

006 - Random Portfolio Gen

December 13, 2023

1 #006 Asset Allocation with Random Portfolio Weights

In this code, we'll define a function to generate a random portfolio weights, perform an asset allocation, and then and analyze their returns.

1.0.1 libs

Install Libs. (remove comments '#' if need to install the libraries)

```
[1]: # !pip install pandas
# !pip install pandas-datareader
# !pip install numpy
# !pip install plotly_express
# !pip install random
```

```
[2]: #import Libraries
import pandas as pd
from pandas_datareader import data as pdr
import numpy as np
import random
import plotly.graph_objects as go
```

1.0.2 Functions

functions already defined that we use on this code

```
[3]: # Define a function using Plotly Express
def plotly_data(df, title):

    # Create figure
    fig = go.Figure()

    # Set title
    fig.update_layout(title_text = title)

    # For loop that plots all stock prices in the pandas dataframe df

    for i in df.columns[0:]:
        # Add range slider
```

```

        #fig.update_layout(xaxis=dict(rangeselector =
↪dict(buttons=list([dict(count=1, label="1m", step="month",
↪stepmode="backward"), dict(count=6, label="6m", step="month",
↪stepmode="backward"), dict(count=1, label="YTD", step="year",
↪stepmode="todate"), dict(count=1, label="1y", step="year",
↪stepmode="backward"), dict(step="all")])), rangeslider=dict( visible=True),
↪type="date"))

        # Add line graph
        fig.add_scatter(x = df.index, y = df[i], name = i)
        # Update Layout
        fig.update_layout({'plot_bgcolor': "white"})
        #fig.update_traces(line_width = 3)
        fig.update_layout(legend=dict(orientation="h",))

fig.show()

# Define a function using Plotly Express, changes axis y to logarithm scale
def log_plotly_data(df, title):

    # Create figure
    fig = go.Figure()

    # Set title
    fig.update_layout(title_text = title)

    # For loop that plots all stock prices in the pandas dataframe df

    for i in df.columns[0:]:
        # Add range slider
        #fig.update_layout(xaxis=dict(rangeselector =
↪dict(buttons=list([dict(count=1, label="1m", step="month",
↪stepmode="backward"), dict(count=6, label="6m", step="month",
↪stepmode="backward"), dict(count=1, label="YTD", step="year",
↪stepmode="todate"), dict(count=1, label="1y", step="year",
↪stepmode="backward"), dict(step="all")])), rangeslider=dict( visible=True),
↪type="date"))

        # Add line graph
        fig.add_scatter(x = df.index, y = df[i], name = i)
        # Update Layout
        fig.update_layout({'plot_bgcolor': "white"})
        #fig.update_traces(line_width = 3)
        fig.update_layout(legend=dict(orientation="h",))

    #changes y to logarithm scale
    fig.update_yaxes(type="log")
    fig.show()

```

```

# Define a function using Plotly Express, changes axis y to logarithm scale
def plotly_line(df, y, title):

    # Create figure
    fig = go.Figure()
    fig.update_layout(title_text = title)
    fig.add_scatter(x = df.index, y = y)
    # Update Layout
    fig.update_layout({'plot_bgcolor': "white"})
    #fig.update_traces(line_width = 3)
    fig.update_layout(legend=dict(orientation="h",))

    #changes y to logarithm scale
    fig.show()

# Define a function using Plotly Express, changes axis y to logarithm scale
def log_plotly_line(df, y, title):

    # Create figure
    fig = go.Figure()
    fig.update_layout(title_text = title)
    fig.add_scatter(x = df.index, y = y)
    # Update Layout
    fig.update_layout({'plot_bgcolor': "white"})
    #fig.update_traces(line_width = 3)
    fig.update_layout(legend=dict(orientation="h",))

    #changes y to logarithm scale
    fig.update_yaxes(type="log")
    fig.show()

```

```

[4]: # Function to scale stock prices based on their initial starting price
# The objective of this function is to set all prices to start at a value of 1
def price_scaling(raw_prices_df):
    scaled_prices_df = raw_prices_df.copy()
    for i in raw_prices_df.columns[0:]:
        scaled_prices_df[i] = raw_prices_df[i]/raw_prices_df[i][0]
    return scaled_prices_df

```

1.1 6.1 Equal Weighted Portfolio

```

[5]: file_name = input('Input the CSV file name: ')
initial_investment = int(input('Input the initial investment: '))
n_runs = int(input('Input the number of simulations: '))

## BRL5

```

```
#      PETR4.SA VALE3.SA TAE11.SA ITSA4.SA WEGE3.SA

## MAG7
#      AAPL AMZN GOOG META MSFT NVDA TSLA

## BRL_top10
#      CRFB3.SA CPLE6.SA ECOR3.SA ITUB4.SA JBSS3.SA RENT3.SA PRI03.SA SBSP3.SA
↪VALE3.SA VIVT3.SA
```

Input the CSV file name: MAG7
 Input the initial investment: 70000
 Input the number of simulations: 5

```
[6]: #read CSV file
Stock_Prices_df = pd.read_csv(file_name)
#The code imports a DataFrame with num index [1,2,3...], this line replace the
↪column Date to Index
Stock_Prices_df.set_index(['Date'], inplace = True)
```

```
[7]: #obtain weights vector
n_assets = len(Stock_Prices_df.columns)
#lock vector to test function
weights = np.ones(n_assets) * 1/n_assets
weights
```

```
[7]: array([0.14285714, 0.14285714, 0.14285714, 0.14285714, 0.14285714,
          0.14285714, 0.14285714])
```

```
[8]: #Define a function that performs an Asset Allocation
def asset_allocation(df, initial_investment, weights):
    ''' Performs an asset Allocation for a given DF, initial investment value
    ↪and weights'''

    portfolio_df = df.copy()

    # Scale stock prices using the "price_scaling"
    scaled_df = price_scaling(df)

    #enumerate method links Stocks tickers in columns along with a counter
    ↪position weight (i), like an index
    for i, stock in enumerate(scaled_df):
        portfolio_df[stock] = weights[i] * scaled_df[stock] *
        ↪initial_investment

    # Sum up all values and place the result in a new column titled "portfolio
    ↪value [$]"
```

```

portfolio_df['Total Value [$]'] = portfolio_df.sum(axis = 1, numeric_only =
↳True)

# Calculate the portfolio percentage daily return and replace NaNs with
↳zeros
portfolio_df['Daily Return [%]'] = portfolio_df['Total Value [$]'].
↳pct_change(1) * 100
portfolio_df.replace(np.nan, 0, inplace = True)

return portfolio_df

```

[9]: *#Asset Allocation with parameters defined*

```

portfolio_df = asset_allocation(Stock_Prices_df, initial_investment, weights)
Eqw = portfolio_df
portfolio_df.round(2)

```

[9]:

	AAPL	AMZN	GOOG	META	MSFT	NVDA	\
Date							
2018-12-14	10000.00	10000.00	10000.00	10000.00	10000.00	10000.00	
2018-12-17	9906.94	9554.00	9754.63	9731.36	9703.86	9804.03	
2018-12-18	10035.66	9746.03	9871.51	9972.23	9805.72	10033.46	
2018-12-19	9722.63	9391.74	9816.81	9248.92	9779.31	9457.84	
2018-12-20	9477.28	9176.59	9686.31	9260.03	9573.71	9224.99	
...	
2023-12-06	48434.34	18156.81	25224.07	22035.96	36628.81	125255.62	
2023-12-07	48925.44	18453.31	26571.35	22670.42	36842.35	128264.31	
2023-12-08	49288.09	18521.15	26223.97	23098.02	37168.11	130769.26	
2023-12-11	48650.92	18328.93	25851.65	22579.48	36877.10	128349.64	
2023-12-12	49036.25	18528.69	25648.21	23200.06	37183.01	131184.92	

	TSLA	Total Value [\$]	Daily Return [%]
Date			
2018-12-14	10000.00	70000.00	0.00
2018-12-17	9527.22	67982.04	-2.88
2018-12-18	9215.77	68680.38	1.03
2018-12-19	9104.76	66522.01	-3.14
2018-12-20	8623.77	65022.68	-2.25
...
2023-12-06	98180.25	373915.85	-1.02
2023-12-07	99521.48	381248.64	1.96
2023-12-08	100013.67	385082.26	1.01
2023-12-11	98332.01	378969.74	-1.59
2023-12-12	97212.27	381993.39	0.80

[1257 rows x 9 columns]

```
[10]: #Plot data:

plotly_line(portfolio_df, portfolio_df['Total Value ($)'], "Portfolio Total Value")
log_plotly_line(portfolio_df, portfolio_df['Total Value ($)'], "Portfolio Total Value - Log Scale")
plotly_line(portfolio_df, portfolio_df['Daily Return (%)'], "Daily Return (%)")

[11]: plotly_data(portfolio_df, "Equal Weighted Portfolio")
log_plotly_data(portfolio_df, "Equal Weighted Portfolio")
```

1.2 6.2 Random Weighted Portfolio

1.2.1 6.2.1 Define a function to generate random weights

```
[12]: def rand_weights(n):
        ''' Produces n random weights that sum to 1 '''
        k = np.random.rand(n)
        return k / sum(k)

[13]: #obtain weights vector
n_assets = len(Stock_Prices_df.columns)

weights = rand_weights(n_assets).round(4)
display(weights)
sum(weights)

array([0.1435, 0.2042, 0.0946, 0.1942, 0.0987, 0.08 , 0.1849])

[13]: 1.0001
```

1.2.2 6.2.2 Asset Allocation Auto

```
[14]: #Eqw      -- Equal Weighted
#Rdw_1 -- Random Weighted 1
#Rdw_2 -- Random Weighted 2 [...]

[15]: def random_port_generate(initial_investment, n_runs):
        #obtain weights vector
        n_assets = len(Stock_Prices_df.columns)
        #lock vector to test function
        eq_weights = np.ones(n_assets) * 1/n_assets
        #Asset Allocation with parameters defined
        Eqw_df = asset_allocation(Stock_Prices_df, initial_investment,
        eq_weights)[['Total Value ($)', 'Daily Return (%)']]
        Eqw_df = Eqw_df.rename({'Total Value ($)':'Eqw ($)', 'Daily Return (%)':
        'Eqw (%)'}, axis="columns")
        All_df = Eqw_df
```

```

# Placeholder to store all weights
weights_runs = np.zeros((n_runs, n_assets))

for i in range(n_runs):
    # Generate random weights
    weights = rand_weights(n_assets)
    # Store the weights
    weights_runs[i,:] = weights
    # Random Asset Allocation
    df = asset_allocation(Stock_Prices_df, initial_investment,
↪weights)[['Total Value [$]', 'Daily Return [%]']]
    #rename columns for iterate
    Rdw = df.rename({'Total Value [$]':'Rdw_{}'.format(i), 'Daily Return_
↪[%]':'Rdw_{}[%]'.format(i)}, axis="columns")

    All_df = pd.merge(All_df, Rdw, on = 'Date')

    #All_df = Eqw_df.join(Rdw)

    print("Simulation Run = {}".format(i))
    print("Weights = {}".format(weights_runs[i].round(3)))
    print('\n')

return All_df

```

```

[16]: df = random_port_generate(initial_investment, n_runs)
daily_returns_df = df.iloc[:, 1::2]
total_values_df = df.iloc[:, 0::2]
display(df.round(2))

```

```

Simulation Run = 0
Weights = [0.098 0.036 0.024 0.067 0.211 0.316 0.247]

```

```

Simulation Run = 1
Weights = [0.149 0.078 0.056 0.115 0.198 0.179 0.224]

```

```

Simulation Run = 2
Weights = [0.211 0.059 0.08 0.161 0.231 0.18 0.078]

```

```

Simulation Run = 3
Weights = [0.212 0.094 0.067 0.115 0.185 0.206 0.122]

```

```

Simulation Run = 4

```

```
Weights = [0.148 0.075 0.171 0.223 0.002 0.305 0.076]
```

	Eqw [\$]	Eqw [%]	Rdw_0[\$]	Rdw_0[%]	Rdw_1[\$]	Rdw_1[%]	\
Date							
2018-12-14	70000.00	0.00	70000.00	0.00	70000.00	0.00	
2018-12-17	67982.04	-2.88	67966.56	-2.90	67947.54	-2.93	
2018-12-18	68680.38	1.03	68356.12	0.57	68366.83	0.62	
2018-12-19	66522.01	-3.14	66198.76	-3.16	66308.68	-3.01	
2018-12-20	65022.68	-2.25	64307.40	-2.86	64560.23	-2.64	
...	
2023-12-06	373915.85	-1.02	553619.59	-1.23	450315.01	-0.95	
2023-12-07	381248.64	1.96	563851.67	1.85	458208.03	1.75	
2023-12-08	385082.26	1.01	571134.59	1.29	463201.13	1.09	
2023-12-11	378969.74	-1.59	561649.39	-1.66	455785.59	-1.60	
2023-12-12	381993.39	0.80	567010.60	0.95	458942.04	0.69	

	Rdw_2[\$]	Rdw_2[%]	Rdw_3[\$]	Rdw_3[%]	Rdw_4[\$]	Rdw_4[%]
Date						
2018-12-14	70000.00	0.00	70000.00	0.00	70000.00	0.00
2018-12-17	68254.94	-2.49	68168.54	-2.62	68281.69	-2.45
2018-12-18	69145.43	1.30	68929.07	1.12	69356.84	1.57
2018-12-19	66862.62	-3.30	66667.35	-3.28	66363.61	-4.32
2018-12-20	65463.02	-2.09	65097.16	-2.36	65101.09	-1.90
...
2023-12-06	388352.90	-1.23	425177.83	-1.21	444582.05	-1.52
2023-12-07	395535.16	1.85	433000.77	1.84	454993.12	2.34
2023-12-08	400330.63	1.21	438217.41	1.20	461271.37	1.38
2023-12-11	394085.36	-1.56	431252.45	-1.59	453187.98	-1.75
2023-12-12	398772.79	1.19	435881.33	1.07	459878.07	1.48

```
[1257 rows x 12 columns]
```

6.2.2.1 Plotting Data

```
[17]: plotly_data(total_values_df, "Portfolios Total Value[$]")
log_plotly_data(total_values_df, "Portfolios Total Value[$]")
plotly_data(daily_returns_df, "Portfolio Daily Returns [%]")
```

```
[18]: import plotly.express as px
# Plot histograms for stocks daily returns using plotly express
fig = px.histogram(daily_returns_df)
fig.update_layout({'plot_bgcolor': "white"})
```


1.2.3 6.2.3 Asset Allocation Manual

```
[19]: #Random Asset Allocation 01
weights_1 = rand_weights(len(Stock_Prices_df.columns)).round(4)

print("Value Invested: $ {}".format(initial_investment))
print("Number of Stocks: {}".format(len(Stock_Prices_df.columns)))
print("Weights: {}".format(weights_1))

Rdw_1 = asset_allocation(Stock_Prices_df, initial_investment, weights_1)
Rdw_1.round(2)
```

Value Invested: \$ 70000

Number of Stocks: 7

Weights: [0.0411 0.4062 0.011 0.2606 0.2414 0.0066 0.033]

```
[19]:
```

	AAPL	AMZN	GOOG	META	MSFT	NVDA	\
Date							
2018-12-14	2877.00	28434.00	770.00	18242.00	16898.00	462.00	
2018-12-17	2850.23	27165.83	751.11	17751.95	16397.58	452.95	
2018-12-18	2887.26	27711.86	760.11	18191.35	16569.70	463.55	
2018-12-19	2797.20	26704.47	755.89	16871.89	16525.08	436.95	
2018-12-20	2726.61	26092.71	745.85	16892.15	16177.65	426.19	
...	
2023-12-06	13934.56	51627.06	1942.25	40198.00	61895.36	5786.81	
2023-12-07	14075.85	52470.13	2045.99	41355.37	62256.20	5925.81	
2023-12-08	14180.18	52663.03	2019.25	42135.40	62806.67	6041.54	
2023-12-11	13996.87	52116.47	1990.58	41189.49	62314.93	5929.75	
2023-12-12	14107.73	52684.47	1974.91	42321.54	62831.85	6060.74	

	TSLA	Total Value [\$]	Daily Return [%]
Date			
2018-12-14	2310.00	69993.00	0.00
2018-12-17	2200.79	67570.43	-3.46
2018-12-18	2128.84	68712.66	1.69
2018-12-19	2103.20	66194.68	-3.66
2018-12-20	1992.09	65053.25	-1.72
...
2023-12-06	22679.64	198063.68	-0.87
2023-12-07	22989.46	201118.81	1.54
2023-12-08	23103.16	202949.23	0.91
2023-12-11	22714.70	200252.79	-1.33
2023-12-12	22456.03	202437.27	1.09

[1257 rows x 9 columns]

```
[20]: #Random Asset Allocation 02
weights_2 = rand_weights(len(Stock_Prices_df.columns)).round(4)
```

```

print("Value Invested: $ {}".format(initial_investment))
print("Number of Stocks: {}".format(len(Stock_Prices_df.columns)))
print("Weights: {}".format(weights_2))

Rdw_2 = asset_allocation(Stock_Prices_df, initial_investment, weights_2)
Rdw_2.round(2)

```

Value Invested: \$ 70000

Number of Stocks: 7

Weights: [0.0104 0.2306 0.1875 0.0708 0.0451 0.2168 0.2388]

```

[20]:
      AAPL      AMZN      GOOG      META      MSFT      NVDA  \
Date
2018-12-14  728.00  16142.00  13125.00  4956.00  3157.00  15176.00
2018-12-17  721.23  15422.06  12802.95  4822.86  3063.51  14878.59
2018-12-18  730.60  15732.04  12956.36  4942.24  3095.66  15226.78
2018-12-19  707.81  15160.14  12884.57  4583.77  3087.33  14353.21
2018-12-20  689.95  14812.85  12713.28  4589.27  3022.42  13999.85
...
2023-12-06  3526.02  29308.72  33106.59  10921.02  11563.71  190087.93
2023-12-07  3561.77  29787.33  34874.89  11235.46  11631.13  194653.92
2023-12-08  3588.17  29896.84  34418.96  11447.38  11733.97  198455.43
2023-12-11  3541.79  29586.55  33930.28  11190.39  11642.10  194783.42
2023-12-12  3569.84  29909.00  33663.28  11497.95  11738.68  199086.23

      TSLA  Total Value [$]  Daily Return [%]
Date
2018-12-14  16716.00      70000.00      0.00
2018-12-17  15925.70      67636.91     -3.38
2018-12-18  15405.08      68088.76      0.67
2018-12-19  15219.51      65996.33     -3.07
2018-12-20  14415.50      64243.11     -2.66
...
2023-12-06  164118.11     442632.10     -1.09
2023-12-07  166360.10     452104.60      2.14
2023-12-08  167182.85     456723.60      1.02
2023-12-11  164371.79     449046.33     -1.68
2023-12-12  162500.03     451965.00      0.65

```

[1257 rows x 9 columns]

```

[21]: #Random Asset Allocation 03
weights_3 = rand_weights(len(Stock_Prices_df.columns)).round(4)

print("Value Invested: $ {}".format(initial_investment))
print("Number of Stocks: {}".format(len(Stock_Prices_df.columns)))
print("Weights: {}".format(weights_3))

```

```
Rdw_3 = asset_allocation(Stock_Prices_df, initial_investment, weights_3)
Rdw_3.round(2)
```

Value Invested: \$ 70000

Number of Stocks: 7

Weights: [0.0653 0.2018 0.2188 0.0631 0.12 0.1424 0.1886]

```
[21]:
```

	AAPL	AMZN	GOOG	META	MSFT	NVDA	\
Date							
2018-12-14	4571.00	14126.00	15316.00	4417.00	8400.00	9968.00	
2018-12-17	4528.46	13495.97	14940.19	4298.34	8151.24	9772.66	
2018-12-18	4587.30	13767.24	15119.20	4404.74	8236.80	10001.35	
2018-12-19	4444.21	13266.77	15035.43	4085.25	8214.62	9427.57	
2018-12-20	4332.07	12962.85	14835.55	4090.16	8041.91	9195.47	
...	
2023-12-06	22139.34	25648.30	38633.18	9733.28	30768.20	124854.80	
2023-12-07	22363.82	26067.14	40696.67	10013.52	30947.57	127853.86	
2023-12-08	22529.59	26162.97	40164.63	10202.39	31221.21	130350.80	
2023-12-11	22238.34	25891.44	39594.38	9973.36	30976.77	127938.92	
2023-12-12	22414.47	26173.62	39282.80	10247.46	31233.73	130765.13	

	TSLA	Total Value [\$]	Daily Return [%]
Date			
2018-12-14	13202.00	70000.00	0.00
2018-12-17	12577.84	67764.71	-3.19
2018-12-18	12166.66	68283.30	0.77
2018-12-19	12020.10	66493.95	-2.62
2018-12-20	11385.11	64843.10	-2.48
...
2023-12-06	129617.57	381394.67	-0.97
2023-12-07	131388.26	389330.84	2.08
2023-12-08	132038.05	392669.64	0.86
2023-12-11	129817.92	386431.13	-1.59
2023-12-12	128339.64	388456.84	0.52

[1257 rows x 9 columns]

```
[22]: #Random Asset Allocation 04
weights_4 = rand_weights(len(Stock_Prices_df.columns)).round(4)

print("Value Invested: $ {}".format(initial_investment))
print("Number of Stocks: {}".format(len(Stock_Prices_df.columns)))
print("Weights: {}".format(weights_4))

Rdw_4 = asset_allocation(Stock_Prices_df, initial_investment, weights_4)
Rdw_4.round(2)
```

Value Invested: \$ 70000

Number of Stocks: 7

Weights: [0.0541 0.1346 0.1001 0.0212 0.1335 0.3238 0.2328]

```
[22]:
```

	AAPL	AMZN	GOOG	META	MSFT	NVDA	\
Date							
2018-12-14	3787.00	9422.00	7007.00	1484.00	9345.00	22666.00	
2018-12-17	3751.76	9001.77	6835.07	1444.13	9068.26	22221.81	
2018-12-18	3800.50	9182.71	6916.97	1479.88	9163.44	22741.84	
2018-12-19	3681.96	8848.89	6878.64	1372.54	9138.76	21437.13	
2018-12-20	3589.05	8646.18	6787.20	1374.19	8946.63	20909.37	
...	
2023-12-06	18342.09	17107.34	17674.50	3270.14	34229.62	283904.39	
2023-12-07	18528.06	17386.70	18618.54	3364.29	34429.17	290723.88	
2023-12-08	18665.40	17450.63	18375.14	3427.75	34733.60	296401.60	
2023-12-11	18424.11	17269.51	18114.25	3350.79	34461.65	290917.30	
2023-12-12	18570.03	17457.73	17971.70	3442.89	34747.52	297343.73	

	TSLA	Total Value [\$]	Daily Return [%]
Date			
2018-12-14	16296.00	70007.00	0.00
2018-12-17	15525.56	67848.36	-3.08
2018-12-18	15018.02	68303.36	0.67
2018-12-19	14837.11	66195.04	-3.09
2018-12-20	14053.30	64305.90	-2.85
...
2023-12-06	159994.54	534522.62	-1.30
2023-12-07	162180.20	545230.86	2.00
2023-12-08	162982.28	552036.39	1.25
2023-12-11	160241.85	542779.47	-1.68
2023-12-12	158417.11	547950.71	0.95

[1257 rows x 9 columns]

```
[23]: #Random Asset Allocation 02
weights_5 = rand_weights(len(Stock_Prices_df.columns)).round(4)

print("Value Invested: $ {}".format(initial_investment))
print("Number of Stocks: {}".format(len(Stock_Prices_df.columns)))
print("Weights: {}".format(weights_5))

Rdw_5 = asset_allocation(Stock_Prices_df, initial_investment, weights_5)
Rdw_5.round(2)
```

Value Invested: \$ 70000

Number of Stocks: 7

Weights: [0.1721 0.146 0.1036 0.0297 0.248 0.0698 0.2307]

```
[23]:
```

	AAPL	AMZN	GOOG	META	MSFT	NVDA	\
Date							
2018-12-14	12047.00	10220.00	7252.00	2079.00	17360.00	4886.00	
2018-12-17	11934.89	9764.18	7074.06	2023.15	16845.90	4790.25	
2018-12-18	12089.95	9960.44	7158.82	2073.23	17022.72	4902.35	
2018-12-19	11712.85	9598.36	7119.15	1922.85	16976.88	4621.10	
2018-12-20	11417.28	9378.47	7024.51	1925.16	16619.95	4507.33	
...	
2023-12-06	58348.85	18556.26	18292.49	4581.28	63587.61	61199.90	
2023-12-07	58940.47	18859.28	19269.54	4713.18	63958.31	62669.94	
2023-12-08	59377.36	18928.61	19017.62	4802.08	64523.84	63893.86	
2023-12-11	58609.77	18732.16	18747.61	4694.27	64018.65	62711.64	
2023-12-12	59073.97	18936.32	18600.08	4823.29	64549.70	64096.95	

	TSLA	Total Value [\$]	Daily Return [%]
Date			
2018-12-14	16149.00	69993.00	0.00
2018-12-17	15385.51	67817.94	-3.11
2018-12-18	14882.55	68090.06	0.40
2018-12-19	14703.27	66654.46	-2.11
2018-12-20	13926.53	64799.24	-2.78
...
2023-12-06	158551.29	383117.67	-0.63
2023-12-07	160717.24	389127.96	1.57
2023-12-08	161512.08	392055.45	0.75
2023-12-11	158796.37	386310.48	-1.47
2023-12-12	156988.09	387068.40	0.20

[1257 rows x 9 columns]

6.2.3.1 Organize and Plot Data

```
[24]: rand_value_df = pd.concat([ Eqw['Total Value [$]'],
                                Rdw_1['Total Value [$]'],
                                Rdw_2['Total Value [$]'],
                                Rdw_3['Total Value [$]'],
                                Rdw_4['Total Value [$]'],
                                Rdw_5['Total Value [$]'],
                                ], axis=1, join='inner').round(2)
#rand_value_df.to_csv('rand_value_df')
```

```
[25]: #read CSV file
rand_value_df = pd.read_csv('rand_value')
#The code imports a DataFrame with num index [1,2,3...], this line replace the
↪column Date to Index
rand_value_df.set_index(['Date'], inplace = True)

log_plotly_data(rand_value_df, "Total Value [$]")
```

```
[26]: rand_daily_df = pd.concat([ Eqw['Daily Return [%]'],
                                Rdw_1['Daily Return [%]'],
                                Rdw_2['Daily Return [%]'],
                                Rdw_3['Daily Return [%]'],
                                Rdw_4['Daily Return [%]'],
                                Rdw_5['Daily Return [%]']
                                ], axis=1, join='inner').round(2)
#rand_daily_df.to_csv('rand_daily')
```

```
[27]: #read CSV file
rand_daily_df = pd.read_csv('rand_daily')
#The code imports a DataFrame with num index [1,2,3...], this line replace the
↪column Date to Index
rand_daily_df.set_index(['Date'], inplace = True)

plotly_data(rand_daily_df, "Total Value [$"])
```