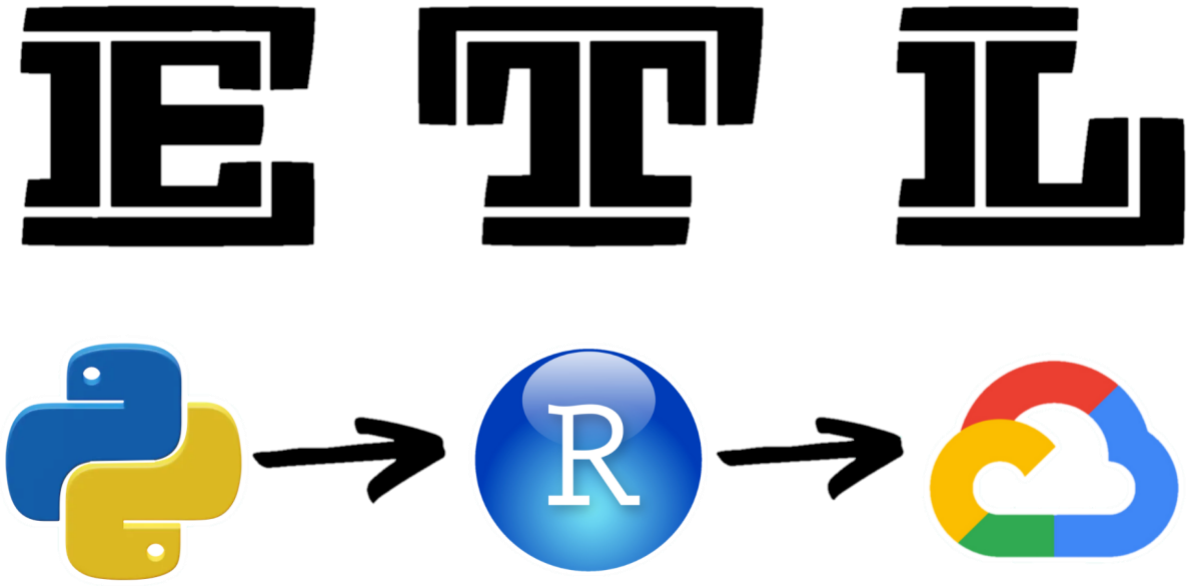


Data Warehousing (ETL)

Sawandi Kirby

2024-05-04

Contents

1 ETL -(Extract Transform Load)

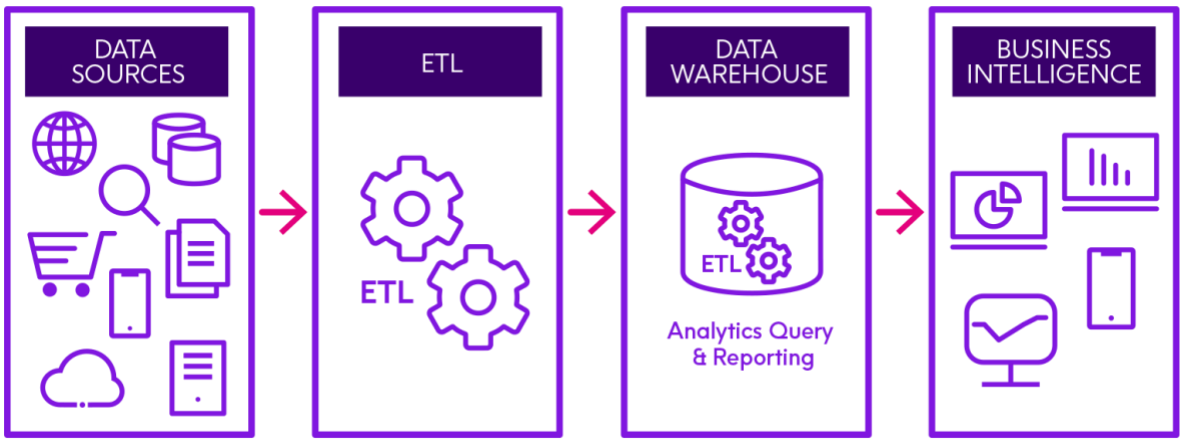


Figure 1: Extract Transform Load

1.1 Definition

1.1.1 ETL stands for "extract, transform, and load". It's a data integration process that combines data from multiple sources into a central repository, such as a data warehouse or data lake, and uses business rules to clean and organize it. The ETL process involves:

1.1.2 Transform: Cleansing, mapping, and transforming the raw data into a format that can be used by different applications.

1.1.3 Load: Writing the converted data from a staging area to a target database.

1.1.4 ETL enables data analysis to provide actionable business information, effectively preparing data for analysis and business intelligence processes. For example, an ETL tool might take updated accounting information from an ERP system (extract), combine it with other accounting data (transform), and store the transformed data in an organization's data lake for analytical analysis.

1.1.5 ETL pipelines are a set of tools and activities that move data from one system to another.

1.1.6 This is an overview of the data pipeline I've created for NBA Data scraped from the internet.

2 Extract

2.1 Python- Web Scrape

2.1.1 Web Scraping Code - The code to scrape NBA data can be found on GitHub on the *Python Web Scrape Page*

– Transform

3 Import data

3.1 Load Required Packages

3.1.1 Use function install_packages to install the required packages if you have not already.

3.1.2 Use function library to load the packages everytime R is restarted.

```
library(tidyverse)
library(readxl)
library(openxlsx)
library(dplyr)
library(stringr)
library(htmltools)
library(httpuv)
library(googleCloudStorage
R) library(googleAuthR)
library(bigrquery)
```

3.2 Load Functions

3.2.1 *Function to read Excel file.*

```
read_excel_file <- function(file_path) {
  sheet_names <- excel_sheets(file_path)

  all_data <- lapply(sheet_names, function(sheet) {
    read_excel(file_path, sheet = sheet)
  })

  return(all_data)
}
```

3.2.2 *Function to trim rows of character columns in a data frame.*

```
trimws_df <- function(df) { char_cols <- sapply(df,
  is.character) df[char_cols] <- lapply(df[char_cols],
  trimws) return(df)
}
```

3.2.3 *Function to convert height to inches.*

```
assign_location <- function(data, boolean_column, Opponent.x, custom_value) {
  data <- data %>% mutate(Away = ifelse(!!rlang::ensym(boolean_column),
    Opponent.x, custom_value),
          Home = ifelse(!!rlang::ensym(boolean_column), custom_value,
          Opponent.x))
  return(data)
}
```

3.2.4 *Function to convert height to inches.*

```
convert_height_to_inches <- function(df, column_name) {
  df <- df %>%
    mutate(Height = sapply(strsplit(df[[column_name]], "-"), function(x)
    as.integer(x[1])
  return(df)
}
```

```
 * 12 +
as.inte
```

3.3 Import Datasets

3.3.1 Use read_excel_file to extract Sheets from Excel file, into a list with the appropriate Team abbreviation.

```
ATL <-
read_excel_file("C:\\Users\\kirby\\OneDrive\\Desktop\\NBA\\NBA_2022\\ATL_data.xls
x")
```

3.3.2 Name the sheet numbers from the list we created into dataframes.

```
ATL_Roster <- ATL[[1]]
ATL_Per_Game <- ATL[[2]]
ATL_Totals <- ATL[[3]]
ATL_Starting_Lineup <- ATL[[4]]
ATL_Splits <- ATL[[5]]
ATL_Game_Log <- ATL[[6]]
ATL_Results <- ATL[[7]]
```

4 Clean Data

4.1 Full list

4.1.1 First thing we are going to do is, replace all empty strings in every data frame with NA.

4.1.2 *This will make them easier to find in our final check.*

```
ATL_Roster <- ATL_Roster %>%
  mutate_if(is.character, ~if_else(. == "",
  NA, .))
ATL_Per_Game <- ATL_Per_Game %>%
  mutate_if(is.character, ~if_else(. == "",
  NA, .))
```

```
ATL_Totals <- ATL_Totals %>%
  mutate_if(is.character, ~if_else(. == "",
  NA, .))
ATL_Starting_Lineup <- ATL_Starting_Lineup %>%
  mutate_if(is.character, ~if_else(. == "",
  NA, .))
ATL_Splits <- ATL_Splits %>%
  mutate_if(is.character, ~if_else(. == "",
  NA, .))
ATL_Game_Log <- ATL_Game_Log %>%
  mutate_if(is.character, ~if_else(. == "",
  NA, .))
```

4.1.3 Since we have built the function to trim all rows of our data frames, we're going to run all of our data frames through it.

```
ATL_Roster <- trimws_df(ATL_Roster)
ATL_Game_Log <- trimws_df(ATL_Game_Log)
ATL_Per_Game <- trimws_df(ATL_Per_Game) ATL_Starting_Lineup <-
trimws_df(ATL_Starting_Lineup)
ATL_Splits <- trimws_df(ATL_Splits)
ATL_Results <- trimws_df(ATL_Results) ATL_Totals <- trimws_df(ATL_Totals)
```

4.2 Roster_df

4.2.1 First start with the roster df, and get a glimpse of the dataframe and check out its structure.

4.2.2 ***This will help us determine if our data columns are the correct data type.***

```
head(ATL_Roster)
```

```
## # A tibble: 6 x 7
##   Player          Position Height Weight BirthDate           BirthCountry College
##   <chr>             <chr>   <chr>  <dbl> <dttm>              <chr>       <chr>
## 1 Cat Barber        pg      6-2      190 1994-07-25 00:00:00 us          nc state
## 2 Bogdan Bogdanović sg      6-5      220 1992-08-18 00:00:00 rs          <NA>
## 3 Chaundee Brown Jr. sg     6-5      215 1998-12-04 00:00:00 us          wake fore~
## 4 Clint Capela      c       6-10     240 1994-05-18 00:00:00 ch          <NA>
## 5 John Collins pf     6-9    235 1997-09-23 00:00:00 us     wake fore~ ## 6
Sharife Cooper     pg     6-1    180 2001-06-11 00:00:00 us     auburn
```

4.2.3 Even though we have a good list of Player names lets get the first and last into their own columns and make the string all lowercase so the system can read them better.

4.2.4 First remove (TW) tag from Player names. Then use the *separate* function.

```
ATL_Roster$Player <- gsub("\\(TW\\)", "", ATL_Roster$Player)

ATL_Roster <- ATL_Roster %>% separate(Player, into = c("FirstName",
  "LastName"), sep = " ", remove = FALSE)
```

```
## Warning: Expected 2 pieces. Additional pieces discarded in 1 rows [3].
```

4.2.5 Now we can use the *trimws* function to first remove the whitespace around any string columns, in our df.

4.2.6 Then use the *tolower* function to transform our string values into all lowercase letters.

```
ATL_Roster$Player <- trimws(tolower(ATL_Roster$Player))
ATL_Roster$FirstName <- trimws(tolower(ATL_Roster$FirstName))
ATL_Roster$LastName <- trimws(tolower(ATL_Roster$LastName))
```

4.2.7 We see that the columns that should be 'chr' are characters, 'num' are numeric, and 'POSIXct' is for date/time.

4.2.8 The Height column is in character format although it would be easier to calculate if they were in numeric format. So let's use our function to convert the height column.

```
ATL_Roster <- convert_height_to_inches(ATL_Roster, 'Height')
```

4.3 Per_Game_df

4.3.1 Now we can move on to the next df, Per_Game.

4.3.2 Start off by getting a view of the df and look at the structure.

```
head(ATL_Per_Game)
```

```
## # A tibble: 6 x 27
##   PlayerAge GamesPlayedPerGame GamesStarted MinutesPlayedPerGame FieldGoalsPerGame
##   <chr>    <dbl> <chr>                <dbl>              <dbl>           <db
                                                                          l>
##  1  trae     23 76                      76               34.9            9.4
yo~
##  2  john     24 54                      53               30.8            6.3
co~
##         3    24 53                      52               29.8            4.8
de'andr~
##  4  kevin    23 74                      60               29.6            4.7
h~
```

```
## 5 bogdan     29 63                        27              29.3            5.4
~
##        6     23 3                          2              27.7             3
chaunde~
## # i 21 more variables: FieldGoalAttemptsPerGame <dbl>,
FieldGoalPercentPerGame <dbl>,
## #ThreePointFieldGoalsPerGame <dbl>, ThreePointFieldGoalAttemptsPerGame <dbl>,
## #ThreePointFieldGoalPercentPerGame <dbl>, TwoPointFieldGoalsPerGame <dbl>,
## #TwoPointFieldGoalAttemptsPerGame <dbl>, TwoPointFieldGoalPercentPerGame <dbl>,
## #  EffectiveFieldGoalPercentPerGame <dbl>, FreeThrowsPerGame
<dbl>, ## # FreeThrowAttemptsPerGame <dbl>,
FreeThrowPercentPerGame <dbl>,
## #OffensiveReboundsPerGame <dbl>, DefensiveReboundsPerGame <dbl>, ...
```

4.3.3 It seems that the only incorrect column in this data frame is the GamesPlayed column.

4.3.4 So let's go ahead and fix that.

```
ATL_Per_Game$GamesPlayed <-as.numeric(ATL_Per_Game$GamesPlayedPerGame)
```

4.4 Totals_df

```
head(ATL_Totals)
```

```
## # A tibble: 6 x 27
##   Player         Age TotalGamesPlayed TotalGamesStarted TotalMinutesPlayed
##   <chr>        <dbl>           <dbl>             <dbl>              <dbl>
## 1 trae young      23              76                76               2652
## 2 kevin huerter   23              74                60               2188
## 3 clint capela    27              74                73               2042
## 4 bogdan          29              63                27               1848
bogdanović
## 5 danilo gallinari  33            66                18               1672
## 6 john collins    24              54                53               1663
## # i 22 more variables: TotalFieldGoalsPerGame <dbl>,
TotalFieldGoalAttempts <dbl>,
## #TotalFieldGoalPercent <dbl>, TotalThreePointFieldGoalsPerGame <dbl>,
##    TotalThreePointFieldGoalAttempts <dbl>,
#     TotalThreePointFieldGoalPercent <dbl>,
##    TotalTwoPointFieldGoalsPerGame <dbl>, TotalTwoPointFieldGoalAttempts
#     <dbl>,
##    TotalTwoPointFieldGoalPercent <dbl>, TotalEffectiveFieldGoalPercent
#     <dbl>,
##    TotalFreeThrows <dbl>, TotalFreeThrowAttempts <dbl>,
#     TotalFreeThrowPercent <dbl>,
##    TotalOffensiveRebounds <dbl>, TotalDefensiveRebounds <dbl>, ...
#
```

4.4.1

It seems that almost all of our data frame is in correct format although there are a couple NA values scattered.

4.4.2 There is a final row that list totals for the team where applicable, but we can calculate these values on our own.

4.4.3 *Let's remove it...*

.

```
ATL_Totals <- ATL_Totals[-c(25), ]
```

4.5 Game_Log_df

```
head(ATL_Game_Log)
```

```
## # A tibble: 6 x 37
##   Date                Opp WinLoss Points OppPoints FieldGoals FieldGoalAttempts
##   <dttm>              <chr> <chr>   <dbl>    <dbl>     <dbl>           <db
                                                                           l>
## 1 NA                  <NA> <NA>       NA       NA        NA             NA
## 2 2021-10-21 00:00:00 dal          W       113       87   45         94
## 3 2021-10-23 00:00:00 cle          L        95      101   38         99
## 4 2021-10-25 00:00:00 det          W       122      104   46         90
## 5 2021-10-27 00:00:00 nop          W       102       99   40         96
## 6 2021-10-28 00:00:00 was          L       111      122   48         88
## # i 30 more variables: FieldGoalPercent <dbl>, ThreePoints
<dbl>,
## #  ThreePointAttempts <dbl>, ThreePointPercent <dbl>, FreeThrows
<dbl>,
## #FreeThrowAttempts <dbl>, FreeThrowPercent <dbl>, OffensiveRebounds <dbl>,
## #TotalRebounds <dbl>, Assists <dbl>, Steals <dbl>, Blocks <dbl>, Turnovers <dbl>,
## #   PersonalFouls <dbl>, OppFieldGoals <dbl>, OppFieldGoalAttempts <dbl>,
## #   OppFieldGoalPercent <dbl>, OppThreePoints <dbl>,
OppThreePointAttempts <dbl>, ## #    OppThreePointPercent <dbl>,
OppFreeThrows <dbl>, OppFreeThrowAttempts <dbl>, ...
```

4.5.1 As we can see, all of the data types seem to be correct.

4.5.2 Although we can go ahead and make sure that the entire Date column is in the same format as the first couple of values we can see.

```
ATL_Game_Log <- ATL_Game_Log[complete.cases(ATL_Game_Log$Date), ]
ATL_Game_Log$Date <- as.Date(ATL_Game_Log$Date, format = "%Y-%m-%d")
```

4.5.3 Also turn the WinLoss column into a boolean because we only have two possible values that can stand for TRUE and FALSE.

```
ATL_Game_Log$WinLoss <-ifelse(ATL_Game_Log$WinLoss == "W", TRUE, FALSE)
```

4.6 Results_df

```
head(ATL_Results)
```

```
## # A tibble: 6 x 7
##   Date                HomeAway Opponent          Winloss Overtime Points OppPoints
##   <dttm>              <chr>    <chr>             <chr>   <chr>     <dbl>     <dbl>
## 1 2021-10-21 00:00:00 <NA>     dallas mavericks  W       <NA>        113        87
## 2 2021-10-23 00:00:00 @        cleveland cavaliers L     <NA>         95       101
## 3 2021-10-25 00:00:00 <NA>     detroit pistons   W       <NA>        122       104
## 4 2021-10-27 00:00:00 @        new orleans pelicans W    <NA>        102        99
## 5 2021-10-28 00:00:00 @        washington wizards L      <NA>        111       122
## 6 2021-10-30 00:00:00 @        philadelphia 76ers L      <NA>         94       122
```

4.6.1 This df has more possible boolean columns that could be converted and a Date column.

4.6.2 If you look closely you can see that there are entire rows of NA values. We can go ahead and take those away.

```
ATL_Results$Date <- as.Date(ATL_Results$Date, format = "%Y-%m-%d")
ATL_Results$HomeAway <- ifelse(is.na(ATL_Results$HomeAway), "Home",
ATL_Results$HomeAway)
ATL_Results$Overtime <- ifelse(is.na(ATL_Results$Overtime), "rt",
ATL_Results$Overtime)

ATL_Results$HomeAway <- ifelse(ATL_Results$HomeAway == "Home", TRUE, FALSE)
ATL_Results$Overtime <- ifelse(ATL_Results$Overtime == "ot", TRUE, FALSE)
ATL_Results$Winloss <- ifelse(ATL_Results$Winloss == "W", TRUE, FALSE)
ATL_Results <- ATL_Results[-c(21,42,63,84), ]
```

4.7 Starting_lineup.

4.7.1 We can continue to use head and str.

```
head(ATL_Starting_Lineup)
```

```
## # A tibble: 6 x 13
##   Date       `Start(ET)` `_`BoxScore HomeAway Opponent WinLoss Overtime TeamPoints
##   <chr>      <lgl>       <lgl> <chr>    <chr>   <chr>    <chr>  <chr>   <chr>
## 1 2021-10-21 NA          NA    Box Score <NA>    Dallas M~ W      <NA>    113
## 2 2021-10-23 NA          NA    Box Score @       Clevelan~ L      <NA>    95
## 3 2021-10-25 NA          NA    Box Score <NA>    Detroit ~ W      <NA>    122
## 4 2021-10-27 NA          NA    Box Score @       New Orle~ W      <NA>    102
## 5 2021-10-28 NA          NA    Box Score @       Washingt~ L      <NA>    111
```

```
## 6 2021-10-30 NA       NA   Box Score @      Philadel~ L      <NA>    94
## # i 4 more variables: OpponentPoints <chr>, Wins <chr>,
Losses <chr>, ## #      StartingLineup <chr>
```

4.7.2 This df seems to have a few issues that need to be attended to.

4.7.3 First, we need to fill in the NA values in the HomeAway and Overtime columns. Then, because they are one of two values. We can convert them into boolean values, including the WinLoss column.

```
ATL_Starting_Lineup$HomeAway <- ifelse(is.na(ATL_Starting_Lineup$HomeAway),
"Home"
ATL_Starting_Lineup$Overtime <- ifelse(is.na(ATL_Starting_Lineup$Overtime),
"rt"

ATL_Starting_Lineup$HomeAway <- ifelse(ATL_Starting_Lineup$HomeAway == "Home",
TRUE, FALSE
ATL_Starting_Lineup$Overtime <- ifelse(ATL_Starting_Lineup$Overtime == "ot",
TRUE, FALSE)
ATL_Starting_Lineup$WinLoss <- ifelse(ATL_Starting_Lineup$WinLoss == "W",
TRUE, FALSE)
```

4.7.4 Next, we see there are multiple columns entirely with NA values, Start(ET), _, and BoxScore.

4.7.5 We can use the *subset* function in order to accomplish this.

```
ATL_Starting_Lineup <- subset(ATL_Starting_Lineup, select = -`Start(ET)`)
ATL_Starting_Lineup <- subset(ATL_Starting_Lineup, select = -`_`)
ATL_Starting_Lineup <- subset(ATL_Starting_Lineup, select = -`BoxScore`)
```

4.7.6 Now we can convert our columns with number values into numeric.

4.7.7 And make sure our Date column is formatted correctly.

```
ATL_Starting_Lineup$TeamPoints <- as.numeric(ATL_Starting_Lineup$TeamPoints)
ATL_Starting_Lineup$OpponentPoints <-
as.numeric(ATL_Starting_Lineup$OpponentPoints)
ATL_Starting_Lineup$Wins <- as.numeric(ATL_Starting_Lineup$Wins)
```

```
ATL_Starting_Lineup$Losses <- as.numeric(ATL_Starting_Lineup$Losses)

ATL_Starting_Lineup$Date <- as.Date(ATL_Starting_Lineup$Date, format = "%Y-%m-

%d")
```

4.7.8 Also let's not forget to remove the empty rows.

```
ATL_Starting_Lineup <- ATL_Starting_Lineup[-c(21,42,63), ]
```

4.7.9 *Repeat these steps for all of our team Excel files, BOS, BRK, CHI, etc...*

5 Combine Data

5.1 Bind Rows

5.1.1 Now we use bind_rows to combine and stack the data frames into one big df.

```
NBA_Roster <- bind_rows(ATL_Roster, BOS_Roster, BRK_Roster, CHI_Roster, CHO_Roster,
DAL_Roster, DEN_Rost
```

5.1.2 Let's give the teams an index to help identify each team in the df by their abbreviation "ATL", "BOS", etc…

5.1.3 First define a data frame containing team names and their respective data frames. Then bind the rows of all team results. And add a column indicating the team.

5.1.4 Finally we're going to add a Date column to help identify the year this df is going to represent. Then Check the df.

```
team_data <- tibble(
   Team = c("ATL", "BOS", "BRK", "CHO", "CHI", "CLE", "DAL", "DEN", "DET",
                                "GSW", "HOU",
     "LAC", "LAL", "MEM", "MIA", "MIL", "MIN", "NOP", "NYK", "OKC", "ORL",
          "PHI", "PHO", "POR", "SAC", "SAS", "TOR", "UTA", "WAS"),
  Roster = list(ATL_Roster, BOS_Roster, BRK_Roster, CHI_Roster, CHO_Roster,
  CLE_Roster, DAL_Roster,
               DEN_Roster, DET_Roster, GSW_Roster, HOU_Roster, IND_Roster,
               LAC_Roster, LAL_Roster, MEM_Roster, MIA_Roster, MIL_Roster,
               MIN_Roster, NOP_Roster, NYK_Roster, OKC_Roster, ORL_Roster,
               PHI_Roster, PHO_Roster, POR_Roster, SAC_Roster, SAS_Roster,
               TOR_Roster, UTA_Roster, WAS_Roster)
)

NBA_Roster <- bind_rows(team_data$Roster, .id = "Team_Index")
```

"IND",

```
NBA_Roster <- NBA_Roster %>% mutate(Team =
  team_data$Team[as.numeric(Team_Index)])

NBA_Roster$Date <- as.Date(paste("2020"), format = "%Y")
```

```
head(NBA_Roster)
```

```
## # A tibble: 6 x 12
##  Team_Index Player  FirstName LastName Position Height Weight BirthDate
##  <chr>      <chr>       <chr>    <chr>   <chr>    <dbl> <dbl> <dttm>
## 1 1         cat barber cat      barber  pg          74        190 1994-07-25
                                                      00:00:00
## 2 1         bogdan bogd~ bogdan bogdano~ sg         77        220 1992-08-18
                                                      00:00:00
## 3 1         chaundee br~ chaundee brown sg          77        215 1998-12-04
                                                      00:00:00
## 4 1         clint capela clint  capela   c          82        240 1994-05-18
                                                      00:00:00
## 5 1         john collins john   collins pf          81        235 1997-09-23
                                                      00:00:00
## 6 1         sharife coo~ sharifecooper  pg          73        180 2001-06-11
                                                      00:00:00
## # i 4 more variables: BirthCountry <chr>, College <chr>, Team <chr>, Date
<date>
```

5.1.5 *Continue on to repeat the steps for Per_Game, Totals, Starting_Lineups, Game_Log and Results...*

5.2 Assign Positions

5.2.1 Check which df needs positions to be assigned to them.

5.2.2 So far we have three data frames (Roster, Per_Game, Totals) that have a list of players but only one (Roster) lists their position which can be a great filtering factor.

```
head(NBA_Per_Game)
```

```
## # A tibble: 6 x 32
##  Team_Index Player                        Age GamesPlayedPerGame GamesStarted
                                                                    MinutesPlayedPerGame
##   <chr>     <chr>                       <dbl> <chr>                <dbl>            <dbl>
## 1 1         trae young                     23 76                      76             34.9
## 2 1         john collins                   24 54                      53             30.8
## 3 1       de'andre hunter                  24 53                      52             29.8
## 4 1         kevin huerter                  23 74                      60             29.6
## 5 1       bogdan bogdano~                  29 63                      27             29.3
## 6 1       chaundee brown~                  23 3                        2             27.7
## # i 26 more variables: FieldGoalsPerGame <dbl>, FieldGoalAttemptsPerGame
<dbl>,
## #FieldGoalPercentPerGame <dbl>, ThreePointFieldGoalsPerGame <dbl>,
## #ThreePointFieldGoalAttemptsPerGame <dbl>, ThreePointFieldGoalPercentPerGame <dbl>,
## #TwoPointFieldGoalsPerGame <dbl>, TwoPointFieldGoalAttemptsPerGame <dbl>,
## #TwoPointFieldGoalPercentPerGame <dbl>, EffectiveFieldGoalPercentPerGame <dbl>,
## #FreeThrowsPerGame <dbl>, FreeThrowAttemptsPerGame <dbl>,
## #FreeThrowPercentPerGame <dbl>, OffensiveReboundsPerGame <dbl>, ...
```

```
head(NBA_Totals)
```

```
## # A tibble: 6 x 31
##  Team_Index Player     Age TotalGamesPlayed TotalGamesStarted TotalMinutesPlayed
##   <chr>     <chr>      <dbl>          <dbl>           <dbl>            <db
                                                                          l>
## 1 1         trae young    23             76              76             26
                                                                          52
## 2 1         kevin         23             74              60             21
              huerter                                                     88
## 3 1         clint         27             74              73             20
              capela                                                      42
## 4 1         bogdan        29             63              27             18
              bogdan~                                                     48
## 5 1         danilo        33             66              18             16
              gallin~                                                     72
## 6 1         john          24             54              53             16
              collins                                                     63
## # i 25 more variables: TotalFieldGoalsPerGame <dbl>, TotalFieldGoalAttempts
<dbl>,
## #TotalFieldGoalPercent <dbl>, TotalThreePointFieldGoalsPerGame <dbl>,
## #TotalThreePointFieldGoalAttempts <dbl>, TotalThreePointFieldGoalPercent <dbl>,
## #TotalTwoPointFieldGoalsPerGame <dbl>, TotalTwoPointFieldGoalAttempts <dbl>,
## #  TotalTwoPointFieldGoalPercent <dbl>, TotalEffectiveFieldGoalPercent
<dbl>, ## # TotalFreeThrows <dbl>, TotalFreeThrowAttempts <dbl>,
TotalFreeThrowPercent <dbl>, ## #   TotalOffensiveRebounds <dbl>,
TotalDefensiveRebounds <dbl>, ...
```

5.3 Build a function that we can run our dfs through.

5.3.1 To locate and assign the desired position per player.

5.3.2 Assign positions from roster dataframe to another dataframe

5.3.3 Initialize an empty vector to store positions. Loop through each player in the per_game_df. Check if the player exists in the NBA_Roster dataframe.

5.3.4 Match the player and extract the position. If the player is not found, assign NA to position. Add the positions column to the per_game_df

5.3.5 *Remember to change per_game_df to totals_df for NBA_Totals.*

5.4 Per_Game

```
assign_positions <- function(per_game_df) { positions <-
  character(nrow(per_game_df)) for (i in
  seq_along(per_game_df$Player)) { player <-
  per_game_df$Player[i] if (player %in%
  NBA_Roster$Player) { position <-
  NBA_Roster$Position[NBA_Roster$Player == player]
  positions[i] <- position
    } else {
      positions[i] <-
      NA
    }
  } per_game_df$Position <-
  positions
  return(per_game_df)
}
```

5.5 Totals

```
assign_positions_totals <- function(totals_df) {
  positions <- character(nrow(totals_df)) for (i in
  seq_along(totals_df$Player)) { player <-
  totals_df$Player[i] if (player %in% NBA_Roster$Player)
  { position <- NBA_Roster$Position[NBA_Roster$Player ==
  player] positions[i] <- position
    } else {
      positions[i] <-
      NA
    }
  }
  totals_df$Position <- positions
  return(totals_df)
}
```

5.5.1 Call the function to assign positions to NBA_Per_Game and NBA_Totals.

```
NBA_Per_Game <- assign_positions(NBA_Per_Game)
NBA_Totals <- assign_positions_totals(NBA_Totals)
```

5.5.2 *Remember to do this, for every Year...*

6 Archive

6.1 Create .csv

6.1.1 Let's create csv files because they are the most common.

6.1.2 Now that our data frames are cleaned, I like to store and archive all files so we are going to give them their own file_names to be able to easily tell them apart.

```
folder_path <- "D:\\BigQuery_example" file_name
<- "NBA_Roster_2022" file_path <-
paste0(folder_path, "\\", file_name, ".csv")
NBA_Roster <- as.data.frame(NBA_Roster)
write.csv(NBA_Roster,file = file_path, row.names = FALSE)

file_name <- "NBA_Starting_Lineups_2022"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Starting_Lineups <- as.data.frame(NBA_Starting_Lineups)
write.csv(NBA_Starting_Lineups,file = file_path, row.names = FALSE)

file_name <- "NBA_Per_Game_2022" file_path <-
paste0(folder_path, "\\", file_name, ".csv")
NBA_Per_Game <- as.data.frame(NBA_Per_Game)
write.csv(NBA_Per_Game,file = file_path, row.names = FALSE)

file_name <- "NBA_Totals_2022"
file_path <- paste0(folder_path, "\\", file_name, ".csv") NBA_Totals <-
as.data.frame(NBA_Totals)
write.csv(NBA_Totals,file = file_path, row.names = FALSE)

file_name <- "NBA_Game_Log_2022"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Game_Log <- as.data.frame(NBA_Game_Log)
write.csv(NBA_Game_Log,file = file_path, row.names = FALSE)

file_name <- "NBA_Results_2022"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Results <- as.data.frame(NBA_Results)
write.csv(NBA_Results,file = file_path, row.names = FALSE)
```

6.1.3 *Repeat steps for corresponding years, 2022, 2021, 2020, and so on...*

7 Remove Objects

7.1 Use the rm function.

7.1.1 Now that we are no longer working with these data frames, we can go ahead and remove them using the rm function to accomplish this.

```
rm(ATL_Game_Log, ATL_Roster, ATL_Per_Game, ATL_Results, ATL_Starting_Lineup, ATL_Totals,
ATL_Splits, ATL
```

7.1.2 If you have been saving and archiving the files then you might have to upload them back into the system.

7.1.3 Since these files are only one sheet it is ok to use the base read_csv function.

```
NBA_Roster_2017 <- read_csv("D:\\BigQuery\\NBA_Roster_2017.csv")
```

```
## Rows: 542 Columns: 12
## -- Column specification --------------------------------------------------------
---------## Delimiter: ","
## chr (7): Player, FirstName, LastName, Position, BirthCountry, College, Team
## dbl (3): Team_Index, Height, Weight
## date (2): BirthDate, Date
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

```
NBA_Roster_2018 <- read_csv("D:\\BigQuery\\NBA_Roster_2018.csv")
```

```
## Rows: 606 Columns: 12
## -- Column specification --------------------------------------------------------
---------## Delimiter: ","
## chr (7): Player, FirstName, LastName, Position, BirthCountry, College, Team
## dbl (3): Team_Index, Height, Weight
## date (2): BirthDate, Date
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

```
NBA_Roster_2019 <- read_csv("D:\\BigQuery\\NBA_Roster_2019.csv")
```

```
## Rows: 622 Columns: 12
## -- Column specification --------------------------------------------------------
---------## Delimiter: ","
## chr (7): Player, FirstName, LastName, Position, BirthCountry, College, Team
## dbl (3): Team_Index, Height, Weight
## date (2): BirthDate, Date
##
## i Use `spec()` to retrieve the full column specification for this data.
```

```
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

```
NBA_Roster_2020 <- read_csv("D:\\BigQuery\\NBA_Roster_2020.csv")
```

```
## Rows: 592 Columns: 12
## -- Column specification --------------------------------------------------
---------## Delimiter: ","
## chr (7): Player, FirstName, LastName, Position, BirthCountry, College, Team
## dbl (3): Team_Index, Height, Weight
## date (2): BirthDate, Date
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

```
NBA_Roster_2021 <- read_csv("D:\\BigQuery\\NBA_Roster_2021.csv")
```

```
## Rows: 626 Columns: 12
## -- Column specification --------------------------------------------------
---------## Delimiter: ","
## chr (7): Player, FirstName, LastName, Position, BirthCountry, College, Team
## dbl (3): Team_Index, Height, Weight
## date (2): BirthDate, Date
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

```
NBA_Roster_2022 <- read_csv("D:\\BigQuery\\NBA_Roster_2022.csv")
## Rows: 716 Columns: 12
## -- Column specification --------------------------------------------------
---------## Delimiter: ","
## chr (7): Player, FirstName, LastName, Position, BirthCountry, College, Team
## dbl (3): Team_Index, Height, Weight
## date (2): BirthDate, Date
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

```
NBA_Roster_2023 <- read_csv("D:\\BigQuery\\NBA_Roster_2023.csv")
```

```
## Rows: 532 Columns: 12
## -- Column specification --------------------------------------------------
---------## Delimiter: ","
## chr (7): Player, FirstName, LastName, Position, BirthCountry, College, Team
## dbl (3): Team_Index, Height, Weight
## date (2): BirthDate, Date
##
```

```
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
message.
```

7.1.4 *Continue this process for NBA_Per_Game, NBA_Totals, NBA_Starting_Lineups, NBA_Game_Log and NBA_Results...*

8 Combine Data Continued...

8.1 Roster

8.1.1 Combine data frames for each year into one compiled data frame.

```
NBA_Roster <- bind_rows(NBA_Roster_2017, NBA_Roster_2018, NBA_Roster_2019,
NBA_Roster_2020, NBA_Roster_ head(NBA_Roster)
## # A tibble: 6 x 12
##  Team_Index PlayerFirstName LastName Position Height Weight BirthDate BirthCountry
##       <dbl> <chr>   <chr>    <chr>    <chr>    <dbl> <dbl> <date> <chr>
##          1 kent ba~ kent    bazemore sf         76   195 1989-07-01 us
1
##          1 deandre~ deandre' bembry  sf         77   210 1994-07-04 us
2
##          1 josé ca~ josé    calderón pg         75   200 1981-09-28 es
3
##          1 malcolm~ malcolm delaney pg         75   190 1989-03-11 us
4
##          1 mike du~ mike    dunleavy sf         81   230 1980-09-15 us
5
##          1 tim har~ tim     hardaway sg         77   205 1992-03-16 us
6
## # i 3 more variables: College <chr>, Team <chr>, Date <date>
```

8.1.2 *Continue binding rows and create the rest of the data frames NBA_Per_Game, NBA_Totals, NBA_Starting_Lineups, NBA_Game_Log and NBA_Results...*

9 Final Check

9.1 Per_Game Check

9.1.1 Build a function to run our data frames through. To check for NA/NULL values, nonnumeric values and find the column / row the errors are in. In order to save space, you can find an image of the results run by the check code.

9.1.2 In this example we are going to use NBA_Per_Game.

9.1.3 The actual code is below, run on the cleaned df to show in use...

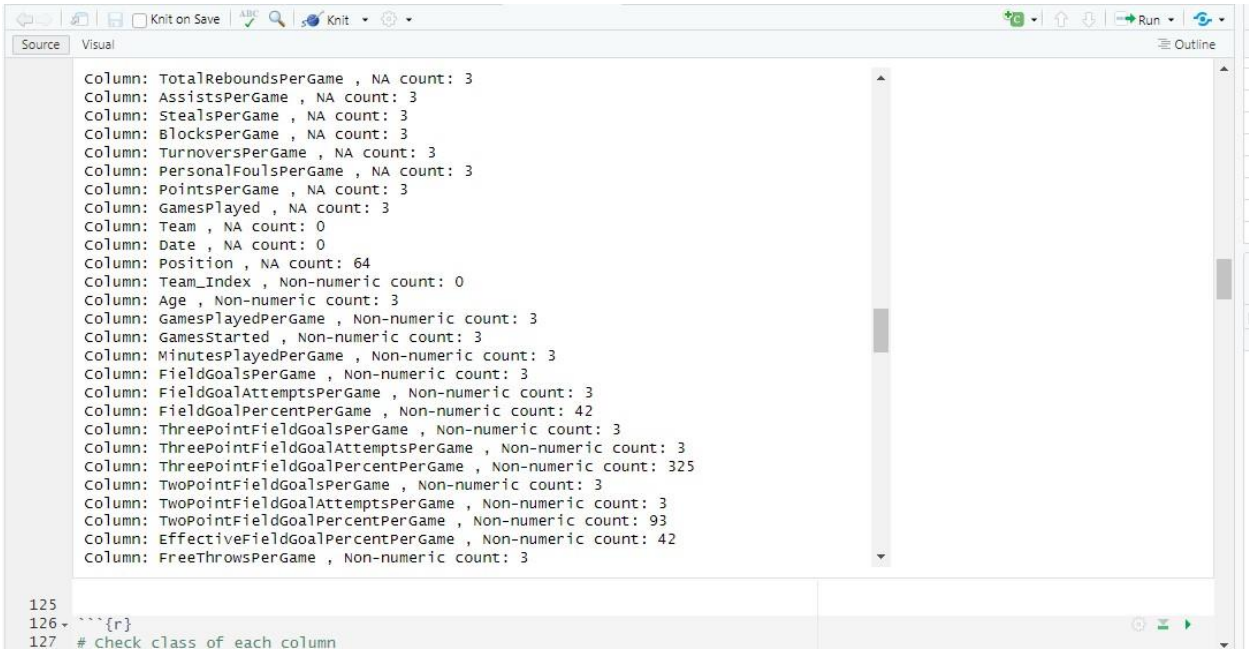


Figure 2: Per_Game Check before cleaning

9.1.4 First thing we notice is that rows 9, 15 and 28 are completely empty. Then we see that the Player column has three empty rows. 3882, 4013 and 4306.

9.1.5 They have no information on them except what team they came from.

9.1.6 We can take these entire rows out…

```
NBA_Per_Game <- NBA_Per_Game[-c(9,15,28,3882,4013,4306), ]
```

9.1.7 In the Position column there are 61 NA values that is not many in comparison to our total data frame of 4,236 rows. So we are going to produce a list of player names that have no position value and see if we can correct them.

9.1.8 First find rows with NA values in the Position column using the subset function. Then extract names from the Player column into a new df players_with_na_positions

9.1.9 *Finally, Print the names…*

```
na_positions <- subset(NBA_Per_Game, is.na(Position))
players_with_na_position <- na_positions$Player
print(players_with_na_position)
```

```
## [1] "ersan ilyasova"    "ersan ilyasova"    "ersan ilyasova"
## [4] "ersan ilyasova"    "ersan ilyasova"    "ersan ilyasova"
## [7] "ersan ilyasova"    "ersan ilyasova"    "armoni brooks"
## [10] "terry taylor"      "ish smith"         "théo maledon"
```

```
## [13] "nathan mensah"     "frank ntilikina"    "james bouknight"
## [16] "dexter dennis"     "killian hayes"      "isaiah livers"
## [19] "kevin knox"        "jaylen nowell"      "joe harris"
## [22] "malcolm cazalon"   "cory joseph"        "joshua primo"
## [25] "d'moi hodge"       "timmy allen"        "zavier simpson"
## [28] "mãozinha pereira"  "jaylen nowell"      "dejon jarreau"
## [31] "wenyen gabriel"    "jack white"         "matthew hurt"
## [34] "shaquille          "dru smith"          "r.j. hampton"
harrison"
## [37] "robin lopez"       "lindell wigginton"  "justin jackson"
## [40] "kaiser gates"      "jalen crutcher"     "izaiah
                                                 brockington"
## [43] "ryan arcidiacono"  "dmytro skapintsev"  "danuel house jr."
## [46] "danny green"       "ricky council iv"   "furkan korkmaz"
## [49] "d.j. wilson"       "filip petrušev"     "javonte smart"
## [52] "théo maledon"      "taze moore"         "juan      toscano-
                                                 anderson"
## [55] "filip petrušev"    "jahmi'us ramsey"    "kobi simmons"
## [58] "otto porter jr."   "markquis nowell"    "ron harper jr."
## [61] "hamidou diallo"
```

9.1.10 Make a function to fix the POsitions column with NA values using a list we made from finding the players positions.

```
fix_na_positions <- function(df, player_list) {
  for (i in seq(1, length(player_list), by
    = 2)) { player <- player_list[i]
    position <- player_list[i + 1]
    df$Position[df$Player == player & is.na(df$Position)] <- position
  }
  return(df)
}
```

9.1.11 Compile the list of Players and their positions.

```
player_list <- c("ersan ilyasova", "pf", "ersan ilyasova", "pf", "ersan ilyasova", "pf",
                 "ersan ilyasova", "pf", "ersan ilyasova", "pf", "armoni brooks", "sg",
                 "terry taylor", "pf", "ish smith", "pg", "théo maledon", "pg",
                 "nathan mensah", "c", "frank ntilikina", "sg", "james
                 bouknight", "sg",
                 "dexter dennis", "sg", "killian hayes", "pg", "isaiah livers",
                 "sf",
                 "kevin knox", "pf", "jaylen nowell", "sg", "joe harris", "sg",
                 "malcolm cazalon", "sg", "cory joseph", "sg", "joshua primo",
                 "sg",
                 "d'moi hodge", "sg", "timmy allen", "sf", "zavier simpson",
                 "pg",
                 "mãozinha pereira", "sf", "jaylen nowell", "sg", "dejon
                 jarreau", "sg",
                 "wenyen gabriel", "pf", "jack white", "sf", "matthew hurt",
                 "pf",
                 "shaquille harrison", "sg", "dru smith", "sg", "r.j. hampton",
                 "sg",
                 "robin lopez", "c", "lindell wigginton", "pg", "justin
                 jackson", "pf",
                 "kaiser gates", "sf", "jalen crutcher", "pg", "izaiah
                 brockington", "pg",
                 "ryan arcidiacono", "pg", "dmytro skapintsev", "c", "danuel
                 house jr.",
                 "danny green", "sg", "ricky council iv", "sg", "furkan
                 korkmaz", "sg",
                 "d.j. wilson", "pf", "filip petrušev", "c", "javonte smart",
                 "pg",
                 "théo maledon", "pg", "taze moore", "sg", "juan toscano-
                 anderson", "sf",
                 "filip petrušev", "c", "jahmi'us ramsey", "sg", "kobi
                 simmons", "pg",
                 "otto porter jr.", "pf", "markquis nowell", "sg", "ron harper
                 jr.", "pf", "hamidou diallo", "sg")
                                                                          "sf",
```

9.1.12 Execute the function to assign players their positions.

```
NBA_Per_Game <- fix_na_positions(NBA_Per_Game, player_list)
```

9.1.13 We see that almost every numeric row has NA values in them, because these are sports statistics any NA value most likely means 0, so we are going to replace the numeric values with 0.

```
NBA_Per_Game$FieldGoalPercentPerGame[is.na(NBA_Per_Game$FieldGoalPercentPerGame)] <- 0
NBA_Per_Game$ThreePointFieldGoalPercentPerGame[is.na(NBA_Per_Game$
NBA_Per_Game$TwoPointFieldGoalPercentPerGame[is.na(NBA_Per_Game$
NBA_Per_Game$EffectiveFieldGoalPercentPerGame[is.na(NBA_Per_Game$
NBA_Per_Game$FreeThrowPercentPerGame[is.na(NBA_Per_Game$FreeThrowPercentPerGame)] <- 0
NBA_Per_Game$GamesPlayed[is.na(NBA_Per_Game$GamesPlayed)] <- 0
NBA_Per_Game$Age[is.na(NBA_Per_Game$Age)] <- 0
NBA_Per_Game$GamesPlayedPerGame[is.na(NBA_Per_Game$GamesPlayedPerGame)] <- 0
NBA_Per_Game$GamesStarted[is.na(NBA_Per_Game$GamesStarted)] <- 0
NBA_Per_Game$MinutesPlayedPerGame[is.na(NBA_Per_Game$MinutesPlayedPerGame)] <- 0
NBA_Per_Game$FieldGoalsPerGame[is.na(NBA_Per_Game$FieldGoalsPerGame)] <- 0
NBA_Per_Game$FieldGoalAttemptsPerGame[is.na(NBA_Per_Game$FieldGoalAttemptsPerGame)] <- 0
NBA_Per_Game$ThreePointFieldGoalsPerGame[is.na(NBA_Per_Game$ThreePointFieldGoalsPerGame)
]
NBA_Per_Game$ThreePointFieldGoalAttemptsPerGame[is.na(NBA_Per_Game$
NBA_Per_Game$TwoPointFieldGoalsPerGame[is.na(NBA_Per_Game$TwoPointFieldGoalsPerGame)] <-
0
NBA_Per_Game$TwoPointFieldGoalAttemptsPerGame[is.na(NBA_Per_Game$
NBA_Per_Game$FreeThrowsPerGame[is.na(NBA_Per_Game$FreeThrowsPerGame)] <- 0
                                                    ThreePointFieldGoalPercentPerGame)] <-
                                                  TwoPointFieldGoalPercentPerGame)] <- 0
                                                    EffectiveFieldGoalPercentPerGame)] <-
                                                                                  <- 0
                                                   ThreePointFieldGoalAttemptsPerGame)]

                                                     TwoPointFieldGoalAttemptsPerGame)]
 <NBA_Per_Game$FreeThrowAttemptsPerGame[is.na(NBA_Per_Game$FreeThrowAttemptsPerGame)] <- 0
NBA_Per_Game$OffensiveReboundsPerGame[is.na(NBA_Per_Game$OffensiveReboundsPerGam
e)] <- 0
NBA_Per_Game$DefensiveReboundsPerGame[is.na(NBA_Per_Game$DefensiveReboundsPerGam
e)] <- 0
NBA_Per_Game$TotalReboundsPerGame[is.na(NBA_Per_Game$TotalReboundsPerGame)] <- 0
NBA_Per_Game$AssistsPerGame[is.na(NBA_Per_Game$AssistsPerGame)] <- 0
NBA_Per_Game$StealsPerGame[is.na(NBA_Per_Game$StealsPerGame)] <- 0
NBA_Per_Game$BlocksPerGame[is.na(NBA_Per_Game$BlocksPerGame)] <- 0
NBA_Per_Game$TurnoversPerGame[is.na(NBA_Per_Game$TurnoversPerGame)] <- 0
NBA_Per_Game$PersonalFoulsPerGame[is.na(NBA_Per_Game$PersonalFoulsPerGame)] <- 0
NBA_Per_Game$PointsPerGame[is.na(NBA_Per_Game$PointsPerGame)] <- 0
```

9.2 Multi-layered Check

9.2.1 First, check the class of each column and the summary statistics for each numeric column.

9.2.2 Then, check for any NA values in each column and check for non-numeric values in each column. Then, identify the rows with NA values in each column and identify rows with non-numeric values in each numeric column.

9.2.3 Finally, display the rows with non-numeric values in each numeric column.

9.2.4 Let's re-run the check to make sure our df is now clean.

```
for (col in names(NBA_Per_Game)) {
cat("Column:", col, ", Class:", class(NBA_Per_Game[[col]]), "\n")
}
```

```
## Column: Team_Index , Class: numeric
## Column: Player , Class: character
## Column: Age , Class: numeric
## Column: GamesPlayedPerGame , Class: numeric
## Column: GamesStarted , Class: numeric
## Column: MinutesPlayedPerGame , Class: numeric
## Column: FieldGoalsPerGame , Class: numeric
## Column: FieldGoalAttemptsPerGame , Class: numeric
## Column: FieldGoalPercentPerGame , Class: numeric
## Column: ThreePointFieldGoalsPerGame , Class: numeric
## Column: ThreePointFieldGoalAttemptsPerGame , Class: numeric
## Column: ThreePointFieldGoalPercentPerGame , Class: numeric
## Column: TwoPointFieldGoalsPerGame , Class: numeric
## Column: TwoPointFieldGoalAttemptsPerGame , Class:
numeric ## Column: TwoPointFieldGoalPercentPerGame ,
Class: numeric
## Column: EffectiveFieldGoalPercentPerGame , Class: numeric
## Column: FreeThrowsPerGame , Class: numeric
## Column: FreeThrowAttemptsPerGame , Class:
numeric ## Column: FreeThrowPercentPerGame ,
Class: numeric
## Column: OffensiveReboundsPerGame , Class: numeric
## Column: DefensiveReboundsPerGame , Class: numeric
## Column: TotalReboundsPerGame , Class: numeric
## Column: AssistsPerGame , Class: numeric
## Column: StealsPerGame , Class: numeric
## Column: BlocksPerGame , Class: numeric
## Column: TurnoversPerGame , Class: numeric
## Column: PersonalFoulsPerGame , Class: numeric
## Column: PointsPerGame , Class: numeric
## Column: GamesPlayed , Class: numeric
## Column: Team , Class: character
## Column: Date , Class: Date
## Column: Position , Class: character
```

```
for (col in names(NBA_Per_Game)) {
  if
  (is.numeric(NBA_Per_Game[[col]]))
  { cat("Column:", col, "\n")
    print(summary(NBA_Per_Game[[col]]))
  }
}
```

```
## Column: Team_Index
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##   1.00   8.00  15.00  15.49  23.00   30.00
## Column: Age
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##  19.00  23.00  25.00  25.99  29.00   43.00
## Column: GamesPlayedPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##   1.00  16.00  41.00  40.43  64.00   82.00
## Column: GamesStarted
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##   0.00   0.00   5.00  19.03  32.00   82.00
## Column: MinutesPlayedPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##    0.5   11.3   18.7   19.0   27.0    43.5
## Column: FieldGoalsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##  0.000  1.300  2.500  3.059  4.300 11.500
## Column: FieldGoalAttemptsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##   0.00   3.30   5.50   6.74   9.30  24.50
## Column: FieldGoalPercentPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.3950 0.4410 0.4373 0.4940 1.0000
## Column: ThreePointFieldGoalsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.2000 0.7000 0.8806 1.4000 5.3000
## Column: ThreePointFieldGoalAttemptsPerGame
## Min. 1st Qu. Median Mean 3rd Qu. Max. ##
0.000 0.800 2.100 2.521 3.800 13.200
## Column: ThreePointFieldGoalPercentPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.2310 0.3330 0.2872 0.3770 1.0000
## Column: TwoPointFieldGoalsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##    0.00  0.80  1.70  2.18  3.00  11.00 ## Column:
TwoPointFieldGoalAttemptsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##   0.00   1.70   3.30   4.22   5.80  19.20
## Column: TwoPointFieldGoalPercentPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.4500 0.5040 0.4923 0.5650 1.0000
## Column: EffectiveFieldGoalPercentPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.4690 0.5150 0.4987 0.5600 1.5000
## Column: FreeThrowsPerGame
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max. ##
0.000 0.400 0.900 1.293 1.700 10.200
## Column: FreeThrowAttemptsPerGame
## Min. 1st Qu. Median Mean 3rd Qu. Max. ##
0.000 0.600 1.200 1.688 2.200 11.800
## Column: FreeThrowPercentPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.6415 0.7560 0.6880 0.8330 1.0000
## Column: OffensiveReboundsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.3000 0.6000 0.8131 1.1000 5.4000
## Column: DefensiveReboundsPerGame
## Min. 1st Qu. Median Mean 3rd Qu. Max. ##
0.000 1.300 2.300 2.641 3.500 11.400
## Column: TotalReboundsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu. Max.
##  0.000  1.700  3.000  3.451       4.600
## Column:               16.000
AssistsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu. Max.
##  0.000  0.600  1.300  1.861       2.400
## Column:               11.700
StealsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu. Max.
## 0.0000 0.3000 0.5000 0.6047 0.9000 2.5000
## Column: BlocksPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
## 0.0000 0.1000 0.3000 0.3829 0.5000 6.0000
## Column: TurnoversPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##  0.000  0.500  0.900  1.043  1.400  5.700
## Column: PersonalFoulsPerGame
##   Min. 1st Qu. Median  Mean 3rd Qu.   Max.
##  0.000  1.000  1.600  1.624  2.200  5.000
## Column: PointsPerGame
## Min. 1st Qu. Median Mean 3rd Qu. Max. ##
0.000 3.700 6.800 8.288 11.500 36.100
## Column: GamesPlayed
## Min. 1st Qu. Median Mean 3rd Qu. Max. ##
1.00 16.00 41.00 40.43 64.00 82.00
```

```r
for (col in names(NBA_Per_Game)) {
       cat("Column:", col, ", NA count:", sum(is.na(NBA_Per_Game[[col]])), "\n")
}
```

```
## Column: Team_Index , NA count: 0
## Column: Player , NA count: 0
## Column: Age , NA count: 0
## Column: GamesPlayedPerGame , NA count: 0
## Column: GamesStarted , NA count: 0
## Column: MinutesPlayedPerGame , NA count: 0
## Column: FieldGoalsPerGame , NA count: 0
```

```
## Column: FieldGoalAttemptsPerGame , NA count: 0
## Column: FieldGoalPercentPerGame , NA count: 0
## Column: ThreePointFieldGoalsPerGame , NA count: 0
## Column: ThreePointFieldGoalAttemptsPerGame , NA count: 0
## Column: ThreePointFieldGoalPercentPerGame , NA count: 0
## Column: TwoPointFieldGoalsPerGame , NA count: 0
## Column: TwoPointFieldGoalAttemptsPerGame , NA
count: 0 ## Column: TwoPointFieldGoalPercentPerGame
, NA count: 0
## Column: EffectiveFieldGoalPercentPerGame , NA count: 0
## Column: FreeThrowsPerGame , NA count: 0
## Column: FreeThrowAttemptsPerGame , NA count: 0
## Column: FreeThrowPercentPerGame , NA count: 0
## Column: OffensiveReboundsPerGame , NA count: 0
## Column: DefensiveReboundsPerGame , NA count: 0
## Column: TotalReboundsPerGame , NA count: 0
## Column: AssistsPerGame , NA count: 0
## Column: StealsPerGame , NA count: 0
## Column: BlocksPerGame , NA count: 0
## Column: TurnoversPerGame , NA count: 0
## Column: PersonalFoulsPerGame , NA count: 0
## Column: PointsPerGame , NA count: 0
## Column: GamesPlayed , NA count: 0
## Column: Team , NA count: 0
## Column: Date , NA count: 0
## Column: Position , NA count: 0
```

```
for (col in names(NBA_Per_Game)) { if
  (is.numeric(NBA_Per_Game[[col]])) { non_numeric <-
  !grepl("^-?\\d+\\.?\\d*$", NBA_Per_Game[[col]])
  cat("Column:", col, ", Non-numeric count:",
  sum(non_numeric), "\n")
  }
}
```

```
## Column: Team_Index , Non-numeric count: 0
## Column: Age , Non-numeric count: 0
## Column: GamesPlayedPerGame , Non-numeric count: 0
## Column: GamesStarted , Non-numeric count: 0
## Column: MinutesPlayedPerGame , Non-numeric count: 0
## Column: FieldGoalsPerGame , Non-numeric count: 0
## Column: FieldGoalAttemptsPerGame , Non-numeric count: 0
## Column: FieldGoalPercentPerGame , Non-numeric count: 0
## Column: ThreePointFieldGoalsPerGame , Non-numeric count: 0
## Column: ThreePointFieldGoalAttemptsPerGame , Non-numeric count: 0
## Column: ThreePointFieldGoalPercentPerGame , Non-numeric count: 0
## Column: TwoPointFieldGoalsPerGame , Non-numeric count: 0
## Column: TwoPointFieldGoalAttemptsPerGame , Non-numeric
count: 0 ## Column: TwoPointFieldGoalPercentPerGame , Non-
numeric count: 0
## Column: EffectiveFieldGoalPercentPerGame , Non-numeric count: 0 ## Column:
FreeThrowsPerGame , Non-numeric count: 0
```

```
## Column: FreeThrowAttemptsPerGame , Non-numeric
count: 0 ## Column: FreeThrowPercentPerGame , Non-
numeric count: 0
## Column: OffensiveReboundsPerGame , Non-numeric count: 0
## Column: DefensiveReboundsPerGame , Non-numeric count: 0
## Column: TotalReboundsPerGame , Non-numeric count: 0
## Column: AssistsPerGame , Non-numeric count: 0
## Column: StealsPerGame , Non-numeric count: 0
## Column: BlocksPerGame , Non-numeric count: 0
## Column: TurnoversPerGame , Non-numeric count: 0
## Column: PersonalFoulsPerGame , Non-numeric count: 0
## Column: PointsPerGame , Non-numeric count: 0
## Column: GamesPlayed , Non-numeric count: 0
```

```
for (col in names(NBA_Per_Game)) {
  na_rows <-
  which(is.na(NBA_Per_Game[[col]]))
  if (length(na_rows) > 0) { cat("Column:",
  col, ", NA rows:", na_rows, "\n") }
}
for (col in names(NBA_Per_Game)) { if
  (is.numeric(NBA_Per_Game[[col]])) { non_numeric_rows <-
  which(grepl("[^0-9.]", NBA_Per_Game[[col]])) if
  (length(non_numeric_rows) > 0) { cat("Column:", col, ", Non-
  numeric rows:", non_numeric_rows, "\n")
    }
  }
}
for (col in names(NBA_Per_Game)) { if
  (is.numeric(NBA_Per_Game[[col]])) { non_numeric_rows <-
  which(!grepl("^-?\\d+\\.?\\d*$", NBA_Per_Game[[col]])) if
  (length(non_numeric_rows) > 0) { cat("Column:", col, "\n")
     print(NBA_Per_Game[non_numeric_rows, ])
    } else { cat("No non-numeric values found in
     column:", col, "\n")
    }
  }
}
```

```
## No non-numeric values found in column: Team_Index
## No non-numeric values found in column: Age
## No non-numeric values found in column: GamesPlayedPerGame
## No non-numeric values found in column: GamesStarted
## No non-numeric values found in column: MinutesPlayedPerGame
## No non-numeric values found in column: FieldGoalsPerGame
## No non-numeric values found in column: FieldGoalAttemptsPerGame
## No non-numeric values found in column: FieldGoalPercentPerGame
## No non-numeric values found in column: ThreePointFieldGoalsPerGame
## No non-numeric values found in column: ThreePointFieldGoalAttemptsPerGame
## No non-numeric values found in column: ThreePointFieldGoalPercentPerGame
## No non-numeric values found in column: TwoPointFieldGoalsPerGame
## No non-numeric values found in column: TwoPointFieldGoalAttemptsPerGame
## No non-numeric values found in column: TwoPointFieldGoalPercentPerGame
## No non-numeric values found in column: EffectiveFieldGoalPercentPerGame
```

```
## No non-numeric values found in column: FreeThrowsPerGame
## No non-numeric values found in column:
FreeThrowAttemptsPerGame ## No non-numeric values found in
column: FreeThrowPercentPerGame
## No non-numeric values found in column: OffensiveReboundsPerGame
## No non-numeric values found in column: DefensiveReboundsPerGame
## No non-numeric values found in column: TotalReboundsPerGame
## No non-numeric values found in column: AssistsPerGame
## No non-numeric values found in column: StealsPerGame
## No non-numeric values found in column: BlocksPerGame
## No non-numeric values found in column: TurnoversPerGame
## No non-numeric values found in column: PersonalFoulsPerGame
## No non-numeric values found in column: PointsPerGame
## No non-numeric values found in column: GamesPlayed
```

9.2.5 Now that we can confirm that the data frame is now clean we can move onto the next.

9.3 Results Check

9.3.1 Let's do the same and drop a .png to show the some of the errors saving space.

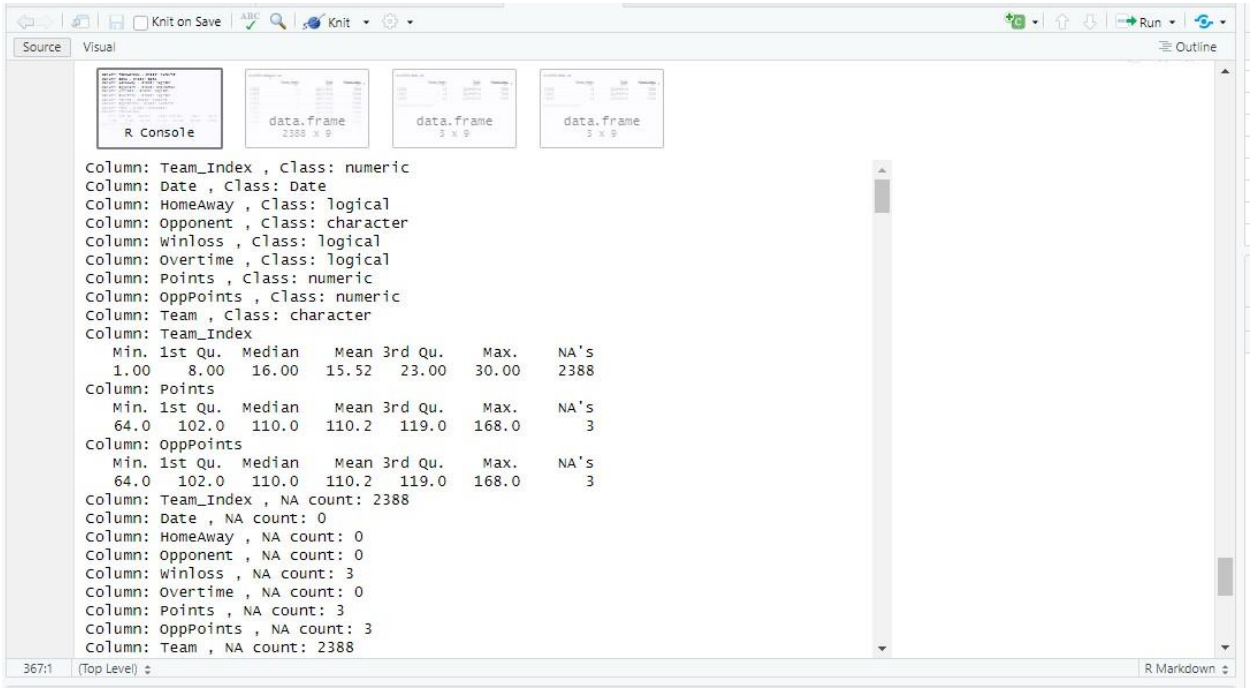


Figure 3: Results Check before cleaning

9.3.2 Fix the results of these games after looking them up.

9.3.3 First, input the row and column index. Then, the new value to assign. Finally, change the value at the specified row and column.

```
row_index <- 15463
col_index <- 5
new_value <- TRUE

NBA_Results[row_index, col_index] <- new_value

row_index <- 15463
col_index <- 7
new_value <- 112

NBA_Results[row_index, col_index] <- new_value

row_index <- 15463
col_index <- 8
new_value <- 94

NBA_Results[row_index, col_index] <- new_value
```

9.3.4 Continue this process for rows 15711, and 16288...

9.3.5 Re-Run the Check.

```
for (col in names(NBA_Results)) {
cat("Column:", col, ", Class:", class(NBA_Results[[col]]), "\n")
}
```

```
## Column: Team_Index , Class: numeric
## Column: Date , Class: Date
## Column: HomeAway , Class: logical
## Column: Opponent , Class: character
## Column: Winloss , Class: logical
## Column: Overtime , Class: logical
## Column: Points , Class: numeric
## Column: OppPoints , Class: numeric
## Column: Team , Class: character
```

```
for (col in names(NBA_Results)) {
  if
  (is.numeric(NBA_Results[[col]]))
  { cat("Column:", col, "\n")
    print(summary(NBA_Results[[col]]))
  }
}
```

```
## Column: Team_Index
##   Min. 1st Qu. Median   Mean 3rd      Ma
                           Qu.           x.
##    1.00    8.00  16.00  15.52  23.00  30.
## Column: Points                        00
##   Min. 1st Qu. Median   Mean 3rd      Ma
                           Qu.           x.
##    64.0  102.0  110.0  110.2  119.0  168
## Column: OppPoints                     .0
```

```
##   Min. 1st Qu. Median   Mean 3rd      Ma
                           Qu.           x.
##    64.0  102.0  110.0  110.2  119.0  168
                                       .0
```

```
for (col in names(NBA_Results)) {
        cat("Column:", col, ", NA count:", sum(is.na(NBA_Results[[col]])), "\n")
}
```

```
## Column: Team_Index , NA count: 0
## Column: Date , NA count: 0
## Column: HomeAway , NA count: 0
## Column: Opponent , NA count: 0
## Column: Winloss , NA count: 0
## Column: Overtime , NA count: 0
## Column: Points , NA count: 0
## Column: OppPoints , NA count: 0
## Column: Team , NA count: 0
```

```
for (col in names(NBA_Results)) { if
  (is.numeric(NBA_Results[[col]])) { non_numeric <- !grepl("^-
  ?\\d+\\.?\\d*$", NBA_Results[[col]]) cat("Column:", col, ",
  Non-numeric count:", sum(non_numeric), "\n")
  }
}
```

```
## Column: Team_Index , Non-numeric count: 0
## Column: Points , Non-numeric count: 0
## Column: OppPoints , Non-numeric count: 0
```

```
for (col in names(NBA_Results)) {
  na_rows <-
  which(is.na(NBA_Results[[col]]))
  if (length(na_rows) > 0) { cat("Column:",
  col, ", NA rows:", na_rows, "\n") }
}
for (col in names(NBA_Results)) { if
  (is.numeric(NBA_Results[[col]])) { non_numeric_rows <-
  which(grepl("[^0-9.]", NBA_Results[[col]])) if
  (length(non_numeric_rows) > 0) { cat("Column:", col, ", Non-
  numeric rows:", non_numeric_rows, "\n")
    }
  }
}
for (col in names(NBA_Results)) { if
  (is.numeric(NBA_Results[[col]])) { non_numeric_rows <-
  which(!grepl("^-?\\d+\\.?\\d*$", NBA_Results[[col]])) if
  (length(non_numeric_rows) > 0) {
      cat("Column:", col, "\n")
      print(NBA_Results[non_numeric_rows, ])
    } else { cat("No non-numeric values found in
      column:", col, "\n")
    }
  }
}
```

```
## No non-numeric values found in column: Team_Index
```

```
## No non-numeric values found in column: Points
## No non-numeric values found in column: OppPoints
```

9.3.6 *Continue this process for NBA_Totals, NBA_Starting_Lineups, NBA_Game_Log and NBA_Results…*

10 Archive Continued…

10.1 Create .CSV files

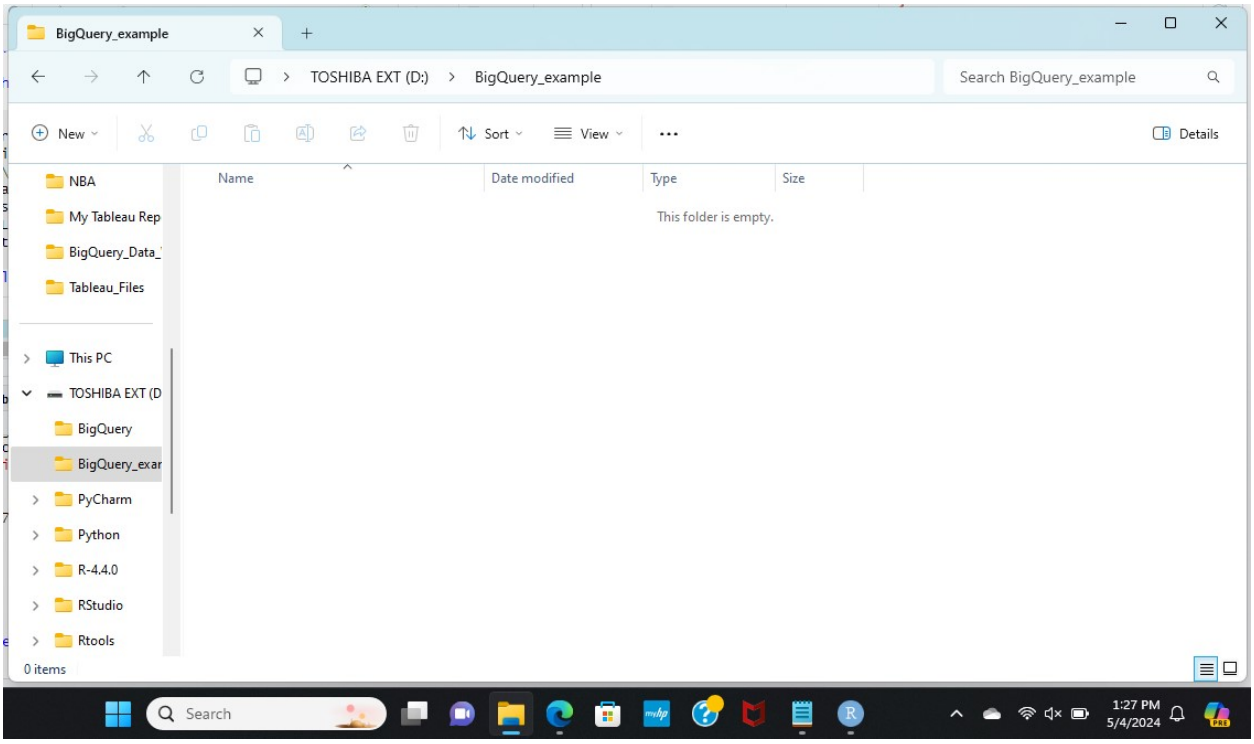


Figure 4: .CSV files before upload

10.1.1 This is, to be optimal for any loading preference and to archive in our records. 10.1.2 Big Query File_Path = "D:\BigQuery_example\"

```
folder_path <- "D:\\BigQuery_example"
file_name <- "NBA_Roster"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Roster <- as.data.frame(NBA_Roster)
write.csv(NBA_Roster,file = file_path, row.names = FALSE)

file_name <- "NBA_Starting_Lineups" file_path <-
paste0(folder_path, "\\", file_name, ".csv")
NBA_Starting_Lineups <-
as.data.frame(NBA_Starting_Lineups)
write.csv(NBA_Starting_Lineups,file = file_path, row.names
= FALSE)

file_name <- "NBA_Per_Game"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Per_Game <- as.data.frame(NBA_Per_Game)
write.csv(NBA_Per_Game,file = file_path, row.names = FALSE)

file_name <- "NBA_Totals"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Totals <- as.data.frame(NBA_Totals)
write.csv(NBA_Totals,file = file_path, row.names = FALSE)

file_name <- "NBA_Game_Log"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Game_Log <- as.data.frame(NBA_Game_Log)
write.csv(NBA_Game_Log,file = file_path, row.names = FALSE)

file_name <- "NBA_Results"
file_path <- paste0(folder_path, "\\", file_name, ".csv")
NBA_Results <- as.data.frame(NBA_Results)
write.csv(NBA_Results,file = file_path, row.names = FALSE)
```

10.2 Create .XLSX files

10.2.1 Tableau always gives me problems when i try to use anything other than .xlsx files so i find it a good practice to make both 10.2.2 Tableau File_Path = "D:\Tableau_example\"

```
write.xlsx(NBA_Roster, file = "D:\\Tableau_example\\NBA_Roster.xlsx")
write.xlsx(NBA_Starting_Lineups, file =
"D:\\Tableau_example\\NBA_Starting_Lineups.xlsx")
write.xlsx(NBA_Per_Game, file = "D:\\Tableau_example\\NBA_Per_Game.xlsx")
write.xlsx(NBA_Totals, file = "D:\\Tableau_example\\NBA_Totals.xlsx")
write.xlsx(NBA_Game_Log, file = "D:\\Tableau_example\\NBA_Game_Log.xlsx")
write.xlsx(NBA_Results, file = "D:\\Tableau_example\\NBA_Results.xlsx")
```

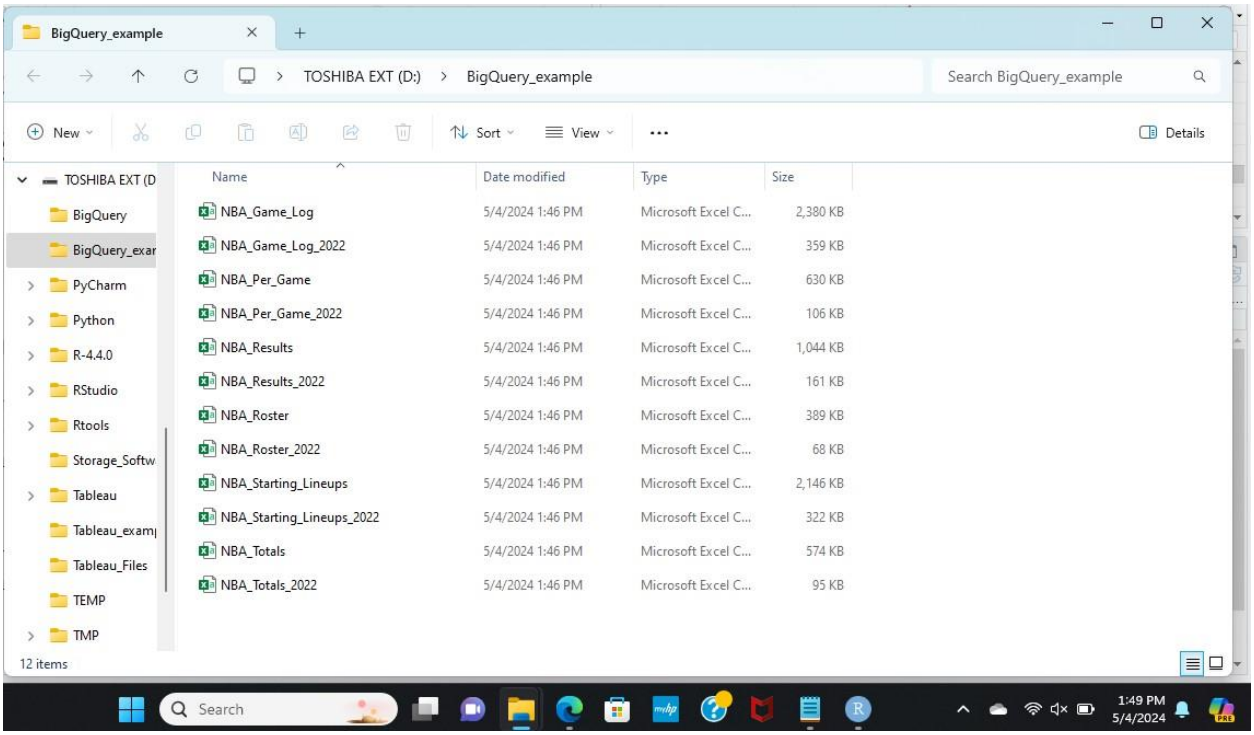


Figure 5: .CSV files after upload

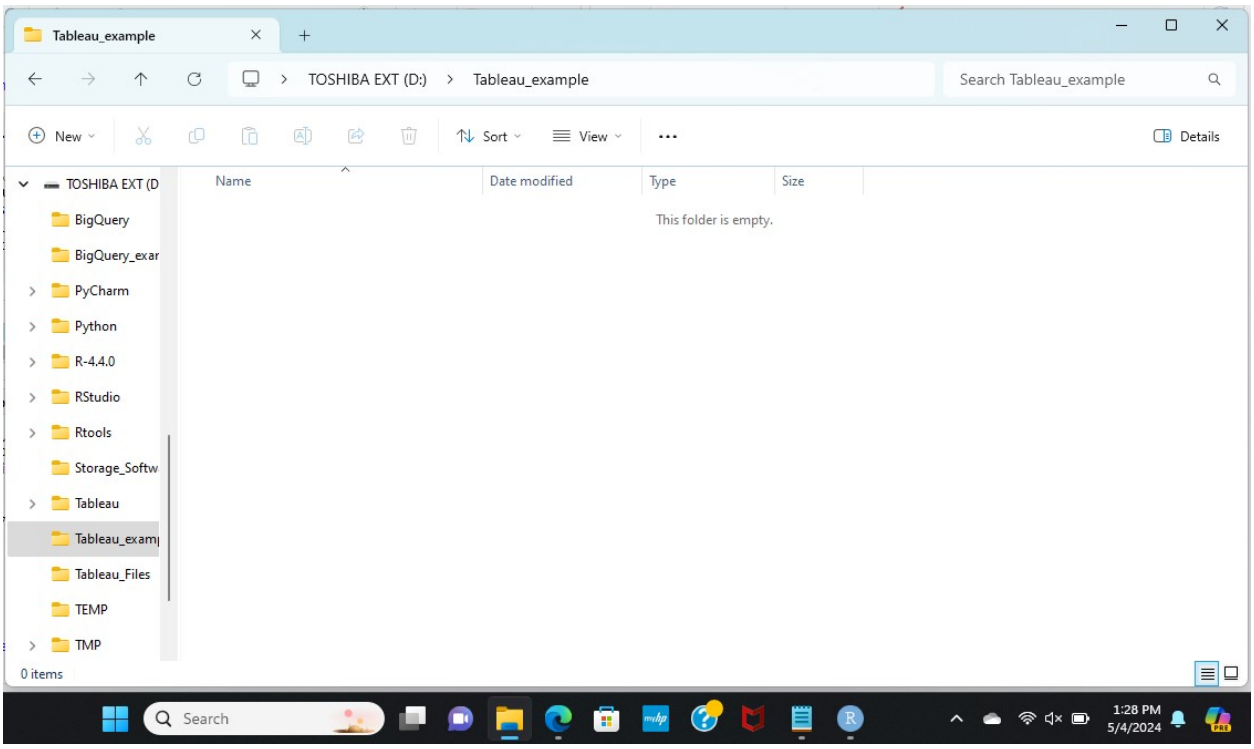


Figure 6: Tableau files before Upload

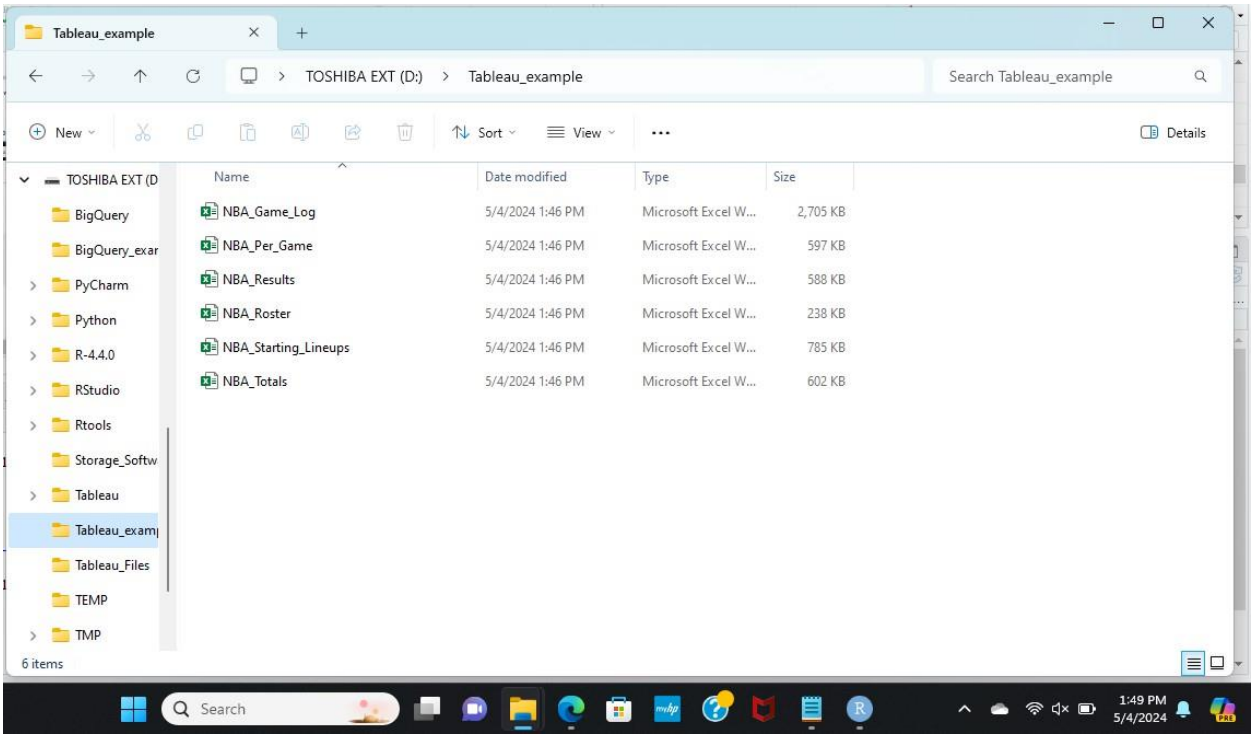


Figure 7: Tableau files after Upload

11 Load Data

11.1 Google Cloud Storage

11.1.1 Let's save our Data to Google Cloud Storage to have an extra layer of storage.

11.1.2 Load environment variables. Use Sys.getenv "System get environment" to accomplish this.

11.1.3 Authenticate with Google Cloud Storage using a service account key file.

```
gcs_key_file <- Sys.getenv("GCS_KEY_FILE")

gcs_auth(gcs_key_file)
```

11.1.4 Upload the files.

predefinedAcl

```
gcs_upload(file = "D:\\BigQuery_example\\NBA_Roster.csv", bucket =
"kirby_studio_bucket", gcs_upload(file =
"D:\\BigQuery_example\\NBA_Starting_Lineups.csv", bucket = gcs_upload(file =
"D:\\BigQuery_example\\NBA_Per_Game.csv", bucket = "kirby_studio_bucket"
                                                                    "kirby_studio_bucket",
                                                                    pred ,
                                                                    predefinedAc
```

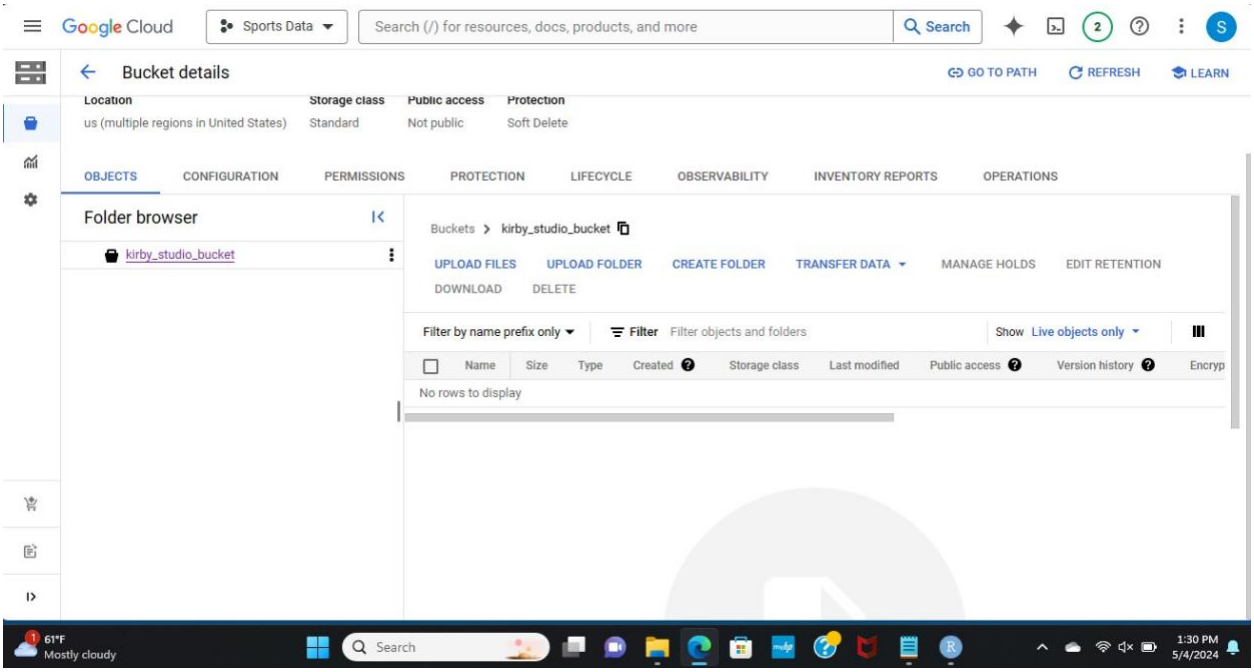
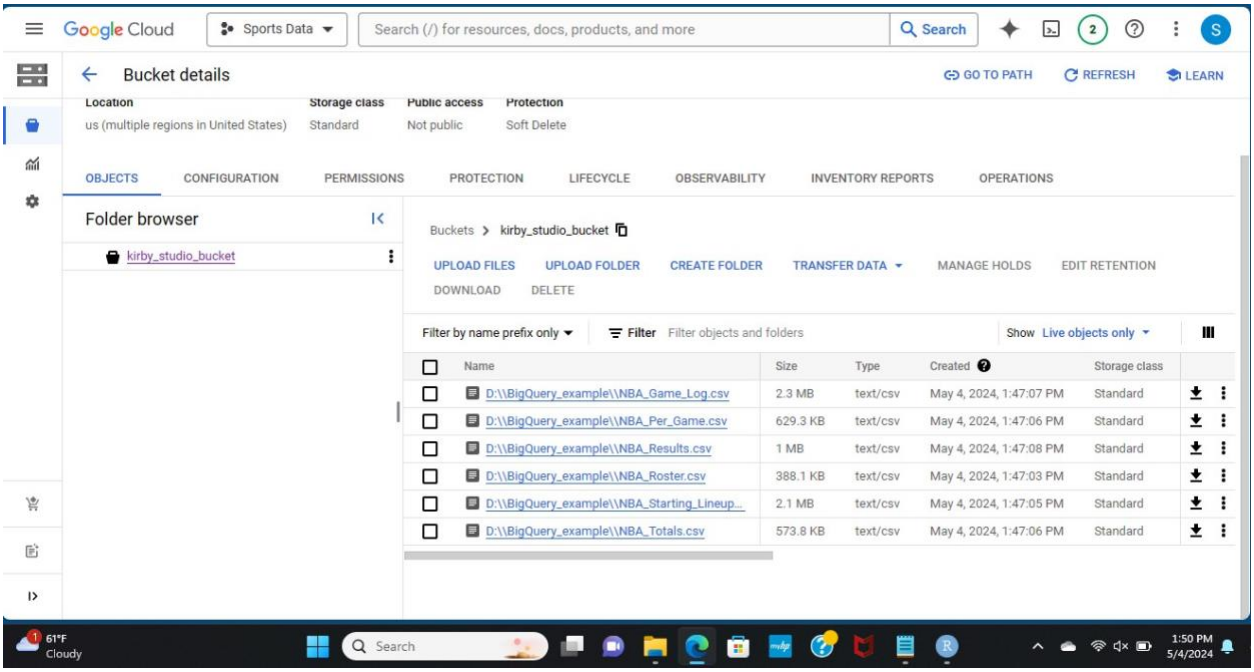


Figure 8: Google Cloud Storage before upload




```
gcs_upload(file = "D:\\BigQuery_example\\NBA_Totals.csv", bucket =
"kirby_studio_bucket", gcs_upload(file =
"D:\\BigQuery_example\\NBA_Game_Log.csv", bucket = "kirby_studio_bucket"
gcs_upload(file = "D:\\BigQuery_example\\NBA_Results.csv", bucket =
"kirby_studio_bucket",
```

Figure 9: Google Cloud Storage after upload `predefinedAcl`

```
,
predefinedA
c
predefinedA
cl
```

11.2 Google BigQuery

11.2.1 Finally we will load our data frames into tables on Google BigQuery. To allow us to store our data as it grows, we can query for smaller sample data sets.

11.2.2 This will benefit in our ETL process saving Time & Money!

```
bq_auth <- Sys.getenv("GCS_KEY_FILE")
```

11.2.3 First, authenticate with the bigquery package.

11.2.4 Then, upload data to BigQuery.

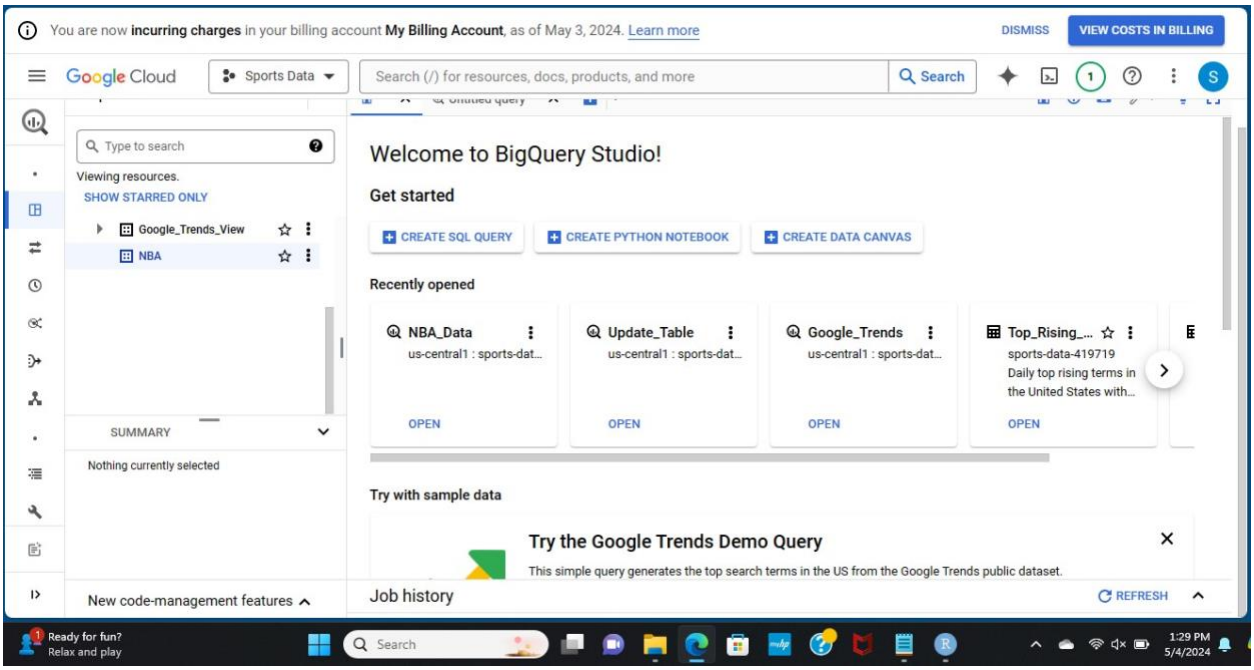


Figure 10: Google BigQuery before upload

```
bq_table_upload("sports-data-419719.NBA.Roster", NBA_Roster,
create_disposition = bq_table_upload("sports-data-419719.NBA.Per_Game",
NBA_Per_Game, create_disposition = bq_table_upload("sports-data-
419719.NBA.Totals", NBA_Totals, create_disposition =
```

```
"CREATE_IF_NEEDED")
```

```
"CREATE_IF_NEEDED
```

```
"CREATE_IF_NEEDED")
```

```
bq_table_upload("sports-data-419719.NBA.Starting_Lineups",
NBA_Starting_Lineups, bq_table_upload("sports-data-419719.NBA.Game_Log",
NBA_Game_Log, create_disposition = bq_table_upload("sports-data-
419719.NBA.Results", NBA_Results, create_disposition =
```

```
create_disposition = "
```

```
"CREATE_IF_NEEDED
```

```
"CREATE_IF_NEEDED")
```

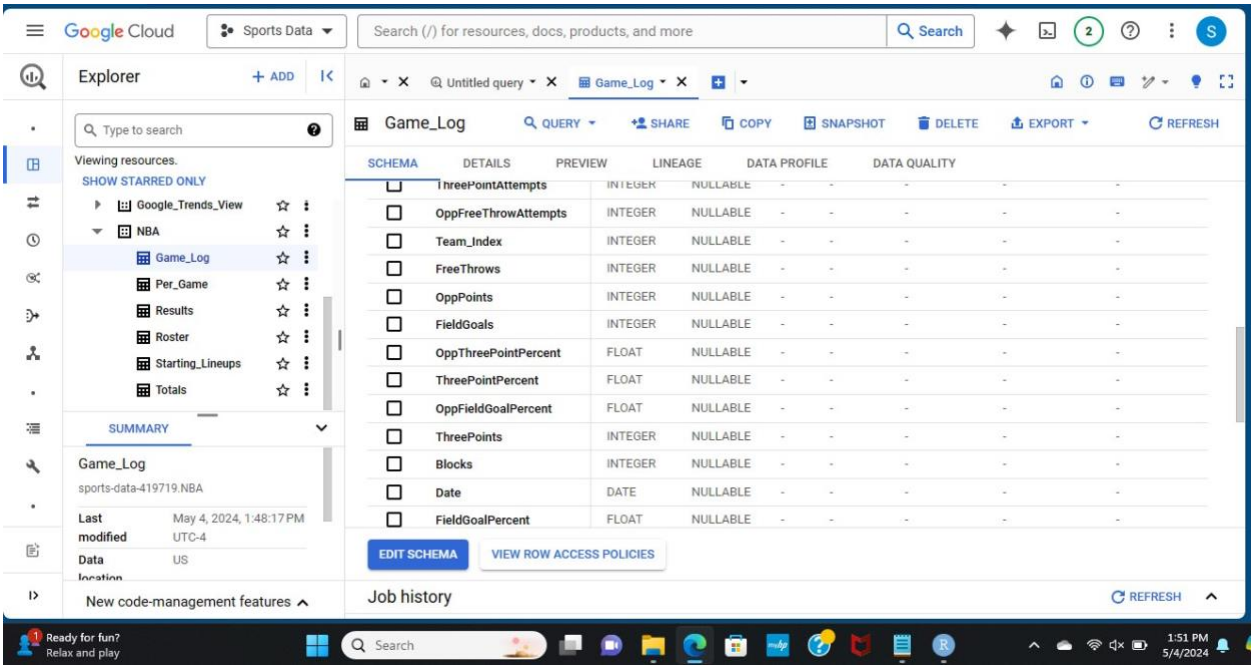


Figure 11: Google BigQuery after upload

12 Conclusion

12.1 ETL

12.1.1 In this overview of the Transform and Load portion of my NBA Data pipeline we have discussed how to Load Required Packages, Load Functions, Clean the Data, Combine the Data, Run a Final Multi-layered Check and how to Load the Data.

12.2 Portfolio Project

12.2.1 Links to the entire *Basketball Data Project* including the *Python Web Scrape Code* and *Tableau Dashboards* can be found on my *GitHub Profile*