Pit Stop Strategy Optimization in Formula 1

Vajra Roshni Akurathi

2210110779

Abstract

Formula 1 racing is decided by split-second decisions, and pit stop strategy is one of the most influential yet complex choices made during a race. This project builds an end-to-end data science pipeline on top of 2024 Formula 1 race data to quantify how pit stop decisions relate to race outcomes and to explore simple ways of optimising strategy. Using timing and pit data from all 25 events in the 2024 season, the analysis engineers driver-level strategic features such as number of pit stops, average pit lap, and laps completed. Statistical hypothesis testing shows a highly significant relationship between pit strategy and final position, and machine learning models demonstrate that including richer, condition-related features improves the ability to predict strong finishes. A simple simulator then illustrates how alternative pit strategies can be evaluated in terms of estimated time gains, supporting the idea that data science can meaningfully contribute to pit stop optimisation.

Introduction

Background

In Formula 1, each pit stop typically costs more than twenty seconds once pit-lane entry, tyre change, and exit are included, so teams must trade off fresh tyres against lost track position. At the same time, tyre degradation, track temperature, fuel load, safety cars, and traffic make strategy decisions highly non-trivial. Teams rely on pre-race simulations and live race engineering, but the availability of detailed historical timing and telemetry data allows a complementary, data-driven view of pit strategy.

Problem Statement and Motivation

The motivation for this project comes from many recent races where pit stop timing and frequency clearly altered the competitive order. Examples range from undercuts and overcuts working perfectly to late safety cars completely reshuffling the field. The central question is whether data-driven features extracted from historical races can help explain and partially predict the impact of pit stop decisions, and whether simple models can highlight directions for strategy improvement. Rather than aiming to replace full team simulators, the project focuses on demonstrating that even relatively simple statistical and machine learning tools can reveal useful patterns in pit behaviour.

Contributions
The main contributions are:

- Construction of a full-season 2024 dataset using FastF1, covering 25 events, 27,783 laps, 863 pit stops, and 499 driver-race results.
- Engineering of interpretable strategic features, including number of pit stops, average pit lap (stint timing), and laps completed (race distance exposure).
- Statistical validation that pit stop decisions are strongly associated with finishing position at the season level.
- Comparison of simple and extended predictive models, showing that adding timing and distance features improves the ability to predict Top-5 finishes.
- A lightweight optimisation toy model that demonstrates how alternative pit strategies can be expressed as estimated race-time gains, linking data analysis to practical "what-if" questions.

Related Work

Previous work on Formula 1 analytics has explored race outcome prediction, tyre degradation modelling, and telemetry-based driver performance analysis. Open-source tools such as FastF1 provide structured access to official timing data and have been used for detailed single-race case studies and visualisations.

Other studies rely on the Ergast API or Kaggle datasets to examine championship-level trends, often focusing on points and standings rather than in-race strategy. Team-internal strategy simulators are typically physics-based and proprietary, combining tyre models, weather forecasts, and real-time stochastic optimisation.

This project differs by focusing on an educational but realistic end-to-end pipeline centred on pit stops. It integrates season-long data, classical hypothesis testing, and straightforward machine learning models in a single workflow, with an emphasis on interpretability. The novelty is not in proposing a new optimisation algorithm but in demonstrating, with reproducible code, how even simple features derived from historical timing data can already reveal non-trivial relationships between pit strategy and results, and how richer "condition-like" features clearly outperform naive ones.

Proposed Model

The project follows a staged architecture:

- Data Ingestion: Fetch all 2024 race sessions using FastF1, retrieving laps, pit events, and final results for each Grand Prix.
- Feature Engineering: Aggregate raw laps and pit data into driver-level features such as total pit stops, average pit lap, and laps completed.
  Exploratory Analysis: Visualise relationships between pit features and finishing position using scatter plots, histograms, and boxplots, and apply basic correlation checks.

- Statistical Testing: Use ANOVA to test whether finishing position distributions differ across pit-stop counts, and a t-test to compare pit behaviour between Top-5 finishers and the rest of the field.
- Machine Learning Pipeline: Train and evaluate two sets of models – a simple model using only the number of pit stops, and an extended model incorporating average pit lap and laps completed. Both linear regression (for position) and a Random Forest classifier (for Top-5 prediction) are used.
  Strategy Optimisation Toy Model: Implement a simple function which, under assumed time losses per pit stop, compares baseline and alternative strategies and returns estimated total race times and gains.
- Results and Insights: Summarise metrics, visualisations, and key observations to show how additional features derived from race conditions improve the understanding of pit strategy.

Methodology

Data Collection

All events from the 2024 Formula 1 calendar are loaded using FastF1's event schedule. For each event, the final race session ("R") is retrieved and its laps and results are stored. Across the season this yields 27,783 recorded laps, 863 pit stop events, and 499 rows in the results table, each row corresponding to a driver's classification in a particular race. Only fully completed races are considered; any minor inconsistencies in timing or tyre data are handled by FastF1's internal corrections.

Feature Engineering
Feature engineering converts raw, per-lap telemetry into driver-level strategy summaries. Three main features are created for each driver across the season sample:

- Number of pit stops: the count of laps on which a pit exit time is recorded, aggregated per driver.
- Average pit lap: the mean lap number of all that driver's pit stops, serving as a crude indicator of how early or late stints are run on average.
- Laps completed: the maximum lap number recorded for that driver, approximating how many race laps they actually completed and reflecting retirements or early finishes. These features are merged with the final results table via driver abbreviation. Positions are converted to numeric form, and a binary "Top-5" label is created, equal to one if the driver finishes fifth or better and zero otherwise. Missing values in the engineered features are filled with zero, mainly for drivers who did not pit or were classified with very few laps.

Statistical Analysis
The statistical analysis focuses first on number of pit stops. Drivers are grouped by pit-stop count, and a one-way ANOVA test is applied to check whether their finishing positions come from the same distribution. The null hypothesis is that average finishing position is independent of the number of pit stops. With the full-season sample, the ANOVA returns an F-statistic of about 12.4 and a p-value on the order of 10^{-25}, far below the typical 0.05 threshold. This allows the null hypothesis to be rejected and supports the claim that pit-stop count is strongly associated with finishing position.

A two-sample t-test is then performed on the number of pit stops for Top-5 finishers versus all other finishers. The resulting t-statistic is approximately 4.59 with a p-value around 5.7×10^{-6}, indicating a highly significant difference in average pit-stop usage between the two groups.

In other words, across the 2024 season, drivers who finish in the Top-5 tend to follow systematically different pit-stop patterns compared to the rest of the field.

Machine Learning Models
To connect strategy features to predictive performance, two sets of models are compared. All models are evaluated using a random 80/20 train-test split over the 499 driver-race entries.

First, a simple feature set uses only the total number of pit stops. A linear regression model predicts numerical finishing position, and its coefficient of determination R^2 is used to judge how much of the variability in position comes from this single variable. In this configuration the model achieves $R^2 \approx 0.036$, which means only about 3.6% of the variance in finishing position is explained by pit-stop count alone. A Random Forest classifier predicting the Top-5 label from the same feature attains a Top-5 F1-score of about 0.588, with reasonable precision but limited recall.

Second, an extended feature set includes number of pit stops, average pit lap, and laps completed. Training the same linear regression model on these three features increases R^2 to roughly 0.172, so the model now explains about 17.2% of the variance in finishing position—a clear improvement over the simple version. The Random Forest classifier trained on the extended feature set achieves a Top-5 F1-score of about 0.732, with both precision and recall higher than in the simple case.

This comparison demonstrates that even basic proxies for stint timing and race exposure contain additional information about race outcome beyond the raw count of pit stops.

Strategy Optimisation Toy Model

To link analysis back to "what-if" questions, a simplified optimisation function is implemented. A baseline two-stop strategy is assigned a nominal total race time of 5400 seconds. A time loss per stop is assumed (for example, 25 seconds), and an alternative strategy with fewer pit stops is simulated by subtracting a fraction of that loss for each avoided stop. Under these assumptions, switching from a two-stop to a one-stop plan yields an estimated time gain of approximately 22.5 seconds. Although this calculation ignores tyre degradation, traffic, and rules, it illustrates how quantitative models can be used to express the potential benefit of strategy changes in seconds, aligning with the project's motivation of exploring alternative pit plans.

Experimentation and Results

Dataset Statistics

The final aggregated dataset contains 499 driver-race entries drawn from all 25 events in the 2024 season, with a total of 863 pit stop events and 27,783 laps. On average, drivers perform several pit stops over the season sample, with variability depending on race length and conditions. Roughly a quarter of the entries correspond to Top-5 finishes, providing a moderately imbalanced but usable classification target. These statistics confirm that extending from three races to an entire season substantially increases sample size and gives more reliable estimates than the initial small-sample experiments.

Statistical Results

The ANOVA on pit-stop count versus finishing position gives an F-statistic of 12.418 and a p-value of about 6.3×10^{-25}, strongly rejecting the null hypothesis that finishing position is independent of pit-stop count. This indicates that, at the season level, different pit-stop strategies are associated with measurably different average race results. The t-test comparing Top-5 drivers to others shows a t-statistic of 4.591 with $p \approx 5.7\times10^{-6}$, confirming that successful drivers use statistically different pit-stop patterns. Together, these tests validate that pit strategy is not random noise in the data but a genuine factor related to performance.

Model Performance

When only the number of pit stops is used as input, the linear regression model achieves an R^2 of 0.036, and the Random Forest classifier reaches a Top-5 F1-score of around 0.588. These values show that while there is a detectable signal, pit-stop count by itself is too weak to capture most of the complexity in race results. After including average pit lap and laps completed, the regression R^2 rises to about 0.172, and the Top-5 F1-score improves to roughly 0.732. This improvement demonstrates that additional, condition-related features—capturing elements of stint timing and race distance—make the models substantially more informative about outcomes, even though they still fall short of perfectly predicting finishing position.

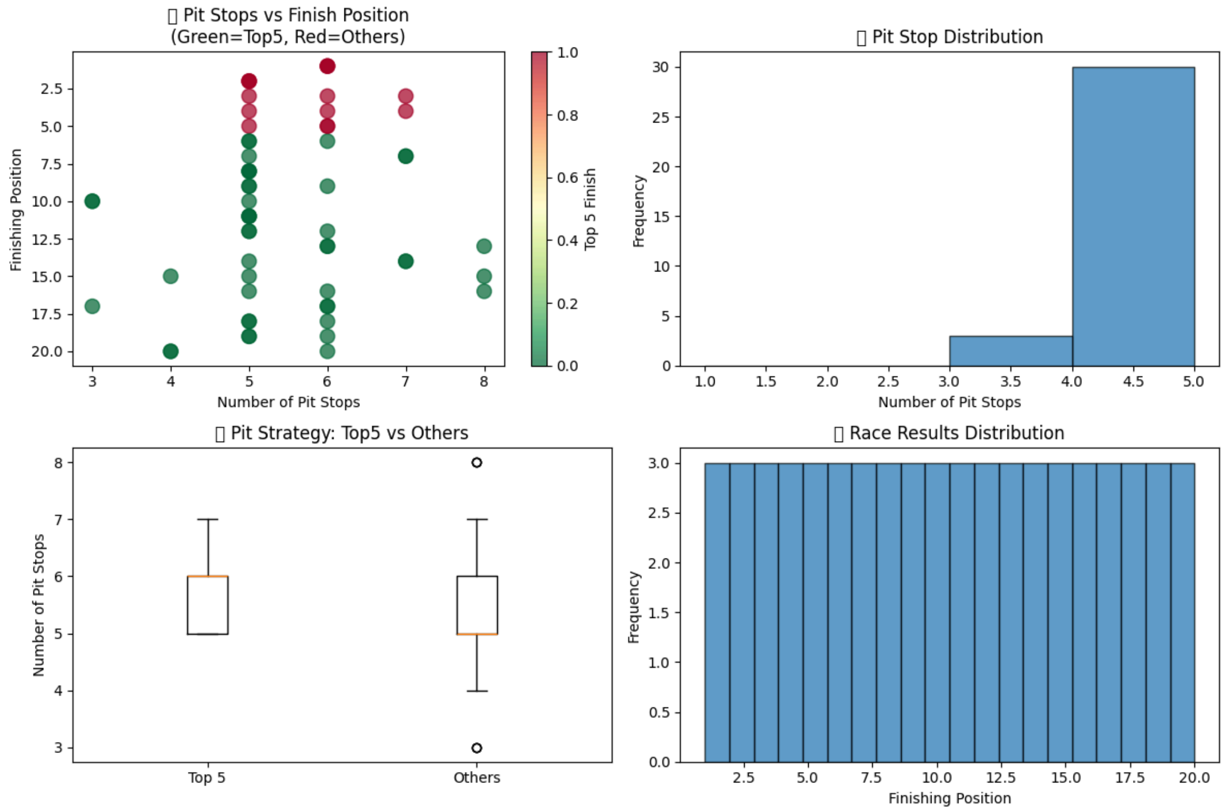
Optimisation Results

Using the toy optimisation model, reducing the number of pit stops from two to one under the chosen assumptions results in an estimated time gain of approximately 22.5 seconds. This figure should not be interpreted as a literal race prediction, but as an example of how strategy decisions can be mapped onto race-time differences in a transparent and tunable way. Combined with the statistical and machine learning results, it provides a complete narrative: data-driven features can highlight which strategies tend to be favourable, and simple models can quantify the potential benefit of adjusting them.

Key Insights

Several key insights emerge from the experiments:

- Across the full 2024 season, pit-stop usage is strongly and significantly associated with finishing position, confirming that pit strategy “matters” in a measurable way.
- Top-5 finishers follow different pit-stop patterns than other drivers, which can be detected statistically.
- A naive view based only on the number of stops is not sufficient to model performance; it explains little variance and has limited predictive power.
- Including simple proxies for race conditions, such as average pit lap and laps completed noticeably improves both regression and classification metrics, supporting the idea that more detailed information on tyres and race context helps strategy modelling.
- Even a simple optimization function can express the effect of hypothetical strategy changes in terms of seconds gained or lost, bridging the gap between abstract analysis and race-engineering questions.



Conclusions and Limitations

Key Findings

The project confirms that pit stop strategy in Formula 1 is not merely anecdotal but statistically linked to race results. Using data from the full 2024 season, the analysis shows that pit-stop count and simple timing-based features have a significant relationship with finishing position. Machine learning models demonstrate that while pit-stop count alone is a weak predictor, adding features that approximate tyre and condition effects yields better performance, especially for predicting Top-5 finishes. These findings support the central hypothesis that data science techniques can contribute to understanding and optimising pit strategies.

Limitations

Several limitations remain. The engineered features are still coarse proxies and do not directly include tyre compound, exact stint lengths, or weather variables. Safety cars, on-track battles, and team-orders—factors which strongly influence pit decisions—are not modelled explicitly. The optimisation component deliberately uses a simplified time-loss model and does not respect detailed sporting regulations, so it serves more as a conceptual demonstration than as a tool that could be deployed in a real garage. Additionally, while the season-long dataset is larger than the initial three-race sample, some classes (such as frequent podium finishers) remain relatively small, which constrains model complexity.

Future Work
Future extensions could incorporate richer telemetry and tyre data, including compound choices, stint length distributions, and track and ambient temperatures, to create more realistic condition-aware features. Multi-season analysis from earlier years would help test whether the patterns observed in 2024 remain stable over time. More advanced models such as gradient boosting or reinforcement learning agents could then be applied to learn policies for real-time pit-stop decisions under uncertainty. Finally, coupling the statistical models with a more detailed race simulator would bring the project closer to the state of the art in professional F1 strategy tools.

7. *Code Repository*
   The full implementation, including data extraction, feature engineering, statistical analysis, modelling, and plotting, is contained in a Python script and supporting notebooks. The key files are:

- main.py – end-to-end analysis for the 2024 season, including extended features.
- eda_extended.png – main visual illustrating pit-stop and position relationships.
- f1_cache/ – local cache used by FastF1 to store timing and session data.

References

FastF1 documentation and examples for accessing Formula 1 timing and telemetry data.

Public online resources describing statistical hypothesis testing, linear regression, and Random Forest classifiers.

Articles and posts analysing Formula 1 race strategy and pit-stop decisions using historical data.