f1_analysis

August 7, 2025

[22]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


base_path = '../data/f1Data/'

drivers = pd.read_csv(base_path + 'drivers.csv')
results = pd.read_csv(base_path + 'results.csv')
races = pd.read_csv(base_path + 'races.csv')
constructors = pd.read_csv(base_path + 'constructors.csv')
lap_times = pd.read_csv(base_path + 'lap_times.csv')
pit_stops = pd.read_csv(base_path + 'pit_stops.csv')


drivers.head()
```

[22]:

	driverId	driverRef	number	code	forename	surname	dob	nationality	url
0	1	hamilton	44	HAM	Lewis	Hamilton	1985-01-07	British	http://en.wikipedia.org/wiki/Lewis_Hamilton
1	2	heidfeld	\N	HEI	Nick	Heidfeld	1977-05-10	German	http://en.wikipedia.org/wiki/Nick_Heidfeld
2	3	rosberg	6	ROS	Nico	Rosberg	1985-06-27	German	http://en.wikipedia.org/wiki/Nico_Rosberg
3	4	alonso	14	ALO	Fernando	Alonso	1981-07-29	Spanish	http://en.wikipedia.org/wiki/Fernando_Alonso
4	5	kovalainen	\N	KOV	Heikki	Kovalainen	1981-10-19	Finnish	http://en.wikipedia.org/wiki/Heikki_Kovalainen

[23]:
```
drivers.isnull().sum()
```

[23]:
```
driverId       0
driverRef      0
number         0
code           0
```

```
forename       0
surname        0
dob            0
nationality    0
url            0
dtype: int64
```

[24]:
```
results.head()

results.isnull().sum()
```

[24]:
```
resultId           0
raceId             0
driverId           0
constructorId      0
number             0
grid               0
position           0
positionText       0
positionOrder      0
points             0
laps               0
time               0
milliseconds       0
fastestLap         0
rank               0
fastestLapTime     0
fastestLapSpeed    0
statusId           0
dtype: int64
```

[25]:
```
merged = results.merge(races, on='raceId', suffixes=('', '_race'))

merged = merged.merge(drivers, on='driverId', suffixes=('', '_driver'))

merged = merged.merge(constructors, on='constructorId', suffixes=('', '_team'))

merged[['raceId', 'year', 'name', 'surname', 'grid', 'positionOrder',␣
 ↪'constructorRef']].head()
```

[25]:

	raceId	year	name	surname	grid	positionOrder	\
0	18	2008	Australian Grand Prix	Hamilton	1	1	
1	19	2008	Malaysian Grand Prix	Hamilton	9	5	
2	20	2008	Bahrain Grand Prix	Hamilton	3	13	
3	21	2008	Spanish Grand Prix	Hamilton	5	3	
4	22	2008	Turkish Grand Prix	Hamilton	3	2	

```
  constructorRef
0        mclaren
1        mclaren
2        mclaren
3        mclaren
4        mclaren
```

[26]:
```
merged['podium_finish'] = merged['positionOrder'].apply(lambda x: 1 if x <= 3
 ↪else 0)

merged['podium_finish'].value_counts()
```

[26]:
```
podium_finish
0    23362
1     3397
Name: count, dtype: int64
```

[27]:
```
ml_data = merged[['grid', 'positionOrder', 'podium_finish']].copy()

ml_data = ml_data.dropna()

X = ml_data[['grid']]
y = ml_data['podium_finish']

X.head(), y.head()
```

[27]:
```
(   grid
 0     1
 1     9
 2     3
 3     5
 4     3,
 0    1
 1    0
 2    0
 3    1
 4    1
 Name: podium_finish, dtype: int64)
```

[28]:
```
# I selected these features because they are likely to influence race outcomes:
# grid: starting position is known to affect race results
# driverId: accounts for the skill/experience of the driver
# constructorId: reflects the team's overall performance and resources
# year and round: shows historical trends and seasonal changes (like new
 ↪regulations, team upgrades)
features = merged[['grid', 'driverId', 'constructorId', 'year', 'round']]
```

```
# Dropping missing values to ensure that the dataset is clean before training␣
 ↪the model.
# I matched the target index with features to keep alignment.
features = features.dropna()
target = merged['podium_finish'].loc[features.index]
```

[29]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(features, target,␣
 ↪test_size=0.2, random_state=42)
```

[30]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
```

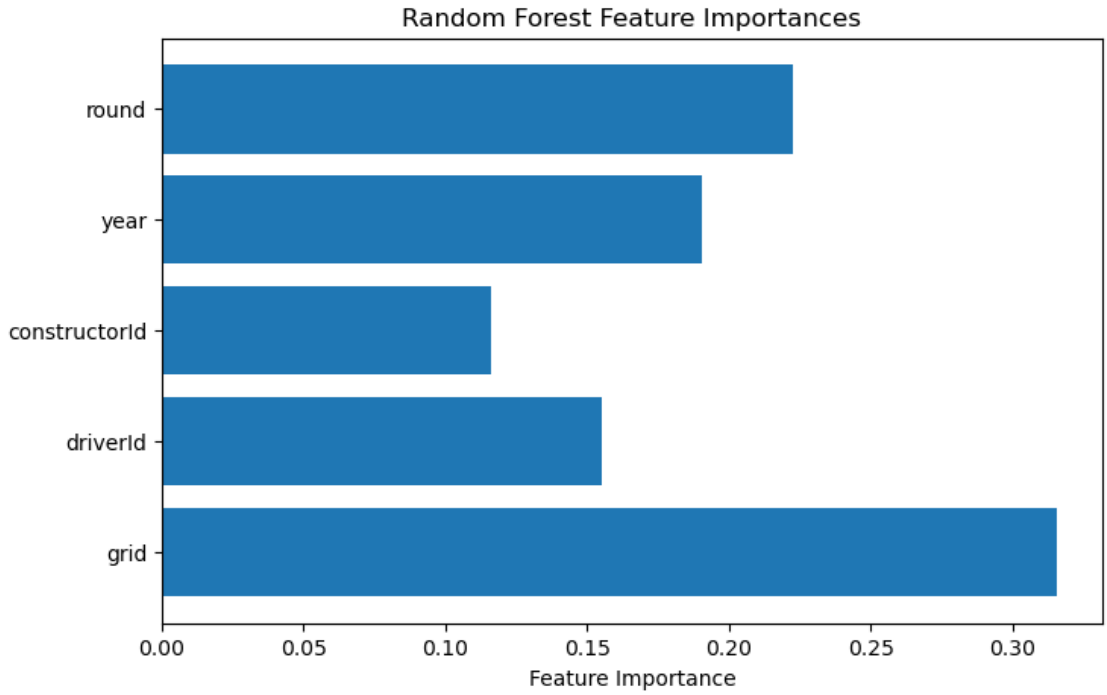
[30]:
```
RandomForestClassifier(random_state=42)
```

[31]:
```
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

y_pred = rf.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8804185351270553

Confusion Matrix:
 [[4417  231]
 [ 409  295]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.95      0.93      4648
           1       0.56      0.42      0.48       704

    accuracy                           0.88      5352
   macro avg       0.74      0.68      0.71      5352
weighted avg       0.87      0.88      0.87      5352
```

[32]:
```
import matplotlib.pyplot as plt

importances = rf.feature_importances_
feature_names = features.columns
```

```
plt.figure(figsize=(8, 5))
plt.barh(feature_names, importances)
plt.xlabel("Feature Importance")
plt.title("Random Forest Feature Importances")
plt.show()
```



[33]:
```
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8804185351270553

Confusion Matrix:
 [[4417  231]
 [ 409  295]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.95      0.93      4648
           1       0.56      0.42      0.48       704

    accuracy                           0.88      5352
   macro avg       0.74      0.68      0.71      5352
```

```
weighted avg       0.87      0.88      0.87      5352
```

[34]:
```
# Unsupervised Learning clustering of drivers based on performance
```

[35]:
```
# i already jhave the merged dataset so i will re-use.
driver_stats = merged.copy()

# Calculating positions gained
driver_stats['positions_gained'] = driver_stats['grid'] -␣
 ↪driver_stats['positionOrder']

# Group by driver and calculate averages
driver_perf = driver_stats.groupby('driverId').agg({
    'grid': 'mean',
    'positionOrder': 'mean',
    'positions_gained': 'mean',
    'raceId': 'count'  # number of races
}).rename(columns={'grid': 'avg_grid', 'positionOrder': 'avg_finish',␣
 ↪'positions_gained': 'avg_gain', 'raceId': 'num_races'})

# Drop any drivers with very few races (less reliable)
driver_perf = driver_perf[driver_perf['num_races'] >= 10]

driver_perf.head()
```

[35]:

driverId	avg_grid	avg_finish	avg_gain	num_races
1	4.300562	5.019663	-0.719101	356
2	11.336957	10.722826	0.614130	184
3	6.902913	8.252427	-1.349515	206
4	8.579208	8.492574	0.086634	404
5	13.741071	13.285714	0.455357	112

[36]:
```
# adding drivername for better overview
```

[37]:
```
# Select only the relevant columns from the drivers dataframe
driver_names = drivers[['driverId', 'forename', 'surname']]

# Merge into the driver_perf dataframe
driver_perf = driver_perf.merge(driver_names, on='driverId')

# Optional: create a full name column for easier readability
driver_perf['driver_name'] = driver_perf['forename'] + ' ' +␣
 ↪driver_perf['surname']

# Reorder columns so names come first
```

```
cols = ['driverId', 'driver_name', 'avg_grid', 'avg_finish', 'avg_gain',␣
 ↪'num_races']
if 'cluster' in driver_perf.columns:
    cols.append('cluster')
if 'pca1' in driver_perf.columns and 'pca2' in driver_perf.columns:
    cols.extend(['pca1', 'pca2'])

driver_perf = driver_perf[cols]

# View result
driver_perf.head()
```

[37]:

	driverId	driver_name	avg_grid	avg_finish	avg_gain	num_races
0	1	Lewis Hamilton	4.300562	5.019663	-0.719101	356
1	2	Nick Heidfeld	11.336957	10.722826	0.614130	184
2	3	Nico Rosberg	6.902913	8.252427	-1.349515	206
3	4	Fernando Alonso	8.579208	8.492574	0.086634	404
4	5	Heikki Kovalainen	13.741071	13.285714	0.455357	112

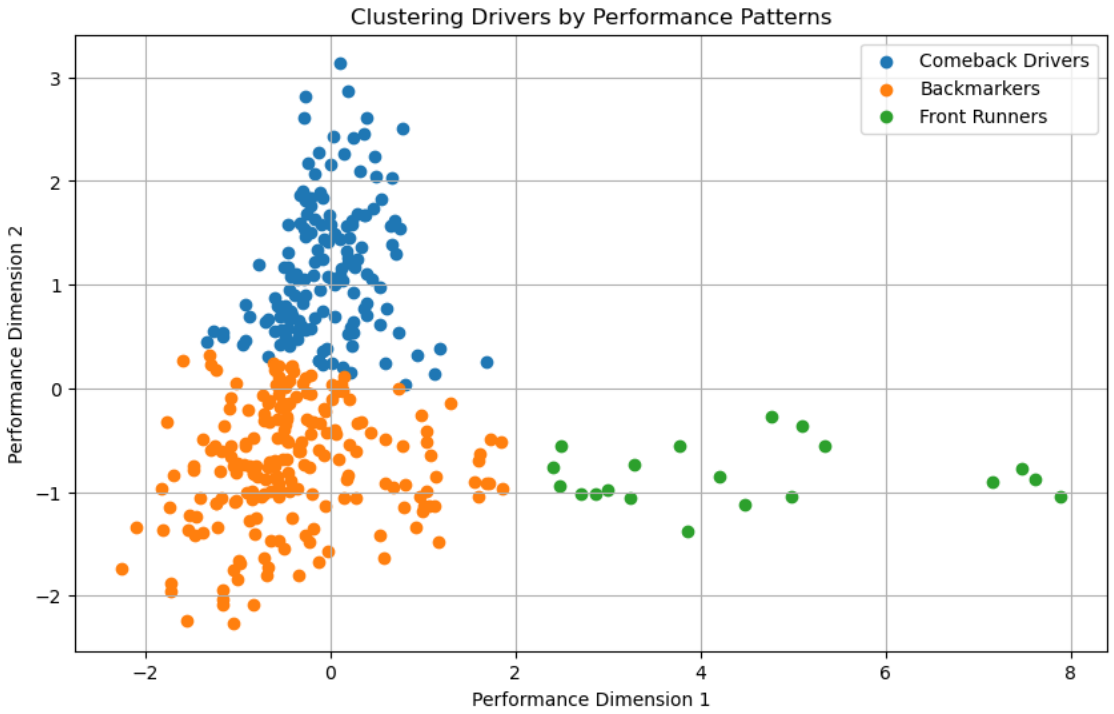
[38]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaled_features = scaler.fit_transform(driver_perf[['avg_grid', 'avg_finish',␣
 ↪'avg_gain']])
```

[39]:
```
from sklearn.cluster import KMeans

# Let's try 3 clusters to start with
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(scaled_features)

# Add cluster labels back to dataframe
driver_perf['cluster'] = clusters

# Check distribution
driver_perf['cluster'].value_counts()
```

```
/Users/vivek/anaconda3/lib/python3.11/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

[39]:
```
cluster
2    208
0    149
1     20
Name: count, dtype: int64
```

[40]:
```python
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Fit PCA to reduce dimensions
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_features)

# Add PCA results to the dataframe with more descriptive names
driver_perf['Performance Dimension 1'] = pca_result[:, 0]
driver_perf['Performance Dimension 2'] = pca_result[:, 1]

# Map cluster numbers to meaningful labels
cluster_labels = {
    0: 'Comeback Drivers',
    1: 'Front Runners',
    2: 'Backmarkers'
}
driver_perf['driver_type'] = driver_perf['cluster'].map(cluster_labels)
# Cluster meanings:
# 0 → Comeback Drivers: strong gainers
# 1 → Front Runners: top performers
# 2 → Backmarkers: lower grid and finish

# Plot the clusters with clearer labels
plt.figure(figsize=(10, 6))

for label in driver_perf['driver_type'].unique():
    subset = driver_perf[driver_perf['driver_type'] == label]
    plt.scatter(
        subset['Performance Dimension 1'],
        subset['Performance Dimension 2'],
        label=label
    )

plt.title('Clustering Drivers by Performance Patterns')
plt.xlabel('Performance Dimension 1')
plt.ylabel('Performance Dimension 2')
plt.legend()
plt.grid(True)
plt.show()
```



[41]:
```
import joblib

# Save the trained model
#joblib.dump(rf, '../part2_app/model.pkl')
```

[42]:
```
##  Reflection

# Working on this project helped me better understand how supervised and␣
 ↪unsupervised machine learning can be applied to real-world data. Even though␣
 ↪the goal was to predict whether a driver would finish on the podium - and␣
 ↪the actual outcomes were already known - it was still valuable to simulate␣
 ↪predictions and see how the model performed.

# Through data cleaning and feature selection, I saw how much impact the input␣
 ↪data has on results. For example, `grid position` turned out to be one of␣
 ↪the most important predictors, which makes sense intuitively.

# For the supervised model, I used Random Forest because it performed well with␣
 ↪minimal tuning. I also used KMeans and PCA to cluster drivers and explore␣
 ↪performance patterns without labels, which helped identify types of drivers␣
 ↪like "Comeback Drivers".
```

```
# One challenge was handling many IDs (drivers, teams, races) and turning them␣
 ↪into meaningful features, which I solved through merging and careful mapping.

# Overall, I gained confidence in training models, cleaning data, and deploying␣
 ↪a working prototype - even if it's just for historical simulation. If I had␣
 ↪more time, I'd experiment with more features (like weather or lap data),␣
 ↪tune hyperparameters more deeply, and try comparing models.
```

```
[ ]:
```