Math23C Spring 2018 Final Project

Project Highlights

Patrick Watts, David Wihl

May 6, 2018

Abstract

Cryptocurrencies such as Bitcoin, Ethereum, etc. generated significant attention in 2017 due a dramatic price increases followed by a spectacular drop in 2018. Cryptocurrencies have significant volatility as there is rampant speculation combined with a lack of tangible resource to provide a proxy for real-world value. Given the high variance in prices, can data science methods explored in this class be used to model the market dynamics?

Contents

Introduction

We obtained historical price information for three major and one minor cryptocurrencies in order to analyze market dynamics. We also obtained historical pricing eightteen traditional securities such as the S&P 500, Gold, LIBOR rates, and VIX index to see if we obtain correlations or predictive factors for the changes in the cryptocurrency prices.

Data Sources

Cryptocurrency Historical Pricing

For the cryptocurrency prices, we downloaded the data from Kaggle, specifically https://www.kaggle.com/sudalairajkumar/cryptocurrencypricehistory/data. The original provenance of the data is coinmarketcap, a well-reputed aggregator of cryptocurrency pricing on various exchanges around the world. Cryptocurrencies have several distinguishing pricing factors: there are a myriad of markets around the world leading to potential arbitrage opportunities and markets are open 24 hours per day. Thus, traditional Open, High, Low, Close (OHLC) metrics have to be artifically imposed on the data.

We selected four different cryptocurrencies Bitcoin (BTC), Ethereum (ETH), Monero (XMR), Ripple (XRP). Bitcoin and Ethereum represent the majority of overall cryptocurrency market capitalization. We chose Monero and Ripple to see if market dynamics affected all cryptocurrencies equally.

The following source CSV files are in the `data/` subdirectory:

- `bitcoin_price.csv` - Bitcoin (BTC) from April 2013 until Feb 2018 (1761 rows)
- `ethereum_price.csv` - Ethereum (ETH) from Aug 2015 until Feb 2018 (930 rows)
- `monero_price.csv` - Monero (XMR) from May 2014 until Feb 2018 (1372 rows)
- `ripple_price.csv` - Ripple (XRP) from Aug 2013 until Feb 2018 (1663 rows)

(REQ: a dataframe, at least two numeric columns, at least 20 rows)

Traditional, Noncryptocurrency Data

For comparison against traditional markets, we used a Python notebook to download many other historical financial metrics. The script can be found in `DownloadOtherMetrics.ipynb`. It is intended to be run once. The script collects 18 additional metrics including: S&P500, NASDAQ, DOW, Russell 2000, Foreign exchange rates (Yen-USD, Euro-USD, etc.), LIBOR rates (1M, 3M, 12M), commodity prices (gold, crude oil). Details of these different metrics can be found at `https://fred.stlouisfed.org/series/METRICNAME` e.g.

https://fred.stlouisfed.org/series/BAMLHYH0A0HYM2TRIV

The downloaded data can be found in `data/noncrypto.csv`

The combination of the two datasets results in over 600 observations of 20 variables for a 2.5 year period.

(REQ: lots of columns, samples can be taken)

Categorical Data

Since our data was entirely numeric, we engineered two categorical features.

We converted VIX, the Volality Index into a logical variable, where +1 represents an increase and -1 represents a decrease in volality respectively.

We converted daily variation in pricing for a subset of the data into a categorical variable representing number of standard deviations.

(REQ: at least two categorical or logical columns)

Clean up, Normalization

In order to process the cryptocurrency data, we performed the following transformations:

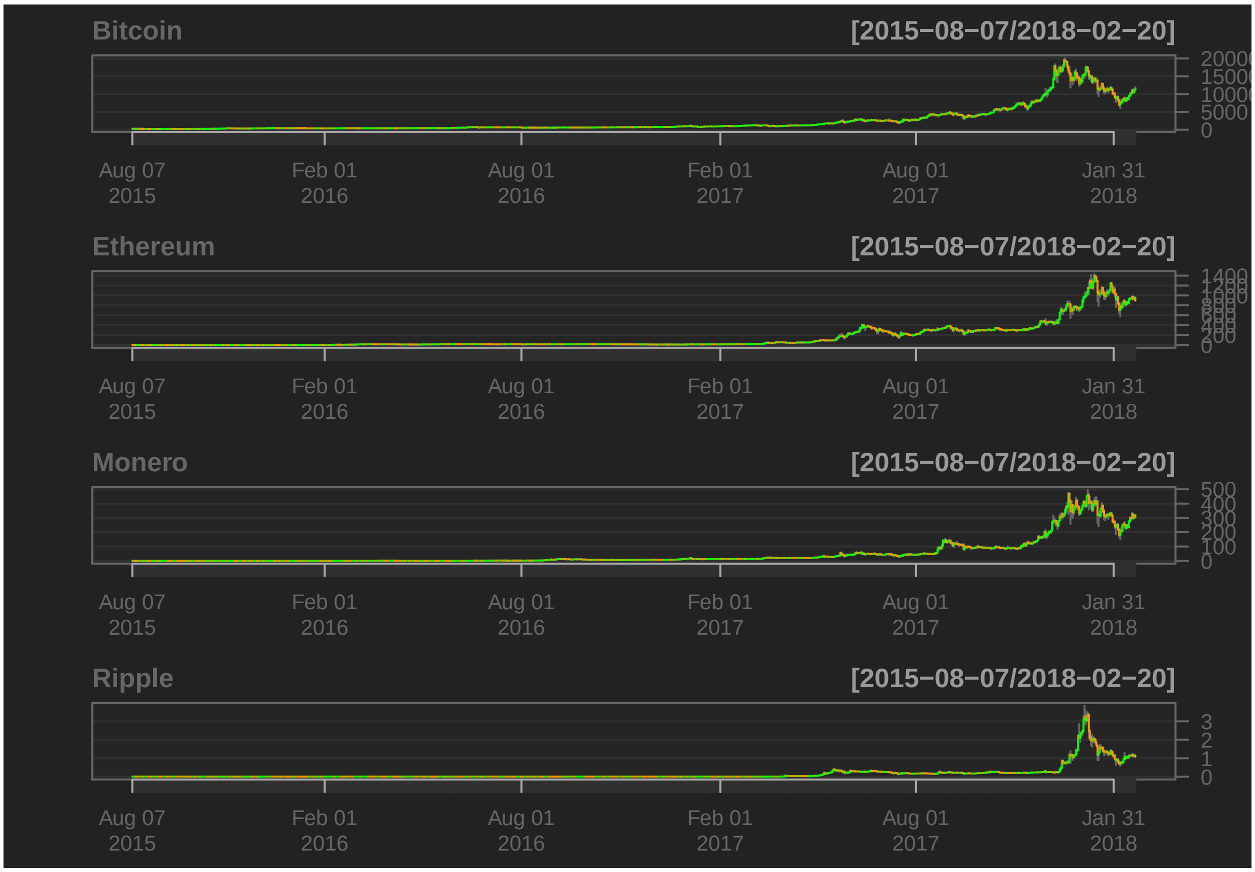
- Converted date strings into native R format
- Converted volume and market capital strings ("1,234") into R numeric fields
- Selected only a subset of data for which we had all values. This meant discarding early pricing information for older currencies such as Bitcoin. Since the market dynamics have changed significantly between 2010-2014 vs 2015-2016 vs late 2017-early 2018, we felt this was a worthwhile tradeoff. Modeling Bitcoin when it had 1/1000 the market capitalization would not be useful for either predictive or analytical purposes. In sum, our data ranged from 2015-08-07 until 2018-02-20.
- Sorted all data chronologically
- In order to account for holidays and other days when traditional markets are closed but cryptocurreny markets are open, we imputed values for the closed market days.

Depending on the context, we both standardized $\frac{x-\bar{x}}{\sigma}$ or normalized $\frac{x-x_{min}}{x_{max}-x_{min}}$ the data to perform appropriate comparison. For specific details, see the appropriate comparison.

Exploratory Data Analysis

Prices over time

For initial exploration, we examine closing price and volume over time for the four cryptocurrencies.



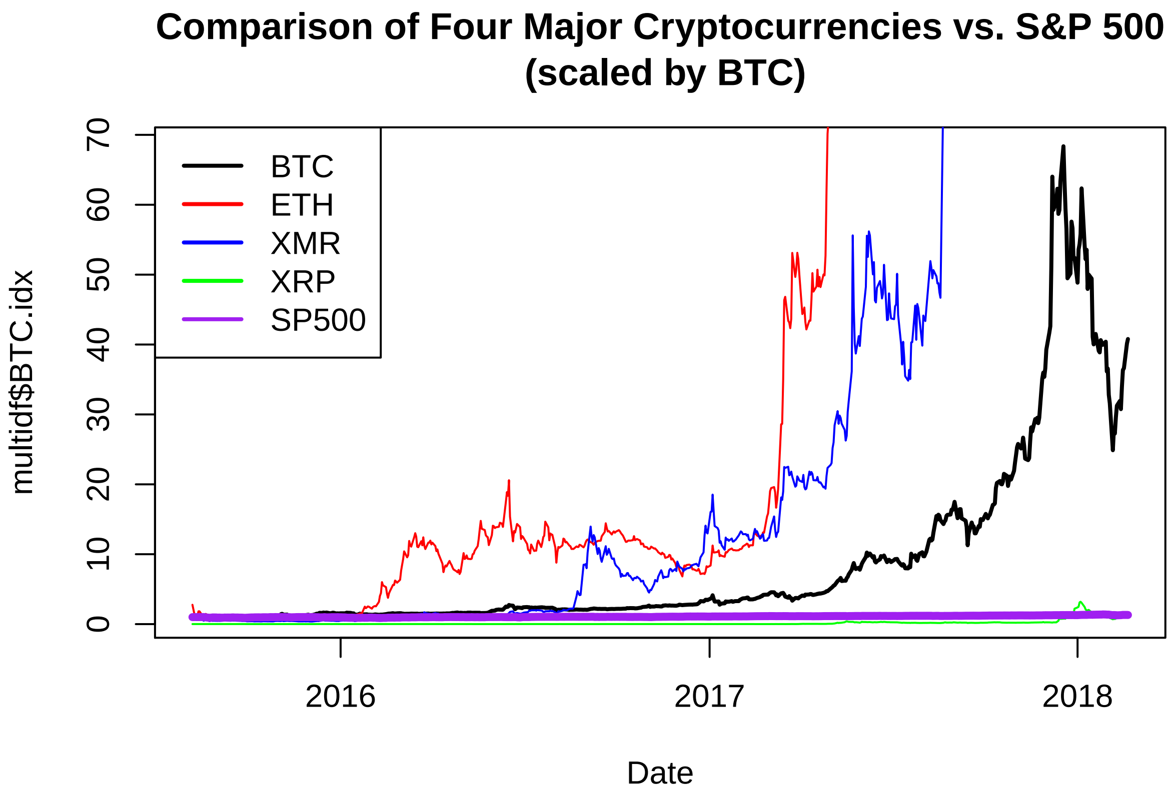

```
## null device
##           1
```

From this comparison, there some commonalities, but certain currencies seem to rise earlier than others.

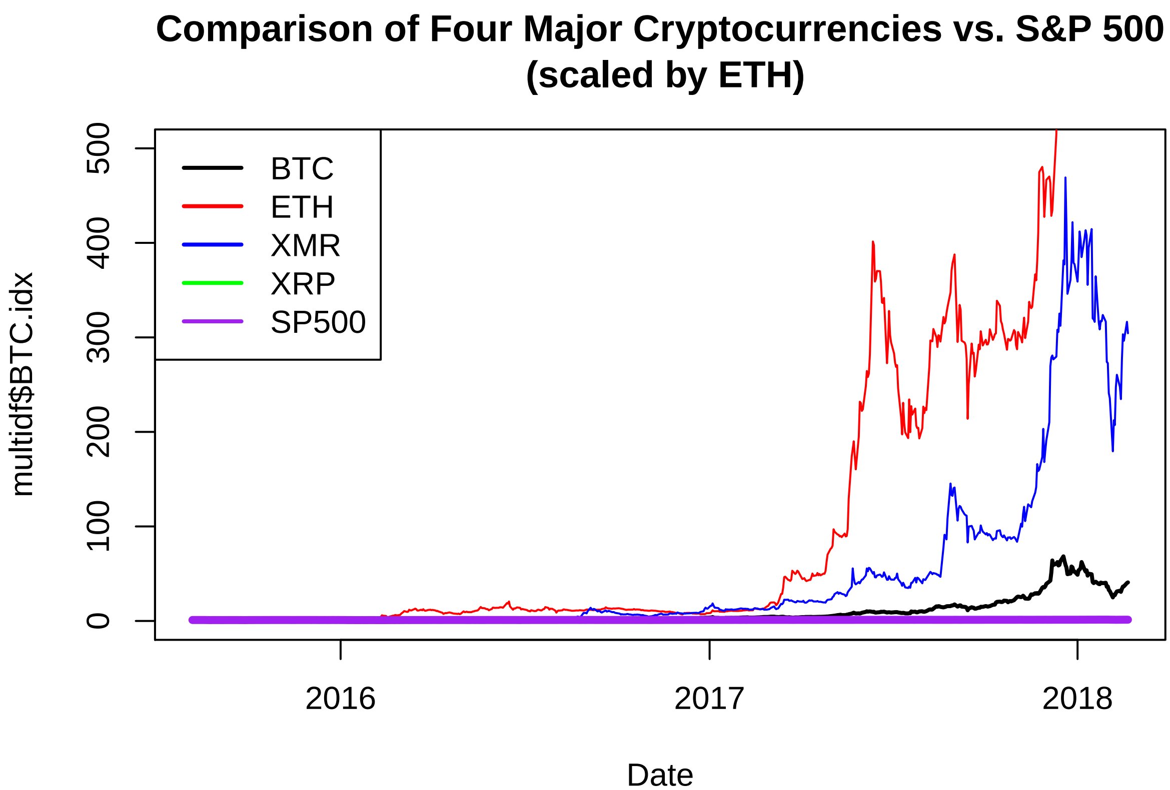
(REQ: A graphical display that is different from those in the textbook or in the class scripts.)

However, if we overlay these change in prices on the same plot, and rescale to a common starting point, the differences become very visible.

The following plot scales to the most popular crytocurrency: Bitcoin (BTC)



Now, if we scale by the currency that rose most aggressively, the story appears different.



The S&P 500 looks like there was no return at all, even though this period was one of the best bull markets in history. Clearly, the cryptocurrency dynamics in 2017 into early 2018 are significantly different from traditional price movements. Let's now quantify more precisely what these differences are and see which probability distributions appropriately model this behavior.

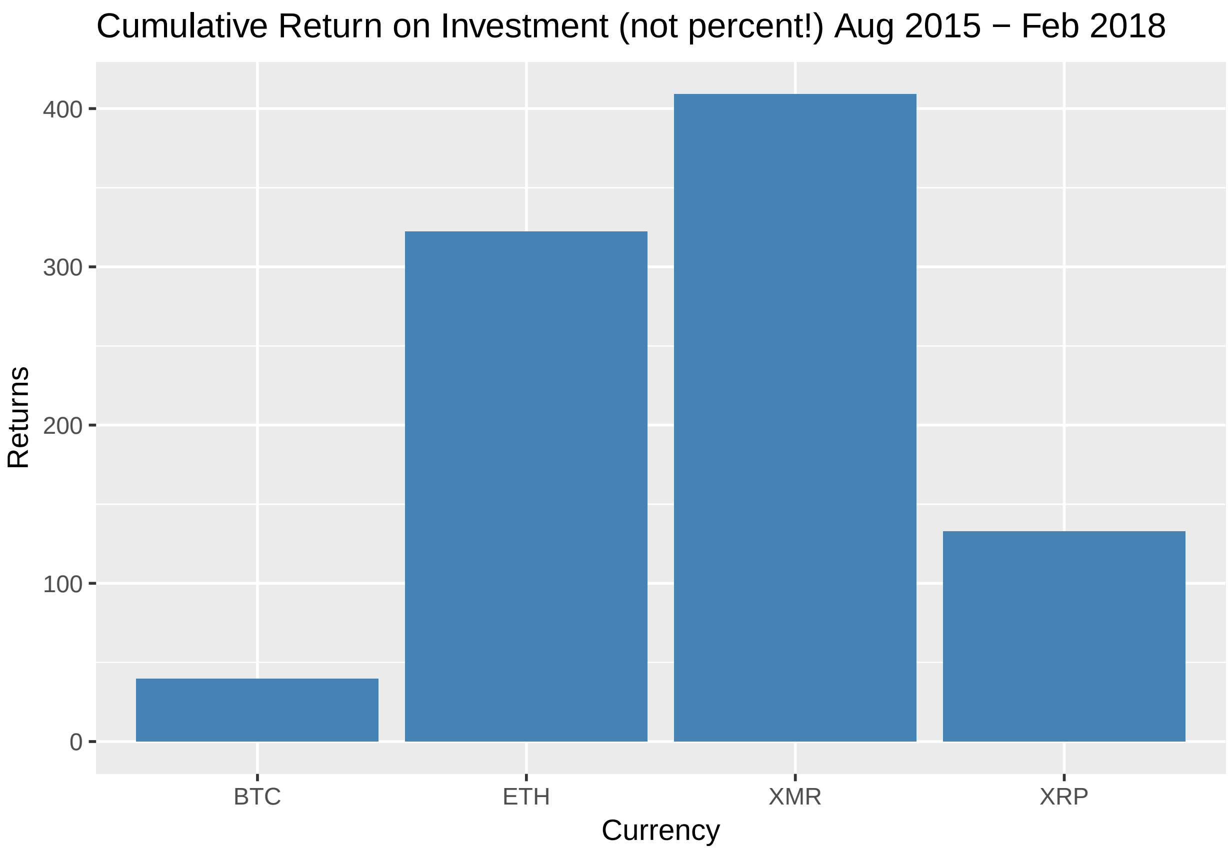
ROI for Crytocurrencies

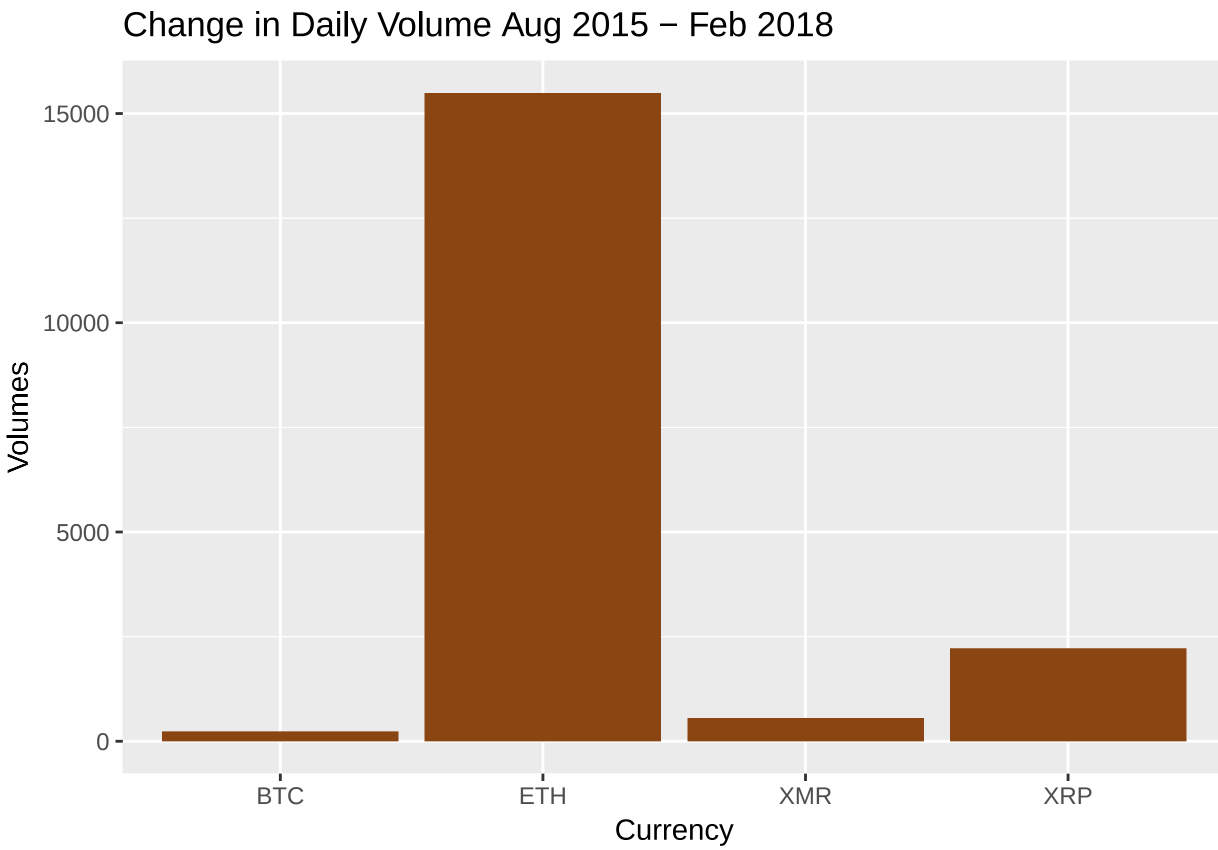
So what is the actual ROI for cryptocurrencies in this period:

Table 1: Cryptocurrency ROI

Currency	Returns	Volumes
BTC	39.79	232.65
ETH	322.24	15487.81
XMR	409.08	551.93
XRP	132.71	2217.31

With numbers like these, there is no wonder that there was rampant speculation! It was like buying lottery tickets! Here is a graphical representation of these returns:





(REQ: barplot)

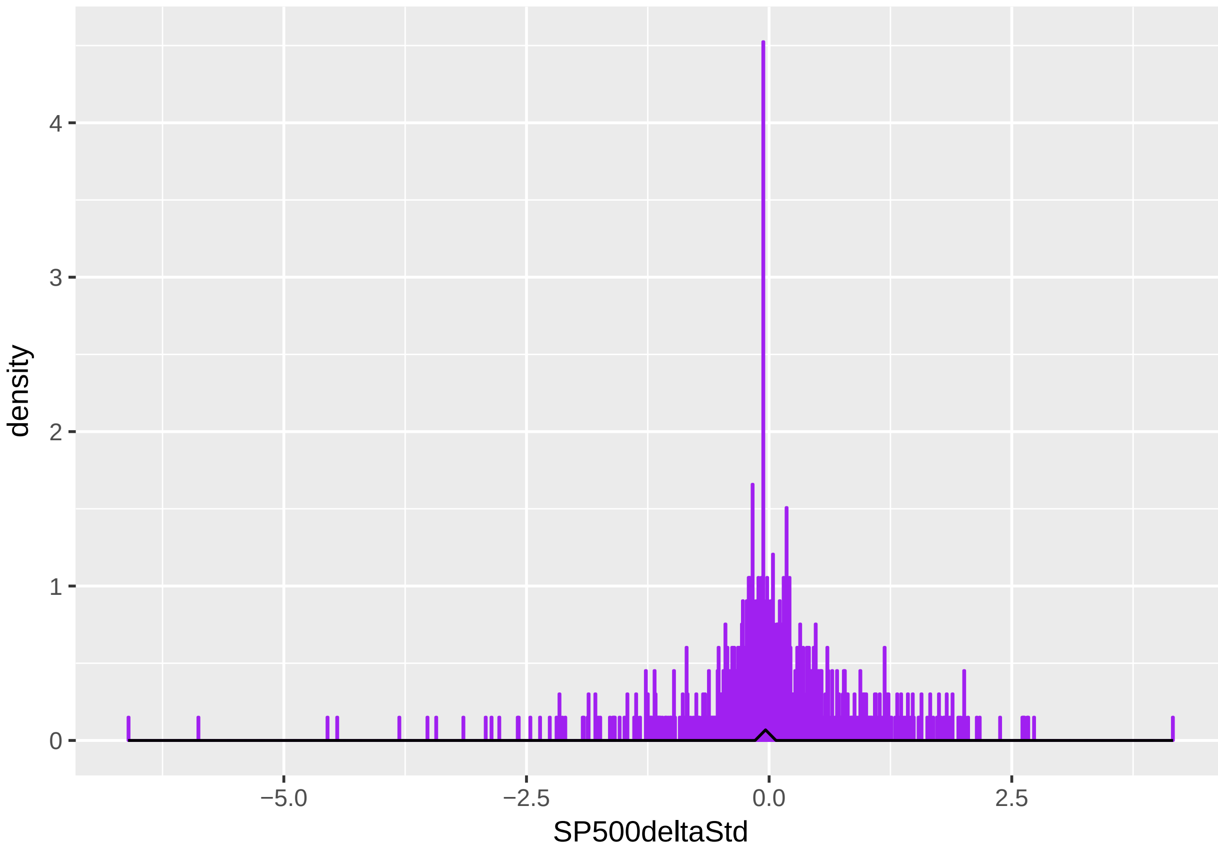
Topic 1: Distribution of Relative Price Changes

Distribution of S&P 500 Price Changes

The S&P 500 index is a broad index representing 500 large companies having stock listed on major US Stock Exchanges. It is generally considered a reasonably accurate proxy for the US Stock Market.

Let's first examine the distribution of relative price changes for the S&P 500. Classic economic theory, notably by A Random Walk Down Wall Street claims that price movements are random and should follow a Gaussian distribution. However, as shown in the empircal plot, the theory is incorrect.

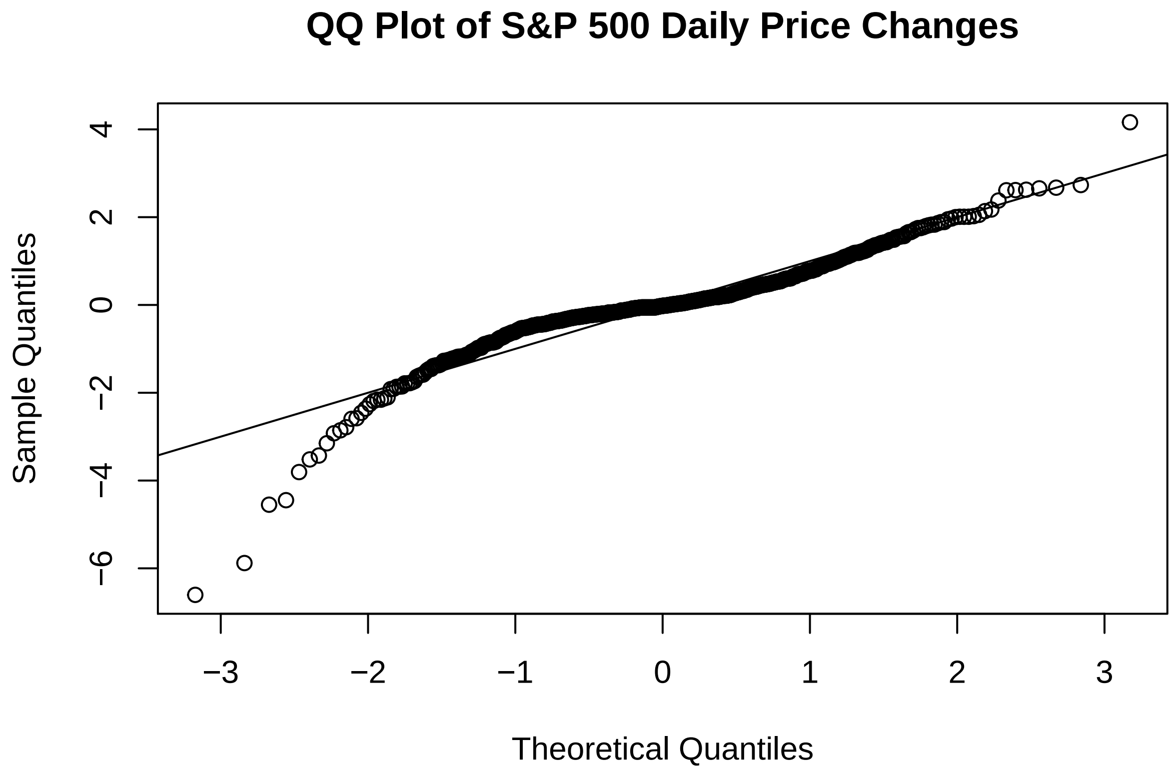
The daily price changes have been standardized, and yet the price fluctuations for this period are vastly different than the predicted stable prices shown in the little bump of the overlaid Gaussian distribution for $\mu = 0$, $\sigma = 0.0083192$. **Clearly this is a not a Gaussian Distribution**. This has been confirmed by other sources as well.



(REQ: A probablity density graph overload on a histogram)

Let's confirm this in two additional ways

```r
# QQplot to see if a distribution is normal
qqnorm(multidf$SP500deltaStd,main="QQ Plot of S&P 500 Daily Price Changes")
abline(0,1)
```



This can also be confirmed analytically via the Shapiro-Wilk Normality test.

```
##
##  Shapiro-Wilk normality test
##
## data:  multidf$SP500deltaStd
## W = 0.90285, p-value < 2.2e-16
```

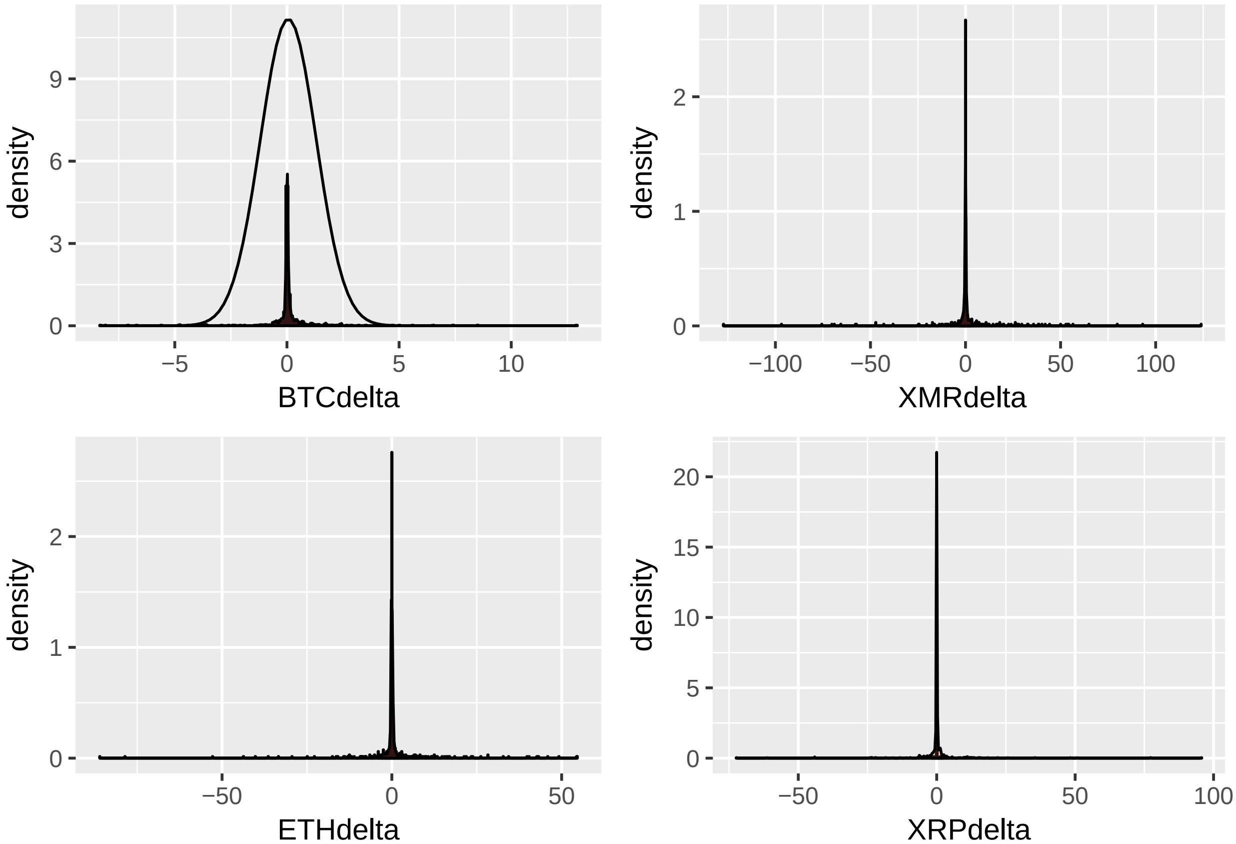
The $p - value < 0.05$ confirms that the distribution of price changes is not normally distributed.

So by three different methods, it is clear that the Random Walk Down Wall St. is empirically wrong for time periods of at least 2.5 years, which is a long time to be wrong in the market.

(REQ: A p-value or other statistic based on a distribution function)

So what is the appropriate distribution for the market?

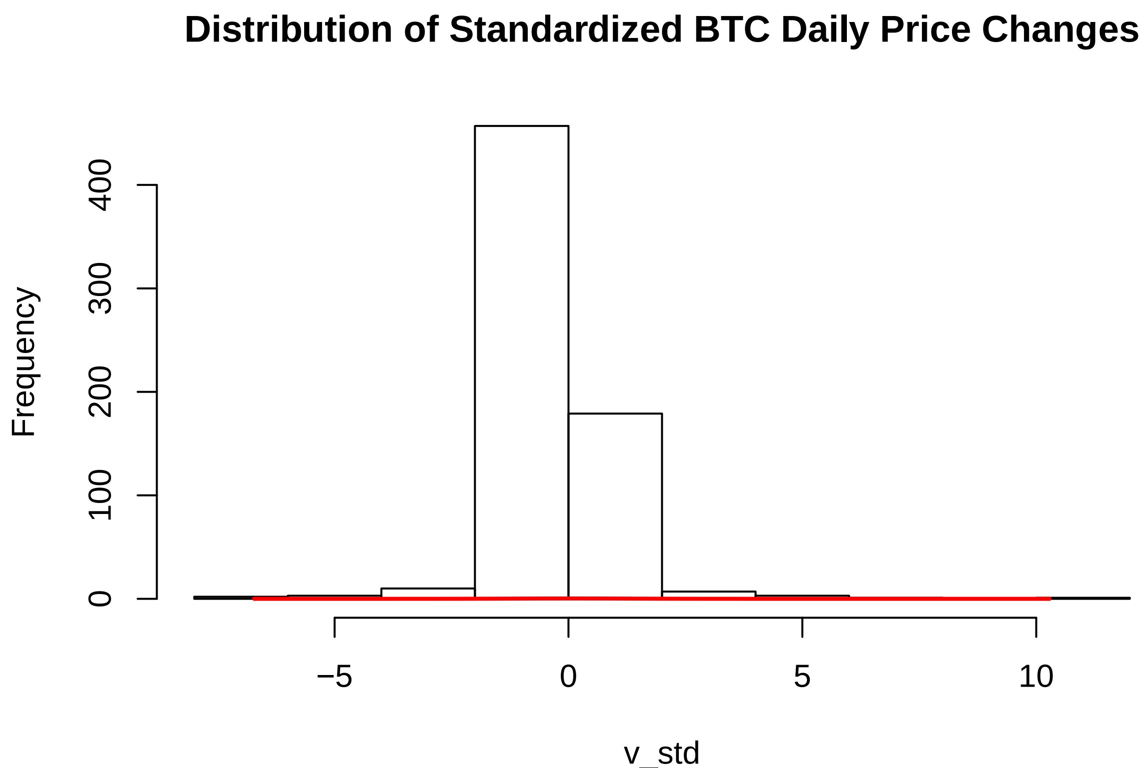
Distribution of Cryptocurrency Price Changes

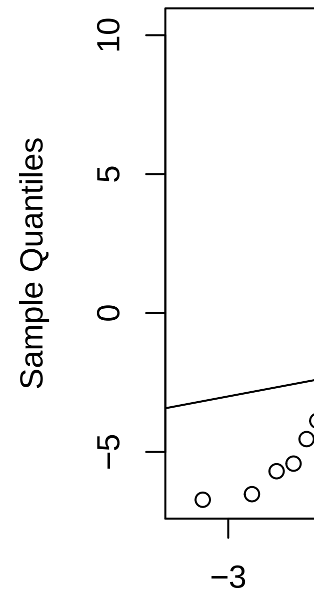



```
# Categorical Variables

# Converting VIX into a categorical
#TODO

multidf$VIXCLS.idx = multidf$VIXCLS / multidf$VIXCLS[1]
multidf$VIXCLSdelta = c(0,diff(multidf$VIXCLS.idx))
multidf$VIXCLSsgn = ifelse(multidf$VIXCLSdelta>=0,1,-1)
multidf$BTCsgn = ifelse(multidf$BTCdelta>=0,1,-1)
```

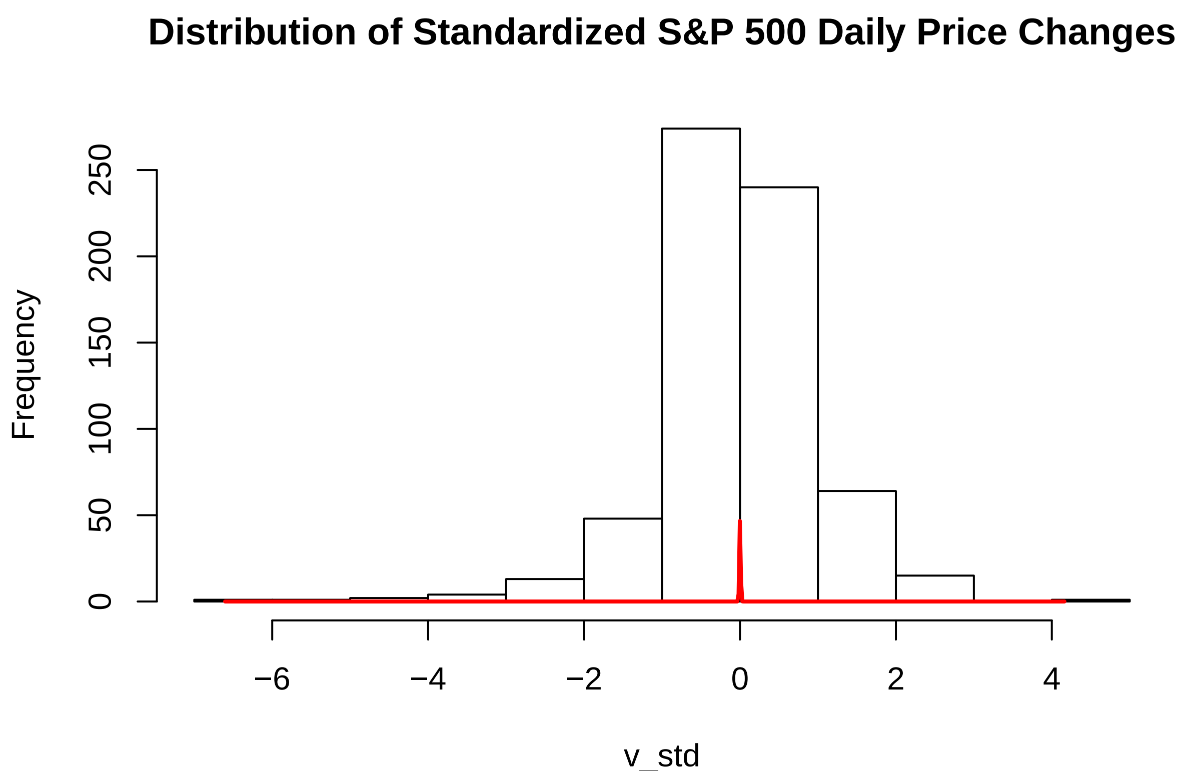
```
# TODO how many standard deviations are exceeded

overlayGaussian = function(v,label){
  mu_v = mean(v)
  sd_v = sd(v)
  v_std = (v - mu_v) / sd_v
  hist(v_std,main=paste("Distribution of Standardized",label))
  xfit = seq(min(v_std), max(v_std), length=length(v_std))
  yfit = dnorm(xfit, mean=mu_v, sd = sd_v)
  lines(xfit,yfit,col="red", lwd=2)
  qqnorm(v_std,main=paste("QQ Plot of",label))
  abline(0,1)
```

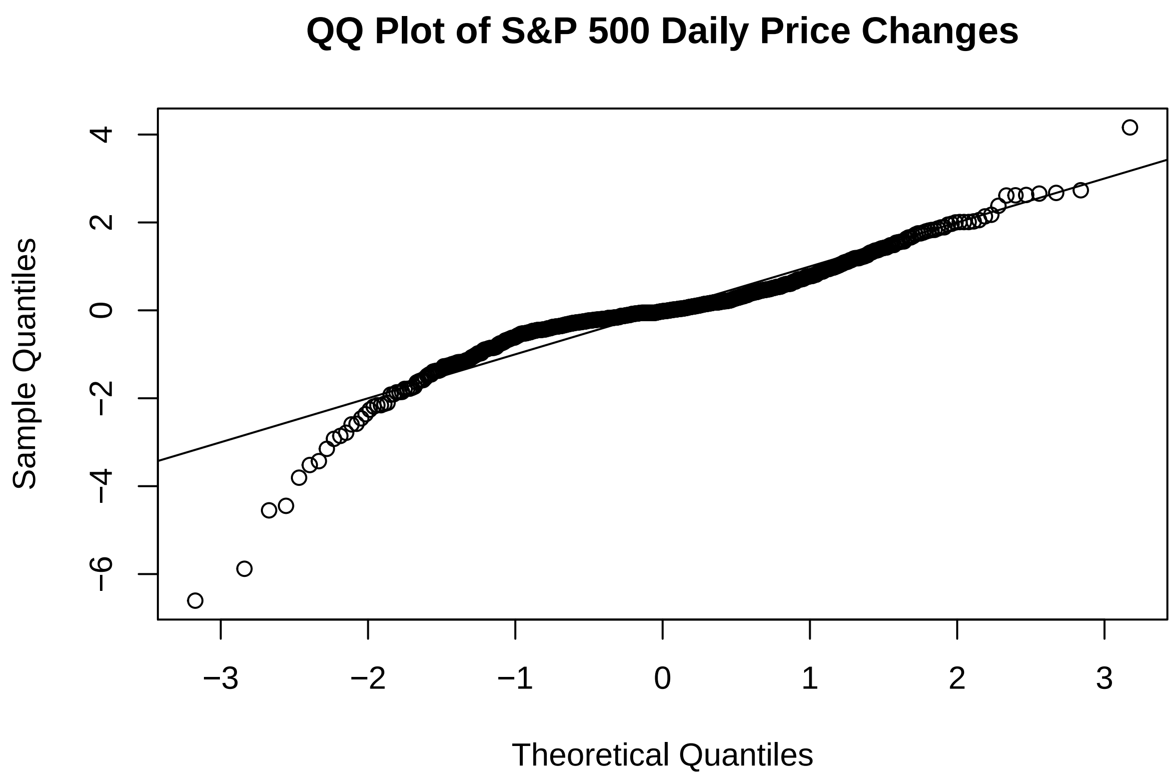
```r
}
overlayGaussian(multidf$BTCdelta,"BTC Daily Price Changes")
```



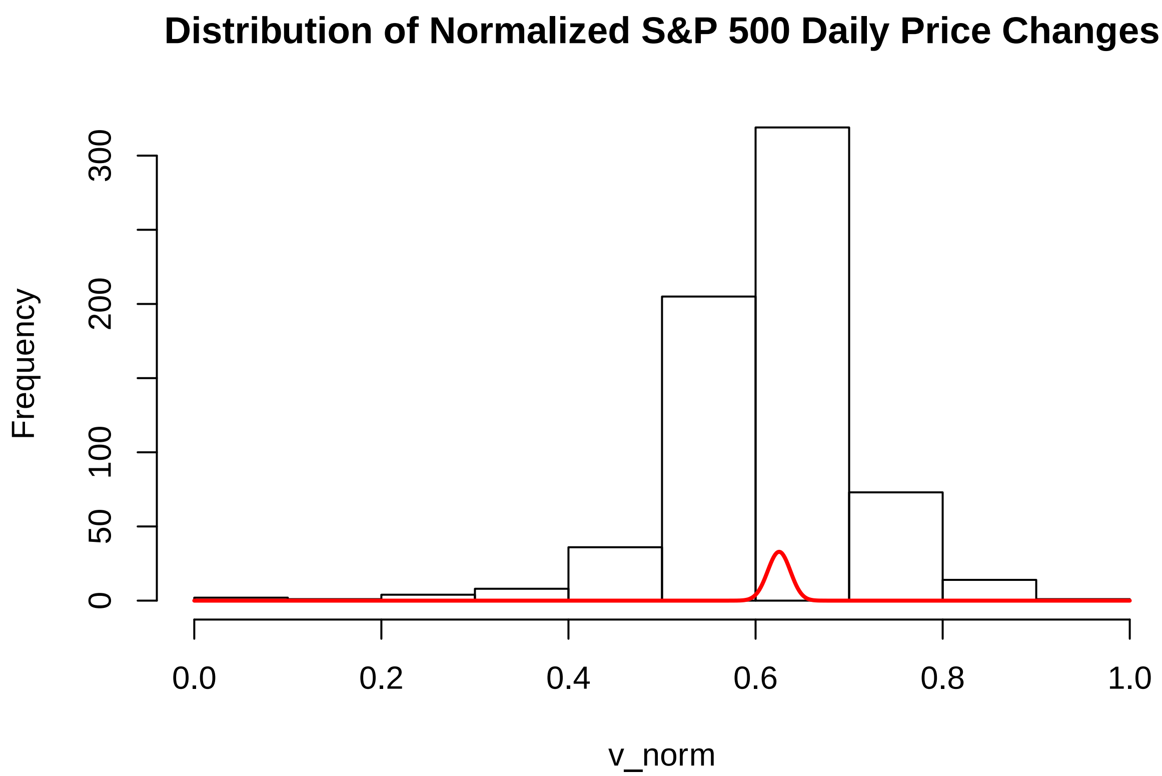



```r
overlayGaussian(multidf$SP500delta,"S&P 500 Daily Price Changes")
```






```r
# Overlay Beta
overlayBeta = function(v,label){
  # this will rescale vector v to [0,1]
  v_norm = (v - min(v)) / (max(v) - min(v))
  hist(v_norm,main=label)
  xfit = seq(0, 1, length=length(v))
  yfit = dbeta(xfit, 1000,600)
  lines(xfit,yfit,col="red", lwd=2)
}
#overlayBeta(multidf$BTCdelta,"Distribution of Normalized BTC Daily Price Changes")
overlayBeta(multidf$SP500delta,"Distribution of Normalized S&P 500 Daily Price Changes")
```



Topic 2 - Correlation between Cryptocurrencies

```
cor(BTCdf$Close, ETHdf$Close)
```

```
## [1] 0.9060949
```

```
cor(BTCdf$Close, XMRdf$Close)
```

```
## [1] 0.9691732
```

```
cor(BTCdf$Close, XRPdf$Close)
```

```
## [1] 0.8049156
```

```
cor(ETHdf$Close, XMRdf$Close)
```

```
## [1] 0.9525516
```

```
cor(ETHdf$Close, XRPdf$Close)
```

```
## [1] 0.8798746
```

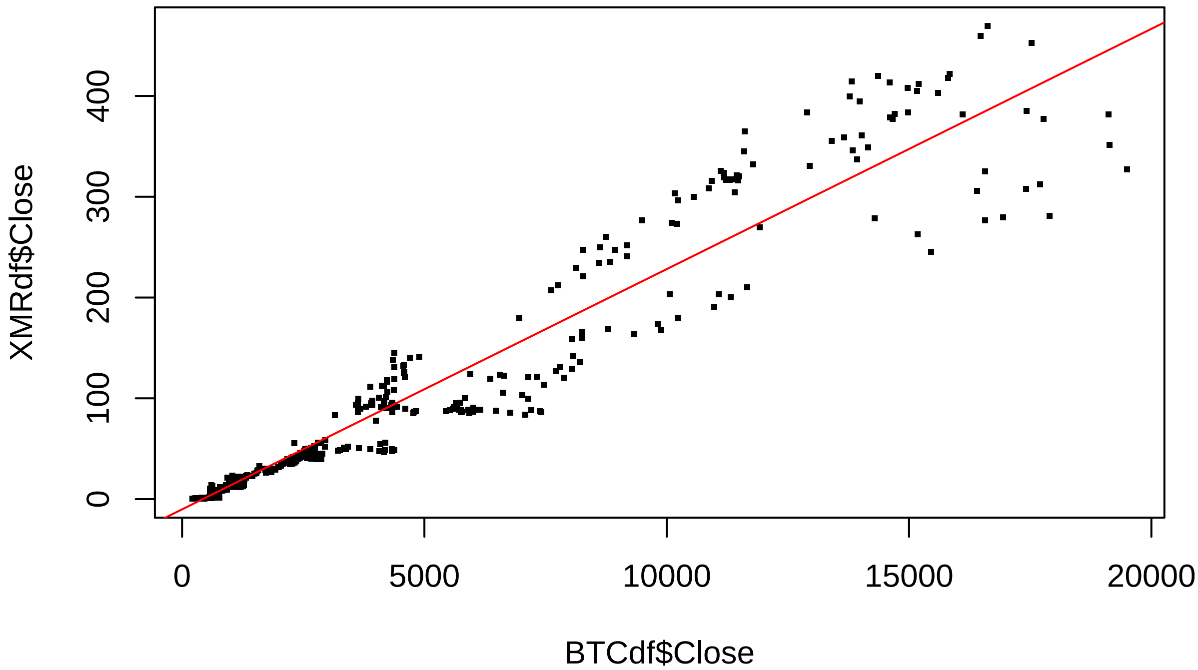
```
cor(XMRdf$Close, XRPdf$Close)
```

```
## [1] 0.8847865
```

```
#Largest correlation between BTC and XMR
plot(BTCdf$Close,XMRdf$Close,pch = ".",cex = 3)
#b is slope
b <- cov(BTCdf$Close,XMRdf$Close)/var(BTCdf$Close)
#a is intercept
a <- mean(XMRdf$Close) - b*mean(BTCdf$Close);a
```

```
## [1] -10.16858
```

```r
#We can add this regression line to the plot of the data
abline(a, b, col = "red")
```



Summary of Project Requirements

Required dataset standards

- [x] A dataframe
- [x] At least two categorical or logical columns
- [x] At least two numeric columns
- [x] At least 20 rows, preferably more, but real-world data may be limited

Required graphical displays (all graphs must be colored and nicely labeled)

- [x] A barplot
- [x] A histogram
- [x] A probability density graph overlaid on a histogram
- [ ] A contingency table

Required Analysis

- [ ] A permutation test
- [x] A p-value or other statistic based on a distribution function (Shapiro-Wilk)
- [ ] Analysis of a contingency table
- [ ] Comparison of analysis by classical methods (chi-square, CLT) and simulation methods

Required submission uploads

- [x] A .csv with the dataset
- [x] A long, well-commented script that loads the dataset, explores it, and does all the analysis.

- [x] A shorter .Rmd with compiled .pdf or .html file that presents highlights in ten minutes.
- [x] A one-page handout that explains the dataset and summarizes the analysis.

Additional points for creativity or complexity (up to 10 points)

- 1. A data set with lots of columns, allowing for comparison of many different variables
- 2. A data set that is so large that it can be used as a population from which samples are taken
- 4. A one-page document that discusses ethical issues raised by conclusions reached from analysis of the data.
- 5. A graphial display that is different from those in the textbook or in the class scripts.
- 6. Appropriate use of R functions for a probability distribution other than binomial, normal, or chi-square
- 9. A convincing demonstration of a relationship that might have been statistically significant but that turns out not to be so.
- 10. Professional-looking software engineering (e.g defining and using your own functions).
- 11. Nicely labeled graphics using ggplot, with good use of color, line styles, etc., that tell a convincing story.
- 13. Appropriate use of novel statistics (e.g. trimmed mean, maximum or minimum, skewness, ratios).
- 14. Use of linear regression.
- 16. Appropriate use of covariance or correlation.
- 22. Team consists of exactly two members (otherwise, 1 or 3 is a possibility).

Conclusion

There is one only possible conclusion: immediately disband the search committee and hire us!

References

Clifford S. Ang, *Analyzing Financial Data and Implementing Financial Models Using R*, Springer, 2015

Berlinger et al. *Mastering R for Quantitative Finance*, Packt Publishing, 2015

Appendix A - Long Script

This is the "long script" used to prepare these reports:

```
knitr::opts_chunk$set(echo = TRUE)
library(xts)
library(quantmod)
library(ggplot2)
library(knitr)
op <- par(no.readonly = TRUE)
# Read one price history file per currency
BTCdf = read.csv("data/bitcoin_price.csv", stringsAsFactors = F)
ETHdf = read.csv("data/ethereum_price.csv", stringsAsFactors = F)
XMRdf = read.csv("data/monero_price.csv", stringsAsFactors = F)
XRPdf = read.csv("data/ripple_price.csv", stringsAsFactors = F)
# Fix rest of data:
# 1- Make dates native format
# 2- Convert Volume and market cap:
#     a) From string ("123,456") to numeric (123456).
#     b) Convert "-" to 0.
# 3- Sort chronologically
fixVolCap = function(df) {
  df$Date = as.Date(df$Date,"%b %d, %Y")
  df$Volume = as.numeric(gsub("-","0",gsub(",","",df$Volume)))
  df$Market.Cap = as.numeric(gsub("-","0",gsub(",","",df$Market.Cap)))
  return (df[order(df$Date),])
}
BTCdf = fixVolCap(BTCdf)
ETHdf = fixVolCap(ETHdf)
XMRdf = fixVolCap(XMRdf)
XRPdf = fixVolCap(XRPdf)

# Ensure that all data start from the same date
earliestCommonDate =  max(min(BTCdf$Date),
                          min(ETHdf$Date),
                          min(XMRdf$Date),
                          min(XRPdf$Date))
BTCdf = BTCdf[BTCdf$Date>=earliestCommonDate,]
ETHdf = ETHdf[ETHdf$Date>=earliestCommonDate,]
XMRdf = XMRdf[XMRdf$Date>=earliestCommonDate,]
XRPdf = XRPdf[XRPdf$Date>=earliestCommonDate,]


# Read in traditional, noncryptocurrency data
noncrypto = read.csv("data/noncrypto.csv",stringsAsFactors = FALSE)
noncrypto$DATE = as.Date(noncrypto$DATE,"%Y-%m-%d")
# Plot price and volume data over time
plotSeries = function(df,label){
  dfdata = xts(df[,2:7],order.by = df[,1])
  OHLC = as.quantmod.OHLC(dfdata)
  chartSeries(OHLC,name=label,layout=NULL, TA=NULL)
}
layout(matrix(1:4,nrow=4))
plotSeries(BTCdf, "Bitcoin")
```

```
plotSeries(ETHdf, "Ethereum")
plotSeries(XMRdf, "Monero")
plotSeries(XRPdf, "Ripple")
dev.off()
# Weekly Comparison - not used
# wk = BTCdata
# data.wk = to.weekly(wk)
# plot(data.wk)
# OHLC = as.quantmod.OHLC(BTCdata)
# chartSeries(OHLC)


BTCdata = xts(BTCdf[,2:7],order.by = BTCdf[,1])

close.prices = BTCdata$Close
close.prices = cbind(close.prices,ETHdf$Close,XMRdf$Close,XRPdf$Close)

multidf = cbind(index(close.prices), data.frame(close.prices))
names(multidf) = paste(c("Date","BTC","ETH","XMR","XRP"))
# Merge in the non-crypto metrics
multidf=merge(multidf,noncrypto,by.x="Date", by.y="DATE")

# Create a new column with the relative price changes (scaled to the starting price)
multidf$BTC.idx = multidf$BTC / multidf$BTC[1]
multidf$ETH.idx = multidf$ETH / multidf$ETH[1]
multidf$XMR.idx = multidf$XMR / multidf$XMR[1]
multidf$XRP.idx = multidf$XRP / multidf$XRP[1]
multidf$SP500.idx = multidf$SP500 / multidf$SP500[1]
multidf$GOLDAMGBD228NLBM.idx = multidf$GOLDAMGBD228NLBM / multidf$GOLDAMGBD228NLBM[1]
# default y scale
par(op)
plot(x = multidf$Date,y=multidf$BTC.idx,type="l",xlab="Date",col="black",lty=1,lwd=2,
     main="Comparison of Four Major Cryptocurrencies vs. S&P 500\n (scaled by BTC)")
lines(x=multidf$Date,y=multidf$ETH,col="red")
lines(x=multidf$Date,y=multidf$XMR,col="blue")
lines(x=multidf$Date,y=multidf$XRP,col="green")
lines(x=multidf$Date,y=multidf$SP500.idx,col="purple",lwd=4)
legend("topleft",c("BTC","ETH","XMR","XRP","SP500"),col=c("black","red","blue","green","purple"),
       lty=c(1,1,1,1,1),
       lwd=c(2,2,2,2,2))
# y scale from 0-500
plot(x = multidf$Date,y=multidf$BTC.idx,type="l",xlab="Date",col="black",lty=1,lwd=2,ylim=c(0,500),
     main="Comparison of Four Major Cryptocurrencies vs. S&P 500\n (scaled by ETH)")
lines(x=multidf$Date,y=multidf$ETH,col="red")
lines(x=multidf$Date,y=multidf$XMR,col="blue")
lines(x=multidf$Date,y=multidf$XRP,col="green")
lines(x=multidf$Date,y=multidf$SP500.idx,col="purple",lwd=4)
legend("topleft",c("BTC","ETH","XMR","XRP","SP500"),col=c("black","red","blue","green","purple"),
       lty=c(1,1,1,1,1),
       lwd=c(2,2,2,2,2))
# Display bar plots showing Overall Return and Change in Daily Volume
overallReturn = function(df){
  return ((df$Close[nrow(df)] - df$Close[1]) / df$Close[1])
```

```
}

volIncrease = function(df){
  return ((df$Volume[nrow(df)] - df$Volume[1]) / df$Volume[1])
}

returns = c(overallReturn(BTCdf),overallReturn(ETHdf),overallReturn(XMRdf),overallReturn(XRPdf))
volumes = c(volIncrease(BTCdf),volIncrease(ETHdf),volIncrease(XMRdf),volIncrease(XRPdf))

barData = data.frame(Currency=c("BTC","ETH","XMR","XRP"), Returns=returns,Volumes=volumes)
kable(barData, caption="Cryptocurrency ROI",
      row.names = F,digits=2)
# REQ: barplot
ggplot(data=barData, aes(x=Currency, y=Returns)) +
  geom_bar(stat="identity",fill="steelblue") +
  ggtitle("Cumulative Return on Investment (not percent!) Aug 2015 - Feb 2018")

ggplot(data=barData, aes(x=Currency, y=Volumes)) +
  geom_bar(stat="identity",fill="chocolate4") +
  ggtitle("Change in Daily Volume Aug 2015 - Feb 2018")

# distribution of relative price changes
multidf$BTCdelta = c(0,diff(multidf$BTC.idx))
multidf$ETHdelta = c(0,diff(multidf$ETH.idx))
multidf$XMRdelta = c(0,diff(multidf$XMR.idx))
multidf$XRPdelta = c(0,diff(multidf$XRP.idx))
multidf$SP500delta = c(0,diff(multidf$SP500.idx))

# REQ: display a histogram
par(op)
mu_SP500delta = mean(multidf$SP500delta)
sd_SP500delta = sd(multidf$SP500delta)
multidf$SP500deltaStd = (multidf$SP500delta - mu_SP500delta) / sd_SP500delta
# Plot histogram of standardized daily price changes in S&P500, overlaid with equivalent
# Gaussian distribution.
ggplot(multidf, aes(x=SP500deltaStd)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.01,colour="purple",
                 fill="white") +
  #geom_density(alpha=0.2,fill="#FF6666") +
  stat_function(
    fun = function(x,mean,sd,n){
      n*dnorm(x=x, mean=mean, sd=sd)
    },
    args=with(multidf, c(mean=mu_SP500delta, sd=sd_SP500delta, n=length(multidf)))
  )

# QQplot to see if a distribution is normal
qqnorm(multidf$SP500deltaStd,main="QQ Plot of S&P 500 Daily Price Changes")
abline(0,1)
shapiro.test(multidf$SP500deltaStd)
# From http://www.cookbook-r.com/Graphs/Multiple_graphs_on_one_page_(ggplot2)/
# Multiple plot function
```

```r
#
# ggplot objects can be passed in ..., or to plotlist (as a list of ggplot objects)
# - cols:   Number of columns in layout
# - layout: A matrix specifying the layout. If present, 'cols' is ignored.
#
# If the layout is something like matrix(c(1,2,3,3), nrow=2, byrow=TRUE),
# then plot 1 will go in the upper left, 2 will go in the upper right, and
# 3 will go all the way across the bottom.
#
multiplot <- function(..., plotlist=NULL, file, cols=1, layout=NULL) {
  library(grid)

  # Make a list from the ... arguments and plotlist
  plots <- c(list(...), plotlist)

  numPlots = length(plots)

  # If layout is NULL, then use 'cols' to determine layout
  if (is.null(layout)) {
    # Make the panel
    # ncol: Number of columns of plots
    # nrow: Number of rows needed, calculated from # of cols
    layout <- matrix(seq(1, cols * ceiling(numPlots/cols)),
                     ncol = cols, nrow = ceiling(numPlots/cols))
  }

 if (numPlots==1) {
    print(plots[[1]])

  } else {
    # Set up the page
    grid.newpage()
    pushViewport(viewport(layout = grid.layout(nrow(layout), ncol(layout))))

    # Make each plot, in the correct location
    for (i in 1:numPlots) {
      # Get the i,j matrix positions of the regions that contain this subplot
      matchidx <- as.data.frame(which(layout == i, arr.ind = TRUE))

      print(plots[[i]], vp = viewport(layout.pos.row = matchidx$row,
                                      layout.pos.col = matchidx$col))
    }
  }
}

p1 = ggplot(multidf, aes(x=BTCdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
  geom_density(alpha=0.2,fill="#FF6666") +
  stat_function(
    fun = function(x,mean,sd,n){
      n*dnorm(x=x, mean=mean, sd=sd)
```

```r
    },
    args=with(multidf, c(mean=mean(BTCdelta), sd=sd(BTCdelta), n=length(multidf)))
  )

p2 = ggplot(multidf, aes(x=ETHdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
  geom_density(alpha=0.2,fill="#FF6666")

p3 = ggplot(multidf, aes(x=XMRdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
  geom_density(alpha=0.2,fill="#FF6666")

p4 = ggplot(multidf, aes(x=XRPdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
  geom_density(alpha=0.2,fill="#FF6666")

multiplot(p1,p2,p3,p4,cols=2)
# TODO: overlay S&P500 over any cryptocurrency

# TODO: normalize values and overlay Gaussian

# Categorical Variables

# Converting VIX into a categorical
#TODO

multidf$VIXCLS.idx = multidf$VIXCLS / multidf$VIXCLS[1]
multidf$VIXCLSdelta = c(0,diff(multidf$VIXCLS.idx))
multidf$VIXCLSsgn = ifelse(multidf$VIXCLSdelta>=0,1,-1)
multidf$BTCsgn = ifelse(multidf$BTCdelta>=0,1,-1)
# TODO how many standard deviations are exceeded

overlayGaussian = function(v,label){
  mu_v = mean(v)
  sd_v = sd(v)
  v_std = (v - mu_v) / sd_v
  hist(v_std,main=paste("Distribution of Standardized",label))
  xfit = seq(min(v_std), max(v_std), length=length(v_std))
  yfit = dnorm(xfit, mean=mu_v, sd = sd_v)
  lines(xfit,yfit,col="red", lwd=2)
  qqnorm(v_std,main=paste("QQ Plot of",label))
  abline(0,1)

}
overlayGaussian(multidf$BTCdelta,"BTC Daily Price Changes")
overlayGaussian(multidf$SP500delta,"S&P 500 Daily Price Changes")
```

```r
# Overlay Beta
overlayBeta = function(v,label){
  # this will rescale vector v to [0,1]
  v_norm = (v - min(v)) / (max(v) - min(v))
  hist(v_norm,main=label)
  xfit = seq(0, 1, length=length(v))
  yfit = dbeta(xfit, 1000,600)
  lines(xfit,yfit,col="red", lwd=2)
}
#overlayBeta(multidf$BTCdelta,"Distribution of Normalized BTC Daily Price Changes")
overlayBeta(multidf$SP500delta,"Distribution of Normalized S&P 500 Daily Price Changes")



cor(BTCdf$Close, ETHdf$Close)
cor(BTCdf$Close, XMRdf$Close)
cor(BTCdf$Close, XRPdf$Close)
cor(ETHdf$Close, XMRdf$Close)
cor(ETHdf$Close, XRPdf$Close)
cor(XMRdf$Close, XRPdf$Close)

#Largest correlation between BTC and XMR
plot(BTCdf$Close,XMRdf$Close,pch = ".",cex = 3)
#b is slope
b <- cov(BTCdf$Close,XMRdf$Close)/var(BTCdf$Close)
#a is intercept
a <- mean(XMRdf$Close) - b*mean(BTCdf$Close);a
#We can add this regression line to the plot of the data
abline(a, b, col = "red")
##
```