



SC1015 Mini-Project

Formula One

Lab Group 3
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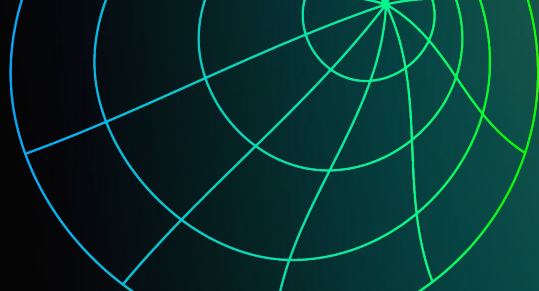


01



About our Project





Formula One




- “Who will win?”
- Complexity and unpredictability of success

Motivation: To better understand which factors contribute most to a driver's success + predict who will win





PROBLEM STATEMENT



Which driver will finish in the top position in the Driver's Championship at the end of the season and which of the new drivers have the potential to become a top F1 driver?



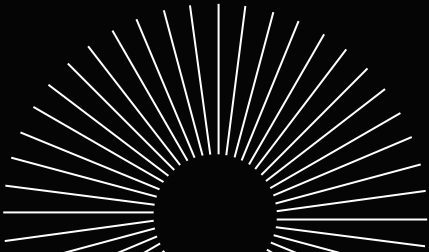


Dataset

Kaggle

Formula 1 World Championship (1950 - 2023)[1]

Kept up-to-date, many useful information





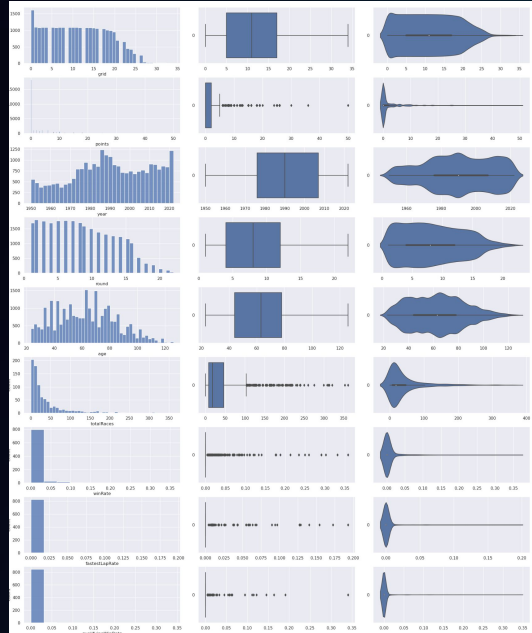
Data exploration and cleaning

02

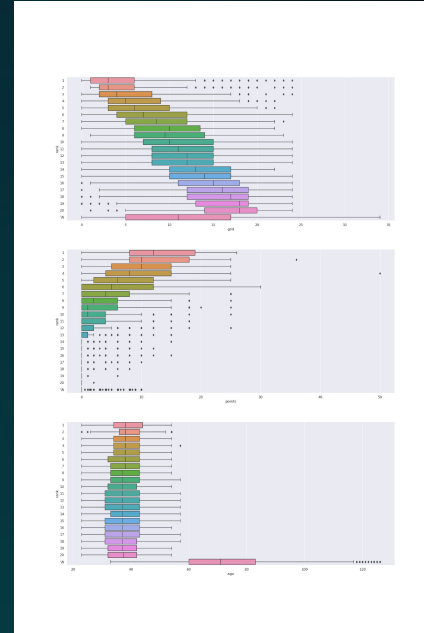


Breakdown of Variable

Numerical Variable



Categorical Variable



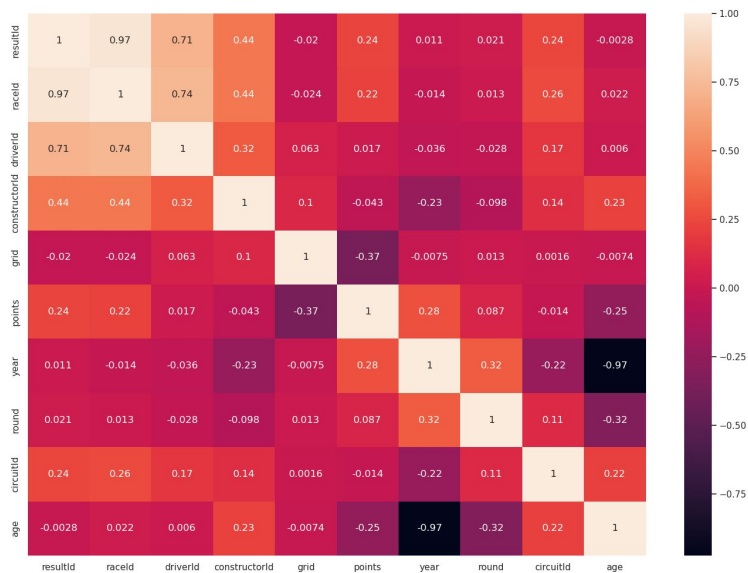
Feature Engineering

	winRate	fastestLapRate	qualifyingWinRate	age
0	0.331190	0.192926	0.340836	38
1	0.000000	0.010309	0.005155	46
2	0.111650	0.097087	0.145631	38
3	0.088643	0.063712	0.063712	42
4	0.009009	0.018018	0.009009	42

- We create new variables to capture important information in dataset
 - $\text{winRate} = (\text{number of winning}) / (\text{total races})$
 - $\text{fastestLapRate} = (\text{number of fastest laps}) / (\text{total laps})$
 - $\text{qualifyingWinRate} = (\text{number of winning qualify}) / (\text{total qualify races})$



Correlation Matrix



- Plot the correlation matrix for points against all other numeric variables
- Interesting Findings:
 - Points and Age (-0.25)
 - Points and Grid (-0.37)



Core Analysis

03



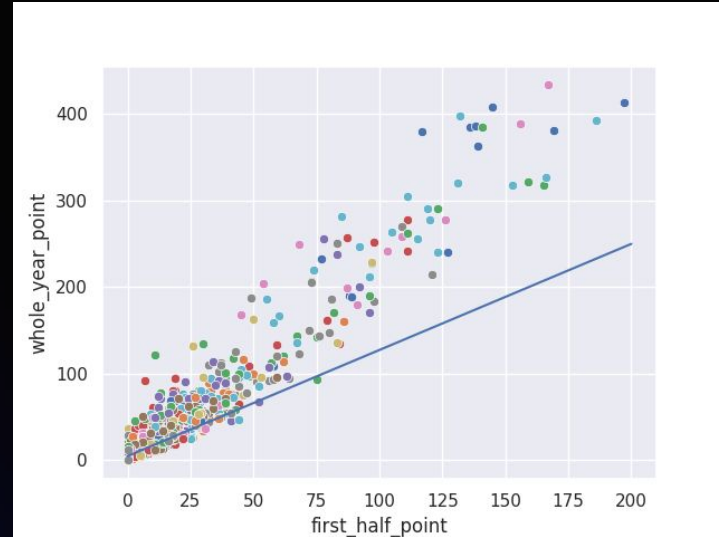
Linear Regression

Train (80%):

Explained Variance (R^2) : 0.79

Test (20%):

Explained Variance (R^2) : 0.87





Polynomial Regression

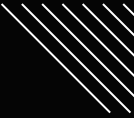
Train (80%):

Explained Variance (R^2) : 0.81

Test (20%):

Explained Variance (R^2) : 0.85

Polynomials	Form	Degree	Examples
Linear Polynomial	$p(x): ax+b, a \neq 0$	Polynomial with Degree 1	$x + 8$
Quadratic Polynomial	$p(x): ax^2+bx+c, a \neq 0$	Polynomial with Degree 2	$3x^2-4x+7$
Cubic Polynomial	$p(x): ax^3+bx^2+cx, a \neq 0$	Polynomial with Degree 3	$2x^3+3x^2+4x+6$





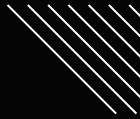
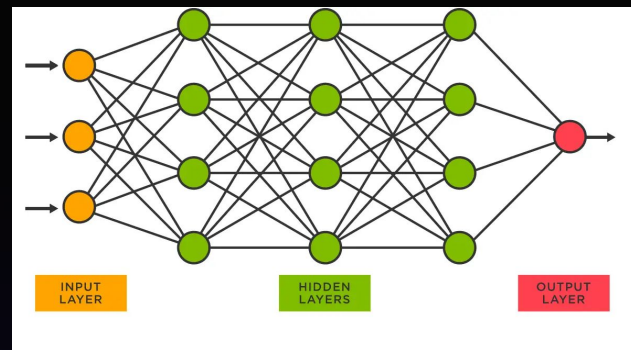
Neural Network

Train (80%):

Accuracy score : 0.86

Test (20%):

Accuracy score : 0.83

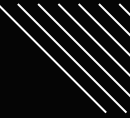




Which driver will finish in the top position in the Driver's Championship at the end of the season
and **which of the new drivers have the potential to become a top F1 driver?**

Unsupervised Learning

- K-means
- DBSCAN





Lewis Hamilton, Mercedes, 1st position, celebrates on arrival in Parc Ferme

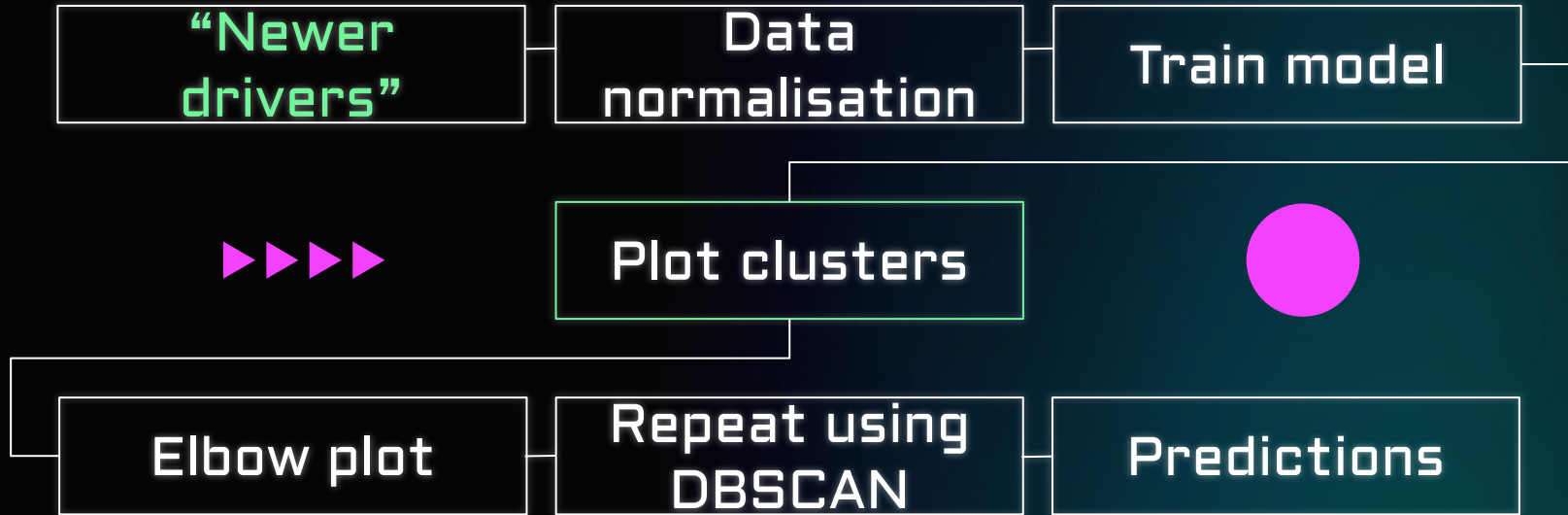
Photo by: Jerry Andre / [Motorsport Images](#)


1. Lewis Hamilton - 103 wins

- First race: 2007 Australian Grand Prix
- World Championships: 7 (2008, 2014-15, 2017-20)
- Number of races: 310
- Number of wins: 103
- Number of pole positions: 103
- Career points: 4415.5

	driverId	driverRef	totalRaces	winRate	fastestLapRate	qualifyingWinRate	age
0	1	hamilton	311.0	0.331190	0.192926	0.340836	38
1	2	heidfeld	194.0	0.000000	0.010309	0.005155	46
2	3	rosberg	206.0	0.111650	0.097087	0.145631	38
3	4	alonso	361.0	0.088643	0.063712	0.063712	42
4	5	kovalainen	111.0	0.009009	0.018018	0.009009	42

CLUSTERING PROCESS

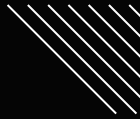




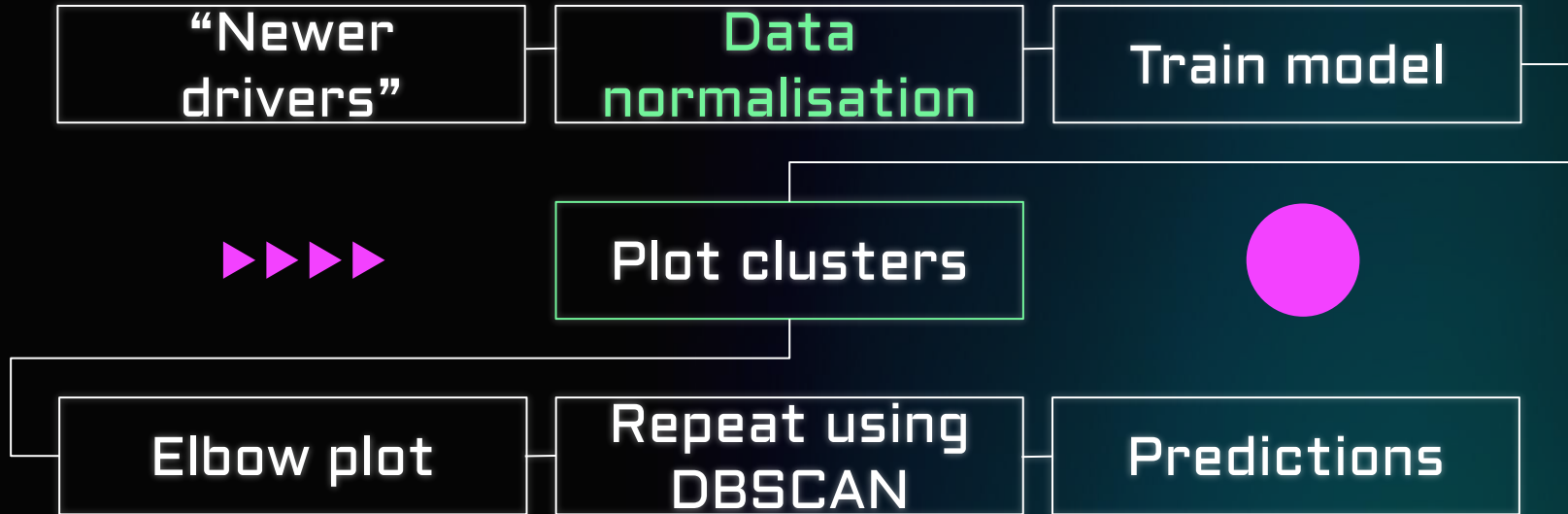
Defining “newer drivers”



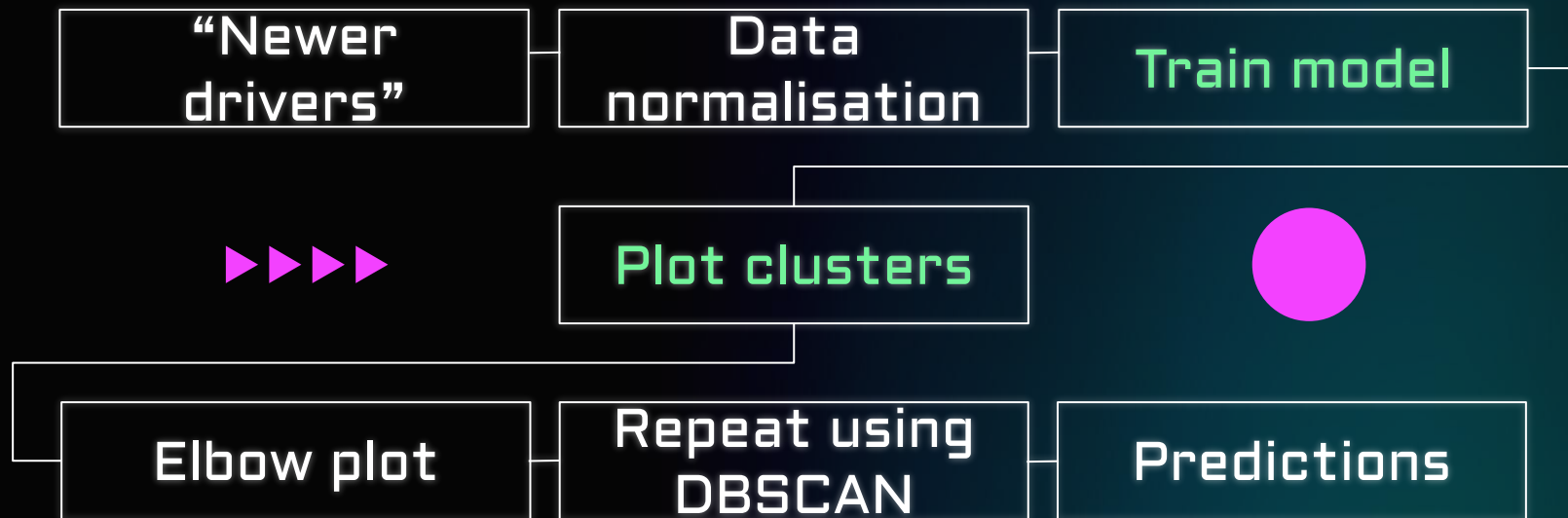
	driverId	driverRef
845	847	russell
850	852	tsunoda
853	855	zhou
854	856	de_vries
855	857	piastri



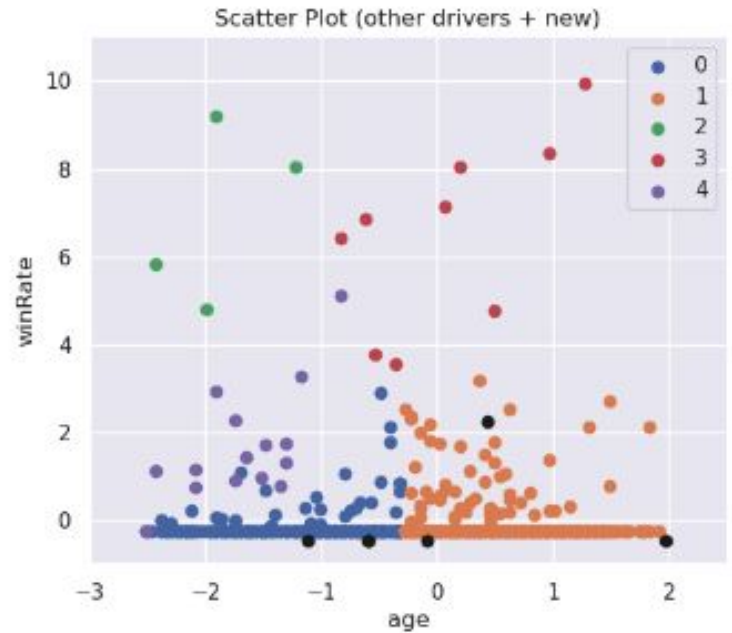
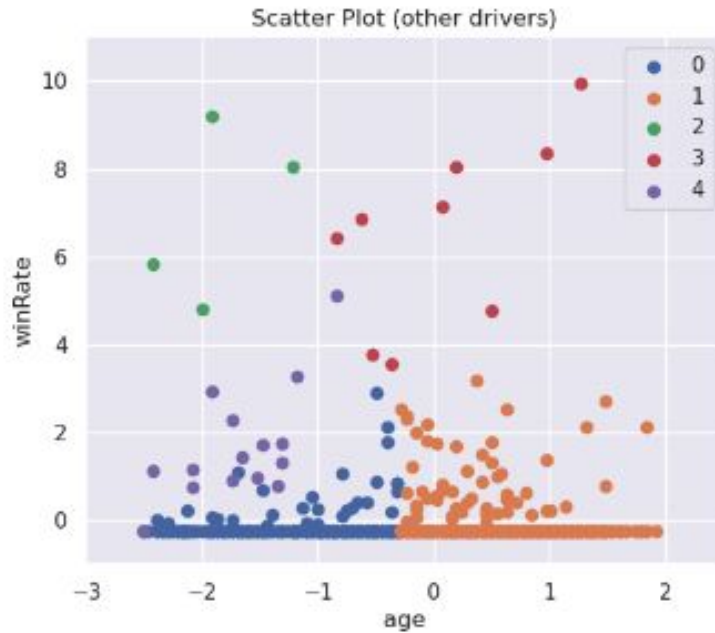
CLUSTERING PROCESS



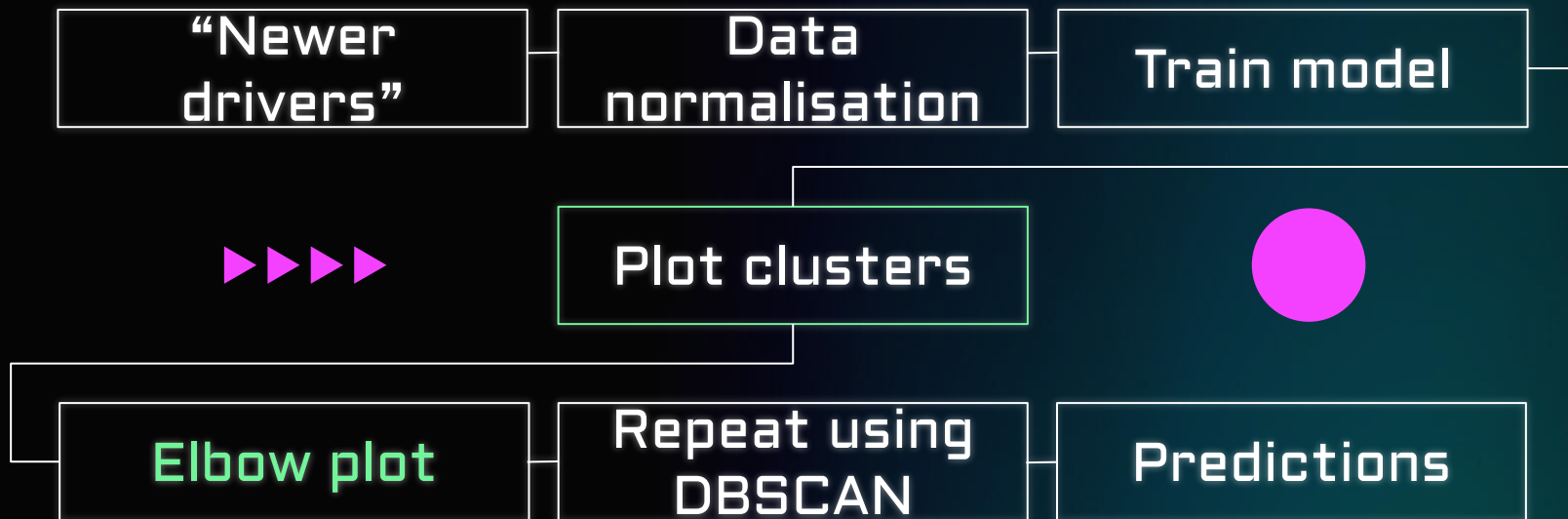
CLUSTERING PROCESS



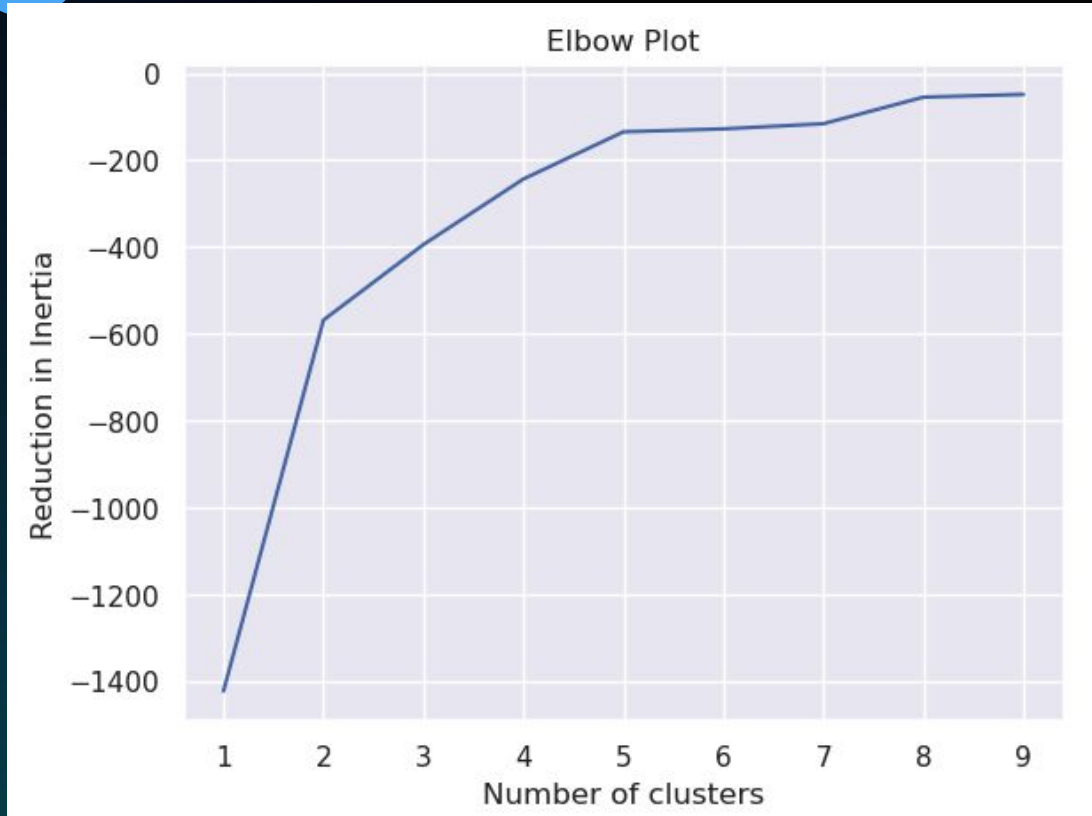
K-means



CLUSTERING PROCESS



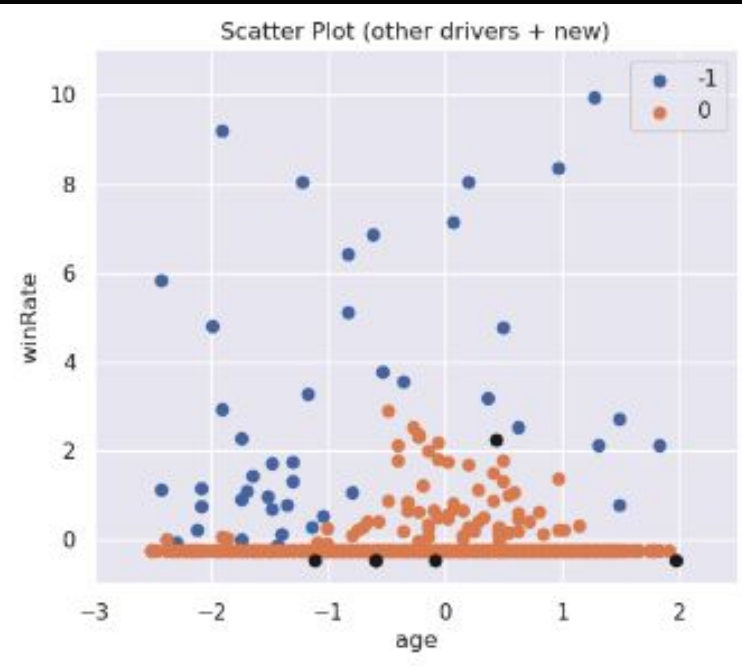
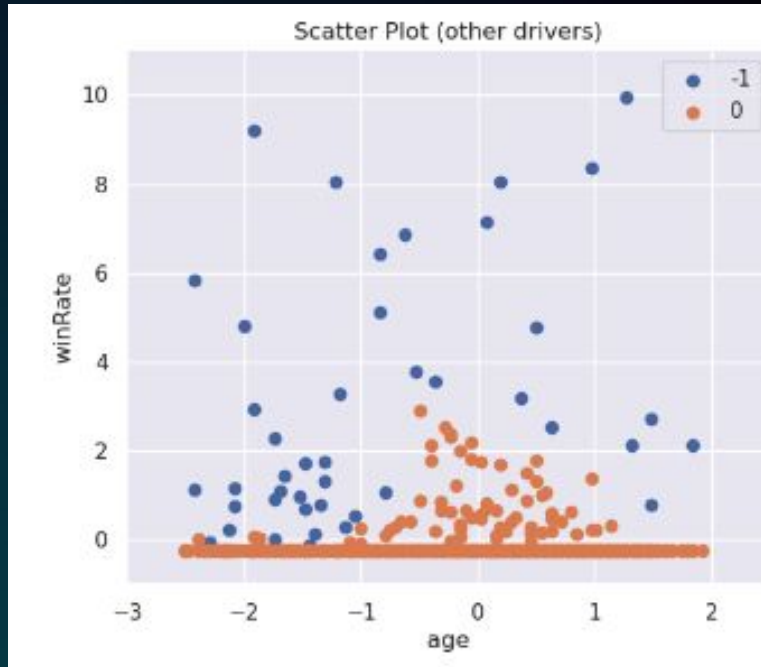
Elbow plot



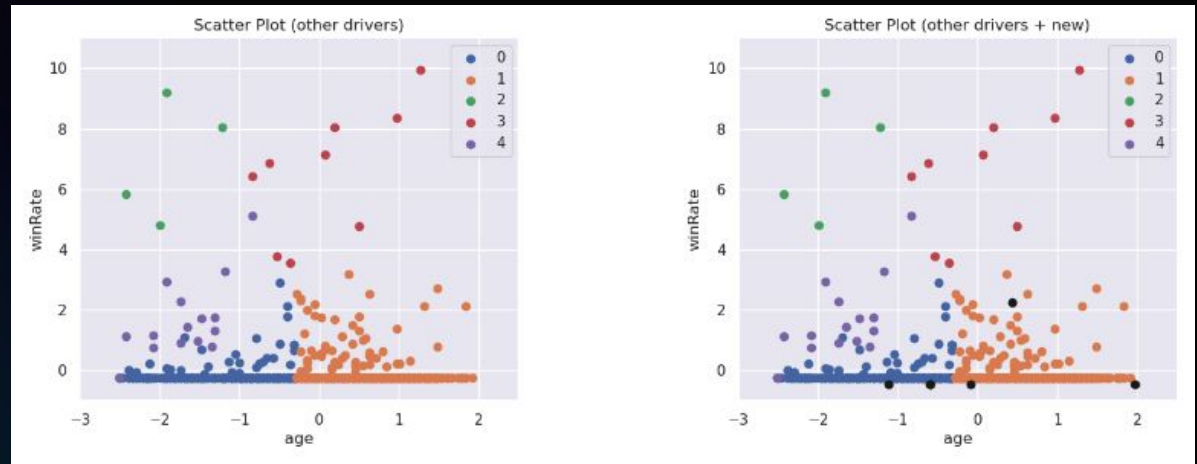
CLUSTERING PROCESS



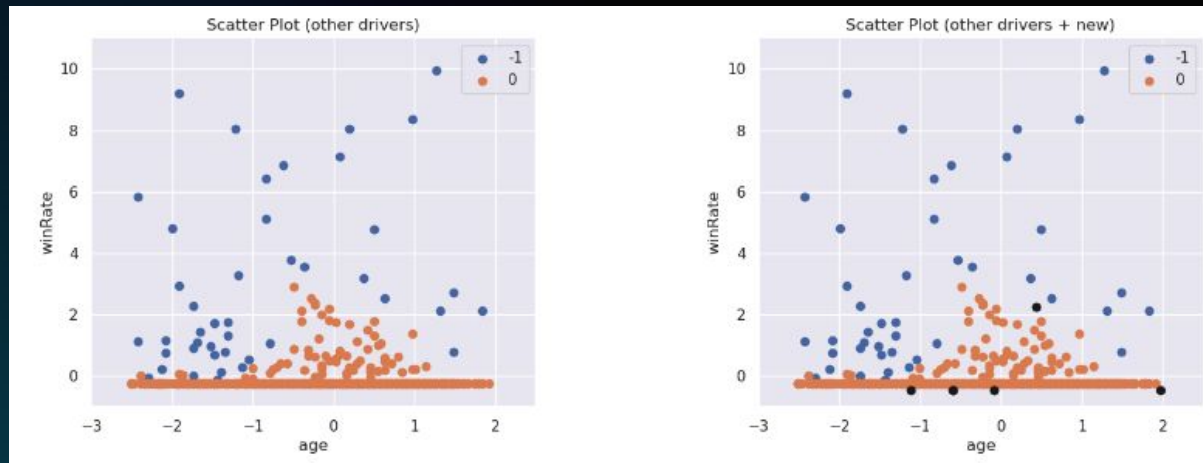
DBSCAN



K-means



DBSCAN





K-means

driverId	driverRef	totalRaces	winRate	fastestLapRate	qualifyingWinRate	age	cluster
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From here, we can see that none of the newer drivers share the same characteristics as the top drivers as they do not fall into the same clusters as them.

DBSCAN

	driverId	driverRef	totalRaces	winRate	fastestLapRate	qualifyingWinRate	age	cluster	cluster_dbscan
845	847	russell	83.0	0.012048	0.060241	0.012048	25	7	-1
850	852	tsunoda	45.0	0.000000	0.000000	0.000000	23	0	-1
853	855	zhou	23.0	0.000000	0.043478	0.000000	24	0	-1
854	856	de_vries	8.0	0.000000	0.000000	0.000000	28	5	-1
855	857	piastri	1.0	0.000000	0.000000	0.000000	22	6	-1
856	858	sargeant	1.0	0.000000	0.000000	0.000000	23	0	-1

From here, we can see that according to DBSCAN, all of the newer drivers share the same characteristics as the top drivers.



04



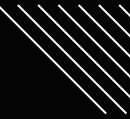
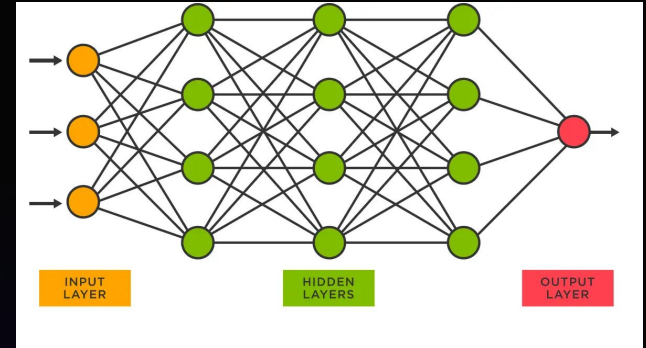
Outcomes and Insights





Supervised Learning

- High accuracy
- Help teams forecast driver performance



Unsupervised Learning



K-means

driverId	driverRef	totalRaces	winRate	fastestLapRate	qualifyingWinRate	age	cluster
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DBSCAN

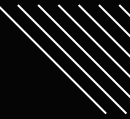
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845	847	russell	83.0	0.012048	0.060241	0.012048	25	7	-1
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From here, we can see that according to DBSCAN, all of the newer drivers share the same characteristics as the top drivers.



Unsupervised Learning

- Different results
- DBSCAN may not be the most accurate



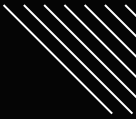


Data Driven Insights

- Correlation matrix: Points obtained by the driver are highly correlated to the age and grid of the driver.
- DBSCAN: Younger drivers more likely to win more often
- Highlight to teams: focus on the potential of younger drivers and placing well in qualifying races.



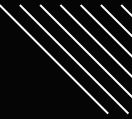
	DBSCAN_cluster	driverId	winRate	fastestLapRate	qualifyingWinRate	age
0	-1	324.854167	0.102665	0.044837	0.039205	58.979167
1	0	432.109589	0.002954	0.000149	0.000048	83.845579





Main learning points

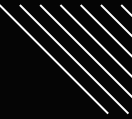
- Polynomial regression could result in better fit on the training set, but it risks worse performance on the validation set
- It is very important to prepare data for clustering
- Learnt more about the different types of clustering models and their algorithms





Recommendations

- More complex models can be integrated to improve performance of prediction such as Recurrent Neural Network to better capture time series data.
- More types of clustering algorithms used - hierarchical clustering
- More data fed into clustering algorithm to improve accuracy, when appropriate





Thank You

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