CS815 Assignment - Portfolio Optimisation using GAs

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PORTFOLIO OPTIMISATION USING GA

PART 1

The aim is to create a portfolio of stocks and to find the optimal solution using Genetic algorithm.

Construction of a portfolio using the GA package

Selection of stocks

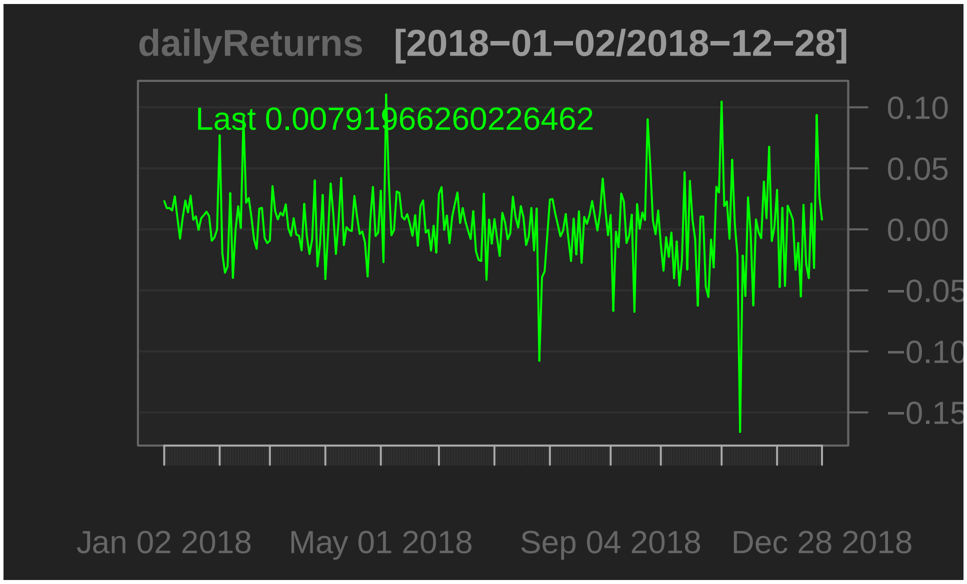
For this part, I have chosen 10 different stocks from different sectors of the economy. The assets chosen have performed well during the year 2018. The stocks are chosen from different sectors and industries to include diversification. By this selection, we are trying to mitigate some risk of impact of poor performance in a specific industry. This selection and diversification also aim to reduce the overall correlation within the portfolio. The selected stocks are as below.
ABMD - Abiomed, Inc.(Medical device technology company) AMD - Advanced Micro Devices, Inc.(Semiconductor company) TRIP - TripAdvisor, Inc.(Company that operates online travel agencies) CMG - Chipotle Mexican Grill, Inc. (Restaurant chain) NFLX - Netflix, Inc. (Video streaming company) UA - Under Armour, Inc.(Sportswear company) AMZN - Amazon.com, Inc.(Ecommerce and AI) BSX - Boston Scientific. (Multinational manufacturer of medical devices) FTNT - Fortinet. (Cybersecurity company) ORLY - O'Reilly Automotive Inc. American auto parts retailer

Data retrieval

The date range chosen is 1 year from 1st Jan 2018 to 31st Dec 2018. The quantmod package is used to retrieve the stock details. The source of retrieval is yahoo finance.

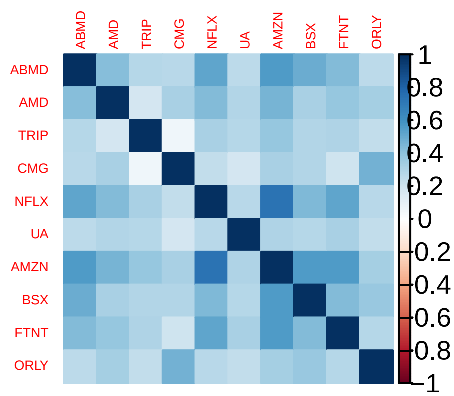
Daily returns for all stocks:

The daily return for each stock is calculated and merged into a single data frame.



Visualise the data

A heat map chart is generated to visualize the correlation among the stocks selected. It is very clear that there is weak correlation. This might be due to the diverse nature if stocks selected from diverse industries.



Fitness function:

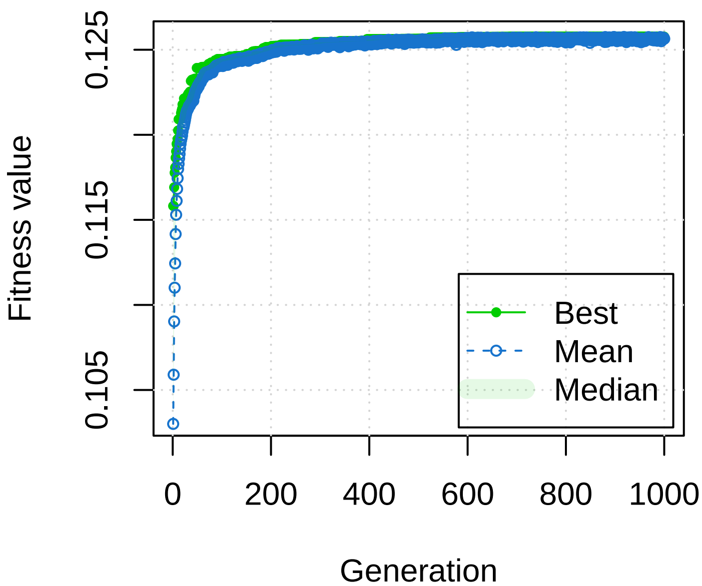
Create the evaluation function which will maximize the weighted mean returns and at the same time minimizing the risk. The mean value of daily returns from the stocks is calculated. The risk associated with holding a particular combination of stocks is represented by the standard deviation of the portfolio. The risk is calculated using the weights vector and the covariance vector and gives an indication on the portfolio variance. The fitness function calculates the portfolio score and aims to maximize this score for better performance. This effectively denotes, the mean return is maximized and the risk is minimized.

GA package:

Run the GA model with adequate parameters. The parameters are adjusted to get a stable output. A population size of 200 is chosen for each generation of the algorithm. Maximum iterations of 1000 will be performed. The number of iterations are increased to attain the stability of the plot. Crossover and mutation values are given which indicates 60% of the offspring will result from crossover and 4% of population will undergo mutation.As weights range from 0 to 1, the lower and upper are kept as 0 and 1 respectively. These parameters are adjusted to get the optimal weights. As seen from the plot, the convergence starts from around 400-600 iterations. The number of iterations is hence kept as 1000 to avoid excessive run time.

GA Solution and plot

The optimal weights are obtained from GA and plotted. The weights for each stock is displayed. The plot displays GA model converging to the best value and getting stable.




```
##    Stocks OptimalWeights
## 1    ABMD   0.4501599216
## 2     AMD   0.1829855505
## 3    TRIP   0.5412112192
## 4     CMG   0.3893482147
## 5    NFLX   0.0014041745
## 6      UA   0.0006048272
## 7    AMZN   0.0038873926
## 8     BSX   0.3541388376
## 9    FTNT   0.9223801416
## 10   ORLY   0.9885456619
```

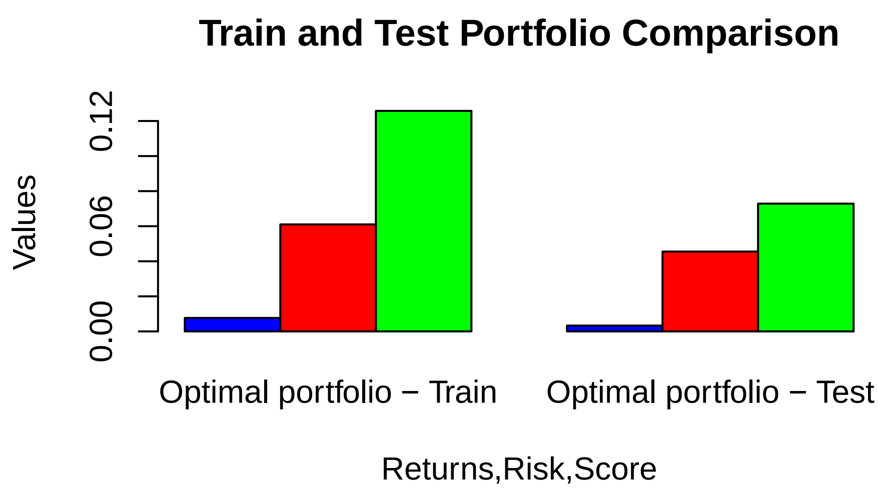
```
## Optimized Returns, Risk and Score derived from GA model:
##  0.00767617884688197, 0.0610340933782287, 0.12576870437499
```

Evaluation of the portfolio on unseen "future" data

In order to evaluate the model and optimal weights, the weights optimized from GA model is applied to the test data of year 2019. The portfolio returns,risk and score of unseen data from 2019 is generated by utilizing these optimal weights. The returns for the training data is significantly higher than the returns from testing data.

```
##                                Returns       Risk      Score
## Optimised Portfolio        0.007676179 0.06103409 0.12576870
## Portfolio on future data 0.003317910 0.04553593 0.07286357
```

The risk on test data is lower than the train data which indicates the weights evolved from the GA is performing better on the on unseen data in terms of risk. The returns on test data is significantly lower than train data. This might indicate the optimal weights performed well on training data and the model may be over fitting on train data. The weights are not generalizing for future data. The case is same with the portfolio score where train data is performing better than test data. The decrease in returns and score for test data could also be due to fluctuating market conditions for which the portfolio is sensitive to.

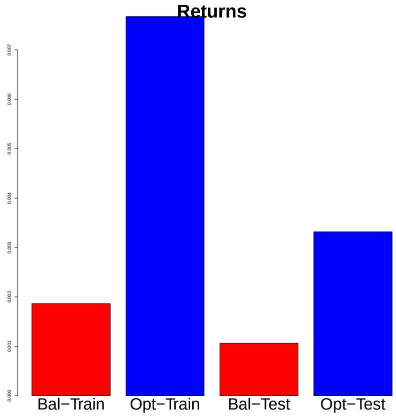


Comparison of the evolved portfolio with balanced and random portfolios

A balanced portfolio is created by assigning equal weights to all stocks. The performance of a balanced portfolio is compared to the train and test data of the optimal weighted portfolios. Similar comparison is made with a random weighted portfolio. To create a random portfolio, the weights are randomly assigned to the stocks and the average of several runs is taken for comparison.

Optimised vs Balanced Portfolio

```
##                                        Returns       Risk      Score
## Balanced weights Portfolio - Train 0.001865976 0.01750739 0.10658221
## Optimal weight portfolio - Train   0.007676179 0.06103409 0.12576870
## Balanced weights Portfolio - Test  0.001063501 0.01264440 0.08410845
## Optimal weight portfolio - Test    0.003317910 0.04553593 0.07286357
```

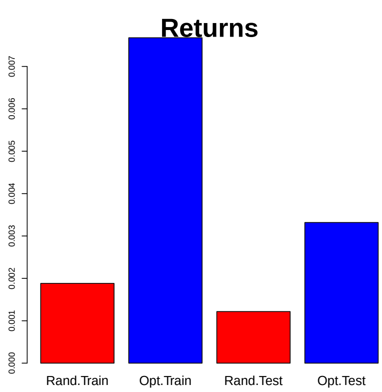


The metrics for both Optimized and balance portfolio is compared. The optimal weighted portfolio is showing significantly better returns and higher risk than the balanced portfolio for both train and test data. The score is hence better for the optimal weighted portfolio in train data and a little lower than the test data. The optimal weighted portfolio outperformed the balanced portfolio in terms of returns and suggests that the weights derived from GA model is better than the balanced weights.

Optimised vs Random generated Portfolio

```
##                                         Returns       Risk      Score
## Random weights Portfolio - Train 0.001881223 0.01831389 0.10279471
## Optimal weight portfolio - Train 0.007676179 0.06103409 0.12576870
## Random weights Portfolio - Test  0.001216951 0.01347828 0.09070132
## Optimal weight portfolio - Test  0.003317910 0.04553593 0.07286357
```

The optimal portfolio has a higher and positive return when compared to the random portfolio on both train and test data. It also performs well with higher score than the random portfolio on train data. The risk associated with optimal portfolio is higher than the random portfolio for train and test data but the returns improved with optimal weights. This suggests that the weights we chose from GA model are giving better returns than randomly assigned weights for both the evolved and future data.



Creation and evaluation of portfolios with differently balanced risk and return

The fitness function and the GA model created will balance the risk and return evenly. The fitness function is modified to handle different preferences to risk or return.

Fitness function to create differently balanced portfolios

In order to vary the balance between risk and returns, a bias is introduced to assign weights for both return and risk, the sum of which will be 1. Run the GA model with the new fitness function. Variable bias is the weight applied for return and (1-bias) is the weight applied for risk. If bias is set to 1, the function will try to maximize the return giving no preference to risk. Similarly, when bias is set to 0, it prioritize risk aversion without giving any preference to return. These are the extreme scenarios without balance. The value of bias can be varied to attain a trade off between these 2 objectives.

Bias of 0.85 which prioritizes portfolio return

The bias is adjusted to give higher priority to increasing the returns. The GA model is executed with the updated fitness function. With the new evolved weights, a new portfolio is created.

Optimal Portfolio vs Return maximising Portfolio

```
##                                     Returns       Risk      Score
## Optimal Portfolio Train         0.007676179 0.06103409 0.12576870
## Return priority Portfolio Train 0.007679069 0.06105089 0.12578144
## Optimal Portfolio Test          0.003317910 0.04553593 0.07286357
## Return priority Portfolio Test  0.003320057 0.04555701 0.07287696
```

The new portfolio with return bias and the optimal portfolio without any bias, show very similar returns, risk and score with only slight variation. The same evolved weights are applied for the test data also from 2019. The observations are the same where both portfolios exhibit almost similar metrics on test data. The return biased portfolio is giving higher returns but with increased risk. The overall performance is higher for return biased portfolio in both train and test periods. When the preference is given for returns, the GA algorithm selects stocks with higher returns from the data. This may also lead to higher risk as the fitness function gives very low weight for aversing the risk.

Balanced & Random Portfolios vs Return maximising Portfolio

```
##                                     Returns       Risk      Score
## Balanced Portfolio Train        0.001865976 0.01750739 0.10658221
## Random Portfolio Train          0.001881223 0.01831389 0.10279471
## Return priority Portfolio Train 0.007679069 0.06105089 0.12578144
## Balanced Portfolio Test         0.001063501 0.01264440 0.08410845
## Random Portfolio Test           0.001216951 0.01347828 0.09070132
## Return priority Portfolio Test  0.003320057 0.04555701 0.07287696
```

The bias 0.85 gives preference to returns and the portfolio is compared with the previously created balanced and random portfolios. The evolved portfolio which gives more preference to returns is shown to give much higher returns compared to the balanced or random portfolios. This observation is for both train and test data with respect to returns. At the same time, the risk seems to have increased for this portfolio compared to balanced or random weights. The score is higher for train but less compared to the other portfolios in test data. This performance is because of the model's priority on maximizing the returns without giving any weight to averse risk.

Bias of 0.3 which prioritizes risk aversion

The bias is adjusted to give priority to aversing the risk. The GA model is executed with the updated fitness function and with the new bias. With the new evolved weights, a new portfolio is created.

Optimal Portfolio vs Risk aversion Portfolio

```
##                                 Returns       Risk      Score
## Optimal Portfolio Train       0.007676179 0.06103409 0.12576870
## Risk priority Portfolio Train 0.007788875 0.06193647 0.12575588
## Optimal Portfolio Test        0.003317910 0.04553593 0.07286357
## Risk priority Portfolio Test  0.003387822 0.04622649 0.07328746
```

The mean returns for both train and test data have slightly varied from the initial returns as this portfolio is giving more preference to minimize the risk. The new portfolio with risk aversion bias, shows a slight change in risk value for both train and test data. The score however, is comparatively equal to the respective original portfolio for train and test periods. When the preference is given for risk aversion, the GA algorithm selects stocks with lower risks. This may also lead to lesser returns.

Balanced/Random Portfolios vs Risk aversion Portfolio

```
##                                 Returns       Risk      Score
## Balanced Portfolio Train      0.001865976 0.01750739 0.10658221
## Random Portfolio Train        0.001881223 0.01831389 0.10279471
## Risk priority Portfolio Train 0.007788875 0.06193647 0.12575588
## Balanced Portfolio Test       0.001063501 0.01264440 0.08410845
## Random Portfolio Test         0.001216951 0.01347828 0.09070132
## Risk priority Portfolio Test  0.003387822 0.04622649 0.07328746
```

The bias 0.3 gives preference to risk aversion and the portfolio is compared with the previously created balanced and random portfolios. The evolved portfolio which gives preference to risk, is showing higher returns but with increased risk too, compared to the balanced and random portfolios for both train and test periods. The performance in terms of score has increased for train data but this is got reduced for test data.

PART 2

USING GAs TO SELECT THE ASSETS

In this part, I got a pool of 50 stocks to choose from. Using GA model, 10 stocks are selected which maximizes returns and minimizes score. This top 10 stocks are given to the first GA model created for optimizing the weights. The optimal weights are assigned to the stocks selected by GA. The returns, risk and score of these new stocks are compared with the performance of the 10 stocks chosen manually in Part 1.

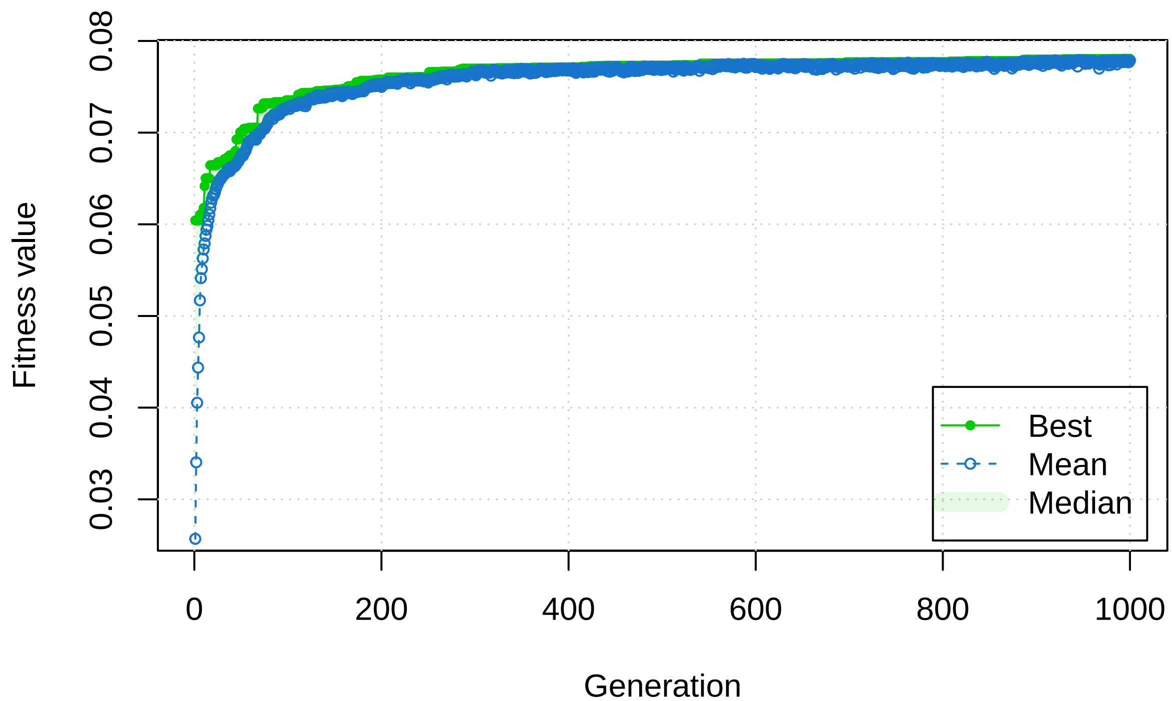
Selection of Assets

The 50 assets are chosen from year 2018. This includes the stocks which performed well for the year. A GA model is created to identify the top 10 best performing stocks from this pool. The final stock selection suggested by the algorithm is as follows:

```
## Top 10 Stocks: ISRG JPM VOO NVDA ADBE IDXX NFLX RL FOSL PRTS
```

Performance of stocks selected by GA

The top 10 stocks selected by GA are given as inputs for the initial GA where we optimized the weights for 10 stocks. After getting the optimal weights as feedback from optimization GA for the new stocks, the performance with these stocks are calculated.



Comparison of GA selected portfolio against other portfolios

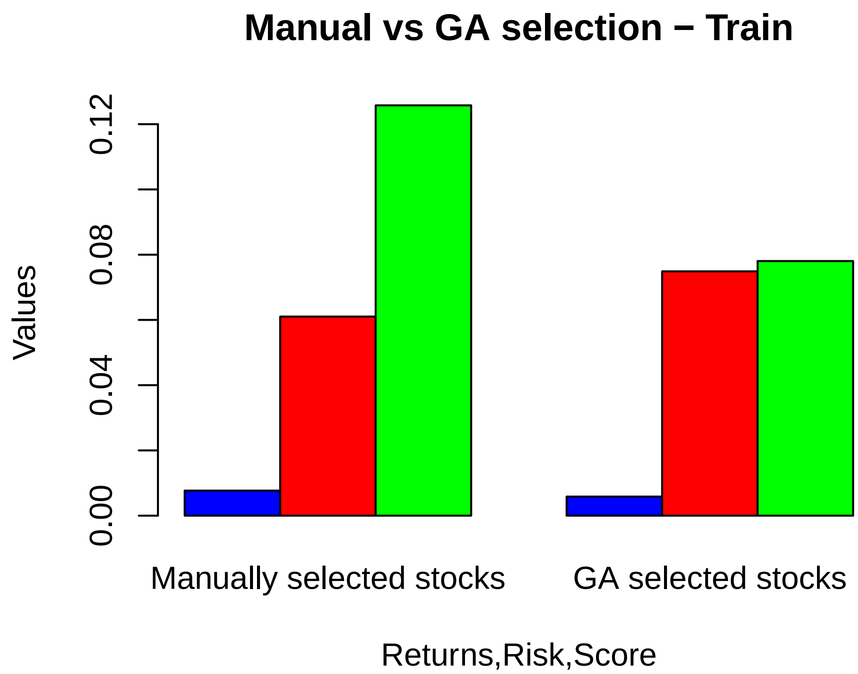
The optimal weights derived from GA for the GA selected stocks is applied to the respective stocks to calculate the performance metrics. This is compared with the stocks manually chosen. The comparison is done for original weights, balanced and random weights on train and test data.

Train data - Manual selection vs GA selection

The returns for GA stocks seems to be much less than the returns compared to manual stocks. However, the risk associated with GA stocks are much less. The manual stocks give a higher score too despite the higher risk associated. From this, I assume the manually selected stocks are better suited to build the portfolio. The table below shows the comparison.

```
##                                                    Returns       Risk      Score
## Optimised Portfolio - Manual selected stocks 0.007676179 0.06103409 0.12576870
## Optimised Portfolio - GA selected stocks     0.005844577 0.07488979 0.07804238
```

The metrics is plotted in bar chart for a better visual representation.



Test data - Manual selection vs GA selection

The daily returns or the final selected stocks are retrieved for the test year of 2019. The metrics is then compared with the optimized portfolio with manual stocks with test data.

```
##                             Returns       Risk      Score
## GA selection - Test     0.001128437 0.04592412 0.02457177
## Manual selection - Test 0.003317910 0.04553593 0.07286357
```

The returns is higher for the stocks selected manually than the final selected stocks when run in test data. The risk for manual stocks is higher in the year 2019. The stocks selected manually perform better for the test data than the GA selected stocks in terms of overall score.

Balanced Portfolio - Manual selection vs GA selection

The metrics for balanced portfolio with manual selection was already calculated. Here, I calculate the metrics for the GA selected stocks by assigning balanced weights to them.

```
##                                              Returns       Risk      Score
## Balanced weights GA portfolio - Train     0.0004128981 0.01731238 0.02384987
## Balanced weights Manual portfolio - Train 0.0018659759 0.01750739 0.10658221
## Balanced weights GA Portfolio - Test      0.0012271977 0.01199510 0.10230826
## Balanced weights Manual Portfolio - Test  0.0010635012 0.01264440 0.08410845
```

When weights are applied equally, manually selected stocks seem to give higher returns and better score for train data than the GA selected stocks. For test data, the GA selected stocks are giving better returns and higher score. The risk is higher for manual stocks in both train and test periods. In terms of score, manual selection is better in train data and GA selection is better in test data.

Random Portfolio - Manual selection vs GA selection

```
##                                              Returns       Risk      Score
## Random weights GA portfolio - Train     0.0004324082 0.01807628 0.02317556
## Random weights Manual portfolio - Train 0.0018812231 0.01831389 0.10279471
## Random weights GA Portfolio - Test      0.0012519218 0.01199510 0.10230826
## Random weights Manual Portfolio - Test  0.0010635012 0.01254680 0.10107490
```

The randomly assigned weighted portfolio is performing well with the manually selected stocks compared to GA selected stocks in both train and test data. There is no major variation in terms of risk. Manual stocks outperform GA stocks in Train data but almost same performance in Test data.

Conclusion

In this document, I have manually selected 10 stocks for the year 2018 and derived a GA model to find t he o ptimal w eights f or t hese s tocks. T he e valuation o f p ortfolio i s d one o f f uture u nseen data of the year 2019. Overall, the the weights evolved give better performance for train data. A comparison is also done with the balanced and random weights. The observation shows GA weighted portfolio performs better than the other weighted models. A multiobjective GA was constructed and the performance is compared with train and test data for all scenarios. In the final s ection, I have used GA to select the stocks rather than choosing manually. The performance of these stocks are compared against the manually selected stocks and the observations are noted. The overall report offers a thorough exploration of the portfolio construction and evaluation process using Genetic Algorithms.
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