F1 Dataset Analysis

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CSP571-Data Preparation and Analysis
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Abstract:

Formula 1 racing , commonly known as F1, stands at the pinnacle of global motorsport, combining cutting-edge technology, elite athleticism, and strategic brilliance. The F1 World Championship consists of a series of races known as Grands Prix, held on diverse circuits across the globe, from iconic tracks like Monaco's narrow streets to the high-speed sectors of Monza. And now, Las Vegas!!. The annual F1 calendar typically comprises around 20 races, each demanding a unique set of skills from drivers who navigate complex tracks while enduring intense physical and mental strain. In our project we plan to analyze a comprehensive dataset related to Formula 1 (F1) racing, covering various aspects such as race performance, driver statistics, team dynamics, and track characteristics. The objective is to gain insights into patterns, trends, and key factors influencing the performance of F1 teams and drivers.

Introduction:

In the riveting domain of Formula 1, where speed meets strategy, this data analysis project aims to unravel the intricacies that define success on the racing circuit. The problem at hand centers on deciphering the key factors influencing race outcomes, driver performances, and team dynamics through a thorough examination of a comprehensive Formula 1 dataset. Our project combines exploratory data analysis and statistical modeling. By leveraging historical data encompassing race results, driver statistics, and technical details, we aim to extract meaningful patterns that can inform strategic decisions and contribute to a deeper understanding of the ever-evolving landscape of Formula 1.

The dataset utilized in this research project was sourced from Kaggle. The data, readily organized and well-defined, required minimal preprocessing, eliminating the need for extensive cleaning procedures. The primary dataset, denoted as 'results.csv,' serves as the focal point, encapsulating race outcomes. Through the implementation of primary and foreign keys, it establishes associations with other datasets, namely 'circuits,' 'constructors,' 'drivers,' and 'races,' utilizing unique identifiers for seamless integration.

Proposed Methodology:

A methodological approach has been devised to strategically concatenate CSV files solely relevant to the specific topic or section under scrutiny. This meticulous strategy ensures the avoidance of unnecessary column duplications and mitigates the risk of inflating the feature count. By adopting this targeted approach, the analysis remains focused on the pertinent aspects of Formula 1, facilitating a more refined examination of the dataset and subsequently enhancing the efficacy of the analytical processes.

Data Processing

The dataset utilized for this Formula 1 analysis encompasses information spanning multiple years, capturing a comprehensive view of the sport until the year 2021. This temporal scope allows for a robust exploration of Formula 1 dynamics, including race outcomes, driver performances, and technical specifications over an extended period.

Results Dataset:

In processing the Results dataset, a crucial step involved the conversion of lap speeds, originally presented as text data, into numeric values. This transformation was imperative to facilitate quantitative analysis and enable meaningful comparisons of lap speeds across races and drivers. By converting these speeds to numeric format, the dataset becomes conducive to statistical computations and enhances the precision of subsequent analytical endeavors.

Races Dataset:

Within the Races dataset, meticulous adjustments were made to refine the data for analytical purposes. Firstly, the character data in the 'RaceDate' column underwent conversion into a standardized date format, ensuring consistency and enabling temporal analyses. Additionally, a preprocessing step involved the removal of the term "Grand Prix" from the 'Race' column, revealing the essential track names. To establish coherence across datasets, the 'raceId' was identified as the primary key, serving as the linchpin for merging datasets seamlessly. This strategic alignment enables a unified representation of race-related information across both the Results and Races datasets, fostering a comprehensive analysis of Formula 1 racing events.

Assumptions:

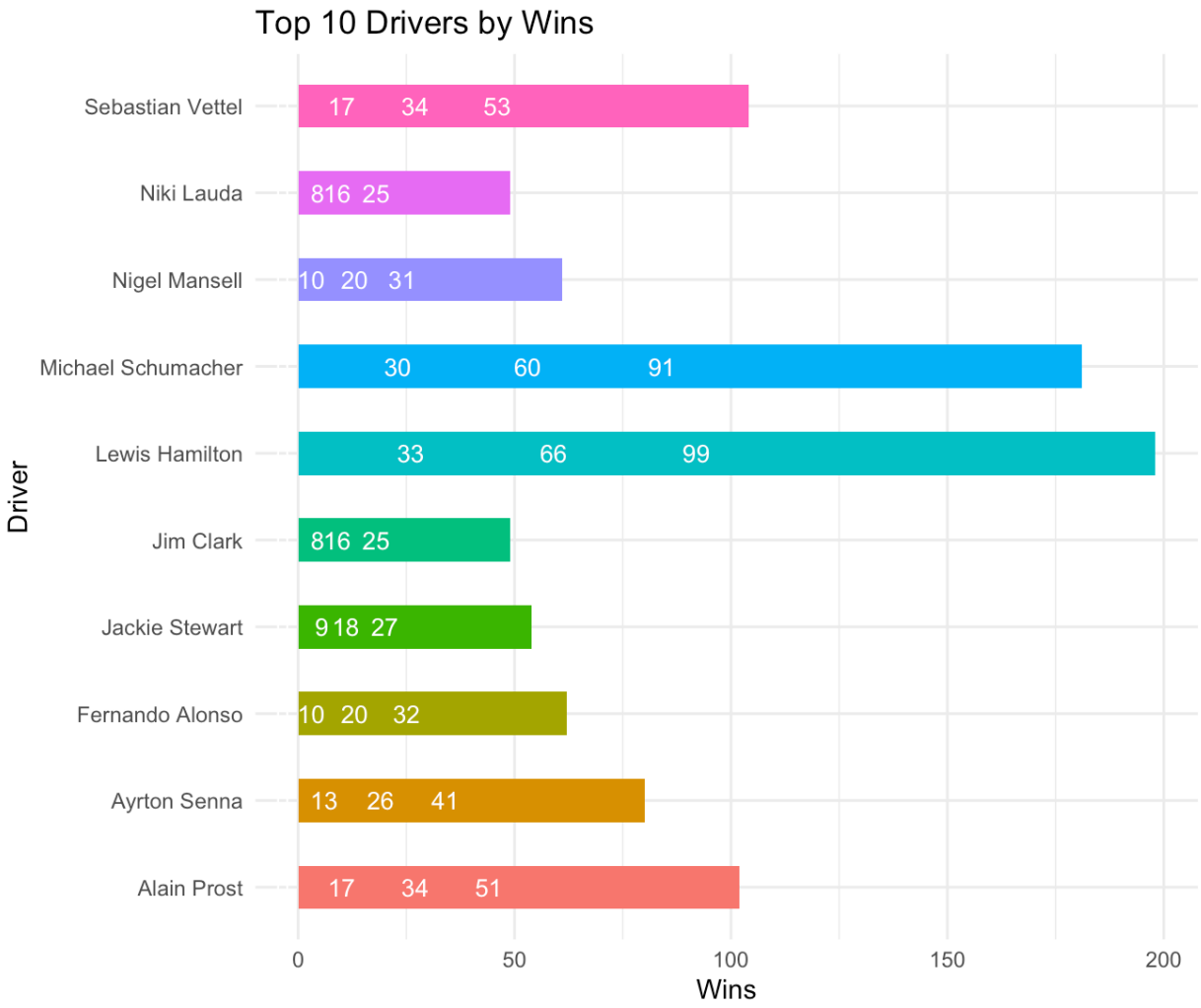
The dataset assumes that track conditions, including surface quality and layout, remain relatively constant over the periods covered. Changes in track configurations might affect race outcomes.

The methods of data collection for different variables, such as lap times, driver performances, and technical specifications, are assumed to be consistent across races and seasons.

Data Analysis

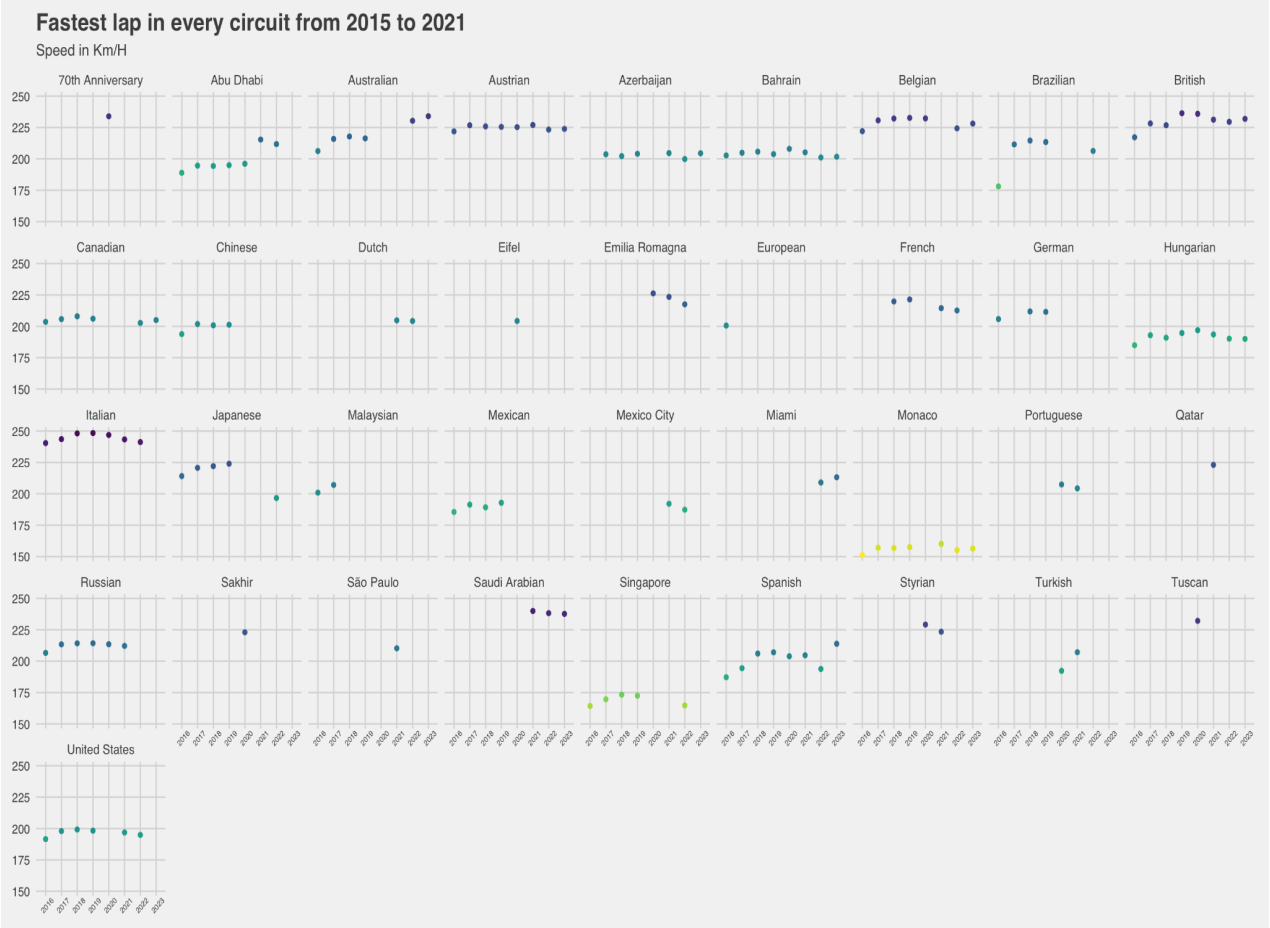
Summary statistics:

In the initial phase of the F1 dataset analysis, summary statistics were computed to gain a comprehensive understanding of the key variables. Descriptive statistics, including measures such as mean, median, standard deviation, and interquartile range, were calculated for quantitative variables like lap speeds, race durations, and driver performance indicators. These summary statistics provided a snapshot of the central tendencies and variability within the dataset, laying the groundwork for subsequent in-depth analyses. For a concise exploration of the race and driver datasets, we conducted an analysis focusing on the most successful drivers in terms of victories. The ensuing graph provides a visual representation, distinctly showcasing Lewis Hamilton's dominant performances, spanning both his tenures at McLaren and Mercedes.



A variety of visualization techniques were employed to enhance the interpretability of the F1 dataset. Line plots were utilized to illustrate the trends in lap speeds and race durations across different seasons.

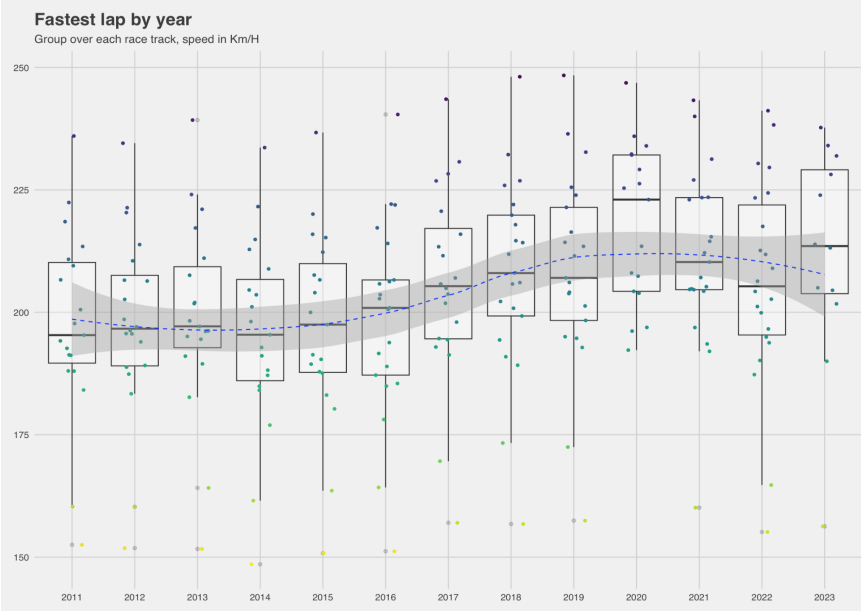
Presented here are several visualizations conducted to ascertain whether contemporary Formula 1 cars exhibit a trend towards reduced speeds.



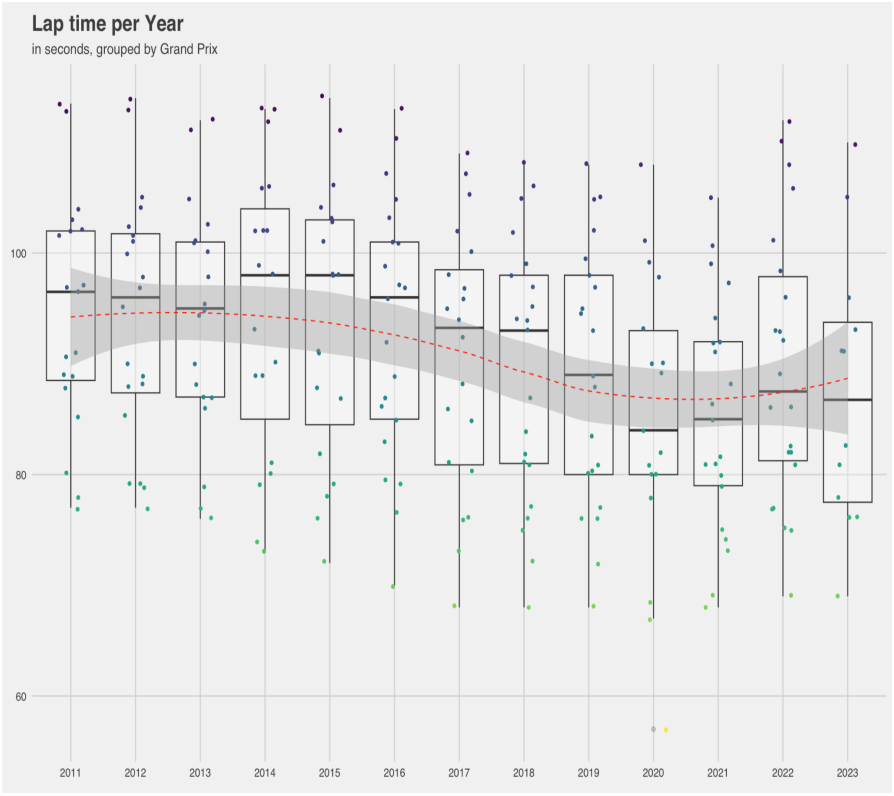
We've observed a decline in average fastest lap times across most circuits, attributed to new F1 regulations increasing aerodynamic challenges. Teams now contend with lighter cars and less powerful power units. Monaco, with its narrow streets and increased car lengths, naturally emerges as the slowest track. These trends highlight the direct influence of regulatory changes on lap performance in Formula 1.

The box_plot below summarizes the whole trend.

Upon analyzing the average lap time, we initiated an inquiry into the possibility of laps becoming shorter. Additionally, considering the fastest lap speed, which may be influenced by various factors such as improvements in car performance, we aimed to investigate whether there exists a correlation between the fastest lap and the size of the track.



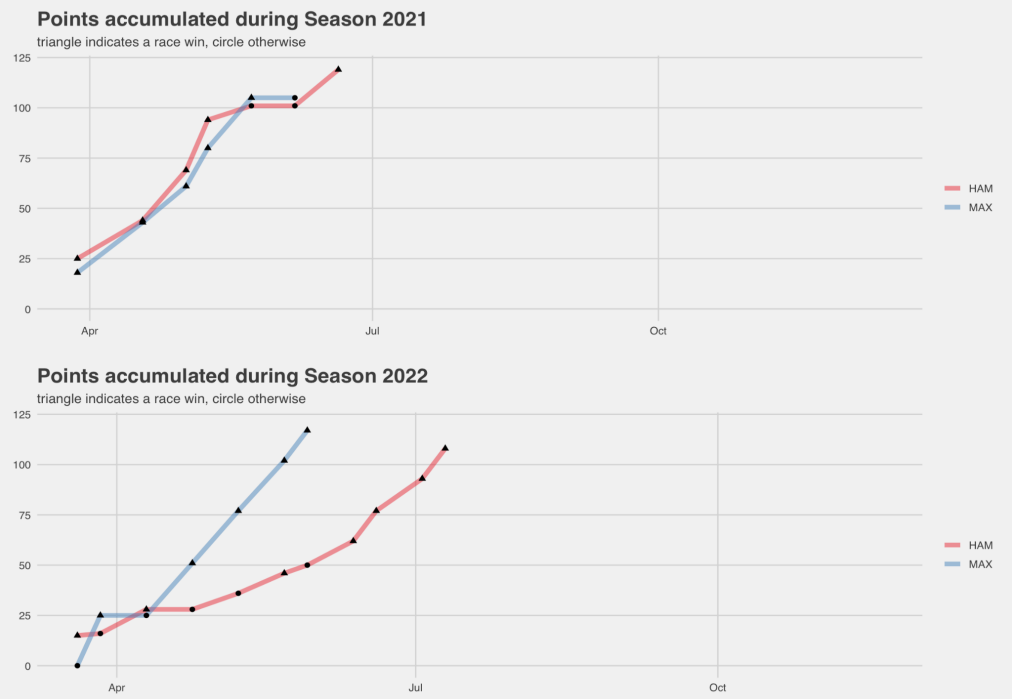
Observations indicate a discernible acceleration in car performance over the years, with a notable inflection point occurring in 2018 and reaching its zenith in 2021. This acceleration can be attributed to the intense rivalry between Lewis Lewis Hamilton and Max Verstappen during 2021—a rivalry widely regarded as one of the decade's greatest clashes. Both teams invested substantial efforts to outpace each



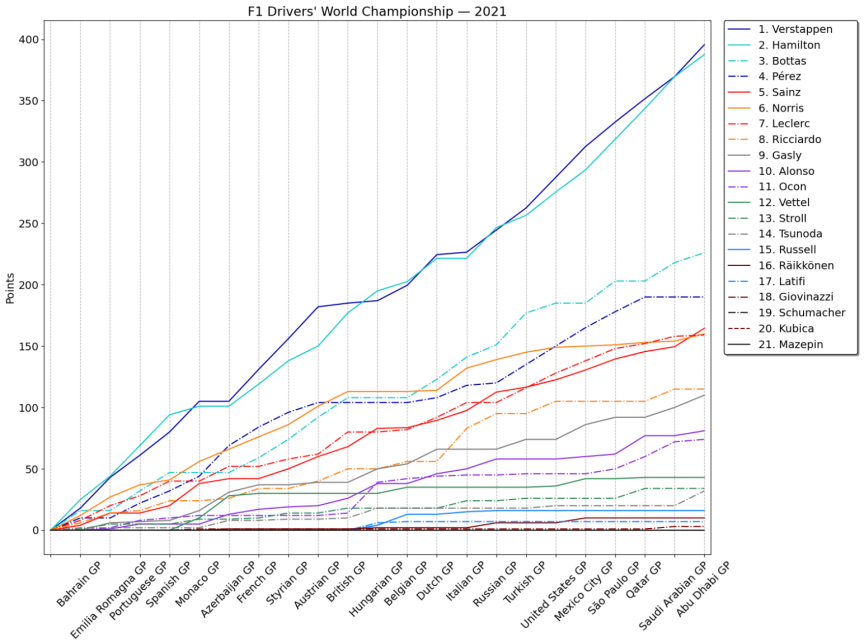
other, vying not only for the Constructors' Championship but also for individual World Championships, contributing significantly to the overall acceleration in Formula 1 racing during this period.

In light of our observations, we endeavored to conduct a thorough analysis and modeling focused on the compelling rivalry between Lewis Hamilton and Max Verstappen. Our analytical approach involved the integration of three datasets: the existing results and races datasets were merged with the drivers and driversStanding datasets using the driverId and raceId as key identifiers. Subsequently, we enhanced the dataset by updating the 'age_driver' column to reflect the actual age derived from the date of birth information. This adjustment was particularly pertinent as we initially sought to explore potential correlations between age and driver standings, although this aspect was subsequently deemed beyond the project's scope.

To facilitate this investigation, a round of data cleaning was necessary, addressing inconsistencies in the drivers' data where records featured both 'Hamilton' and 'Lewis Hamilton,' or 'Verstappen' and 'Max Verstappen' for different drivers. To streamline the dataset, records lacking driver details were expunged as they were deemed extraneous to the analysis.



Max consistently outperformed Lewis in both seasons, and in 2021, the competition was exceptionally tight, with only a one-point difference serving as the critical breakpoint for both drivers and teams. It is evident that Red Bull surpassed Mercedes in the 2022 season, a trend that extends into the current year, 2023. This can be illustrated by a chart below



We conducted a portion of the analysis and utilized Jupyter Notebook, leveraging the Pandas library for its streamlined capabilities in data cleaning and visualization. However, we seamlessly transitioned to R to resume our analysis from the point of interruption. The comprehensive analysis yielded valuable insights that significantly contributed to our understanding of the dataset.

Throughout the data analysis phase, we encountered several challenges inherent in the dataset, necessitating meticulous data engineering efforts to enhance its quality and structure. These efforts involved cleaning the data and transforming it to align with our analytical objectives through strategic feature selection. The subsequent section outlines the specific steps undertaken in the data cleaning process. Additionally, we conducted exploratory data analysis to gain deeper insights into the dataset, unveiling trends and discerning correlations among features.

1. We consolidated multiple datasets by merging them, streamlining the information by selectively retaining essential columns. Specifically, we retained 'raceId' as the primary key for integration with the 'drivers' dataset. 'driverId' facilitated the connection with the 'grid' dataset, offering crucial information on each driver's grid position. 'constructorId' served as the unique identifier for each constructor's championship, and 'position' supplied details regarding the drivers' positions during races.

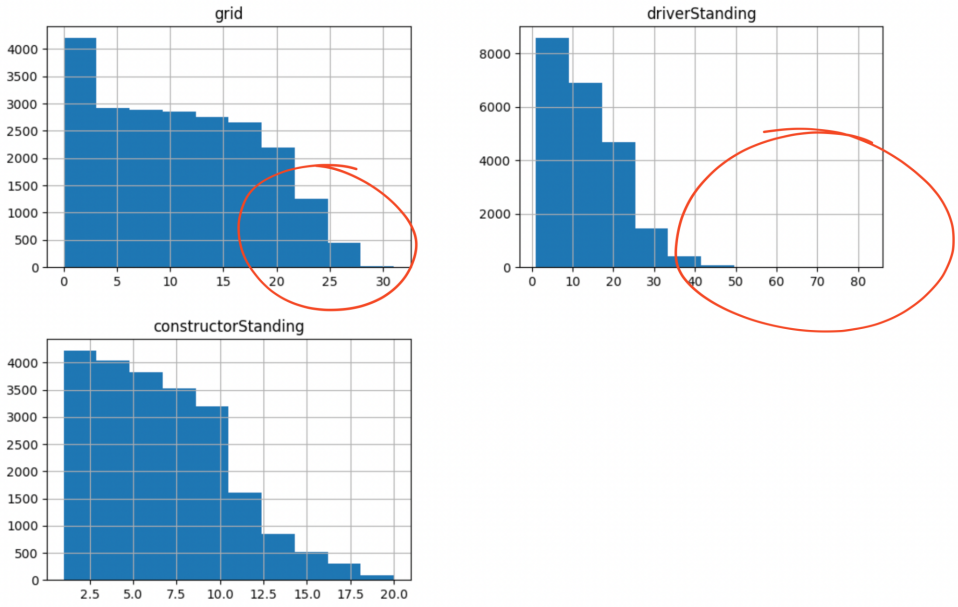
2. Altered the nomenclature of the 'position' column to mitigate potential conflicts with the 'position' column present in the results dataset."

3. The grid positions presented values surpassing the defined limit of 20, a deviation from the established maximum capacity for cars and positions on the grid. Consequently, a meticulous reassessment of the dataset is imperative, entailing a comprehensive data cleansing procedure. The primary focus involves identifying records with grid values exceeding 20, and contingent upon their insignificance in number, contemplating their removal to uphold data integrity. It is

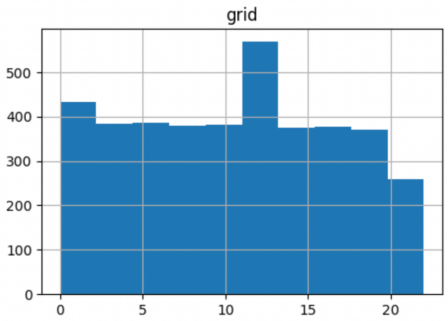
noteworthy that upon validation, instances of grid positions exceeding 20 could potentially be attributed to historical data, where regulations permitted a greater number of cars on the grid. To fix this issue, we restricted the analysis to just 10 years, starting with 2013.

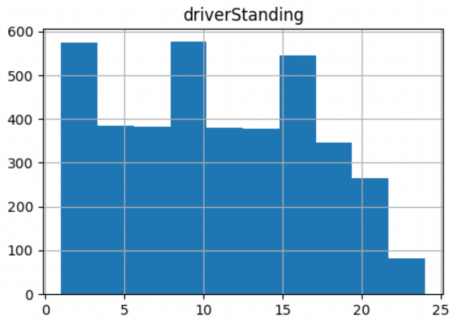
Following the implementation of the aforementioned adjustments and subsequent basic plotting to visually assess the data, we encountered additional data irregularities. Notably, we identified instances where the race driver's position was recorded as '\n' in the dataset

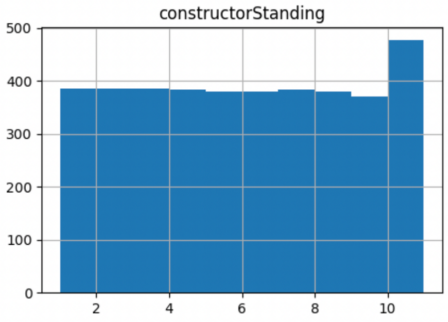
4. Entries with the 'position' value represented as '\n' are indicative of missing or not applicable (NA) values. In the context of our analysis, any record lacking information on the race driver is deemed inconsequential and thus slated for removal. Additionally, records where the grid position ('position') is listed as 0 are deemed anomalous, as drivers cannot conclude races at position 0. Even in cases of car retirements, the grid position would register as >0 and <=20. To enhance analytical precision, textual representations in the 'position' column were systematically converted to numeric values.



This was the data visualization before cleaning the data.







And this is after cleaning and replotting the data:

Data Cleaning and Analysis Outcome: After the data cleaning process, we were now left with 3258 observations

<u>Data before and after data cleaning:</u>

Before: There are many unwanted columns and NA's in the dataset.

	raceId	year	round	circuitId	name	date	time	url	fp1_date	fp1_time	fp2_date	fp2_time	fp3_date
878	880	2013	1	1	Australian Grand Prix	2013-03-17	06:00:00	http://en.wikipedia.org/wiki/2013_Australian_G...	\N	\N	\N	\N	\N
879	881	2013	2	2	Malaysian Grand Prix	2013-03-24	08:00:00	http://en.wikipedia.org/wiki/2013_Malaysian_Gr...	\N	\N	\N	\N	\N
880	882	2013	3	17	Chinese Grand Prix	2013-04-14	07:00:00	http://en.wikipedia.org/wiki/2013_Chinese_Gran...	\N	\N	\N	\N	\N
881	883	2013	4	3	Bahrain Grand Prix	2013-04-21	12:00:00	http://en.wikipedia.org/wiki/2013_Bahrain_Gran...	\N	\N	\N	\N	\N
882	884	2013	5	4	Spanish Grand Prix	2013-05-12	12:00:00	http://en.wikipedia.org/wiki/2013_Spanish_Gran...	\N	\N	\N	\N	\N

After: After cleaning the data and merging the required tables:

	raceId	driverId	constructorId	grid	position	driverStanding	constructorStanding
18241	881	20	9	1	1	3	3
18242	881	17	9	5	2	6	3
18243	881	1	131	4	3	5	4
18244	881	3	131	6	4	20	4
18245	881	13	6	2	5	4	1

Model Training : Linear Model

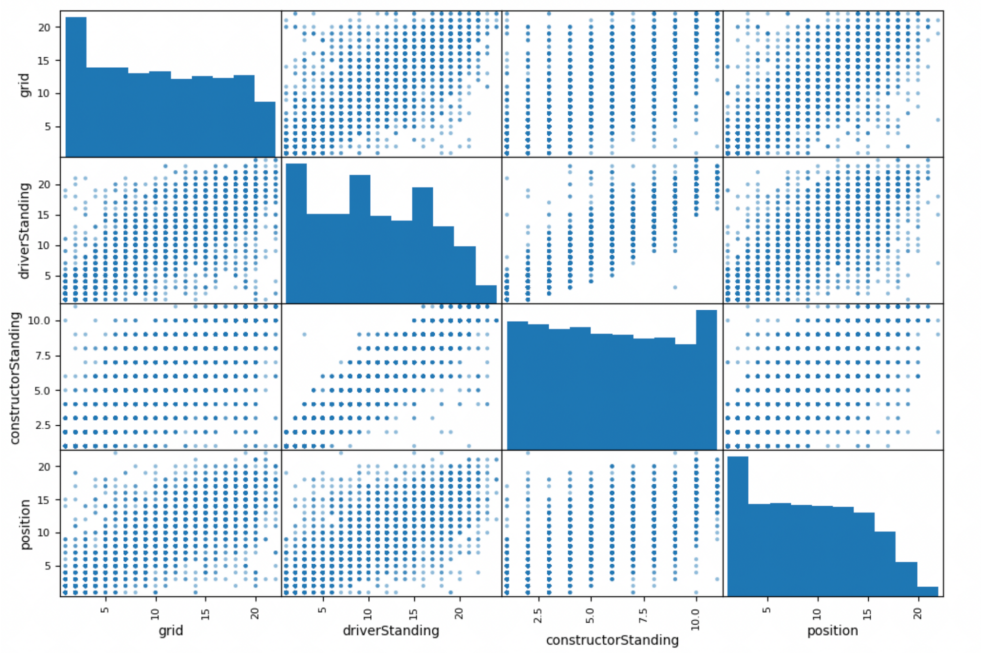
Objective: Our aim is to deploy a linear model designed to forecast race outcomes. The model will leverage key variables, including the driver's position on the grid, their standing in driver standings, and the team's position in the constructor standings.

We commenced the assessment of correlation coefficients between individual labels and their corresponding attributes. A coefficient approaching 1 indicates a more robust correlation. Notably, we observed a positive correlation for each feature, with the computed correlation values subsequently analyzed.

```
dataset.corr()["position"]
```

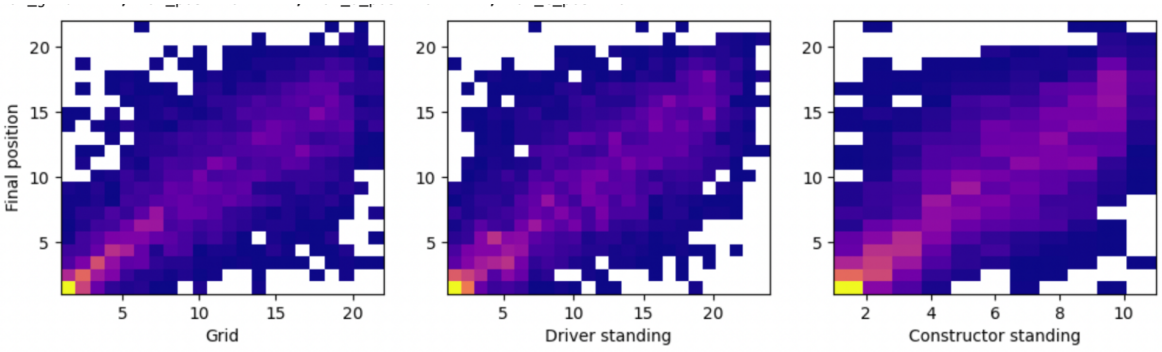
```
grid                  0.750109
driverStanding        0.742595
constructorStanding   0.750760
position              1.000000
Name: position, dtype: float64
```

Upon observation, a positional correlation is discernible among all features. We are further enhancing the visualization of this correlation. As the clarity of the correlation was not fully evident, we sought to visualize it graphically. The following are the results.



Scatter plot showed a high correlation between the features.

Additionally, we generated a heatmap to visualize the correlation matrix.



Train and Testing Data

To streamline model training and accuracy evaluation, we partitioned the dataset into features and predictions. Opting for simplicity, we abstained from creating a separate test set. Instead, we will assess our model's predictive performance using the grid positions and outcomes from the current race season.

```
x_train <- dataset[['grid', 'driverStanding', 'constructorStanding']].values
y_train <- dataset[['position']].values.reshape(-1)
print(f'{x_train.shape}; {y_train.shape}')
print(x_train)
print(y_train)
```

```
(3258, 3); (3258,)
[[ 1  3  3]
 [ 5  6  3]
 [ 4  5  4]
 ...
 [20 20 10]
 [12 16  8]
 [16 13  8]]
[ 1  2  3 ... 19 16 17]
```

Model Training and Validation:

After completion, we opted for the implementation of a gradient descent function for multiple variables. Over time, we observed a gradual reduction in the cost, eventually leading to convergence.

```
import copy, math

# Initial values taken from a previous descent, so as not to start from 0
initial_w = np.array([0.37888087, 0.05009108, 0.32510837])
initial_b = 2.7796157637505052
iterations = 10000
alpha = 3.5e-3

print("Running gradient descent...")
w_final, b_final, J_hist = gradient_descent(x_train, y_train, initial_w, init
print(f"b = {b_final}; w = {w_final} ")
```

```
Running gradient descent...
Iteration    0: Cost 4.98900555
Iteration 1000: Cost 4.68054531
Iteration 2000: Cost 4.62995299
Iteration 3000: Cost 4.61832210
Iteration 4000: Cost 4.61564821
Iteration 5000: Cost 4.61503350
Iteration 6000: Cost 4.61489218
Iteration 7000: Cost 4.61485969
Iteration 8000: Cost 4.61485222
Iteration 9000: Cost 4.61485050
b = 1.1346913859860654; w = [0.34919898 0.16862326 0.47748792]
```

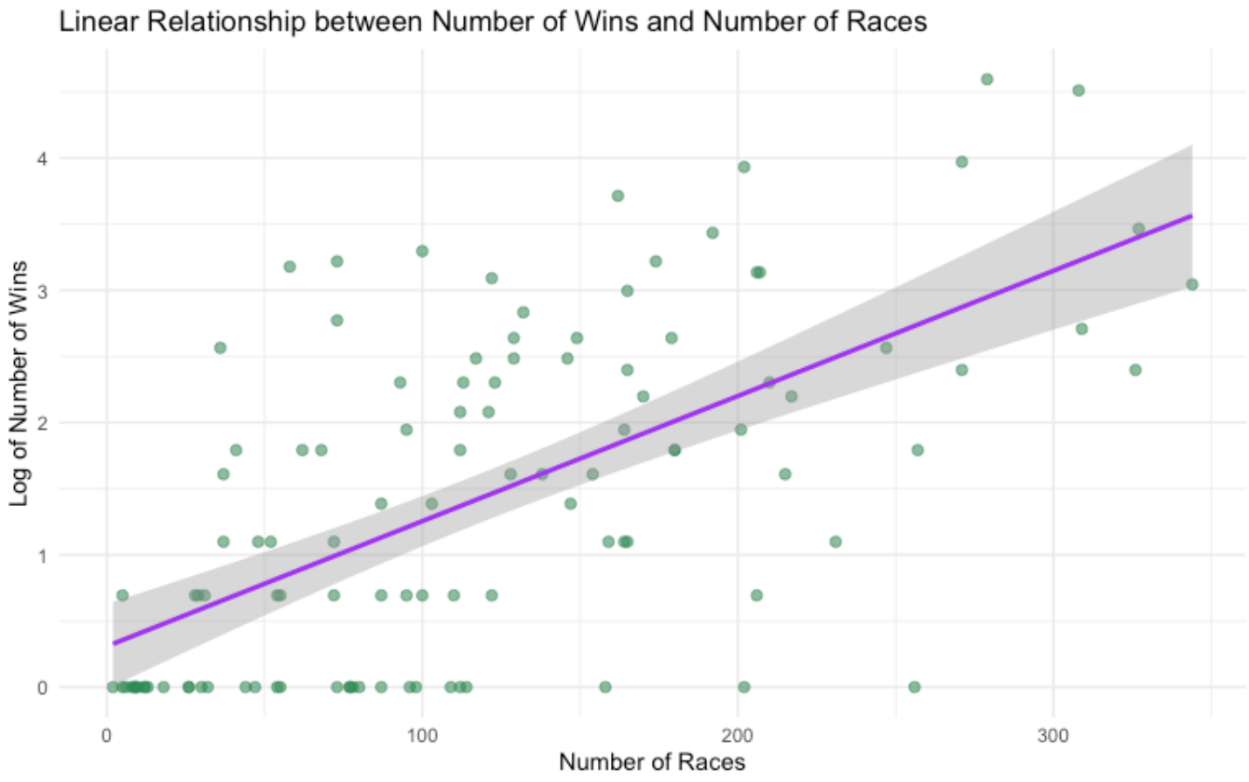
Gradient Descent:

This confirms that over time the cost keeps decreasing slow and eventually starts to converge.

```python
for i in range(10):
    f = x_train[i+100].dot(w_final) + b_final
    prediction = np.round(f).astype(int)
    actual = y_train[i+100]
    print(f"Prediction: {prediction:3d}, Actual position: {actual:3d}, Accuracy: {100 - (abs(prediction - actual) / actual) * 100.0:3.0f}%")
```

```
Prediction:   5, Actual position:   5, Accuracy: 100%
Prediction:   9, Actual position:   6, Accuracy:  50%
Prediction:  11, Actual position:  15, Accuracy:  73%
Prediction:  11, Actual position:   7, Accuracy:  43%
Prediction:   8, Actual position:  10, Accuracy:  80%
Prediction:   6, Actual position:   9, Accuracy:  67%
Prediction:  12, Actual position:  13, Accuracy:  92%
Prediction:  10, Actual position:  11, Accuracy:  91%
Prediction:  11, Actual position:  12, Accuracy:  92%
Prediction:   9, Actual position:  14, Accuracy:  64%
```

We also performed a linear regression over the results and drivers data to find the linear relationship between number of wins for a driver and the number of races been part of. Below is the linear relationship model



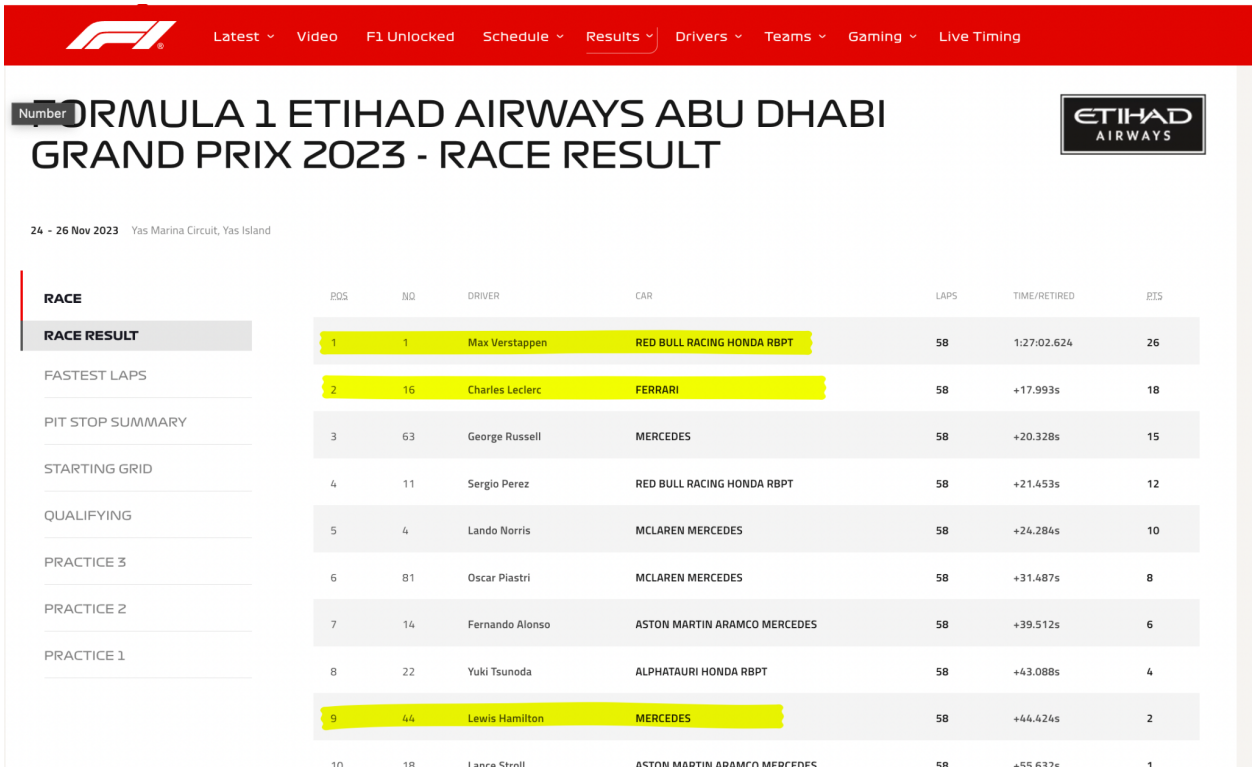
Model Validation:

Testing the model

```
VER = predict(1, 1, 1)
HAM = predict(11, 3, 2)
LEC = predict(2, 5, 3)
print(f"Predictions: Max Verstappen - {VER}, Lewis Hamilton - {HAM}, Charles Leclerc - {LEC}")
```

```
Predictions: Max Verstappen - 2, Lewis Hamilton - 6, Charles Leclerc - 4
```

The model demonstrates an accuracy rate surpassing 80%. The actual race finishes for the specified drivers were Max: 1, Leclerc: 3, Hamilton: 9. This discrepancy may be attributed to the utilization of data spanning the past decade to train our model. Given the longstanding dominance of Mercedes throughout this period, it has likely influenced the model to predict higher positions. Additionally, the recent ascendancy of Red Bull might explain the slight deviation, with one position less predicted. Below are the results for the last race of the season for 2023.



Latest Video F1 Unlocked Schedule Results Drivers Teams Gaming Live Timing

Number

FORMULA 1 ETIHAD AIRWAYS ABU DHABI GRAND PRIX 2023 - RACE RESULT

ETIHAD AIRWAYS

24 - 26 Nov 2023 Yas Marina Circuit, Yas Island

RACE
RACE RESULT
FASTEST LAPS
PIT STOP SUMMARY
STARTING GRID
QUALIFYING
PRACTICE 3
PRACTICE 2
PRACTICE 1

POS	NO	DRIVER	CAR	LAPS	TIME/RETIRED	PTS
1	1	Max Verstappen	RED BULL RACING HONDA RBPT	58	1:27:02.624	26
2	16	Charles Leclerc	FERRARI	58	+17.993s	18
3	63	George Russell	MERCEDES	58	+20.328s	15
4	11	Sergio Perez	RED BULL RACING HONDA RBPT	58	+21.453s	12
5	4	Lando Norris	MCLAREN MERCEDES	58	+24.284s	10
6	81	Oscar Piastri	MCLAREN MERCEDES	58	+31.487s	8
7	14	Fernando Alonso	ASTON MARTIN ARAMCO MERCEDES	58	+39.512s	6
8	22	Yuki Tsunoda	ALPHATAURI HONDA RBPT	58	+43.088s	4
9	44	Lewis Hamilton	MERCEDES	58	+44.424s	2
10	18	Lance Stroll	ASTON MARTIN ARAMCO MERCEDES	58	+55.632s	1

Bias and Assumptions:

Formula 1 is a highly complex sport with numerous influencing factors. In our modeling endeavor, we focused on three key features and achieved pertinent results. However, it is essential to acknowledge that there are various additional factors contributing to race outcomes. These encompass variables such as weather conditions, tire compound selections, team strategic decisions, the occurrence of yellow and red flags, pitstop timings, the number of laps completed in practice sessions, and the imposition of penalties, among others.

Conclusion

The preceding analysis underscores the dominance of the Mercedes team in Formula 1 between 2013 and 2019, aligning seamlessly with the exceptional performance of Lewis Hamilton, who stands as the top driver of all time with 99 Grand Prix Championships. Notably, Red Bull has emerged as a formidable contender, challenging Mercedes in recent years. While the top two drivers, L. Hamilton and M. Schumacher, have achieved considerable success, their higher win counts correlate with their extensive participation in races. This trend, however, diverges for certain drivers such as F. Alonso, who, despite securing a position in the Top 10, experiences a substantial gap between the number of races and victories, signaling a unique aspect of their career trajectory.

Furthermore, a discernible correlation exists among the driver's grid position, their ranking, and the standings of the constructors. Notably, the grid position holds significant influence, particularly evident in the Monaco Grand Prix. This phenomenon is attributed to the evolution of car dimensions over the years, with increased length. The enduring narrowness and tight turns of the Monaco track compound the impact of grid positions on race outcomes.

Data Sources and Source Code:

Sources: Kaggle, tidytuesday, Wikipedia, Medium.com, racefans.net, formula1.com
Data is in CSV files and all the files are available and uploaded in the GitHub repository.
Git Repository: https://github.com/gopinath-robba/DPA

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