Project 2

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Due 2/28/17

Calculate Daily Returns for Each Stock

```
### Calculate Daily Returns
returnsMat <- diff(priceMat)/priceMat[-nrow(priceMat),]</pre>
```

Calculate Correlation Matrix

```
### Calculate the Correlation Matrix
rho <- cor(returnsMat, use = "complete.obs")</pre>
```

Code the Integer Program

```
constructFunds <- function(rh,q,pMat,sMat,ut,ud){</pre>
  library("lpSolve")
  #set n to be the number of stocks we're looking at
  n <- length(ut)
  Q <- q
  #Create the y constraint portion of the A matrix
  y_{constraint} \leftarrow c(rep(0,n*n),rep(1,n))
  y_constraint <- matrix(y_constraint, 1, n*n+n)</pre>
  \#Create\ the\ x\ constraint\ portion\ of\ the\ A\ matrix
  x_constraint <- c()</pre>
  for (i in 1:n) {
    x_constraint <- append(x_constraint,rep(0, n*(i-1)))</pre>
    x_constraint<- append(x_constraint,rep(1, n))</pre>
    x_constraint <- append(x_constraint,rep(0, n*(n-i)+n))</pre>
  }
  x_constraint <- matrix(x_constraint, byrow = TRUE,n, n*n+n)</pre>
  #Create the xy constraint portion of the A matrix
  xy_x \leftarrow diag(n*n)
  xy_y \leftarrow rep(c(diag(x=-1,n)),n)
  xy_constraint <- cbind(xy_x, matrix(xy_y, byrow=TRUE,n*n,n))</pre>
  A <- rbind(y_constraint,x_constraint,xy_constraint)
  b \leftarrow c(Q,rep(1,n),rep(0,n*n))
  dir <- c(rep("=",n+1),rep("<=",n*n))</pre>
  c \leftarrow c(rh, rep(0,n))
```

```
sol <- lp("max",c,A,dir,b,binary.vec = 1:((n^2)+n))

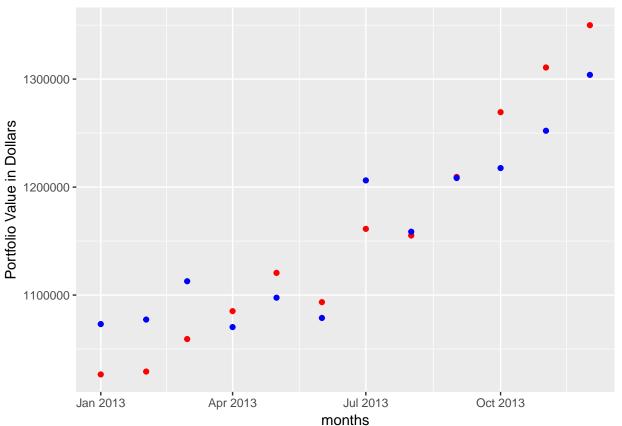
# Calculate the weights
xij_solution <- matrix(sol$solution[1:(n*n)],byrow = TRUE,n,n)
valueMat <- sMat*pMat
lastValueDate <- valueMat[nrow(valueMat),]
wj <- colSums(xij_solution*lastValueDate)
total <- sum(wj)
wt <- wj/total
return(wt)
}</pre>
```

Use Weights to Construct Index Portfolio at the End of 2012

```
## Create a function that returns the montly value of our index fund assuming a 1MM investment
getPerformance <- function(pMat,wts, mtpMat){</pre>
  lastPriceDate <- pMat[nrow(pMat),]</pre>
  portfolio <- wts*1000000
  portfolioShares <- portfolio/lastPriceDate</pre>
  portfolioReturn <- c()
  for (i in c(1:12)){
    portfolioReturn<-append(portfolioReturn,sum(portfolioShares*mtpMat[i,]))</pre>
  }
  return(portfolioReturn)
}
q = 25
weights <- constructFunds(rho, q, priceMat, sharesMat, unique_tickers, unique_dates)</pre>
#Stocks in our portfolio
subset(data.frame(unique_tickers, weights), weights!=0)
##
      unique_tickers
                           weights
```

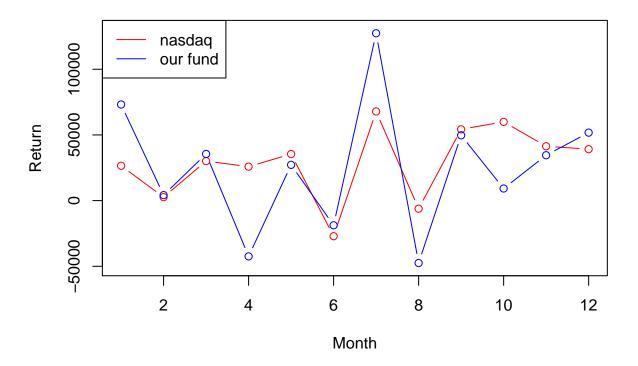
```
## 3
                 ADI 0.2964807551
## 4
                ADP 0.1080383349
## 11
                AMZN 0.1390916618
                BIDU 0.0093990660
## 15
                CELG 0.0488368463
## 19
                CTRX 0.0033017861
## 27
## 29
                CTXS 0.2053599706
## 36
                ESRX 0.0150775179
## 39
                FAST 0.0047217151
## 40
                  FB 0.0151813120
## 44
                GMCR 0.0020976887
                KRFT 0.0257411154
## 53
## 57
                LMCA 0.0122518221
## 60
                MNST 0.0029896074
## 63
                MWW 0.0002246126
## 66
                NFLX 0.0017565763
## 71
                ORLY 0.0065926647
## 73
                PCAR 0.0258156869
## 76
                REGN 0.0055596826
## 77
                ROST 0.0041338535
```

```
SBAC 0.0030749654
## 78
## 87
                 TRIP 0.0018607787
                  VOD 0.0084671149
## 93
                  WDC 0.0117989434
## 96
## 97
                  WFM 0.0421459214
#Overal Return
pReturn <- getPerformance(priceMat, weights, monthlyPriceMat)</pre>
\#\# Calculate the monthly value of the NASDAQ assuming a 1MM investment
nasdaq <- c(2731.53, 2738.58, 2818.69, 2887.44, 2981.76, 2909.60, 3090.19, 3073.81, 3218.20, 3377.73, 3
# calculate our index's return
total_investment = 1000000
shares <- total_investment/2660.93</pre>
nasdaqVal <- nasdaq*shares
## Plot NASDAQ vs Index Fund performance
months \leftarrow seq(as.Date("2013/1/1"), by = "month", length.out = 12)
library(ggplot2)
df <- data.frame(nasdaqVal,pReturn)</pre>
g <- ggplot(df,aes(months))</pre>
g <- g+geom_point(aes(y=nasdaqVal),color = "red")</pre>
g <- g+geom_point(aes(y=pReturn),color = "blue")</pre>
g <- g+ylab("Portfolio Value in Dollars")</pre>
g
```



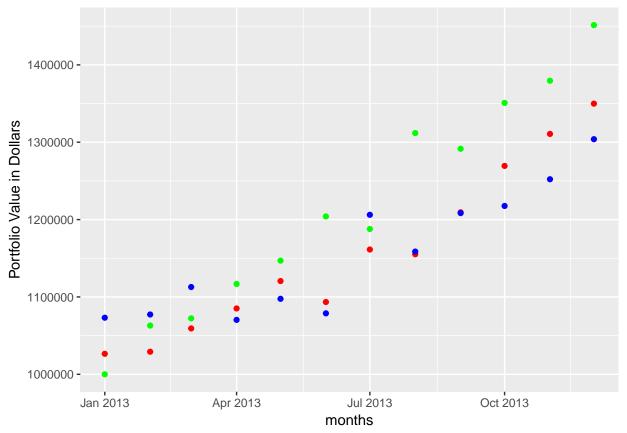
##Plot real returns
monthlyPriceMat = matrix(NA, length(unique_mdates), length(unique_tickers))

```
for (i in 1:length(unique_tickers)) {
  tic = unique_tickers[i]
  idx = is.element(unique_mdates, mdate[mticker == tic])
  monthlyPriceMat[idx, i] = mprice[mticker == tic]
monthlyPriceMat = rbind(priceMat[250,], monthlyPriceMat)
# calculate monthly return
returnMonthlyMat = matrix(NA, length(unique_mdates), length(unique_tickers)) #initialize matrix for dai
for (i in 1:length(unique_tickers)) {
  prices = monthlyPriceMat[, i]
  monthly_returns = diff(prices)
  returnMonthlyMat[, i] = monthly_returns
}
investment_vector = weights * total_investment
share_vector = investment_vector / priceMat[250,]
total_value = share_vector * monthlyPriceMat[1,]
real_return = NULL
for (i in 1:dim(returnMonthlyMat)[1]) {
 r = sum(share_vector * returnMonthlyMat[i,])
 real_return = c(real_return, r)
}
real_return
## [1] 73152.376 4159.371 35517.915 -42461.182 27212.774 -18771.812
## [7] 127382.091 -47517.114 49721.466
                                           9218.980 34551.767 51753.977
# calculate nasdag return
nasdaq_2013 = c(2660.93, 2731.53, 2738.58, 2818.69, 2887.44, 2981.76, 2909.60, 3090.19, 3073.81, 3218.2
num_share_nasdaq = total_investment / nasdaq_2013[1]
nasdaq_monthly_return = NULL
for (i in 1:length(nasdaq_2013)) {
  monthly_return = nasdaq_2013[i+1] - nasdaq_2013[i]
  nasdaq_monthly_return = c(nasdaq_monthly_return, monthly_return)
}
nasdaq_return = nasdaq_monthly_return[1:12] * num_share_nasdaq
par(mfrow=c(1, 1))
plot(nasdaq_return, type='b', xlab='Month', ylab='Return', col='red', ylim=c(-50000,130000))
lines(real_return, type='b', col='blue')
legend('topleft',legend=c('nasdaq', 'our fund'), col=c('red', 'blue'), lty=c(1, 1))
```

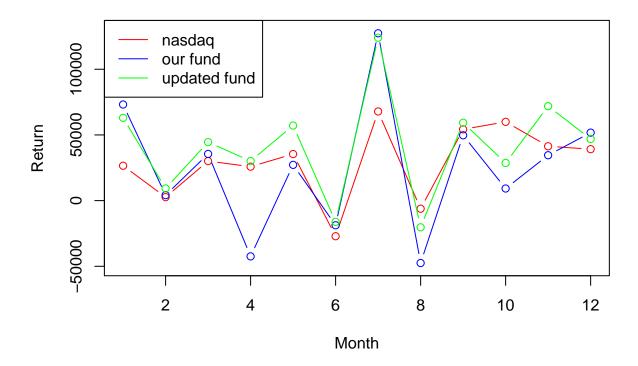


Calculate New Similarity Matrix Using Correlation Between Stocks Using 20 Day Moving Averages

```
i <- 20
similarityMat <- function(pMat, sMat, ut,ud){</pre>
### Create New Similarity Matrix
csCol <- function(stock,i){</pre>
    stock[which(is.na(stock))] <- 0</pre>
    cs <- cumsum(stock)</pre>
    rsum <- (cs[(i+1):length(stock)] - cs[1:(length(stock) - i)]) / i</pre>
  }
  maStocks <- apply(pMat,2, csCol,20)</pre>
  corVarMat <- cor(maStocks,maStocks)</pre>
  return(corVarMat)
}
rho_new <- similarityMat(priceMat,sharesMat,unique_tickers,unique_dates)</pre>
weights_new <- constructFunds(rho_new,q,priceMat,sharesMat,unique_tickers,unique_dates)</pre>
newpReturn <- getPerformance(priceMat, weights_new, monthlyPriceMat)</pre>
df <- data.frame(nasdaqVal,pReturn, newpReturn)</pre>
g <- ggplot(df,aes(months))</pre>
g <- g+geom_point(aes(y=nasdaqVal),color = "red")</pre>
g <- g+geom_point(aes(y=pReturn),color = "blue")</pre>
g <- g+geom_point(aes(y=newpReturn),color = "green")</pre>
g <- g+ylab("Portfolio Value in Dollars")</pre>
```



```
investment_vector_new = weights_new * total_investment
share_vector_new = investment_vector_new / priceMat[250,]
total_value_new = share_vector_new * monthlyPriceMat[1,]
real_return_new = NULL
for (i in 1:dim(returnMonthlyMat)[1]) {
  r_new = sum(share_vector_new * returnMonthlyMat[i,])
  real_return_new = c(real_return_new, r_new)
real_return_new
   [1] 63015.253
                     9269.211 44512.520 30117.911 57121.185 -16196.694
##
   [7] 124010.944 -20308.488 59303.685 28669.435 71903.871 46949.189
par(mfrow=c(1, 1))
plot(nasdaq_return, type='b', xlab='Month', ylab='Return', col='red', ylim=c(-50000,130000))
lines(real_return, type='b', col='blue')
lines(real_return_new, type='b', col='green')
legend('topleft',legend=c('nasdaq', 'our fund', 'updated fund'), col=c('red', 'blue','green'), lty=c(1,
```



Comparing Models

We decided to use a rolling 20 day average stock price to calculate a new correlation matrix. This metric was selected as it smooths volitility to give a clearer picture when determining a more optimal allocation of stocks to purchase based on their potential similarity. What can be seen by the output is that this returned the highest amount of profit of any of the three choices because the new similarity matrix took into account the stocks' relevant histories.