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## 8.1 Analysing the Relationship Between Friends and Followers for Twitter Users

### 8.1.1 Retrieve the posts from Twitter

relevant posts can be retrieved from twitter by utilising the `rtweet` package, packages can be loaded for use in **R** thusly:

The `rtweet` API will search for tweets that contain all the words of a query regardless of uppercase or lowercase usage [5].

In order to leverage the *Twitter* API it is necessary to use tokens provided through a *Twitter* developer account:

and hence all tweets containing a mention of *Ubisoft* can be returned and saved to disk as shown in listing 3:

### 8.2.2 Count of Followers and Friends

In order to identify the number of users that are contained in the *tweets* the `unique()` function can be used to return a vector of names which can then be passed as an index to the vector of counts as shown in listing 4, this provides that 81.7% of the tweets are by unique users.

### 8.1.3 Summary Statistics

The average number of friends and followers from users who posted tweets mentioning *Ubisoft* can be returned using the `mean()` as shown in listing 5 this provides that on average each user has 586 friends and 63,620 followers.

```

1  # Load Packages
   ↪ -----
2  setwd("~/Dropbox/Notes/DataSci/Social_Web_Analytics/SWA-Project/scripts_1
   ↪ /")
3
4  if (require("pacman")) {
5    library(pacman)
6  } else{
7    install.packages("pacman")
8    library(pacman)
9  }
10
11  pacman::p_load(xts, sp, gstat, ggplot2, rmarkdown, reshape2,
12                ggmap, parallel, dplyr, plotly, tidyverse,
13                reticulate, UsingR, Rmpfr, swirl, corrplot,
14                gridExtra, mise, latex2exp, tree, rpart,
15                lattice, coin, primes, epitools, maps, clipr,
16                ggmap, twitterR, ROAuth, tm, rtweet, base64enc,
17                httpuv, SnowballC, RColorBrewer, wordcloud,
18                ggwordcloud, tidyverse, boot)

```

Listing 1: Load the Packages for *R*

### 8.1.4 Above Average Followers

Each user can be compared to the average number of followers, by using a logical operator on the vector (e.g. `y > ybar`), this will return an output of logical values. *R* will coerce logicals into 1/0 values meaning that the mean value will return the proportion of TRUE responses as shown in listing 6. This provides that:

- 20.6% of the users identified have above **\*average friend counts**.
- 2.4% of the have identified have an above average **number of followers**.

### 8.1.5 Bootstrap confidence intervals

#### a/b.) Generate a bootstrap distribution

A bootstrap assumes that the population is an infinitely large repetition of the sample and may be produces with respect to follower counts by resampling with replacement/repetition and plotted using the ggplot2 library as deomonstrated in listings 7 and .1 and shown in figure 1.

This shows that the population follower counts is a non-normal skew-right distribution, which is expected because the number of friends is an integer value bound by zero [6].

```

1  # Set up Tokens
   ↪ =====
2
3  options(RCurlOptions = list(
4    verbose = FALSE,
5    capath = system.file("CurlSSL", "cacert.pem", package = "RCurl"),
6    ssl.verifypeer = FALSE
7  ))
8
9  setup_twitter_oauth(
10     consumer_key = "*****",
11     consumer_secret =
12     ↪ "*****",
13     access_token = "*****",
14     access_secret = "*****"
15   )
16
17  # rtweet
   ↪ =====
18  tk <- rtweet::create_token(
19     app = "SWA",
20     consumer_key = "*****",
21     consumer_secret =
22     ↪ "*****",
23     access_token =
24     ↪ "*****",
25     access_secret = "*****",
26     set_renv = FALSE

```

Listing 2: Import the twitter tokens (redacted)

```

1  n <- 1000
2  tweets.company <- search_tweets(q = 'ubisoft', n = n, token = tk,
3                                include_rts = FALSE)
4  save(tweets.company[,], file = "resources/Download_1.Rdata")

```

Listing 3: Save the Tweets to the HDD as an rdata file

```

1 (users <- unique(tweets.company$name)) %>% length()
2 x <- tweets.company$followers_count[duplicated(tweets.company$name)]
3 y <- tweets.company$friends_count[duplicated(tweets.company$name)]
4
5 ## > [1] 817

```

Listing 4: Return follower count of twitter posts

```

1 x<- rnorm(090)
2 y<- rnorm(090)
3 (xbar <- mean(x))
4 (ybar <- mean(y))
5
6 ## > [1] 4295.195
7 ## > [1] 435.9449

```

Listing 5: Determine the average number of friends and followers

```

1 (px_hat <- mean(x>xbar))
2 (py_hat <- mean(y>ybar))
3
4 ## > [1] 0.0244798
5 ## > [1] 0.2729498

```

Listing 6: Calculate the proportion of users with above average follower counts

```

1 ## Resample the Data
2 (bt_pop <- sample(x, size = 10^6, replace = TRUE)) %>% head()
3
4 ## > [1] 7 515 262 309 186 166

```

Listing 7: Bootstrapping a population from the sample.

```

1  ## Make the Population
2  bt_pop_data <- tibble("Followers" = bt_pop)
3  ggplot(data = bt_pop_data, aes(x = Followers)) +
4    geom_histogram(aes(y = ..density..), fill = "lightblue", bins = 35,
5      ↪ col = "pink") +
6    geom_density(col = "violetred2") +
7    scale_x_continuous(limits = c(1, 800)) +
8    theme_bw() +
9    labs(x = "Number of Followers", y = "Density",
10      title = "Bootstrapped population of Follower Numbers")

```

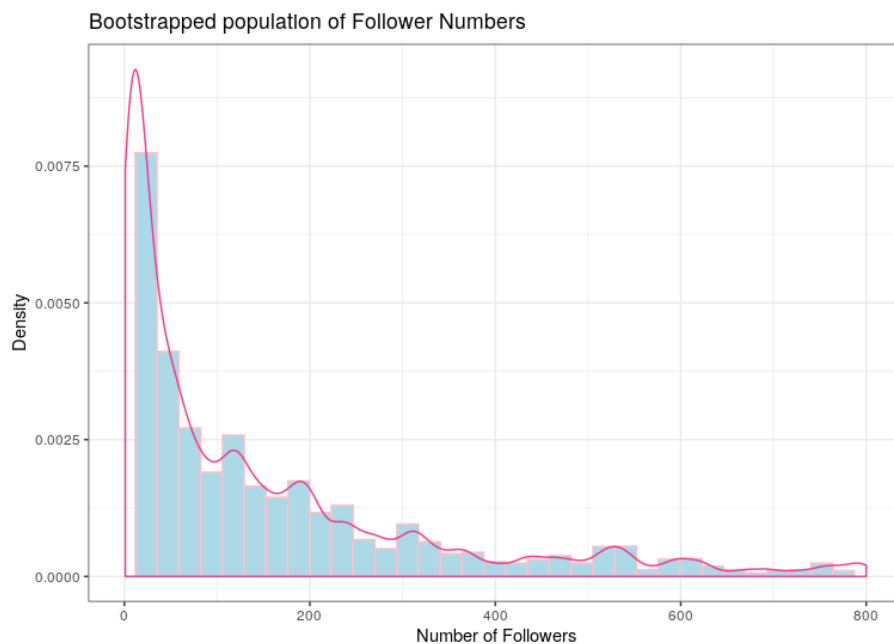


Figure 1: Histogram of the bootstrapped population of follower counts

### c.) Estimate a Confidence Interval for the population mean Follower Counts

In order to perform a bootstrap for the population mean value of follower counts it is necessary to:

1. Resample the data with replacement
  - that is randomly select values from the sample allowing for repetition
2. Measure the statistic in concern
3. Replicate this a sufficient number of times
  - Greater than or equal to 1000 times [2, Ch. 5]

This is equivalent to drawing a sample from a population that is infinitely large and constructed of repetitions of the sample. This can be performed in **R** as shown in listings

```
1 xbar_boot_loop <- replicate(10^3, {  
2   s <- sample(x, replace = TRUE)  
3   mean(s)  
4 })  
5 quantile(xbar_boot_loop, c((1-0.97)/2, (1+0.97)/2))  
6  
7 ##          1.5%          98.5%  
8 ##    588.4189 10228.7352
```

Listing 8: Confidence Interval of Mean Follower Count in Population

This provides that 97% of samples drawn from a population will contain the population mean

A 97% probability interval is such that a sample drawn from a population will contain the population mean in that interval 97% of the time, this means that it may be concluded with a high degree of certainty that the true population mean lies between 588 and 10228.

1. Alternative Approaches If this data was normally distributed it may have been appropriate to consider bootstrapping the standard error, however it is more appropriate to use a percentile interval for skewed data such as this, in saying that however this method is not considered to be very accurate in the literature and is often too narrow. [3, Section 4.1]
  - It's worth noting that the normal  $t$  value bootstrap offers no advantage over using a  $t$  distribution (other than being illustrative of bootstrapping generally) [3, Section 4.1]

The boot package is a bootstrapping library common among authors in the data science sphere [4, p. 295] [8, p. 237] that implements confidence intervals consistent with work by Davison and Hinkley [7] in their textbook *Bootstrap Methods and their Application*. In this work it is provided that the  $BC_a$  method of constructing confidence intervals is superior to mere percentile methods in terms of accuracy [2, Ch. 5], a sentiment echoed in the literature. [1, 2, Ch. 5]

Such methods can be implemented in **R** by passing a function to the boot call as shown in listing 9. This provides a broader interval, providing that the true confidence interval could lie between 1079 and 16227 followers.

references

```

1  xbar_boot <- boot(data = x, statistic = mean_val, R = 10^3)
2  boot.ci(xbar_boot, conf = 0.97, type = "bca", index = 1)
3
4  ## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
5  ## Based on 1000 bootstrap replicates
6  ##
7  ## CALL :
8  ## boot.ci(boot.out = xbar_boot, conf = 0.97, type = "bca", index = 1)
9  ##
10 ## Intervals :
11 ## Level          BCa
12 ## 97%      ( 1079, 16227 )
13 ## Calculations and Intervals on Original Scale
14 ## Warning : BCa Intervals used Extreme Quantiles
15 ## Some BCa intervals may be unstable
16 ## Warning message:
17 ## In norm.inter(t, adj.alpha) : extreme order statistics used as
   ↪ endpoints

```

Listing 9: Bootstrap of population mean follower count implementing the  $BC_a$  method

#### d.) Estimate a Confidence Interval for the population mean Friend Counts

A Confidence interval for the population mean friend counts may be constructed in a like wise fashion as shown in listings 10. This provides that the 97% confidence interval for the population mean friend count is between 384 and 502 (or 387 and 496 if the  $BC_a$  method used, they're quite close and so the more conservative percentile method will be accepted).

### FIXME 8.1.6 Estimate a 97% Confidence Interval for the High Friend Count Proportion

In order to bootstrap a confidence interval for the proportion of users with above average follower counts assume that the population mean value is equal to the sample proportion and draw a sample of the same number of observations with that probability.

In order to bootstrap a confidence interval for the proportion of users with above average follower counts draw samples from a population that is infinitely large composed of

In order to bootstrap a confidence interval for the proportion of users with above average follower counts repeatedly draw random samples from an infinitely large population composed entirely of the sample, this can be achieved by resampling the observations of above and below as shown in listing 11.

Take a population of infinite size by

```

1  # d.) Estimate a Confidence Interval for the populattion mean Friend
   ↪ Count ===
2  # Using a Percentile Method
   ↪ #####
3  ybar_boot_loop <- replicate(10^3, {
4    s <- sample(y, replace = TRUE)
5    mean(s)
6  })
7  quantile(ybar_boot_loop, c(0.015, 0.985))
8
9  # Using BCA Method
   ↪ #####
10 mean_val <- function(data, index) {
11   X = data[index]
12   return(mean(X))
13 }
14
15 xbar_boot <- boot(data = y, statistic = mean_val, R = 10^3)
16 boot.ci(xbar_boot, conf = 0.97, type = "bca", index = 1)
17
18
19 ##      1.5%      98.5%
20 ## 383.7619 501.5903
21 ##
22 ## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
23 ## Based on 1000 bootstrap replicates
24 ##
25 ## CALL :
26 ## boot.ci(boot.out = xbar_boot, conf = 0.97, type = "bca", index = 1)
27 ##
28 ## Intervals :
29 ## Level      BCa
30 ## 97%      (386.8, 496.7 )
31 ## Calculations and Intervals on Original Scale
32 ## Some BCa intervals may be unstable

```

Listing 10: Bootstrap of population mean follower count



```

1  # 8.1.6 High Friend Count Proportion
   ↪ -----
2  prop <- factor(c("Below", "Above"))
3  ## 1 is above average, 2 is below
4  py_hat_bt <- replicate(10^3, {
5    rs      <- sample(c("Below", "Above"),
6                      size = length(y),
7                      prob = c(py_hat, 1-py_hat),
8                      replace = TRUE)
9    isabove <- rs == "Above"
10   mean(isabove)
11 })
12 quantile(py_hat_bt, c(0.015, 0.985))
13
14
15 ##      1.5%      98.5%
16 ## 0.6976744 0.7601163

```

Listing 11: Bootstrap of Proportion of Friends above average

## References

- [1] James Carpenter and John Bithell. “Bootstrap Confidence Intervals: When, Which, What? A Practical Guide for Medical Statisticians”. en. In: *Statistics in Medicine* 19.9 (2000), pp. 1141–1164. ISSN: 1097-0258. DOI: [10.1002/\(SICI\)1097-0258\(20000515\)19:9<1141::AID-SIM479>3.0.CO;2-F](https://doi.org/10.1002/(SICI)1097-0258(20000515)19:9<1141::AID-SIM479>3.0.CO;2-F). URL: [https://doi-org.ezproxy.uws.edu.au/10.1002/\(SICI\)1097-0258\(20000515\)19:9%3C1141::AID-SIM479%3E3.0.CO;2-F](https://doi-org.ezproxy.uws.edu.au/10.1002/(SICI)1097-0258(20000515)19:9%3C1141::AID-SIM479%3E3.0.CO;2-F) (visited on 04/27/2020) (cit. on p. 6).
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- [8] Matt Wiley and Joshua Wiley. *Advanced R Statistical Programming and Data Models*. New York, NY: Springer Berlin Heidelberg, 2019. ISBN: 978-1-4842-2871-5 (cit. on p. 6).