1. Loading Data

```
pip install fastf1 matplotlib pandas numpy seaborn bar_chart_race geopandas --quiet
```

```
import os
import fastf1
import fastf1.plotting
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import geopandas as gpd
import bar_chart_race as bcr
import plotly.express as px

# Ensure cache directory exists
if not os.path.exists("cache"):
    os.makedirs("cache")

# Enable caching for faster data loading
fastf1.Cache.enable_cache('cache')
```

```
results = pd.read_csv("winners.csv")
drivers = pd.read_csv("drivers_updated.csv")
fastest_laps = pd.read_csv("fastest_laps_updated.csv")
teams = pd.read_csv("teams_updated.csv")
```

```
results.sample(10)
```

	Grand Prix	Date	Winner	Car	Laps	Time	Name Code
985	Canada	2018-06-10	Sebastian Vettel	Ferrari	68.0	1:28:31.377	VET
532	Portugal	1992-09-27	Nigel Mansell	Williams Renault	71.0	1:34:46.659	MAN
791	Spain	2008-04-27	Kimi RÃ¤ikkÃ¶nen	Ferrari	66.0	1:38:19.051	RAI
717	Malaysia	2004-03-21	Michael Schumacher	Ferrari	56.0	1:31:07.490	MSC
937	Abu Dhabi	2015-11-29	Nico Rosberg	Mercedes	55.0	1:38:30.175	ROS
490	Monaco	1990-05-27	Ayrton Senna	McLaren Honda	78.0	1:52:46.982	SEN
901	Malaysia	2014-03-30	Lewis Hamilton	Mercedes	56.0	1:40:25.974	HAM
556	Canada	1994-06-12	Michael Schumacher	Benetton Ford	69.0	1:44:31.887	MSC
142	United States	1965-10-03	Graham Hill	BRM	110.0	2:20:36.100	HIL

```
results.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1110 entries, 0 to 1109
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Grand Prix  1110 non-null   object 
 1   Date        1110 non-null   object 
 2   Winner      1110 non-null   object 
 3   Car         1110 non-null   object 
 4   Laps        1107 non-null   float64
 5   Time        1107 non-null   object 
 6   Name Code   1110 non-null   object 
dtypes: float64(1), object(6)
memory usage: 60.8+ KB
```

```
results.shape
```

```
(1110, 7)
```

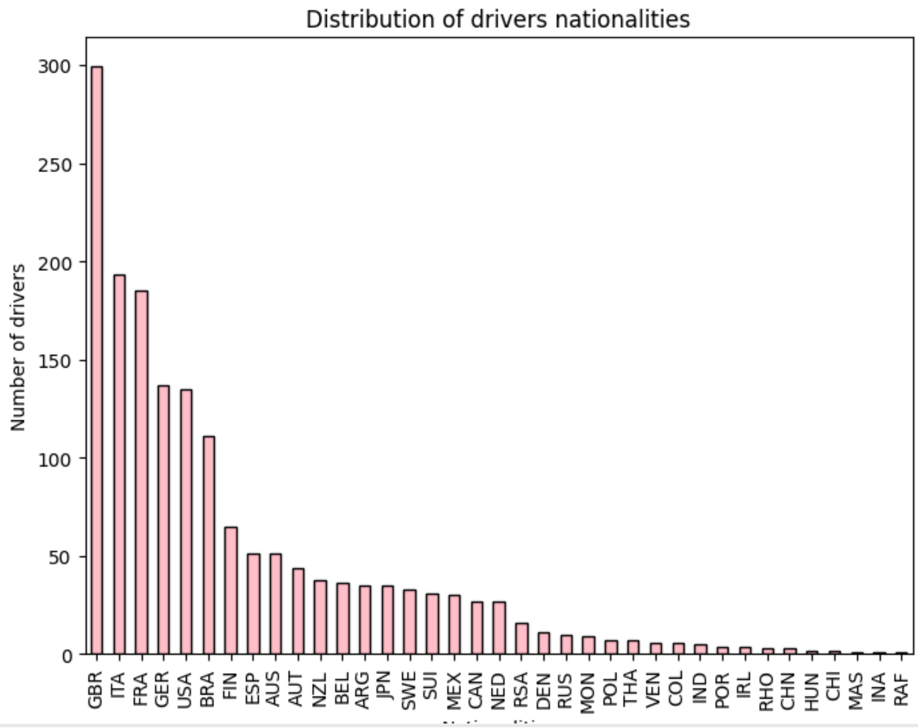
2. Pre-processing Data

```
results['Date'] = pd.to_datetime(results['Date'])
results['Year'] = results['Date'].dt.year
results['Month'] = results['Date'].dt.month


month_dict = {1:'Jan', 2:'Feb', 3:'Mar', 4:'Apr', 5:'May', 6:'Jun', 7:'Jul', 8:'Aug', 9:'Sep', 10:'Oct', 11:'Nov', 12:'Dec'}
results['Month'] = results['Month'].map(month_dict)


hr = []
min = []
sec = []

for i in results['Time']:
    if i is not np.nan:
        if len(i.split(':')) != 3:
            hr.append(0)
            min.append(int(i.split(':')[0]))
            sec.append(float(i.split(':')[1]))
        else:
            hr.append(int(i.split(':')[0]))
            min.append(int(i.split(':')[1]))
            sec.append(float(i.split(':')[2]))
    else:
        hr.append(np.nan)
        min.append(np.nan)
        sec.append(np.nan)


results['Hours'] = hr
results['Minutes'] = min
results['Seconds'] = sec


results['Total Time in Seconds'] = results['Hours'] * 3600 + results['Minutes'] * 60 + results['Seconds']


results['Average Time per lap'] = results['Total Time in Seconds']/results['Laps']
```

3. Visualising Data

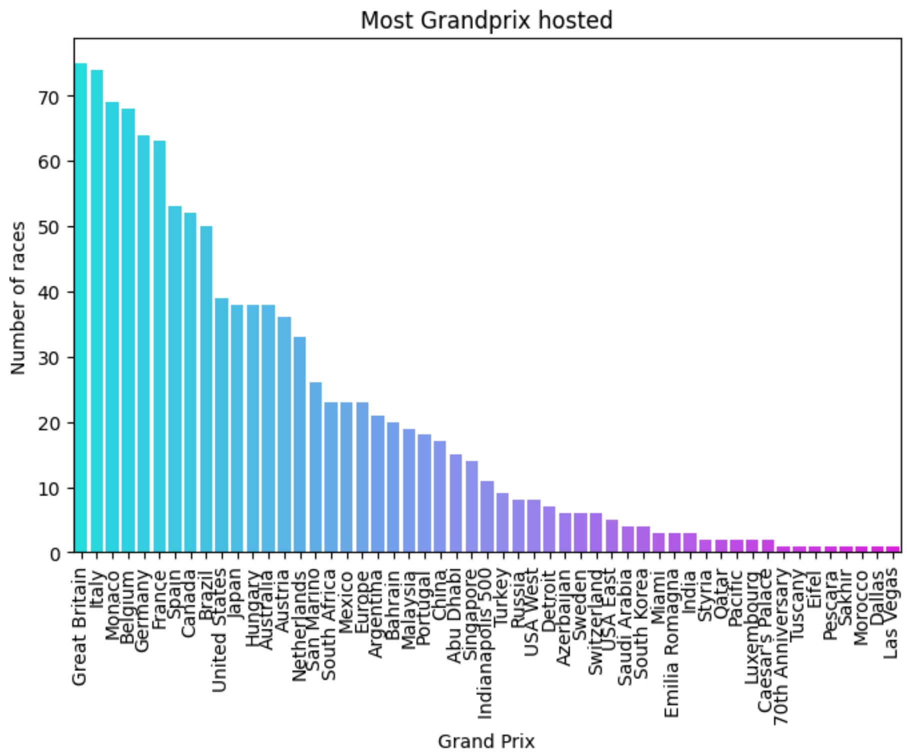
Part 1: Analysing Races and Race Winners for the past 50 Years

```
plt.figure(figsize=(8, 6))
drivers['Nationality'].value_counts().plot(kind='bar', color='pink', edgecolor='black')
plt.title('Distribution of drivers nationalities')
plt.xlabel('Nationalities')
plt.ylabel('Number of drivers')
plt.show()
```



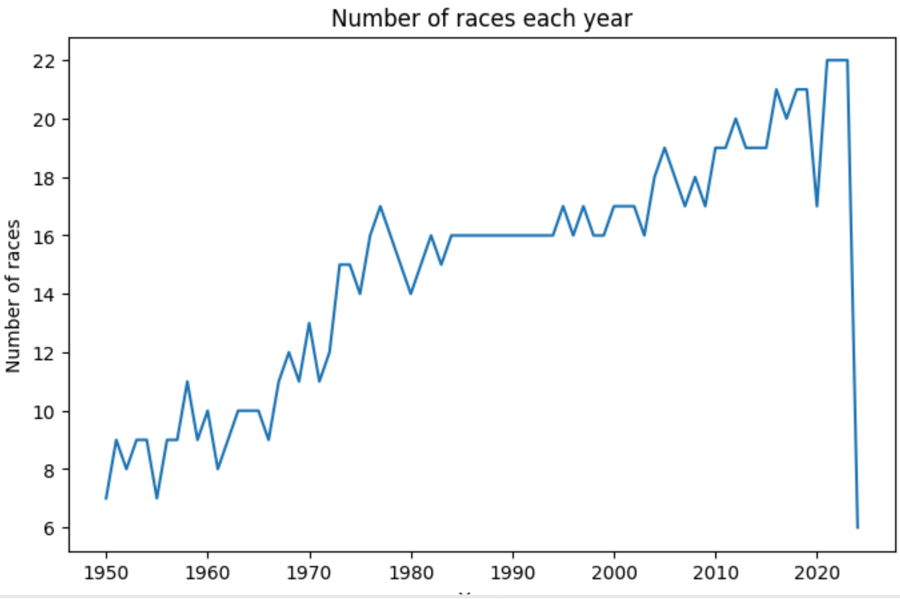

```
plt.figure(figsize=(8,5))
sns.countplot(data = results, x = 'Grand Prix', order=results['Grand Prix'].value_counts().index, palette="cool")
plt.xticks(rotation = 90)
plt.title('Most Grandprix hosted')
plt.ylabel('Number of races')
plt.xlabel('Grand Prix')
plt.show()
```

```
<ipython-input-61-ab9c3b08a6ba>:2: FutureWarning:


Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue`
```

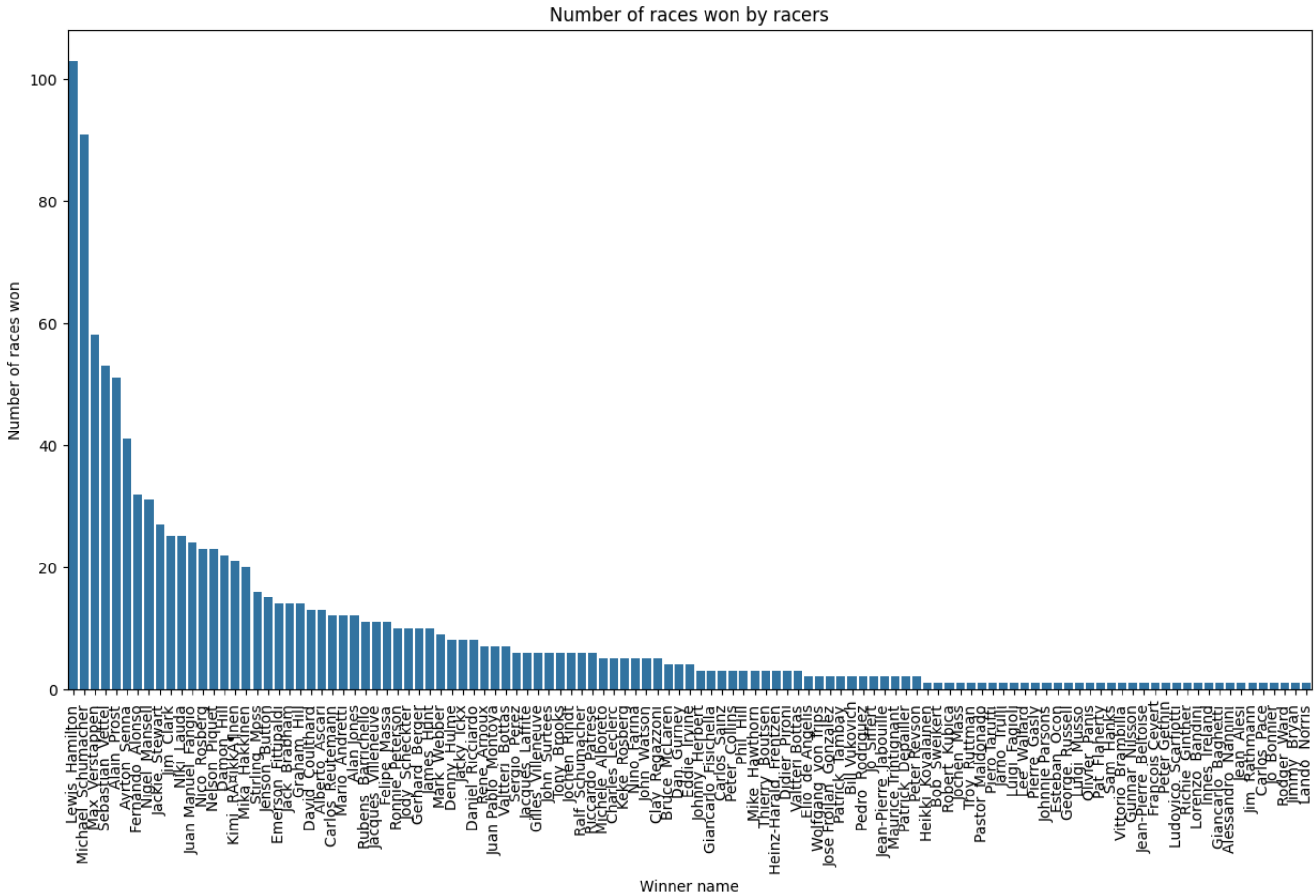



```
years =results['Year'].value_counts()
plt.figure(figsize=(8,5))
sns.lineplot(years)
```

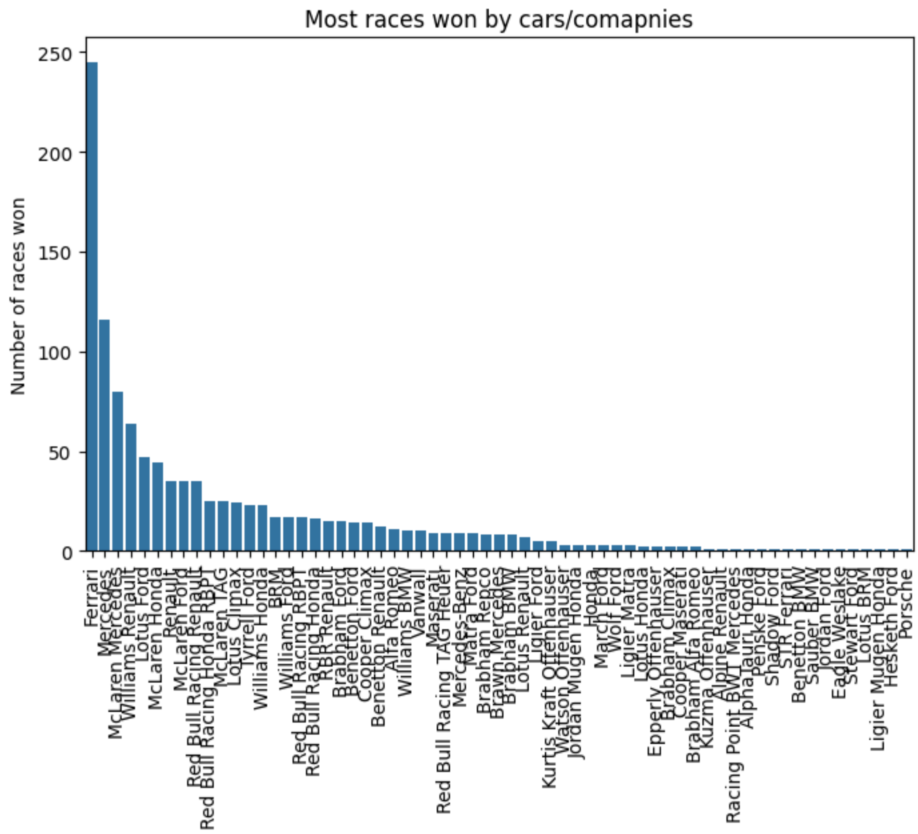
```
plt.title('Number of races each year')
plt.xlabel('Years')
plt.ylabel('Number of races')
plt.show()
```



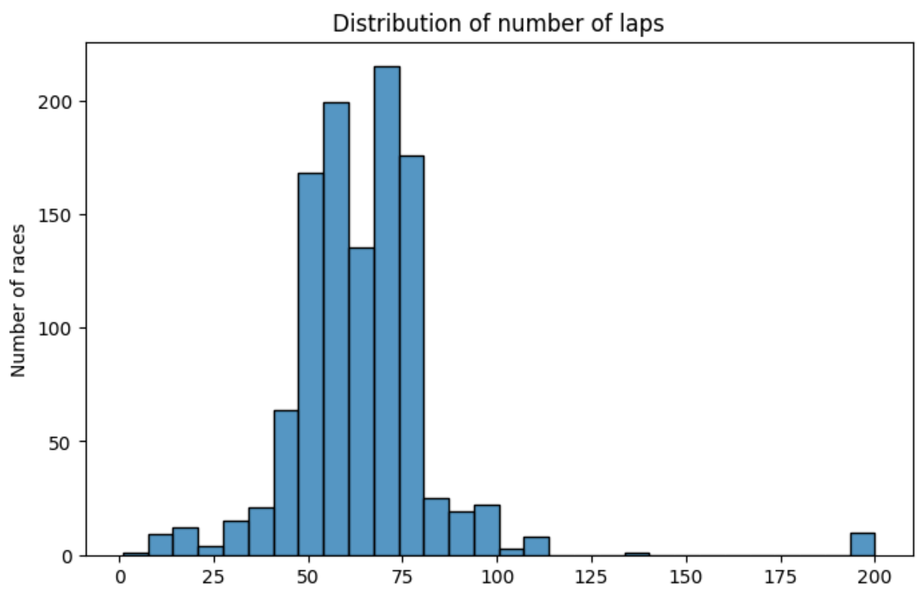

```
plt.figure(figsize=(15,8))
sns.countplot(data = results, x = 'Winner', order=results['Winner'].value_counts().index)
plt.xticks(rotation = 90)
plt.title('Number of races won by racers')
plt.ylabel('Number of races won')
plt.xlabel('Winner name')
plt.show()
```




```
plt.figure(figsize=(8,5))
sns.countplot(data = results, x = 'Car', order=results['Car'].value_counts().index)
plt.xticks(rotation = 90)
plt.title('Most races won by cars/comapnies')
plt.ylabel('Number of races won')
plt.xlabel('Car name')
plt.show()
```



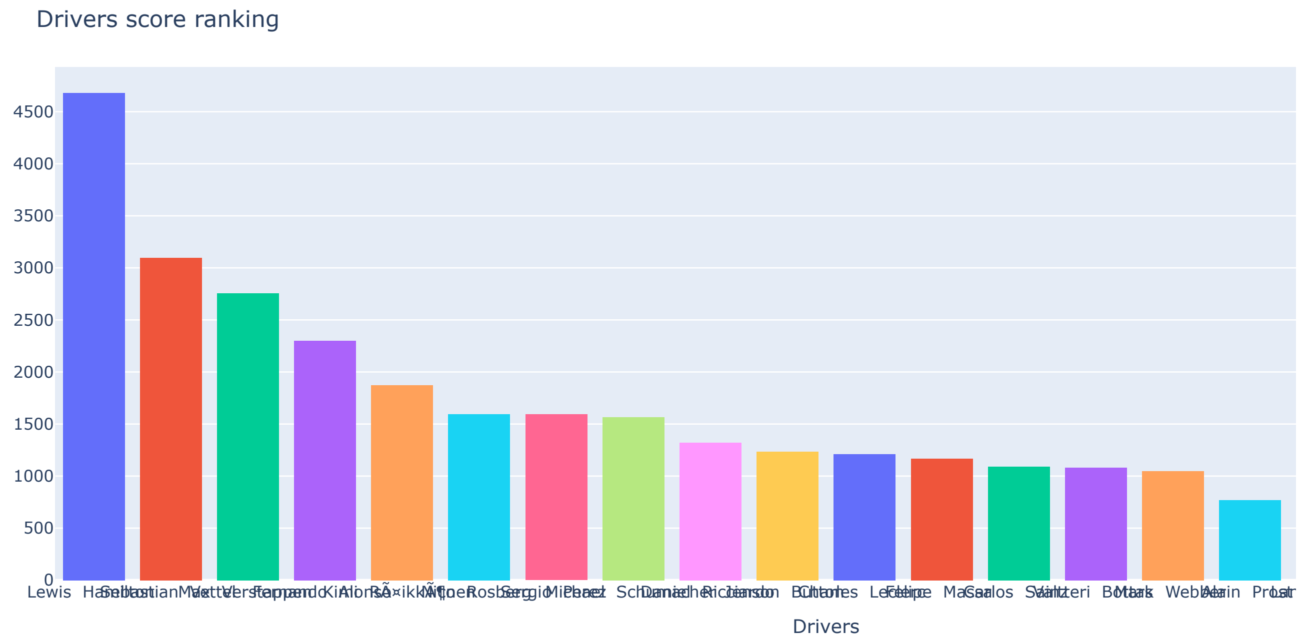

```
plt.figure(figsize=(8,5))
sns.histplot(data = results, x = 'Laps', bins = 30)
plt.title('Distribution of number of laps')
plt.ylabel('Number of races')
plt.xlabel('Number of laps')
plt.show()
```




```
# Group the drivers according to thier respective points tally from f1_drivers dataset
f1_points = drivers.groupby('Driver').agg(total=('PTS', sum)).reset_index()
f1_points = f1_points.sort_values('total', ascending=False).head(20)

# Create a histogram of the points tally
fig = px.histogram(f1_points, x='Driver',y='total',
                   color='total')
fig.update_layout(
    title='Drivers score ranking',
    xaxis_title='Drivers',
    yaxis_title='Total')
```

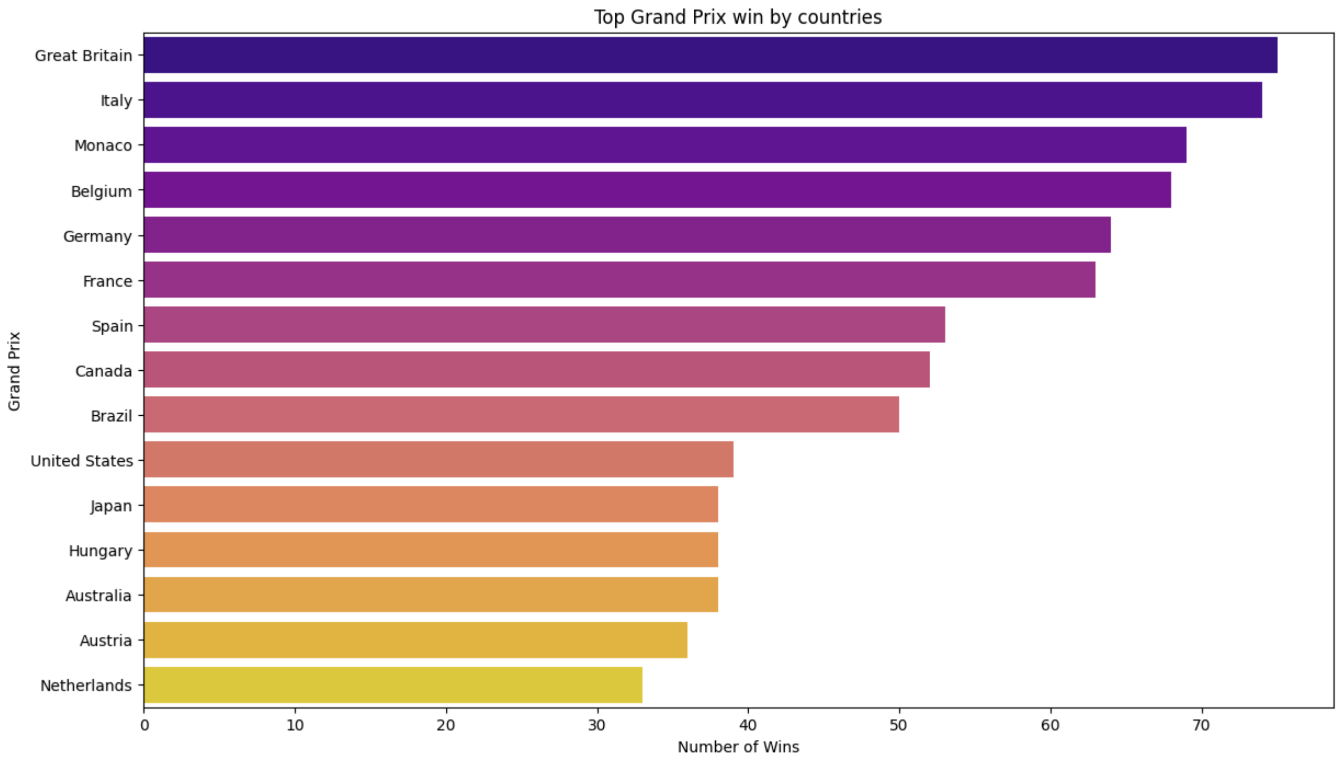
```
fig.show()
```

```
<ipython-input-66-ac5267382be4>:2: FutureWarning:

The provided callable <built-in function sum> is currently using SeriesGroupBy.sum. In a future version of pandas, the p
```




```
# Group grand prix wins according to countries
top_grand_prix_wins = results.groupby("Grand Prix").size().reset_index(name="count").sort_values("count",ascending=False).he

# create a barplot
plt.figure(figsize=(14, 8))
sns.barplot(x="count", y="Grand Prix", data=top_grand_prix_wins, palette="plasma")


plt.xlabel("Number of Wins")
plt.ylabel("Grand Prix")
plt.title("Top Grand Prix win by countries")
plt.show()
```

```
<ipython-input-67-df580cd75025>:6: FutureWarning:


Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue`
```

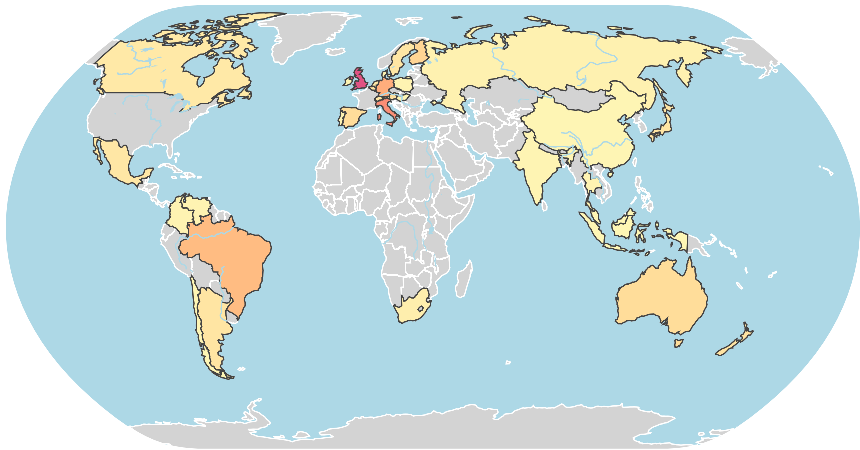



```
import geopandas as gpd
import plotly.express as px

# Step 2: Count the number of drivers by nationality
driver_counts = drivers['Nationality'].value_counts().reset_index()
driver_counts.columns = ['Nationality', 'Count']

# Step 3: Map nationalities to country names
nationality_to_country = {
    'BRA': 'Brazil',
    'SWE': 'Sweden',
    'GBR': 'United Kingdom',
    'ITA': 'Italy',
    'FRA': 'France',
    'GER': 'Germany',
    'USA': 'United States',
    'AUS': 'Australia',
    'CAN': 'Canada',
    'JPN': 'Japan',
    'ESP': 'Spain',
    'NED': 'Netherlands',
    'ARG': 'Argentina',
    'FIN': 'Finland',
    'AUT': 'Austria',
    'NZL': 'New Zealand',
    'BEL': 'Belgium',
    'SUI': 'Switzerland',
    'MEX': 'Mexico',
    'RSA': 'South Africa',
    'DEN': 'Denmark',
    'RUS': 'Russia',
    'MON': 'Monaco',
    'POL': 'Poland',
    'THA': 'Thailand',
    'VEN': 'Venezuela',
    'COL': 'Colombia',
```

```
    'IND': 'India',
    'POR': 'Portugal',
    'IRL': 'Ireland',
    'RHO': 'Rhodesia',
    'CHN': 'China',
    'HUN': 'Hungary',
    'CHI': 'Chile',
    'MAS': 'Malaysia',
    'INA': 'Indonesia'}

# Apply the mapping to convert nationalities to country names
driver_counts['Country'] = driver_counts['Nationality'].map(nationality_to_country)

# Load the world map
world = gpd.read_file("ne_110m_admin_0_countries.shp")
print(world.columns)

# Merge driver counts with the world map
world = world.merge(driver_counts, how="left", left_on="NAME", right_on="Country")

# Plot the map
fig = px.choropleth(world,
                    locations='ISO_A3',
                    color='Count',
                    hover_name='Country',
                    hover_data=['Count'],
                    projection='natural earth',
                    title='Racing Nations: A World of Formula 1 Drivers',
                    color_continuous_scale='pinkyl')

# Customize the map style
fig.update_geos(
    visible=False,
    showcountries=True,
    countrycolor="White",
    coastlinecolor="White",
    showland=True,
    landcolor="LightGrey",
    showocean=True,
    oceancolor="LightBlue",
    showlakes=True,
    lakecolor="LightBlue",
    showrivers=True,
    rivercolor="LightBlue"
)

# Add subtitle and data source
fig.update_layout(
    title={
        'text': "Racing Nations: A World of Formula 1 Drivers",
        'y':0.95,
        'x':0.5,
        'xanchor': 'center',
        'yanchor': 'top'},
    annotations=[
        dict(
            text="Number of Drivers by Nationality Worldwide",
            xref="paper",
            yref="paper",
            x=0.5,
            y=-0.25,
            showarrow=False,
            font=dict(
                family="Arial",
                size=12,
                color="grey"
            )
        )
    ]
)

# Show the plot
fig.show()
```

```
Index(['featurecla', 'scalerank', 'LABELRANK', 'SOVEREIGNT', 'SOV_A3',
       'ADM0_DIF', 'LEVEL', 'TYPE', 'TLC', 'ADMIN',
       ...
       'FCLASS_TR', 'FCLASS_ID', 'FCLASS_PL', 'FCLASS_GR', 'FCLASS_IT',
       'FCLASS_NL', 'FCLASS_SE', 'FCLASS_BD', 'FCLASS_UA', 'geometry'],
      dtype='object', length=169)
```

Racing Nations: A World of Formula 1 Drivers



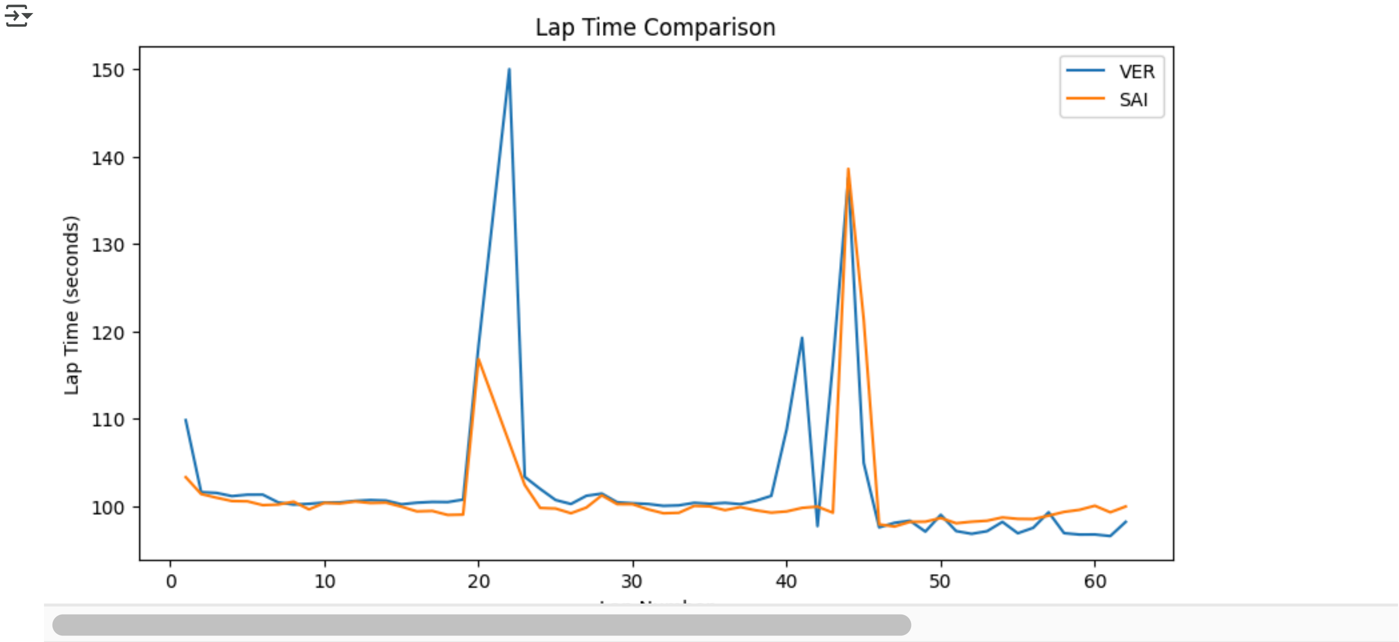
Part 2: Analysing A Specific Race - the Drivers and their Strategies

```
# Load race data (Choose a specific race - Year, Location, Session)
race = fastf1.get_session(2023, 'Singapore', 'R')
race.load()

if race is None:
    raise ValueError("Error: Race data not found. Check the event name and year.")
```

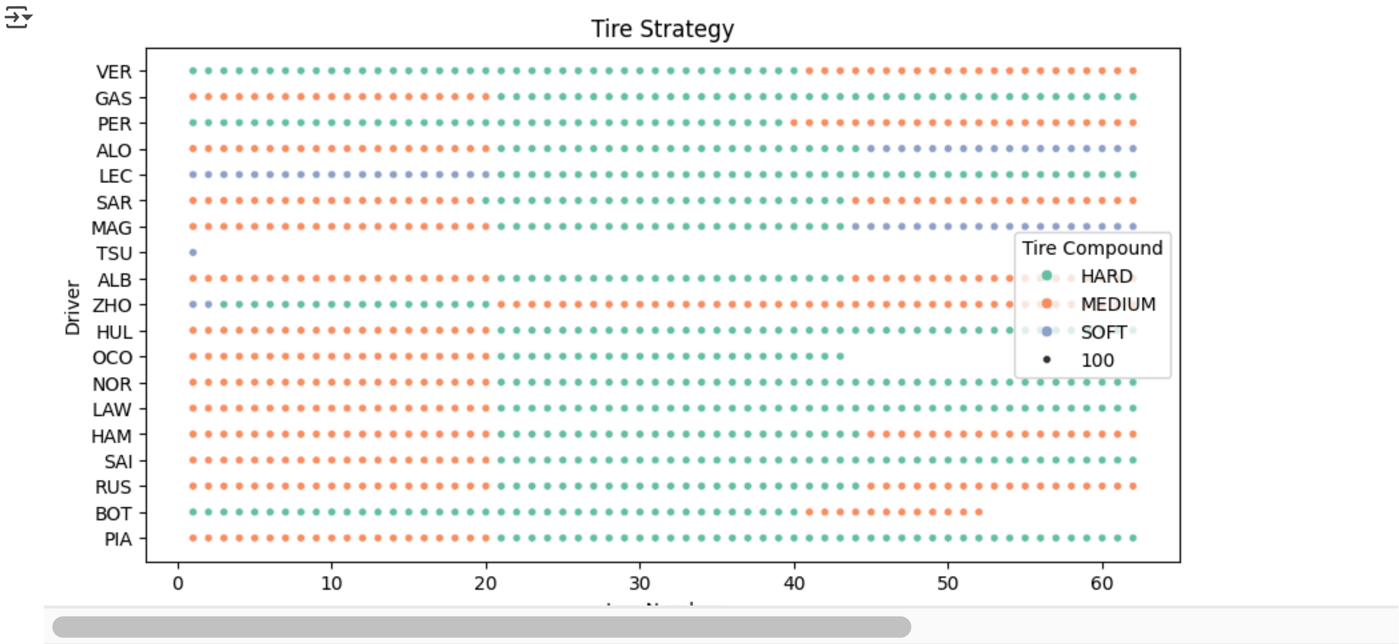
```
core           INFO     Loading data for Singapore Grand Prix - Race [v3.5.0]
INFO:fastf1.fastf1.core:Loading data for Singapore Grand Prix - Race [v3.5.0]
req            INFO     Using cached data for session_info
INFO:fastf1.fastf1.req:Using cached data for session_info
req            INFO     Using cached data for driver_info
INFO:fastf1.fastf1.req:Using cached data for driver_info
req            INFO     Using cached data for session_status_data
INFO:fastf1.fastf1.req:Using cached data for session_status_data
req            INFO     Using cached data for lap_count
INFO:fastf1.fastf1.req:Using cached data for lap_count
req            INFO     Using cached data for track_status_data
INFO:fastf1.fastf1.req:Using cached data for track_status_data
req            INFO     Using cached data for _extended_timing_data
INFO:fastf1.fastf1.req:Using cached data for _extended_timing_data
req            INFO     Using cached data for timing_app_data
INFO:fastf1.fastf1.req:Using cached data for timing_app_data
core           INFO     Processing timing data...
INFO:fastf1.fastf1.core:Processing timing data...
core        WARNING     No lap data for driver 18
WARNING:fastf1.fastf1.core:No lap data for driver 18
core        WARNING     Failed to perform lap accuracy check - all laps marked as inaccurate (driver 18)
WARNING:fastf1.fastf1.core:Failed to perform lap accuracy check - all laps marked as inaccurate (driver 18)
req            INFO     Using cached data for car_data
INFO:fastf1.fastf1.req:Using cached data for car_data
req            INFO     Using cached data for position_data
INFO:fastf1.fastf1.req:Using cached data for position_data
req            INFO     Using cached data for weather_data
INFO:fastf1.fastf1.req:Using cached data for weather_data
req            INFO     Using cached data for race_control_messages
INFO:fastf1.fastf1.req:Using cached data for race_control_messages
core           INFO     Finished loading data for 20 drivers: ['55', '4', '44', '16', '1', '10', '81', '11', '40', '20',
INFO:fastf1.fastf1.core:Finished loading data for 20 drivers: ['55', '4', '44', '16', '1', '10', '81', '11', '40', '20',
```

```
# Select drivers for comparison
drivers = ['VER', 'SAI']

# Get lap data for selected drivers
```

```
laps = race.laps[race.laps['Driver'].isin(drivers)]

# Ensure lap times are not null and convert to seconds
laps = laps.dropna(subset=['LapTime'])
laps['LapTime'] = laps['LapTime'].dt.total_seconds()


# Plot lap times
plt.figure(figsize=(10,5))
for driver in drivers:
    driver_laps = laps[laps['Driver'] == driver]
    plt.plot(driver_laps['LapNumber'], driver_laps['LapTime'], label=driver)

plt.xlabel("Lap Number")
plt.ylabel("Lap Time (seconds)")
plt.title("Lap Time Comparison")
plt.legend()
plt.show()
```




```
# Analyze Tire Strategies
pit_stops = race.laps[["Driver", "LapNumber", "Compound"]].drop_duplicates()
plt.figure(figsize=(10, 5))
sns.scatterplot(data=pit_stops, x="LapNumber", y="Driver", hue="Compound", palette="Set2", size=100, legend="full")
plt.xlabel("Lap Number")
plt.ylabel("Driver")
plt.title("Tire Strategy")
plt.legend(title="Tire Compound")
plt.show()
```

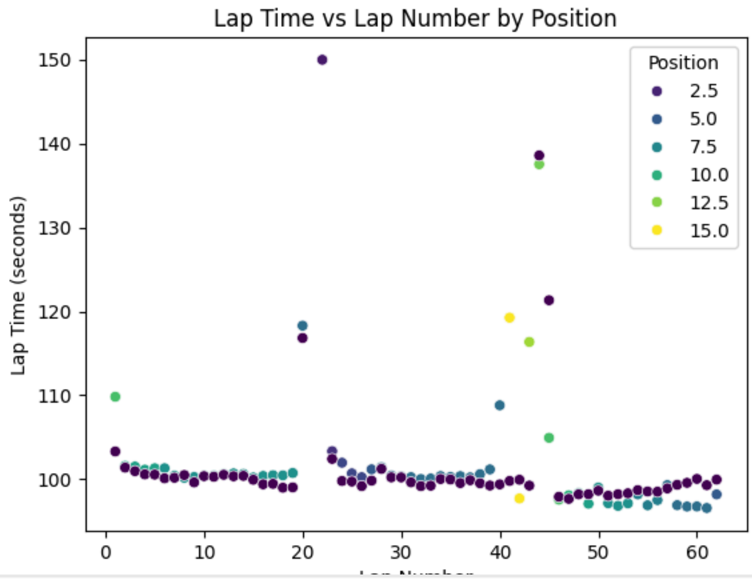


```
# Overtakes Analysis
positions = race.laps[["LapNumber", "Driver", "Position"]].drop_duplicates()
positions['PositionChange'] = positions.groupby('Driver')['Position'].diff().fillna(0)
overtakes = positions[positions['PositionChange'] < 0]
overtakes
```

	LapNumber	Driver	Position	PositionChange
1	2.0	VER	9.0	-2.0
5	6.0	VER	8.0	-1.0
19	20.0	VER	6.0	-2.0
20	21.0	VER	2.0	-4.0
42	43.0	VER	13.0	-2.0
...	...	...	...	...
1064	39.0	PIA	10.0	-1.0
1066	41.0	PIA	9.0	-1.0
1068	43.0	PIA	8.0	-1.0
1069	44.0	PIA	7.0	-1.0
1087	62.0	PIA	7.0	-1.0

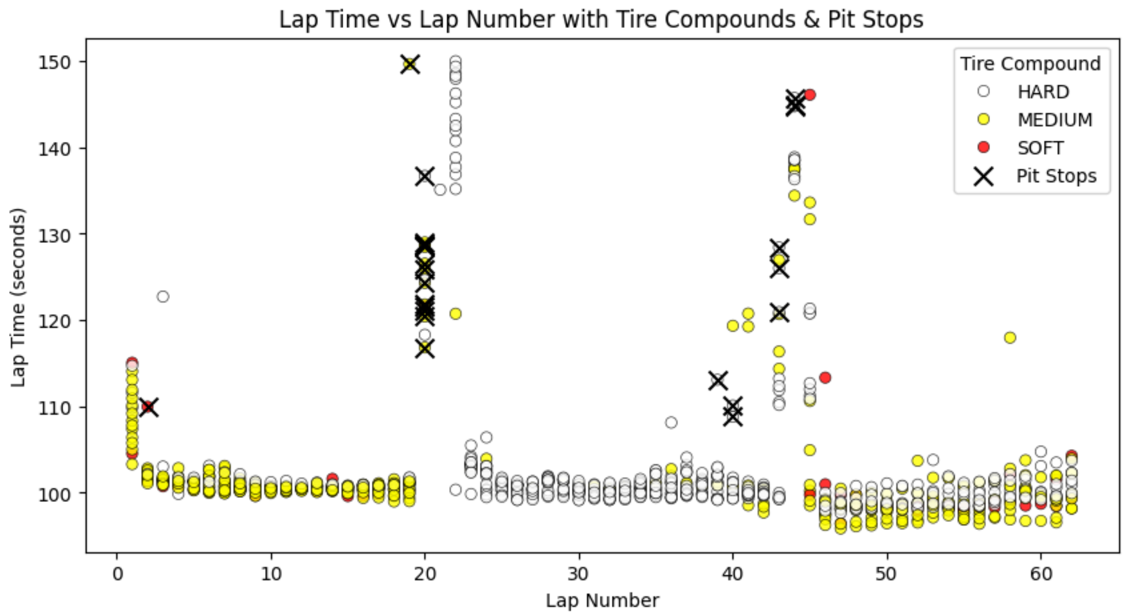
Next steps: Generate code with overtakes | View recommended plots | New interactive sheet

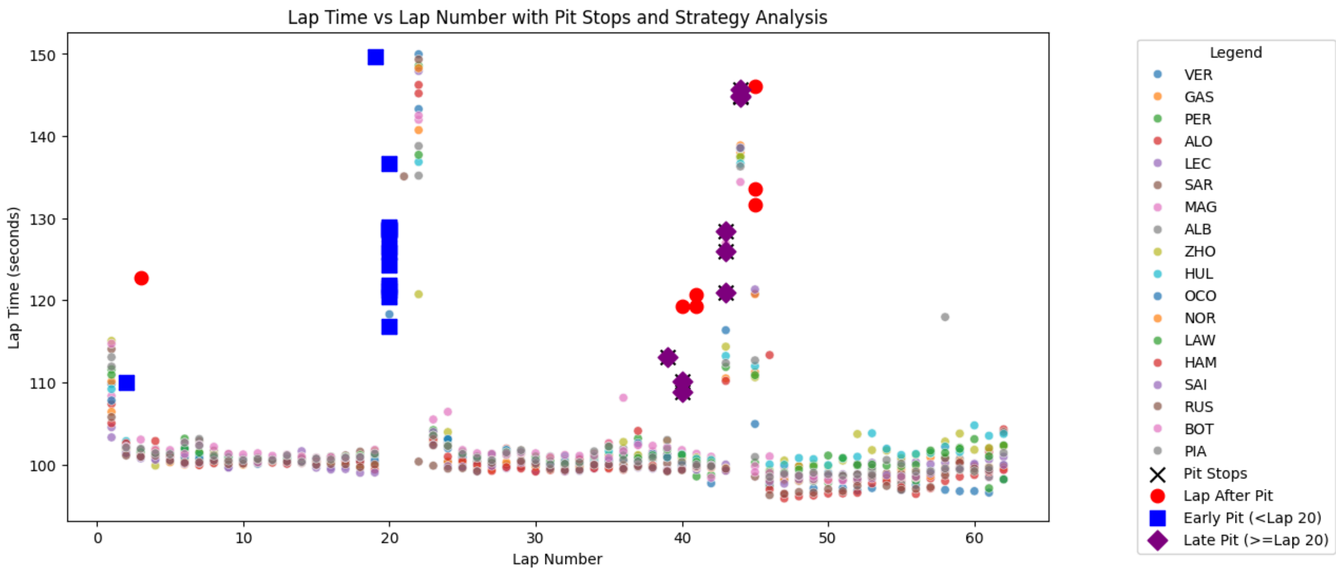
```
# Lap Time vs Position Analysis
sns.scatterplot(x=laps['LapNumber'], y=laps['LapTime'], hue=laps['Position'], palette='viridis')
plt.xlabel("Lap Number")
plt.ylabel("Lap Time (seconds)")
plt.title("Lap Time vs Lap Number by Position")
plt.show()
```




```
# Get lap data and convert lap time to seconds
laps = race.laps[['Driver', 'LapNumber', 'LapTime', 'Compound', 'Position']].dropna()
laps['LapTime'] = laps['LapTime'].dt.total_seconds()

# Extract pit stop lap numbers
pit_stops = race.laps[race.laps['PitInTime'].notna()][['Driver', 'LapNumber']]

# Merge to get lap times for pit stops
pit_stop_lap_times = pit_stops.merge(laps, on=['Driver', 'LapNumber'], how='left')

# Get lap times immediately after a pit stop (lap after pitting)
pit_stop_lap_times['PostPitLap'] = pit_stop_lap_times['LapNumber'] + 1
post_pit_laps = pit_stop_lap_times.merge(laps, left_on=['Driver', 'PostPitLap'],
                                          right_on=['Driver', 'LapNumber'],
                                          suffixes=('_Pit', '_PostPit'))

# Define color mapping for tire compounds
compound_colors = {
```

```
    'SOFT': 'red',
    'MEDIUM': 'yellow',
    'HARD': 'white',
    'INTERMEDIATE': 'green',
    'WET': 'blue'}

# Create the scatter plot
plt.figure(figsize=(10,5))
sns.scatterplot(data=laps, x="LapNumber", y="LapTime", hue="Compound", palette=compound_colors, edgecolor="black", alpha=0.8

# Overlay pit stops with red "X" markers
plt.scatter(pit_stop_lap_times['LapNumber'], pit_stop_lap_times['LapTime'], color='black', marker='x', s=100, label="Pit Sto

# Labels and title
plt.xlabel("Lap Number")
plt.ylabel("Lap Time (seconds)")
plt.title("Lap Time vs Lap Number with Tire Compounds & Pit Stops")
plt.legend(title="Tire Compound")
plt.show()

# Create the scatter plot for lap times
plt.figure(figsize=(12, 6))
sns.scatterplot(data=laps, x="LapNumber", y="LapTime", hue="Driver", palette="tab10", alpha=0.7)

# Overlay pit stops with "X" markers
plt.scatter(pit_stop_lap_times['LapNumber'], pit_stop_lap_times['LapTime'], color='black', marker='x', s=100, label="Pit Sto

# Overlay post-pit lap times with "o" markers to track lap time drop
plt.scatter(post_pit_laps['LapNumber_PostPit'], post_pit_laps['LapTime_PostPit'], color='red', marker='o', s=80, label="Lap

# Split early vs. late pit stops and visualize
early_pits = pit_stop_lap_times[pit_stop_lap_times['LapNumber'] < 30]
late_pits = pit_stop_lap_times[pit_stop_lap_times['LapNumber'] >= 30]

plt.scatter(early_pits['LapNumber'], early_pits['LapTime'], color='blue', marker='s', s=90, label="Early Pit (<Lap 20)")
plt.scatter(late_pits['LapNumber'], late_pits['LapTime'], color='purple', marker='D', s=90, label="Late Pit (>=Lap 20)")

# Labels and title
plt.xlabel("Lap Number")
plt.ylabel("Lap Time (seconds)")
plt.title("Lap Time vs Lap Number with Pit Stops and Strategy Analysis")
plt.legend(title="Legend", loc="upper right", bbox_to_anchor=(1.3, 1))
plt.show()
```





4. Prediction

Goal - to predict the winner of an F1 race using historical race data. The model should consider factors like: Driver and car performance, Track characteristics, Weather conditions, Qualifying results, Pit strategies.

Model - Logistic Regression and Random Forest Model.

Logistic Regression VS Random Forest Model

Outputs probability values instead of just binary classifications (0/1)

Less prone to overfitting compared to Random Forest, especially with small datasets

Easier to interpret (feature coefficients directly show impact on winning probability)

Model 1: Logistic Regression

Step 1: Data Collection and PreProcessing

```
import requests
import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
import matplotlib.pyplot as plt
import seaborn as sns

# Function to fetch race data from the Ergast API
def fetch_race_data(year):
    url = f"http://ergast.com/api/f1/{year}/results.json?limit=1000"
    response = requests.get(url)
    data = response.json()

    race_results = []
    for race in data['MRData']['RaceTable']['Races']:
        race_name = race['raceName']
        round_num = race['round']
        circuit = race['Circuit']['circuitName']

        for result in race['Results']:
            driver = result['Driver']['code'] if 'code' in result['Driver'] else result['Driver']['familyName']
            constructor = result['Constructor']['name']
            grid_position = int(result['grid'])
            finishing_position = int(result['position'])
            points = float(result['points'])
            status = result['status']

            race_results.append([year, round_num, race_name, circuit, driver, constructor, grid_position, finishing_positior

    return pd.DataFrame(race_results, columns=['Year', 'Round', 'Race', 'Circuit', 'Driver', 'Constructor', 'Grid', 'Positic

# Fetching data
years = list(range(2010, 2025))
all_race_data = [fetch_race_data(year) for year in years]
data = pd.concat(all_race_data, ignore_index=True)
```

Step 2: Model Training

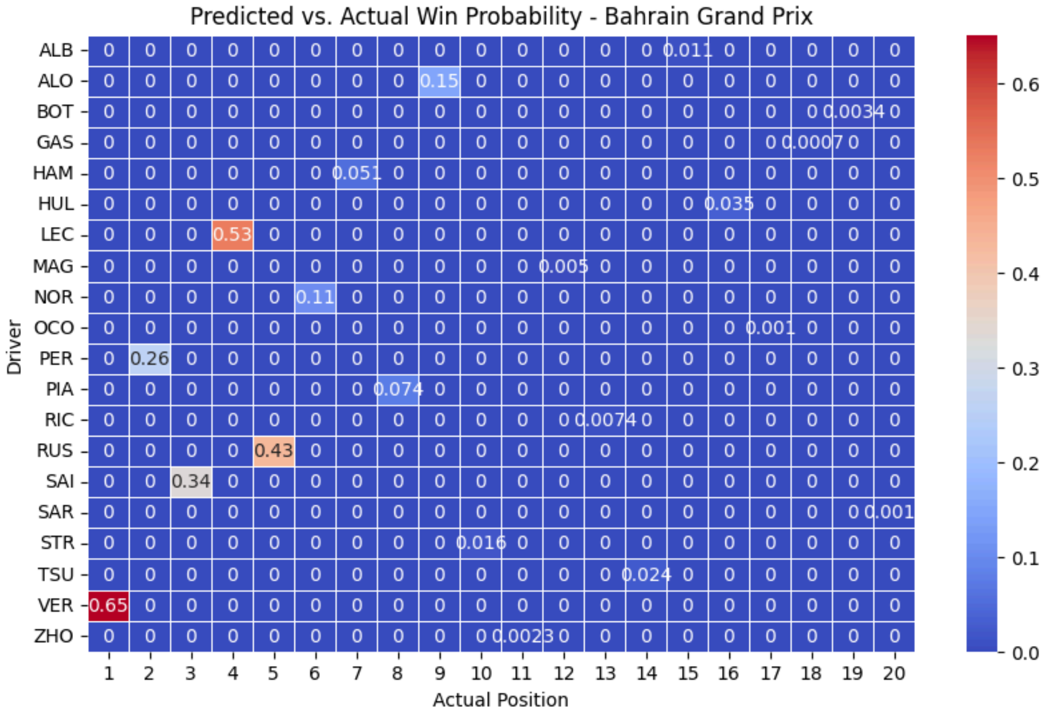
```
# Feature Engineering
data['Win'] = (data['Position'] == 1).astype(int)  # Target variable

data['Grid_Top5'] = (data['Grid'] <= 5).astype(int)  # Top 5 Grid Start Indicator

data['Constructor_Wins'] = data.groupby(['Constructor'])['Win'].transform('sum')  # Constructor Strength

data['Driver_Wins'] = data.groupby(['Driver'])['Win'].transform('sum')  # Driver Strength

data['Constructor_Points'] = data.groupby(['Constructor'])['Points'].transform('sum')  # Constructor Performance

data['Driver_Points'] = data.groupby(['Driver'])['Points'].transform('sum')  # Driver Performance

X = data[['Grid', 'Grid_Top5', 'Constructor_Wins', 'Driver_Wins']]
y = data['Win']

# Create a pipeline with feature scaling + Logistic Regression
log_reg_model = Pipeline([
    ('scaler', StandardScaler()),  # Standardizes features
    ('classifier', LogisticRegression(max_iter=1000, class_weight='balanced'))  # Handles class imbalance
])

# Train model
log_reg_model.fit(X, y)

# Predict probabilities on test set
y_pred_prob = log_reg_model.predict_proba(X_test)[:, 1]
```

Step 3: Model Evaluation

```
# Evaluate model
print("Logistic Regression Model Performance:")
print(classification_report(y_test, (y_pred_prob > 0.5).astype(int)))

# Function to test Logistic Regression on a specific race
def test_race_logistic(year, round_num):
    race_data = fetch_race_data(year)
```

```
    race_data = fetch_race_data(year)
    specific_race = race_data[race_data['Round'] == str(round_num)].copy()

    if specific_race.empty:
        print("Race data not found!")
        return

    # Ensure required features exist
    specific_race['Win'] = (specific_race['Position'] == 1).astype(int)
    specific_race['Grid_Top5'] = (specific_race['Grid'] <= 5).astype(int)
    specific_race['Constructor_Wins'] = specific_race.groupby(['Constructor'])['Win'].transform('sum')
    specific_race['Driver_Wins'] = specific_race.groupby(['Driver'])['Win'].transform('sum')

    X_race = specific_race[['Grid', 'Grid_Top5', 'Constructor_Wins', 'Driver_Wins']]

    # Predict probabilities using logistic regression
    predicted_probabilities = log_reg_model.predict_proba(X_race)[:, 1]

    # Assign probabilities to dataset
    specific_race['Predicted_Win_Prob'] = predicted_probabilities

    # Sort drivers by predicted win probability
    specific_race = specific_race.sort_values(by='Predicted_Win_Prob', ascending=False)

    predicted_winner = specific_race.iloc[0]['Driver']
    actual_winner = specific_race[specific_race['Win'] == 1]['Driver'].values[0]

    print(f"Predicted Winner: {predicted_winner}")
    print(f"Actual Winner: {actual_winner} {'Correct' if predicted_winner == actual_winner else 'Incorrect'}")

    print("\nPredictions vs Actual Results for", specific_race['Race'].iloc[0])
    print(specific_race[['Driver', 'Grid', 'Position', 'Predicted_Win_Prob']])

    # Heatmap visualization
    plt.figure(figsize=(10, 6))
    heatmap_data = specific_race.pivot(index='Driver', columns='Position', values='Predicted_Win_Prob').fillna(0)
    sns.heatmap(heatmap_data, annot=True, cmap='coolwarm', linewidths=0.5)
    plt.xlabel("Actual Position")
    plt.ylabel("Driver")
    plt.title(f"Predicted vs. Actual Win Probability – {specific_race['Race'].iloc[0]}")
    plt.show()

    return specific_race

# Test Logistic Regression on a specific 2024 race
test_race_logistic(2024, 1)
```

```
Logistic Regression Model Performance:
              precision    recall  f1-score   support

           0       1.00      0.86      0.92       287
           1       0.24      1.00      0.39        13

    accuracy                           0.86       300
   macro avg       0.62      0.93      0.66       300
weighted avg       0.97      0.86      0.90       300

Predicted Winner: VER
Actual Winner: VER Correct

Predictions vs Actual Results for Bahrain Grand Prix
   Driver  Grid  Position  Predicted_Win_Prob
0     VER     1         1            0.651525
3     LEC     2         4            0.527063
4     RUS     3         5            0.428793
2     SAI     4         3            0.335835
1     PER     5         2            0.260114
8     ALO     6         9            0.150047
5     NOR     7         6            0.106275
7     PIA     8         8            0.074159
6     HAM     9         7            0.051192
15    HUL    10        16            0.035068
13    TSU    11        14            0.023895
9     STR    12        10            0.016222
14    ALB    13        15            0.010985
12    RIC    14        13            0.007426
11    MAG    15        12            0.005014
18    BOT    16        19            0.003383
10    ZHO    17        11            0.002281
19    SAR    18        20            0.001538
16    OCO    19        17            0.001036
17    GAS    20        18            0.000698
```



	Year	Round	Race	Circuit	Driver	Constructor	Grid	Position	Points	Status	Win	Grid_Top5	Constructor_Win
0	2024	1	Bahrain Grand Prix	Bahrain International Circuit	VER	Red Bull	1	1	26.0	Finished	1	1	
3	2024	1	Bahrain Grand Prix	Bahrain International Circuit	LEC	Ferrari	2	4	12.0	Finished	0	1	
4	2024	1	Bahrain Grand Prix	Bahrain International Circuit	RUS	Mercedes	3	5	10.0	Finished	0	1	
2	2024	1	Bahrain Grand Prix	Bahrain International Circuit	SAI	Ferrari	4	3	15.0	Finished	0	1	
1	2024	1	Bahrain Grand Prix	Bahrain International Circuit	PER	Red Bull	5	2	18.0	Finished	0	1	
8	2024	1	Bahrain Grand	Bahrain International	ALO	Aston Martin	6	9	2.0	Finished	0	0	

			Prix	Circuit								
5	2024	1	Bahrain Grand Prix	Bahrain International Circuit	NOR	McLaren	7	6	8.0	Finished	0	0
7	2024	1	Bahrain Grand Prix	Bahrain International Circuit	PIA	McLaren	8	8	4.0	Finished	0	0
6	2024	1	Bahrain Grand Prix	Bahrain International Circuit	HAM	Mercedes	9	7	6.0	Finished	0	0
15	2024	1	Bahrain Grand Prix	Bahrain International Circuit	HUL	Haas F1 Team	10	16	0.0	+1 Lap	0	0
13	2024	1	Bahrain Grand Prix	Bahrain International Circuit	TSU	RB F1 Team	11	14	0.0	+1 Lap	0	0
9	2024	1	Bahrain Grand Prix	Bahrain International Circuit	STR	Aston Martin	12	10	1.0	Finished	0	0
14	2024	1	Bahrain Grand Prix	Bahrain International Circuit	ALB	Williams	13	15	0.0	+1 Lap	0	0
12	2024	1	Bahrain Grand Prix	Bahrain International Circuit	RIC	RB F1 Team	14	13	0.0	+1 Lap	0	0
11	2024	1	Bahrain Grand Prix	Bahrain International Circuit	MAG	Haas F1 Team	15	12	0.0	+1 Lap	0	0
18	2024	1	Bahrain Grand Prix	Bahrain International Circuit	BOT	Sauber	16	19	0.0	+1 Lap	0	0
10	2024	1	Bahrain Grand Prix	Bahrain International Circuit	ZHO	Sauber	17	11	0.0	+1 Lap	0	0
19	2024	1	Bahrain Grand Prix	Bahrain International Circuit	SAR	Williams	18	20	0.0	+2 Laps	0	0
16	2024	1	Bahrain Grand Prix	Bahrain International Circuit	OCO	Alpine F1 Team	19	17	0.0	+1 Lap	0	0
17	2024	1	Bahrain Grand Prix	Bahrain International Circuit	GAS	Alpine F1 Team	20	18	0.0	+1 Lap	0	0

Model 2: RandomForestClassifier

Step 1: Data Collection

```
import requests
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report
import matplotlib.pyplot as plt
import seaborn as sns

# Function to fetch race data from the Ergast API
def fetch_race_data(year):
    url = f"http://ergast.com/api/f1/{year}/results.json?limit=1000"
    response = requests.get(url)
    data = response.json()

    race_results = []
    for race in data['MRData']['RaceTable']['Races']:
        race_name = race['raceName']
        round_num = race['round']
        circuit = race['Circuit']['circuitName']

        for result in race['Results']:
            driver = result['Driver']['code'] if 'code' in result['Driver'] else result['Driver']['familyName']
            constructor = result['Constructor']['name']
            grid_position = int(result['grid'])
            finishing_position = int(result['position'])
            points = float(result['points'])
            status = result['status']

            race_results.append([year, round_num, race_name, circuit, driver, constructor, grid_position, finishing_positior

    return pd.DataFrame(race_results, columns=['Year', 'Round', 'Race', 'Circuit', 'Driver', 'Constructor', 'Grid', 'Positic

# Fetching data
years = list(range(2010, 2025))
all_race_data = [fetch_race_data(year) for year in years]
data = pd.concat(all_race_data, ignore_index=True)
```

Step 2: Feature Engineering

```
# Feature Engineering
data['Win'] = (data['Position'] == 1).astype(int)  # Target variable

data['Grid_Top5'] = (data['Grid'] <= 5).astype(int)  # Top 5 Grid Start Indicator

data['Constructor_Wins'] = data.groupby(['Constructor'])['Win'].transform('sum')  # Constructor Strength

data['Driver_Wins'] = data.groupby(['Driver'])['Win'].transform('sum')  # Driver Strength

data['Constructor_Points'] = data.groupby(['Constructor'])['Points'].transform('sum')  # Constructor Performance

data['Driver_Points'] = data.groupby(['Driver'])['Points'].transform('sum')  # Driver Performance

data['DNF'] = (data['Status'] != 'Finished').astype(int)

data['DNF_Rate'] = data.groupby('Driver')['DNF'].transform('mean')

# Splitting data into train and test
X = data[['Grid', 'Grid_Top5', 'Constructor_Wins', 'Driver_Wins']]
y = data['Win']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 3: Model Selection & Training