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Portfolio Optimization using R and Plotly

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44

In this post we'll focus on showcasing Plotly's **WebGL** capabilities by charting financial portfolios using an R package called **PortfolioAnalytics**. The package is a generic portfolio optimization framework developed by folks at the **University of Washington** and *Brian Peterson* (of the PerformanceAnalytics fame).

You can see the vignette [here](#)

Let's pull in some data first.

```
1 library(PortfolioAnalytics)
2 library(quantmod)
3 library(PerformanceAnalytics)
4 library(zoo)
5 library(plotly)
6
7 # Get data
8 getSymbols(c("MSFT", "SBUX", "IBM", "AAPL", "^GSPC", "AMZN"))
9
10 # Assign to dataframe
11 # Get adjusted prices
12 prices.data <- merge.zoo(MSFT[,6], SBUX[,6], IBM[,6], AAPL[,6], GSPC[,6], AMZN[,6])
13
14 # Calculate returns
15 returns.data <- CalculateReturns(prices.data)
16 returns.data <- na.omit(returns.data)
17
18 # Set names
19 colnames(returns.data) <- c("MSFT", "SBUX", "IBM", "AAPL", "^GSPC", "AMZN")
20
21 # Save mean return vector and sample covariance matrix
22 meanReturns <- colMeans(returns.data)
23 covMat <- cov(returns.data)
```

Now that we have some data, let's get started by creating a portfolio specification. This can be done by using `portfolio.spec()`

```
1 # Start with the names of the assets
2 port <- portfolio.spec/assets = c("MSFT", "SBUX", "IBM", "AAPL", "^GSPC", "AMZN"))
```

Now for some constraints. Let's use the following:

- Box constraints
- Leverage (weight sum)

```
1 # Box
2 port <- add.constraint(port, type = "box", min = 0.05, max = 0.8)
3
4 # Leverage
5 port <- add.constraint(portfolio = port, type = "full_investment")
```

Let's use the built-in **random** solver. This essentially creates a set of feasible portfolios that satisfy all the constraints we have specified. For a full list of supported constraints see [here](#)

```

1 # Generate random portfolios
2 rportfolios <- random_portfolios(port, permutations = 500000, rp_method = "sample")

```

Now let's add some objectives and optimize. For simplicity's sake let's do some mean-variance optimization.

```

1 # Get minimum variance portfolio
2 minvar.port <- add.objective(port, type = "risk", name = "var")
3
4 # Optimize
5 minvar.opt <- optimize_portfolio(returns.data, minvar.port, optimize_method = "random",
6                                 rp = rportfolios)
7
8 # Generate maximum return portfolio
9 maxret.port <- add.objective(port, type = "return", name = "mean")
10
11 # Optimize
12 maxret.opt <- optimize_portfolio(returns.data, maxret.port, optimize_method = "random",
13                                 rp = rportfolios)
14
15 # Generate vector of returns
16 minret <- 0.06/100
17 maxret <- maxret.opt$weights %>% meanReturns
18
19 vec <- seq(minret, maxret, length.out = 100)

```

Now that we have the minimum variance as well as the maximum return portfolios, we can build out the efficient frontier. Let's add a weight concentration objective as well to ensure we don't get highly concentrated portfolios.

Note:

- `random_portfolios()` ignores any *diversification* constraints. Hence, we didn't add it previously.
- Using the **random** solver for each portfolio in the loop below would be very compute intensive. We'll use the **ROI** (R Optimization Infrastructure) solver instead.

```

1 eff.frontier <- data.frame(Risk = rep(NA, length(vec)),
2                             Return = rep(NA, length(vec)),
3                             SharpeRatio = rep(NA, length(vec)))
4
5 frontier.weights <- mat.or.vec(nr = length(vec), nc = ncol(returns.data))
6 colnames(frontier.weights) <- colnames(returns.data)
7
8 for(i in 1:length(vec)){
9   eff.port <- add.constraint(port, type = "return", name = "mean", return_target = vec[i])
10  eff.port <- add.objective(eff.port, type = "risk", name = "var")
11  # eff.port <- add.objective(eff.port, type = "weight_concentration", name = "HHI",
12  #                           conc_aversion = 0.001)
13
14  eff.port <- optimize_portfolio(returns.data, eff.port, optimize_method = "ROI")
15
16  eff.frontier$Risk[i] <- sqrt(t(eff.port$weights) %>% covMat %>% eff.port$weights)
17
18  eff.frontier$return[i] <- eff.port$weights %>% meanReturns
19
20  eff.frontier$Sharperatio[i] <- eff.port$return[i] / eff.port$Risk[i]
21
22  frontier.weights[i,] = eff.port$weights
23
24  print(paste(round(i/length(vec) * 100, 0), "% done..."))
25 }

```

Now lets plot !

```

1 feasible.sd <- apply(rportfolios, 1, function(x){
2   return(sqrt(matrix(x, nrow = 1) %>% covMat %>% matrix(x, ncol = 1)))

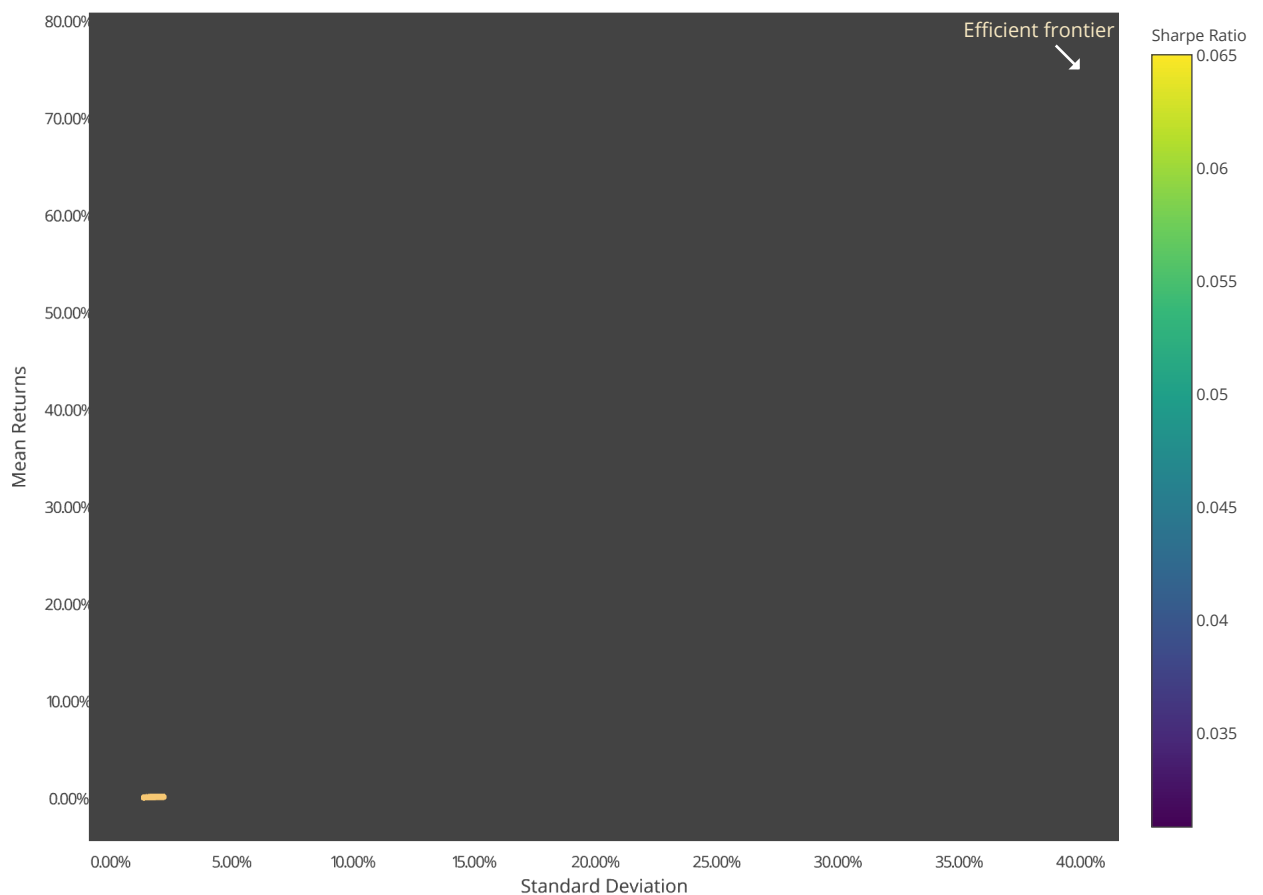
```

```

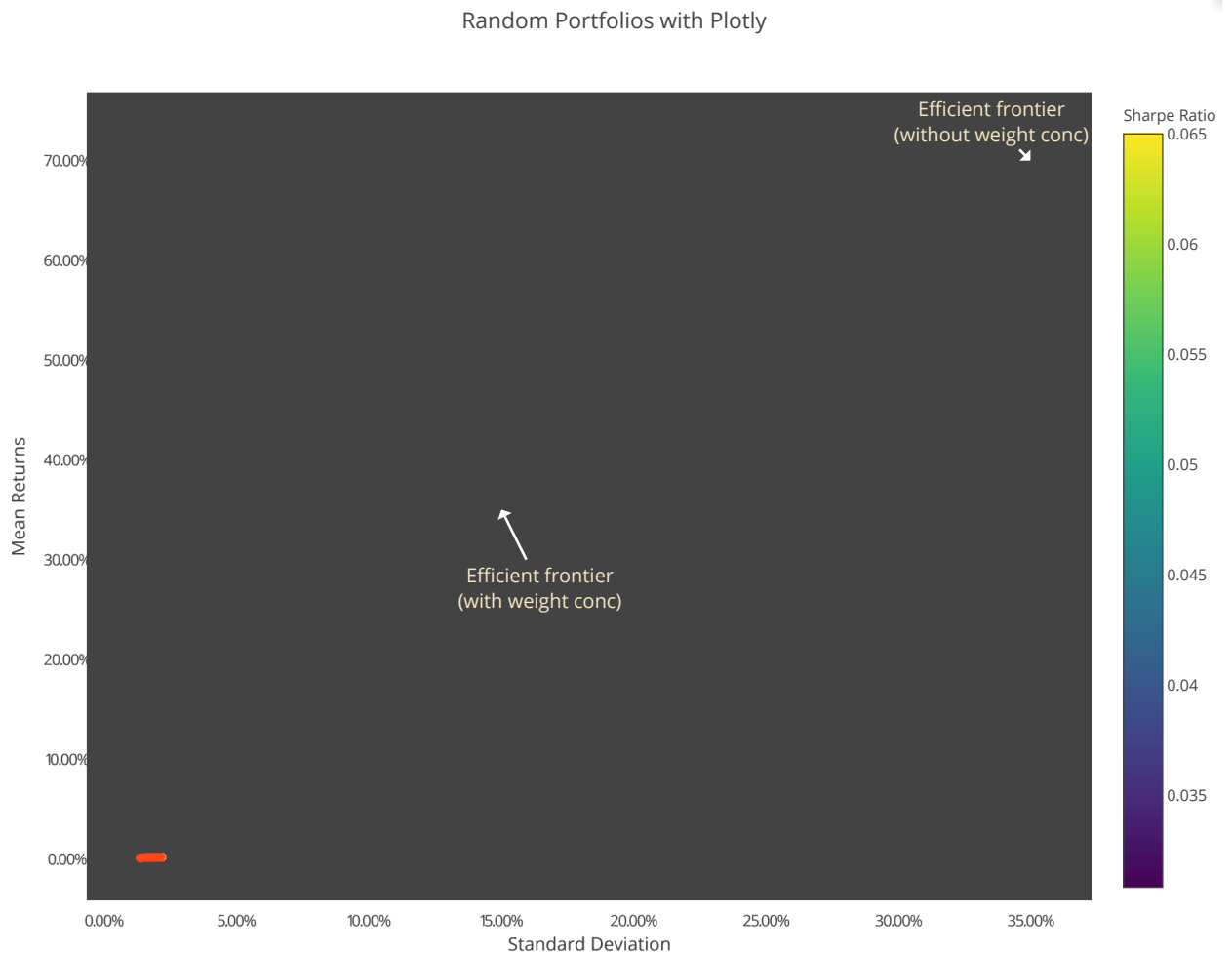
3  })
4
5  feasible.means <- apply(rportfolios, 1, function(x){
6    return(x %*% meanReturns)
7  })
8
9  feasible.sd <- feasible.means / feasible.sd
10
11 p <- plot_ly(x = feasible.sd, y = feasible.means, color = feasible.sd,
12             mode = "markers", type = "scattergl", showlegend = F,
13
14             marker = list(size = 3, opacity = 0.5,
15                           colorbar = list(title = "Sharpe Ratio"))) %>%
16
17 add_trace(data = eff.frontier, x = Risk, y = Return, mode = "markers",
18           type = "scattergl", showlegend = F,
19           marker = list(color = "#F7C873", size = 5)) %>%
20
21 layout(title = "Random Portfolios with Plotly",
22        yaxis = list(title = "Mean Returns", tickformat = "%.2%"),
23        xaxis = list(title = "Standard Deviation", tickformat = "%.2%"),
24        plot_bgcolor = "#434343",
25        paper_bgcolor = "#F8F8F8",
26        annotations = list(
27          list(x = 0.4, y = 0.75,
28              ax = -30, ay = -30,
29              text = "Efficient frontier",
30              font = list(color = "#F6E7C1", size = 15),
31              arrowcolor = "white")
32        ))

```

Random Portfolios with Plotly



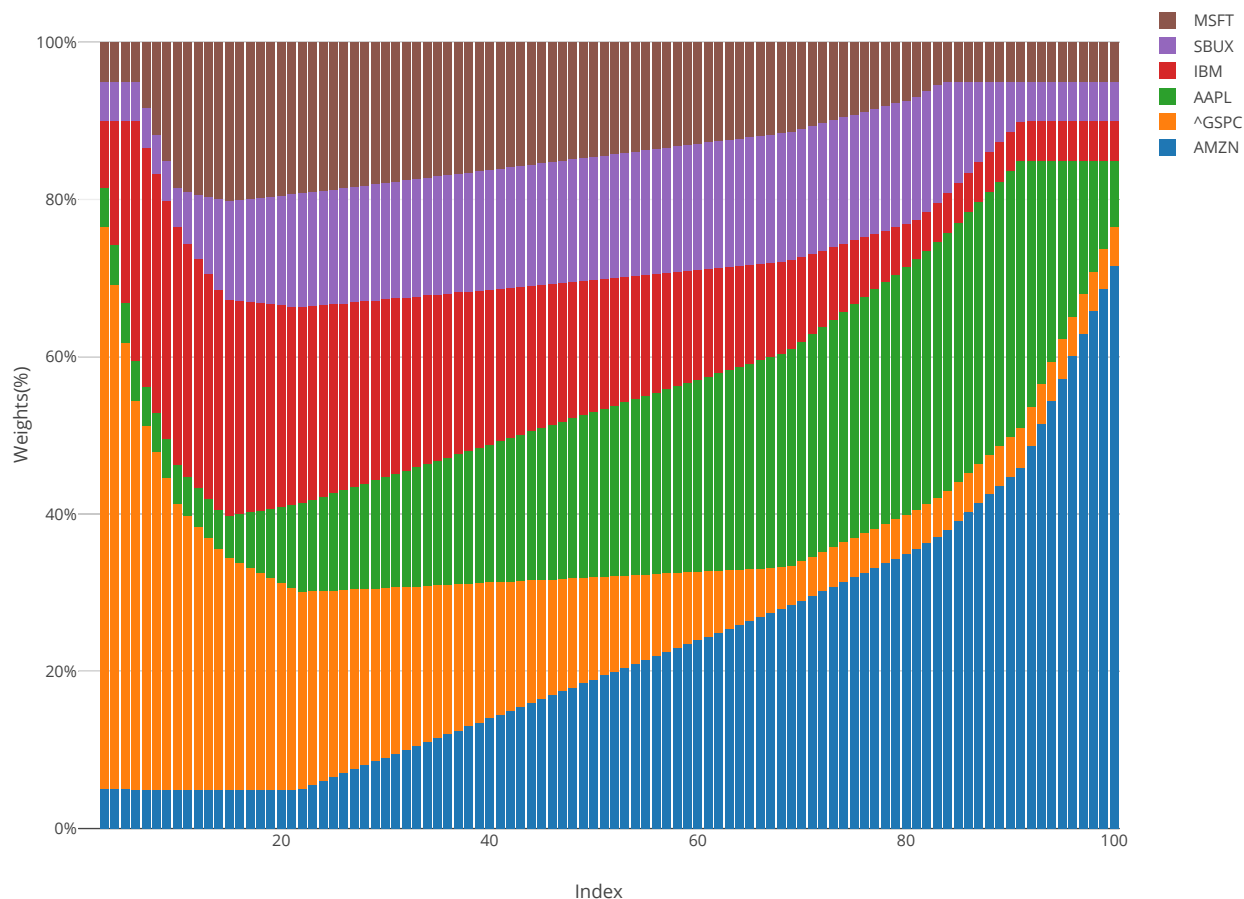
The chart above is plotting **42,749** data points ! Also, you'll notice that since the portfolios on the frontier (beige dots) have an added weight concentration objective, the frontier seems sub optimal. Below is a comparison.



Let's also plot the weights to check how diversified our optimal portfolios are. We'll use a barchart for this.

```
1 frontier.weights.melt <- reshape2::melt(frontier.weights)
2
3 q <- plot_ly(frontier.weights.melt, x = Var1, y = value, group = Var2, type = "bar") %>%
4   layout(title = "Portfolio weights across frontier", barmode = "stack",
5     xaxis = list(title = "Index"),
6     yaxis = list(title = "Weights(%)", tickformat = ".0%"))
```

Portfolio weights across frontier



44

**Riddhiman**Tags: [Data Visualization](#), [Optimization](#), [Plotly](#), [R](#)

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