# Math23C Spring 2018 Final Project

# Project Highlights

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#### Abstract

Cryptocurrencies such as Bitcoin, Ethereum, etc. generated significant attention in 2017 due a dramatic price increases followed a spectacular drop in 2018. Cryptocurrencies have significant volalility 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

Appendix A - Long Script	2
References	. 20
Conclusion	
Additional points for creativity or complexity (up to 10 points)	
Required submission uploads	
Required Analysis	
Required graphical displays (all graphs must be colored and nicely labeled)	
Required dataset standards	
Topic 3 - Correlation between Cryptocurrencies	. 1
Topic 2	
Exploratory Data Analysis	. ;
Clean up, Normalization	
Categorical Data	
Traditional, Noncryptocurrency Data	
Cryptocurrency Historical Pricing	
Data Sources	•
Introduction	

#### 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 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 run once. The collects 18 additional metrics.

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 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.
- 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**

```
plotSeries = function(df){
   dfdata = xts(df[,2:7],order.by = df[,1])
   # TODO fix weekly plot
   #wk = dfdata
   #data.wk = to.weekly(wk)
   #plot(data.wk)
   #plot.new()
   OHLC = as.quantmod.OHLC(dfdata)
   chartSeries(OHLC)
}
plotSeries(BTCdf)
```







plotSeries(XRPdf)

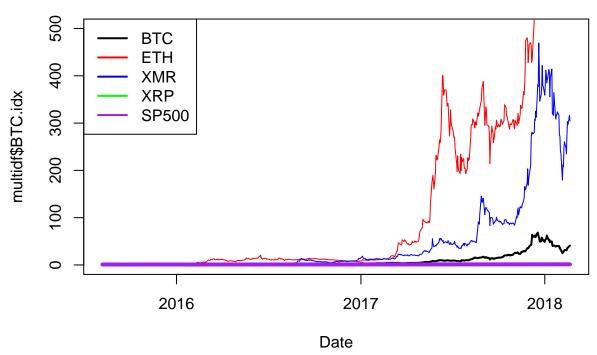


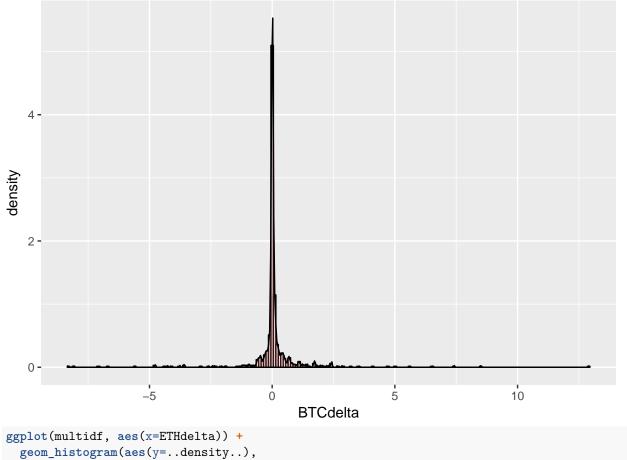
```
# wk = BTCdata
# data.wk = to.weekly(wk)
# plot(data.wk)
# OHLC = as.quantmod.OHLC(BTCdata)
#chartSeries(OHLC)
close.prices = BTCdata$Close
close.prices = cbind(close.prices,ETHdf$Close,XMRdf$Close,XRPdf$Close)
multidf = cbind(index(close.prices), data.frame(close.prices))
names(multidf) = paste(c("Date","BTC","ETH","XMR","XRP"))
# Merge in the non-crypto metrics
multidf=merge(multidf,noncrypto,by.x="Date", by.y="DATE")
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
plot(x = multidf$Date,y=multidf$BTC.idx,type="1",xlab="Date",col="black",lty=1,lwd=2)
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")
```

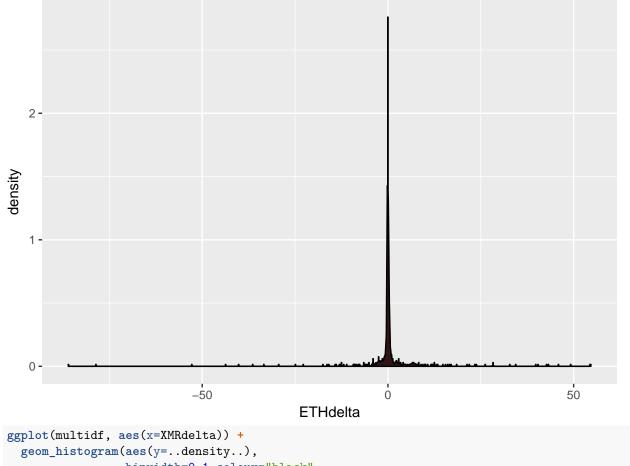
1wd=c(2,2,2,2,2)

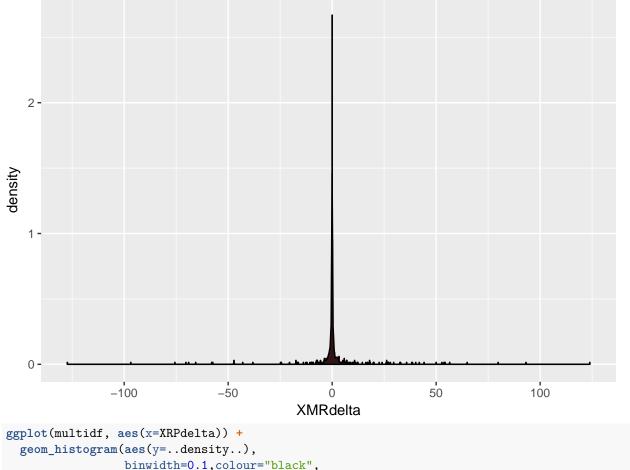
# 

Date

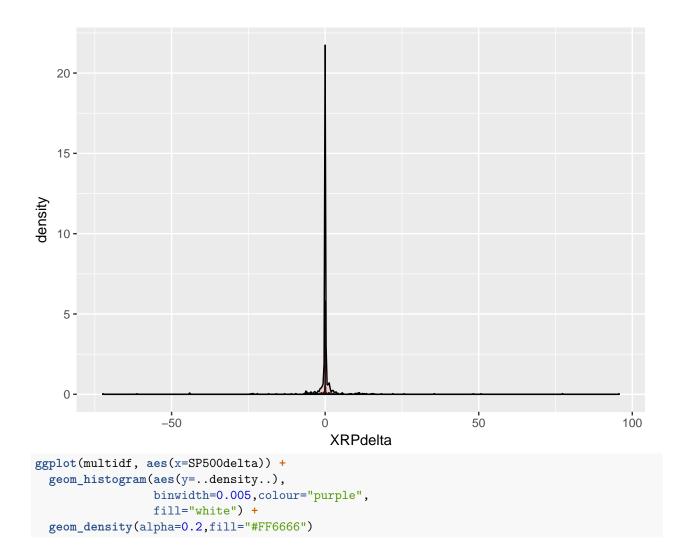


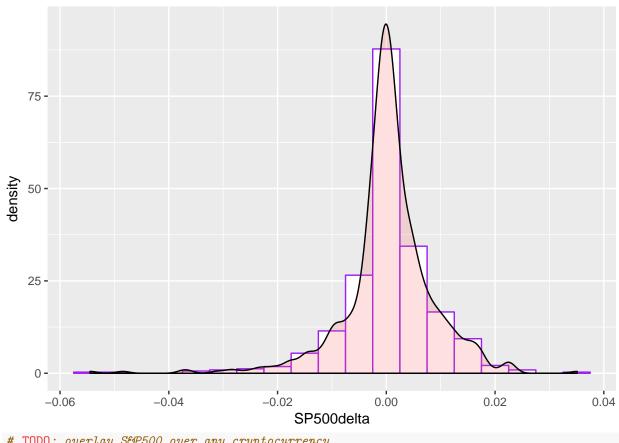






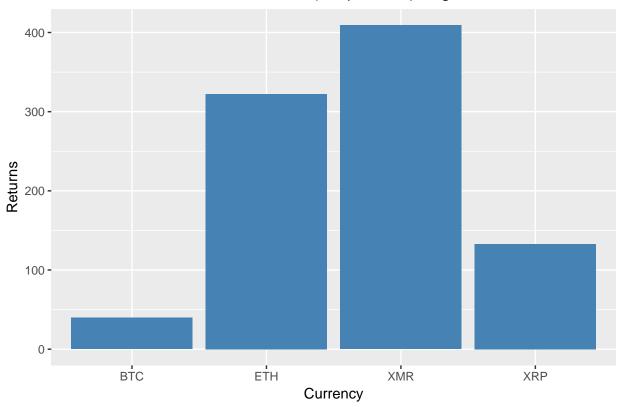
```
fill="white") +
geom_density(alpha=0.2,fill="#FF6666")
```





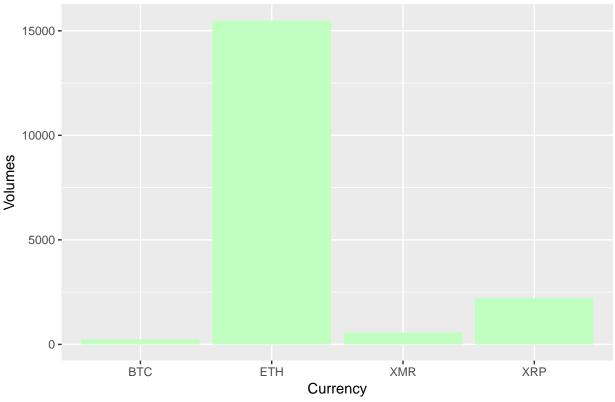
```
# TODO: overlay S&P500 over any cryptocurrency
# TODO: normalize values and overlay Gaussian
# Display bar plots showing Overall Return and Change in Daily Volume
overallReturn = function(df){
  return ((df$Close[nrow(df)] - df$Close[1]) / df$Close[1])
}
volIncrease = function(df){
  return ((df$Volume[nrow(df)] - 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)
barData
##
     Currency
                Returns
                           Volumes
## 1
          BTC 39.78868
                          232.6492
## 2
          ETH 322.23827 15487.8060
## 3
          XMR 409.08121
                          551.9270
          XRP 132.70952 2217.3103
## 4
# REQ: barplot
ggplot(data=barData, aes(x=Currency, y=Returns)) +
 geom_bar(stat="identity",fill="steelblue") +
```

# Cumulative Return on Investment (not percent!) Aug 2015 - Feb 2018



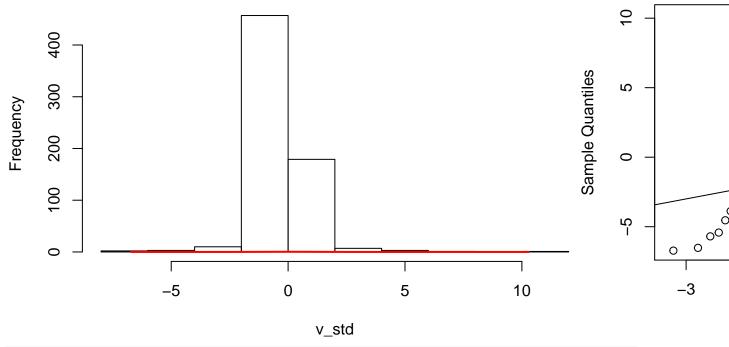
```
ggplot(data=barData, aes(x=Currency, y=Volumes)) +
  geom_bar(stat="identity",fill="darkseagreen1") +
  ggtitle("Change in Daily Volume Aug 2015 - Feb 2018")
```

# Change in Daily Volume Aug 2015 - Feb 2018



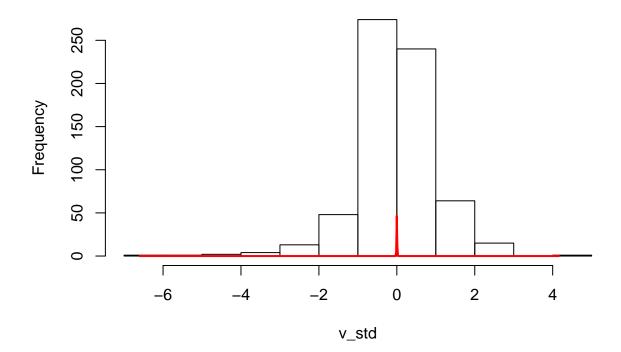
```
# Categorical Variables
# Converting VIX into a categorical
#TODO
multidf$VIXCLS.idx = multidf$VIXCLS / multidf$VIXCLS[1]
multidf$VIXCLSdelta = c(0,diff(multidf$VIXCLS.idx))
multidf$VIXCLSsgn = ifelse(multidf$VIXCLSdelta>=0,1,-1)
multidf$BTCsgn = ifelse(multidf$BTCdelta>=0,1,-1)
# TODO how many standard deviations are exceeded
overlayGaussian = function(v,label){
  mu_v = mean(v)
  sd_v = sd(v)
  v_std = (v - mu_v) / sd_v
  hist(v_std,main=paste("Distribution of Standardized",label))
  xfit = seq(min(v_std), max(v_std), length=length(v_std))
  yfit = dnorm(xfit, mean=mu_v, sd = sd_v)
  lines(xfit,yfit,col="red", lwd=2)
  qqnorm(v_std,main=paste("QQ Plot of",label))
  abline(0,1)
overlayGaussian(multidf$BTCdelta,"BTC Daily Price Changes")
```

# **Distribution of Standardized BTC Daily Price Changes**

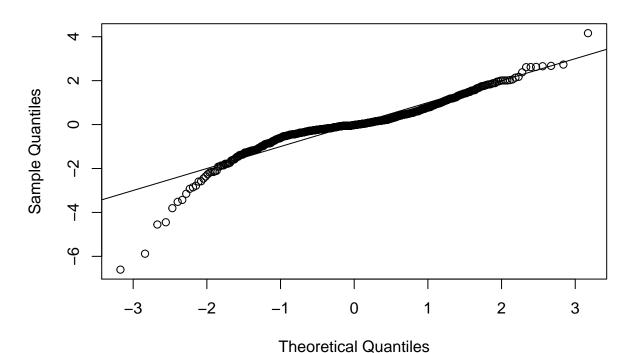


overlayGaussian(multidf\$SP500delta,"S&P 500 Daily Price Changes")

# Distribution of Standardized S&P 500 Daily Price Changes

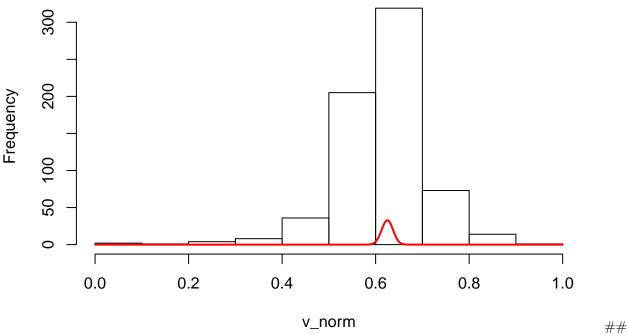


# QQ Plot of S&P 500 Daily Price Changes



# 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")

# Distribution of Normalized S&P 500 Daily Price Changes



Topic 1 - Volalitility Exploration

# Topic 2 -

# Topic 3 - 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
```

10000

BTCdf\$Close

15000

20000

##

Summary of Project Requirements

0

## Required dataset standards

• [x] A dataframe

100

- [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

5000

## 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
- [] A p-value or other statistic based on a distribution function
- [] 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$set(echo = TRUE)
library(xts)
library(quantmod)
library(ggplot2)
# Read one price history file per currency
BTCdf = read.csv("data/bitcoin_price.csv", stringsAsFactors = F)
ETHdf = read.csv("data/ethereum_price.csv", stringsAsFactors = F)
XMRdf = read.csv("data/monero_price.csv", stringsAsFactors = F)
XRPdf = read.csv("data/ripple_price.csv", stringsAsFactors = F)
# Fix rest of data:
# 1- Make dates native format
# 2- Convert Volume and market cap:
    a) From string ("123,456") to numeric (123456).
     b) Convert "-" to O.
# 3- Sort chronologically
fixVolCap = function(df) {
  df$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")
plotSeries = function(df){
 dfdata = xts(df[,2:7], order.by = df[,1])
  # TODO fix weekly plot
  #wk = dfdata
  #data.wk = to.weekly(wk)
  #plot(data.wk)
  #plot.new()
  OHLC = as.quantmod.OHLC(dfdata)
  chartSeries(OHLC)
}
```

```
plotSeries(BTCdf)
plotSeries(ETHdf)
plotSeries(XMRdf)
plotSeries(XRPdf)
BTCdata = xts(BTCdf[,2:7],order.by = BTCdf[,1])
# wk = BTCdata
# data.wk = to.weekly(wk)
# plot(data.wk)
# OHLC = as.quantmod.OHLC(BTCdata)
#chartSeries(OHLC)
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")
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
plot(x = multidf$Date,y=multidf$BTC.idx,type="l",xlab="Date",col="black",lty=1,lwd=2)
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"),
       ltv=c(1,1,1,1,1),
      1wd=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))
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))
# 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
ggplot(multidf, aes(x=BTCdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
```

```
geom_density(alpha=0.2,fill="#FF6666")
ggplot(multidf, aes(x=ETHdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
  geom_density(alpha=0.2,fill="#FF6666")
ggplot(multidf, aes(x=XMRdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
  geom_density(alpha=0.2,fill="#FF6666")
ggplot(multidf, aes(x=XRPdelta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.1,colour="black",
                 fill="white") +
  geom_density(alpha=0.2,fill="#FF6666")
ggplot(multidf, aes(x=SP500delta)) +
  geom_histogram(aes(y=..density..),
                 binwidth=0.005,colour="purple",
                 fill="white") +
  geom density(alpha=0.2,fill="#FF6666")
# TODO: overlay S&P500 over any cryptocurrency
# TODO: normalize values and overlay Gaussian
# 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(XMRdf))
volumes = c(volIncrease(BTCdf), volIncrease(ETHdf), volIncrease(XMRdf), volIncrease(XRPdf))
barData = data.frame(Currency=c("BTC","ETH","XMR","XRP"), Returns=returns, Volumes=volumes)
barData
# 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="darkseagreen1") +
  ggtitle("Change in Daily Volume Aug 2015 - Feb 2018")
```

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

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