Is This the Tom Brady of Racing?- A deep dive into the world of Formula 1 (E109)

John Wu and Scotty Smith

03/25/2022

Background and Purpose

Formula 1 also known as F1 is a series of races (Grand Prix) is a globally recognized sport and is one of the fastest growing sports in the United States. The sport has been around since the early 1950s and is considered as the pinnacle of motorsport. To be the F1 world champion is synonymous with being the absolute best. Each year a driver and a team (also known as constructor) is awarded a championship based on the points won each season.

Unlike other major sports in the United States such as the NBA where sixty rookies enter the league each year; opportunities in F1 are rare. There are a total of 20 "seats" across all of Formula 1 and in 2022, only one rookie was given a Formula 1 seat. The average career in Formula 1 is about 8 seasons. With such small opportunities and sample sizes, teams are left with the hard choice of either locking up a former world champion for a high amount or risk giving a chance to a newbie or average driver for 3-4 years on a contract.

There is a common saying that there is F1 and then there is F1.5. This is referring to the large gap in performance between the top two or three teams in a given season and the rest of the field. This discrepancy is due to the difference in budgets between the top teams (approximately $485 million per year) and the back marker teams ($145 million per year). As small teams have to rely heavily on sponsors to continue with the added pressure of performing to appease the said sponsors.

The purpose of this project can be broken into two different sections. First, we want to analyze & understand the difference between the aforementioned skill "Tiers." These are Top-Tier, Mid-Pack, and Back-Marker. In doing so we will illustrate the beauty behind the sport, and where the strategy comes to play.

Next, we want to dive deeper into the individuals & teams, and answer the looming question… Is Lewis Hamilton really worth $40 million?

The Data

The data used for this project was a mixture of a public dataset from Kaggle (https://www.kaggle.com/datasets/rohanrao/formula-1-world-championship-1950-2020) with further enrichment from a package FastF1 (https://theoehrly.github.io/Fast-F1/).

This data was broken down into multiple sheets with cross referenced ids and had data available for races from 1950 to 2020. The sheets are broken down into mainly two types of data: reference data and result data. Not all data was used to create the models and a summary of the data used is listed below. Additionally, enhancements to some of the data was used to further enrich additional variables for data modeling.

Dataset Name	Description	Additional Enhancements
qualifying	Summary of qualifying session for each race. Data included all session times	Track Temp, Air Temp, Wind Speed was added via python package FastF1
results	Summary of race results per driver and team	Air Temp, Track Temp, Wind Speed, Weather, Car Performance Metric, Fastest Lap was found per driver, Turns, Sharp Turns,

Data Assumptions and Wrangling

The majority of the data provided and extracted are categorical variables. The results of each race and amount of each race is a discrete distribution. However, the variables within each category are assumed to be normally distributed (average speed, lap times, temperature of environment, etc.).

In the original dataset, there were 4 explanatory variables available to model our classification models. (grid, circuit, driver, fastest_speed) Our concern was the lack of additional variables given to us to produce models with different combination of variables. Therefore, a large effort was made to create additional variables such as Air.Temp, Track.Temp, Wind.Speed, Weather, Race.Circuit type (street or racing circuit), n_of_Sharp_Turns, car_performance, track_type based on speed, and turns per mile. We normalized car performance data by using the qualifying times of each team and comparing the difference in time of each team against the fastest team of the qualifying session.

Lastly, due to the nature of the data there is some existence of dependencies with certain variables such as car performance, driver performance, and grid order. In our models we viewed each as a system of variables that describes a certain feature. (i.e grid is the location of the each racer relative to each other, car performance is the pure performance of a car by averaging two drivers, and driver's racecraft such as maneuvering, blocking, and/or ability to read situations). We also assume that all environmental variables are equal for all drivers during the time of the race and affect drivers equally. In reality, car set-ups have some effects on these and will affect each car differently.

Data Selection

Formula 1 as a sport has changed drastically over the years and is broken down into separate eras of similar cars based on their technology. We would like to compare as similar of cars as possible so the era chosen was the most recent era called the "Turbo-Hybrid" era which comes from the use of a hybrid engine along with turbos and occurred between 2014 to 2021 which is the subset of our analysis.

Furthermore, most contracts for drivers range between 1-5 years and many young drivers don't make it past 3-4 years in the sport. We decided to take data from 2018 to 2021 to build our model and make an applicable equivalency to a typical contract length and to keep similar drivers and teams.

Additionally, we omitted races where a driver had to retire and was not able to complete the race. In racing, these could be a result of a collision, mechanical issue, or illness.

Throughout the four years, there were 32 total drivers that participated in at least 1 formula one race. There were many drivers that had less than 40 races and many did not have race data in one of the four years. We chose to go after the top 10 drivers with completed races in an effort to limit the driver variables and to limit the amount of incomplete data in the dataset. These drivers were Hamilton, Vettel, Bottas, Perez, Sainz, Rakkonen, Gasly, Stroll, Leclerc, and Verstappen.

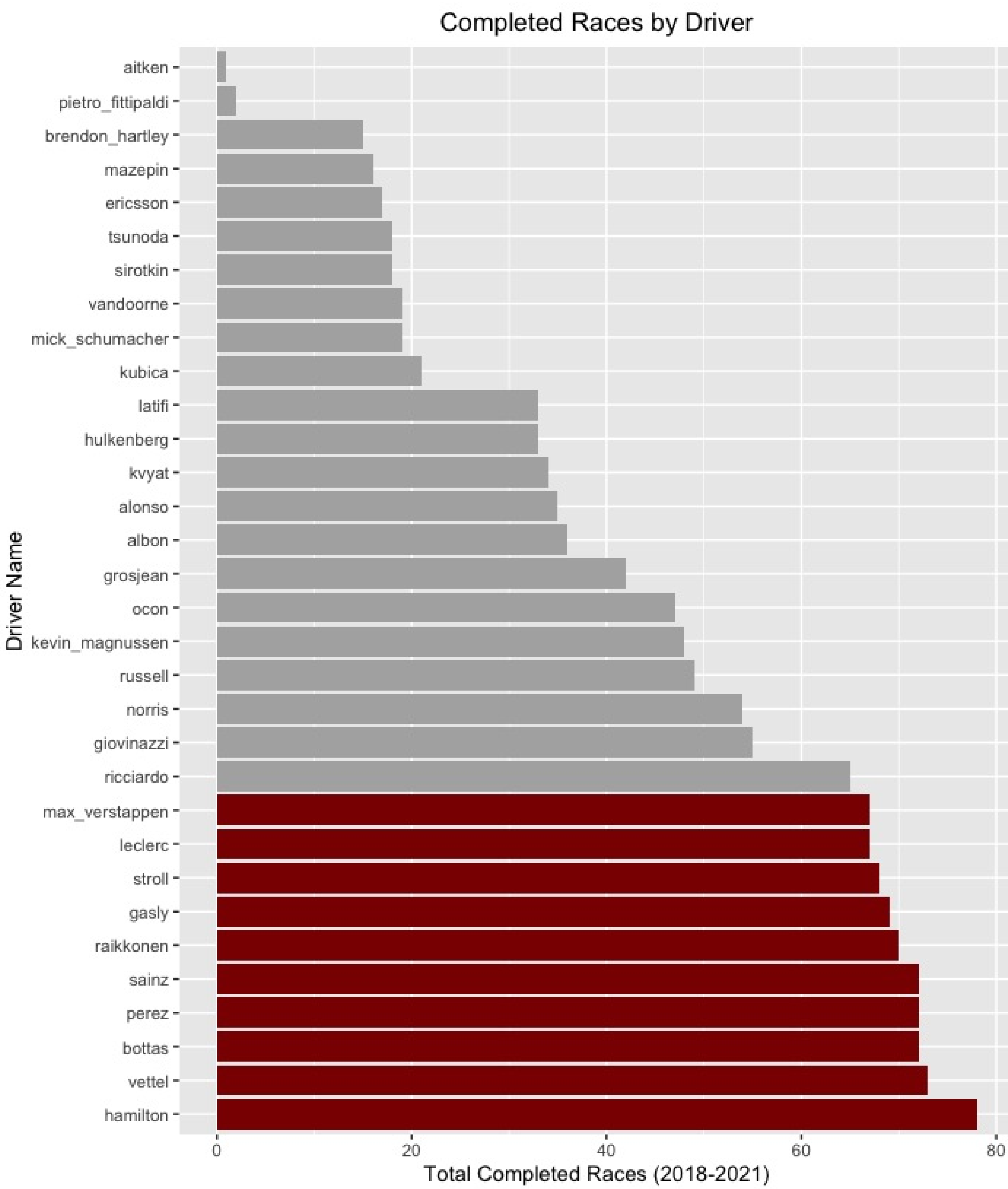


Figure 1: Total Completed Races by Driver

Purpose 1

To understand the differences between top, mid-tier, and backmarkers, we decided to run classification models for 3 different types of race results. In our first analysis, we looked at classification models to predict race wins.

Race Wins:

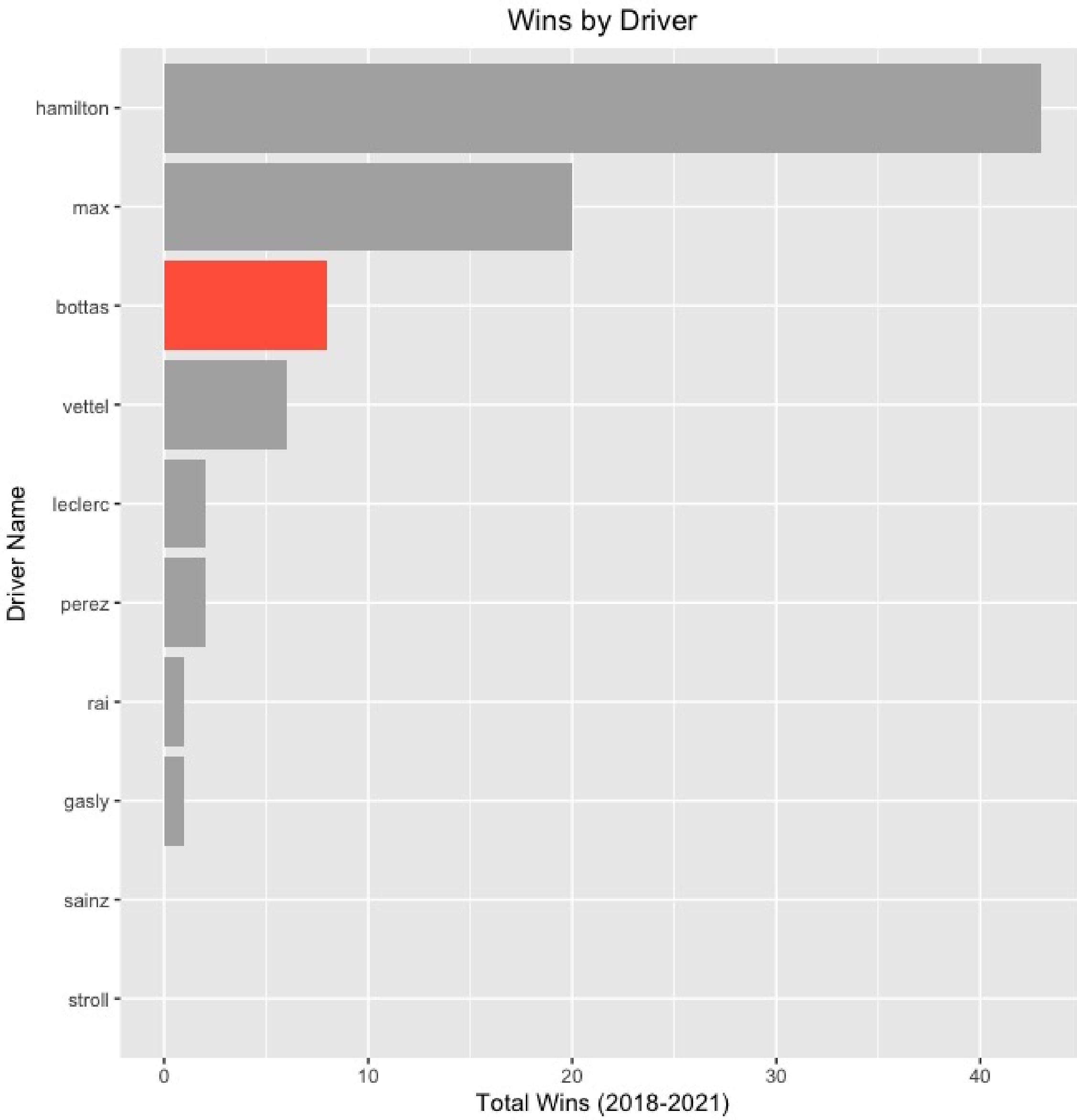


Figure 2: Race Wins per Driver

To find the best classification model, we decided to run 3 different types of models: logistic regression, random forest, and XgBoost. One issue with classifying race wins is that the "Win" positive class is extremely small when compared with the "Lose" category. In the 81 races, there is a proportion of 5% (1 in 20 average) in the Win class and 95% in the Lose class. Therefore, to evaluate our model we will be heavily relying on the sensitivity accuracy.

We used ROC curves based on test data to give us an overview with default parameters to find the optimal threshold for each model and looked at the overall accuracy, specificity, and sensitivity (with "Win" as the positive class) for all three models.

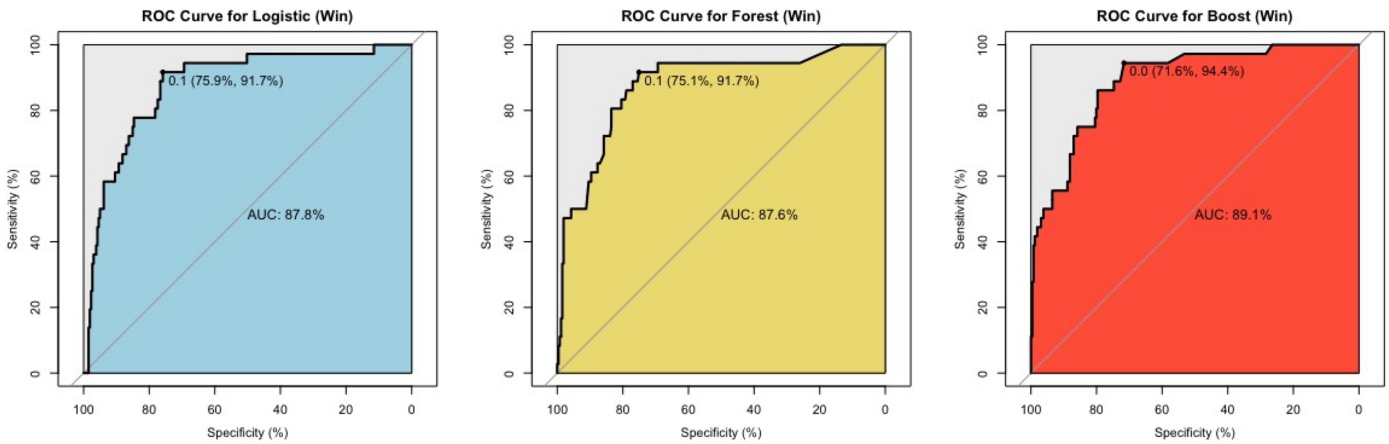


Figure 3: ROC Win Classification Models

Overall, it appears that all models were comparable with the Boost model having a slightly higher AUC. For our analysis, we are primarily interested in the "Win" prediction and what factors are important to achieve this result. Therefore, setting the threshold to 0.1 for both Logistic and Forest models looked to give us the best overall score and highest specificity score and setting the threshold value to 0.05 appeared to be the best threshold for the boost model.

With the following thresholds, we then ran the models with a 60/40 split with cross validation of 5 folds and found the following accuracy, specificity, and sensitivity on the test data.

Table 2: Accuracy Scores for Classification Models (Race Wins)

Model Type	Accuracy (95% CI)	Sensitivity (Win Class)	Specificity (Lose Class)
Logistic Regression (Threshold > 0.1)	77.7% (72.6%, 82.3%)	91.6%	75.8%
Random Forest (Threshold >0.1)	79.5% (74.4%, 83.9%)	86.1%	78.5%
Extreme Gradient Boost (Threshold >0.05)	75.1% (69.8%, 80.0%)	88.9%	73.2%

Comparing across all 3 models, it appears that the Logistic Regression model performed the best when it came to fitting against the Win class and the Random Forest model gave slightly better predictions against the Lose class. All three accuracy scores are within the 95% confidence intervals between each other and therefore the model accuracy is similar. In the analysis below, we will use the Logistic Regression model to explain our race win data and the Random Forest Model to explain our lose data. While performing the analysis below, we will attempt to improve our model further through the use of stepAIC to limit siginificant variables in our logistic model and in the Random Forest we will leave only top importance variables.

Win Model: Using the stepAIC function to tune our logistic model revealed that the two variables with the most amount of importance was "Grid" and "driverRef". The sensitivity score from this model was 88.9% and had a specificity score of 74.0%. A summary of the winning model is shown below:

```
##
## Call:
## glm(formula = win ~ grid + driverRef, family = "binomial", data = train_win)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.48917  -0.31900  -0.03224  -0.00003   3.07221
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)               -1.2855     0.5959  -2.157 0.030982 *
## grid                      -0.4168     0.1248  -3.341 0.000835 ***
## driverRefgasly           -16.1000  2400.2514  -0.007 0.994648
## driverRefhamilton          2.4107     0.6147   3.922 8.79e-05 ***
## driverRefleclerc           0.3154     0.9308   0.339 0.734703
## driverRefmax_verstappen    1.5088     0.6581   2.293 0.021862 *
## driverRefperez            -0.4409     1.1746  -0.375 0.707393
## driverRefraikkonen        -0.1053     1.1833  -0.089 0.929104
## driverRefsainz           -16.0613  2353.8897  -0.007 0.994556
## driverRefstroll          -15.0108  2224.9785  -0.007 0.994617
## driverRefvettel            0.5895     0.8260   0.714 0.475445
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 302.36  on 454  degrees of freedom
## Residual deviance: 169.31  on 444  degrees of freedom
## AIC: 191.31
##
## Number of Fisher Scoring iterations: 19
```

The reference driver used in this model was Bottas and a brief look at these coefficients shows that the top drivers (Hamilton and Verstappen) had a high effect on the potential for a race win than compared with the reference driver and both coefficients were significant. Both of these drivers stayed on the same team for all of the four years and were involved in the top team (Mercedes and Red Bull) with the most amount of wins.

When looking at the top three drivers (Hamilton, Verstappen, and Vettel) seem to be able to outweigh the negative effect of a one or two bad grid units. Hamilton appears to erase almost 6 grid units and Max with 3 when compared with Bottas in securing wins. A comparison of actual race wins reflects this behavior.

Outside of our top 3 finishers only Vettel and Leclerc had positive coefficients. While these coefficients were not significant at any level, this could indicate some candidates to explore. However, what is clear is that Hamilton's and Verstappen's effect is extremely large even compared to this tier of drivers.

Gasly, Sainz, and Stroll all have extremely large standard errors indicating that the estimates for these drivers are not reliable. This may be due to the fact that Sainz and Stroll has never won a race, therefore the model cannot learn from any situation where this has occurred.

When comparing Leclerc, Perez, and Raikkonen (all with similar race wins during the period), it would appear that Leclerc may be the strongest driver in this pack by a very small margin.

The dominance from Hamilton is extremely clear when evaluating against the entire field and to a smaller degree Max Verstappen. Bottas still seems to hold his own when compared to the rest of the field when looking at race wins and is evident based on the amount of wins each driver has over the past 4 years. Leclerc is primarily interesting as he is the only driver with a positive coefficient when grouped with drivers that have similar amounts of wins.

Podium Finish (Top 3)

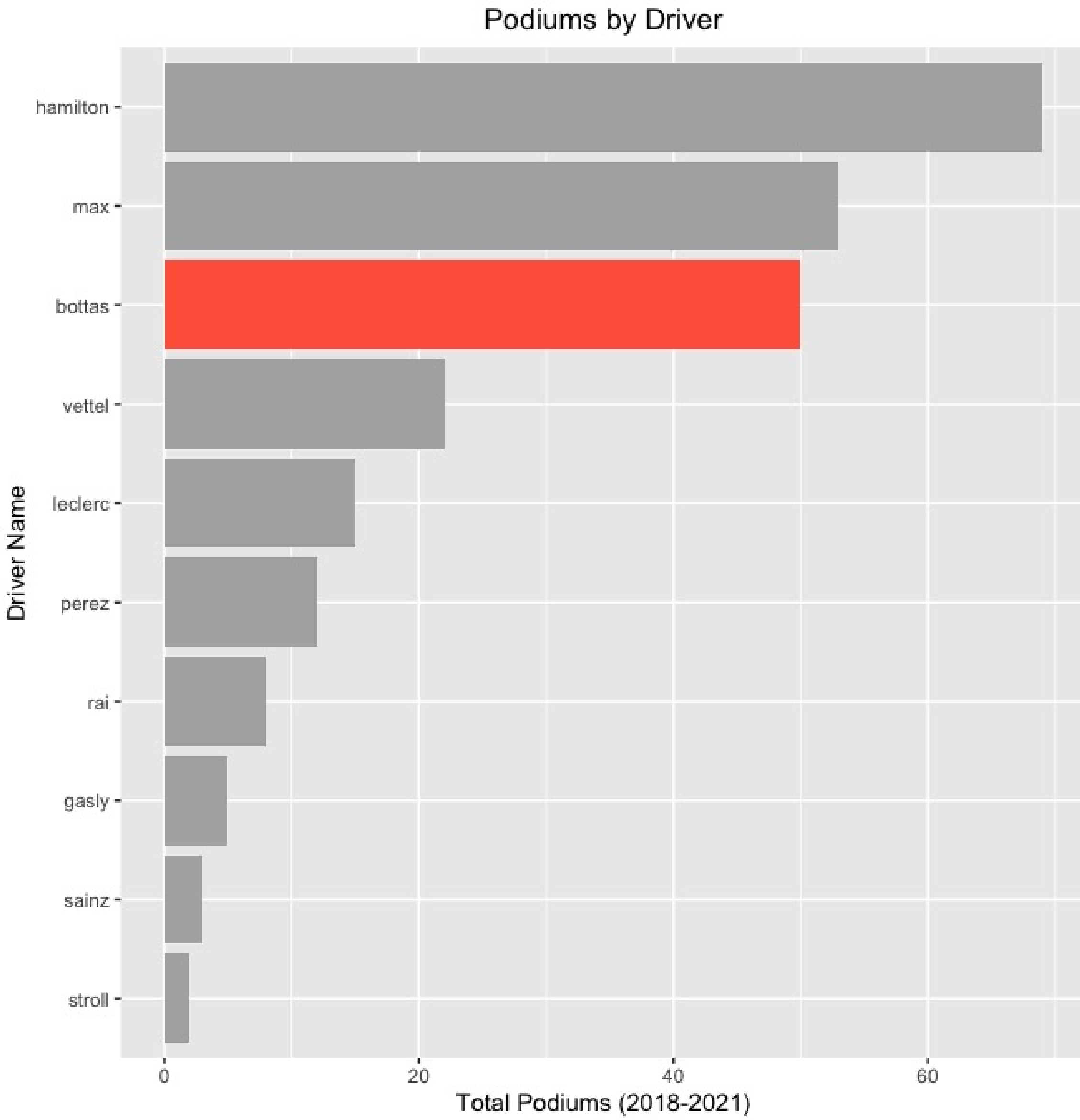
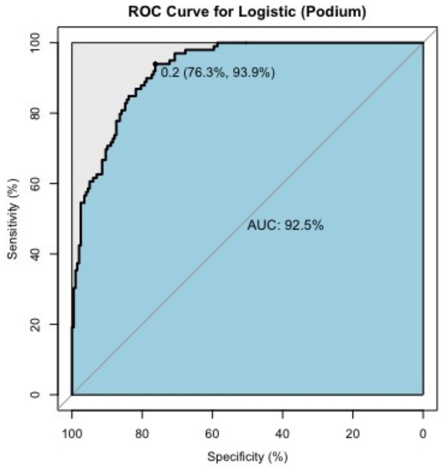
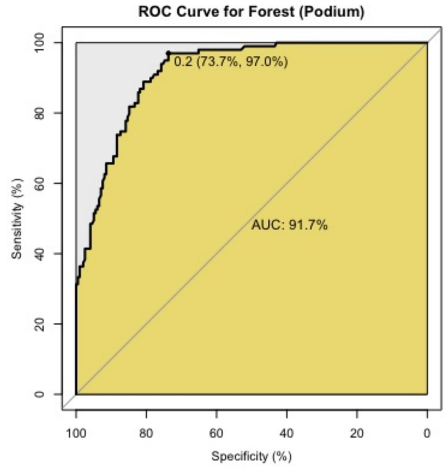
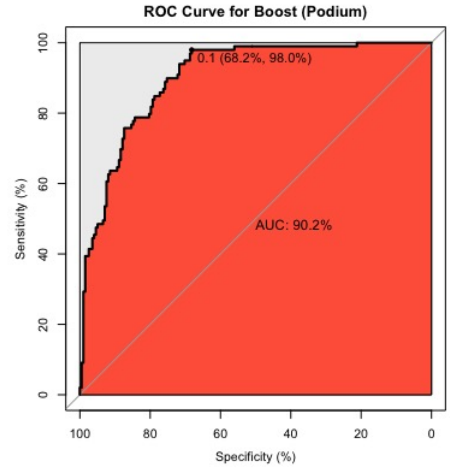


Figure 4: Podiums per Driver

We ran the same analysis for podium finishes with the following model assessments with ROC curves to find the best thresholds and AUCs.







The AUC for all models were comparable with the Logistic model showing the highest AUC. The same 60/40 split was performed and 5 fold cross validation for both the Random Forest and Gradient Boost models.

Model Type	Accuracy (95% CI)	S ensitivity (Podium)	S pecificity (Not Podium)
Logistic Regression (Threshold > 0.2)	80.8% (75.9%, 85.1%)	93.9%	74.2%
Random Forest (Threshold > 0.2)	81.5% (76.7%, 85.7%)	97.0%	73.7%
Gradient Boost (Threshold > 0.1)	76.7% (7 1 .5%,81.5%)	97.9%	66.6%

Although the Boost model had the highest sensitivity parameter, the accuracy for that model is the weakest out of the 3 with a confidence interval that does not overlap either of the two models. The Random Forest Model showed a very high sensitivity at a threshold of 0.2 with an overall higher accuracy throughout across all three models. The specificity in the logistic regression is slightly higher with comparable accuracy to the Random Forest Model.

In the analysis below, we used the Random Forest Model to explain differences in gaining podium places and removed less important features to try to generalize and get a better sensitivity. All three models showed relatively weak specificity compared to their sensitivity and therefore are not good models for exploration. However due to logistic regression's ability to show coefficients, we will explore the logistic model to look at specificity for podium spots.

The overall model showed high importance on grid, qualifying_dif (car performance), and driver and marginal importance on Type(track type) and track distance (mile). After cycling through a variety of these elements, the model that improved overall accuracy while keeping the relatively high sensitivity was based on the grid, driver, car performance, track type, and distance.

The most important variables for determining podium places were grid and car performance. More interesting results come from looking at the drivers and their relative rank of importance with each other. Max appears to have an ever slight higher importance than Hamilton when it comes to gaining podiums. Perez, Gasly, and Sainz are all in a comparable group. Without completely understanding the coefficients, it is hard to discern if these drivers had positive effects or negative.

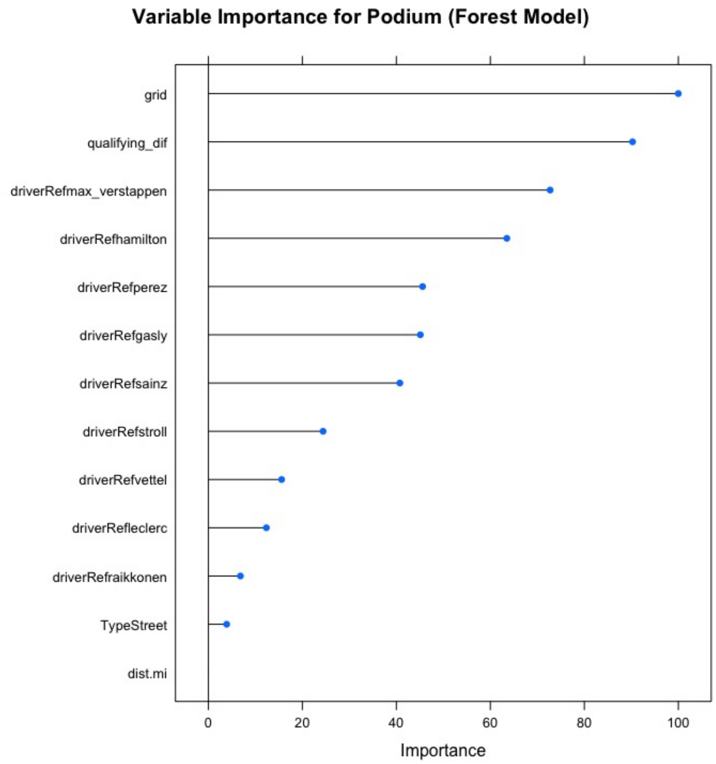


Figure 5: Variable Importance Podium

To gain insights into the magnitude and direction of each variable, we passed the most important variables based on the Random Forest into a logistic regression model and got the following coefficients.

```
##
## Call:
## glm(formula = finish_tier ~ grid + driverRef + qualifying_dif,
##     family = "binomial", data = test_pod)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9589  -0.4205  -0.1401   0.5209   2.6472
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)              81.29992   33.67401   2.414   0.0158 *
## grid                     -0.32318    0.07607  -4.249 2.15e-05 ***
## driverRefgasly           -0.72496    0.96197  -0.754   0.4511
## driverRefhamilton         0.96132    0.61164   1.572   0.1160
## driverRefleclerc         -0.75862    0.69701  -1.088   0.2764
## driverRefmax_verstappen   1.43881    0.68298   2.107   0.0351 *
## driverRefperez           -1.12109    0.83047  -1.350   0.1770
## driverRefraikkonen       -0.49542    0.87485  -0.566   0.5712
## driverRefsainz           -0.69287    0.83411  -0.831   0.4062
## driverRefstroll          -1.06744    1.31878  -0.809   0.4183
## driverRefvettel          -0.21598    0.65702  -0.329   0.7424
## qualifying_dif          -79.68606   33.70312  -2.364   0.0181 *
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 378.09  on 296  degrees of freedom
## Residual deviance: 202.33  on 285  degrees of freedom
## AIC: 226.33
##
## Number of Fisher Scoring iterations: 6
```

In terms of variables outside of driver comparisons, grid and car performance both saw significance in influence at 95% with grid being signficant well past the 99%. Also, Verstappen shows significant difference against Bottas and Hamilton is significant only at a 85%. When comparing to the grid coefficient, Max has the potential to erase close to 4 grid units meanwhile Hamilton can potentially erase 3.

The difference between mid-tier drivers are fairly insignificant, however we must keep in mind that all other drivers in this field arguably suffer from weaker cars when compared to Bottas. The results may be different if we were able to compare drivers that has been in multiple cars. Gasly, Stroll, and Sainz have some of the highest standard errors across all drivers in the field and may indicate some lack of consistency when achieving podiums.

Overall from both our models, the most important aspects to achieve a podium are grid position and car performance. The most siginificant factor between drivers is Verstappen's influence on the overall podium achievement. Red Bull racing has achieved second place in overall standings in 2020 and 2021 which may be a primary reason why Max is able to achieve this outside of the other drivers. Another potential reason for Max's dominance in the podium results could be due to race strategy.

Avoiding the BackMarkers (Rank 1-6)

Similarly, we looked at all three types of classification models and performed a ROC analysis to find the best thresholds and compare AUCs.

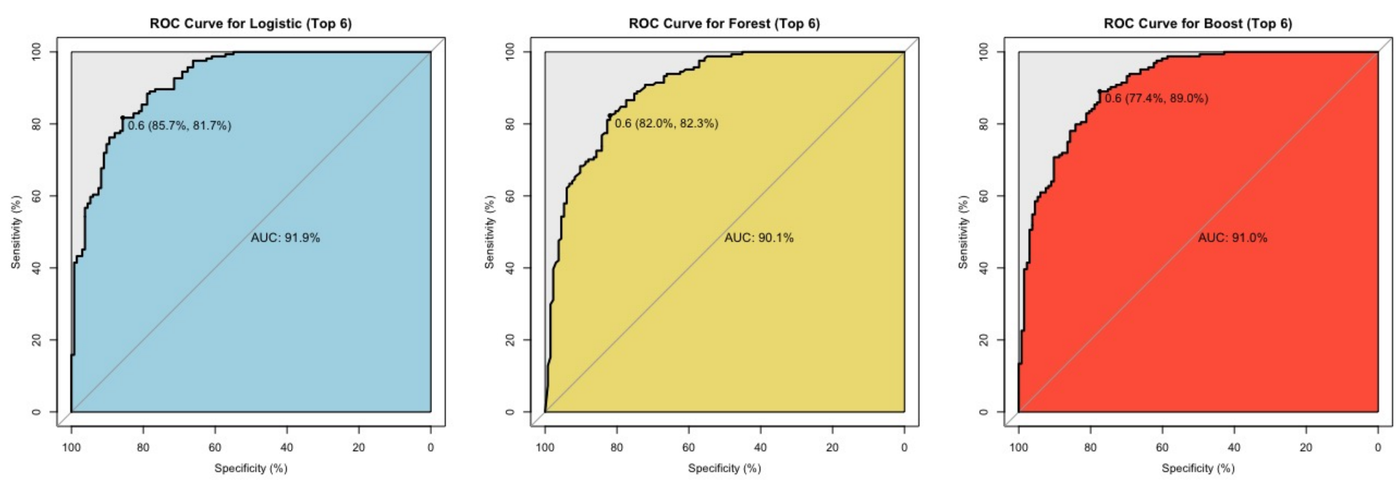


Figure 6: ROC Top Team Classification

Again logistic regression had the highest AUC and the gradient boost was able to provide the highest sensitivity.

Model Type	Accuracy (95% CI)	S ensitivity (Podium)	S pecificity (Not Podium)
Logistic Regression (Threshold > 0.5)	82.5% (77.7%, 86.6%)	85.4%	79.0%
Random Forest (Threshold > 0.6)	82.2% (77.3%, 86.3%)	82.3%	82.0%
Gradient Boost (Threshold > 0.6)	82.5% (77.7%, 86.6%)	86.0%	78.2%

Comparing the 3 models, the logistic regression had the highest AUC and all were above 90%. In terms of sensitivity, Gradient Boost gave the higher sensitivity with almost an equal drop in the specificity. The two models used to show Top6 and out of Top6 would be Gradient Boost and Random Forest. Similar to all analysis previously ran, we tried to tune our models to score even higher in either sensitivity or specificity while maintaining optimal accuracy, however was unable to get a better model than the default settings. The tuning parameter charts are found in the appendix.

Trying to optimize our boost model gave us a worse performing model with respect to Sensitivity (80.8%), indicating potential overfitting issues. As a result, the original gradient model was used to explain the top 6 finishes.

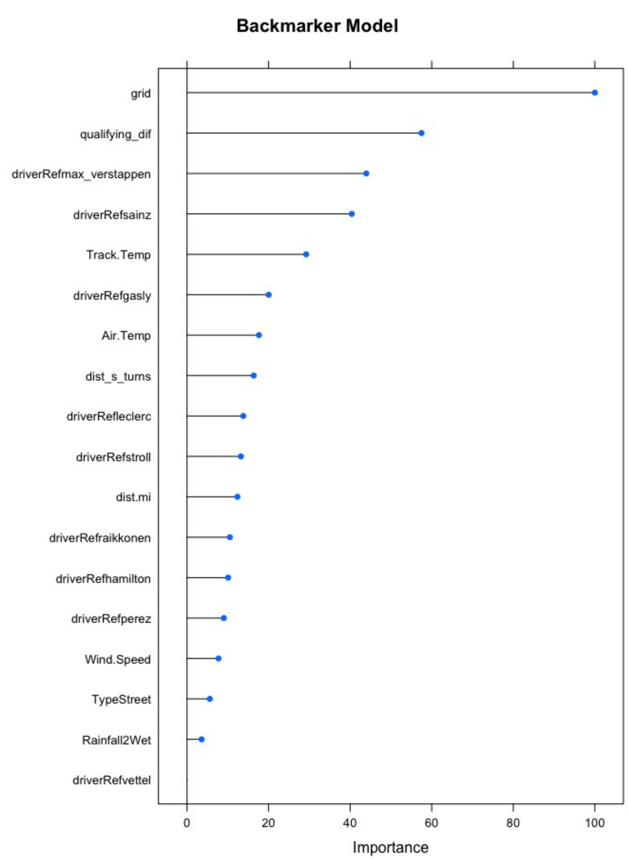


Figure 7: Variable Importance for Top 6 Model

Based on the variable importance on the XgBoost model, the most important root node was grid, car performance, and track temperature. The first two variables may be obvious as the faster your car, the easier it is to get towards the front and also the higher up in the grid a driver is placed the more likely they are to defend and keep that position. There are certainly relationships between grid, car performance, and drivers in specific cars that may be magnifying the importance of these variables. These are all prevalent in the two models above. However as we move towards the middle, we start to see environmental variables become slightly more important than the previous podium and race-win models.

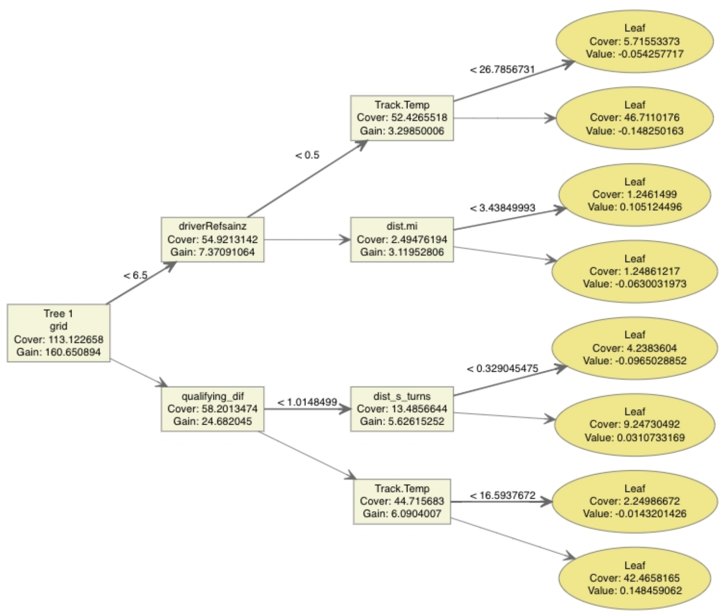


Figure 8: Example of XgBoost Tree

In fact, when looking at an example tree diagram from the model, it appears that having grids at 6 or below was crucial. This may be obvious since it's many times easier to defend your position in a race versus overtaking potential opponents. As XgBoost is an ensemble model, this example is just one tree of many to find the likely probability of a Top 6 finish. However it is still valuable to see where the trees split and the decisions made. For instance, Sainz as a driver has a relative high level of importance as it is close to the root nodes. As seen in the variable importance chart above, Sainz's importance is close to that of Verstappen.

Conclusion to Purpose 1

By looking at finishes in tiers (Wins, Podiums, Teams), we are able to see some obvious relationships. Firstly, grid position appears to be a huge portion of importance when it comes to determining all finishes. In a real life setting, rid position, car performance, and teams are closely related variables.

For race wins, it appears that environmental factors are not as important as compared to other finishes. The main portions that are important is the driver and the position at which they start the race. This is evident in the dominance that is seen with Hamilton throughout this period with 47 wins out of a possible 81. The reasons behind this could be Hamilton's racecraft and experience as a 7 time world champion. However, we also see Max performing well against Bottas in a car arguably slower. That is to say we cannot rule out the potential cause that strategy may be an explanation for these differences. Outside of these top 3 drivers, Vettel and Leclerc may be candidates to explore for top teams. Leclerc when grouped with drivers with similar race wins appears to have a slight edge.

For podiums, we see a similar result with the top drivers and a great emphasis on the car performance. The difference between winning and podiums from our model is that Verstappen is the most dominant figure when it comes to podiums. Even though he has less overall podiums than Hamilton, his rating for podiums is measurably higher based on our logistic model. As far as mid-tier performers, there is no tangible difference between all drivers outside of our top 2.

As we move away from the front of the grid, our models start to show that environmental factors start to outweigh some individual drivers. For instance, track temp was relatively high as compared to driver importance on the back marker models, but was not seen on either Race win model or Podium model. Environmental factors start to have a larger effect on the outcome. A possible explanation for this could be due to drivers having to battle through more traffic and avoiding collisions and nursing your car to take fewer pit stops may be a critical component of success for back marker teams.

To answer our original question of the factors that surround top teams, mid teams, and back markers; if you are a top team manager getting the right driver is critical. The difference between Bottas, Hamilton, and Max are fairly significant. If you are a mid tier team, your driver becomes slightly less important; getting someone like LeClerc where there may be some marginal gains may be an option. If you are on the backmarker, invest in your car and technology would be the advise. The environmental variables start to matter more in the back and the driver influences are harder to discern from each other. Understanding how a driver deals with certain environmental effects may be more important if large improvements on the vehicle is not possible.

However, in reality all Formula 1 teams employ a variety of these strategies. Some portions that are not highlighted in this model are how well the drivers can develop a car through experience. The different strategies employed by each team for each driver is also crucial to understand. Formula 1 is an exciting sport with a lot of interconnected variables. This project's purpose was to shed some light on potential factors that may matter more than others.

PURPOSE 2

As seen in purpose 1, the influence of strategy and car are extremely significant when predicting race outcomes. It can be difficult to compare driver vs driver based on results due to these massive differences between cars. However, comparing teammates may shed some light into the relative differences between drivers.

A teammate in F1 is the closest rival because this is the closest scenario in which two drivers may be operating equal machinery. The second purpose of this project is to evaluate individual drivers and their relative values when compared to their teammates.To analyze the variable importance and coefficients found within Teams, which have very similar cars, and for Individuals. In other words… what factors have a higher importance for each team/individual?

To analyze the variable importance and coefficients found within Teams, which have very similar cars, and for Individuals. What factors could be correlated to the cars performance, good or bad? What about individual Driver?

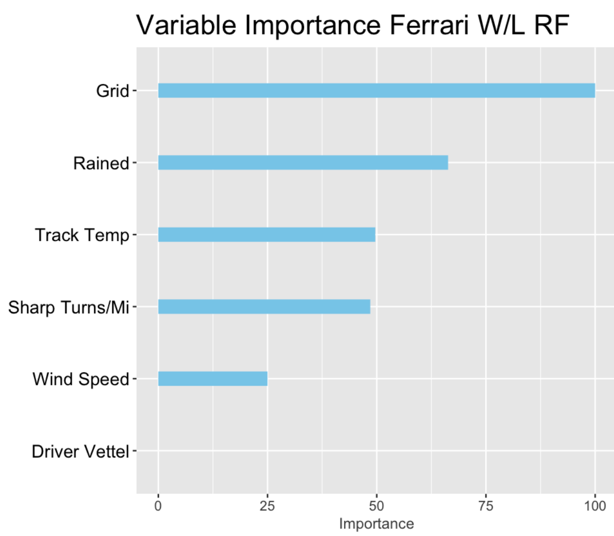
Is Lewis Hamilton really worth $40 million?

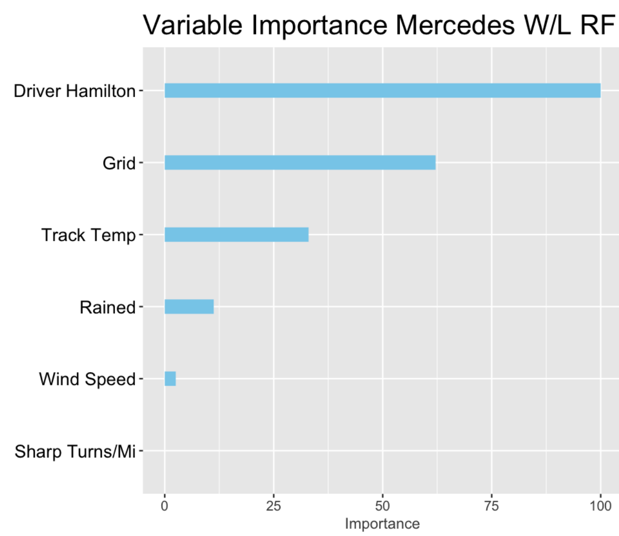
Method

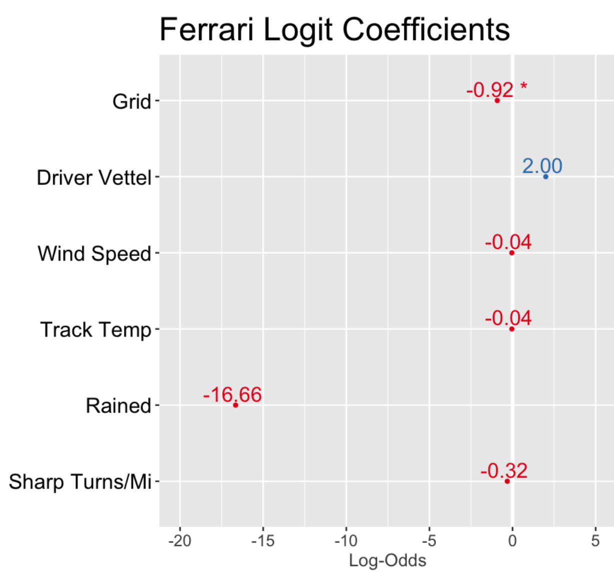
For each ind/team a random forest model will be used to assess Variable Importance. Secondly, a Logistic Regression model will be used to analyze coefficients. The Logit Regression models show values that did not have low P-Values and futher steps with a StepAIC analysis would without doubt remove many of the variables presented in the below graphs. These are purposefully kept in, as our purpose with the Logit Regression model is to understand whether or not an explanatory variable has a negative or positive association. However, variables with a significant p-value will be more than insightful. The classification (Win, Top3, Top6) chosen for each individual/team had the highest specificity/sensitivity. Since these are independent models, we chose the classification that best represented each ind/team.

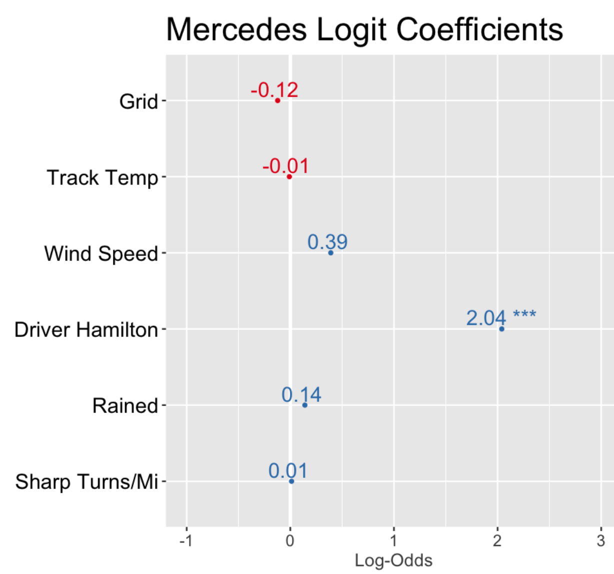
TEAMS

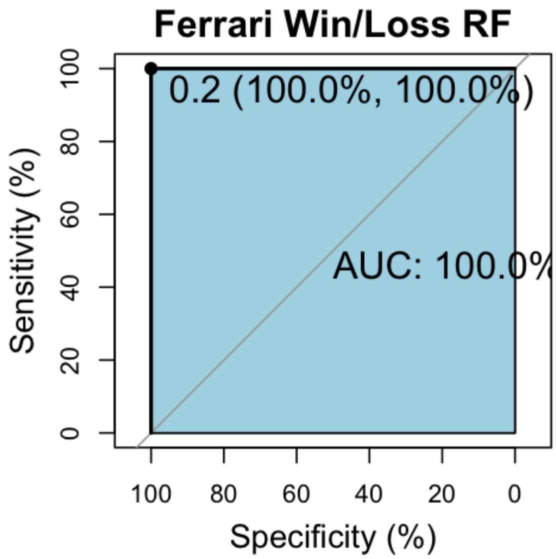
Team	Years	Individuals	Sample Size (Train,Test)
Ferrari	2018,2019,2020, & 2021	Leclerc & Vettel	113 (80% , 20%)
Mercedes	2018,2019,2020, & 2021	Bottas & Hamilton	162 (70%, 30%)

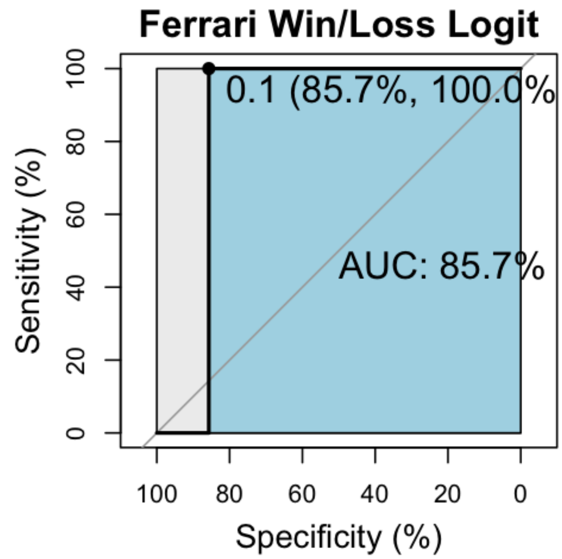


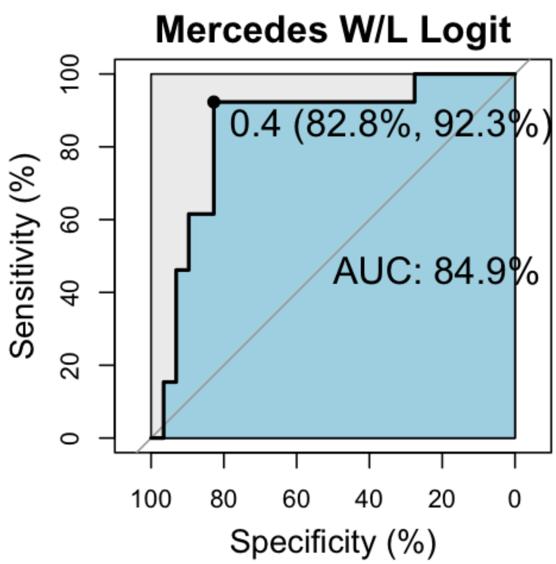


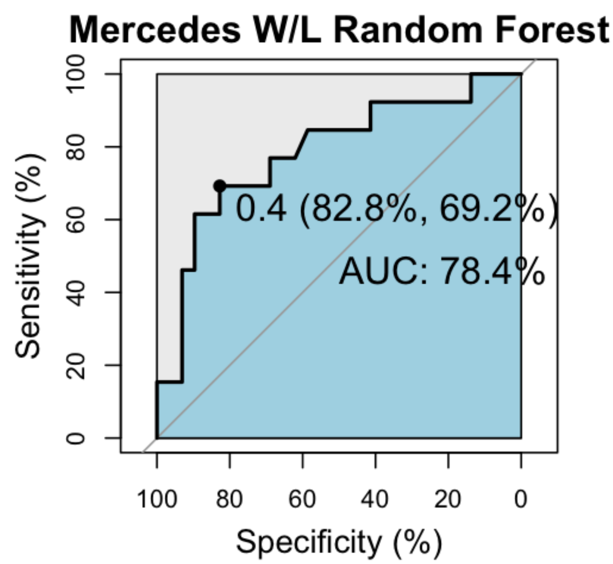












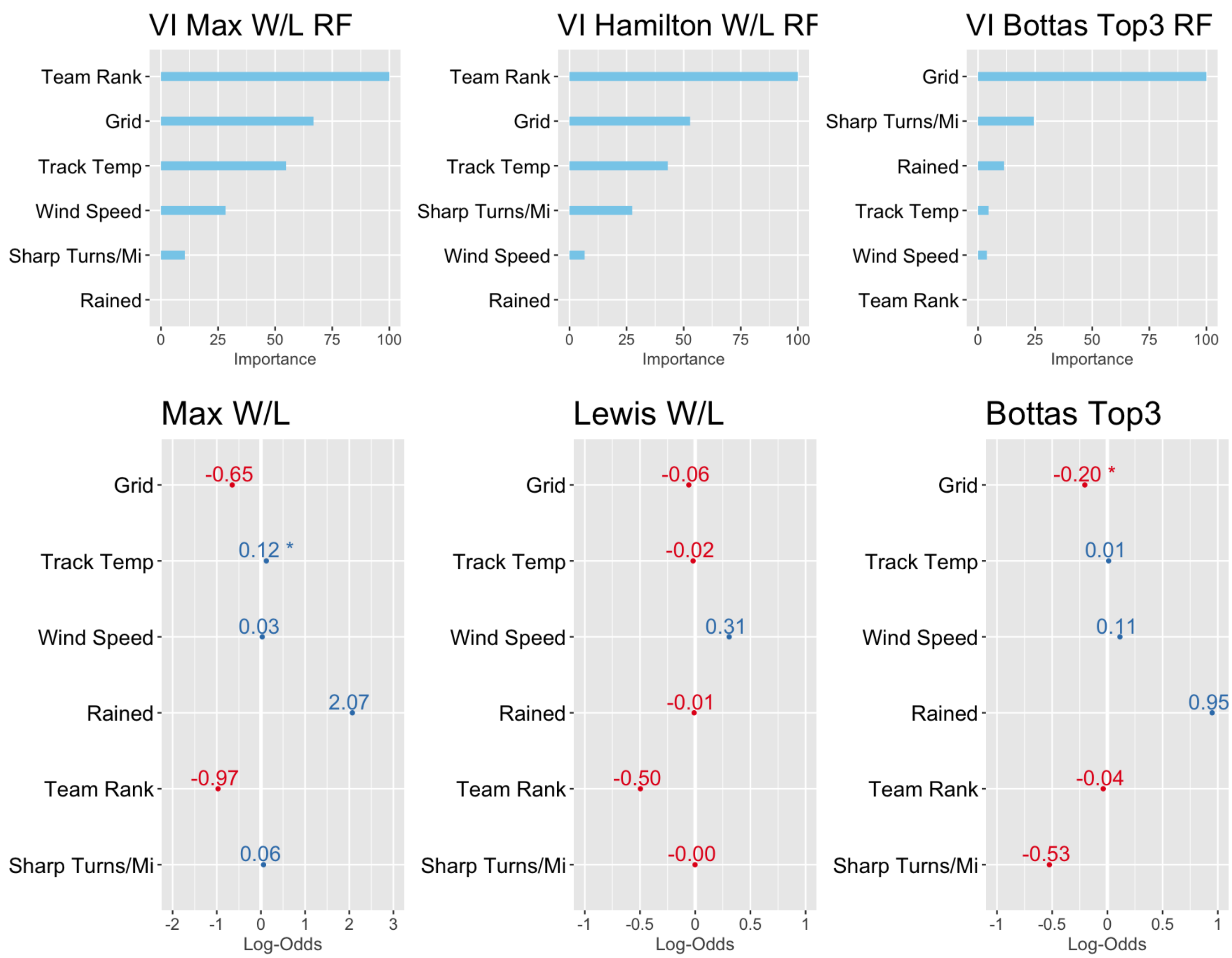
Insights (Teams):

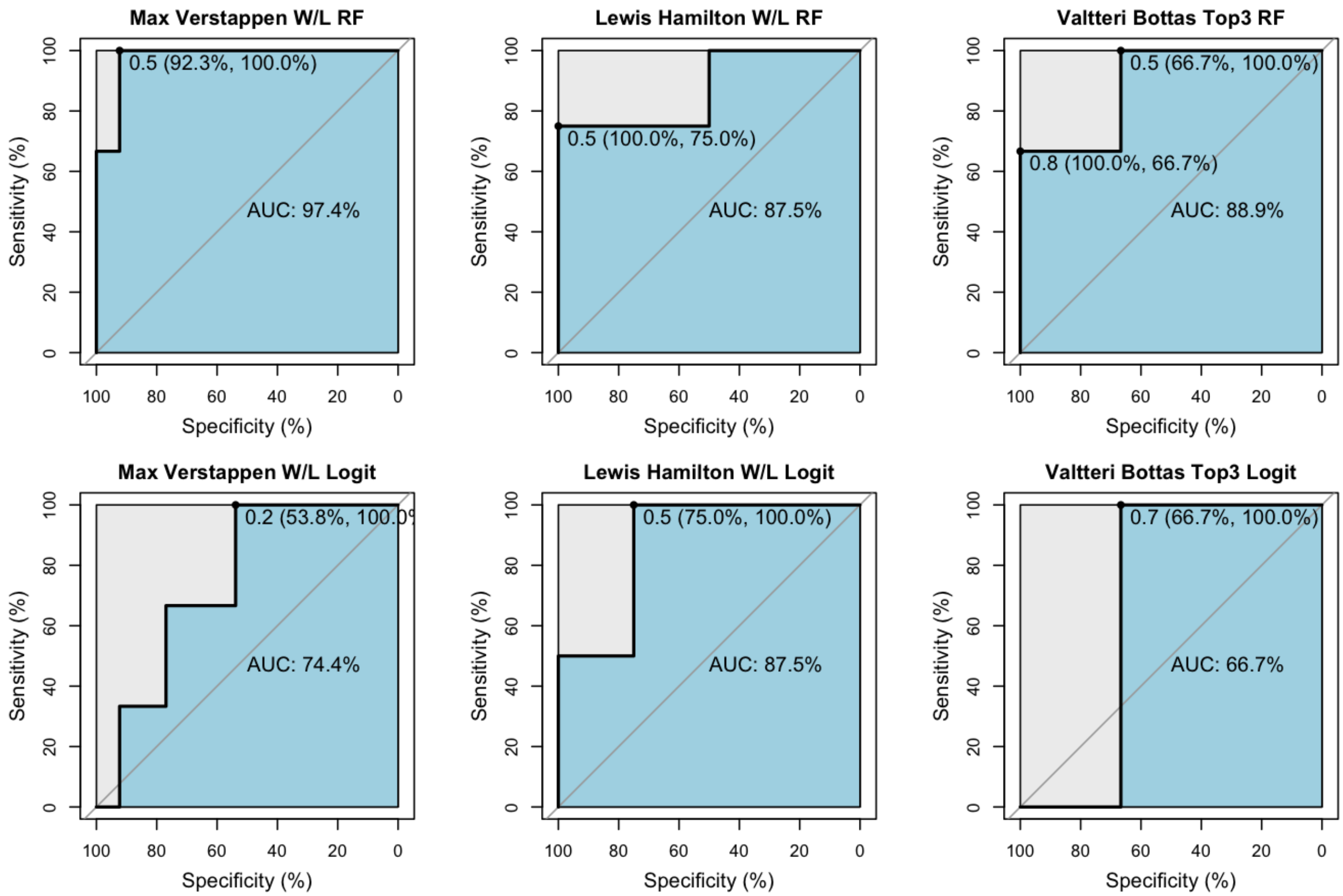
The most notable insight between Ferrari and Mercedes is the Variable Importance of Driver Reference. On Mercedes the most valuable node is if the Driver is Lewis Hamilton or not. Secondly, we see that this is a positive coefficient from our Logit model with a high P-value represented by the. On the other hand, Driver Reference for Ferrari had the lowest Variable Importance and while did not show any significance in our Ferrari W/L Logit model coefficient graph, it did have a pvalue of .1082 with 97 degrees of freedom. What this indicates is that when the "car" is accounted for Lewis Hamilton is showing why he is paid the highest amount in the league.Driver Ref == "Hamilton" had less than a .005 pvalue with 113 degrees of freedom. No other variable had a significance level less than .12.

Another Insight considered, was the higher Variable Importance of environmental factors (Wind Speed, Track Temp, Weather) on the Ferrari team. As these environmental factors increase we see a negative correlation within our Ferrari Logit Coefficients. A deeper analysis shows that the Logit P-Values for Ferrari were (Wind Speed : .93, Track Temp: .53, & Rained : .99). In other words… there may be some value discovered by the Random Forest Variable Importance, but without more data these coefficients are unreliable.

INDIVIDUALS

Individual	Years	Team	Sample Size (Train,Test)
Bottas	2018,2019,2020, & 2021	Mercedes	78 (83% , 17%)
Max Verstappen	2018,2019,2020, & 2021	Red Bull	69 (70% , 30%)
Hamilton	2018,2019,2020, & 2021	Mercedes	84 (75% , 25%)





Insights (Individuals):

One notable insight from our individual racer models is the Importance of Team Rank for Hamilton and lack there of for Bottas. Keep in mind these two racers have been on the same team for the last four years. With that said, it might be plausible that the Team Rank variable (How well the "car" qualified) would indicate similar Importance for the two. If the overall Qualifying rank for the team is lower, insinuating a better environmental fit for the Mercedes car, then both Bottas & Hamilton might see a positive correlation. However, this isn't true for Bottas. This could be a further indication of Lewis Hamilton's ability to overcome environmental factors and only have the machine and himself to account for any mistakes. Secondly, Grid has very rarely been outside of the #1 Variable Importance factor. In further examination of the Lewis Hamilton Logit model, the p-value for "Grid" is .59. After doing a StepAIC() analysis the only remaining coefficient is Team_Rank and Gris is removed. Lewis Hamilton is showing that even when he falls lower in the Grid ranking position there is no significance in his ability to secure the Win. For further validation on this, the only coefficient with a significant P-Value for Bottas is the Grid at a p-value of 0.034.

Purpose 2 Conclusion:

Each driver and each team have different Variable Importance factors and correlation. It can be difficult to dive further into this with such small sample sizes, and we aren't following the best practices for either model. We used the two different models to piece together an understanding of the factors that effect drivers/teams. That being said we were able to make some considerable correlations that we can be confident in. Lewis Hamilton is showing the ability to be beyond environmental factors, and even the strongest factor for any other driver… the starting position. Where other teams have very little difference between drivers, indicating a potential strength of the car, Mercedes winning a race is highly correlated with that driver being Lewis Hamilton. Another interesting item to note, is that Bottas had 8 wins himself. The true difference is that Hamilton had 47 alone. I'll leave you with the final answer. Is Lewis Hamilton worth $40 million?

Overall Project Challenges/Experiments

As stated in the previous section (Data Assumptions) above; the data lends itself to a lot of variables where there is influence with each other. We attempted to view these as systems of variables rather than specific factors and also tried to normalize estimates as much as possible. We categorized a car's performance only based on the pure pace it can achieve in one lap based on two drivers. However, a car's performance throughout a race weekend has many more factors such as reliability, tire degradation, differences between driving behind cars and having clear space.

Data wrangling did take a majority of the time and to prepare our data for modeling and we used a public github repo (https://github.com/jywu86/F1-Stats-Project) to collaborate on the modeling and data wrangling. We experimented with numerous different variables such as track speed, relative finishing positions (1-8), team rank (instead of % of qualifying times), track ids, throttle response, and braking response. All of these variables were eliminated primarily due to not having a large influence in our models or have compounding effects on each other. The variables used in our model was distilled at an attempt to have as much independence as possible.

Future Steps

The dataset from Kaggle and the use of the Ergast API is very rich and we simply did not have time to fully explore each and every piece. In reality, a race has multitudes of factors such as collisions causing safety cars, incidents such as punctures, team strategies such as number of pit stops and tire selection, car reliability, etc. As our own team, we hope to continue to build on this project by incorporating additional models that take into more of these specific details.