SEC-1-SA2-GROUP-2-SIGUE,-JP, QUIJANO, JP-SA2

Sigue, John Patrick A., Quijano, Julian Philip S.

2025-05-16

1. Find out which probability distribution function best fits Bitcoin's returns for trading data every minute, from January 1, 2012 to April 15, 2025, for Bitcoin quoted in United States dollars or the BTC/USD pair.

Load the data

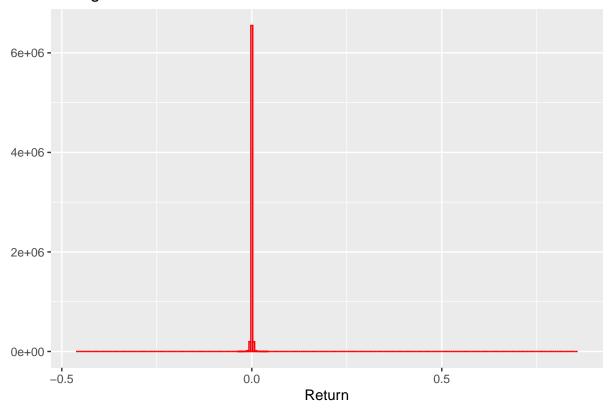
Summary of Data

```
# Summary
summary(clean)
```

```
Close
     Timestamp
                                                    SimpleReturn
##
          :2012-01-01 10:02:00.00
                                  Min. :
                                              3.8 Min.
                                                         :-0.4604705
## 1st Qu.:2015-04-28 14:41:15.00
                                  1st Qu.:
                                            423.2 1st Qu.:-0.0002378
## Median :2018-08-23 19:20:30.00
                                  Median: 6556.0 Median: 0.0000000
## Mean :2018-08-23 19:27:57.39
                                  Mean : 17164.2 Mean : 0.0000031
                                  3rd Qu.: 27093.0 3rd Qu.: 0.0002485
## 3rd Qu.:2021-12-18 23:59:45.00
## Max. :2025-04-15 23:59:00.00
                                  Max. :109036.0 Max. : 0.8532000
```

Histogram of Data

Histogram of return



Kolmogorov-Smirnov tests

The Kolmogorov-Smirnov (KS) test is a non-parametric statistical test used to compare a sample with a reference probability distribution or to compare two samples. It measures the largest absolute difference (D statistic) between the cumulative distribution function (CDF) of the sample and that of the theoretical or simulated distribution. A smaller D value indicates that the sample distribution is closer to the reference distribution. The KS test also provides a p-value, which assesses the statistical significance of the observed

difference — a high p-value (typically > 0.05) suggests that there is no strong evidence to reject the null hypothesis that both distributions are the same. In practice, especially with large datasets, even small differences can lead to very low p-values, so when identifying the distribution that best fits your data, the D statistic is more reliable for comparing closeness, while the p-value helps assess statistical significance.

```
sim n <- rnorm(length(clean$SimpleReturn), mean = mean(clean$SimpleReturn),</pre>
    sd = sd(clean$SimpleReturn))
nor <- ks.test(clean$SimpleReturn, sim_n)</pre>
Normal Distribution
## Warning in ks.test.default(clean$SimpleReturn, sim_n): p-value will be
## approximate in the presence of ties
print(nor)
##
   Asymptotic two-sample Kolmogorov-Smirnov test
##
##
## data: clean$SimpleReturn and sim_n
## D = 0.21406, p-value < 2.2e-16
## alternative hypothesis: two-sided
sim_t <- rt(length(clean$SimpleReturn), df = length(clean$SimpleReturn) -</pre>
    1)
stu <- ks.test(clean$SimpleReturn, sim_t)</pre>
Student's T Distribution
## Warning in ks.test.default(clean$SimpleReturn, sim_t): p-value will be
## approximate in the presence of ties
print(stu)
##
##
   Asymptotic two-sample Kolmogorov-Smirnov test
##
## data: clean$SimpleReturn and sim_t
## D = 0.49456, p-value < 2.2e-16
```

alternative hypothesis: two-sided

```
library(rmutil)
Laplace Distribution
##
## Attaching package: 'rmutil'
## The following object is masked from 'package:stats':
##
##
       nobs
## The following objects are masked from 'package:base':
##
##
       as.data.frame, units
sim_laplace <- rlaplace(length(clean$SimpleReturn), m = mean(clean$SimpleReturn),</pre>
    s = sd(clean$SimpleReturn))
lap <- ks.test(clean$SimpleReturn, sim_laplace)</pre>
## Warning in ks.test.default(clean$SimpleReturn, sim_laplace): p-value will be
## approximate in the presence of ties
print(lap)
##
   Asymptotic two-sample Kolmogorov-Smirnov test
## data: clean$SimpleReturn and sim_laplace
## D = 0.20248, p-value < 2.2e-16
## alternative hypothesis: two-sided
library(poweRlaw)
Power Law Distribution
## Warning: package 'poweRlaw' was built under R version 4.4.3
set.seed(1)
sim_powerlaw <- rplcon(n = length(clean$SimpleReturn), xmin = 0.01, alpha = 2.5)
clean_positive <- clean$SimpleReturn[clean$SimpleReturn > 0]
sim_powerlaw <- sim_powerlaw[1:length(clean_positive)]</pre>
```

pow <- ks.test(clean_positive, sim_powerlaw)</pre>

```
## Warning in ks.test.default(clean_positive, sim_powerlaw): p-value will be
## approximate in the presence of ties
print(pow)
##
## Asymptotic two-sample Kolmogorov-Smirnov test
## data: clean_positive and sim_powerlaw
## D = 0.99559, p-value < 2.2e-16
## alternative hypothesis: two-sided
sim_uniform <- runif(length(clean$SimpleReturn), min = min(clean$SimpleReturn),</pre>
   max = max(clean$SimpleReturn))
uni <- ks.test(clean$SimpleReturn, sim_uniform)</pre>
Uniform Distribution
## Warning in ks.test.default(clean$SimpleReturn, sim_uniform): p-value will be
## approximate in the presence of ties
print(uni)
##
## Asymptotic two-sample Kolmogorov-Smirnov test
## data: clean$SimpleReturn and sim_uniform
## D = 0.64066, p-value < 2.2e-16
## alternative hypothesis: two-sided
returns_pos <- clean$SimpleReturn - min(clean$SimpleReturn) + 1e-06 # Make all values positive
sim_exp <- rexp(length(returns_pos), rate = 1/mean(returns_pos))</pre>
exp <- ks.test(clean$SimpleReturn, sim_exp)</pre>
Exponential Distribution
## Warning in ks.test.default(clean$SimpleReturn, sim_exp): p-value will be
## approximate in the presence of ties
print(exp)
```

```
##
   Asymptotic two-sample Kolmogorov-Smirnov test
##
##
## data: clean$SimpleReturn and sim_exp
## D = 0.98157, p-value < 2.2e-16
## alternative hypothesis: two-sided
sim_cauchy <- rcauchy(length(clean$SimpleReturn), location = median(clean$SimpleReturn),</pre>
    scale = IQR(clean$SimpleReturn)/2)
cau <- ks.test(clean$SimpleReturn, sim_cauchy)</pre>
Cauchy Distribution
## Warning in ks.test.default(clean$SimpleReturn, sim_cauchy): p-value will be
## approximate in the presence of ties
print(cau)
##
##
   Asymptotic two-sample Kolmogorov-Smirnov test
##
## data: clean$SimpleReturn and sim_cauchy
## D = 0.13508, p-value < 2.2e-16
## alternative hypothesis: two-sided
results <- data.frame(Distribution = c("Normal", "Student's t", "Laplace",
    "Power Law", "Uniform", "Exponential", "Cauchy"), D_Statistic = c(nor$statistic,
    stu$statistic, lap$statistic, pow$statistic, uni$statistic, exp$statistic,
    causstatistic))
print(results[order(results$D_Statistic), ])
```

Test Results

```
Distribution D_Statistic
## 7
          Cauchy
                   0.1350828
## 3
         Laplace
                   0.2024805
## 1
          Normal
                   0.2140647
## 2 Student's t
                   0.4945578
## 5
         Uniform
                   0.6406632
## 6 Exponential
                   0.9815688
## 4
       Power Law
                   0.9955866
```

The results of the Kolmogorov-Smirnov test show the D-statistic values for different distributions compared to the sample data. The Cauchy distribution has the smallest D value (0.135), indicating the closest fit, followed by the Laplace distribution (0.202). Other distributions, such as Normal (0.214), Student's t (0.495), and Exponential (0.632), show progressively larger D values, indicating a poorer fit. The Uniform (0.641) and Power Law (0.996) distributions have the highest D values, suggesting they are the least similar to the sample data.

2. Test using Shapiro-Wilk normality test the Ethereum returns for trading data every five minutes, from August 7, 2015 to April 15, 2025.

```
library(dplyr)
## Warning: package 'dplyr' was built under R version 4.4.3
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
       intersect, setdiff, setequal, union
library(lubridate)
## Warning: package 'lubridate' was built under R version 4.4.3
##
## Attaching package: 'lubridate'
## The following objects are masked from 'package:base':
##
       date, intersect, setdiff, union
data = read.csv("ETHUSD_1m_Binance.csv")
data = data[data$Open.time <= as.POSIXct("2025-04-15 23:59:59", tz = "UTC"),
   ]
clean_data = data[, c("Open.time", "Close")]
clean_data$SimpleReturn <- c(NA, (diff(clean_data$Close)/head(clean_data$Close,
    <del>-1</del>)))
clean_data = na.omit(clean_data)
clean_data$Open.time <- as.POSIXct(clean_data$Open.time, format = "%Y-%m-%d %H:%M:%S",
   tz = "UTC")
# Group the 1 min interval data into 5 min
clean_data_5min <- clean_data %>%
   mutate(Time_5min = floor_date(Open.time, "5 minutes")) %>%
   group by (Time 5min) %>%
   summarise(Open_5min = first(Close), Close_5min = last(Close), .groups = "drop") %>%
```

```
mutate(SimpleReturn_5min = (Close_5min - Open_5min)/Open_5min) %>%
    select(Time_5min, SimpleReturn_5min) %>%
    filter(!is.na(SimpleReturn_5min))

summary(clean_data_5min$SimpleReturn_5min)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## -1.217e-01 -9.061e-04 0.000e+00 -6.880e-06 9.013e-04 1.211e-01
```

Shapiro-Wilks Test Importantly, we could not use the built-in function shapiro.test() since it is limited to data sets lower than 5000, while this particular data set is larger than 4 million.

```
manual_shapiro_wilk <- function(x) {</pre>
    x \leftarrow sort(x)
    n <- length(x)
    if (n < 3)
         stop("Sample size must be at least 3.")
    mean_x <- mean(x)</pre>
    ssd \leftarrow sum((x - mean_x)^2)
    m \leftarrow qnorm(((1:n) - 0.375)/(n + 0.25))
    m \leftarrow m - mean(m)
    a <- m/sqrt(sum(m^2))
    numerator \leftarrow (sum(a * x))^2
    W <- numerator/ssd
    if (n >= 3 \& n <= 5000) {
         mu < -1.2725 + 1.0521 * log(n)
         sigma \leftarrow 1.0308 - 0.26758 * log(n)
         y \leftarrow log(1 - W)
         z \leftarrow (y - mu)/sigma
         p_value <- pnorm(z)</pre>
    } else {
         mu \leftarrow -1.2725 + 1.0521 * log(5000)
         sigma \leftarrow 1.0308 - 0.26758 * log(5000)
         y \leftarrow log(1 - W)
         z \leftarrow (y - mu)/sigma
         p_value <- pnorm(z)</pre>
         warning("P-value approximation may not be reliable for sample sizes > 5000")
    }
    return(list(W = W, p_value = p_value))
result <- manual_shapiro_wilk(clean_data_5min$SimpleReturn_5min)
```

Warning in manual_shapiro_wilk(clean_data_5min\$SimpleReturn_5min): P-value
approximation may not be reliable for sample sizes > 5000

```
cat("\nManual Shapiro-Wilk W statistic:", result$W, "\n")

##
## Manual Shapiro-Wilk W statistic: 0.7610889

cat("Approximate p-value:", result$p_value, "\n")
```

Approximate p-value: 1

With a W statistic of 0.7610889, significantly lower than 1, typically indicating deviations from normality. However, the interpretation must consider the p-value.

An approximate p-value of 1 suggests that the data does not significantly deviate from a normal distribution. In statistical terms, this means that the null hypothesis (that the data is normally distributed) cannot be rejected.

With a dataset exceeding 4 million elements, the Shapiro-Wilk test is sensitive to even minor deviations from normality. However, the high p-value indicates that these deviations are not statistically significant.

The results imply that the dataset can be treated as normally distributed for the purposes of further statistical analysis. This allows for the use of parametric tests, which assume normality.

Github Link: https://github.com/SylTana/APM1110-QUIJANO-JULIAN_PHILIP/tree/main/SA2