Project

December 11, 2023

1 Project: F1 race prediction

1.1 1) Import necessary libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV, KFold
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import r2_score, mean_squared_error
import xgboost as xgb
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor

import warnings
warnings.filterwarnings('ignore')
```

1.2 2) Helper Functions

[2]:
```
# Convert timestamp to numeric value
def time_str_to_numeric(time_str):
    if isinstance(time_str, str) and time_str != "\\N":
        minutes, seconds = map(float, time_str.split(':'))
        return minutes * 60 + seconds
    else:
        return np.nan
```

[3]:
```
# Map the race positions to the points
def attach_raceId_to_predictions(raceIds, y_pred):
    predictions_with_raceId = pd.DataFrame(raceIds)
    predictions_with_raceId['y_pred'] = y_pred
    predictions_with_raceId['new_y_pred'] = predictions_with_raceId.
  ↪groupby('raceId')['y_pred'].transform(lambda x: x.rank(ascending=False,␣
  ↪method='first'))
```

```
    rank_to_points = {1: 25, 2: 18, 3: 15, 4: 12, 5: 10, 6: 8, 7: 6, 8: 4, 9:␣
↪2, 10: 1}

    predictions_with_raceId['new_y_pred'] =␣
↪predictions_with_raceId['new_y_pred'].map(rank_to_points).fillna(0)
    new_y_pred = predictions_with_raceId['new_y_pred'].values

    return new_y_pred
```

1.3 3) Data loading

1. All the csv files are in the data sub folder but we only need these 6 csv files

[4]:
```
# Read the data from a csv files to dataframes
circuts = pd.read_csv("data/circuits.csv")
constructors = pd.read_csv("data/constructors.csv")
drivers = pd.read_csv("data/drivers.csv")
qualifying = pd.read_csv("data/qualifying.csv")
races = pd.read_csv("data/races.csv")
results = pd.read_csv("data/results.csv")
```

1.4 4) Data Pre-Processing

1.4.1 4.1) Raw data from multiple csv files

[5]:
```
qualifying.head()
```

[5]:
```
   qualifyId  raceId  driverId  constructorId  number  position        q1  \
0          1      18         1              1      22         1  1:26.572
1          2      18         9              2       4         2  1:26.103
2          3      18         5              1      23         3  1:25.664
3          4      18        13              6       2         4  1:25.994
4          5      18         2              2       3         5  1:25.960

         q2        q3
0  1:25.187  1:26.714
1  1:25.315  1:26.869
2  1:25.452  1:27.079
3  1:25.691  1:27.178
4  1:25.518  1:27.236
```

[6]:
```
races.head()
```

[6]:
```
   raceId  year  round  circuitId                   name        date  \
0       1  2009      1          1  Australian Grand Prix  2009-03-29
1       2  2009      2          2   Malaysian Grand Prix  2009-04-05
2       3  2009      3         17     Chinese Grand Prix  2009-04-19
```

```
3       4  2009      4          3     Bahrain Grand Prix  2009-04-26
4       5  2009      5          4     Spanish Grand Prix  2009-05-10

       time                                                url fp1_date  \
0  06:00:00  http://en.wikipedia.org/wiki/2009_Australian_G…       \N
1  09:00:00  http://en.wikipedia.org/wiki/2009_Malaysian_Gr…       \N
2  07:00:00  http://en.wikipedia.org/wiki/2009_Chinese_Gran…       \N
3  12:00:00  http://en.wikipedia.org/wiki/2009_Bahrain_Gran…       \N
4  12:00:00  http://en.wikipedia.org/wiki/2009_Spanish_Gran…       \N

  fp1_time fp2_date fp2_time fp3_date fp3_time quali_date quali_time  \
0       \N       \N       \N       \N       \N         \N         \N
1       \N       \N       \N       \N       \N         \N         \N
2       \N       \N       \N       \N       \N         \N         \N
3       \N       \N       \N       \N       \N         \N         \N
4       \N       \N       \N       \N       \N         \N         \N

  sprint_date sprint_time
0          \N          \N
1          \N          \N
2          \N          \N
3          \N          \N
4          \N          \N
```

[7]:
```
results.head()
```

[7]:
```
   resultId  raceId  driverId  constructorId number  grid position  \
0         1      18         1              1     22     1        1
1         2      18         2              2      3     5        2
2         3      18         3              3      7     7        3
3         4      18         4              4      5    11        4
4         5      18         5              1     23     3        5

  positionText  positionOrder  points  laps         time milliseconds  \
0            1              1    10.0    58  1:34:50.616      5690616
1            2              2     8.0    58       +5.478      5696094
2            3              3     6.0    58       +8.163      5698779
3            4              4     5.0    58      +17.181      5707797
4            5              5     4.0    58      +18.014      5708630

  fastestLap rank fastestLapTime fastestLapSpeed  statusId
0         39    2       1:27.452         218.300         1
1         41    3       1:27.739         217.586         1
2         41    5       1:28.090         216.719         1
3         58    7       1:28.603         215.464         1
4         43    1       1:27.418         218.385         1
```

1.4.2 4.2) Data Selection, Handling missing data , Data Cleaning

[8]:
```
# Remove unwanted columns
qualifying = qualifying.drop(['number'], axis = 1)
races = races[['raceId','year','round','circuitId']]
results = results.drop(['number', 'positionText',␣
 ↪'positionOrder','time','milliseconds','rank','statusId'], axis=1)

# Collecting races which happened on or after 2000 for our analysis
races = races[races['year'] >= 2000]
unique_race_ids = races['raceId'].unique()
results = results[results['raceId'].isin(unique_race_ids)]
qualifying = qualifying[qualifying['raceId'].isin(unique_race_ids)]

# Replacing the missing value of fastestLapTime with 100:0 (very large time␣
 ↪value)
results['fastestLapTime'] = results['fastestLapTime'].replace({'\\N': '100:0'})

# Replacing the missing value of fastestLapSpeed with 0 (Least speed)
results['fastestLapSpeed'] = results['fastestLapSpeed'].replace({'\\N': '0'})

# Replacing the missing value of fastestLap with 0 (Indicating no lap)
results['fastestLap'] = results['fastestLap'].replace({'\\N': '0'})

# Replacing the missing value of position with 20 (last position)
results['position'] = results['position'].replace({'\\N': '20'})

# Converting the timestamp to numberic values
results['fastestLapTime'] = results['fastestLapTime'].apply(time_str_to_numeric)
qualifying['q1'] = qualifying['q1'].apply(time_str_to_numeric)
qualifying['q2'] = qualifying['q2'].apply(time_str_to_numeric)
qualifying['q3'] = qualifying['q3'].apply(time_str_to_numeric)

# Converting position, fastestLap, fastestLapSpeed from object to int
results['position'] = results['position'].astype(int)
results['fastestLap'] = results['fastestLap'].astype(int)
results['fastestLapSpeed'] = results['fastestLapSpeed'].astype(float)
```

1.4.3 4.3) Feature Engineering

1. Generate qualifying_time feature from q1, q2, q3
2. Generate features grid_pos1, grid_pos2, …, grid_pos10 to capture past 10 grid positions of that driver
3. Generate features result_pos1, result_pos2, …, result_pos10 to capture past 10 results positions of that driver
4. We believe that these features will give the models idea about the race car performance and driver skills

[9]:
```python
# Merge results and races on raceId and create a main dataframe
df = pd.merge(results, races[['raceId','year','circuitId']], on="raceId")

# create qualifying_time feature from q1, q2, q3
qualifying['qualifying_time'] = qualifying[['q1','q2','q3']].min(axis=1)

# adding qualifying_time feature to the main dataframe
df = pd.merge(df, qualifying[["raceId", "driverId", "constructorId",␣
↪"qualifying_time"]], on=["raceId", "driverId", "constructorId"])

# fill the missing values if any with max value
df['qualifying_time'] = df.groupby('raceId')['qualifying_time'].
↪transform(lambda x: x.fillna(x.max()))
```

[10]:
```python
# temporary data frame to generate grid_pos1, grid_pos2, ..., grid_pos10␣
↪features
df_grid = pd.merge(races[['raceId','year','round']],␣
↪results[['raceId','driverId','grid']] , on=['raceId'])
df_grid = df_grid.sort_values(by=['year', 'driverId', 'round'])

previous_rounds = 10

# generating and updating grid_pos1, grid_pos2, ..., grid_pos10 features
for i in range(1, previous_rounds + 1):
    df_grid[f'grid_pos{i}'] = df_grid.groupby(['year', 'driverId'])['grid'].
↪shift(i)

df_grid = df_grid.reset_index(drop=True)

for i in range(1, previous_rounds + 1):
    df_grid.loc[df_grid['round'] <= i, f'grid_pos{i}'] = None

df_grid = df_grid.sort_values(by=['driverId', 'round'])

# Filling the None values with mean values
for i in range(1, previous_rounds + 1):
    if i == 1:
        df_grid[f'grid_pos{i}'].fillna(df_grid['grid'], inplace=True)
    else:
        df_grid[f'grid_pos{i}'].fillna(df_grid[[f'grid_pos{j}' for j in␣
↪range(1, i)] + ['grid']].mean(axis=1), inplace=True)

# making grid_pos1, grid_pos2, ..., grid_pos10 features as int type
for i in range(1, previous_rounds + 1):
    df_grid[f'grid_pos{i}'] = df_grid[f'grid_pos{i}'].astype(int)
```

[11]:

```
# temporary data frame to generate result_pos1, result_pos2, ..., result_pos10␣
↪features
df_result = pd.merge(races[['raceId','year','round']],␣
↪results[['raceId','driverId','position']] , on=['raceId'])
df_result = df_result.sort_values(by=['year', 'driverId', 'round'])

previous_rounds = 10

# generating and updating result_pos1, result_pos2, ..., result_pos10 features
for i in range(1, previous_rounds + 1):
    df_result[f'result_pos{i}'] = df_result.groupby(['year',␣
↪'driverId'])['position'].shift(i)

df_result = df_result.reset_index(drop=True)

for i in range(1, previous_rounds + 1):
    df_result.loc[df_result['round'] <= i, f'result_pos{i}'] = None

df_result = df_result.sort_values(by=['driverId', 'round'])

# Filling the None values with mean values
for i in range(1, previous_rounds + 1):
    if i == 1:
        df_result[f'result_pos{i}'].fillna(df_result['position'], inplace=True)
    else:
        df_result[f'result_pos{i}'].fillna(df_result[[f'result_pos{j}' for j in␣
↪range(1, i)] + ['position']].mean(axis=1), inplace=True)

# making result_pos1, result_pos2, ..., result_pos10 features as int type
for i in range(1, previous_rounds + 1):
    df_result[f'result_pos{i}'] = df_result[f'result_pos{i}'].astype(int)
```

[12]:

```
# adding grid_pos1, grid_pos2, ..., grid_pos10 feature to the main dataframe
df = pd.merge(df,␣
↪df_grid[["raceId","driverId","grid_pos1","grid_pos2","grid_pos3","grid_pos4","grid_pos5","g
↪on=["raceId","driverId"])

# adding result_pos1, result_pos2, ..., result_pos10 feature to the main␣
↪dataframe
df = pd.merge(df,␣
↪df_result[["raceId","driverId","result_pos1","result_pos2","result_pos3","result_pos4","res
↪on=["raceId","driverId"])

# position to points mapping
points_mapping = {
    1: 25, 2: 18, 3: 15, 4: 12, 5: 10, 6: 8, 7: 6, 8: 4, 9: 2, 10: 1
}
```

```python
# modifying points according to the position using our mapping
df['points'] = df['position'].map(points_mapping).fillna(0)

# drop resultId, year, position as they are irrelevant in predictions
df = df.drop(['resultId','year','position'],axis=1)
```

1.4.4 4.4) Descriptive stats of the data and data exploration

[13]:
```python
df.head()
```

[13]:
```
   raceId  driverId  constructorId  grid  points  laps  fastestLap  \
0      18         1              1     1    25.0    58          39
1      18         2              2     5    18.0    58          41
2      18         3              3     7    15.0    58          41
3      18         4              4    11    12.0    58          58
4      18         5              1     3    10.0    58          43

   fastestLapTime  fastestLapSpeed  circuitId  …  result_pos1  result_pos2  \
0          87.452          218.300          1  …            1            1
1          87.739          217.586          1  …            2            2
2          88.090          216.719          1  …            3            3
3          88.603          215.464          1  …            4            4
4          87.418          218.385          1  …            5            5

   result_pos3  result_pos4  result_pos5  result_pos6  result_pos7  \
0            1            1            1            1            1
1            2            2            2            2            2
2            3            3            3            3            3
3            4            4            4            4            4
4            5            5            5            5            5

   result_pos8  result_pos9  result_pos10
0            1            1             1
1            2            2             2
2            3            3             3
3            4            4             4
4            5            5             5

[5 rows x 31 columns]
```

[14]:
```python
df.dtypes
```

[14]:
```
raceId              int64
driverId            int64
constructorId       int64
grid                int64
```

```
points               float64
laps                   int64
fastestLap             int64
fastestLapTime       float64
fastestLapSpeed      float64
circuitId              int64
qualifying_time      float64
grid_pos1              int64
grid_pos2              int64
grid_pos3              int64
grid_pos4              int64
grid_pos5              int64
grid_pos6              int64
grid_pos7              int64
grid_pos8              int64
grid_pos9              int64
grid_pos10             int64
result_pos1            int64
result_pos2            int64
result_pos3            int64
result_pos4            int64
result_pos5            int64
result_pos6            int64
result_pos7            int64
result_pos8            int64
result_pos9            int64
result_pos10           int64
dtype: object
```

[15]:

```
df.describe()
```

[15]:

	raceId	driverId	constructorId	grid	points	\
count	8409.000000	8409.000000	8409.000000	8409.000000	8409.000000	
mean	648.171483	355.634201	49.058628	10.911167	4.809609	
std	427.310243	396.306270	75.318693	6.178142	7.086527	
min	1.000000	1.000000	1.000000	0.000000	0.000000	
25%	102.000000	14.000000	4.000000	6.000000	0.000000	
50%	886.000000	37.000000	9.000000	11.000000	0.000000	
75%	998.000000	822.000000	51.000000	16.000000	8.000000	
max	1110.000000	858.000000	214.000000	24.000000	25.000000	

	laps	fastestLap	fastestLapTime	fastestLapSpeed	circuitId	\
count	8409.000000	8409.000000	8409.000000	8409.00000	8409.000000	
mean	52.434416	38.391247	670.015369	183.45365	19.355809	
std	18.738098	20.325476	1756.901843	63.80533	20.863197	
min	0.000000	0.000000	55.404000	0.00000	1.000000	
25%	51.000000	24.000000	81.695000	188.01300	6.000000	

```
50%      56.000000    43.000000      92.804000        202.41400    13.000000
75%      66.000000    53.000000     103.256000        214.81500    21.000000
max      87.000000    85.000000    6000.000000        257.32000    79.000000

         …  result_pos1  result_pos2  result_pos3  result_pos4  result_pos5  \
count    …  8409.000000  8409.000000  8409.000000  8409.000000  8409.000000
mean     …    11.329766    11.338923    11.327268    11.309906    11.300987
std      …     6.394765     6.347120     6.271143     6.186931     6.114017
min      …     1.000000     1.000000     1.000000     1.000000     1.000000
25%      …     6.000000     6.000000     6.000000     6.000000     6.000000
50%      …    11.000000    11.000000    11.000000    11.000000    11.000000
75%      …    17.000000    17.000000    17.000000    17.000000    16.000000
max      …    24.000000    23.000000    23.000000    23.000000    23.000000

       result_pos6  result_pos7  result_pos8  result_pos9  result_pos10
count  8409.000000  8409.000000  8409.000000  8409.000000   8409.000000
mean     11.287668    11.259841    11.256987    11.247711     11.224878
std       6.036886     5.943570     5.865866     5.772703      5.676413
min       1.000000     1.000000     1.000000     1.000000      1.000000
25%       6.000000     6.000000     6.000000     7.000000      7.000000
50%      11.000000    11.000000    11.000000    11.000000     11.000000
75%      16.000000    16.000000    16.000000    16.000000     16.000000
max      23.000000    23.000000    23.000000    23.000000     23.000000

[8 rows x 31 columns]
```

[16]:
```python
df.isna().sum()
```

[16]:
```
raceId            0
driverId          0
constructorId     0
grid              0
points            0
laps              0
fastestLap        0
fastestLapTime    0
fastestLapSpeed   0
circuitId         0
qualifying_time   0
grid_pos1         0
grid_pos2         0
grid_pos3         0
grid_pos4         0
grid_pos5         0
grid_pos6         0
grid_pos7         0
grid_pos8         0
```

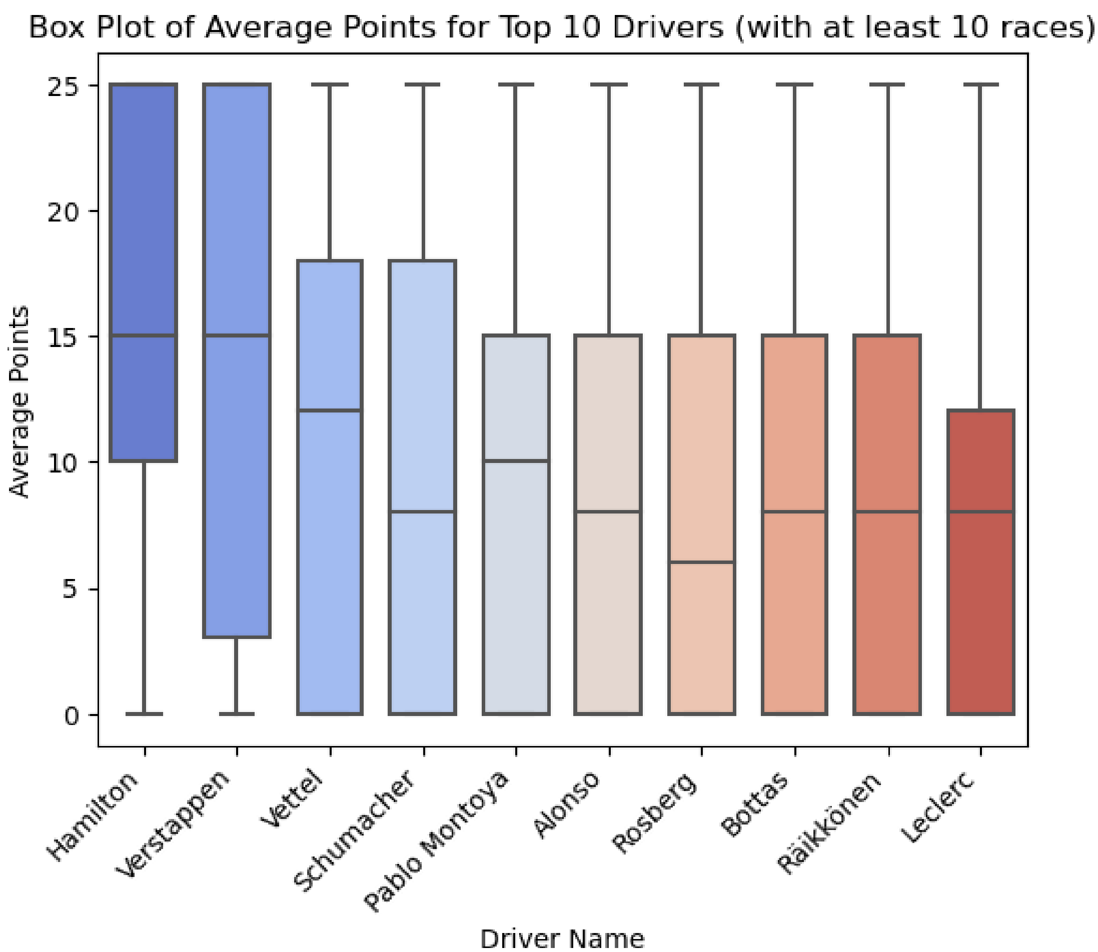
```
grid_pos9          0
grid_pos10         0
result_pos1        0
result_pos2        0
result_pos3        0
result_pos4        0
result_pos5        0
result_pos6        0
result_pos7        0
result_pos8        0
result_pos9        0
result_pos10       0
dtype: int64
```

[17]:
```python
print("Number of records = "+str(df.shape[0]))
print("Number of features(including raceID) = "+str(df.shape[1]))
```

```
Number of records = 8409
Number of features(including raceID) = 31
```

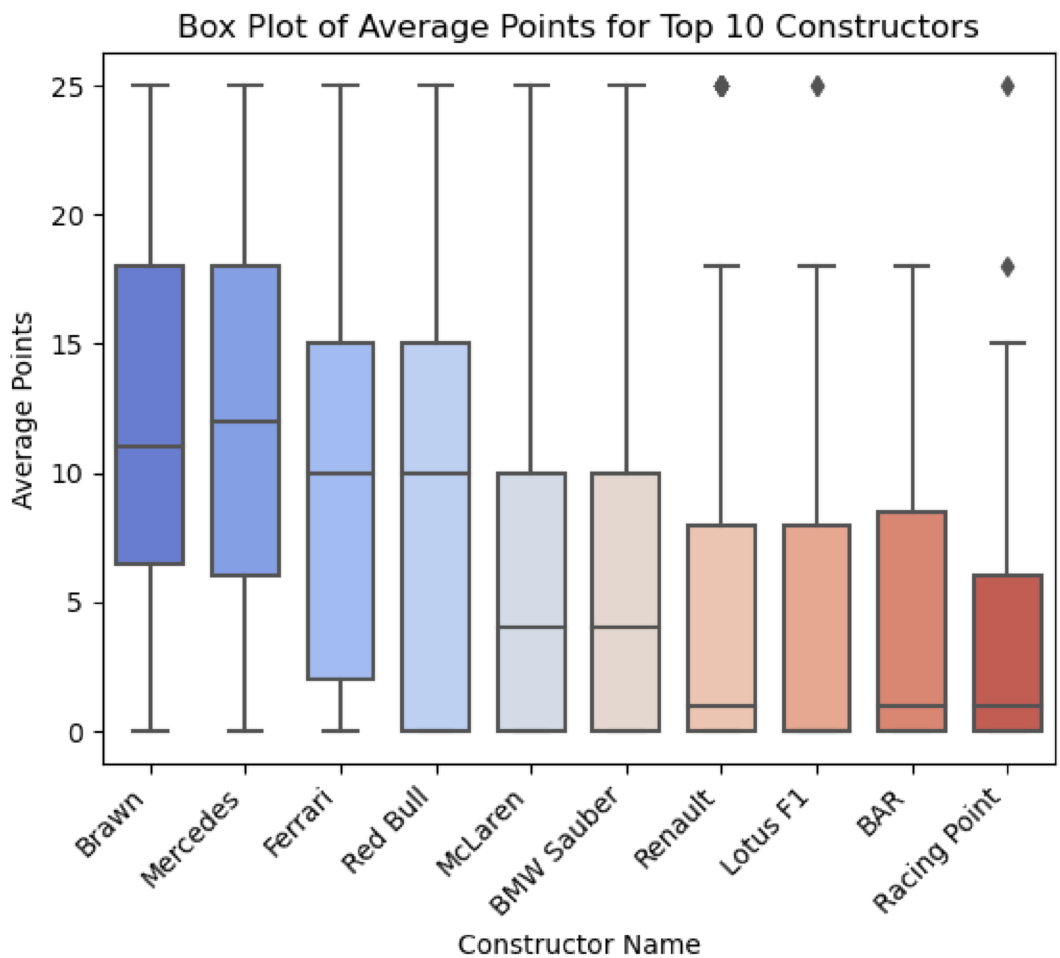
[18]:
```python
# Count the number of races each driver has participated in
race_counts = df['driverId'].value_counts()

# Filter out drivers with less than 5 races
eligible_drivers = race_counts[race_counts >= 10].index

# Filter the main DataFrame for only eligible drivers
df_eligible = df[df['driverId'].isin(eligible_drivers)]

# Group by driverId and calculate the mean points for each eligible driver
df_avg_points = df_eligible.groupby('driverId')['points'].mean().reset_index()

# Sort the Series by average points in descending order to get the best drivers
df_avg_points_sorted = df_avg_points.sort_values('points', ascending=False)

# Select the top N drivers (adjust N based on your preference)
top_n_drivers = 10
df_top_n_avg_points = df_avg_points_sorted.head(top_n_drivers)

# Merge with the original DataFrame to get additional information including␣
↪driver names
df_top_n_avg_info = pd.merge(df_top_n_avg_points, df_eligible, on='driverId',␣
↪how='left')
df_top_n_avg_info = pd.merge(df_top_n_avg_info, drivers[['driverId',␣
↪'driverRef', 'forename', 'surname']], on='driverId', how='left')

# Create a box plot using Seaborn with switched axes and a cool color gradient
```

```
plt.figure()
sns.boxplot(x='surname', y='points_y', data=df_top_n_avg_info, width=0.7,␣
 ↪palette="coolwarm")
plt.title('Box Plot of Average Points for Top {} Drivers (with at least 10␣
 ↪races)'.format(top_n_drivers))
plt.xlabel('Driver Name')
plt.ylabel('Average Points')
plt.xticks(rotation=45, ha="right")  # Rotate x-axis labels for better␣
 ↪visibility
plt.show()
```



[19]:
```
# Group by constructorId and calculate the mean points for each constructor
df_avg_points_constructor = df.groupby('constructorId')['points'].mean().
 ↪reset_index()
```

```python
# Sort the DataFrame by average points in descending order to get the best␣
↪constructors
df_avg_points_constructor_sorted = df_avg_points_constructor.
↪sort_values('points', ascending=False)

# Select the top N constructors (adjust N based on your preference)
top_n_constructors = 10
df_top_n_avg_points_constructor = df_avg_points_constructor_sorted.
↪head(top_n_constructors)

# Merge with the original DataFrame to get additional information including␣
↪constructor names
df_top_n_avg_info_constructor = pd.merge(df_top_n_avg_points_constructor, df,␣
↪on='constructorId', how='left')
df_top_n_avg_info_constructor = pd.merge(df_top_n_avg_info_constructor,␣
↪constructors[['constructorId', 'name']], on='constructorId', how='left')

# Create a box plot using Seaborn with switched axes
plt.figure()
sns.boxplot(x='name', y='points_y', data=df_top_n_avg_info_constructor, width=0.
↪7, palette="coolwarm")
plt.title('Box Plot of Average Points for Top {} Constructors'.
↪format(top_n_constructors))
plt.xlabel('Constructor Name')
plt.ylabel('Average Points')
plt.xticks(rotation=45, ha="right")  # Rotate x-axis labels for better␣
↪visibility
plt.show()
```

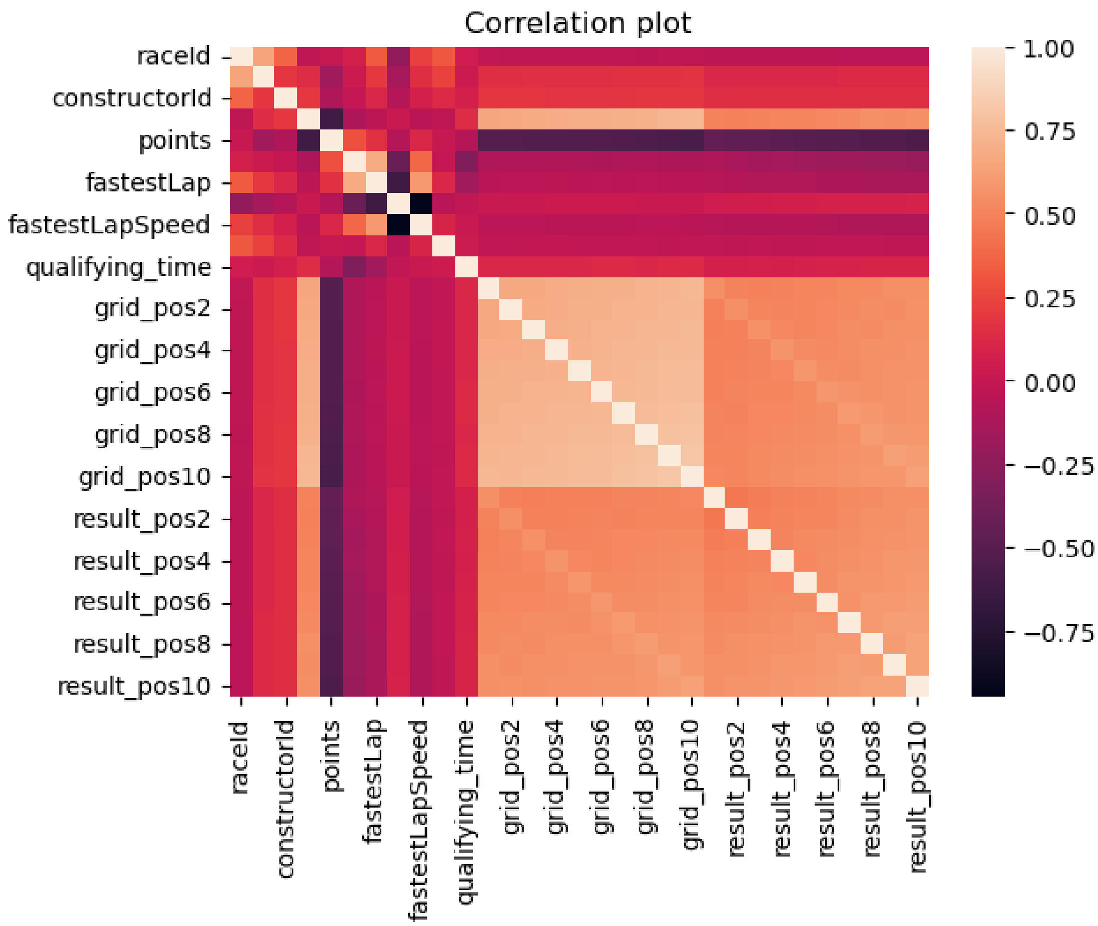


1.4.5 4.5) Feature Correlation Analysis

[20]:
```
# Pair-wise Correlation of all the features
correlation = df.corr()

# Number of pairs of feaures which have correlation coefficient > 0.8
correlation_count = (np.sum(np.where(np.abs(correlation)>=0.8,1,0)) -␣
↪correlation.shape[0])/2
print("Number of pairs of feaures which have correlation coefficient > 0.8 = "␣
↪+ str(correlation_count))

# Correlation heat map plot
plt.title('Correlation plot')
print("Correlation plot:")
sns.heatmap(correlation);
```

```
Number of pairs of feaures which have correlation coefficient > 0.8 = 2.0
```

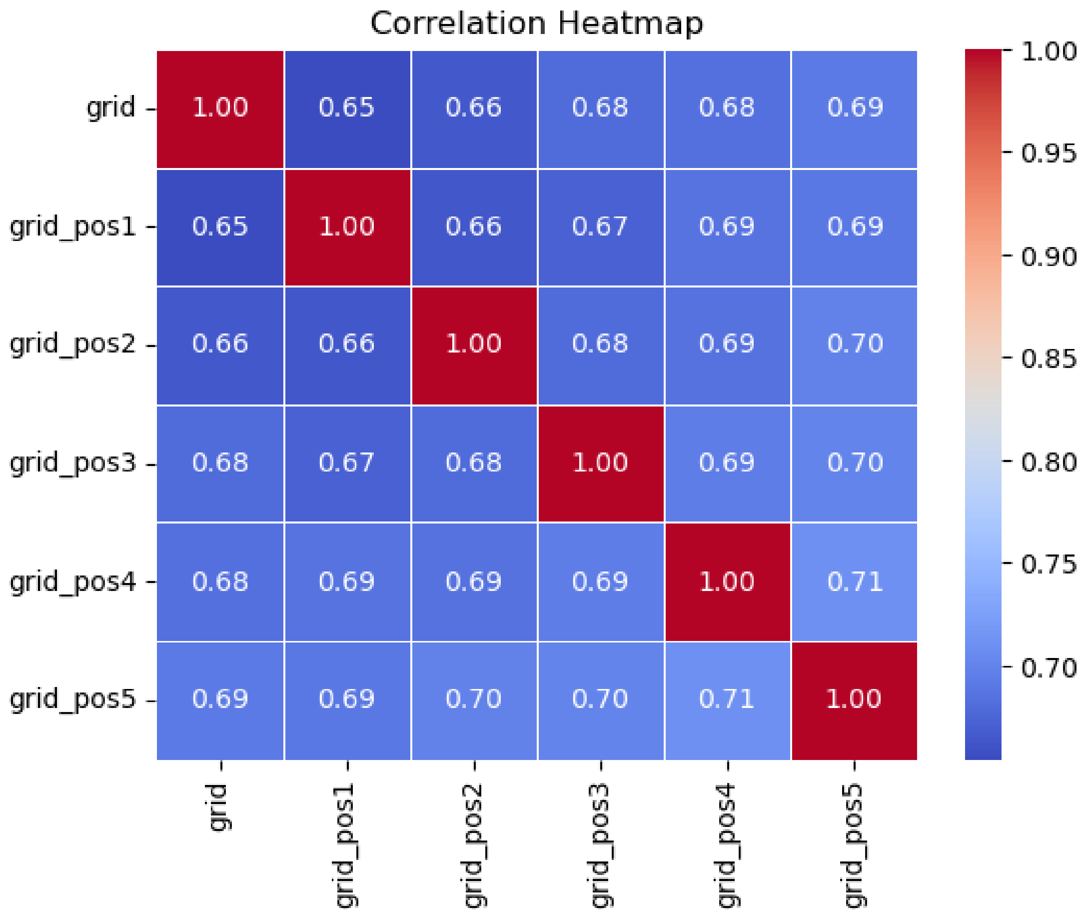
Correlation plot:



We can observe that the the features are mostly independent and not correlated with eachother. So data reduction using pca or svd is not necessary

[21]:
```python
# correlation between 'grid_pos1', 'grid_pos2', 'grid_pos3', 'grid_pos4',␣
↪'grid_pos5' and 'grid'
columns_of_interest = ['grid', 'grid_pos1', 'grid_pos2', 'grid_pos3',␣
↪'grid_pos4', 'grid_pos5']
df_selected = df[columns_of_interest]

# Calculate the correlation matrix
correlation_matrix = df_selected.corr()

# Create a heatmap using Seaborn
plt.figure()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f',␣
↪linewidths=.5)
```

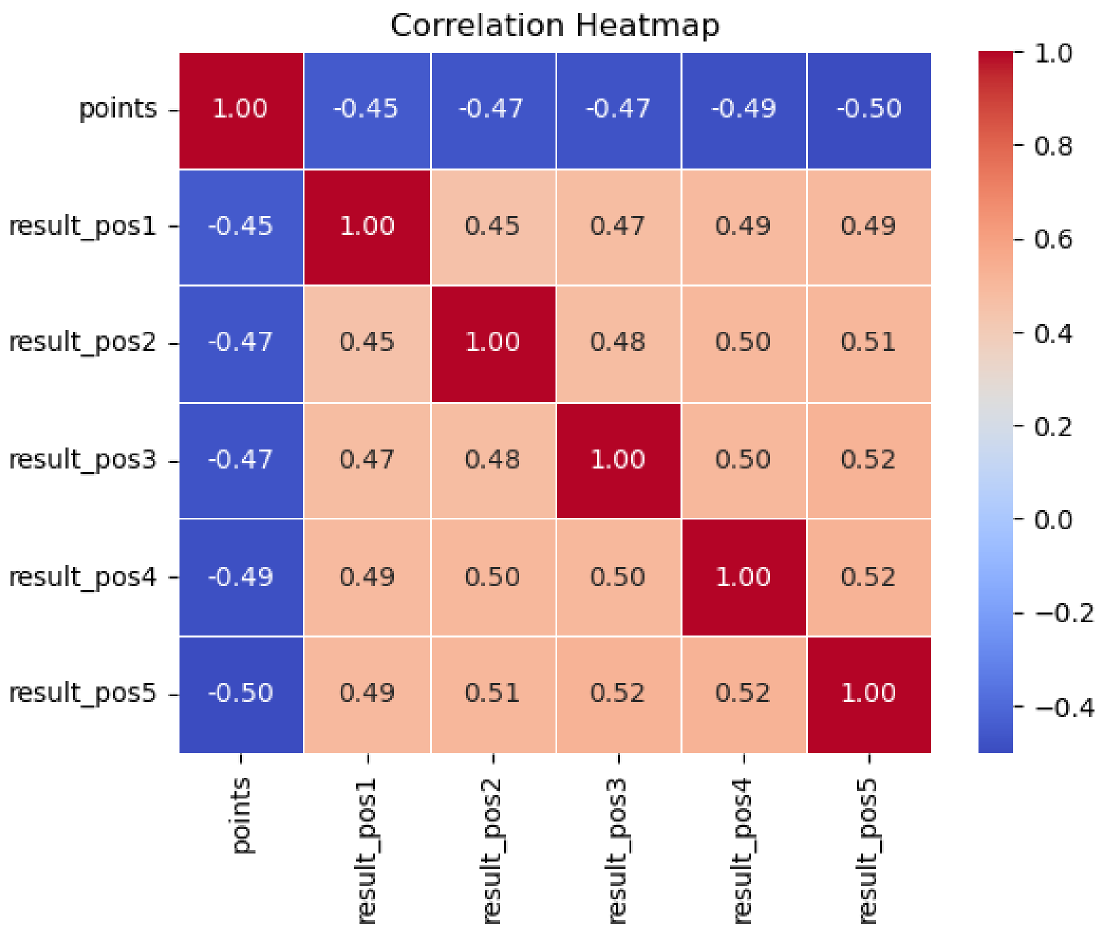
```
plt.title('Correlation Heatmap')
plt.show()
```



[22]:

```
# correlation between 'result_pos1', 'result_pos2', 'result_pos3',␣
↪'result_pos4', 'result_pos5' and 'points'
columns_of_interest = ['points', 'result_pos1', 'result_pos2', 'result_pos3',␣
↪'result_pos4', 'result_pos5']
df_selected = df[columns_of_interest]

# Calculate the correlation matrix
correlation_matrix = df_selected.corr()

# Create a heatmap using Seaborn
plt.figure()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f',␣
↪linewidths=.5)
plt.title('Correlation Heatmap')
```

```
plt.show()
```



1.4.6 4.6) Encoding categorical features

[23]:
```
# OneHot encoding 'driverId','constructorId','circuitId' (Qualitative Nominal)␣
↪features
enc = OneHotEncoder()
encoded = enc.fit_transform(df[['driverId','constructorId','circuitId']])
df_enc = df.drop(['driverId','constructorId','circuitId'],axis=1)
df_enc = pd.concat([df_enc,pd.DataFrame(encoded.toarray())],axis =1)
df_enc.columns = df_enc.columns.astype(str)
```

1.4.7 4.7) Data Split to train and test

[24]:
```
# get unique raceIds
unique_raceIds = df_enc['raceId'].unique()

# Split the unique raceIds to train(80%) and test(20%)
train_raceIds, test_raceIds = train_test_split(unique_raceIds, test_size=0.2,␣
↪random_state=42)

# Split the recored corresponding to train_raceIds and test_raceIds
train_set = df_enc[df_enc['raceId'].isin(train_raceIds)]
test_set = df_enc[df_enc['raceId'].isin(test_raceIds)]

train_raceId_list = df_enc[df_enc['raceId'].isin(train_raceIds)]['raceId']
test_raceId_list = df_enc[df_enc['raceId'].isin(test_raceIds)]['raceId']

# Split as X(features) and Y(target)
X_train = train_set.drop(columns=['raceId','points'])
Y_train = train_set['points']

# Split as X(features) and Y(target)
X_test = test_set.drop(columns=['raceId','points'])
Y_test = test_set['points']
```

[25]:
```
print("Train data samples: " +str(X_train.shape[0]))
print("Test data samples: " +str(X_test.shape[0]))
```

```
Train data samples: 6720
Test data samples: 1689
```

1.5 5) Models

1.5.1 5.1) Linear Regression

[26]:
```
# Linear regression
linear_reg = LinearRegression().fit(X_train, Y_train)

# Train predictions
Y_train_pred = linear_reg.predict(X_train)
Y_train_pred = attach_raceId_to_predictions(train_raceId_list, Y_train_pred)

# Test predictions
Y_test_pred = linear_reg.predict(X_test)
Y_test_pred = attach_raceId_to_predictions(test_raceId_list, Y_test_pred)

# Calculate R2 score for train and test
linear_reg_train_score = r2_score(Y_train, Y_train_pred)
linear_reg_test_score = r2_score(Y_test, Y_test_pred)
```

```python
# Calculate RootMeanSquareError for train and test
linear_reg_train_rmse = np.sqrt(mean_squared_error(Y_train, Y_train_pred))
linear_reg_test_rmse = np.sqrt(mean_squared_error(Y_test, Y_test_pred))

# Print the evaluation metics
print("Train R2 score = "+str(linear_reg_train_score))
print("Test R2 score = "+str(linear_reg_test_score))
print("Train RootMeanSquareError = "+str(linear_reg_train_rmse))
print("Test RootMeanSquareError = "+str(linear_reg_test_rmse))
```

```
Train R2 score = 0.5642283556406484
Test R2 score = 0.6269702783572284
Train RootMeanSquareError = 4.676005748703134
Test RootMeanSquareError = 4.334312409318795
```

1.5.2 5.2) Ridge Regression

[27]:
```python
# Ridge regression
ridge_reg = Ridge(alpha=0.001).fit(X_train, Y_train)

# Train predictions
Y_train_pred = ridge_reg.predict(X_train)
Y_train_pred = attach_raceId_to_predictions(train_raceId_list, Y_train_pred)

# Test predictions
Y_test_pred = ridge_reg.predict(X_test)
Y_test_pred = attach_raceId_to_predictions(test_raceId_list, Y_test_pred)

# Calculate R2 score for train and test
ridge_reg_train_score = r2_score(Y_train, Y_train_pred)
ridge_reg_test_score = r2_score(Y_test, Y_test_pred)

# Calculate RootMeanSquareError for train and test
ridge_reg_train_rmse = np.sqrt(mean_squared_error(Y_train, Y_train_pred))
ridge_reg_test_rmse = np.sqrt(mean_squared_error(Y_test, Y_test_pred))

# Print the evaluation metics
print("Train R2 score = "+str(ridge_reg_train_score))
print("Test R2 score = "+str(ridge_reg_test_score))
print("Train RootMeanSquareError = "+str(ridge_reg_train_rmse))
print("Test RootMeanSquareError = "+str(ridge_reg_test_rmse))
```

```
Train R2 score = 0.5642283556406484
Test R2 score = 0.6269702783572284
Train RootMeanSquareError = 4.676005748703134
Test RootMeanSquareError = 4.334312409318795
```

1.5.3 5.3) Lasso Regression

[28]:
```
# Lasso regression
lasso_reg = Lasso(alpha=0.001).fit(X_train, Y_train)

# Train predictions
Y_train_pred = lasso_reg.predict(X_train)
Y_train_pred = attach_raceId_to_predictions(train_raceId_list, Y_train_pred)

# Test predictions
Y_test_pred = lasso_reg.predict(X_test)
Y_test_pred = attach_raceId_to_predictions(test_raceId_list, Y_test_pred)

# Calculate R2 score for train and test
lasso_reg_train_score = r2_score(Y_train, Y_train_pred)
lasso_reg_test_score = r2_score(Y_test, Y_test_pred)

# Calculate RootMeanSquareError for train and test
lasso_reg_train_rmse = np.sqrt(mean_squared_error(Y_train, Y_train_pred))
lasso_reg_test_rmse = np.sqrt(mean_squared_error(Y_test, Y_test_pred))

# Print the evaluation metics
print("Train R2 score = "+str(lasso_reg_train_score))
print("Test R2 score = "+str(lasso_reg_test_score))
print("Train RootMeanSquareError = "+str(lasso_reg_train_rmse))
print("Test RootMeanSquareError = "+str(lasso_reg_test_rmse))
```

```
Train R2 score = 0.5620751959433383
Test R2 score = 0.6258651792764083
Train RootMeanSquareError = 4.687543650590411
Test RootMeanSquareError = 4.3407278531196845
```

1.5.4 5.4) Decision Tree

[29]:
```
# hyper-parameter tuning on max_depth parameter
param_grid = {
    'max_depth': [2, 4, 6, 8,10, 12, 14, 16, 32, 64],
}

# Decision tree regression
decisiontree_reg = DecisionTreeRegressor(random_state=42)

# Grid search on max_depth hyper-parameter tuning
decisiontree_reg_grid_search = GridSearchCV(estimator= decisiontree_reg,␣
 ↪param_grid=param_grid, scoring='r2')
decisiontree_reg_grid_result = decisiontree_reg_grid_search.fit(X_train,␣
 ↪Y_train)
```

```
# Get best model and it's hyper paramets
decisiontree_reg_best_params = decisiontree_reg_grid_result.best_params_
decisiontree_reg_best_model = decisiontree_reg_grid_result.best_estimator_

# Train predictions on best model
Y_train_pred = decisiontree_reg_best_model.predict(X_train)
Y_train_pred = attach_raceId_to_predictions(train_raceId_list, Y_train_pred)

# Test predictions on best model
Y_test_pred = decisiontree_reg_best_model.predict(X_test)
Y_test_pred = attach_raceId_to_predictions(test_raceId_list, Y_test_pred)

# Calculate R2 score for train and test
decisiontree_reg_train_score = r2_score(Y_train, Y_train_pred)
decisiontree_reg_test_score = r2_score(Y_test, Y_test_pred)

# Calculate RootMeanSquareError for train and test
decisiontree_reg_train_rmse = np.sqrt(mean_squared_error(Y_train, Y_train_pred))
decisiontree_reg_test_rmse = np.sqrt(mean_squared_error(Y_test, Y_test_pred))

# Print the evaluation metics
print("Train R2 score = "+str(decisiontree_reg_train_score))
print("Test R2 score = "+str(decisiontree_reg_test_score))
print("Train RootMeanSquareError = "+str(decisiontree_reg_train_rmse))
print("Test RootMeanSquareError = "+str(decisiontree_reg_test_rmse))
print("Best Prameters: "+str(decisiontree_reg_best_params))
```

```
Train R2 score = 0.6671885375302121
Test R2 score = 0.615166879664214
Train RootMeanSquareError = 4.086435896148786
Test RootMeanSquareError = 4.402351489630001
Best Prameters: {'max_depth': 6}
```

1.5.5 5.5) Random Forest

[30]:
```
# hyper-parameter tuning on max_depth and n_estimators parameter
param_grid = {
    'n_estimators': [50, 100, 150, 200, 250],
    'max_depth': [2, 4, 6, 8,10, 12, 14, 16, 32, 64],
}

# Random Forest Regressor
rf_model = RandomForestRegressor(random_state=42)

# Grid search on max_depth hyper-parameter tuning
rf_model_grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid,␣
 ↪scoring='r2', cv=5)
```

```
rf_model_grid_result = rf_model_grid_search.fit(X_train, Y_train)

# Get best model and it's hyper paramets
rf_model_best_params = rf_model_grid_result.best_params_
rf_model_best_model = rf_model_grid_result.best_estimator_

# Train predictions on best model
Y_train_pred = rf_model_best_model.predict(X_train)
Y_train_pred = attach_raceId_to_predictions(train_raceId_list, Y_train_pred)

# Test predictions on best model
Y_test_pred = rf_model_best_model.predict(X_test)
Y_test_pred = attach_raceId_to_predictions(test_raceId_list, Y_test_pred)

# Calculate R2 score for train and test
rf_model_train_score = r2_score(Y_train, Y_train_pred)
rf_model_test_score = r2_score(Y_test, Y_test_pred)

# Calculate RootMeanSquareError for train and test
rf_model_train_rmse = np.sqrt(mean_squared_error(Y_train, Y_train_pred))
rf_model_test_rmse = np.sqrt(mean_squared_error(Y_test, Y_test_pred))

# Print the evaluation metics
print("Train R2 score = "+str(rf_model_train_score))
print("Test R2 score = "+str(rf_model_test_score))
print("Train RootMeanSquareError = "+str(rf_model_train_rmse))
print("Test RootMeanSquareError = "+str(rf_model_test_rmse))
print("Best Prameters: "+str(rf_model_best_params))
```

```
Train R2 score = 0.9596860884772198
Test R2 score = 0.6946634752440572
Train RootMeanSquareError = 1.422240435771272
Test RootMeanSquareError = 3.9213704543665497
Best Prameters: {'max_depth': 16, 'n_estimators': 250}
```

1.5.6 5.6) XGBoost

[31]:
```
# hyper-parameter tuning on these parameter
param_grid = {
    'max_depth': [4, 6],
    'learning_rate': [0.1, 0.01],
    'n_estimators': [50, 100, 150],
    'min_child_weight': [1, 2, 3],
    'subsample': [0.9],
    'colsample_bytree': [0.9],
}
```

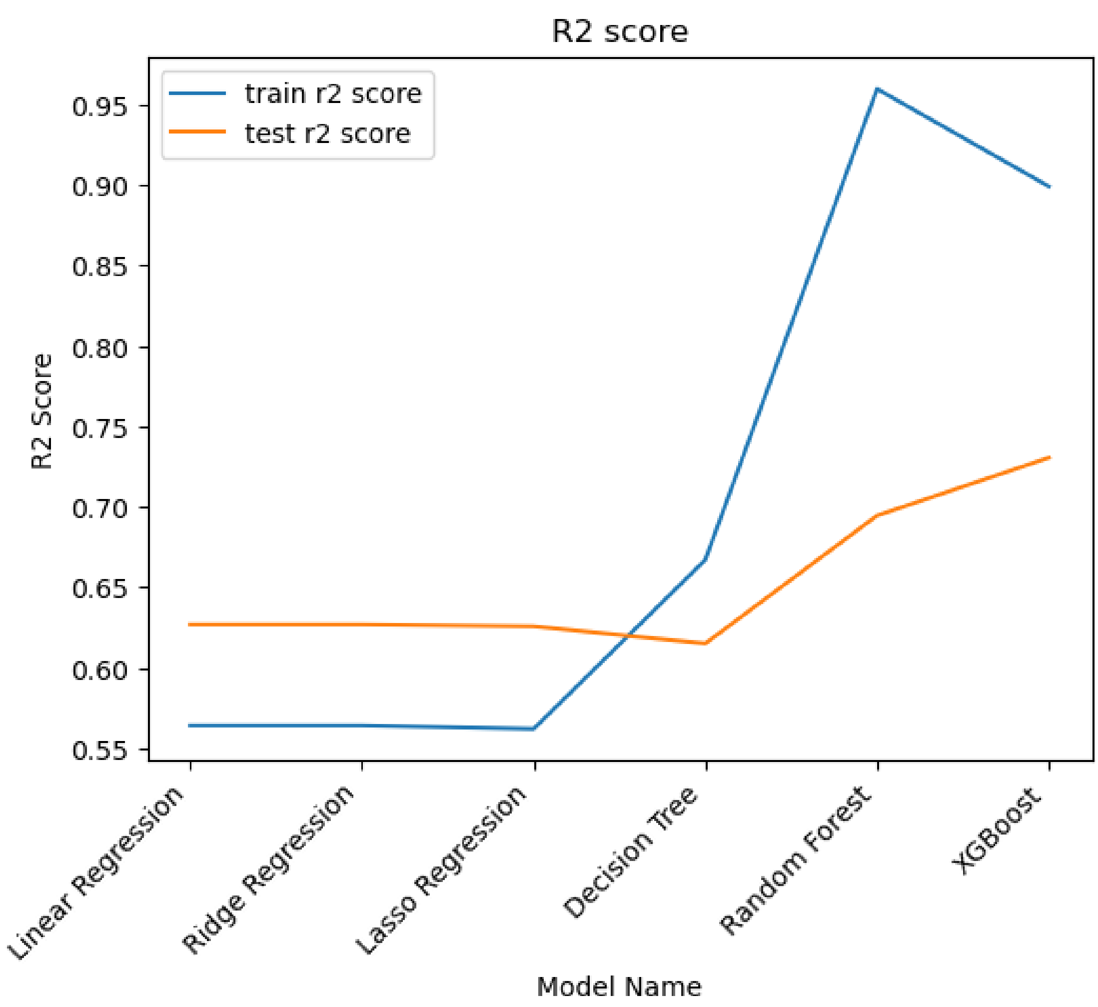
```python
# XGBoost Regressor
xgb_regressor = xgb.XGBRegressor(objective='reg:squarederror')

# 5-fold cross validation and Grid search on max_depth hyper-parameter tuning
kf = KFold(n_splits=5, shuffle=True, random_state=42)
xgb_regressor_grid_search = GridSearchCV(estimator=xgb_regressor,␣
 ↪param_grid=param_grid, scoring='neg_mean_squared_error', cv=kf)
xgb_regressor_grid_result = xgb_regressor_grid_search.fit(X_train, Y_train)

# Get best model and it's hyper paramets
xgb_regressor_best_params = xgb_regressor_grid_result.best_params_
xgb_regressor_best_model = xgb_regressor_grid_result.best_estimator_

# Train predictions on best model
Y_train_pred = xgb_regressor_best_model.predict(X_train)
Y_train_pred = attach_raceId_to_predictions(train_raceId_list, Y_train_pred)

# Test predictions on best model
Y_test_pred = xgb_regressor_best_model.predict(X_test)
Y_test_pred = attach_raceId_to_predictions(test_raceId_list, Y_test_pred)

# Calculate R2 score for train and test
xgb_regressor_train_score = r2_score(Y_train, Y_train_pred)
xgb_regressor_test_score = r2_score(Y_test, Y_test_pred)

# Calculate RootMeanSquareError for train and test
xgb_regressor_train_rmse = np.sqrt(mean_squared_error(Y_train, Y_train_pred))
xgb_regressor_test_rmse = np.sqrt(mean_squared_error(Y_test, Y_test_pred))

# Print the evaluation metics
print("Train R2 score = "+str(xgb_regressor_train_score))
print("Test R2 score = "+str(xgb_regressor_test_score))
print("Train RootMeanSquareError = "+str(xgb_regressor_train_rmse))
print("Test RootMeanSquareError = "+str(xgb_regressor_test_rmse))
print("Best Prameters: "+str(xgb_regressor_best_params))
```

```
Train R2 score = 0.8991484910371411
Test R2 score = 0.7305909517439093
Train RootMeanSquareError = 2.24950391356469
Test RootMeanSquareError = 3.6834483290333226
Best Prameters: {'colsample_bytree': 0.9, 'learning_rate': 0.1, 'max_depth': 6,
'min_child_weight': 3, 'n_estimators': 100, 'subsample': 0.9}
```

1.6 6) Results, Models Evaluations and Conclusion

1.6.1 6.1) R2 score comparion plot

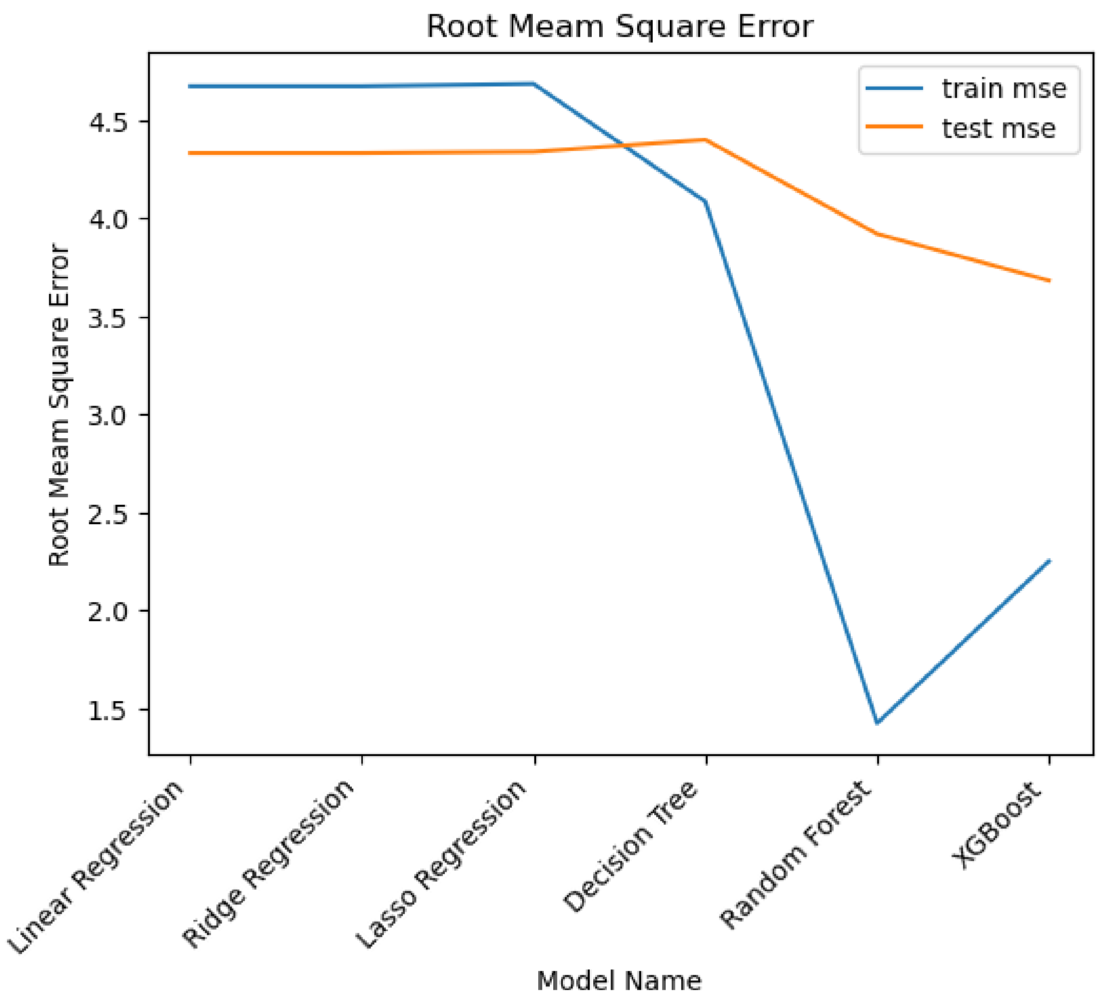
[32]:
```
# different model comparisions with R2 metrics
models = ['Linear Regression', 'Ridge Regression', 'Lasso Regression',␣
↪'Decision Tree', 'Random Forest', 'XGBoost']
train_r2 = [linear_reg_train_score, ridge_reg_train_score,␣
↪lasso_reg_train_score, decisiontree_reg_train_score, rf_model_train_score,␣
↪xgb_regressor_train_score]
test_r2 = [linear_reg_test_score, ridge_reg_test_score, lasso_reg_test_score,␣
↪decisiontree_reg_test_score, rf_model_test_score, xgb_regressor_test_score]

plt.plot(models, train_r2, label = 'train r2 score')
plt.plot(models, test_r2, label = 'test r2 score')
plt.title('R2 score')
plt.xlabel('Model Name')
plt.ylabel('R2 Score')
plt.xticks(rotation=45, ha="right")  # Rotate x-axis labels for better␣
↪visibility
plt.legend()
plt.show()
```



1.6.2 6.2) RMSE comparion plot

[33]:
```
# different model comparisions MSE metrics
models = ['Linear Regression', 'Ridge Regression', 'Lasso Regression',␣
↪'Decision Tree', 'Random Forest', 'XGBoost']
train_r2 = [linear_reg_train_rmse, ridge_reg_train_rmse, lasso_reg_train_rmse,␣
↪decisiontree_reg_train_rmse, rf_model_train_rmse, xgb_regressor_train_rmse]
test_r2 = [linear_reg_test_rmse, ridge_reg_test_rmse, lasso_reg_test_rmse,␣
↪decisiontree_reg_test_rmse, rf_model_test_rmse, xgb_regressor_test_rmse]

plt.plot(models, train_r2, label = 'train mse')
plt.plot(models, test_r2, label = 'test mse')
plt.title('Root Meam Square Error')
plt.xlabel('Model Name')
plt.ylabel('Root Meam Square Error')
```

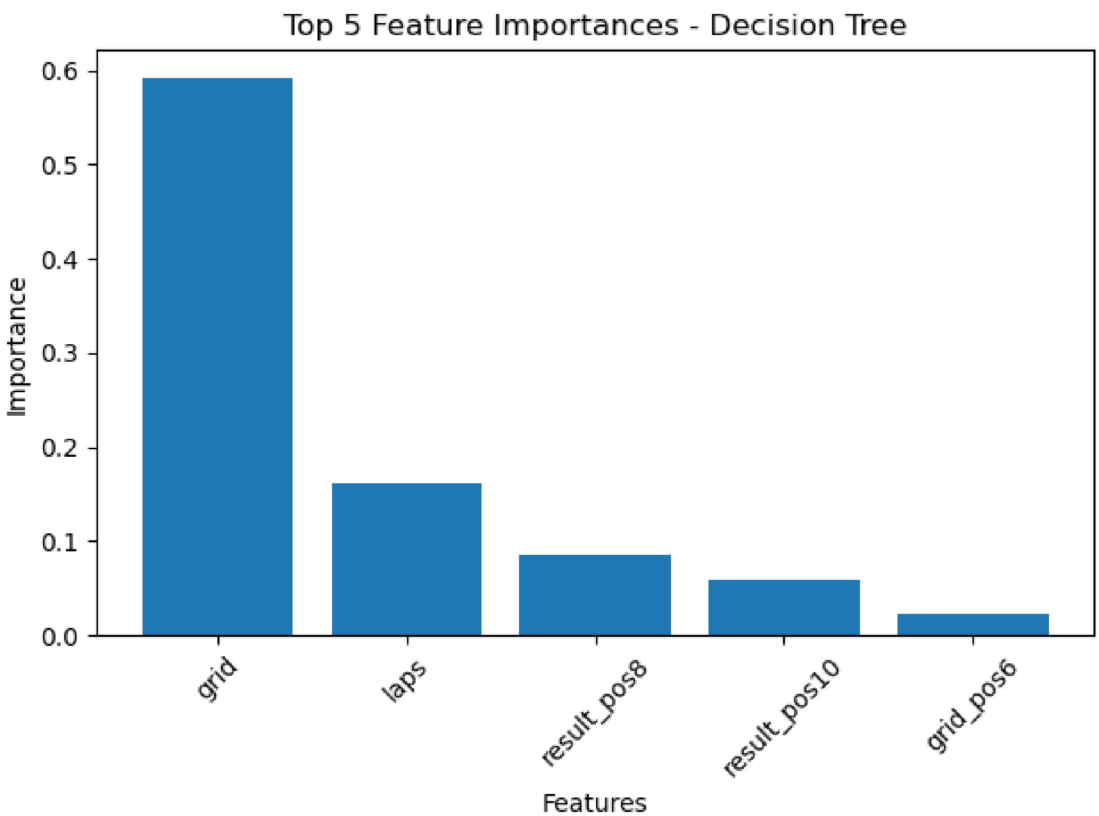
```
plt.xticks(rotation=45, ha="right")  # Rotate x-axis labels for better
 ↪visibility
plt.legend()
plt.show()
```



1.6.3 6.3) Decision tree top 5 important features

[34]:
```
# Get feature importances
decisiontree_reg_importances = decisiontree_reg_best_model.feature_importances_
indices = np.argsort(decisiontree_reg_importances)[::-1]

# Get top 5 feature indices and importances
top_5_indices = indices[:5]
top_5_importances = decisiontree_reg_importances[top_5_indices]
top_5_feature_names = [X_train.columns[i] for i in top_5_indices]
```

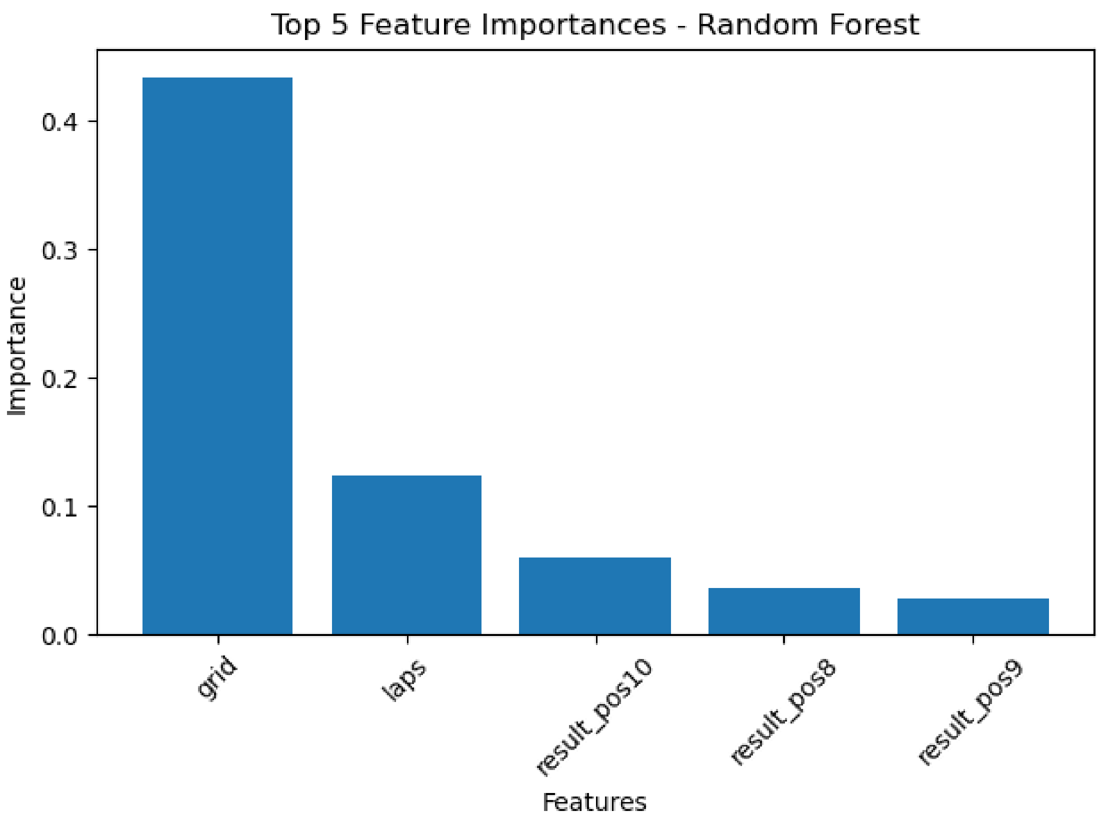
```
# Plot the top 5 feature importances
plt.figure()
plt.title("Top 5 Feature Importances - Decision Tree")
plt.bar(range(len(top_5_importances)), top_5_importances, align="center")
plt.xticks(range(len(top_5_importances)), top_5_feature_names, rotation=45)
plt.xlabel("Features")
plt.ylabel("Importance")
plt.tight_layout()
plt.show()
```



1.6.4 6.4) Random Forest top 5 important features

[35]:
```
# Get feature importances
rf_model_importances = rf_model_best_model.feature_importances_
indices = np.argsort(rf_model_importances)[::-1]

# Get top 5 feature indices and importances
top_5_indices = indices[:5]
top_5_importances = rf_model_importances[top_5_indices]
```

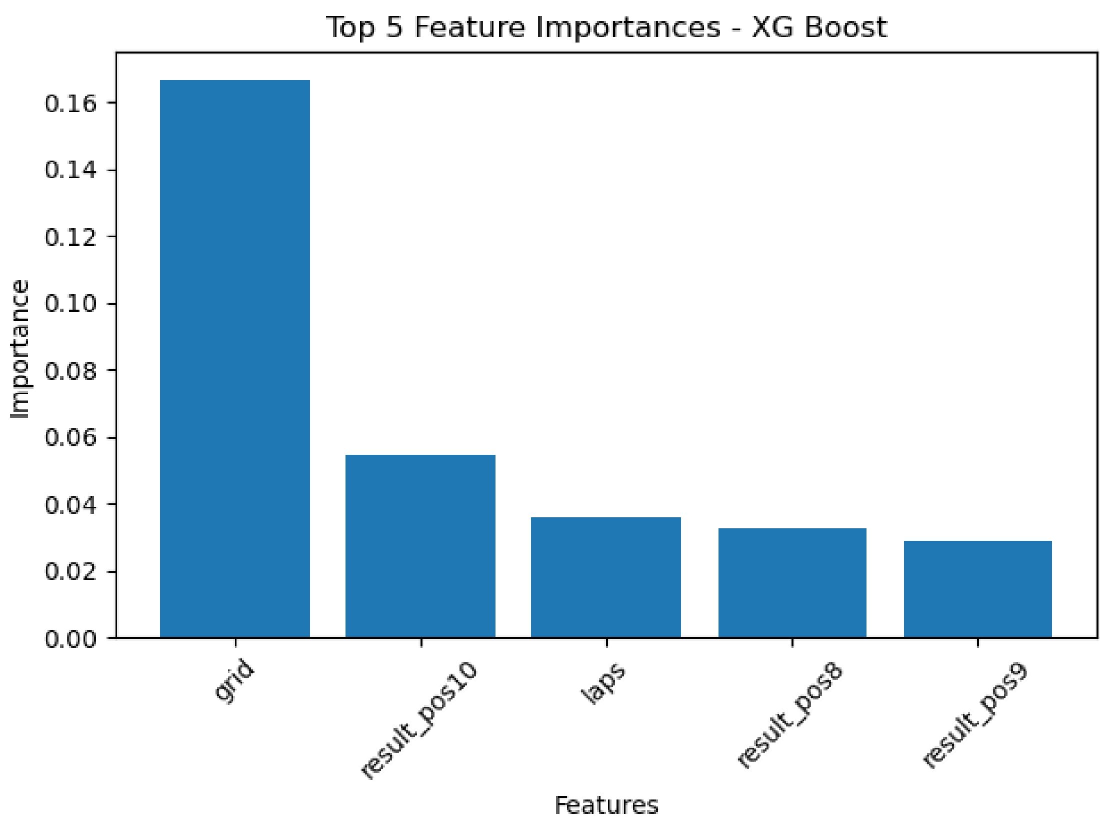
```
top_5_feature_names = [X_train.columns[i] for i in top_5_indices]

# Plot the top 5 feature importances
plt.figure()
plt.title("Top 5 Feature Importances - Random Forest")
plt.bar(range(len(top_5_importances)), top_5_importances, align="center")
plt.xticks(range(len(top_5_importances)), top_5_feature_names, rotation=45)
plt.xlabel("Features")
plt.ylabel("Importance")
plt.tight_layout()
plt.show()
```



1.6.5 6.3) XGBoost top 5 important features

[36]:
```
# Get feature importances
xgb_regressor_importances = xgb_regressor_best_model.feature_importances_
indices = np.argsort(xgb_regressor_importances)[::-1]

# Get top 5 feature indices and importances
top_5_indices = indices[:5]
```

```
top_5_importances = xgb_regressor_importances[top_5_indices]
top_5_feature_names = [X_train.columns[i] for i in top_5_indices]

# Plot the top 5 feature importances
plt.figure()
plt.title("Top 5 Feature Importances - XG Boost")
plt.bar(range(len(top_5_importances)), top_5_importances, align="center")
plt.xticks(range(len(top_5_importances)), top_5_feature_names, rotation=45)
plt.xlabel("Features")
plt.ylabel("Importance")
plt.tight_layout()
plt.show()
```



1.6.6 6.4) Final remarks and conclusion

1. Since it's a regression problem, we wanted to start with basic regression model and go to more complex models. That's why we trained our data on 'Linear Regression', 'Ridge Regression', 'Lasso Regression', 'Decision Tree', 'Random Forest' and 'XGBoost' untill we got the reasonably performaing model
2. Since it's a regression problem we choose RMSE and R2 score as metrics for model evaluations
3. Based on the R2 scores and RMSE values we can see that 'XGBoost' outperforams all the

other models ‘Linear Regression’, ‘Ridge Regression’, ‘Lasso Regression’, ‘Decision Tree’, ‘Random Forest’

4. ‘Linear Regression’, ‘Ridge Regression’, ‘Lasso Regression’ didn’t give good results the R2 score are less than 0.6 and have high RMSE
5. There is a slight improvement when we come to ‘Decision Tree’ because of increase in model complexity
6. Performance of ensemble methods ‘Random Forest’ and ‘XGBoost’ are higher than ‘Decision Tree’ which is expected and between ‘Random Forest’ and ‘XGBoost’, ‘XGBoost’ outperformed ‘Random Forest’
7. Given the complexity of the problem we are trying to study these results makes sense because as the model complexity increases we observe good results
8. From the feature imporance of all ‘Decision Tree’, ‘Random Forest’ and ‘XGBoost’ models we can see that features grid, laps, result_pos10, result_pos9, result_pos8 seems to have high significance while deciding the points in the race
9. This makes sense beacuse all grid, laps, result_pos10, result_pos9, result_pos8 in someway indicates the performance of the race car and driver