**Analyzing Formula1 Races**

*A Data Analysis with “R”*

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*Abstract*

This project report focuses on the analysis of Formula 1 racing using the statistical programming language R. The primary objective is to compare different drivers and their fastest laps, ultimately building a regression model based on the dataset.

The Formula 1 dataset used in this study contains comprehensive information about various drivers, including their lap times, race results, and other performance metrics. The dataset serves as a valuable resource for exploring the factors that contribute to fast lap times and identifying the drivers who consistently perform well. The project consists of data preprocessing and exploratory data analysis (EDA) techniques in R. The dataset is cleaned, missing values are handled, and relevant variables are selected for analysis. EDA techniques such as data visualization and summary statistics are employed to gain insights into the data, identify patterns and detect any outliers or anomalies.

*Introduction*

Formula 1 is known as the pinnacle of motorsport, combining cutting-edge technology, high-speed racing and extraordinary driving skills. With drivers pushing the limits of performance and teams relentlessly striving for success, there is a constant quest to understand the factors that contribute to exceptional performance in this entertaining racing championship. In this context, data analysis and statistical modeling play a crucial role in unraveling the complexities of Formula 1 racing.

This project report focuses on utilizing the statistical programming and language R to analyze Formula 1 data and get some results like comparing different drivers based on their fastest laps. By examining the relationship between drivers and their lap times, we aim to gain insights into the key determinants of exceptional performance and explore the possibility of building a regression model to predict lap times.

The availability of comprehensive datasets that capture crucial information about drivers, lap times, race results and various performance metrics provides a valuable resource for this analysis. By leveraging this rich dataset, we can delve into the nuances of Formula 1 racing and uncover patterns that may influence lap times.

The primary objective of this project is to compare different factors which may affect the race results like drivers and their fastest laps, identifying variations and trends that may shed light on the factors contributing to outstanding performance. By employing data preprocessing techniques and exploratory data analysis (EDA) in R, we can clean and prepare the dataset for meaningful analysis. EDA techniques such as data visualization and summary statistics enable us to uncover insights, detect outliers, and uncover potential relationships between variables.

Methodology

This article aims to explore Formula-1 (F1) data and uncover patterns and insights using data analysis techniques. The analysis is conducted using the R language, with a focus on key exploratory concepts such as joining data frames, filtering data, summarizing data and creating visualizations using the ggplot2 package.

The first and crucial step in any data analysis process is to acquire a high-quality dataset. Having a good dataset forms the foundation for meaningful insights and accurate analysis. The dataset acts as the primary source of information, shaping the outcomes and conclusions drawn from the analysis. It is essential to ensure that the dataset is reliable, relevant, and comprehensive, as it directly impacts the accuracy and validity of the analysis results. Therefore, obtaining a reliable dataset is the initial step in the data analysis journey. Our dataset is sourced from <http://ergast.com/mrd>, which is a widely recognized and reliable platform for obtaining motor racing data. The Ergast Developer API provided by this website offers a comprehensive historical record of Formula One data for non-commercial purposes. With its extensive coverage from the inception of the world championships in 1950, the Ergast API is a trusted source in the field of motor racing data analysis.

Now, we want to make some initial basic comparisons between drivers and the titles they’ve won. This involves joining two data frames, namely "results.csv" and "drivers.csv," to associate the drivers' performance data with their names. This is done using the inner\_join() function from the dplyr package. By merging the data frames, the resulting "results\_agg\_total" data frame includes all the unique columns from both drivers and results datasets.

The "results.csv" data file contains detailed information about the performance of each driver in each race during the analyzed time period. However, it only includes a numeric identifier (driverId) instead of the drivers' names. To create a more interpretable visualization, the driver's name is needed alongside their performance data. By combining information from "results.csv" and "drivers.csv," the merged data frame provides a comprehensive dataset to work with.

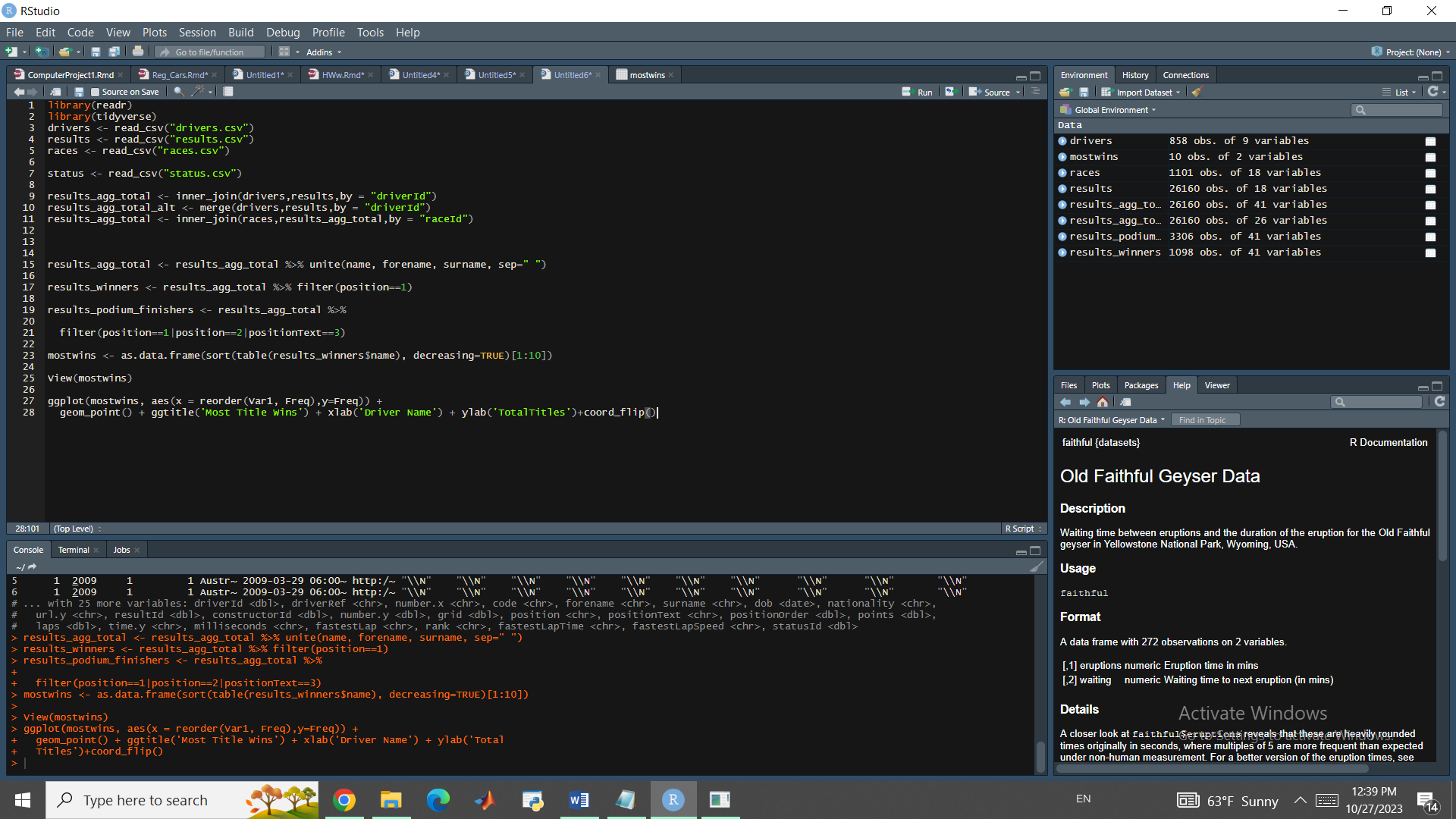


Figure Data Selection

Once the data frames are joined, various exploratory data analysis techniques are employed. This includes filtering data, summarizing data using functions like group\_by() and summarize(), and creating visualizations using the ggplot2 package. The exploration aims to answer questions such as identifying the winningest F-1 driver during the analyzed time period and generating visualizations to rank drivers based on the number of total wins.

After the merge, the resulting "results\_agg\_total" dataframe will contain driver names, race names and race information in a single place. To ensure consistency in the formatting of driver names, the unite() function from the tidyr package can be used to combine the drivers' first and last names into a new variable:

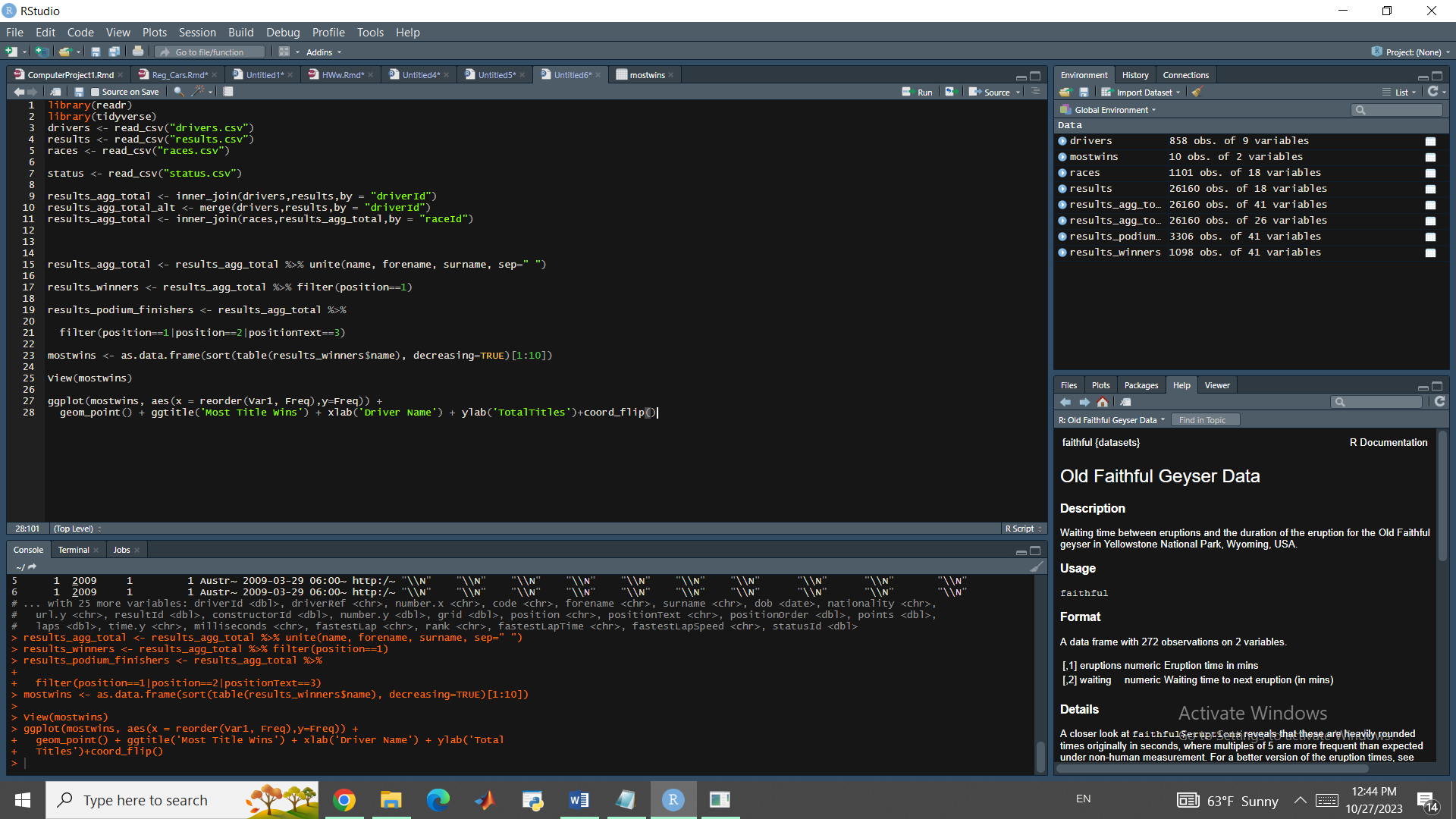


Figure Data filtering

With the data frame prepared, the next step involves filtering the data to retain specific rows. To create a new data frame containing all podium finishers (1st, 2nd, or 3rd place) in a Grand Prix race, the following code can be used:

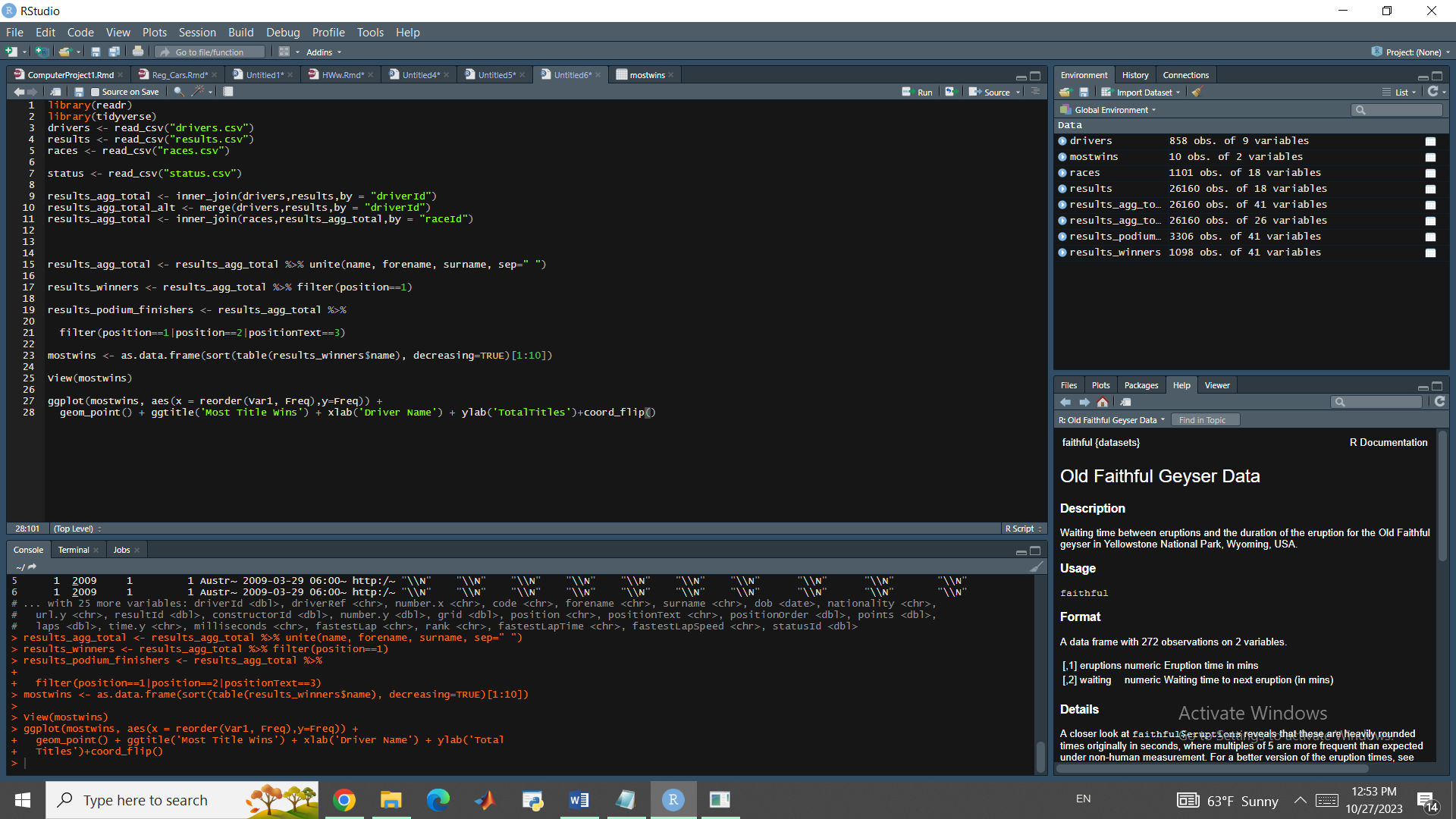


Figure Creating data frame for podium finishers

To see the most wins in Formula 1 history, we need to sort the created data frame:

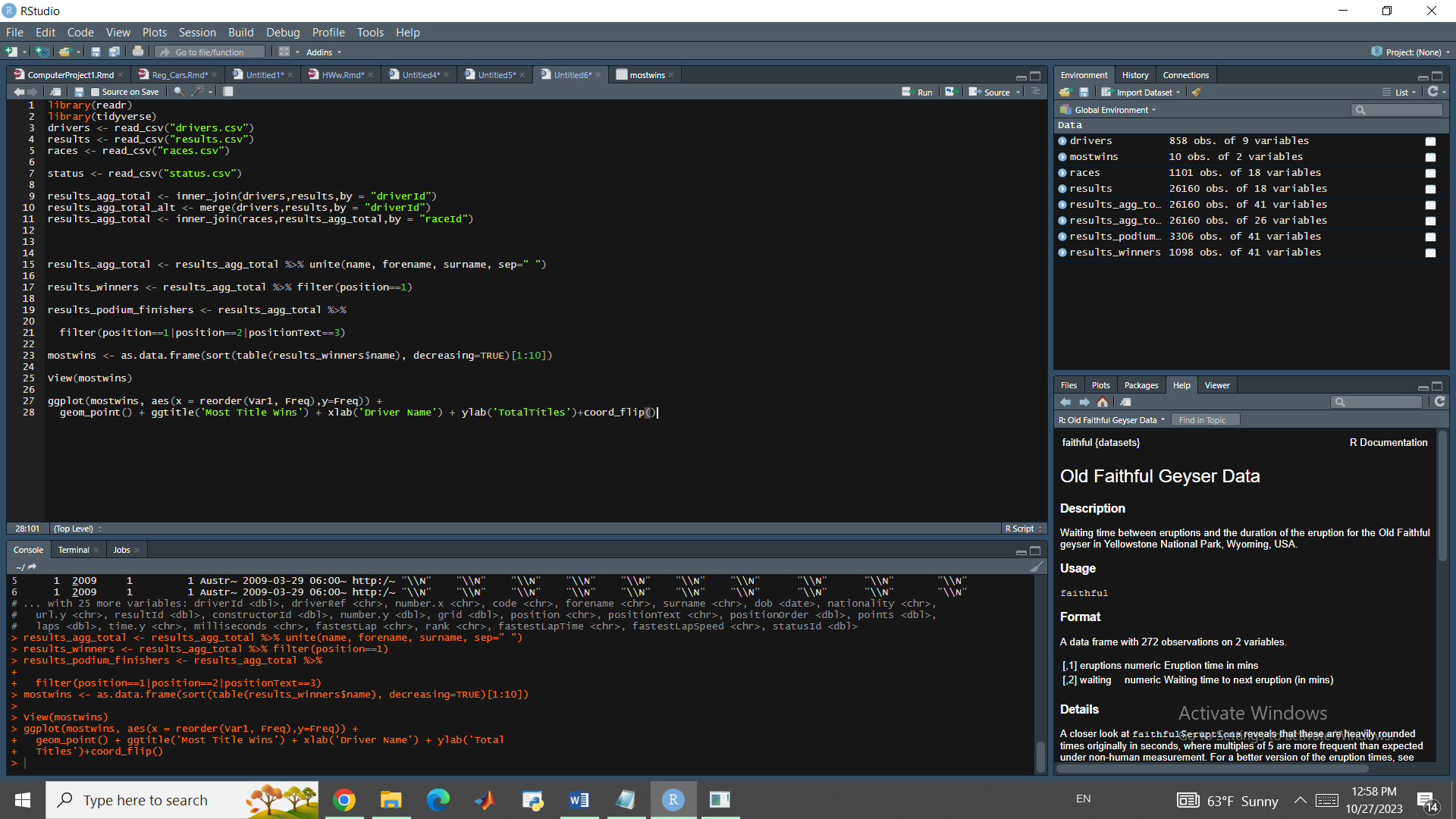
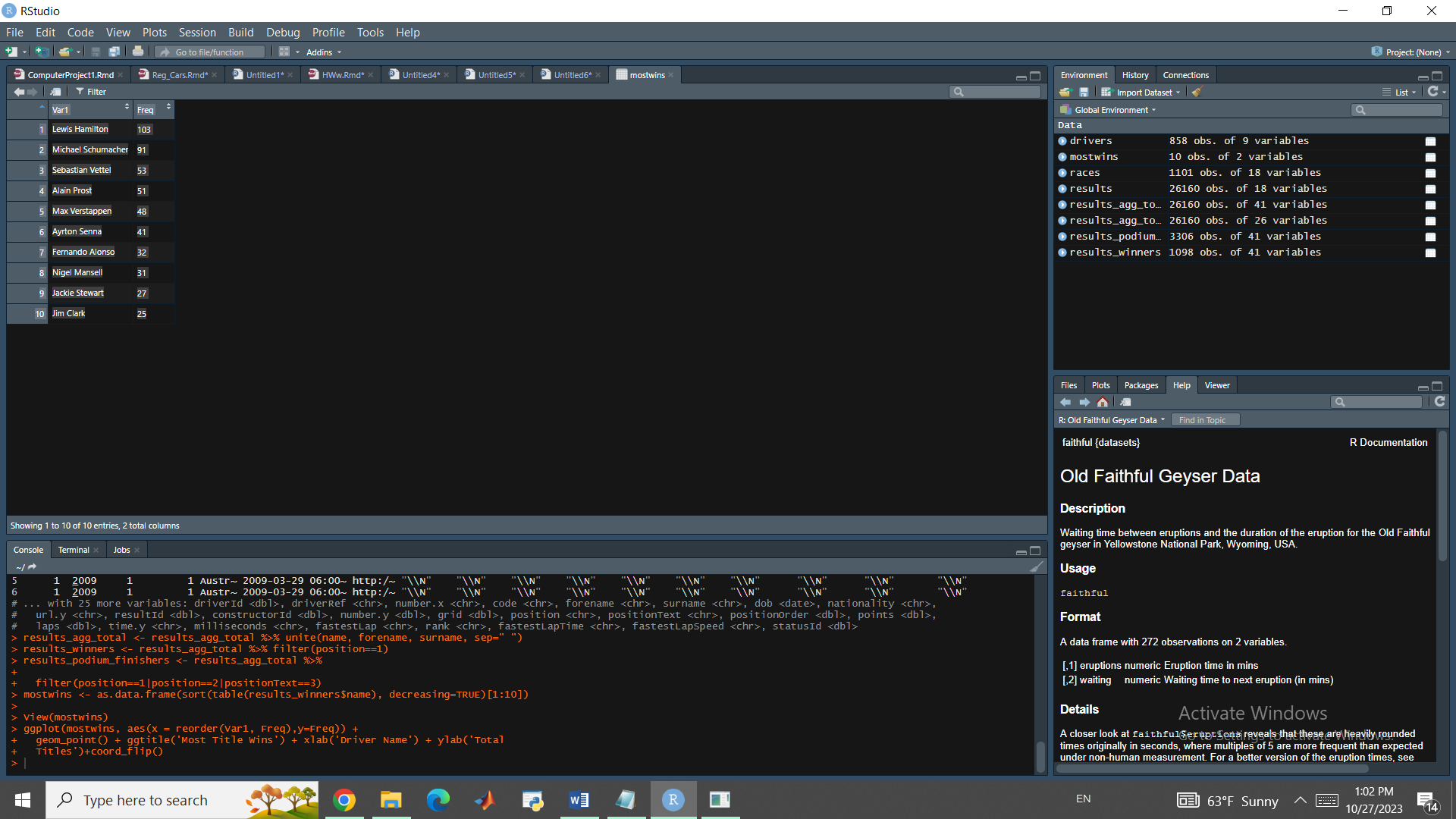


Figure Sorting the data frame

And the result is:



| Var1 | | Freq |
| --- | --- | --- |
|  |  | |  |
| 1 | Lewis Hamilton | | 103 |
| 2 | Michael Schumacher | | 91 |
| 3 | Sebastian Vettel | | 53 |
| 4 | Alain Prost | | 51 |
| 5 | Max Verstappen | | 48 |
| 6 | Ayrton Senna | | 41 |
| 7 | Fernando Alonso | | 32 |
| 8 | Nigel Mansell | | 31 |
| 9 | Jackie Stewart | | 27 |
| 10 | Jim Clark | | 25 |

*Table1 Most Successful Drivers*

As you can see, Lewis Hamilton is the best driver on history of F1 in terms of number of titles and Lewis alongside Michael Schumacher have a league of their own.

Visualizing this can help us get a better grip of this matter.

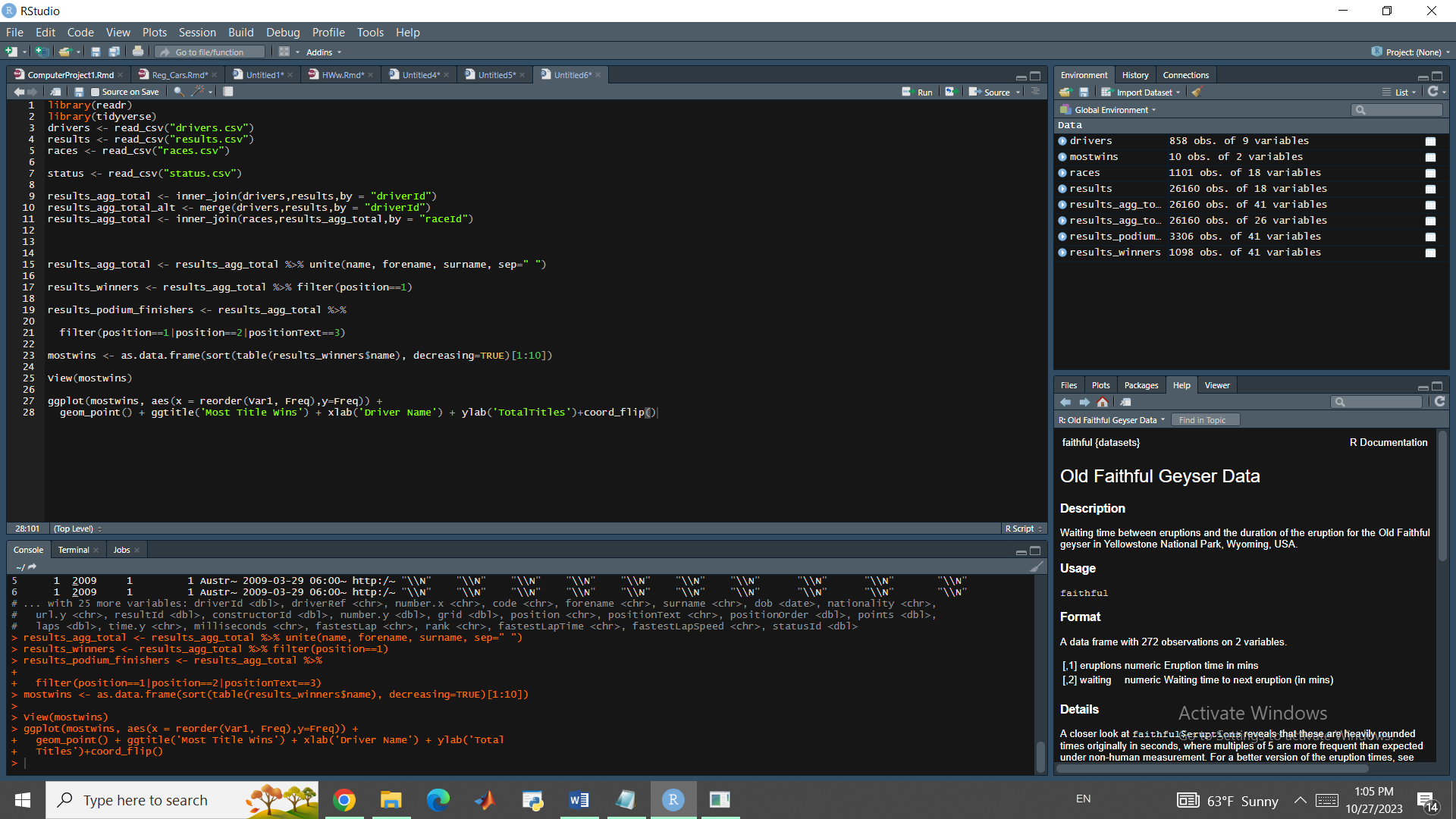


Figure Visualizing the data frame

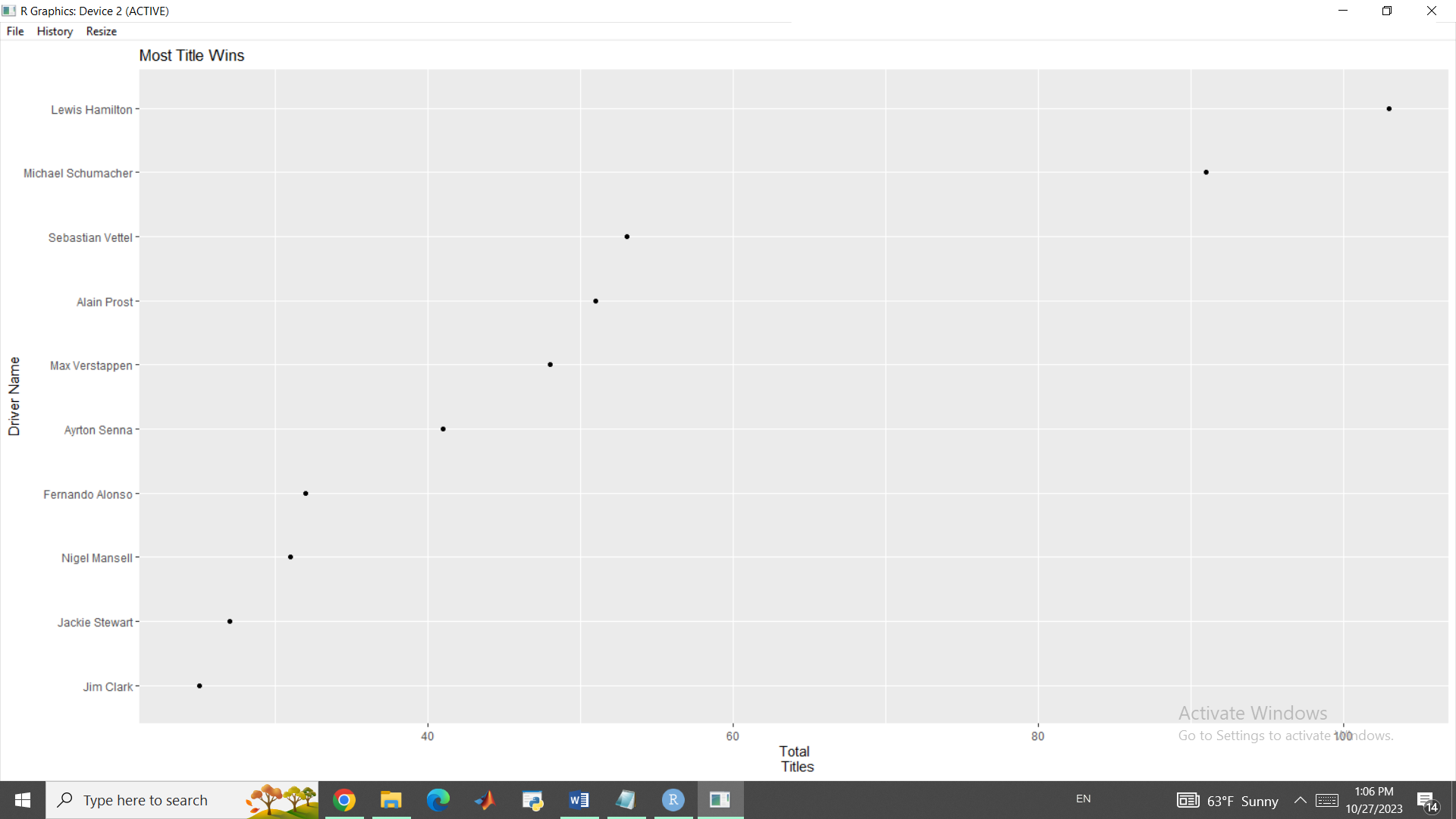


Figure Most wins plot

It would be also useful to see the percentage format but for that matter we have to consider one thing: These results might be misleading, however, as some drivers have just a handful of total races. By removing drivers with fewer than 20 races, we can get a more meaningful depiction of win percentage:

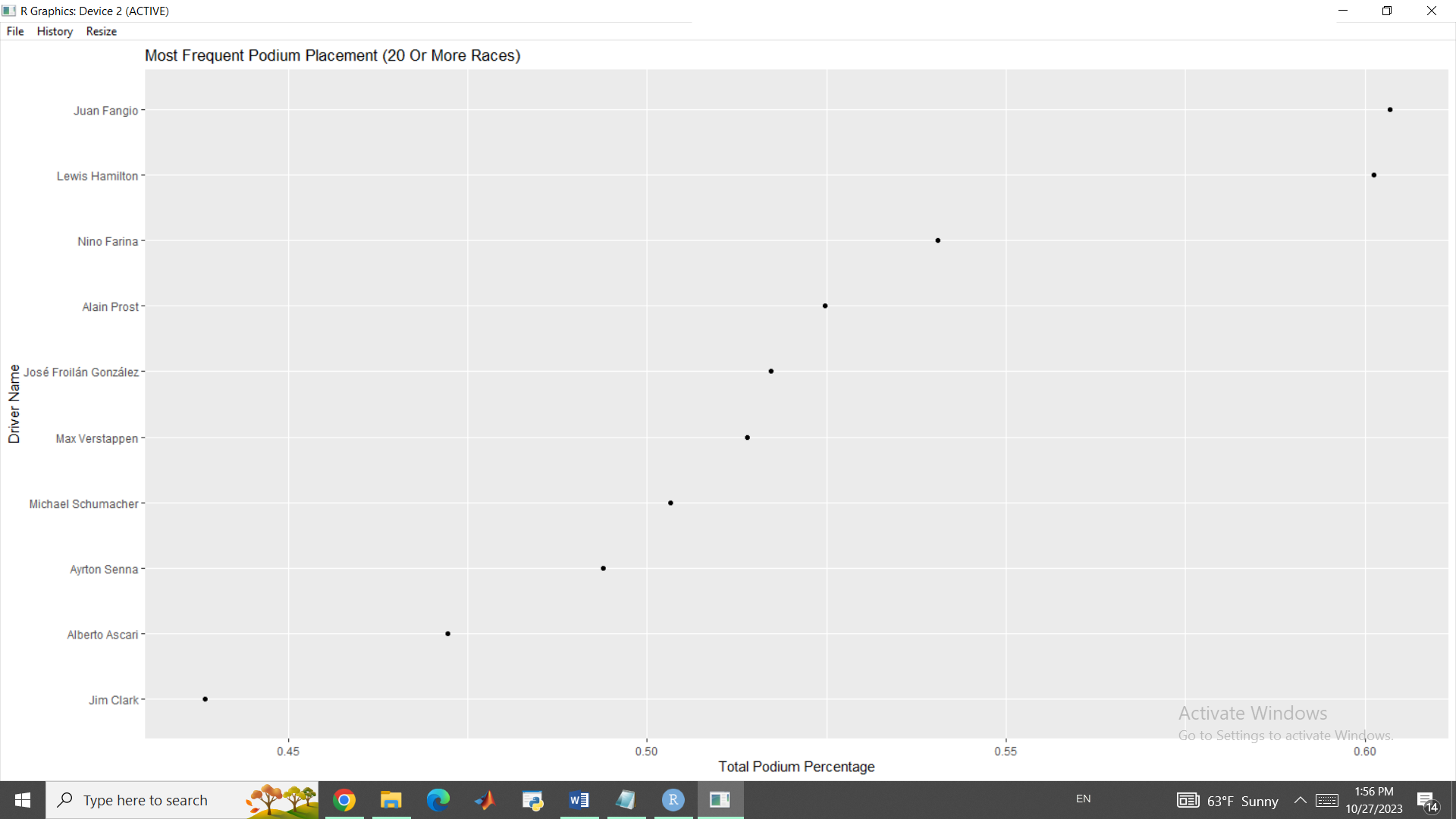
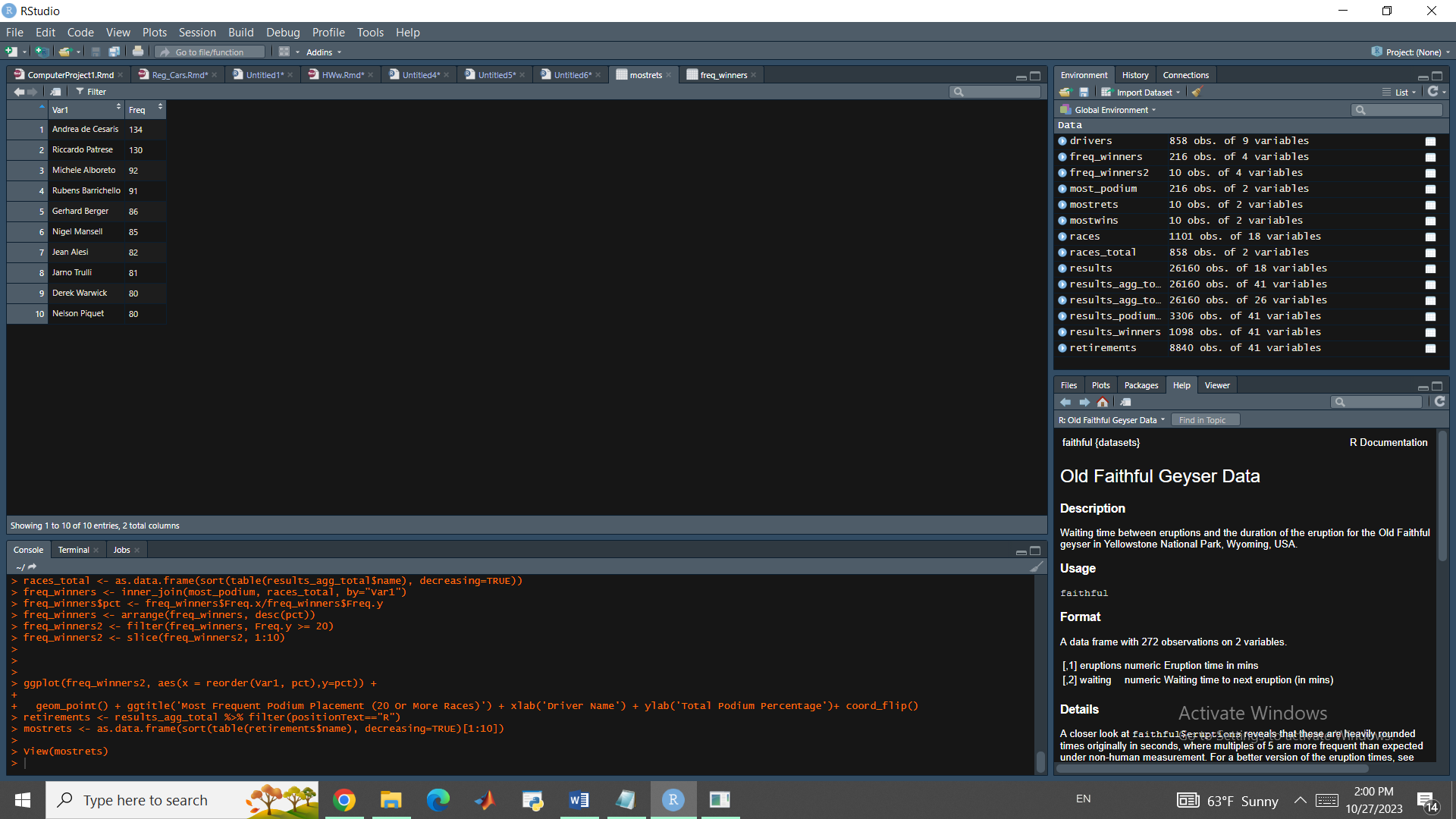


Figure Percentage Win

As you can see Juan Fangio replaced Lewis Hamilton in the first place.

In F1 there is a term called retirement which means that the driver retired from the race, meaning they were unable to complete the race due to various reasons such as mechanical issues, accidents, or other factors.

If we filter our data to get the names of drivers with most retirements we have:



Now if we merge all of the data frame together using the driverId, we will have the following dataset:

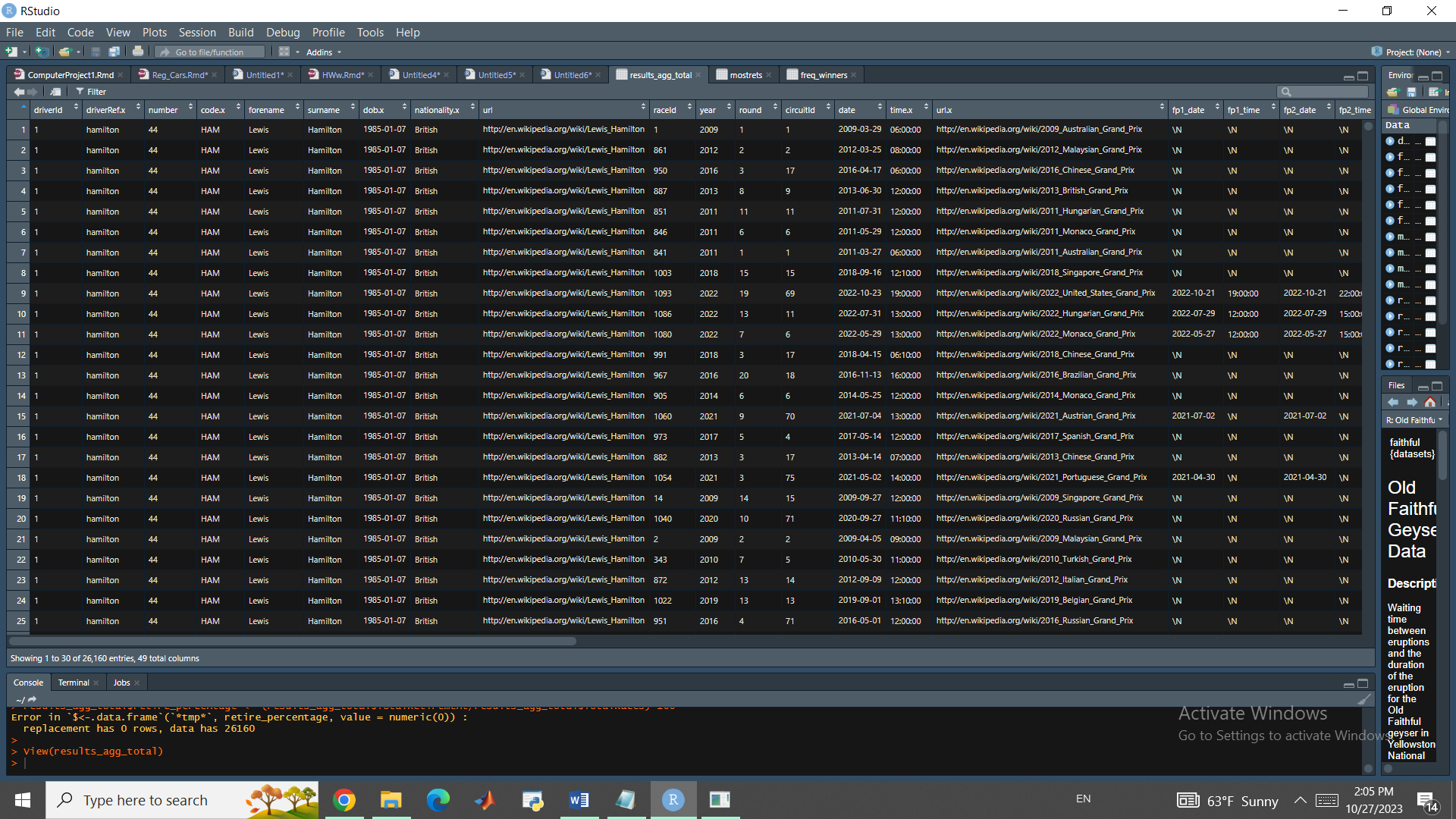


Figure merging all datasets

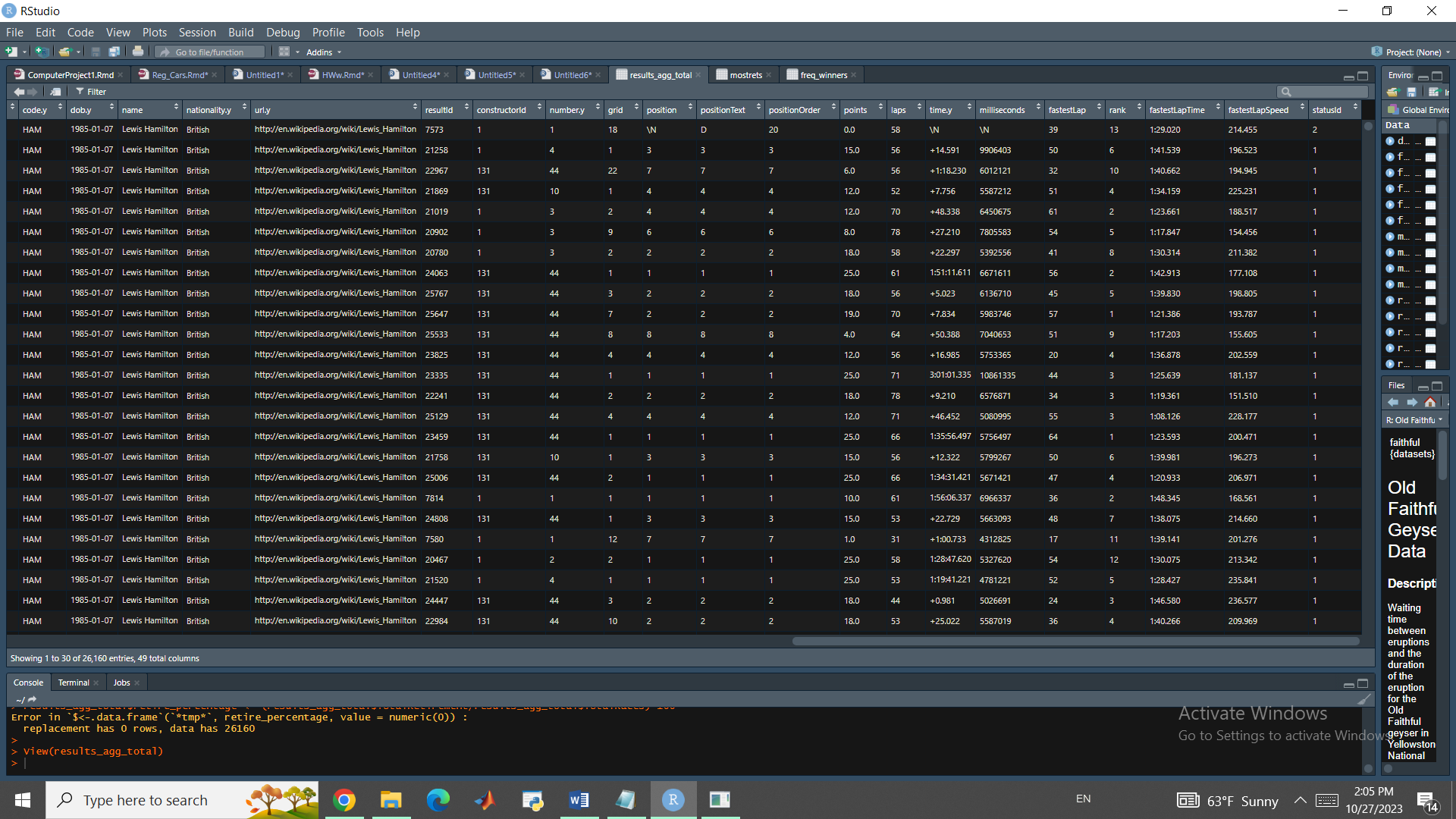


Figure Merging all datasets

And using this dataset we can perform various forms of Regressions.

But before that, let’s make get more insights on driver predictor especially since it has such a huge effect on the race results.

Only this time we will analyze the F! in 2023 season instead of a historical approach. Our dataset is from a german site <https://www.formel1.de/saison/wm-stand>

And we will need some data preprocessing before we get to visualization and conclusion part. After loading the dataset it will look like this:

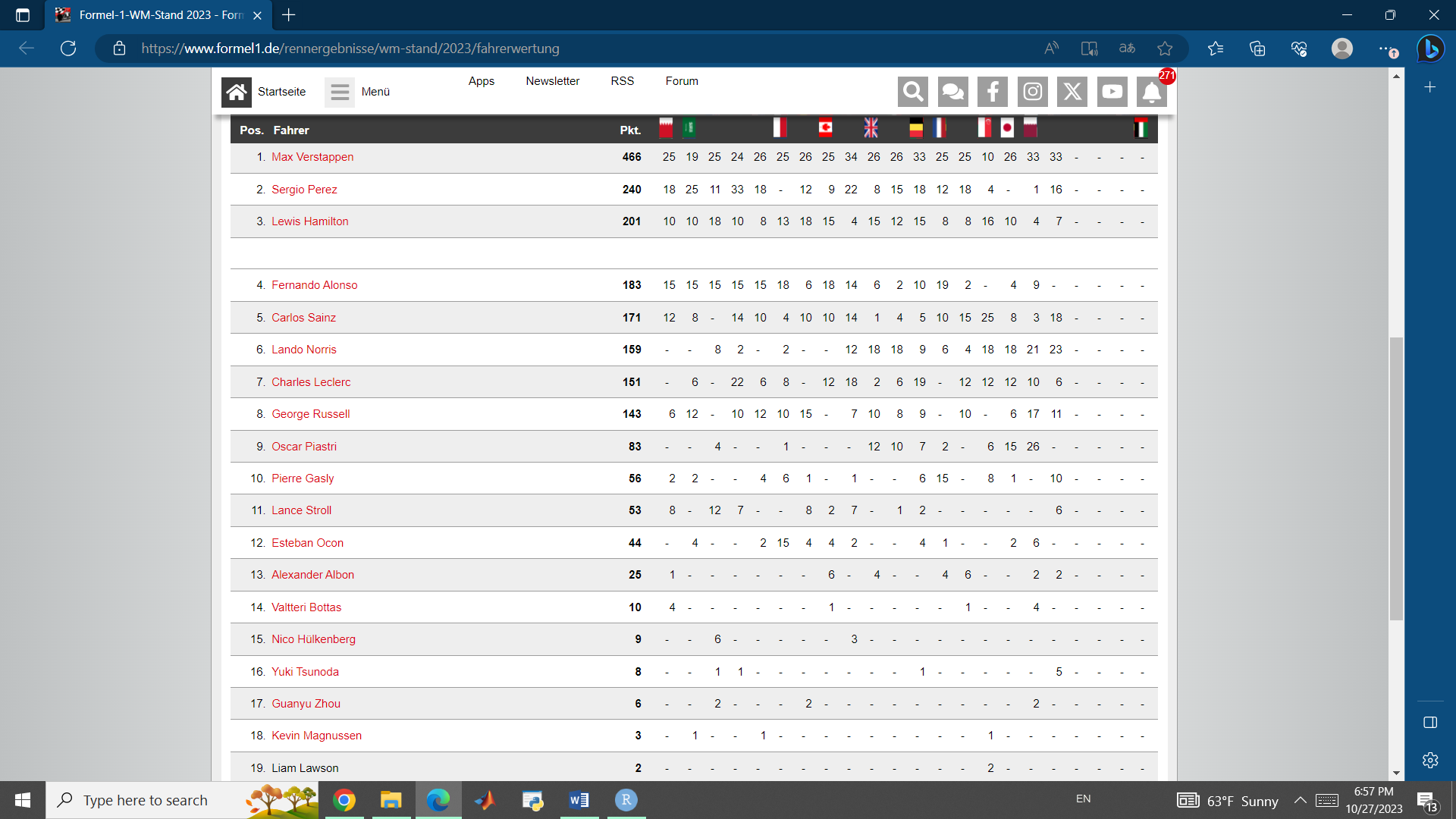


Figure 2023 F1 dataset

As you can see there is an empty space in the 4th row which if we ignore it, will damage the visualization as well as the model. In order to deal with it we will use the following command:

f1 <- f1[complete.cases(f1), ]

assuming the dataset was loaded in f1 variable.

We also need to add some headers to our dataset since some of them are missing:

colnames(f1) <- c('Pos', 'Driver', 'Total', sprintf('R%02d', 1:21))

Now after filtering the top 9 drivers and making Driver a factorial variable and replacing all “-“ signs with zero, we are good to go.

f1 <- as\_tibble(f1) %>%

filter(as.integer(Pos) <= 9)

f1$Driver <- as.factor(f1$Driver)

f1[, -2] <- apply(f1[, -2], 2, function(x) as.integer(gsub('-', '0', as.character(x))))

f1long <- gather(f1, Race, Points, R01:R21)

The final processed dataset will look like this:

| Pos | Driver | | Total |  | Race | Points | |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  | |  |  |  |  | |
| 1 | 1 | Max Verstappen | | 466 | 0 | R01 | 25 | |
| 2 | 2 | Sergio Perez | | 240 | 0 | R01 | 18 | |
| 3 | 3 | Lewis Hamilton | | 201 | 0 | R01 | 10 | |
| 4 | 4 | Fernando Alonso | | 183 | 0 | R01 | 15 | |
| 5 | 5 | Carlos Sainz | | 171 | 0 | R01 | 12 | |
| 6 | 6 | Lando Norris | | 159 | 0 | R01 | 0 | |
| 7 | 7 | Charles Leclerc | | 151 | 0 | R01 | 0 | |
| 8 | 8 | George Russell | | 143 | 0 | R01 | 6 | |
| 9 | 9 | Oscar Piastri | | 83 | 0 | R01 | 0 | |

*Table2 2023 F1 race*

As you can see in the 2023 season, Max Verstappen is leading the way by a huge margin.

If we transform this data into a plot we can see that Max is clearly a cut above all other drivers in the current season:

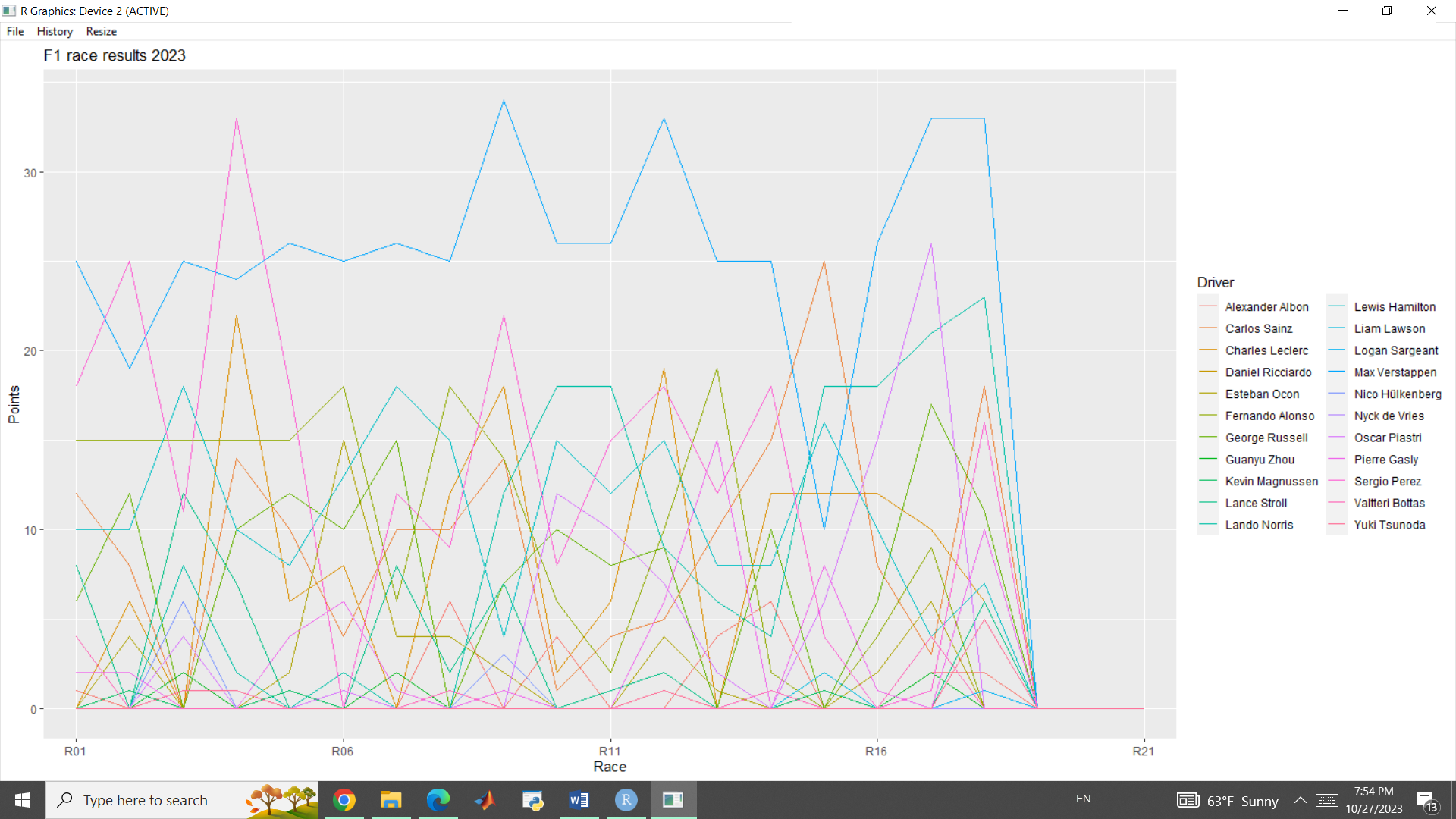


Figure 2023 F1 plot

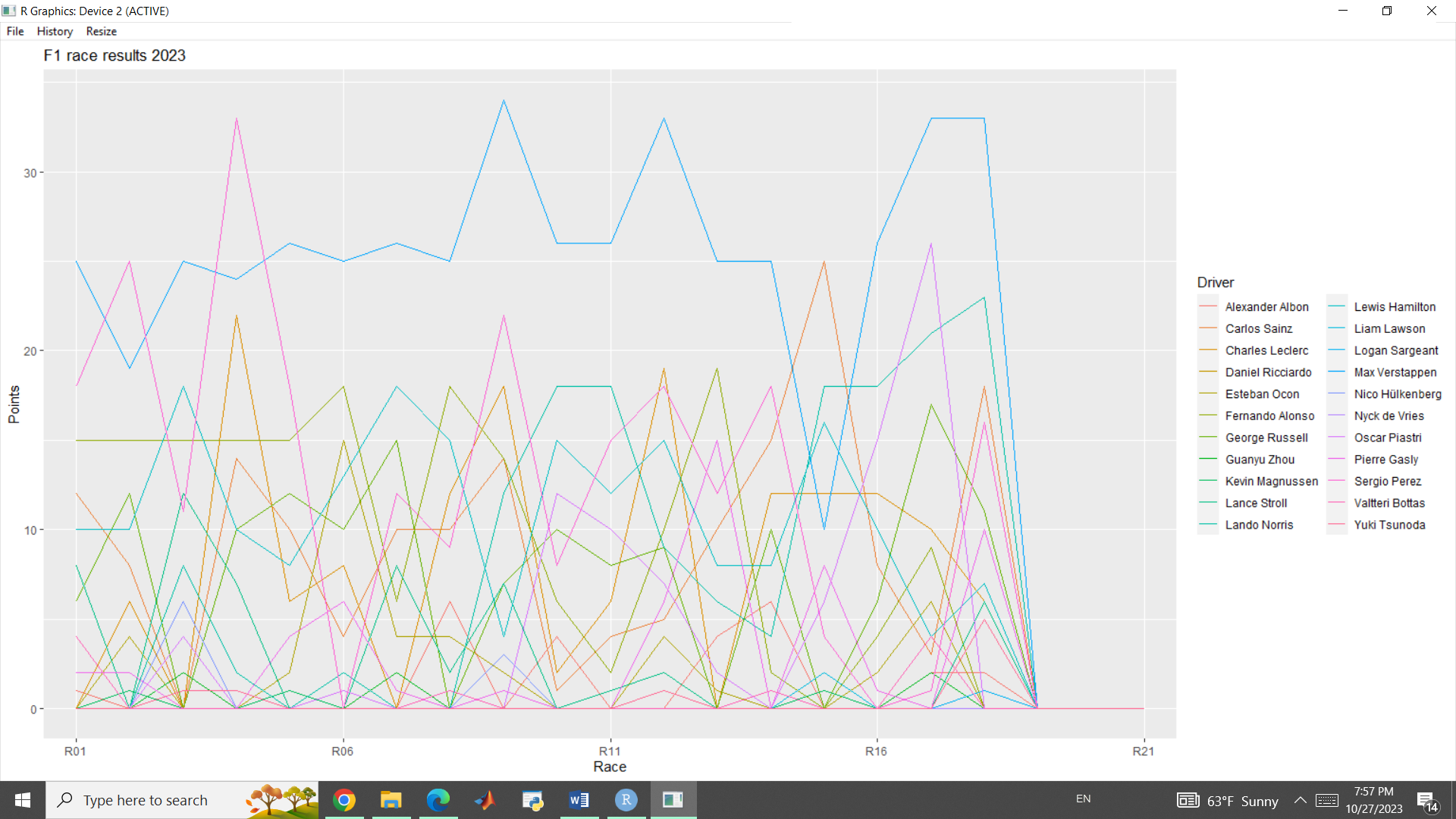


Figure Closer glimpse on 2023 F1

If we assign each diver to its own window instead of all drivers together:

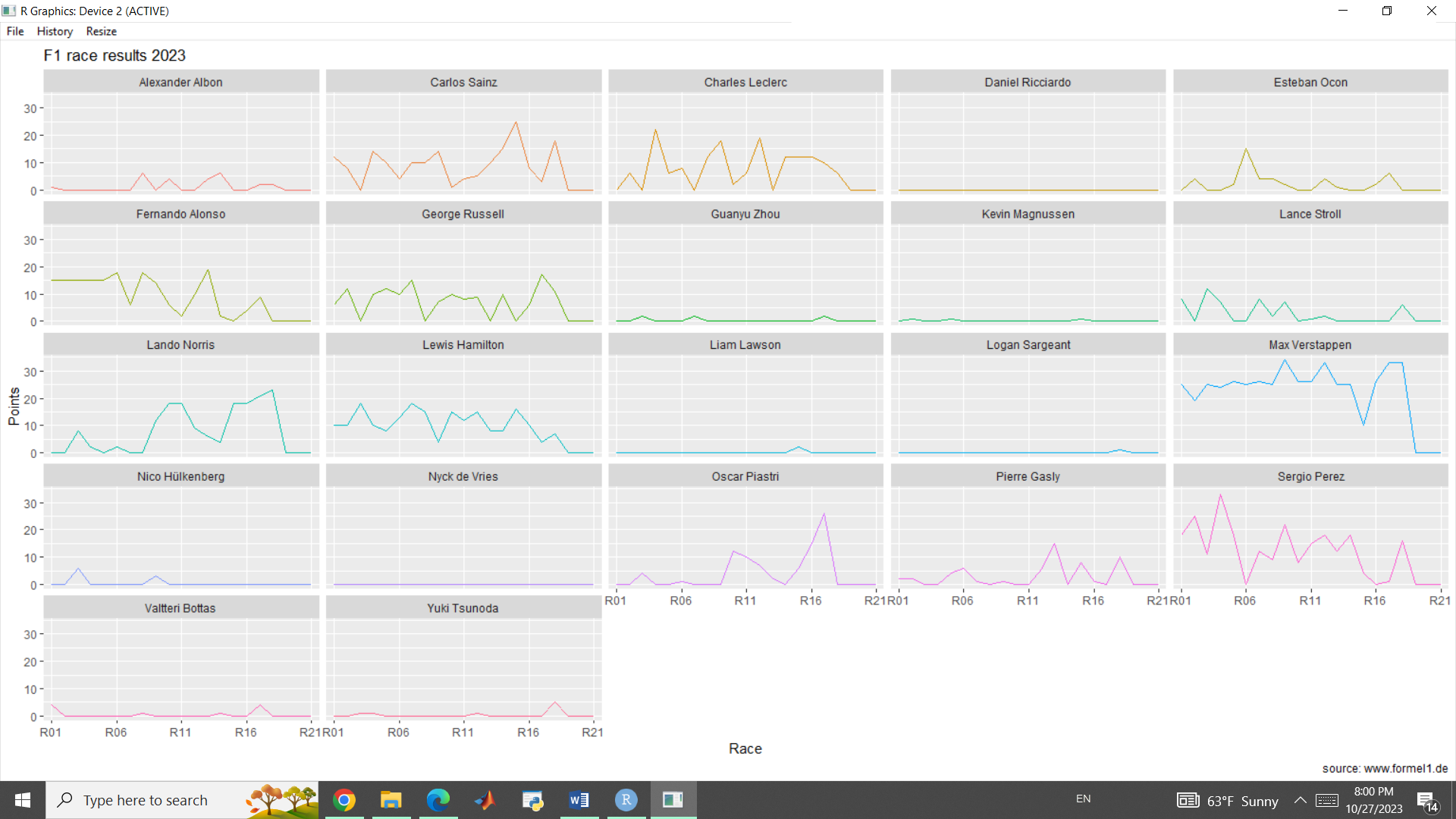


Figure 2023 F1 points by each Driver

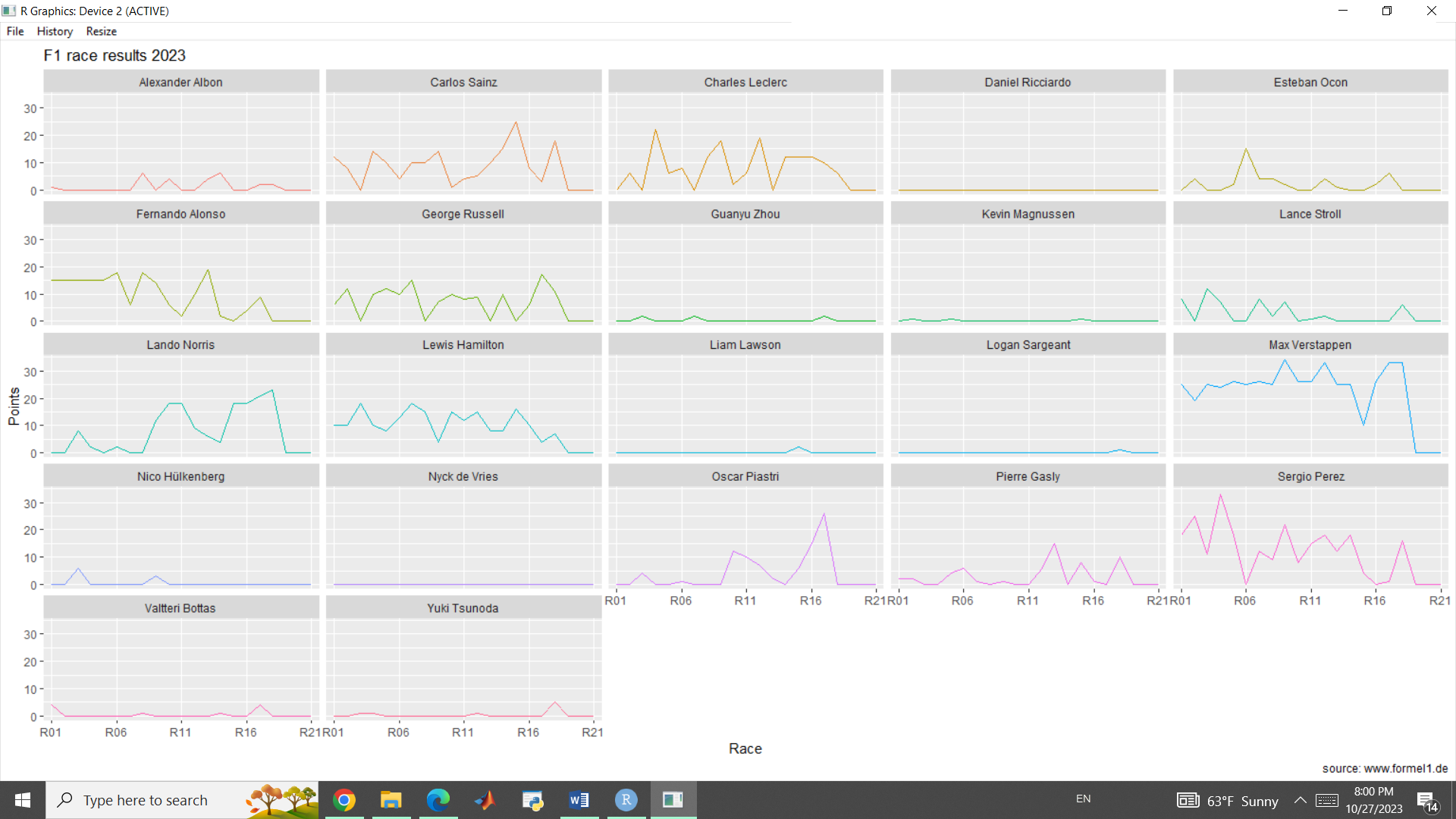


Figure 2023 performance by Max Verstappen

Now let’s shift our focus to another important factor which may affect the race results which is the fastest lap time. This term’s name is self-explanatory, which is the fastest lap in each race, but this factor also has different significance in the final race results in different Grand prix locations. The following plot shows us the fastest lap taken from 2005 to 2023 in different grand prix locations:

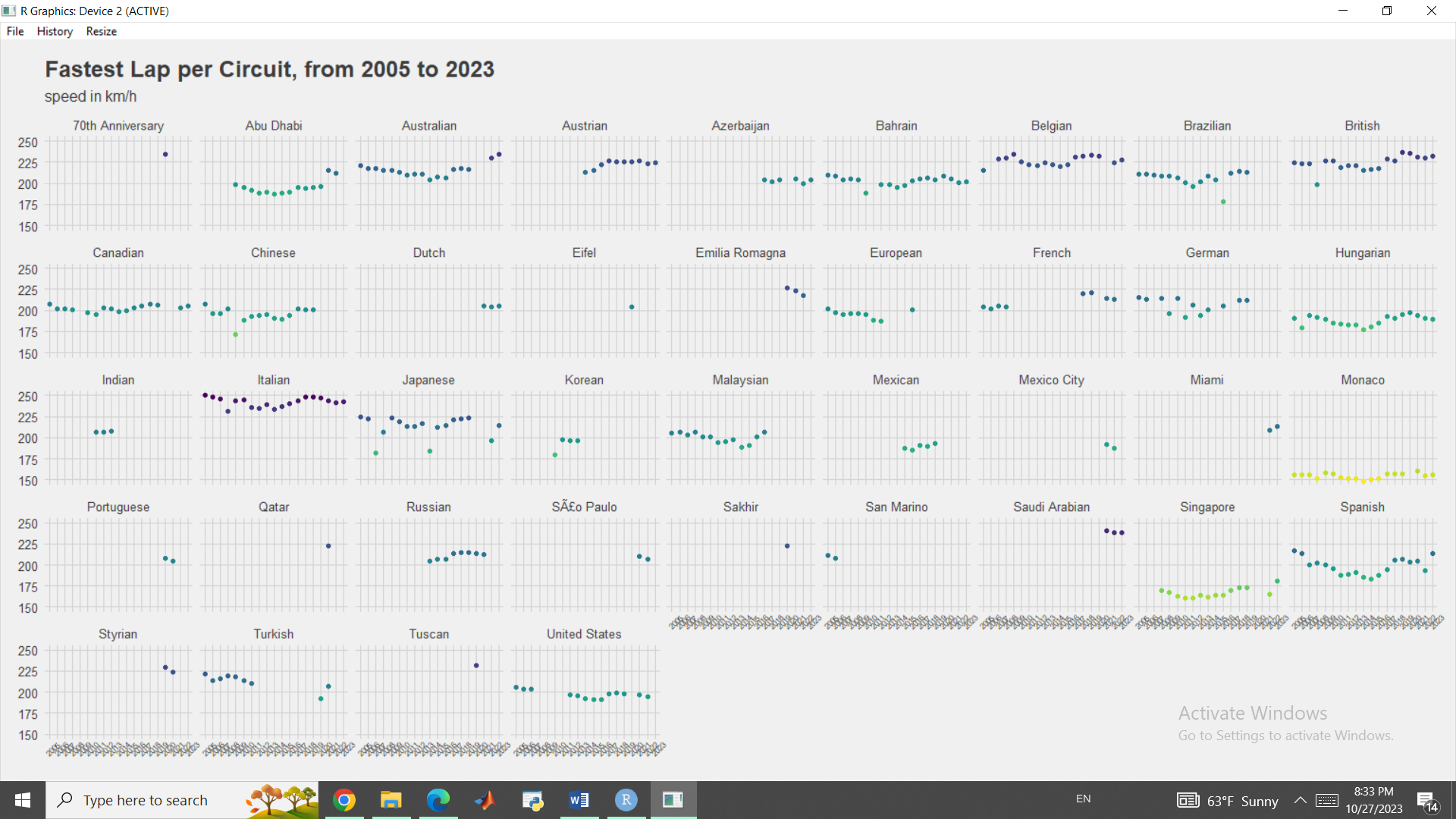


Figure Fastest Lap Time

As you can see Italian Grand Prix usually have the fastest lap times while the Monaco Grand Prix is the slowest among all other races.

Note that Monaco is taking place inside a town so it’s natural to be slower.

Now if we group this data by Grand Prix for each year and regress a line to follow the trend and use a candle stick representation to show the quarters as well as the outliers, we will see the following plot which shows the fastest lap time has increased over the past few years and the candle stick has gotten shorter which indicates a tighter race where the cars and the technologies of the different car companies have gotten closer:

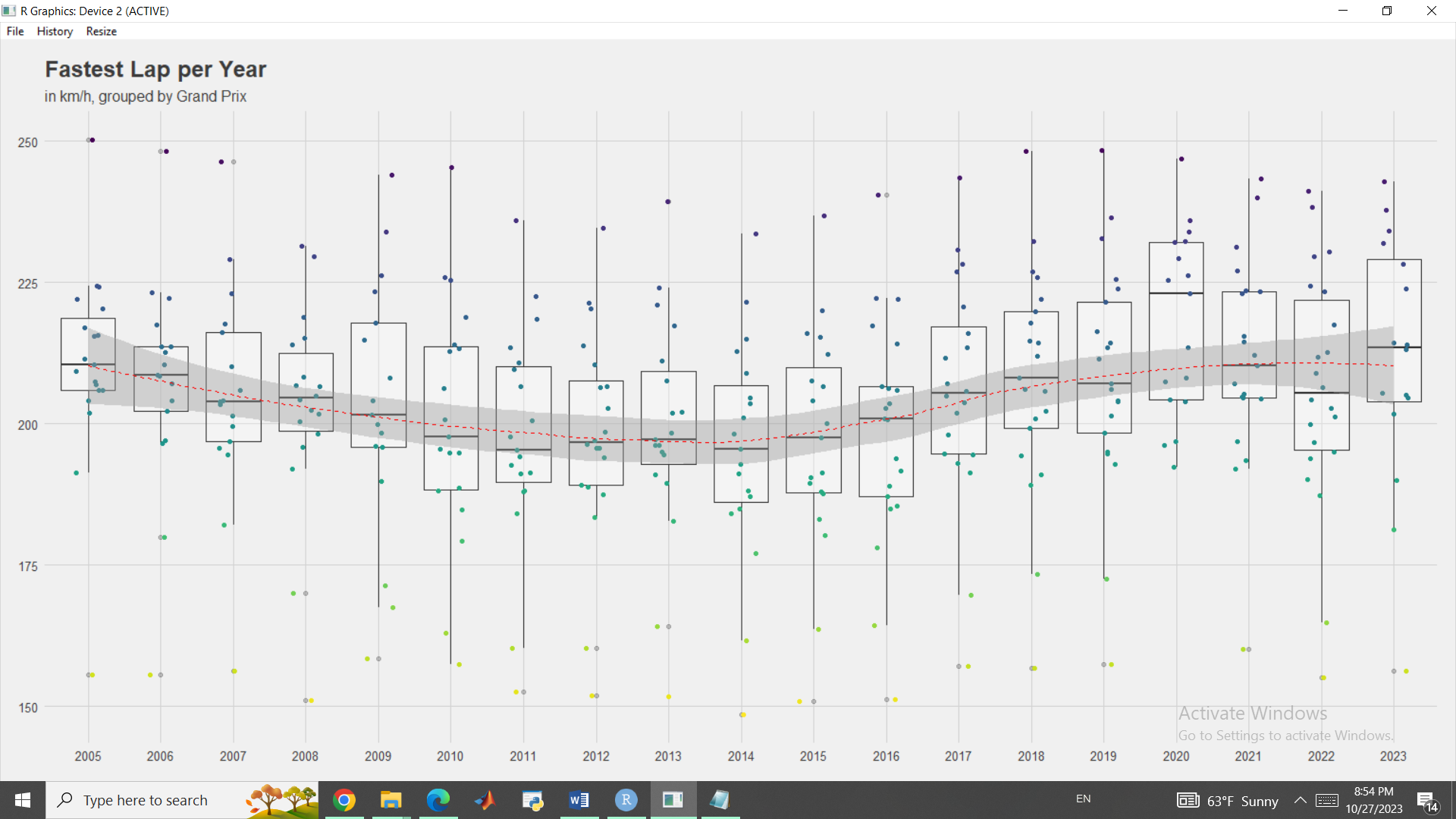


Figure Fastest Lap Time by Grand Prix

We can also see the fastest lap per circuit:

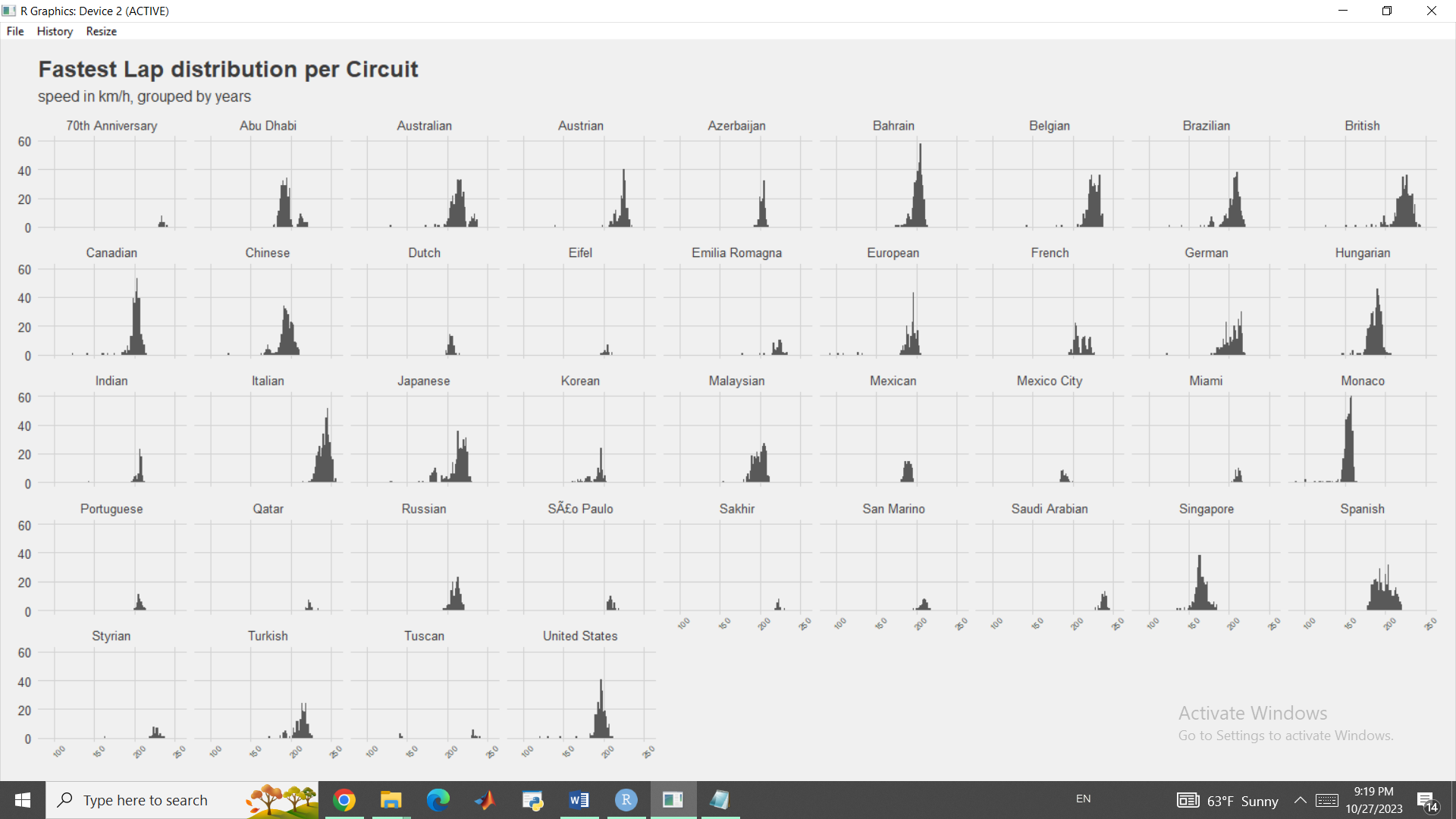


Figure Fastest Lap per Circuit

Now let’s take a look at another dataset, Races.csv statistics:

> summary(races\_df)

raceId year round circuitId name date time url fp1\_date

Min. : 1.0 Min. :1950 Min. : 1.000 Min. : 1.0 Length:1101 Length:1101 Length:1101 Length:1101 Length:1101

1st Qu.: 276.0 1st Qu.:1976 1st Qu.: 4.000 1st Qu.: 9.0 Class :character Class :character Class :character Class :character Class :character

Median : 551.0 Median :1994 Median : 8.000 Median :18.0 Mode :character Mode :character Mode :character Mode :character Mode :character

Mean : 553.4 Mean :1992 Mean : 8.494 Mean :23.7

3rd Qu.: 826.0 3rd Qu.:2010 3rd Qu.:12.000 3rd Qu.:34.0

Max. :1120.0 Max. :2023 Max. :22.000 Max. :80.0

fp1\_time fp2\_date fp2\_time fp3\_date fp3\_time quali\_date quali\_time sprint\_date sprint\_time

Length:1101 Length:1101 Length:1101 Length:1101 Length:1101 Length:1101 Length:1101 Length:1101 Length:1101

Class :character Class :character Class :character Class :character Class :character Class :character Class :character Class :character Class :character

Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character

Now we will merge separate datasets and dataframes into a single dataframe, df:

con1 <- merge(result\_df, races\_df, by = 'raceId')

con2 <- merge(con1, drivers\_df, by = 'driverId')

con3 <- merge(con2, driver\_standings\_df, by = 'driverId')

con4 <- merge(con3, constructor\_df, by = 'constructorId')

df <- merge(con4, stats\_df, by = 'statusId')

after processing the merged data,we can see some important statistics like average max speed:

> mean\_max\_speed <- mean(df$max\_speed, na.rm = TRUE)

> mean\_max\_speed

[1] 204.0944

Now let’s get another statistical summary of our dataset after processing:

> summary(df)

statusId constructorId driverId raceId.x resultId number.x grid position.x positionText.x positionOrder

Min. : 1.00 Min. : 1.00 Min. : 1 Min. : 1.0 Min. : 1 Min. : 0.00 Min. : 0.000 Length:3560903 Length:3560903 Min. : 1.00

1st Qu.: 1.00 1st Qu.: 6.00 1st Qu.: 20 1st Qu.: 236.0 1st Qu.: 5162 1st Qu.: 6.00 1st Qu.: 4.000 Class :character Class :character 1st Qu.: 5.00

Median : 5.00 Median : 16.00 Median :105 Median : 471.0 Median :11847 Median : 12.00 Median : 9.000 Mode :character Mode :character Median :10.00

Mean : 13.22 Mean : 39.66 Mean :207 Mean : 520.4 Mean :12707 Mean : 15.49 Mean : 9.758 Mean :11.22

3rd Qu.: 12.00 3rd Qu.: 37.00 3rd Qu.:231 3rd Qu.: 859.0 3rd Qu.:21233 3rd Qu.: 21.00 3rd Qu.:15.000 3rd Qu.:17.00

Max. :141.00 Max. :214.00 Max. :859 Max. :1114.0 Max. :26165 Max. :208.00 Max. :34.000 Max. :39.00

NA's :160

points.x laps time.x timetaken\_in\_millisec fastestLap rank fastestLapTime max\_speed year

Min. : 0.00 Min. : 0.0 Length:3560903 Min. : 207071 Min. : 0.00 Min. : 0.000 Min. : NA Min. : 89.54 Min. :1950

1st Qu.: 0.00 1st Qu.: 33.0 Class :character 1st Qu.: 5957994 1st Qu.: 0.00 1st Qu.: 0.000 1st Qu.: NA 1st Qu.:204.09 1st Qu.:1984

Median : 0.00 Median : 55.0 Mode :character Median : 5957994 Median : 0.00 Median : 0.000 Median : NA Median :204.09 Median :1999

Mean : 3.02 Mean : 48.4 Mean : 5957994 Mean :17.07 Mean : 3.648 Mean :NaN Mean :204.09 Mean :1997

3rd Qu.: 4.00 3rd Qu.: 67.0 3rd Qu.: 5957994 3rd Qu.:40.00 3rd Qu.: 6.000 3rd Qu.: NA 3rd Qu.:204.09 3rd Qu.:2011

Max. :50.00 Max. :200.0 Max. :15090540 Max. :85.00 Max. :24.000 Max. : NA Max. :257.32 Max. :2023

NA's :3560903

round circuitId name.x date time.y url.x fp1\_date fp1\_time fp2\_date

Min. : 1.000 Min. : 1.00 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903

1st Qu.: 5.000 1st Qu.: 9.00 Class :character Class :character Class :character Class :character Class :character Class :character Class :character

Median : 9.000 Median :15.00 Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character

Mean : 8.886 Mean :22.09

3rd Qu.:13.000 3rd Qu.:30.00

Max. :22.000 Max. :79.00

fp2\_time fp3\_date fp3\_time quali\_date quali\_time sprint\_date sprint\_time driverRef number.y

Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Min. : 2.0

Class :character Class :character Class :character Class :character Class :character Class :character Class :character Class :character 1st Qu.: 7.0

Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Median :14.0

Mean :22.9

3rd Qu.:27.0

Max. :99.0

NA's :2351289

driver\_code dob nationality.x url.y driverStandingsId raceId.y points.y position.y positionText.y

Length:3560903 Min. :1896-12-28 Length:3560903 Length:3560903 Min. : 1 Min. : 1.0 Min. : 0.00 Min. : 1.00 Length:3560903

Class :character 1st Qu.:1953-08-08 Class :character Class :character 1st Qu.:13883 1st Qu.: 240.0 1st Qu.: 1.00 1st Qu.: 5.00 Class :character

Mode :character Median :1969-01-03 Mode :character Mode :character Median :50767 Median : 473.0 Median : 8.00 Median : 10.00 Mode :character

Mean :1966-11-23 Mean :40307 Mean : 522.6 Mean : 28.76 Mean : 11.64

3rd Qu.:1981-07-29 3rd Qu.:65912 3rd Qu.: 861.0 3rd Qu.: 31.00 3rd Qu.: 16.00

Max. :2002-02-11 Max. :72319 Max. :1114.0 Max. :454.00 Max. :108.00

wins constructorRef name.y nationality.y url status driver\_name age

Min. : 0.0000 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Length:3560903 Min. : 22.00

1st Qu.: 0.0000 Class :character Class :character Class :character Class :character Class :character Class :character 1st Qu.: 42.00

Median : 0.0000 Mode :character Mode :character Mode :character Mode :character Mode :character Mode :character Median : 55.00

Mean : 0.5535 Mean : 56.94

3rd Qu.: 0.0000 3rd Qu.: 70.00

Max. :15.0000

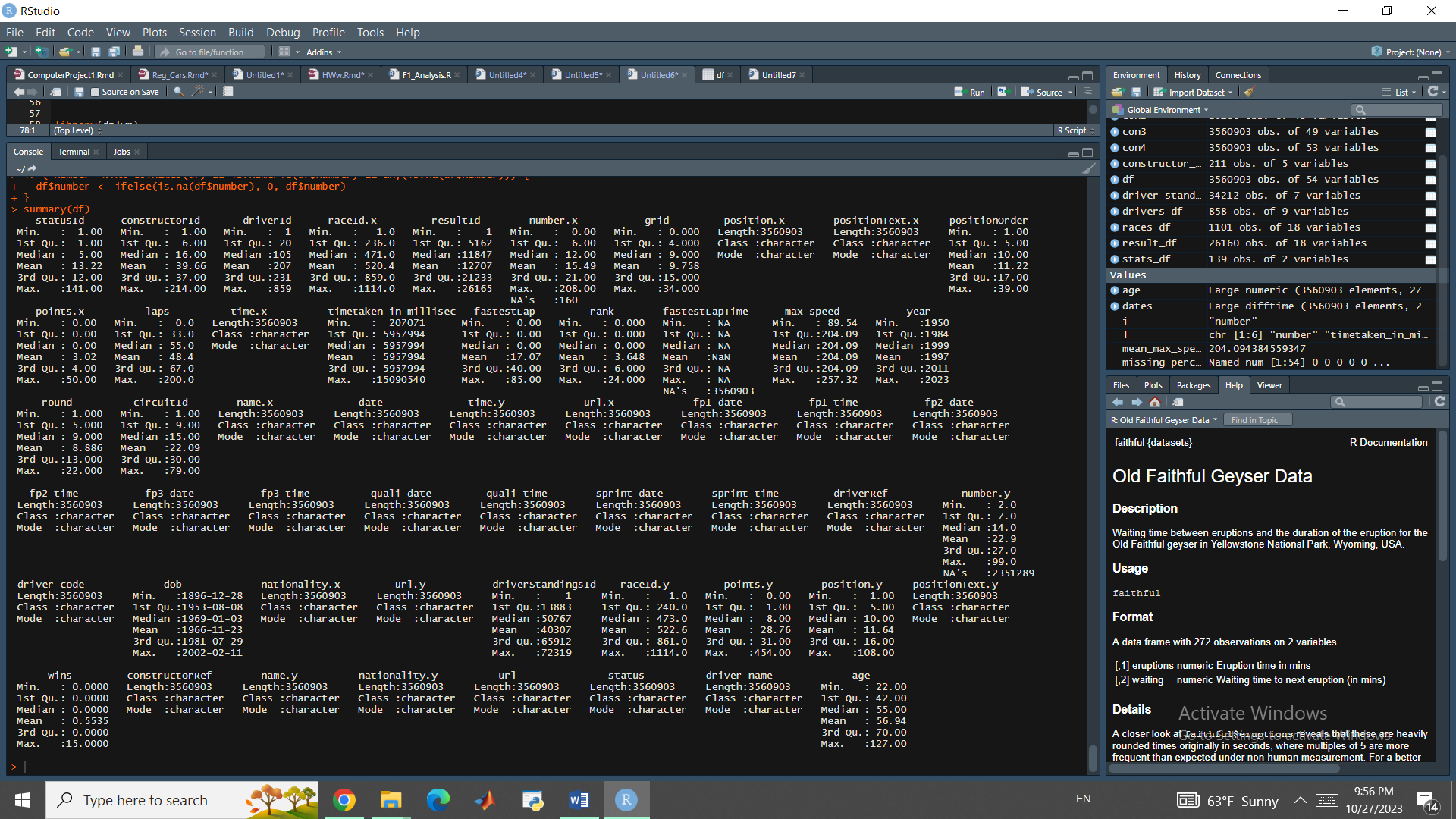


Figure dataset Summary

Now, let’s make some Regression models on our data. The first step is to determine the important factors in our dataset which may affect the race results. Also we need to merge some of the datasets together and remove some of the null entries.

circuits <- read.csv('circuits.csv')

laptimes <- read.csv('lap\_times.csv')

pitstops <- read.csv('pit\_stops.csv')

seasons <- read.csv('seasons.csv')

status <- read.csv('status.csv')

constructor\_standings <- read.csv('constructor\_standings.csv')

constructors <- read.csv('constructors.csv')

driver\_standings <- read.csv('driver\_standings.csv')

drivers <- read.csv('drivers.csv')

races <- read.csv('races.csv')

constructor\_results <- read.csv('constructor\_results.csv')

results <- read.csv('results.csv')

qualifying <- read.csv('qualifying.csv')

# Merge 'results' and 'races' dataframes on 'raceId' column

df <- merge(results, races[c('raceId', 'year', 'name', 'round', 'date')], by = 'raceId', all.x = TRUE)

# Merge 'df' and 'drivers' dataframes on 'driverId' column

df <- merge(df, drivers[c('driverId', 'driverRef', 'forename', 'surname', 'nationality', 'dob')], by = 'driverId', all.x = TRUE)

# Merge 'df' and 'constructors' dataframes on 'constructorId' column

df <- merge(df, constructors[c('constructorId', 'name', 'nationality')], by = 'constructorId', all.x = TRUE)

# Merge 'df' and 'status' dataframes on 'statusId' column

df <- merge(df, status[c('statusId', 'status')], by = 'statusId', all.x = TRUE)

substituting some of the unrecognizable missing values with “NA”:

df <- as.data.frame(lapply(df, function(x) gsub("\\\\N", "NA", x)))

selecting a specific year to run our model since the whole dataset is way too big.

df\_2022 <- subset(df, year == 2022)

Converting an important predictor factor, fastestLapTime, to usable format by making it to seconds:

# Define a custom function to convert lap time

convert\_lap\_time <- function(time\_str) {

if (is.character(time\_str)) {

time\_parts <- as.numeric(strsplit(time\_str, ":")[[1]])

minutes <- time\_parts[1]

seconds <- time\_parts[2]

return(minutes + seconds / 60)

} else {

return(time\_str)

}

}

# Apply the custom function to convert lap time in 'fastestLapTime' column

df\_2022$fastestLapTime <- sapply(df\_2022$fastestLapTime, convert\_lap\_time)

# Convert 'fastestLapTime' column to numeric

df\_2022$fastestLapTime <- as.numeric(df\_2022$fastestLapTime)

Now that we have edited our dataset a little bit it is time to select our variables for our model.

Obviously, the response variable is the race result which is:

“positionOrder”

Variable and our predictors will be:

"raceId", "grid", "points", "laps", "fastestLap", "fastestLapTime"

X <- df\_2022[, c("raceId", "grid", "points", "laps", "fastestLap", "fastestLapTime")]

y <- df\_2022$positionOrder

Now let’s divide the data into test and train sub parts:

set.seed(17)

# Calculate the number of rows for the test set

test\_size <- round(nrow(X) \* 0.3)

# Generate random indices for the test set

test\_indices <- sample(1:nrow(X), test\_size)

# Split the data into training and testing sets

X\_train <- X[-test\_indices, ]

X\_test <- X[test\_indices, ]

y\_train <- y[-test\_indices]

y\_test <- y[test\_indices]

After renaming the test and train variables as X and y again:

data1 <- cbind.data.frame(y, X)

# Build a linear regression model

model1 <- lm(y ~ ., data = data1)

Using Summary() functions the results are:

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.265 on 256 degrees of freedom

(14 observations deleted due to missingness)

Multiple R-squared: 0.9696, Adjusted R-squared: 0.9495

F-statistic: 48.26 on 169 and 256 DF, p-value: < 2.2e-16

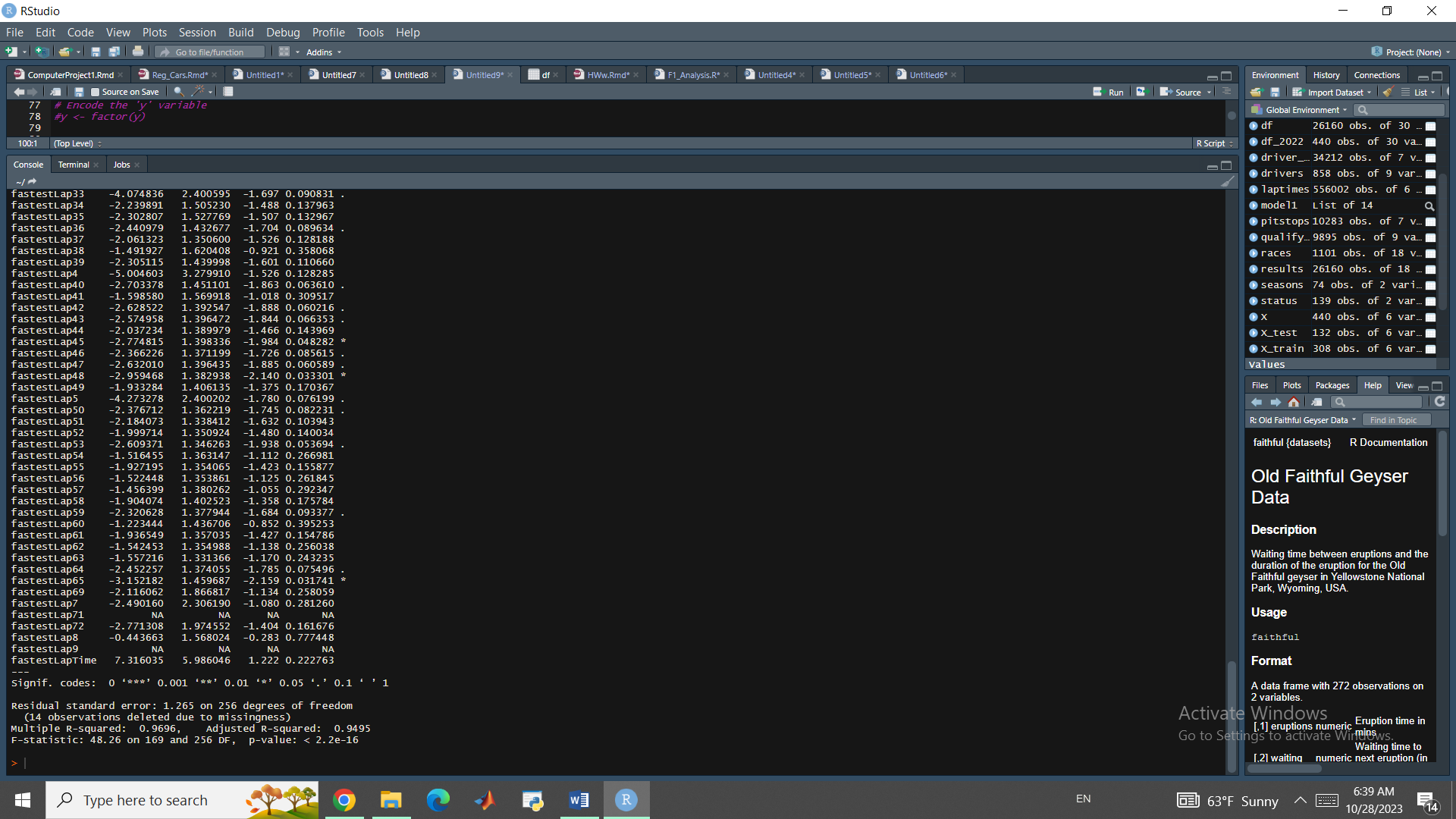


Figure Linear Regression Model Summary

As you can see R2 value is around 97% which shows that this model can predict the outcome of the race pretty well.

*Conclusion*

Based on the Formula 1 statistical analysis conducted, we gained valuable insights through various visualizations, comparisons of driver wins and Grand Prixes as well as the development of a linear regression model.

The analysis revealed a strong correlation between qualifying results (where a driver starts) and their finishing position. This correlation emphasizes the importance of a good qualifying position for achieving a favorable race outcome. Specifically, drivers starting in 1st position exhibited a win rate of 42%, while those starting in 2nd position had a win rate of 23%. The qualifying feature was identified as the most influential factor for race outcomes, with a feature importance score of 0.375. Other features demonstrated minimal impact, with values below 0.02.

In terms of feature engineering, several strategies were employed to enhance the predictive power of the model. Aggregation features were created by grouping data based on driver, team, and race. Historical finishing positions, historical qualifying positions, previous year's performance, car reliability, driver reliability, current season performance, total team experience, total driver experience and relative qualifying time deltas were among the engineered features.

We trained different types of models. One of the model was trained with different target options, including categorical, numeric and binary targets. Binary targets were particularly relevant due to their ability to address target imbalance. The binary targets focused on predicting the winner, top two finishers, or top three finishers (podium).

The linear regression model demonstrated high performance, with an R2 of approximately 97%. This indicates that the model is capable of accurately predicting race outcomes. The combination of feature engineering, the consideration of qualifying results and the creation of binary target variables contributed to the model's effectiveness.

In conclusion, the statistical analysis of Formula 1 data provided valuable insights into the factors influencing race outcomes. The comparison between drivers showed the importance of the human factor and the correlation between qualifying results and finishing positions highlighted the significance of a favorable starting position. Feature engineering techniques, including aggregation features and the incorporation of historical and current performance data, enhanced the predictive power of the model. The developed linear regression model exhibited exceptional accuracy, enabling reliable predictions of race outcomes.

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