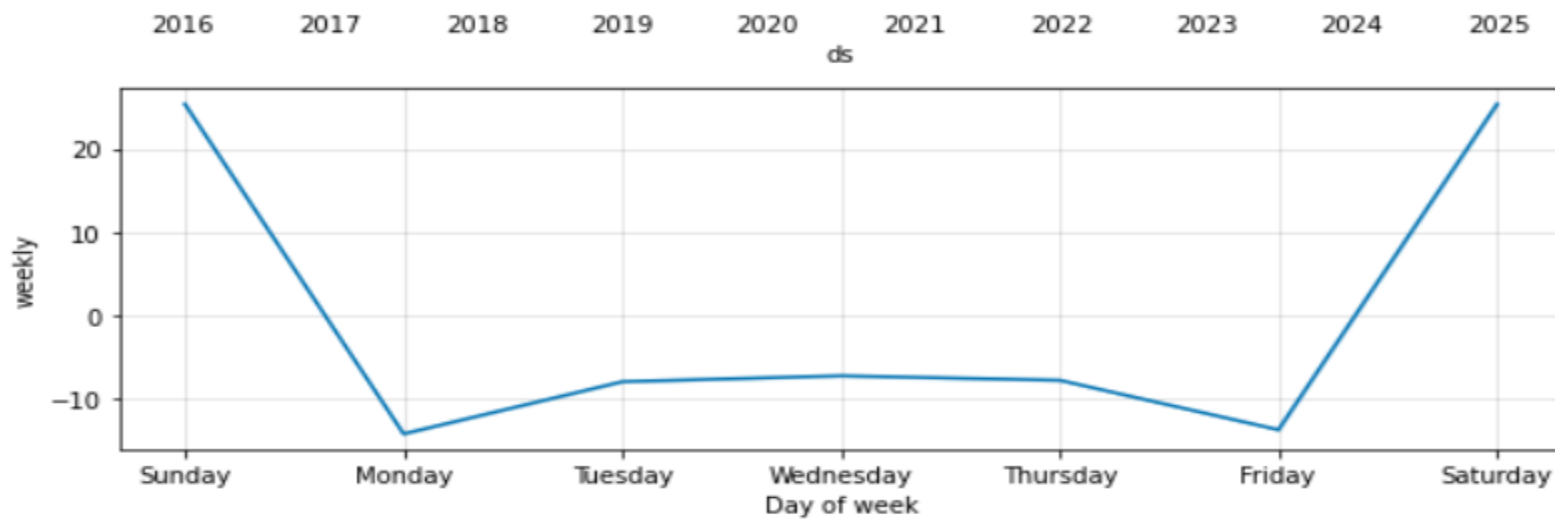
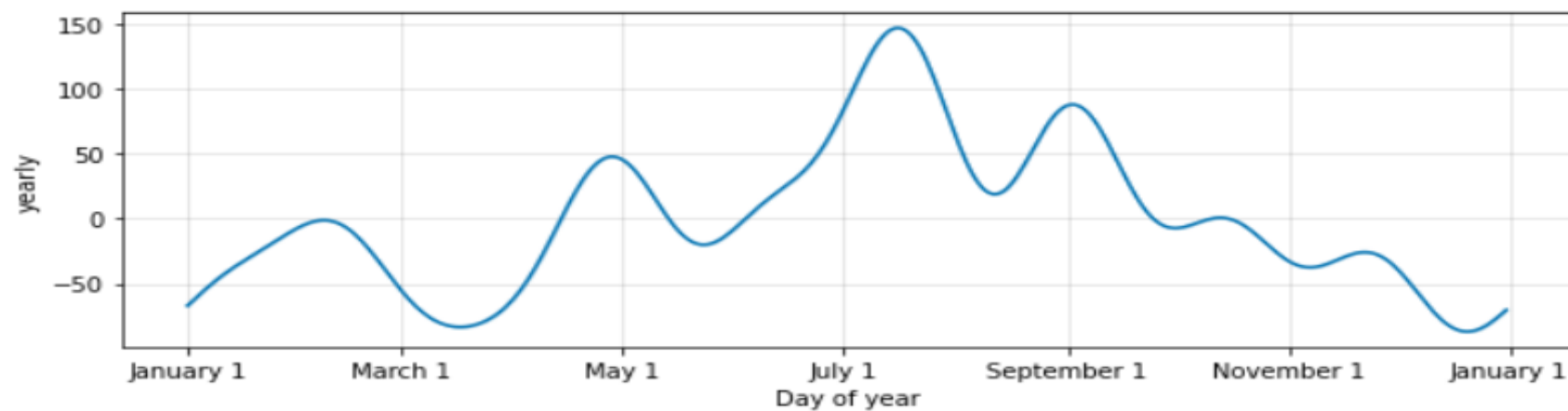


# Amazon Close Price Trend (USD)

Daily plot:



YEARLY SEASONALITY (USD) above  
WEEKLY VARIABILITY (USD) below



# MC Simulation Code Slide1

```
In [1]: 1 # Initial imports
        2 import os
        3 import requests
        4 import pandas as pd
        5 from dotenv import load_dotenv
        6 import alpaca_trade_api as tradeapi
        7 from MCForecastTools import MCSimulation
        8
        9 %matplotlib inline
```

```
In [2]: 1 # Load .env environment variables
        2 load_dotenv()
```

Out[2]: True

```
In [3]: 1 # Set start and end dates of three years back from today.
        2 start_date = pd.Timestamp('2019-01-01', tz='America/New_York').isoformat()
        3 end_date = pd.Timestamp('2021-12-17', tz='America/New_York').isoformat()
```

```
In [4]: 1 # Set Alpaca API key and secret
        2 alpaca_api_key = os.getenv("ALPACA_API_KEY")
        3 alpaca_secret_key = os.getenv("ALPACA_SECRET_KEY")
        4
        5 # Create the Alpaca API object
        6 api = tradeapi.REST(
        7     alpaca_api_key,
        8     alpaca_secret_key,
        9     api_version = "v2"
       10 )
       11
```

## MC Simulation Code 2

```
5]: 1 # Get 5 years' worth of historical data for AMZN, GOOG
    2 tickers = ["AMZN", "GOOG"]
    3
    4 # Set timeframe to '1D' for Alpaca API
    5 timeframe = "1D"
    6
    7 # Get current closing prices for AMZN, GOOG
    8 df_stock_data_1 = api.get_barset(
    9     tickers,
   10     timeframe,
   11     start=start_date,
   12     end=end_date,
   13     limit=756
   14 ).df
   15
   16 next_start_date = pd.Timestamp('2017-01-01', tz='America/New_York').isoformat()
   17 next_end_date = pd.Timestamp('2019-01-01', tz='America/New_York').isoformat()
   18
   19 df_stock_data_2 = api.get_barset(
   20     tickers,
   21     timeframe,
   22     start=next_start_date,
   23     end=next_end_date,
   24     limit=756
   25 ).df
   26
   27 df_stock_data = pd.concat([df_stock_data_2, df_stock_data_1])
   28
   29 # Display sample data
   30 df_stock_data.head()
```

# MC Simulation Code 3

## Dataframe heads

[5]:

time	AMZN					GOOG				
	open	high	low	close	volume	open	high	low	close	volume
2017-01-03 00:00:00-05:00	757.92	758.7595	747.7000	753.66	2511913	778.81	789.6300	775.8000	786.14	1061256
2017-01-04 00:00:00-05:00	758.24	759.6800	754.2000	757.18	1671835	788.36	791.3400	783.1600	786.87	634357
2017-01-05 00:00:00-05:00	761.55	782.3999	760.2557	780.45	4401014	786.08	794.4800	785.0200	794.02	762295
2017-01-06 00:00:00-05:00	782.28	799.4400	778.4800	795.99	4559445	795.26	807.9000	792.2041	806.12	967970
2017-01-09 00:00:00-05:00	798.00	801.7742	791.7700	796.92	2551340	806.40	809.9664	802.8300	806.58	777816

[6]: 1 df\_stock\_data\_1

[6]:

time	AMZN					GOOG				
	open	high	low	close	volume	open	high	low	close	volume
2019-01-02 00:00:00-05:00	1465.20	1553.36	1460.9300	1536.730	7132821	1016.57	1052.3200	1015.7100	1044.61	1184257
2019-01-03 00:00:00-05:00	1520.01	1538.00	1498.1062	1502.070	6340704	1041.00	1056.9800	1014.0800	1017.70	1381117
2019-01-04 00:00:00-05:00	1530.00	1594.00	1518.3100	1574.540	8285596	1033.00	1070.3000	1027.4178	1068.36	1629932
2019-01-07 00:00:00-05:00	1602.31	1634.56	1589.1850	1631.120	7252880	1071.50	1073.9999	1054.7600	1068.00	1599905
2019-01-08 00:00:00-05:00	1664.69	1676.61	1616.6100	1655.835	8184304	1076.11	1084.5600	1060.5300	1076.12	1301107



## MC Simulation Code Slide 4

```
In [7]: 1 # Configuring a Monte Carlo simulation to forecast 3 years cumulative returns
        2 MC_stocks_dist = MCSimulation(
        3     portfolio_data = df_stock_data,
        4     weights = [0.4, 0.6],
        5     num_simulation = 504,
        6     num_trading_days = 252*3
        7 )
```

```
In [8]: 1 # Plot simulation outcomes
        2 MC_stocks_dist.plot_simulation()
```





# MC Simulation Summary Stats & Code

```
In [10]: 1 # Fetch summary statistics from the Monte Carlo simulation results
          2 summary = MC_stocks_dist.summarize_cumulative_return()
          3
          4 # Print summary statistics
          5 summary
```

```
Out[10]: count          504.000000
          mean           3.178783
          std            1.155397
          min            1.054909
          25%            2.331218
          50%            3.005301
          75%            3.779923
          max            8.076236
          95% CI Lower    1.567885
          95% CI Upper    5.993991
          Name: 756, dtype: float64
```

```
In [11]: 1 # Set initial investment
          2 initial_investment = 500000
          3
          4 # Use the lower and upper `95%` confidence intervals to calculate the range of the possible outcomes of our $500,0
          5 ci_lower = round(summary[8]*initial_investment, 2)
          6 ci_upper = round(summary[9]*initial_investment, 2)
          7 # Print results
          8 print(f"There is a 95% chance that an initial investment of ${initial_investment} in the portfolio
          9       f" over the next 3 years will end within in the range of"
         10       f" ${ci_lower} and ${ci_upper}")
```

There is a 95% chance that an initial investment of \$500000 in the portfolio over the next 3 years will end within the range of \$783942.27 and \$2996995.27



## MC (2<sup>nd</sup>) Simulation

```
In [12]: 1 # Configuring a Monte Carlo simulation to forecast 3 years cumulative returns
          2 MC_stocks_3 = MCSimulation(
          3     portfolio_data = df_stock_data,
          4     weights = [0.2, 0.8],
          5     num_simulation = 504,
          6     num_trading_days = 252*3
          7 )
```

```
In [13]: 1 # Running a Monte Carlo simulation to forecast 3 years cumulative returns
          2 MC_stocks_3.calc_cumulative_return()
```



# MC 2<sup>nd</sup> Simulation Code & Summary (con't)

```
In [16]: 1 # Fetch summary statistics from the Monte Carlo simulation results
          2 summary_3 = MC_stocks_3.summarize_cumulative_return()
          3
          4 # Print summary statistics
          5 summary_3
```

```
Out[16]: count          504.000000
          mean           3.034797
          std            1.247481
          min            0.825814
          25%           2.187174
          50%           2.836664
          75%           3.653575
          max            9.183340
          95% CI Lower   1.207008
          95% CI Upper   5.636321
          Name: 756, dtype: float64
```

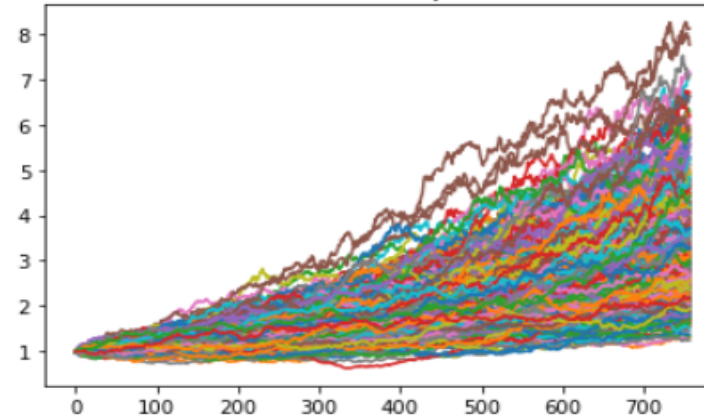
```
In [17]: 1 # Set initial investment
          2 initial_investment = 500000
          3
          4 # Use the lower and upper `95%` confidence intervals to calculate the range of the possible outcomes of our $500,000
          5 ci_lower_five = round(summary_3[8]*initial_investment, 2)
          6 ci_upper_five = round(summary_3[9]*initial_investment, 2)
          7
          8 # Print results
          9 print(f"There is a 95% chance that an initial investment of ${initial_investment} in the portfolio"
          10       f" over the next 3 years will end within in the range of"
          11       f" ${ci_lower_five} and ${ci_upper_five}")
```

```
There is a 95% chance that an initial investment of $500000 in the portfolio over the next 3 years will
the range of $603504.19 and $2818160.71
```



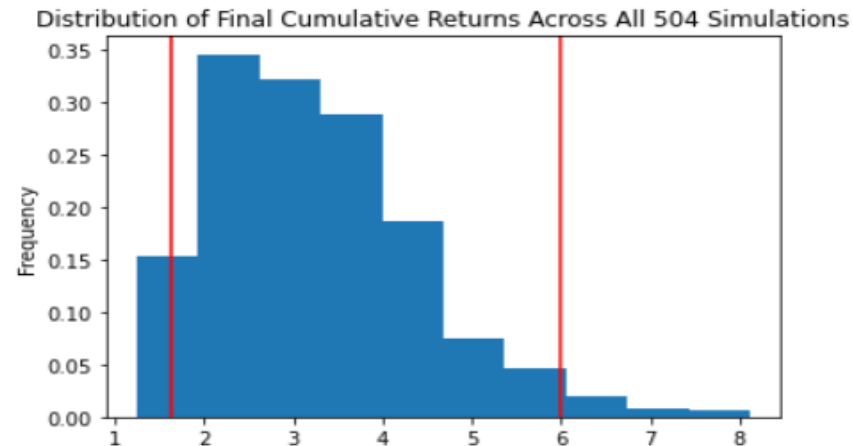
# MC Simulation 3 Year Growth

504 Simulations of Cumulative Portfolio Return Trajectories Over the Next 756 Trading Days.



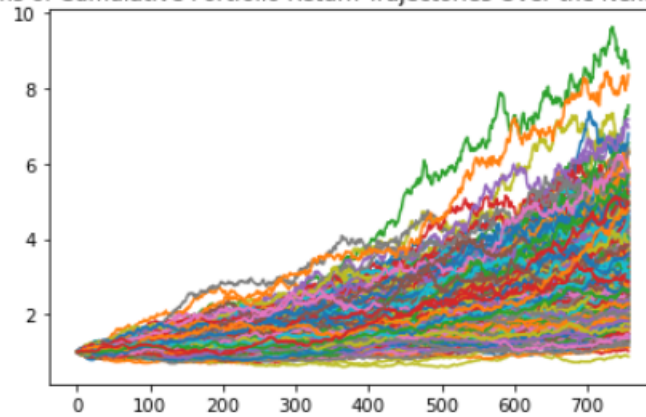
```
In [8]: 1 # Plot probability distribution and confidence intervals  
        2 MC_stocks_dist.plot_distribution()
```

```
Out[8]: <AxesSubplot:title={'center':'Distribution of Final Cumulative Returns Across All 504 Simulations'}, ylabel='Frequency'>
```



# MC Simulation Visualization 2

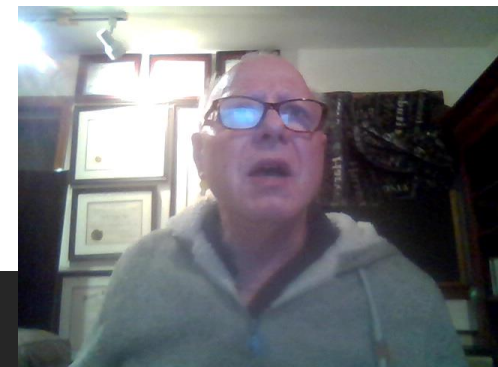
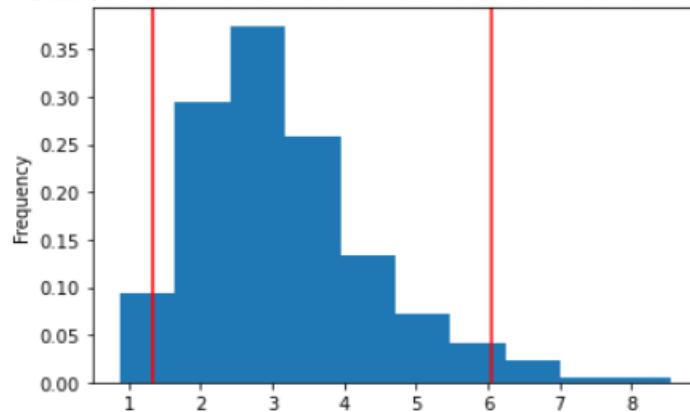
504 Simulations of Cumulative Portfolio Return Trajectories Over the Next 756 Trading Days.



```
In [14]: 1 # Plot probability distribution and confidence intervals  
        2 MC_stocks_3.plot_distribution()
```

```
Out[14]: <AxesSubplot:title={'center':'Distribution of Final Cumulative Returns Across All 504 Simulations'}, ylabel='Frequency'>
```

Distribution of Final Cumulative Returns Across All 504 Simulations



## Machine Learning Random Forest Reg sklearn Code 1

```
In [1]: 1 import numpy as np
        2 import pandas as pd
        3 from pathlib import Path
        4 from datetime import date
        5 import matplotlib.pyplot as plt
        6 import talib
```

```
In [2]: 1 from sklearn import metrics
        2 from sklearn.ensemble import RandomForestRegressor
        3 from sklearn.model_selection import ParameterGrid
```

```
In [3]: 1 import yfinance as yf
        2 START = "2019-01-01"
        3 TODAY = date.today().strftime("%Y-%m-%d")
        4 ticker= "AMZN"
        5 stock_data = yf.download(ticker, start=START, end=TODAY)
        6 ## preview data
        7 stock_data
```





## Machine Learning Random Forest Reg sklearn Code 2

```
In [6]: 1 feature_names = []
        2 #for n in [14, 30, 50, 100, 200, 250]:
        3 for n in [14,30,50]:
        4     stock_data['ma' + str(n)] = talib.SMA(stock_data['Close'].values, timeperiod=n)
        5     stock_data['rsi' + str(n)] = talib.RSI(stock_data['Close'].values, timeperiod=n)
        6
        7     feature_names = feature_names + ['ma' + str(n), 'rsi' + str(n)]
```

```
In [7]: 1 stock_data['Volume_1d_change'] = stock_data['Volume'].pct_change()
        2
        3 volume_features = ['Volume_1d_change']
        4 feature_names.extend(volume_features)
```

```
In [8]: 1 stock_data['5d_future_close'] = stock_data['Close'].shift(-5)
```

```
In [9]: 1 stock_data.dropna(inplace=True)
        2 stock_data
```



## Machine Learning Random Forest Reg sklearn Code 3

```
[75]: 1 #stock_data.dropna(inplace=True)
      2
      3 X = stock_data[feature_names]
      4 y = stock_data['5d_future_close']
      5
      6 train_size = int(0.85 * y.shape[0])
      7 X_train = X[:train_size]
      8 y_train = y[:train_size]
      9 X_test = X[train_size:]
     10 y_test = y[train_size:]
```

```
[76]: 1 #grid = {'n_estimators': [200], 'max_depth': [3], 'max_features': [4, 8], 'random_state': [42]}
      2 grid = {'n_estimators': [200], 'max_depth': [3], 'max_features': [4, 13], 'random_state': [42]}
      3 test_scores = []
      4
      5 rf_model = RandomForestRegressor()
      6
      7 for g in ParameterGrid(grid):
      8     rf_model.set_params(**g)
      9     rf_model.fit(X_train, y_train)
     10     test_scores.append(rf_model.score(X_test, y_test))
     11
     12 best_index = np.argmax(test_scores)
     13 print(test_scores[best_index], ParameterGrid(grid)[best_index])
```

```
0.2800579360364345 {'random_state': 42, 'n_estimators': 200, 'max_features': 13, 'max_depth': 3}
```



# Machine Learning Random Forest Reg sklearn Code 4

```
In [77]: 1 print('Predicting base on: ')
         2 print(feature_names)
```

```
Predicting base on:
['ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50', 'ma100', 'rsi100', 'ma200', 'rsi200', 'ma
250', 'rsi250', 'Volume_1d_change']
```

```
In [78]: 1 print('MA: Moving Average', '\nRSI: Relative Strength Index')
```

```
MA: Moving Average
RSI: Relative Strength Index
```

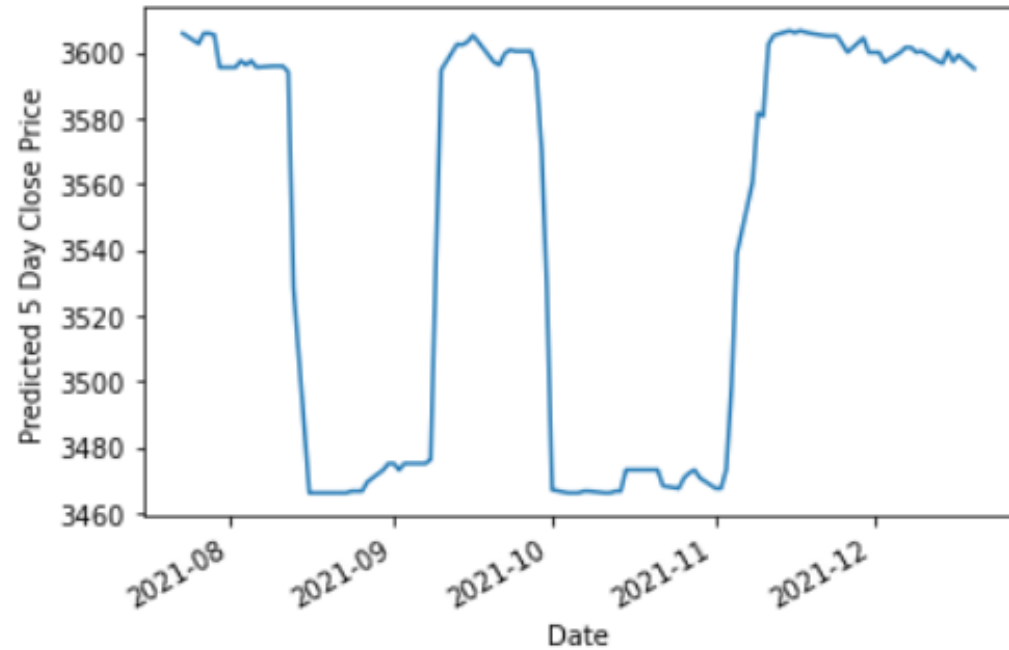
```
In [79]: 1 rf_model = RandomForestRegressor(n_estimators=200, max_depth=3, max_features=4, random_state=42)
         2 rf_model.fit(X_train, y_train)
         3
         4 y_pred = rf_model.predict(X_test)
         5
         6 y_pred_series = pd.Series(y_pred, index=y_test.index)
         7 y_pred_series.plot()
         8 plt.ylabel("Predicted 5 Day Close Price")
         9 plt.show()
```

<

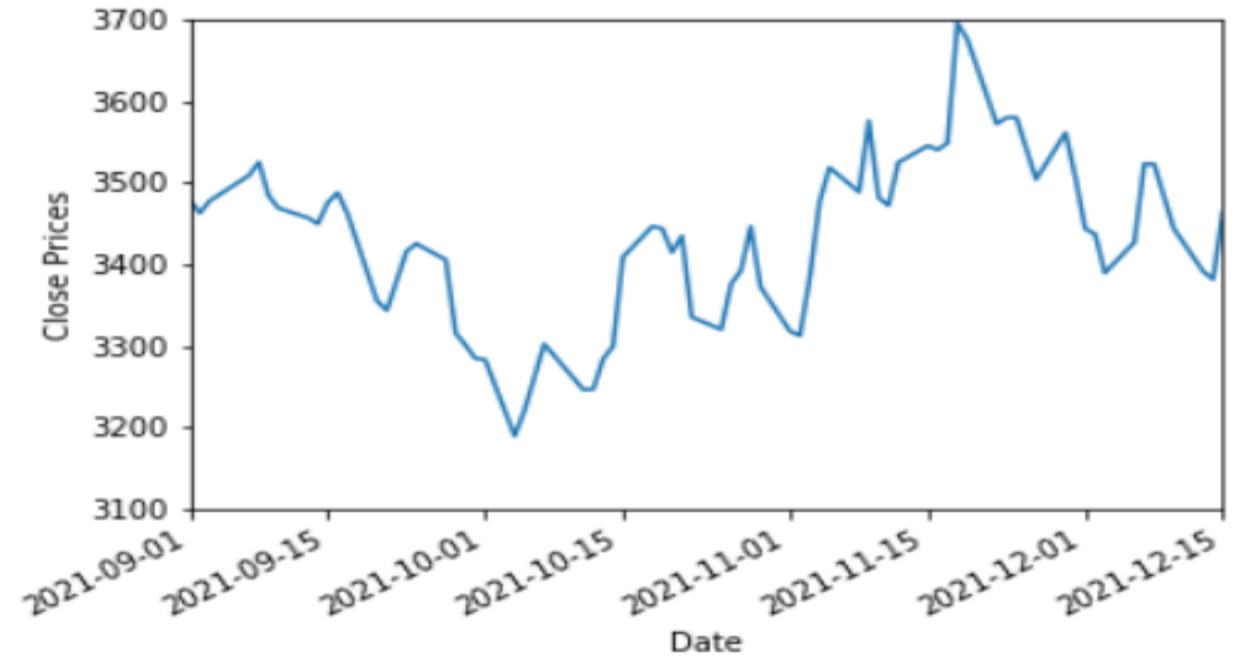


# Machine Learning Random Forest Reg sklearn (round 1)

Predicted 5-Day Closing Price



Actual Closing Prices

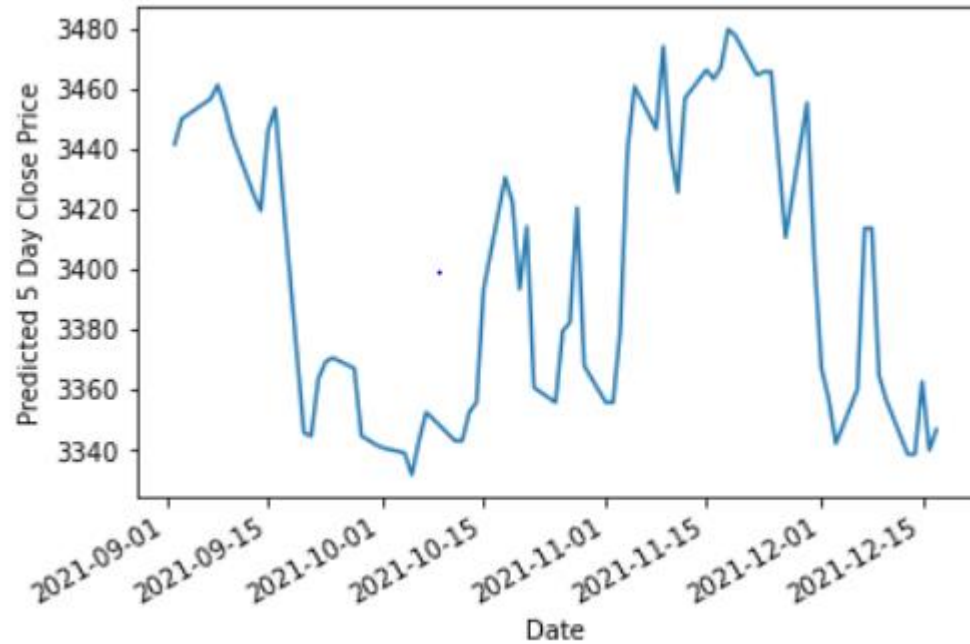


Model Mean Squared Error: 35,170

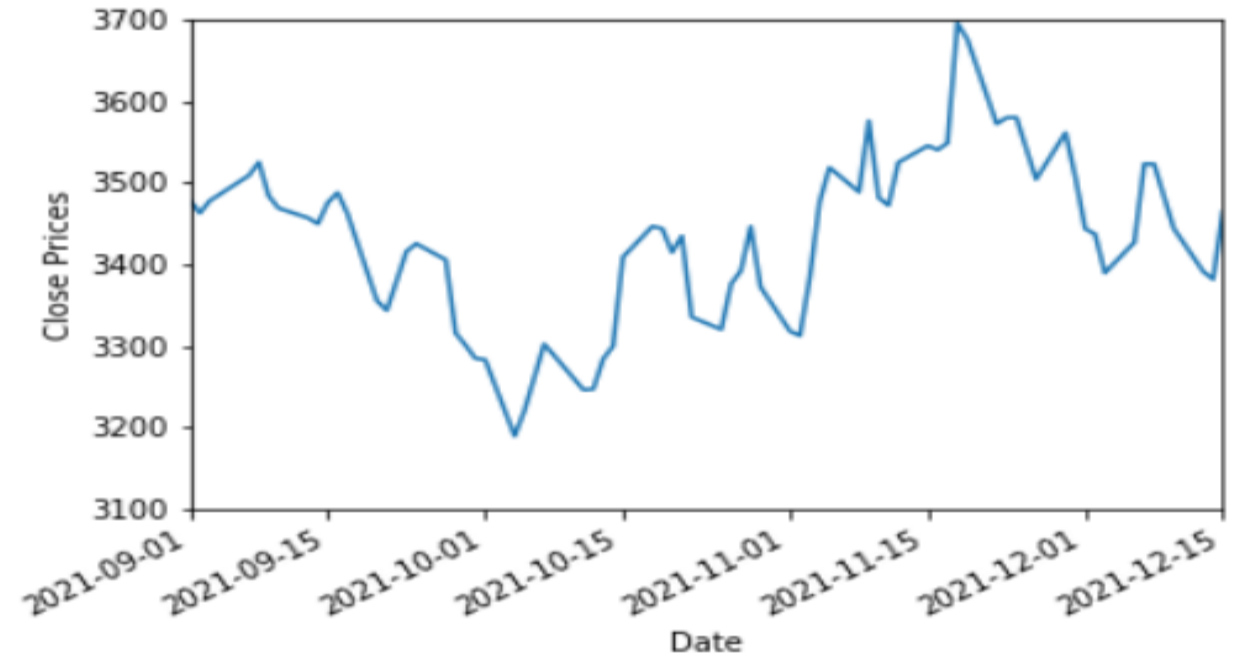


# Machine Learning Random Forest Reg sklearn (final round)

Predicted 5-Day Closing Price



Actual Closing Prices

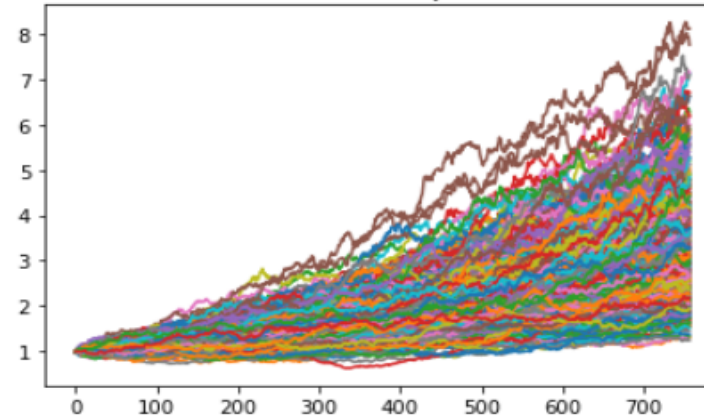


Model Mean Squared Error: 7,656



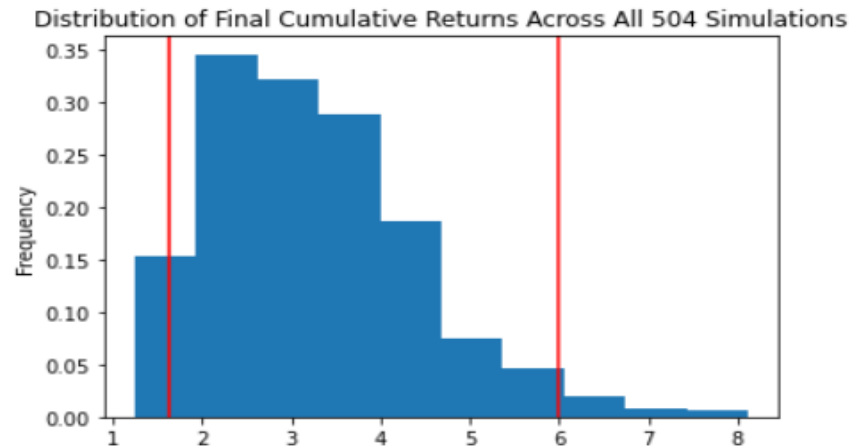
# MC Simulation 3 Year Growth

504 Simulations of Cumulative Portfolio Return Trajectories Over the Next 756 Trading Days.



```
In [8]: 1 # Plot probability distribution and confidence intervals  
        2 MC_stocks_dist.plot_distribution()
```

```
Out[8]: <AxesSubplot:title={'center':'Distribution of Final Cumulative Returns Across All 504 Simulations'}, ylabel='Frequency'>
```





# Portfolio Python (P3 )– Client's Portrait

## – Interview for Portfolio analysis - 2

Current Portfolio Composition	Proposed Portfolio Composition – Birthday Cake	Crypto Thoughts for future – Wedding Cake	Benchmarks
ADP : 1000 shares (from former employer from 24 yrs.)	AMZN, GOOG	BTC or ETH or SOL or DODG	SPY, NASD, DJIA
BR: 500 Shares			
CDK: 950 shares			
IRA value: 500K			

# Conclusion & Recommendations - TDB

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1. The current portfolio has performed well. ADP is a sound and growing Corporation. Its spin-offs helped diversify Anthon's holdings.
2. Anthon's IRA, managed by Morgan Stanley has seen healthy returns. Cupcake analyzed this portfolio.
3. The Anthon Portfolio can be replaced by a higher yielding Proposed Portfolio AMZN, GOOG. This provides strong results within the acceptable risk level of the investor.
4. Wedding Cake may include Cryptocurrencies.

## Portfolio Python (P3 )– Client's Portrait – Interview for Portfolio analysis – Background Data

Demographics	Finance : current	Comments : Future
64 Years old	Annual Income: 100 K	Projected Social Security Monthly 2.8K
Married, 3 dependents	Home Value: 400K	Homes appreciating 2% annually
BS in Finance (has not yet studied Python nor pandas)	Mortgage owed: 200K Monthly payment \$1,900	4-5 years into a 15 year mortgage @ 2.75%
Excellent Health	Annual Spending: 100K	Plays in league bowling and softball
Morgan Stanley Advisor(MS)	Savings: Stock, IRA, Pension	Largest asset IRA now managed by MS
Proposed retirement date : 11/1/2024	Monthly Mortgage: 1.9K	Retirement Net Worth Required : 1, 500K