

# Portfolio Optimization Using Genetic Algorithm

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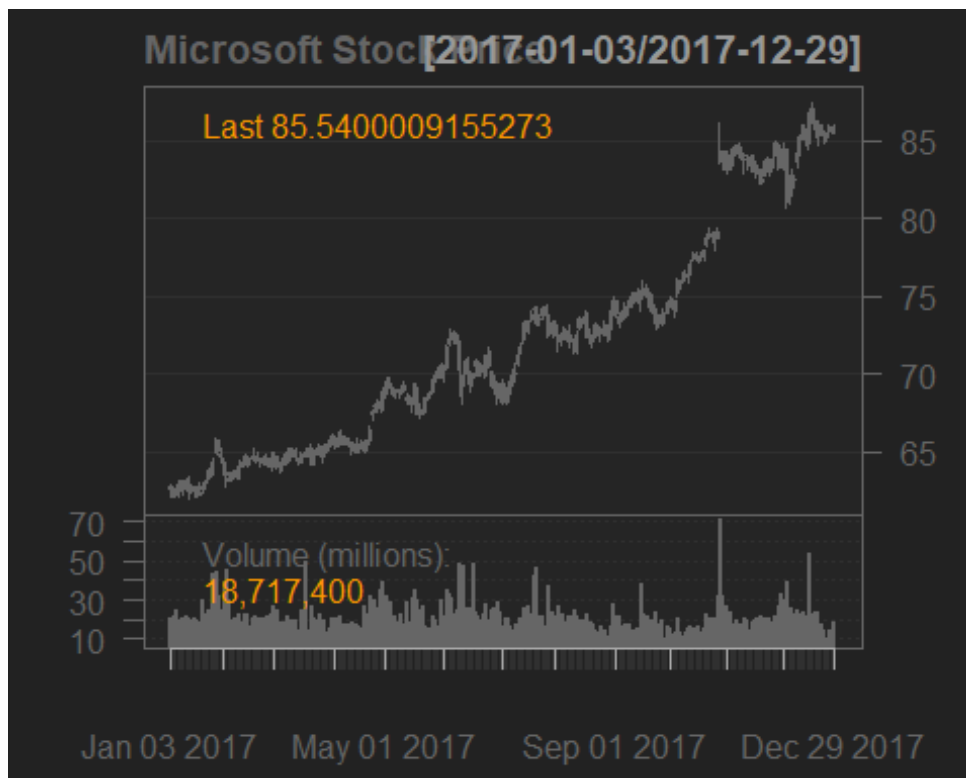
## Part 1

### Construction of a portfolio using the Genetic Algorithm package

The purpose of the Assignment is to understand how Genetic Algorithm will be used for portfolio optimization.

A Portfolio which results in better returns and risk adjusted is built when there is diversification in the assets selected for the portfolio. The diversity contributes to healthy stock market. So, it is always recommended to choose stocks from different sectors. Choosing companies from different sector strengthen the portfolio returns and reduce the risk related to specific industry. As, part 1 of the assignment I have chosen 10 assets from the list of S&P 500 list top companies from various sector. Saving the selected assets in tickers variable and downloading the historical stock data using the “**Quantmod**” package in the tickers vector from Yahoo Finance.

```
tickers <- c("MSFT","AAPL","AMZN","NFLX", "NVDA", "META", "TSLA", "PG", "V",  
"JNJ")  
  
getSymbols(tickers,src="yahoo", from="2017-01-01", to="2017-12-31")  
  
## [1] "MSFT" "AAPL" "AMZN" "NFLX" "NVDA" "META" "TSLA" "PG" "V" "JNJ"  
  
chartSeries(MSFT,name = "Microsoft Stock Price")
```



```
chartSeries(AAPL,name = "Apple Stock Price")
```



```
chartSeries(AMZN,name = "Amazon Stock Price")
```



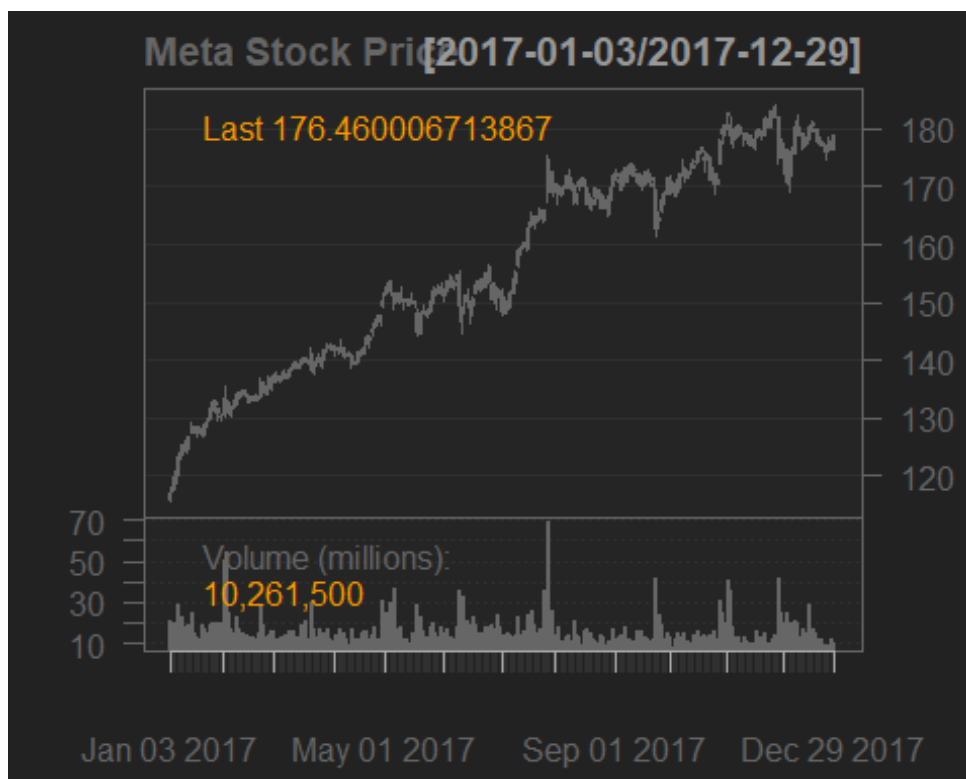
```
chartSeries(NFLX,name = "Netflix Stock Price")
```



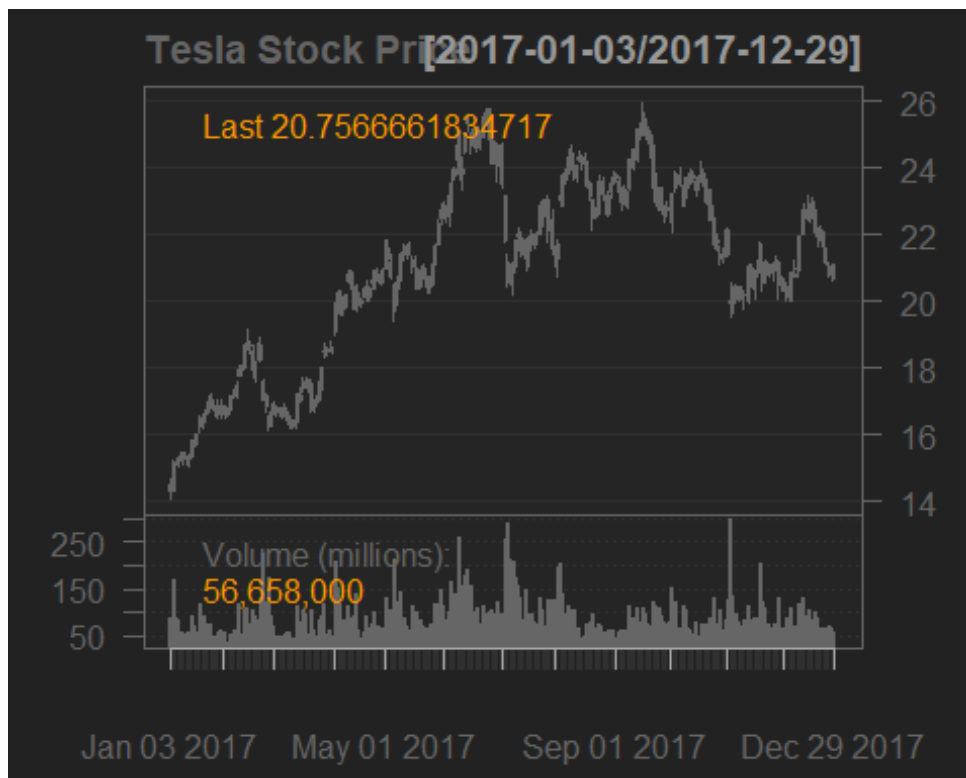
```
chartSeries(NVDA,name = "NVIDIA Stock Price")
```



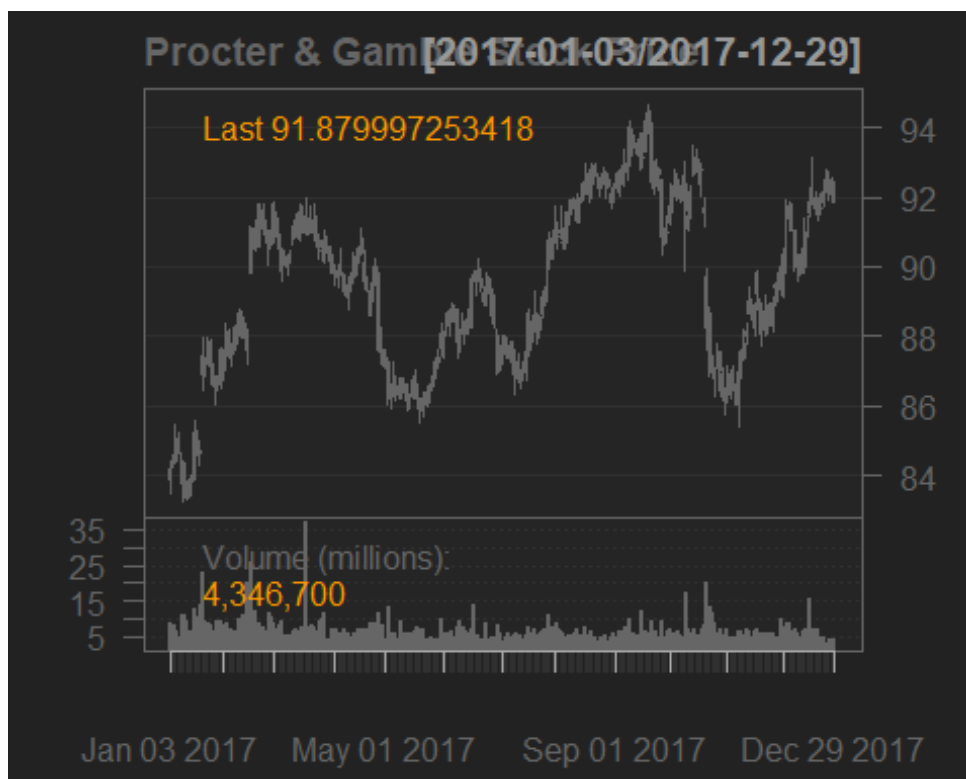
```
chartSeries(META,name = "Meta Stock Price")
```



```
chartSeries(TSLA,name = "Tesla Stock Price")
```



```
chartSeries(PG,name = "Procter & Gamble Stock Price")
```



```
chartSeries(JNJ,name = "Johnson & J Stock Price")
```

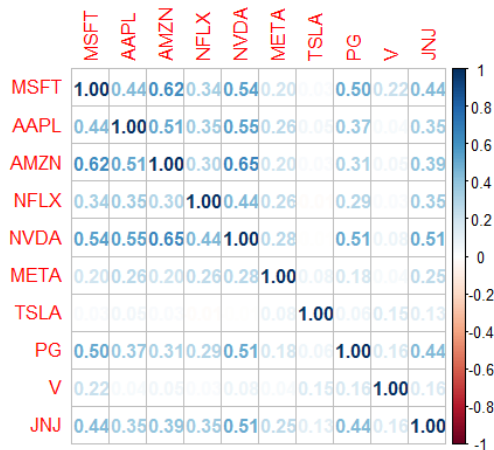


```
chartSeries(V,name = "Visa Stock Price")
```



For the optimization process the returns of the selected stocks is stored in a data-frame “myRetData”.

To visualize the selected stocks better I have used the corrplot package to generate a heat-map that helps us understand the correlations of the stocks selected. Most of the stocks have negligible correlation with the other stocks because of being from different industry. This is useful to get a glimpse of how various stocks relate to each other.



Next step is to extract returns of the portfolio for which I have defined a function which returns weights of the stocks. Multiply the returns by the weights of the stocks which results in overall portfolio return.

For optimizing the portfolio the GA function will perform Genetic algorithm to find the optimal weights for the portfolio. The fitness function defined as  $-\text{obj}(x)$  typically aims to minimize the objective function and maximize the sharpe ratio

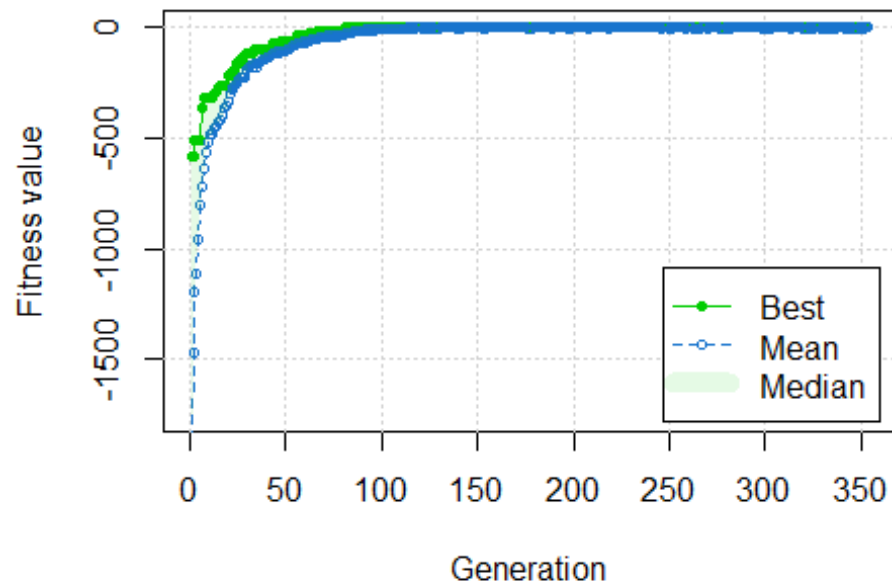
After GA obtains the optimal weights for my portfolio the below summary of the result displays the weights of the stocks in solution section

```
## — Genetic Algorithm —————
##
## GA settings:
## Type = real-valued
## Population size = 50
## Number of generations = 10000
## Elitism = 2
## Crossover probability = 0.8
## Mutation probability = 0.1
## Search domain =
##      x1 x2 x3 x4 x5 x6 x7 x8 x9 x10
## lower 0  0  0  0  0  0  0  0  0  0
## upper 1  1  1  1  1  1  1  1  1  1
##
## GA results:
## Iterations = 353
## Fitness function value = 0.1969136
```

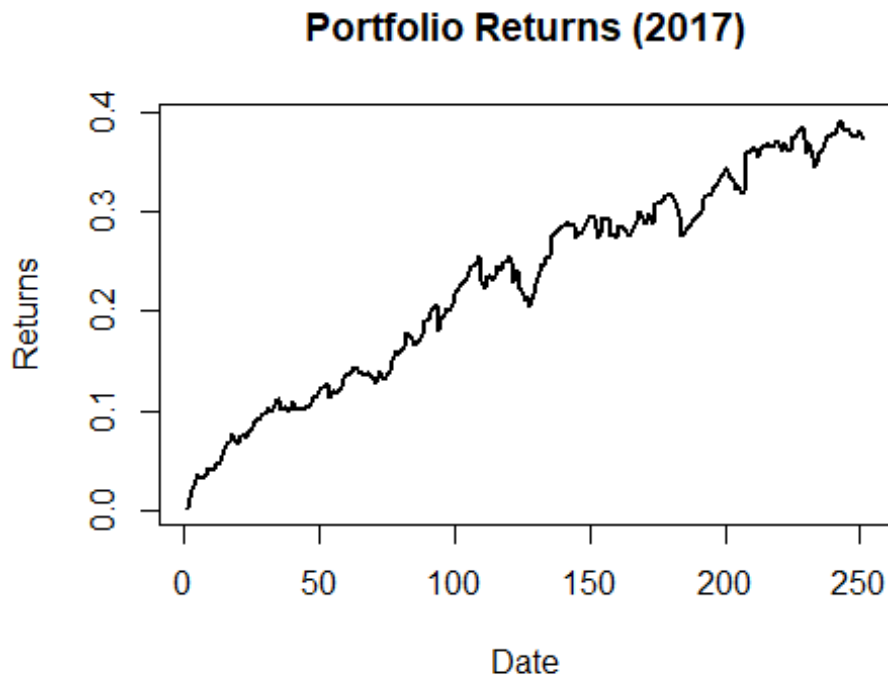
```

## Solution =
##           x1           x2           x3           x4           x5           x6
x7
## [1,] 0.1130085 0.06859431 0.1465211 0.07256733 0.1587442 0.07667776
0.1040569
##           x8           x9           x10
## [1,] 0.06838992 0.1287252 0.06251886

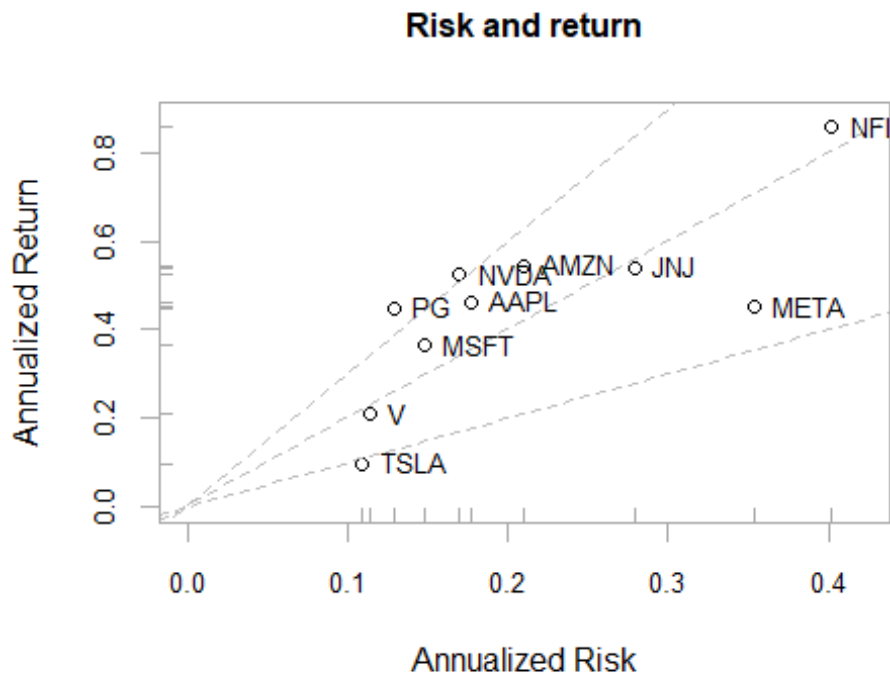
```







The below figure shows relationship between the annualized return and risk for each stock. This can help in visualizing the choice according to the risk tolerance and desired returns. Amazon, Apple, Microsoft, PG and Nvidia have reasonable risk with reasonable returns while, Netflix stands out with higher returns and higher risk. Conversely, Tesla and Visa have minimal risk but give in lower returns.



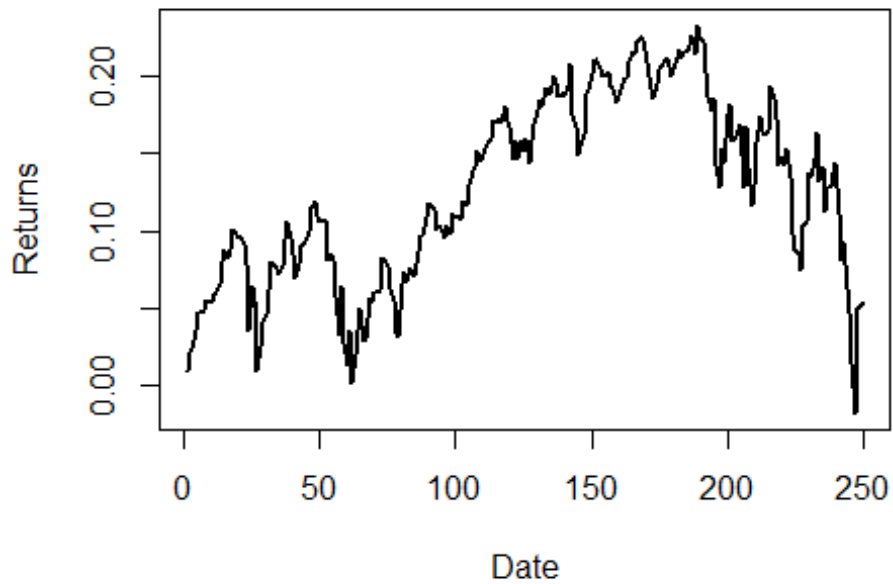
### Evaluation of the portfolio on unseen “future” data

After the optimal weights are stored in a vector, the portfolios performance is evaluated by comparing it to other portfolios and observing its future performance. The optimal weights derived from GA for the year 2017 is used for the subsequent year, 2018. The visual representation of the year's graph shows that the returns for year 2018 declined as compared to the previous year 2017.

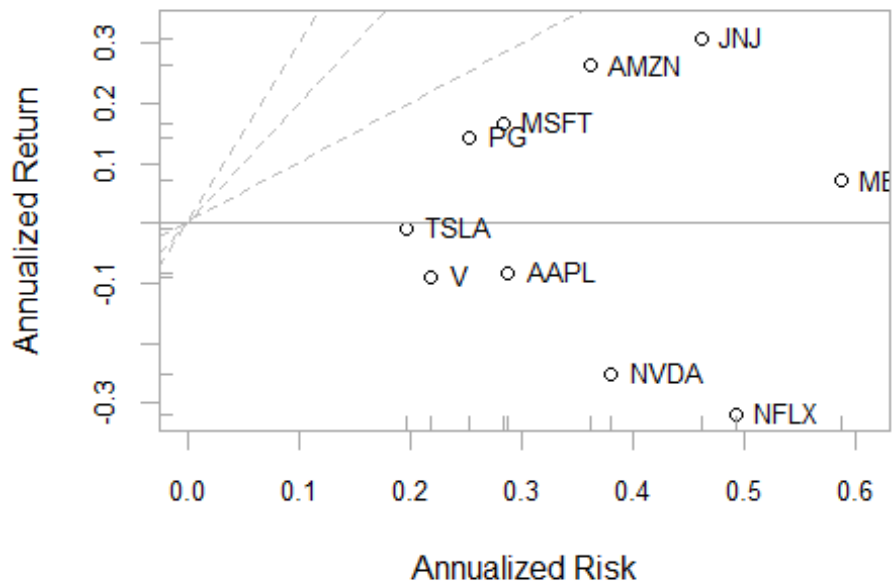
```
# Filtering data for the year 2018 (testing period)
getSymbols(tickers,src ="yahoo",from="2018-01-01",to="2018-12-31",auto.assign
= TRUE)

## [1] "MSFT" "AAPL" "AMZN" "NFLX" "NVDA" "META" "TSLA" "PG" "V" "JNJ"
```

### Portfolio Returns - Test Period (2018)



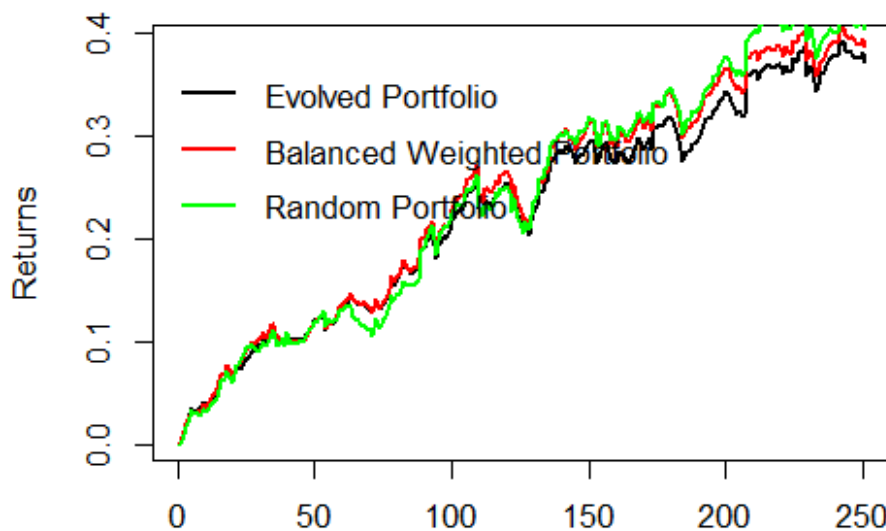
### Risk and return



## Comparison of the evolved portfolio with balanced and random portfolios

All three portfolios seem to follow a similar upward trend over time, suggesting an increase in returns. However, there are variations in performance, with each portfolio taking turns in having the highest return at different times. The Random and balanced lines appear to finish slightly higher than the evolved line, indicating that the Random and Evenly Weighted Portfolios may have performed slightly better than the Evolved Portfolio by the end of the period shown.

### Comparing Blanced, Random and evolved portfolio



The Sortino ratio measures the risk-adjusted return of a portfolio strategy by penalizing only those returns falling below a user-specified target or required rate of return. A higher Sortino ratio indicates better risk adjusted performance.

The Evenly weighted portfolio has the lowest risk-adjusted return, it has higher downside volatility compared to the other portfolios although having higher returns. The random and evolved portfolio has the highest risk adjusted returns with very negligible difference

```
## Sortino Ratio for Evenly Weighted Portfolio: 0.2280889
```

```
## Sortino Ratio for Random Portfolio: 0.2350135
```

```
## Sortino Ratio for Optimal Portfolio: 0.2389112
```

## Creation and evaluation of portfolios with differently balanced risk and return (to emulate a multi-objective approach)

Previously the Portfolio\_return function optimized the portfolio weights based on the sharpe ratio with constraints on weights for evaluation I'm modifying the optimization objective to include a balance between risk and return by calculating the Standard deviation and Mean (return) of portfolio returns.

```
## — Genetic Algorithm —————
##
## GA settings:
## Type = real-valued
## Population size = 50
## Number of generations = 10000
## Elitism = 2
## Crossover probability = 0.8
## Mutation probability = 0.1
## Search domain =
##      x1 x2 x3 x4 x5 x6 x7 x8 x9 x10
## lower 0 0 0 0 0 0 0 0 0 0
## upper 1 1 1 1 1 1 1 1 1 1
##
## GA results:
## Iterations = 599
## Fitness function value = -0.09199833
## Solution =
##      x1      x2      x3      x4      x5      x6
## [1,] 0.04693455 0.04433119 0.00769796 0.01606268 0.03592822 0.9607139
##      x7      x8      x9      x10
## [1,] 0.01468155 0.02184958 0.05691735 0.01953492
```

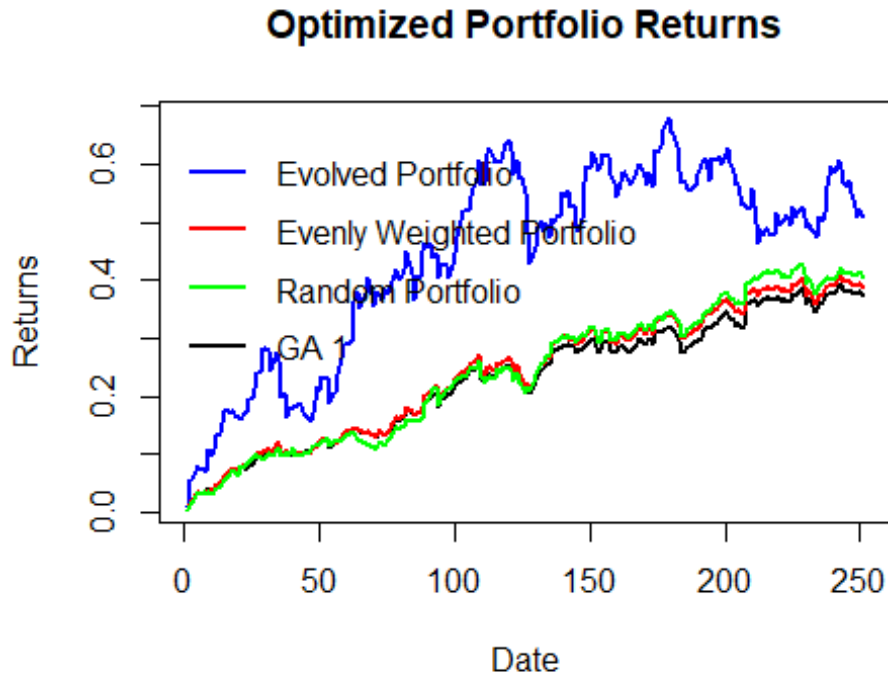
## Evaluating performance of both the Genetic Algorithm's (Risk & Return)

The GA 1 portfolio has a lower mean return (0.001507967) compared to the GA 2 evolved portfolio (0.002027437) so, the second portfolio provides better returns. When it comes to standard deviation(risk) of the portfolios the GA 1 portfolio has lower standard deviation (0.007546885) compared to the GA 2 portfolio (0.02203776). In summary, the first portfolio has lower returns and less risk than the second portfolio whereas, the second portfolio yields high returns but is more vulnerable.

```
## [1] "GA 1"
## Mean Return: 0.001485561
## Standard Deviation (Risk): 0.007544078
## [1] "GA 2"
## Mean Return: 0.002027437
```

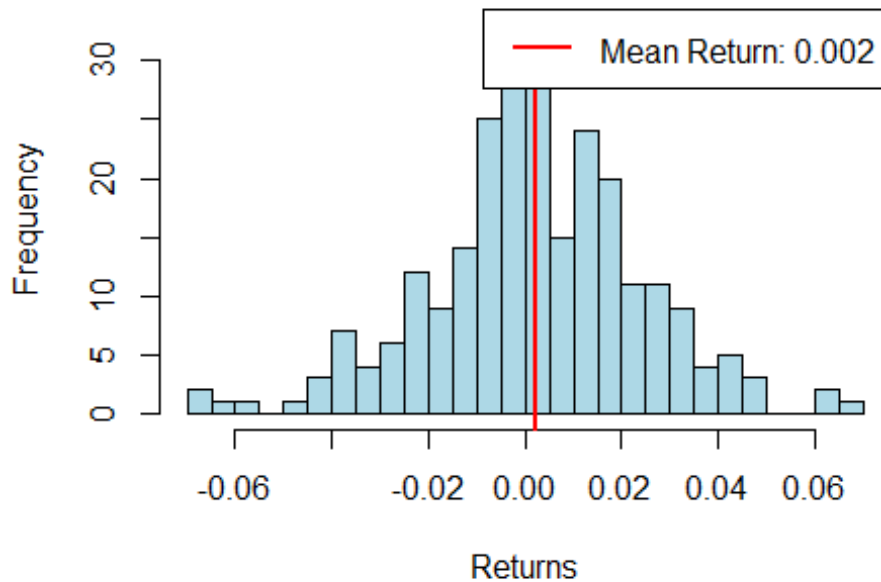
```
## Standard Deviation (Risk): 0.02203776
```

As represented in the graph it is observable that the evolved portfolio outperforms with sharper increases and decline compared to the balanced and the random portfolio.



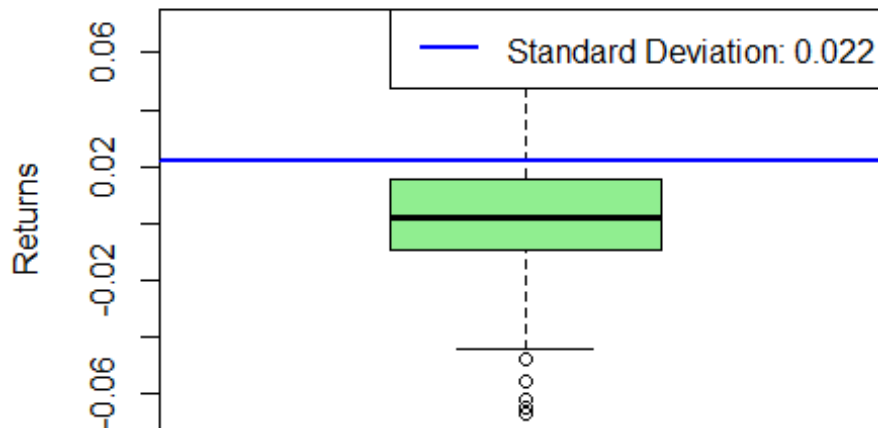
```
# Plot mean return
hist(optimal_returns, breaks = 20, col = "lightblue", main = "Distribution of
Portfolio Returns", xlab = "Returns")
abline(v = optimal_mean, col = "red", lwd = 2)
legend("topright", legend = paste("Mean Return:", round(optimal_mean, 4)),
col = "red", lwd = 2)
```

## Distribution of Portfolio Returns



```
# Plot standard deviation (risk)
boxplot(optimal_returns, col = "lightgreen", main = "Distribution of
Portfolio Returns", ylab = "Returns")
abline(h = optimal_sd, col = "blue", lwd = 2)
legend("topright", legend = paste("Standard Deviation:", round(optimal_sd,
4)), col = "blue", lwd = 2)
```

## Distribution of Portfolio Returns



## Part 2

### Using Genetic Algorithm's to select the assets

For this part I manually selected 50 assets from the S&p 500 index stock list and tried to choose the best assets based on volatility of the assets

```
tickers2 <- c("TMUS", "CCI", "AMT", "SBAC", "EQIX", "AMT", "GS", "SPG",  
"BXP", "PSA", "PLD", "AVB", "ESS", "MAA", "COST", "WBA", "C", "BAC", "WFC",  
"PFE", "JPM", "CME", "ICE", "NDAQ", "LMT", "BA", "RTX", "GD", "CAT", "JPM",  
"KO", "INTC", "AMD", "CSCO", "ORCL", "IBM", "HPQ", "DELL", "XOM", "EXC",  
"DUK", "SO", "AEP", "XEL", "NEE", "DTE", "EIX", "SRE", "T", "VZ")
```

Median value of the Stocks

```
## [1] 55.6211  
  
## [1] "EIX.Adjusted" "CSCO.Adjusted" "VZ.Adjusted" "EXC.Adjusted"  
## [5] "XOM.Adjusted" "ORCL.Adjusted" "MAA.Adjusted" "DUK.Adjusted"  
## [9] "AMD.Adjusted" "DELL.Adjusted"
```

## Conclusion

The portfolio constructed using the Genetic Algorithm in part 1 resulted in having a high fitness value 0.1997912 compared to the fitness value of the portfolio generated with the modified fitness function (-0.09199833 ). The weights assigned to the stocks seems quite



balanced reflecting portfolio's ability to generate returns while managing risk, as exhibited its performance on unseen data

The Sortino ratio (0.2333693) indicates favorable risk adjusted returns for the portfolio.