Formula E Racing Lap Prediction

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Agenda

Signal

Business CaseIntroduction



Data Preprocessing



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Data Modelling



Model Evaluation and Results



Conclusion and Future Recommendations

Business Case Introduction

Formula E Racing

- World's first fully electric, international one-seater, street racing championship





Predict the number of laps a driver will need to complete the race

Why should we solve this problem?

Real Time Prediction will optimize race performance and result in better energy optimization strategy for the racer

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If number of laps left = 30, battery status = Low:
Strategy: Drive conservatively and save energy
```

If number of laps left = 30, battery status = High : Strategy: Drive aggressively and expend energy

Data Preprocessing

Data Merging

- 1. Concatenating datasets across all seasons
- 2. Keeping the common columns

Defining New Parameters

Creation of new columns:

Location

Match Type

▼ Total Lap Number

▼ Total Pit Count

		66243
Q		
FP2		
FP2		
FP1		
Race		
Race		
FP1		
FP1		
FP2		
Race		
match_type,	dtype:	object

HongKong
Montreal
Zurich
Long Beach
Berlin
Punta
Mexico
Mexico city
Punta
location, dtype: object

Berlin

28191

33092

40606

Aggregation of Data

- Aggregation of data by driver name, match type, group and team
- Including data of KPH, S1, S2 and S3 summary statistics

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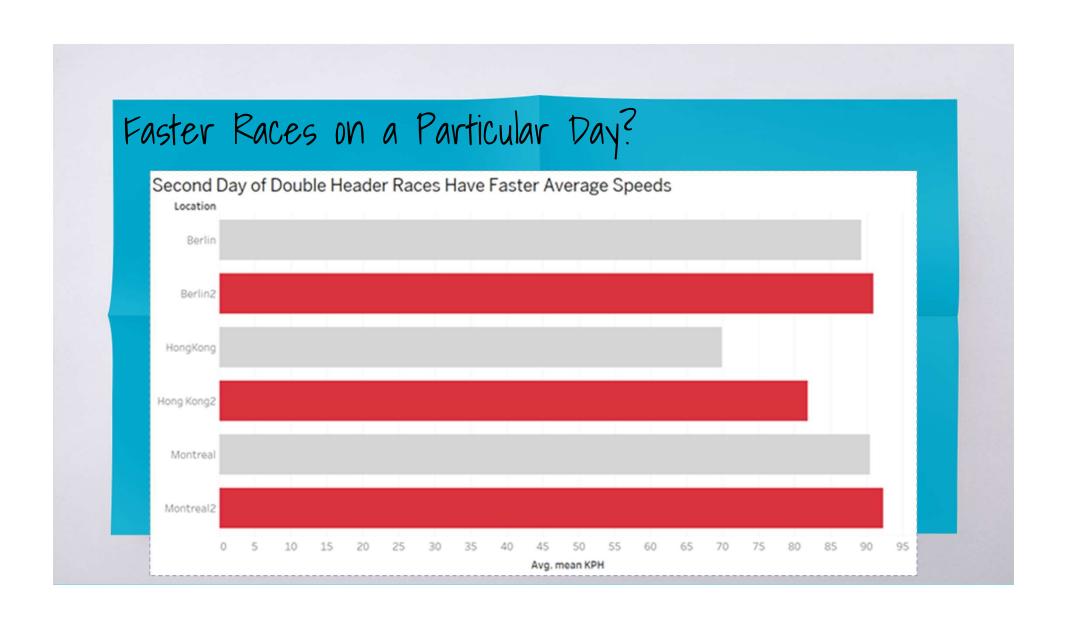
 Including data of KPH, S1,
- Conversion of Lap Number into total laps done
- Summation of all pit time into total pit time taken

mean_KPH	std_KPH	med_KPH	max_KPH	min_KPH	range_KPH	skew_KPH	mean_S1
103.200000	27.378660	114.20	123.5	14.2	109.3	-2.195524	4.994981e+04
109.641176	28.468537	118.50	127.0	9.7	117.3	-3.125489	7.058582e+04
55.950000	74.034080	55.95	108.3	3.6	104.7	0.000000	1.205626e+06
118.713889	12.634514	121.95	139.3	68.7	70.6	-3.401031	2.122811e+04

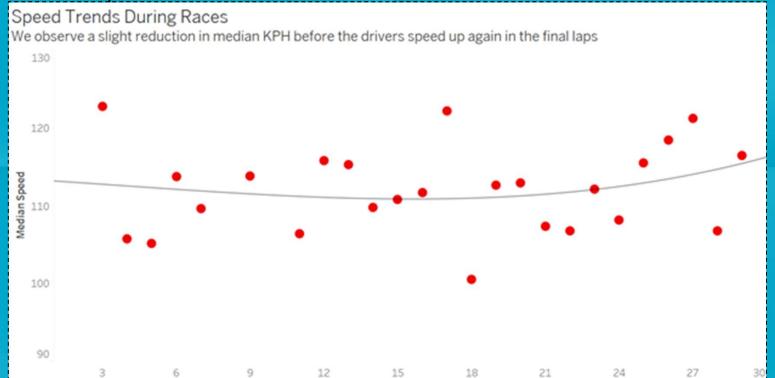
Aggregation of Weather Data

mean_air_temp	std_air_temp	med_air_temp	max_air_temp	min_air_temp	range_air_temp	skew_air_temp	mean_track_temp
27.101836	0.574968	27.4444	27.7222	26.3889	1.3333	-0.406788	21.574100
16.888880	1.024915	17.3333	19.2222	15.0556	4.1666	-0.614885	21.913584
25.546313	0.219368	25.6667	25.7778	25.1667	0.6111	-0.918498	20.555600
27.262177	0.175923	27.2778	27.5000	26.9444	0.5556	-0.645954	23.245589
27.817464	0.145223	27.8889	27.9444	27.5556	0.3888	-1.383638	22.222200

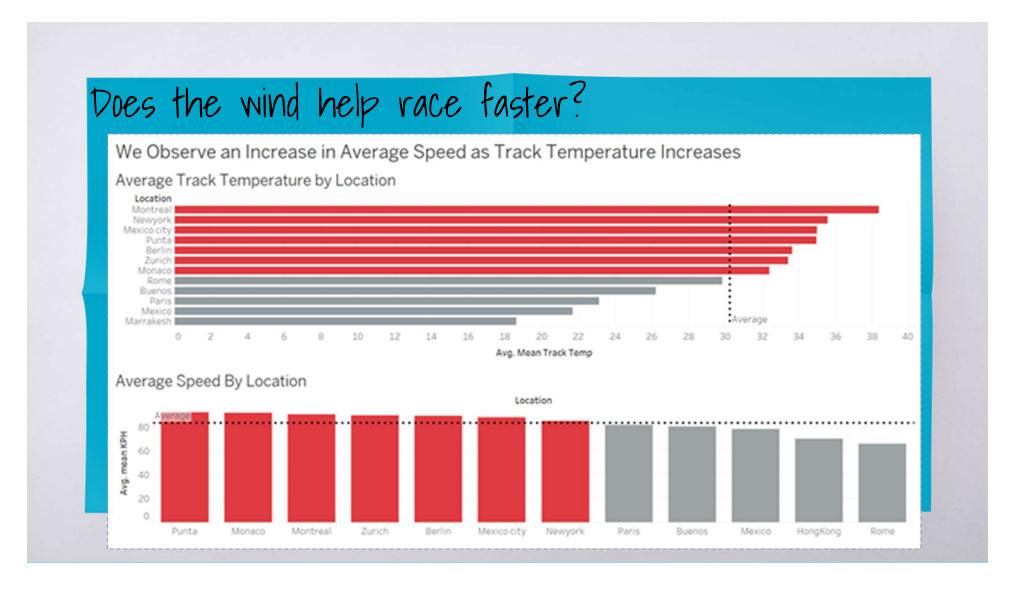
3. Graphical Data Analysis



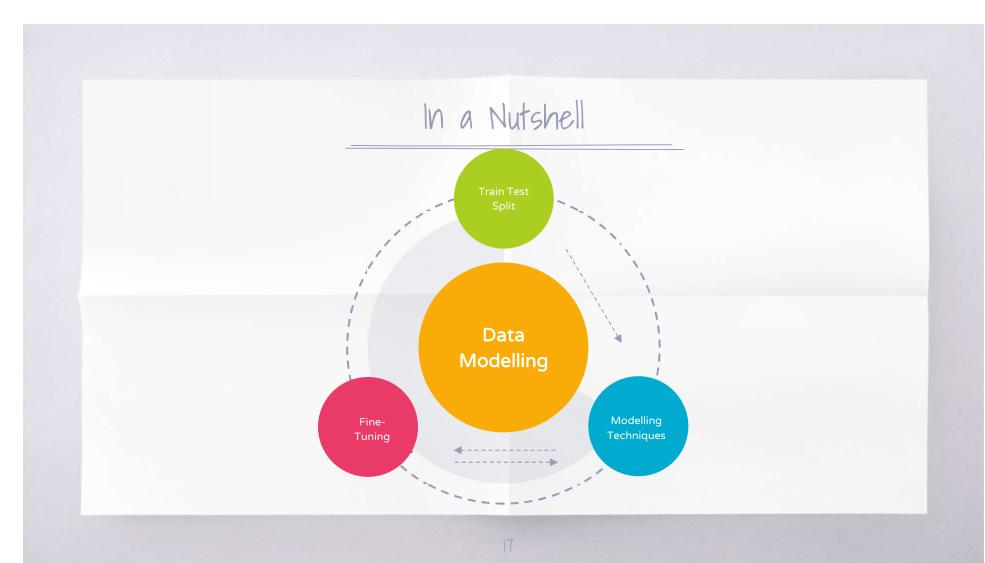




Lap Number



4. Data Modelling



Train Test Split

Since we concatenated train and test data together in the beginning for data preprocessing purposes, eventually, we separated them out into train and test respectively.

▼ Test - 15%

Feature Training Dataset Size: (2377, 182)
Predictor Variable Training Size: (2377,)
Feature Testing Dataset Size: (793, 182)
Predictor Variable Testing Size: (793,)

Training Data: Independent Variables

Training Data: Predictor Variable = Total Number of Laps



Remaining Laps =

Total Predicted Laps - Laps Already Completed

Data Models

Random Forest

Number of estimators = 1000

ElasticNet

Max Iterations = 10000

K-Nearest Neighbours

- Number of neighbours = 5
- Algorithm = "kd_tree"
- Weights = "Distance"

Weighted Average Ensemble Model

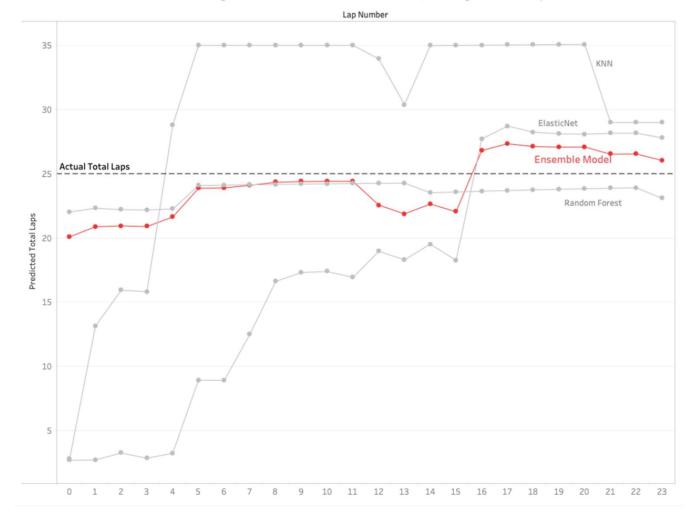
Weights assigned to each baseline model using Linear Regression

5. Model Evaluation and Results

Models with their accuracies (Excluding Weather Data)

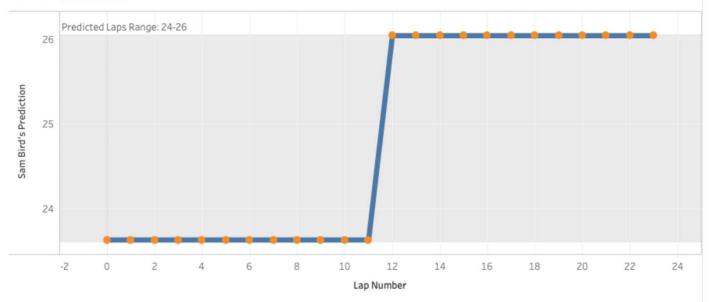
	R2 values	MSE Score
Random Forest	0.9698	5.489
K Nearest Neighbours	0.8811	20.184
ElasticNet	0.7948	29.03

Ensemble model converges better than baseline models, throughout the laps in the race



Model Output

Ensemble Model predicts the lap range accuractely throught the race for **Virgin Racing's** driver Sam Bird



Customized Predictions Conclusion & Future Recommendations

Conclusive Insights

Insight 1

Weather definitely has an effect on the average speed of a racer. Specifically, a higher wind and temperature would lead to a slightly faster speed.

Insight 2

Out of the models we tried, Ensemble Model seems to fit the data best. At any given point, we can thus, predict the total laps in the race

