Actuarial data science

“Analysis of the pit crew performance and its relationship to the Formula 1 championship standings”

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Abstract

This study investigates the role of pit crew efficiency in Formula 1 by identifying the best performing teams in pit stops and analyzing the impact on overall performance. The focus is on the seasons 2011 to 2023 where complete data have been gathered. A "Pit Stop Championship" was developed, ranking drivers and awarding points based on the average time spent in the pit lane for each race. The distribution of points follows the same pattern as the official Formula 1 Championship ranking. This provides a baseline to compare ranks and points between our “Pit Stop Championship” and the official Formula 1 Championship. This analysis has been conducted for both the individual drivers and the constructors. The analysis revealed that the top performing teams; “Red Bull”, “Mercedes”, “Ferrari” and “McLaren”, all consistently performed well in the “Pit Stop Championship” as well as in the official championship. “Red Bull” has dominated our ranking for the last 5 seasons in line with their recent success. The linear and rank-based correlation analysis found strong relationship between pit stop efficiency and overall race performance. A simple OLS regression model also highlights the relevance of the pit crew in Formula 1. These findings underscore the critical role of pit crew efficiency in Formula 1 with more efficient teams achieving significantly higher standings. Future work could expand the analysis to compare the relationships season by season allowing to get more precise understanding of the relationship between pit crew efficiency and overall performance. Another interesting approach would be to include other potential explanatory variables for the overall performance and explore causal relationships.

Introduction

Formula 1 is a sport of precision, where every second counts. During a race, cars spend dozens of seconds in the pit lane. This time can have a significant impact on the final standings, especially when the gap between positions is often just a few seconds. While car performance and driver skills are often discussed and analyzed, the efficiency of pit crews is less studied, despite its critical role.

This report investigates the performance of Formula 1 teams in the pit lane and explores the relationship between pit stop efficiency and overall performance. By creating a "Pit Stop Championship", we rank teams based on their average pit stop times and compare these rankings with the official Formula 1 standings. The goal is to identify the teams that performed the best and whether pit stop performance correlates with overall success in the drivers and constructors' championships.

The report is structured as follows:

1. Data Characteristics
2. Model Selection and Interpretation
    - Pit Stop Championship
    - Metrics and Models for the Relationship
3. Summary and Concluding Remarks

Data Characteristics

The dataset consists of all available information on the Formula 1 races, drivers, constructors, qualifying, circuits, lap times, pit stops, championships from 1950 to the current 2024 season. We found this dataset on Kaggle. We used information scattered across several dataframes imported as csv files, more specifically the lap times, the pit stops, the circuits, the drivers, the races, the status, the driver standings, the results, and the constructors. These dataframes are linked together through driver IDs and race IDs.

The study focuses on utilizing pit stop data to assess the performance of the teams in this area and to show a potential relationship to the drivers and constructors' official championships. The pit stop dataframe has both identifications columns: driver ID and race ID (integers), as well as the number of the stop in a specific race, for a specific driver (integer), the lap this stop took place (integer), the time the stop happened (object), the duration of the stop (object) and the duration in milliseconds (integer). We have panel data due to the repeated measures for individual drivers over multiple stops and multiple races.

	raceId	driverId	stop	lap	time	duration	milliseconds
0	841	153	1	1	17:05:23	26.898	26898
1	841	30	1	1	17:05:52	25.021	25021
2	841	17	1	11	17:20:48	23.426	23426
3	841	4	1	12	17:22:34	23.251	23251
4	841	13	1	13	17:24:10	23.842	23842

Figure 1. Original pit stop dataframe

The main variable we will need for our model is the duration, which represents the time spent in the pit lane for a specific stop. One could argue to use the stopping time, if available, to focus only on the work of pit crew technicians, but the time spent in the pitlane also include strategy and management of traffic that are part of a good pit stop. The first step is to transform the duration values in a float without introducing NaN. We noted that there were no NaN across the 10 990 observations in the original dataframe. A function was created to deal with the different cases encountered: if the stop is more than 1min (e.g. 1:14.221) or less than a minute (e.g. 27.543). We could have used the milliseconds column but wanted to apply a function in our code.

We also had to exclude the "Did Not Finish" (DNF) drivers from our dataset. To do so, we had to create a dataset containing the driver IDs and Race IDs for all non-DNF drivers for a specific race. We selected the corresponding status in the status dataframe: "finished" and every status "+1 lap", "+2 laps", and so on. We limited the valid status to "+3 laps" as we considered the drivers beyond this threshold did not perform well enough to gain points in our "Pit Stop Championship". 200 observations were excluded, corresponding to drivers that could not gain points in the official driver championship, as they are too far from the leader. The goal of this assumption is to avoid having drivers scoring well in the "Pit Stop Championship" while having a bad tire management strategy with one less stop than every other driver in the same race. It would be easier for them to do one good stop even though it was not the right strategy for a particular race, making our “Pit Stop Championship” unfair. Selecting the valid status and matching them with the “Status ID” in the results dataframe we can identify which driver to keep for each race. We applied an inner join to have our filtered pit stop data.

By adding a column with the year from the races data in the pitstop dataframe, we notice that data is only available from 2011. We also excluded the current season 2024 since it is not a complete season, and we are left with 9203 observations. For a better understanding of the data, we dropped some useless columns and added the name of the race and the driver in place of the driver ID and race ID. We could do that matching the races and drivers’ dataframes information.

	stop	duration	name	year	driverRef
0	1	26.898	Australian Grand Prix	2011	alguersuari
1	1	23.426	Australian Grand Prix	2011	webber
2	1	23.251	Australian Grand Prix	2011	alonso
3	1	23.842	Australian Grand Prix	2011	massa
4	1	22.603	Australian Grand Prix	2011	vettel

Figure 2. Our transformed pit stop dataframe

Now we are finally able to show the distribution of our data through a histogram. To be able to see something on the histogram, we had to deal with the outliers. We decided to bring back every outlier to 60 seconds, just to be able to display a better histogram while keeping some information on those extreme points as they will appear in the last bar of the histogram. Further in the study, the data will be used with the outliers as they can reflect issues in the pitlane.

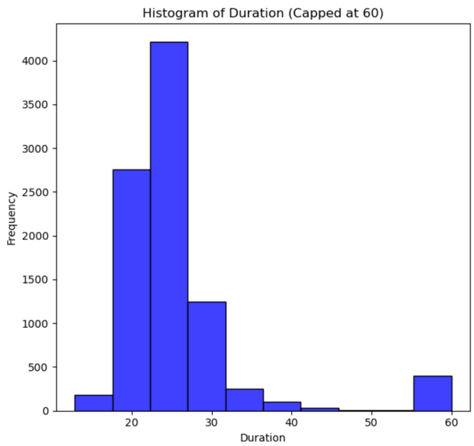

Figure 3. Histogram of pit stop’s duration

We also did a boxplot to show the distribution of our data.

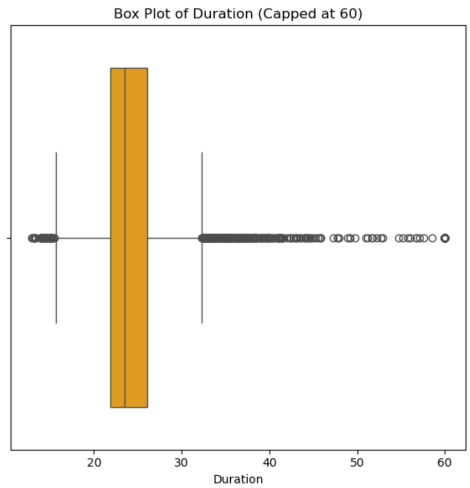

Figure 4. Box plot of pit stop’s duration

We observed a median at 23.529 and a mean at 82.347 highlighting the presence of outliers. We checked the highest durations and found out they happened in the same races when the race was interrupted (e.g. Silverstone 2022). It was recorded that all drivers stayed in the pit lane until the race resumed creating those outliers. They do not have significant impact on our championship since they impacted every driver equally. For the lowest durations, we did not notice any abnormal observations. They come from racetracks with shorter pitlane.

Model Selection and Interpretation

1. **Pit Stop Championship**

To visualize the teams’ pit stop performance, we established a “Pit Stop Championship” for every available season. The criterion selected is the average duration spent in the pitlane for each race. Taking the average allows us to deal with the different numbers of stops per race. In fact, some teams have different strategies, for example using soft tires versus hard tires, some cars sustain damages... leading to different number of stops.

The average duration then reflects the pit stop crew efficiency. Other events, such as driver penalties or damages on the car, can have an impact on the duration. But these unexpected events are very much in the minority and also have a negative impact on the global performance and the official ranking just like in the “Pit Stop Championship”. We can note that these events may have a greater impact on 2 or 3 stops of 20-30 seconds than on a race of more than 1 hour. Thus, it may be harder for a top team to be as consistent in the “Pit Stop Chamionship” and may imply a wider distribution of the points across all teams.

Drivers were ranked starting from the lower average stopping time for each race. We then distributed points race per race so one bad stop in one race would not have a negative impact on a whole season for a driver and a team. We decided that it was important to keep the outliers as damages are often a key factor of performance in a race and the pit crew efficiency can have positive or negative impact through fixing the car in the shortest possible time. The number of points we distributed are the same as the official Formula 1 drivers and teams' championships:

Position	Points
1st	25
2nd	18
3rd	15
4th	12
5th	10
6th	8
7th	6
8th	4
9th	2
10th	1

Figure 5. Points distribution

Note that no points are awarded after the 10th position. By using the same distribution, 1 point in our "Pit Stop Championship" will have the same value as one point in the official Formula 1 rankings. This will facilitate comparisons and the interpretation of future models we will use to study the relationship between the two. A dictionary was created holding 13 dataframes with the ranking of the drivers and their points for seasons 2011 to 2023. The constructor championship is created by adding up the points of the drivers competing for the same team and stored in another dictionary. There are usually two drivers, but it often happens that a replacement driver competes and get some points during the season.

We finally can discuss about the performance of constructors in the pit stops. Here is a graph showing the evolution of the rank of every constructor in our "Pit Stop Championship" from 2011 to 2023:

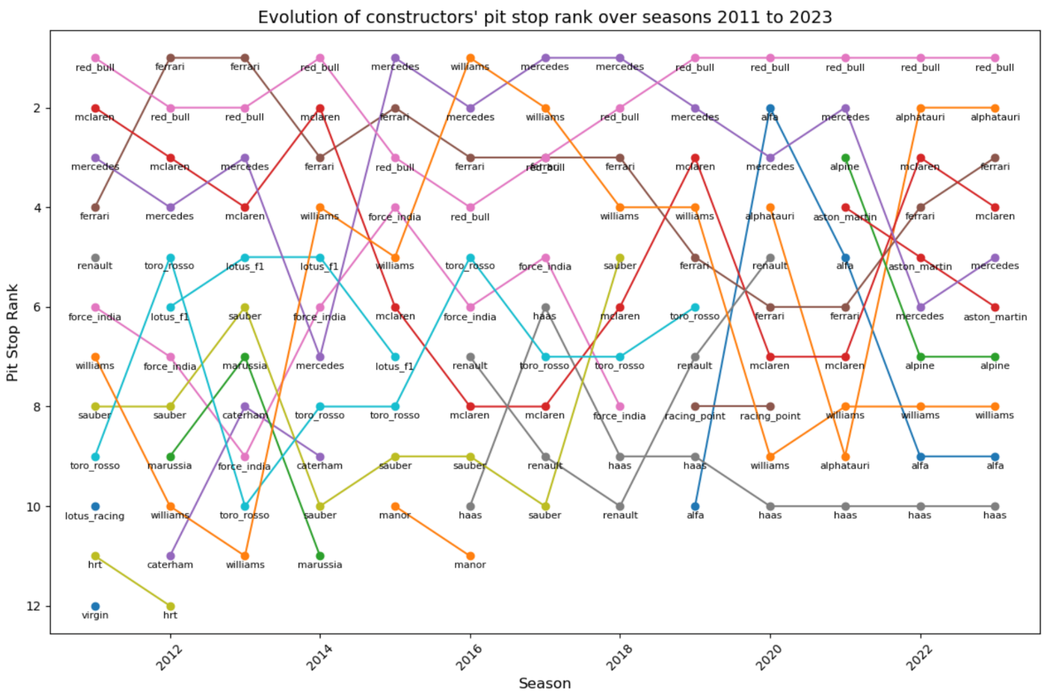

Figure 6. Evolution of constructors' pit stop rank (2011-2023)

We first notice that “Red Bull” consistently achieved first place in the five last seasons.

We also notice that all top performing teams (“Ferrari”, “Red Bull”, “Mercedes” and McLaren”) fighting for the higher spots in the official formula 1 championship are consistently achieving higher standards in our “Pit Stop Championship”. The times where “Ferrari” and “McLaren” were not found in the top 4 correspond to years where the teams were not competitive or had strategy and management issues. The only exception is “Mercedes” in 2014 that won the championship thanks to a better adaptation to a major technology update; hybridization of the cars, despite preforming poorly in the pit stops.

On the other hand, we notice that smaller teams do not perform in the “Pit Stop Championship” just as in the Formula 1 championship. We also notice that those teams are more unstable, with many rebranding, teams out or new teams in across the seasons. Note that the number of teams competing also changed until 2017.

This instability can be one of the key reasons of achieving lower standards in the pit stops performance. They are also less attractive, and the best engineers and pit stop crew members rather sign in the top teams. Williams achieved multiple top 4 finishes in our championship, but they were a stronger team overall during those years often fighting for a podium in constructors’ championship. Red Bull sister’s team “Alpha Tauri” also achieved very strong results the past two seasons. They surely have benefited from the experience and training methods of “Red Bull” team. This leaves us with one big offset; Alfa Romeo in 2020 for which it is hard to pinpoint specific reasons that allowed them to perform well.

To better understand the relationship of the pit stop performance with the official Formula 1 standings, we recreated the official drivers and constructors’ ranking thanks to the data contained in the driver standings dataframe. We added the official rank and the points alongside our pit stop rank and pit stop points for each driver or team in every season.

That way we already see some relationship between the efficiency of the pit stops and the overall performance in the Formula 1 season. We decided to showcase two particularly interesting seasons.

We could easily notice some clear relationship in the case of season 2015:

driverRef	points	pit_points	rank_std	pit_rank	constructorRef
hamilton	381.0	271	1	1	mercedes
rosberg	322.0	209	2	3	mercedes
vettel	278.0	239	3	2	ferrari
raikkonen	150.0	155	4	4	ferrari
bottas	136.0	96	5	8	williams
massa	121.0	90	6	9	williams
kvyat	95.0	123	7	5	red_bull
ricciardo	92.0	102	8	7	red_bull
perez	78.0	108	9	6	force_india
hulkenberg	58.0	86	10	10	force_india
grosjean	51.0	47	11	16	lotus_f1
max_verstappen	49.0	73	12	12	toro_rosso
nasr	27.0	34	13	17	sauber
maldonado	27.0	69	14	13	lotus_f1
sainz	18.0	16	15	18	toro_rosso
button	16.0	80	16	11	mclaren
alonso	11.0	66	17	14	mclaren
ericsson	9.0	49	18	15	sauber
merhi	0.0	6	19	19	manor
rossi	0.0	0	21	20	manor
stevens	0.0	0	22	21	manor

constructorRef	points	pit_points	rank_std	pit_rank
mercedes	703.0	480	1	1
ferrari	428.0	394	2	2
williams	257.0	186	3	5
red_bull	187.0	225	4	3
force_india	136.0	194	5	4
lotus_f1	78.0	116	6	7
toro_rosso	67.0	89	7	8
sauber	36.0	83	8	9
mclaren	27.0	146	9	6
manor	0.0	6	10	10

Figure 7. Drivers and Constructors' Championships in 2015

Moving on to season 2014:

driverRef	points	pit_points	rank_std	pit_rank	constructorRef
hamilton	384.0	65	1	13	mercedes
rosberg	317.0	86	2	10	mercedes
ricciardo	238.0	219	3	1	red_bull
bottas	186.0	72	4	11	williams
vettel	167.0	185	5	4	red_bull
alonso	161.0	208	6	2	ferrari
massa	134.0	113	7	7	williams
button	126.0	161	8	5	mclaren
hulkenberg	96.0	99	9	9	force_india
perez	59.0	58	10	14	force_india
kevin_magnussen	55.0	200	11	3	mclaren
raikkonen	55.0	118	12	6	ferrari
vergne	22.0	20	13	19	toro_rosso
kvyat	8.0	31	15	16	toro_rosso
grosjean	8.0	106	14	8	lotus_f1
jules_bianchi	2.0	2	17	22	marussia
maldonado	2.0	67	16	12	lotus_f1
stevens	0.0	0	22	23	caterham
sutil	0.0	12	23	20	sauber
gutierrez	0.0	20	24	18	sauber
chilton	0.0	29	20	17	marussia
ericsson	0.0	12	19	21	caterham
kobayashi	0.0	36	21	15	caterham

constructorRef	points	pit_points	rank_std	pit_rank
mercedes	701.0	151	1	7
red_bull	405.0	404	2	1
williams	320.0	185	3	4
ferrari	216.0	326	4	3
mclaren	181.0	361	5	2
force_india	155.0	157	6	6
toro_rosso	30.0	51	7	8
lotus_f1	10.0	173	8	5
marussia	2.0	31	9	11
caterham	0.0	48	10	9
sauber	0.0	32	11	10

Figure 8. Drivers and Constructors' Championships in 2014

This season is the first season with the hybrid power train. This major change of technology can explain how pit stop did not play a role as important as other seasons in overall performance. In fact, some teams especially "Mercedes" adapted much better and the gap in performance on the track was more important this particular season. Resource allocation may have been unbalanced, in favor of research and development of the car at the expense of race operations such as pit stops, especially under Formula 1 capped budgets. We explored other potential reasons like if there was a difference in the number of races with rain in the season. Pit stops could play a bigger role in those races to adapt to the changing track conditions. We found that both 2014 and 2015 seasons had only 2 rainy races which suggest weather did not play a big role in this difference of relationship between the pit stop performance and official championship.

Another interesting fact is that even though the standings for the drivers were very different in season 2014, the constructor standings are looking pretty similar.
This suggests that looking at every driver and not just the teams could allow us to better understand the relationship as there can be big differences in overall performance between two drivers from a same team that is not captured in the constructor’s championship.

Now, we will quantify and visualize this relationship thanks to correlation coefficients and some simple regression models.

2. Metrics and models for the relationship

To quantify the relationship between our “Pit Stop Championship” and the overall performance in Formula 1, we can use correlation coefficients.

The results of our correlation analysis reveal a strong relationship between the constructors' performance in the official Formula 1 championship and their standings in our "Pit Stop Championship":

First, we used the most common correlation: Pearson correlation. This metric is more appropriate for the championship’s points that are continuous and numerical. We have a **Pearson correlation of 0.7554** measuring the linear relationship between the “Pit Stop Championship” points and the official championship points.
For the relationship between both championships’ ranks, we used the **Spearman correlation (0.7380)** and the **Kendall Tau (0.5980)**. Both metrics are designed for ordinal data and are more relevant to use on ranks of both championships. The Kendall Tau value is lower since it counts the number of concordant and discordant pairs while Spearman uses the ranks of the data.

Finally, we have p-values very close to 0 for our correlations highlighting the robustness of this relationship.

Looking at the drivers’ championships we have very similar correlation:

For the championships’ points we have a **Pearson correlation of 0.7443.** The slightly weaker Pearson correlation can be explained by various reasons including a performance imbalance between two drivers of the same team that can weaken the direct relationship between pit stop rankings and Formula 1 championship standings, the fact that individual drivers are more affected by incidents than the team as a whole or just by the smaller sample size for constructors smoothing out variability and outliers.

For the ranks we have a higher **Spearman correlation (0.7584)** implying that the relationship between the ranks is stronger for the drivers than for the teams. This could be explained by the gaps in points between teams that can be much larger making rank-based correlations less sensitive for constructors. The slightly weaker

Kendall Tau (0.5842) is understandable since the bigger sample size for drivers make it more difficult for pairs to be concordant.

We have high coefficients both for Pearson and rank-based correlations across constructors and drivers. These highlight the significant role of pit stop performance on overall performance in Formula 1. We also noticed small differences in correlation strength between drivers and constructors' championships.

We will now visualize this relationship with a scatterplot and fitting a line using a small regression model for both constructors and drivers' championship. Our regression uses our "Pit Stop Championship" points as the only variable to predict the official Formula 1 championships points.

For the constructors we have:

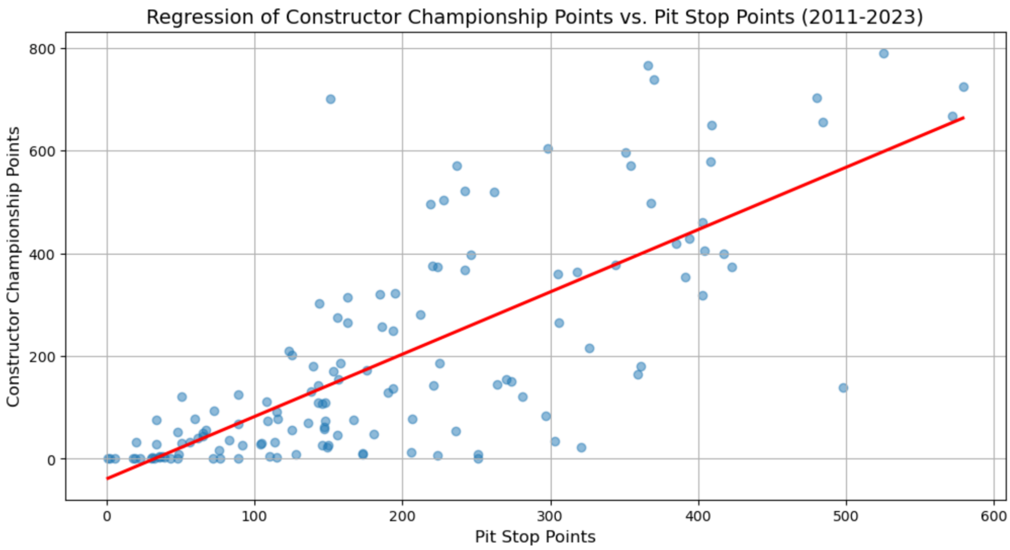

Figure 9. Constructors' championship points vs. Pit stop Points (2011-2023)

For the drivers we have:

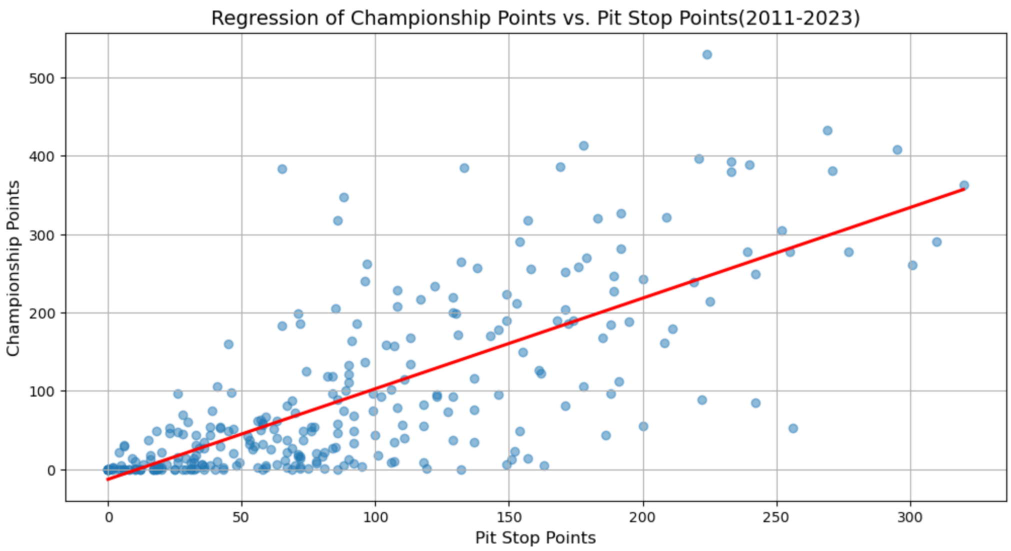

Figure 10. Drivers' championship points vs. Pit stop Points (2011-2023)

The goal of the model is not to predict the overall performance with our pit stop data. In fact, one would need to wait until the end of the season to gather all the season's pitstop data. Many other variables should be considered quantifying the cars' and drivers' performances, the strategies of the teams... Finding relevant variables would be challenging and predicting the results with data available at the beginning of the season seems almost impossible. Many factors have influence on performance: the weather, a specific racetrack, updates of the car brought in the middle of the season, and we often observe massive changes of dynamic within a same season.

But our models allow us to notice several interesting facts. First, we see that the maximum points are higher in the official championship than in our pit stop championship. In fact, it is easier for top teams to make a bigger difference on track using strategy, a better performing car and skilled drivers than being consistent on the 1 to 3 pit stops of 20-30 seconds per race. This is the case for Hamilton in 2014 with almost 400 drivers' championship points but barely 70 in the "Pit Stop Championship". On the other hand, smaller teams can perform better in the "Pit Stop Championship" with the extreme case being Massa in 2016 scoring more than 250 points in the pit stop championship despite a poor overall performance.

Despite those outliers, we notice a linear relationship between both championships. Our two models have a p-value close to 0 highlighting the significance of pit stop efficiency on overall performance. The **R-squared** is higher for the constructors' championships **(0.571)**, than for the drivers' championships **(0.554)**. As explained before, the individual driver's performance is more sensitive to race incidents, driver's skills... In both cases, we have more than 55% of the variance in official championship that can be explained by pit stop efficiency only. We tested alternative models with non-linear relationships. Adding a polynomial term to our regression for the drivers we obtained a **R-squared of 0.556**, and **0.558** using a more complex spline regression. The usefulness of these more complex models appears very limited with such slight improvement in the R-squared value and more difficult interpretation.

Our models complete the correlation analysis and strengthen the strong relevance of pit stop efficiency on Formula 1 performance.

Summary and Concluding Remarks

The study highlights the importance of pit stop efficiency in overall performance in Formula 1. By creating a model, the "Pit Stop Championship" based on the average duration spent in the pit stop, we identified clear trends in the pit stop efficiency of constructors. The top teams, particularly "Red Bull", consistently perform better in the pit stop. Our analysis showed strong correlation metrics between our "Pit Stop Championship" and the official Formula 1 championships both for the points and ranks. We also noted a slightly higher correlation for team than for individual drivers whose performance is more sensitive to race incidents, car performance and drivers' skills. The regression models allow us to visualize the relationship. The R-squared values over 55% show another evidence for the importance of pit stop efficiency in overall performance but also implies that many other factors play a role. We also noted variability of the results across seasons especially for seasons with major technological changes.

Our model has several limitations, which provide opportunities for future research to better evaluate the impact of pit stop efficiency on overall performance. As mentioned before, a model including more explanatory variables like weather, car upgrades, age of the driver or drivers' skill variations would be more useful to predict the overall performance in Formula 1. It would also give more insights on what the share of pit crew efficiency on championships' standings is. Another improvement would be to use the stopping time and not the time spent in the pit lane to have an easier interpretation and to better show the direct impact of pit crew technicians. For the 200 observations that were removed due to finishing more than 3 laps behind the leader, we checked the correlations and did not notice any major changes. Therefore, this assumption is not something that impacted our study significantly.

Future research could also focus on analyzing relationships across seasons to identify trends over time and investigate causal relationships to better understand the relationship. We may have an impact of the previous year constructors' championship on the pit crew efficiency since it determines the position of the teams in the pit lane. Thus, studying causal relationships seems like a good improvement to assess this effect.

References and appendix

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2. Wissler, C. (1905). The Spearman correlation formula. Science, 22(558), 309-311.

3. Dependence Modelling from Enkelejd Hashorva for Linear Correlation, Kendall τ & Spearman's ρ

4. Actuarial Data Science from José Miguel Flores-Contró for the code

5. Python's documentation for libraries statsmodels.api, seaborn, matplotlib.pyplot, scipy.stats

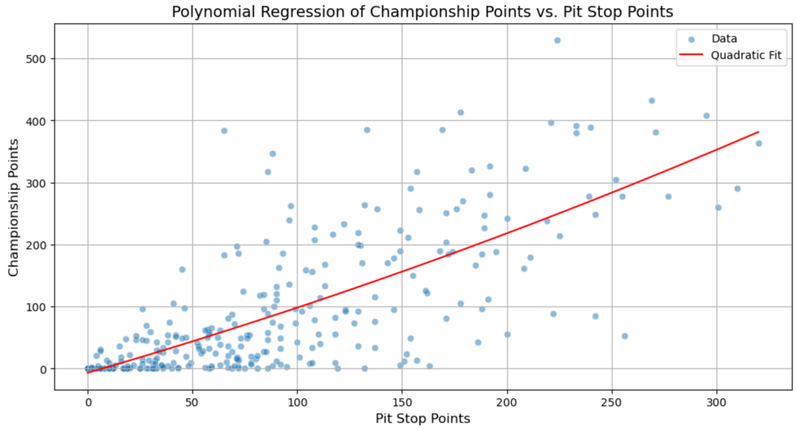
6. Official Formula 1 website: official rankings https://www.formula1.com/en/results/2024/races

7. Wikipedia for the weather conditions during races

Data from Kaggle: Formula 1 World Championship (1950–2024) https://www.kaggle.com/datasets/rohanrao/formula-1-world-championship-1950-2020

Our Github repository:
https://github.com/thomashoffer/Project_DataScience/tree/main

Polynomial regression:



Spline regression: