About Dataset

Context

- **The Pakistan Super League (PSL) is a professional Twenty20 cricket league in Asia, primarily held in Pakistan and the UAE. Established in 2015 by the Pakistan Cricket Board (PCB), PSL features six franchise teams representing major cities. The league follows a round-robin format, where teams compete in group-stage matches before advancing to playoffs and the grand final. Known for its thrilling contests, international star players, and passionate fanbase, PSL has grown into one of the most competitive T20 leagues in the world.**
- **This dataset captures the entire history of PSL matches, enabling cricket analysts, data scientists, and fans to explore match trends, player performances, and strategic insights.**

Content

- Geography:Pakistan, UAE (Asia)
- Time Period: February 4, 2016 – March 18, 2024
- Unit of Analysis: Pakistan Super League (PSL) Matches

Variables

The dataset consists of ball-by-ball records and match summaries, making it ideal for detailed performance analysis. Below is a breakdown of the dataset's key columns:

Column Name Description

- id Unique identifier for each delivery
- match_id Unique identifier for each match
- date Date of the match
- season PSL season in which the match was played
- venue Stadium where the match was played
- inning Inning number
- batting_team Team currently batting
- bowling_team Team currently bowling

- over Over number in the innings (0 to 19)
- ball Ball number in the over (1 to 6)
- batter Name of the batsman on strike
- bowler Name of the bowler delivering the ball
- non_striker Name of the non-striking batsman
- batsman_runs Runs scored by the batsman on that delivery
- extra_runs Runs awarded as extras (wides, no-balls, etc.)
- total_runs Sum of batsman and extra runs for the delivery
- extras_type Type of extra run (wide, no-ball, bye, etc.)
- is_wicket Indicates if a wicket fell on that delivery (1 = Yes, 0 = No)
- player_dismissed Name of the dismissed player (if any)
- dismissal_kind Method of dismissal (bowled, caught, run out, etc.)
- fielder Name of the fielder involved in the dismissal (if applicable)
- winner Team that won the match
- win_by Margin of victory (runs or wickets)
- match_type Type of match (league, playoff, final)
- player_of_match Name of the best-performing player of the match
- umpire_1 Name of the first on-field umpire
- umpire_2 Name of the second on-field umpire

Acknowledgements

- Data Source: Cricsheet

Data Exploration

Import Libraraies

In [208…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report

import warnings
warnings.filterwarnings('ignore')

pd.set_option('display.max_columns',None)
```

Load Dataset

In [209…

```
df = pd.read_csv('D:/DS Bootcamp/Machine Learning/machine learning projects/Machine-Learning-Projects/PSL 2025 Winner
df.sample(5)
```

Out[209…

	id	match_id	date	season	venue	inning	batting_team	bowling_team	over	ball	batter	bowler	non_s
62400	311	959189	2016-02-08	2016	Dubai International Cricket Stadium	1	Lahore Qalandars	Quetta Gladiators	8	4	CS Delport	Umar Gul	Az
30609	231	1247020	2021-02-27	2021	National Stadium	1	Islamabad United	Peshawar Zalmi	17	2	Hasan Ali	Wahab Riaz	Moha
7088	54	1128825	2018-02-26	2018	Dubai International Cricket Stadium	1	Karachi Kings	Lahore Qalandars	4	5	JL Denly	Yasir Shah	Kh Ma
36061	286	1247043	2021-06-22	2021	Sheikh Zayed Stadium, Abu Dhabi	2	Peshawar Zalmi	Islamabad United	2	2	Hazratullah	Akif Javed	JW
56406	305	1416486	2024-02-28	2024	National Stadium, Karachi	1	Karachi Kings	Islamabad United	11	4	Mohammad Nawaz	Imad Wasim	KA F

Summary of Dataset

- The dataset contains 65,448 rows and 21 Features
- The dataset contains 12 categorical Features
- The dataset contains 9 numerical Features
- The dataset contains 1 date feature and 1 boolean feature

==========

No of Unique values in columns

- No of unique values in venue: 10
- No of unique values in batting_team: 6
- No of unique values in bowling_team: 6
- No of unique values in batter: 342
- No of unique values in bowler: 244
- No of unique values in non_striker: 336
- No of unique values in winner: 7
- No of unique values in win_by: 73
- No of unique values in match_type: 4
- No of unique values in player_of_match: 127
- No of unique values in umpire_1: 20
- No of unique values in umpire_2: 17
- No of unique values in season: 9
- No of unique values in inning: 4
- No of unique values in over: 20
- No of unique values in ball: 11
- No of unique values in batsman_runs: 7
- No of unique values in extra_runs: 6
- No of unique values in total_runs: 8

==========

Features Summary

PSL played on 10 different venues

- Dubai International Cricket Stadium'
- 'Sharjah Cricket Stadium'
- 'Gaddafi Stadium'
- National Stadium'
- 'Sheikh Zayed Stadium'
- 'Multan Cricket Stadium'
- 'Rawalpindi Cricket Stadium'
- 'National Stadium, Karachi'
- 'Sheikh Zayed Stadium, Abu Dhabi'
- 'Gaddafi Stadium, Lahore'

==========

PSL played on 2 Different countries

- UAE
- Pakistan

==========

PSL has 6 Teams

- Islamabad United
- Karachi Kings
- Lahore Qalander
- Multan Sultan
- Quetta Gladiators
- Peshawar Zalmi

==========

The format of PSL is T20

==========

The dataset contains 9 seasons record

- 2016
- 2017
- 2018
- 2019
- 2020
- 2021
- 2022
- 2023
- 2024

In [210…

```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 66112 entries, 0 to 66111
Data columns (total 27 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   id                66112 non-null  int64
 1   match_id          66112 non-null  int64
 2   date              66112 non-null  object
 3   season            66112 non-null  int64
 4   venue             66112 non-null  object
 5   inning            66112 non-null  int64
 6   batting_team      66112 non-null  object
 7   bowling_team      66112 non-null  object
 8   over              66112 non-null  int64
 9   ball              66112 non-null  int64
 10  batter            66112 non-null  object
 11  bowler            66112 non-null  object
 12  non_striker       66112 non-null  object
 13  batsman_runs      66112 non-null  int64
 14  extra_runs        66112 non-null  int64
 15  total_runs        66112 non-null  int64
 16  extras_type       3561 non-null   object
 17  is_wicket         66112 non-null  bool
 18  player_dismissed  3504 non-null   object
 19  dismissal_kind    3504 non-null   object
 20  fielder           2301 non-null   object
 21  winner            66112 non-null  object
 22  win_by            66112 non-null  object
 23  match_type        66112 non-null  object
 24  player_of_match   65448 non-null  object
 25  umpire_1          66112 non-null  object
 26  umpire_2          66112 non-null  object
dtypes: bool(1), int64(9), object(17)
memory usage: 13.2+ MB
```

Out[210…

	id	match_id	season	inning	over	ball	batsman_runs	extra_runs	tot
count	66112.000000	6.611200e+04	66112.000000	66112.000000	66112.000000	66112.000000	66112.000000	66112.000000	66112
mean	260.512570	1.221449e+06	2020.286468	1.483392	10.141714	3.617392	1.280025	0.069382	1
std	107.596957	1.270599e+05	2.487097	0.502625	5.654251	1.811348	1.652216	0.356554	1
min	1.000000	9.591750e+05	2016.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0
25%	182.000000	1.128843e+06	2018.000000	1.000000	5.000000	2.000000	0.000000	0.000000	0
50%	260.000000	1.211672e+06	2020.000000	1.000000	10.000000	4.000000	1.000000	0.000000	1
75%	339.000000	1.293031e+06	2022.000000	2.000000	15.000000	5.000000	1.000000	0.000000	1
max	521.000000	1.416505e+06	2024.000000	4.000000	20.000000	11.000000	6.000000	5.000000	7

Data Preprocessing

Deal with data anomilies

- Remove id and match_id columns it didn't help in information
- Change date column type into date format

In [211…

```
df.drop(columns=['id'], axis=1, inplace=True)
```

In [212…

```
df['date']= pd.to_datetime(df['date'])
```

In [213…

```
df['venue'].value_counts()
```

Out[213…

```
venue
Dubai International Cricket Stadium    14111
Gaddafi Stadium, Lahore                 9008
Sharjah Cricket Stadium                 8772
National Stadium, Karachi               8686
National Stadium                        8093
Rawalpindi Cricket Stadium              5739
Sheikh Zayed Stadium, Abu Dhabi         4716
Multan Cricket Stadium                  3129
Gaddafi Stadium                         2888
Sheikh Zayed Stadium                     970
Name: count, dtype: int64
```

In [214…

```
df['venue'] = df['venue'].replace({'National Stadium' : 'National Stadium, Karachi',
                                   'Gaddafi Stadium' : 'Gaddafi Stadium, Lahore',
                                   'Sheikh Zayed Stadium' : 'Sheikh Zayed Stadium, Abu Dhabi'})
```

Deal with Missing values

In [215…

```
(df.isnull().sum() / len(df) * 100).sort_values(ascending=False).reset_index()
```

Out[215…

	index	0
0	fielder	96.519543
1	dismissal_kind	94.699903
2	player_dismissed	94.699903
3	extras_type	94.613686
4	player_of_match	1.004356
5	match_id	0.000000
6	date	0.000000
7	umpire_1	0.000000
8	match_type	0.000000
9	win_by	0.000000
10	winner	0.000000
11	is_wicket	0.000000
12	total_runs	0.000000
13	extra_runs	0.000000
14	batsman_runs	0.000000
15	non_striker	0.000000
16	bowler	0.000000
17	batter	0.000000
18	ball	0.000000
19	over	0.000000
20	bowling_team	0.000000
21	batting_team	0.000000

	index	0
22	inning	0.000000
23	venue	0.000000
24	season	0.000000
25	umpire_2	0.000000

Remove those columns which has missing values > 40%:

In [216…
```
df.drop(columns=['fielder', 'dismissal_kind', 'player_dismissed', 'extras_type'], axis=1, inplace=True)
```

The player_of_match column contains missing values in approximately 1% of the records. Since this feature represents a match outcome that cannot be accurately imputed or predicted beforehand, and given its minimal impact on the dataset, we chose to remove rows with missing values in this column

In [217…
```
df.dropna(inplace=True)
```

Now we remain with 21 column and drop 1% of data out of 100%.

In [218…
```
df.shape
```

Out[218…
```
(65448, 22)
```

Deal with Duplicates

In [219…
```
df.duplicated().sum()
```

Out[219…
```
0
```

No duplicates in the dataset

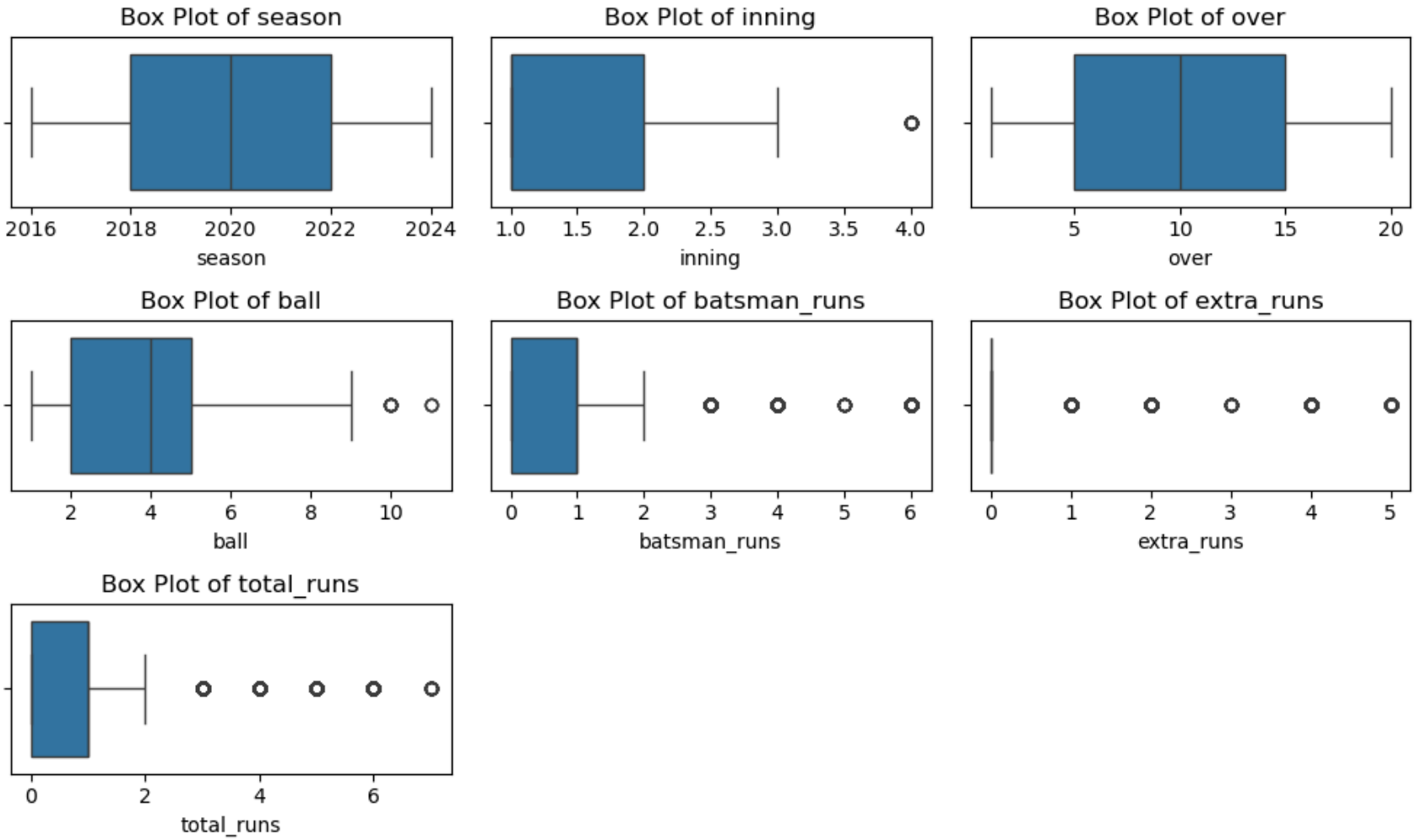
Deal with Outliers

In [220…

```
num = ['season', 'inning', 'over', 'ball', 'batsman_runs', 'extra_runs','total_runs']
```

In [221…

```
plt.figure(figsize=(10, 6))

for i, col in enumerate(num):
    plt.subplot(3, 3, i+1)
    sns.boxplot(data=df, x= df[col])
    plt.title(f'Box Plot of {col}')

plt.tight_layout()
plt.show()
```



Their are no outliers

Exploratory Data Analysis

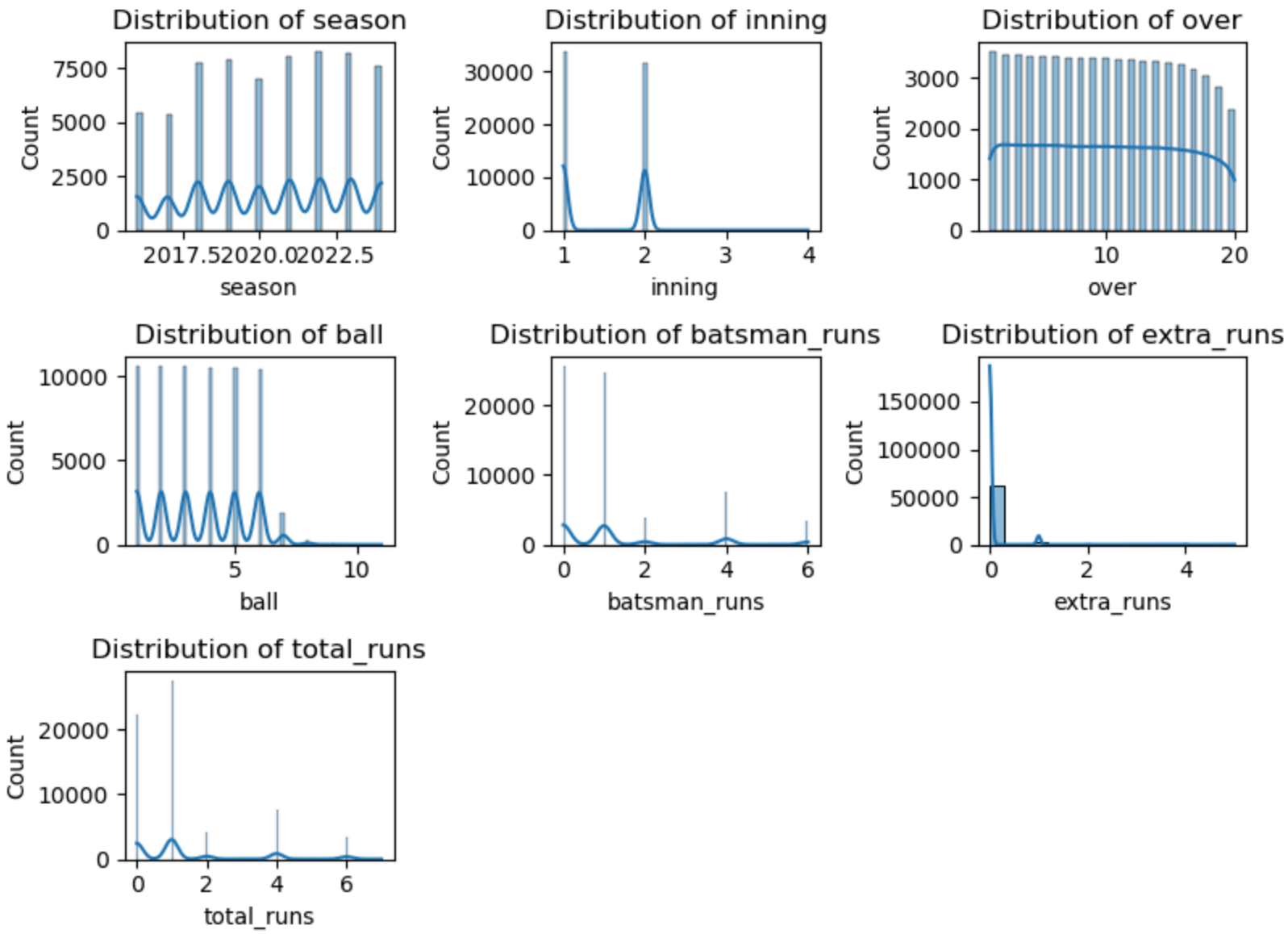
Univariate Analysis

In [222…

```
cat = ['venue', 'batting_team', 'bowling_team', 'batter', 'bowler',
       'non_striker', 'winner', 'win_by', 'match_type', 'player_of_match',
       'umpire_1', 'umpire_2']
```

In [223…

```
plt.figure(figsize=(8, 6))
for i, col in enumerate(num):
    plt.subplot(3, 3, i + 1)
    sns.histplot(data=df, x=df[col], kde=True)
    plt.title(f'Distribution of {col}')

plt.tight_layout()
plt.show()
```



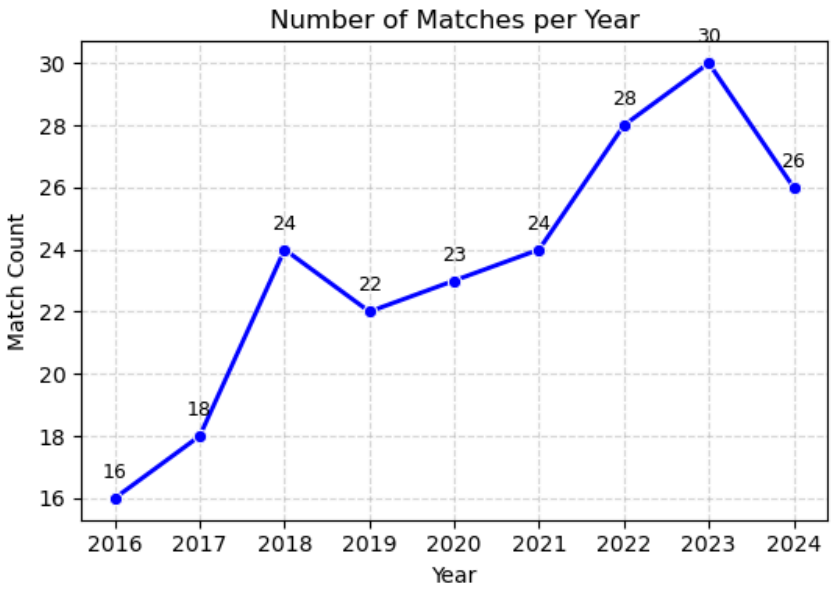
In [224…

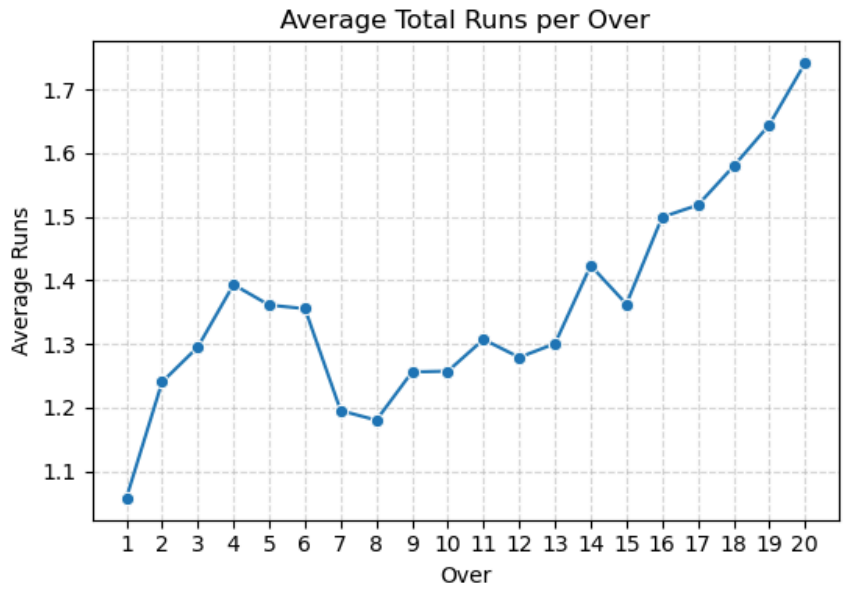
```
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.strftime('%b')
```

Matches per year & Avg Runs per Over

In [225…

```
matches_per_year = df.groupby('year')['date'].nunique().reset_index(name='matches')
avg_runs_per_over = df.groupby('over')['total_runs'].mean().reset_index()

fig, axes = plt.subplots(1, 2, figsize=(11, 4))

sns.lineplot(x='year', y='matches', data=matches_per_year, marker='o', linewidth=2, color='blue', ax=axes[0])
axes[0].set_title('Number of Matches per Year')
axes[0].set_xlabel('Year')
axes[0].set_ylabel('Match Count')
axes[0].grid(True, linestyle='--', alpha=0.5)

for i in range(len(matches_per_year)):
    year = matches_per_year.loc[i, 'year']
    count = matches_per_year.loc[i, 'matches']
    axes[0].text(year, count + 0.5, str(count), ha='center', va='bottom', fontsize=9)

sns.lineplot(data=avg_runs_per_over, x='over', y='total_runs', marker='o', ax=axes[1])
axes[1].set_title('Average Total Runs per Over')
axes[1].set_xlabel('Over')
axes[1].set_ylabel('Average Runs')
axes[1].set_xticks(range(1, 21))
axes[1].grid(True, linestyle='--', alpha=0.5)

plt.tight_layout()
plt.show()
```



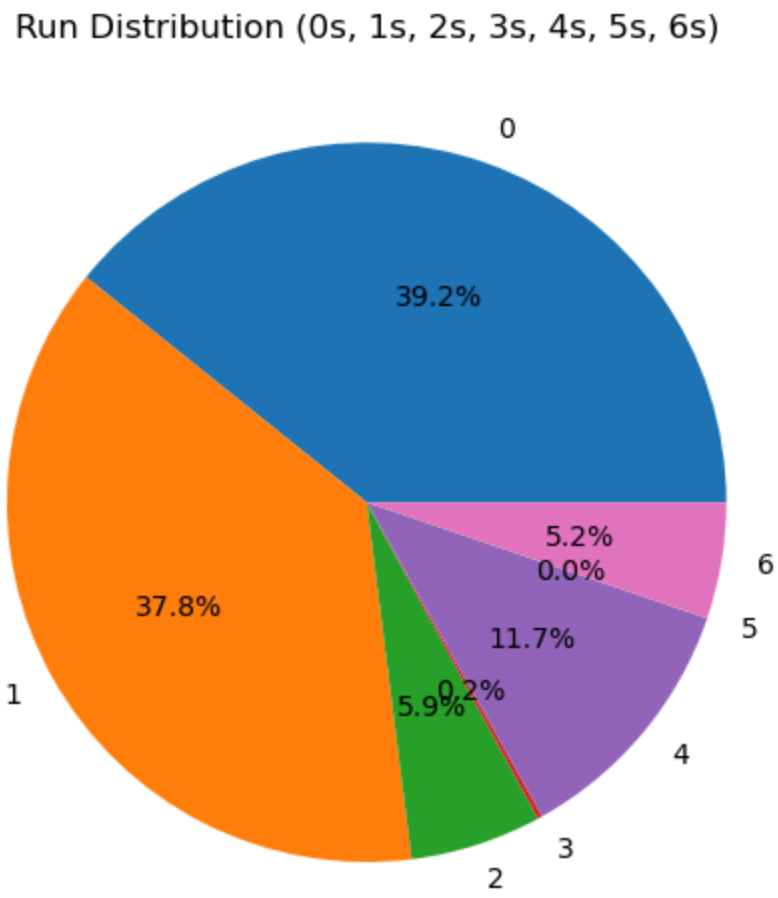


- The number of matches has shown a consistent increase each year, indicating the growing scale and popularity of the PSL tournament over time.
- Runs are scored more rapidly during the Powerplay (overs 1–6) and the death overs (16–20)

Runs Scored on Each Ball

In [226…

```
run_distribution = df['batsman_runs'].value_counts().loc[[0, 1, 2, 3, 4, 5, 6]].sort_index()

plt.figure(figsize=(5, 5))
plt.pie(run_distribution, labels=run_distribution.index, autopct='%1.1f%%')
plt.title('Run Distribution (0s, 1s, 2s, 3s, 4s, 5s, 6s)')
plt.tight_layout()
plt.show()
```

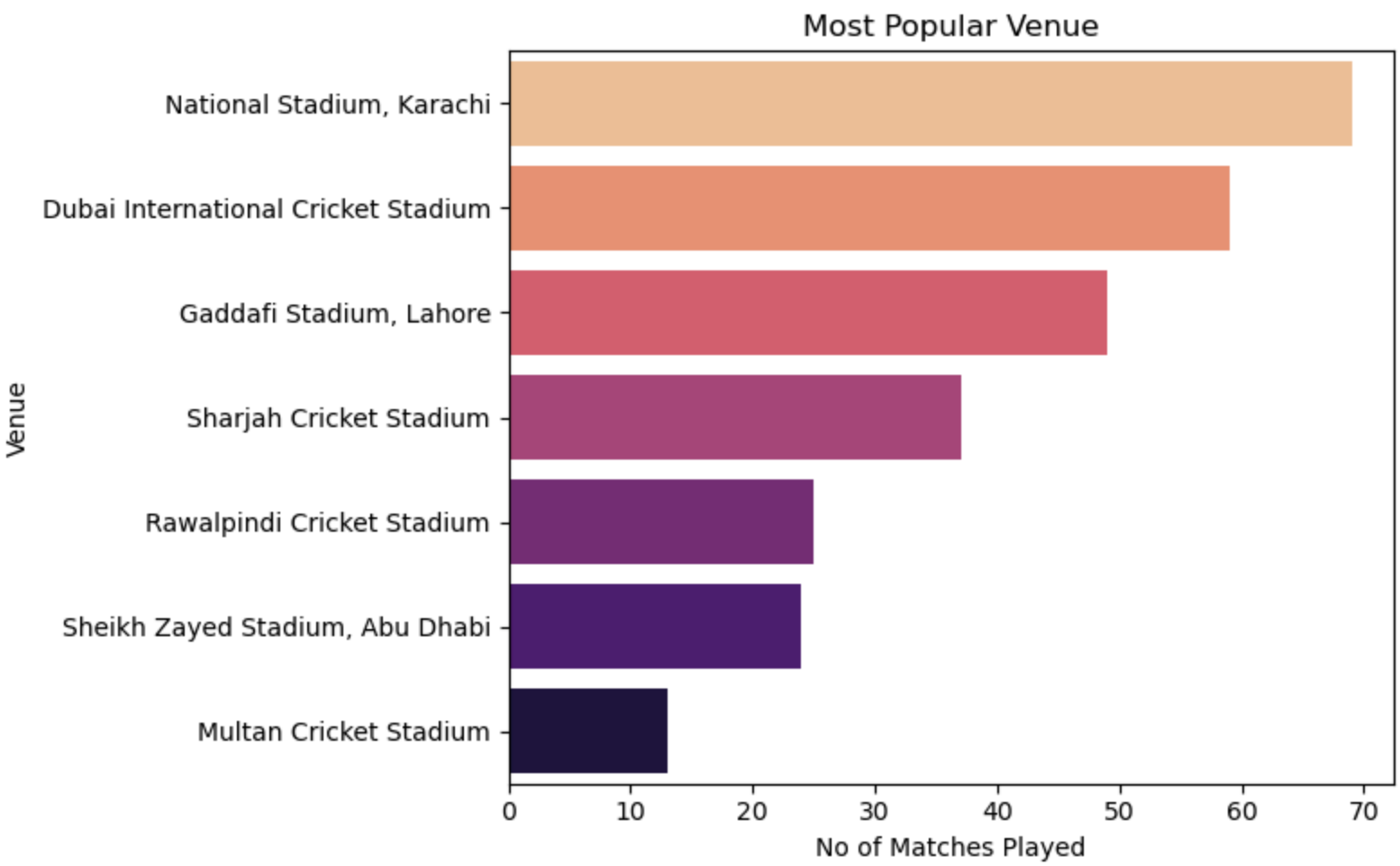


Most freq Venue

In [227…

```
most_freq_venue = df.groupby('venue')['match_id'].nunique().sort_values(ascending=False).reset_index(name='count')

# Plotting
plt.figure(figsize=(8, 5))
sns.barplot(y='venue', x='count', data=most_freq_venue, palette='magma_r')
plt.title('Most Popular Venue')
plt.ylabel('Venue')
plt.xlabel('No of Matches Played')
```

```
plt.tight_layout()
plt.show()
```



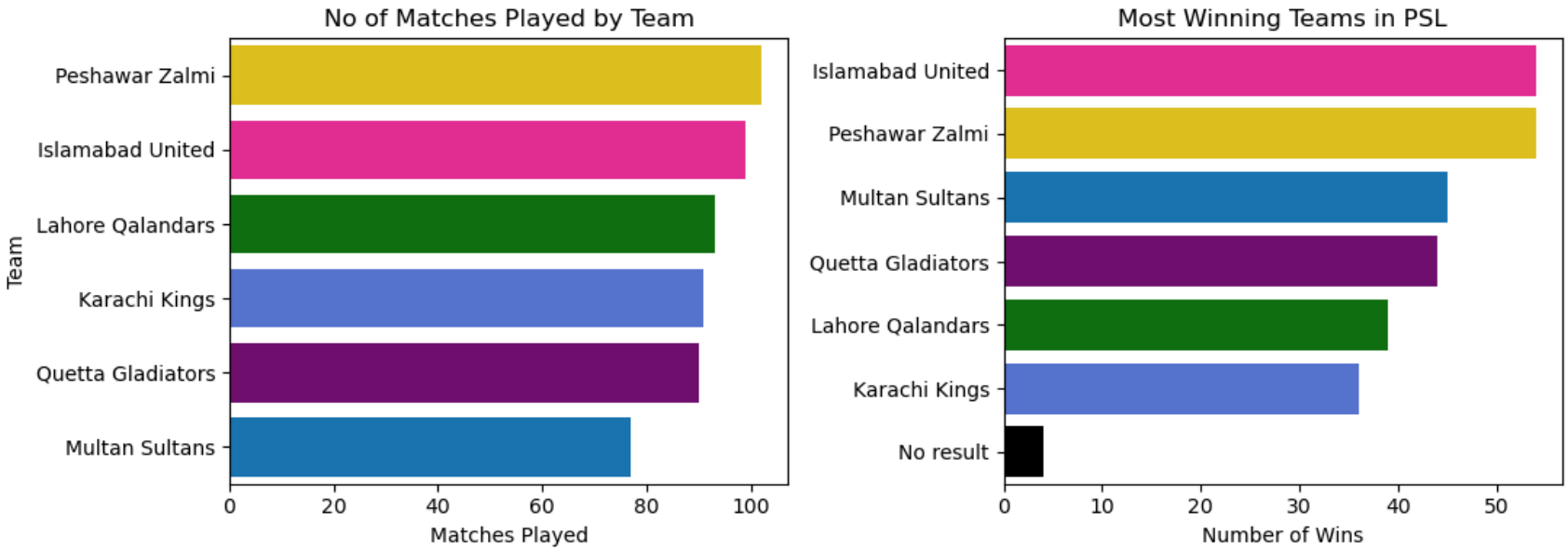
National Stadium Karachi leading with the most matches played venue over the last 10 years.

Matches played by each team

In [228…

```
matches_played_by_team = df.groupby('batting_team')['match_id'].nunique().sort_values(ascending=False).reset_index(na

unique_winners = df[['match_id', 'winner']].drop_duplicates()
winning_teams = unique_winners['winner'].value_counts().reset_index()
winning_teams.columns = ['Team', 'Wins']
```

```
team_colors = {'Peshawar Zalmi': 'gold',
               'Quetta Gladiators': 'purple',
               'Karachi Kings': 'royalblue',
               'Islamabad United': 'deeppink',
               'Multan Sultans': '#007acc',
               'Lahore Qalandars': 'green',
               'No result': 'black'}

fig, axes = plt.subplots(1, 2, figsize=(11, 4))

sns.barplot(data=matches_played_by_team, y='batting_team', x='matches_played',
            palette=team_colors, ax=axes[0])
axes[0].set_title('No of Matches Played by Team')
axes[0].set_xlabel('Matches Played')
axes[0].set_ylabel('Team')

sns.barplot(data=winning_teams, y='Team', x='Wins',
            palette=team_colors, ax=axes[1])
axes[1].set_title('Most Winning Teams in PSL')
axes[1].set_xlabel('Number of Wins')
axes[1].set_ylabel('')

plt.tight_layout()
plt.show()
```



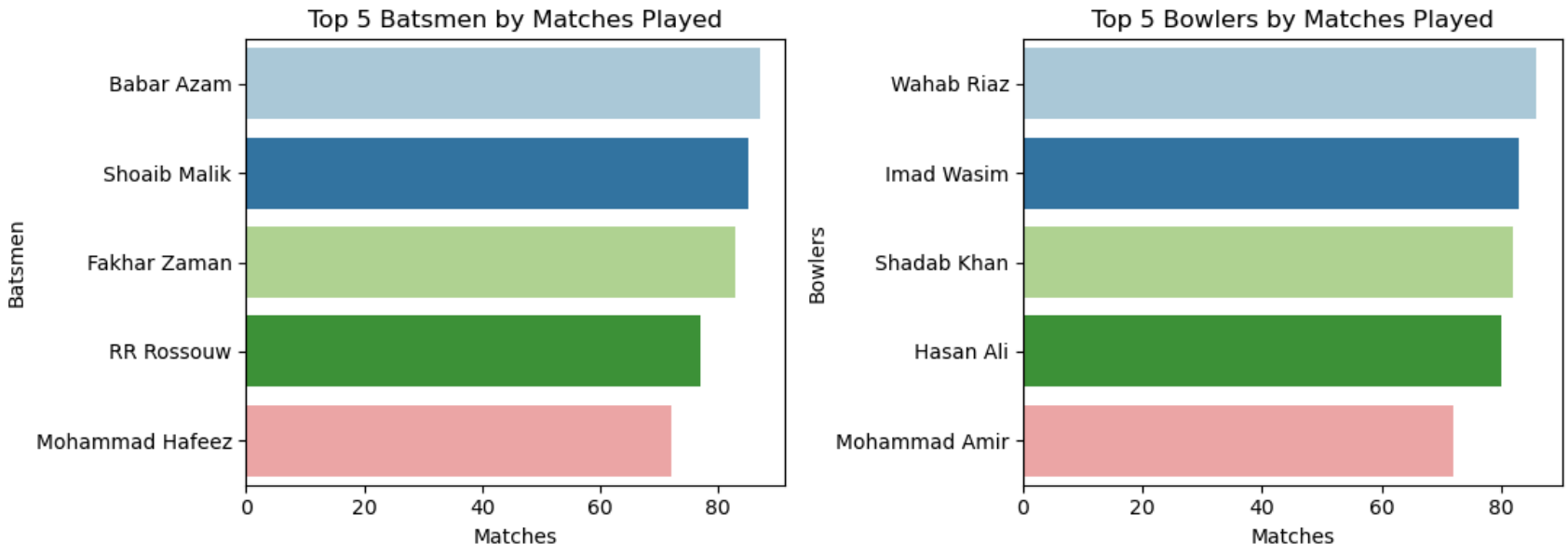
- Peshawar Zalmi had played the most matches among all teams, while Multan Sultans has played the fewest matches, as they joined the PSL in 2018.
- Islamabad United & Peshawar Zalmi have the most wins in the PSL, Karachi Kings have the fewest wins.

No of Matches played by top 5 Batsmen and Bowler

In [229…

```
batsmen_matches = df.groupby('batter')['match_id'].nunique().sort_values(ascending=False).head(5)
bowler_matches = df.groupby('bowler')['match_id'].nunique().sort_values(ascending=False).head(5)

fig, axes = plt.subplots(1, 2, figsize=(11, 4))

sns.barplot(y=batsmen_matches.index, x=batsmen_matches.values, palette='Paired', ax=axes[0])
axes[0].set_title('Top 5 Batsmen by Matches Played')
axes[0].set_xlabel('Matches')
axes[0].set_ylabel('Batsmen')

sns.barplot(y=bowler_matches.index, x=bowler_matches.values, palette='Paired', ax=axes[1])
axes[1].set_title('Top 5 Bowlers by Matches Played')
axes[1].set_xlabel('Matches')
axes[1].set_ylabel('Bowlers')
```

```
plt.tight_layout()
plt.show()
```



- Among all batsmen, Babar Azam has played the highest number of matches.
- Among bowlers, Wahab Riaz holds the record for most matches played.

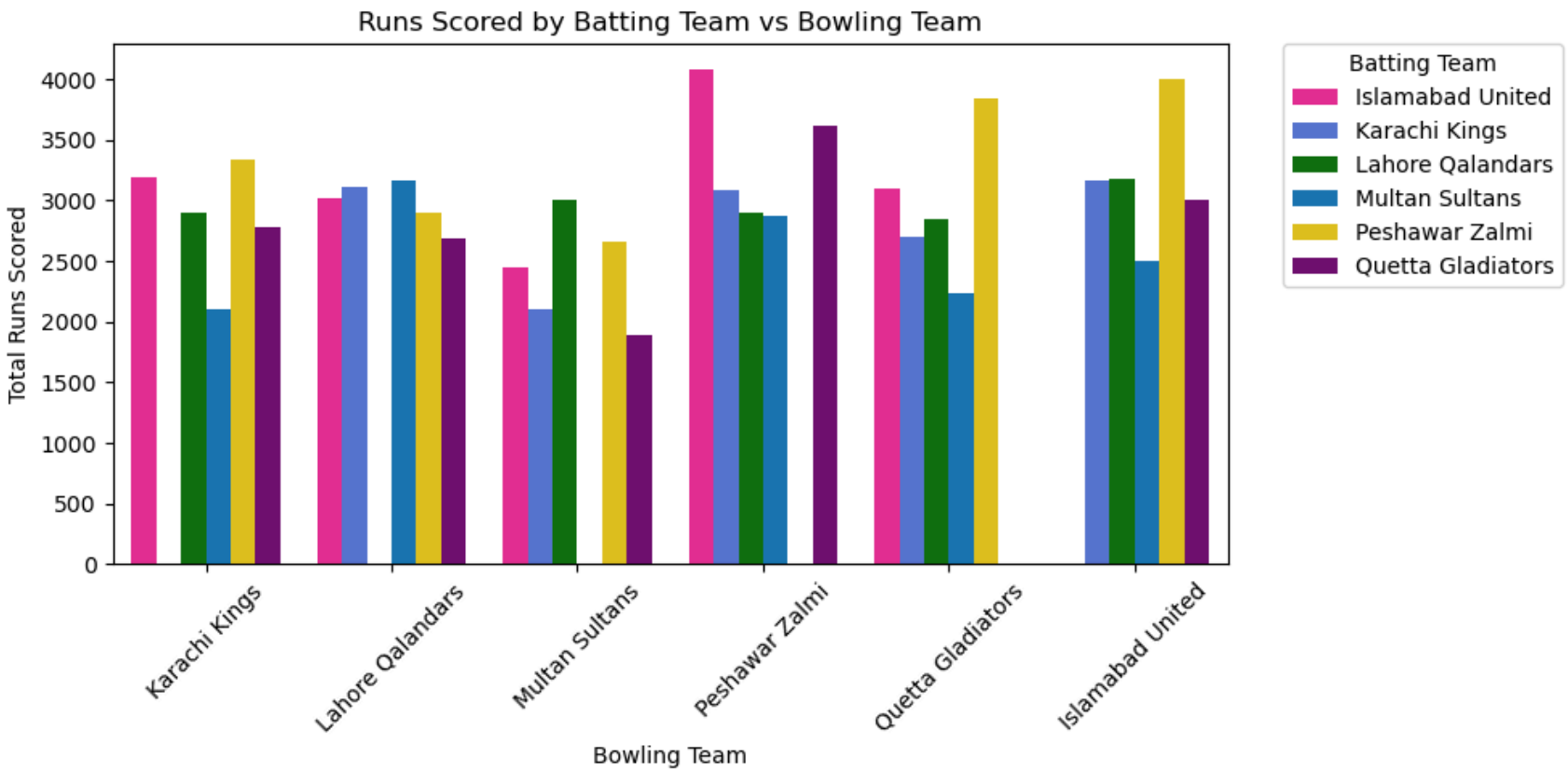
Bivariate Analysis

Which batting team scores the most against which bowling team

In [230…

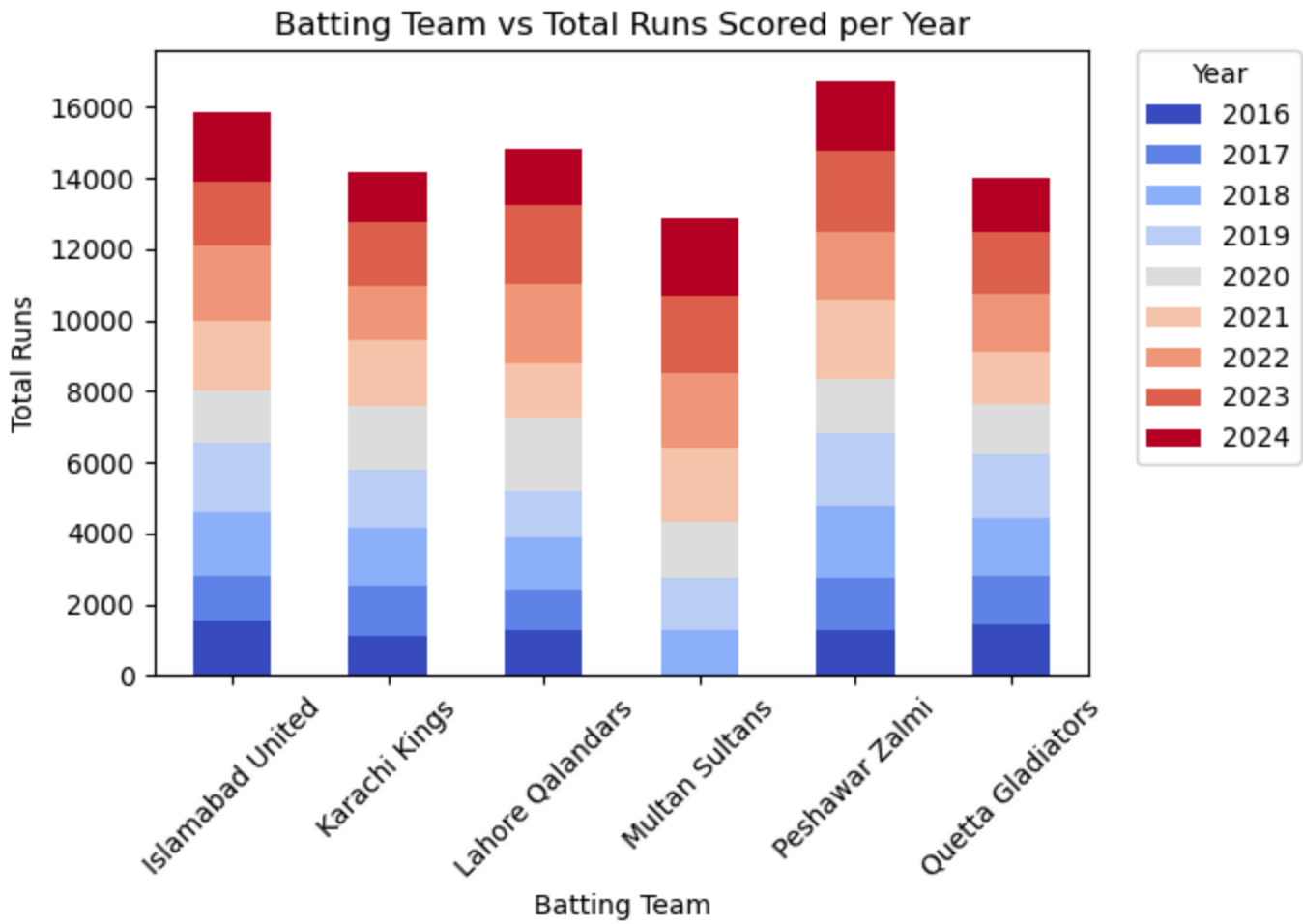
```
runs_by_teams = df.groupby(['batting_team', 'bowling_team'])['total_runs'].sum().reset_index()

plt.figure(figsize=(10, 5))
sns.barplot(data=runs_by_teams, x='bowling_team', y='total_runs', hue='batting_team', palette=team_colors)
plt.title('Runs Scored by Batting Team vs Bowling Team')
plt.xlabel('Bowling Team')
plt.ylabel('Total Runs Scored')
plt.legend(title='Batting Team', bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [231…

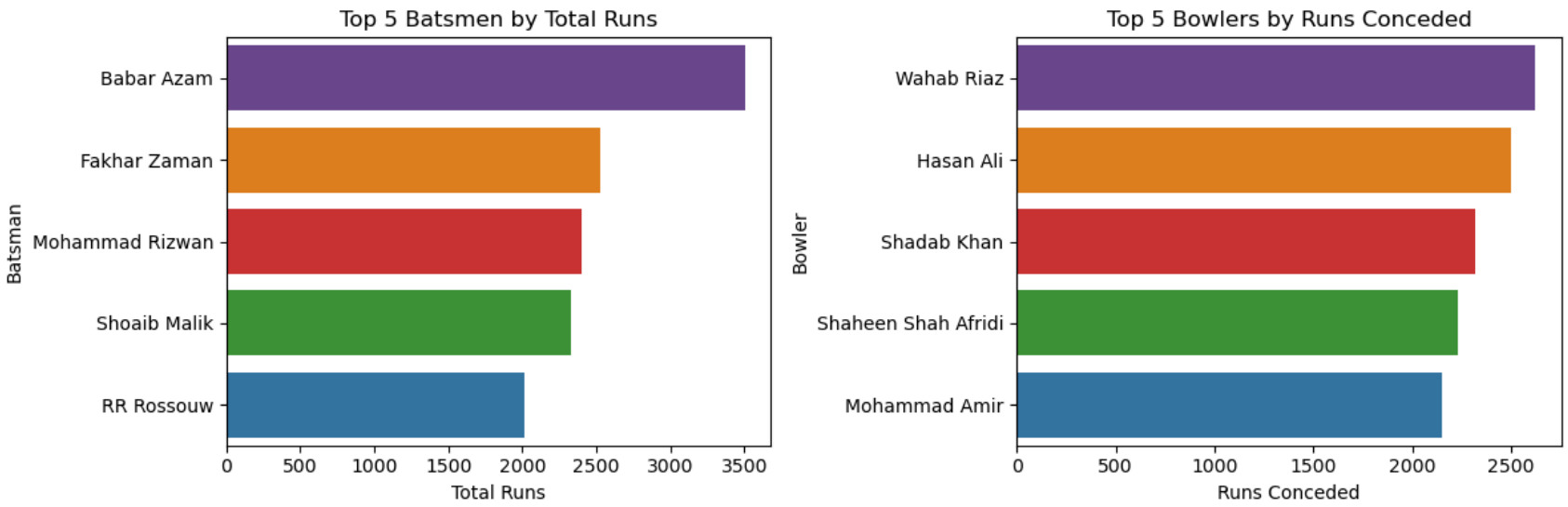
```
team_runs = df.groupby(['batting_team', 'year'])['total_runs'].sum().unstack().fillna(0)

team_runs.plot(kind='bar', stacked=True, figsize=(7, 5), colormap='coolwarm')
plt.title('Batting Team vs Total Runs Scored per Year')
plt.xlabel('Batting Team')
plt.ylabel('Total Runs')
plt.legend(title='Year', bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [232…

```
top_batsmen = df.groupby('batter')['batsman_runs'].sum().sort_values(ascending=False).head(5).reset_index()
top_batsmen.columns = ['Batsman', 'Total Runs']

top_bowlers_conceded = df.groupby('bowler')['total_runs'].sum().sort_values(ascending=False).head(5).reset_index()
top_bowlers_conceded.columns = ['Bowler', 'Runs Conceded']

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

sns.barplot(data=top_batsmen, x='Total Runs', y='Batsman', ax=axes[0], palette='Paired_r')
axes[0].set_title('Top 5 Batsmen by Total Runs')
axes[0].set_xlabel('Total Runs')
axes[0].set_ylabel('Batsman')
```

```
sns.barplot(data=top_bowlers_conceded, x='Runs Conceded', y='Bowler', ax=axes[1], palette='Paired_r')
axes[1].set_title('Top 5 Bowlers by Runs Conceded')
axes[1].set_xlabel('Runs Conceded')
axes[1].set_ylabel('Bowler')

plt.tight_layout()
plt.show()
```

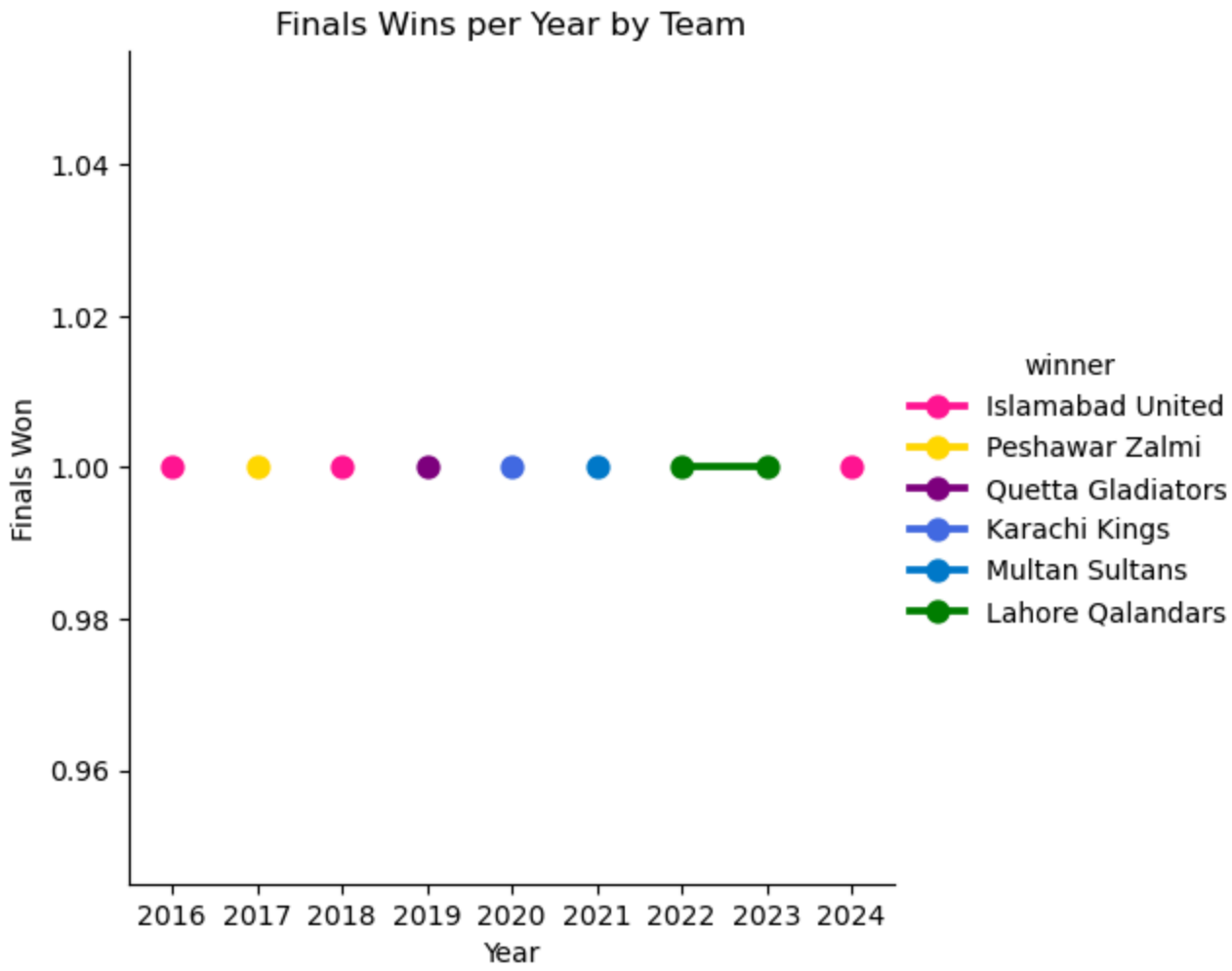


- Babar Azam leads the charts with the most runs scored in PSL history
- Wahab Riaz has conceded the most runs throughout all PSL seasons

In [233…

```
finals_df = df[df['match_type'] == 'final']
unique_finals = finals_df.drop_duplicates(subset=['year', 'date'])
final_wins_per_year = unique_finals.groupby(['year', 'winner']).size().reset_index(name='Finals_Won')

plt.figure(figsize=(8, 5))
sns.catplot(data=final_wins_per_year, x='year', y='Finals_Won', hue='winner', kind='point', palette=team_colors)

plt.title('Finals Wins per Year by Team')
plt.xlabel('Year')
plt.ylabel('Finals Won')
plt.show()
```

```
<Figure size 800x500 with 0 Axes>
```



- Islamabad Wins 3 time in 2016, 2018 and 2024
- Lahore Qalandars Wins 2 times in 2022 and 2023
- Remian teams win one one time

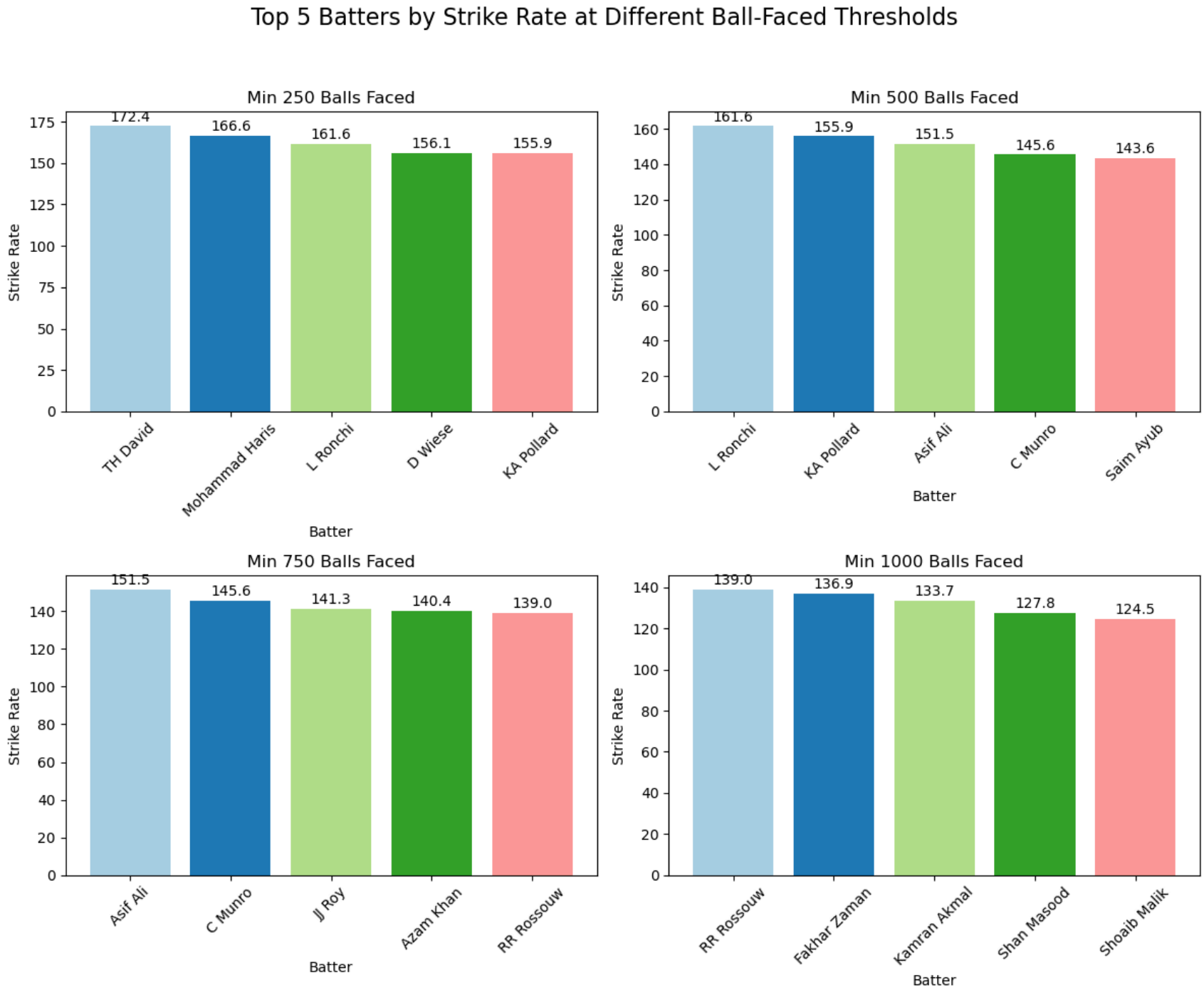
Multivariate Analysis

In [234…

```
from matplotlib import cm
```

In [235…

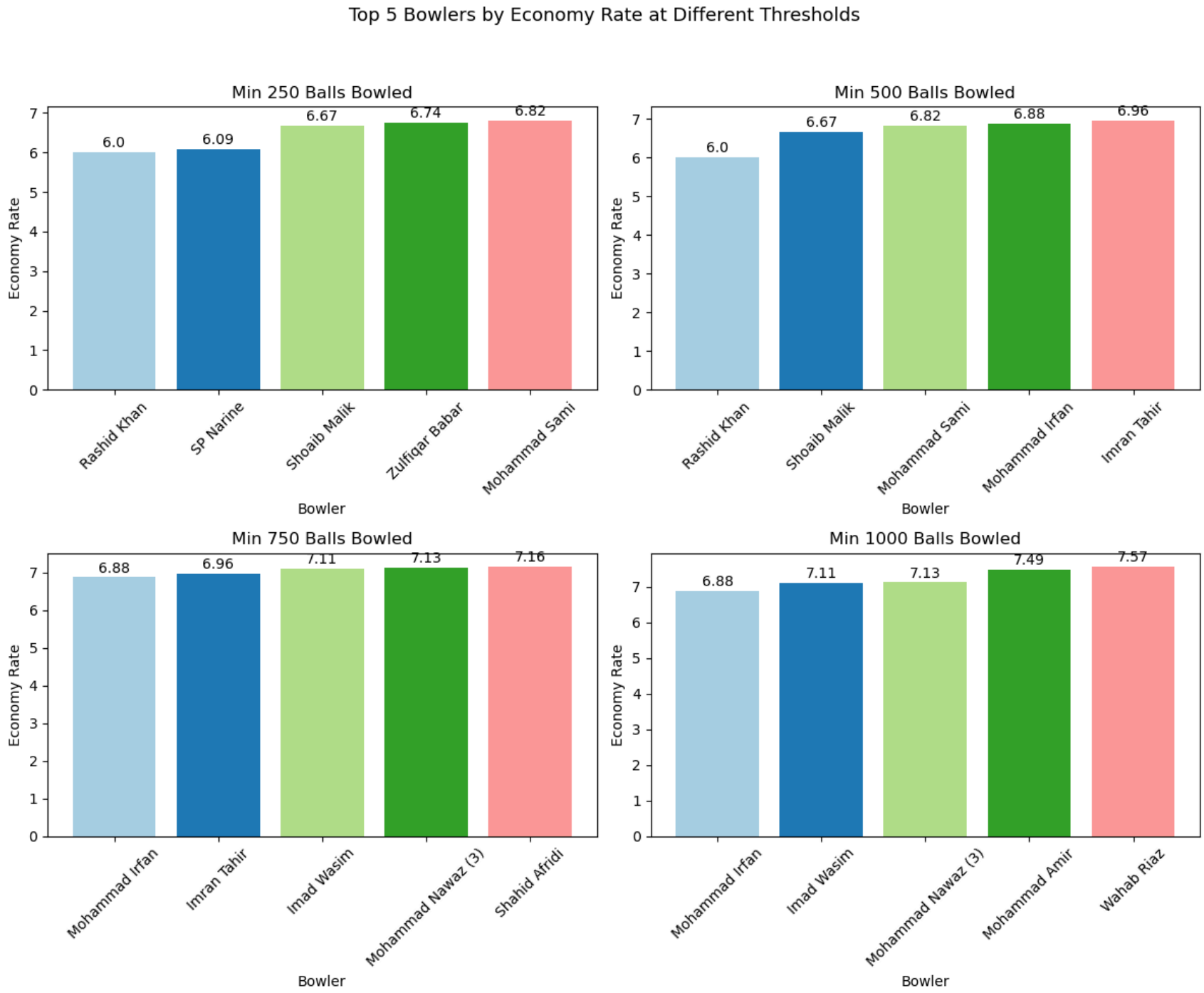
```
batting_stats = df.groupby('batter').agg({'batsman_runs': 'sum','ball': 'count'}).reset_index()
batting_stats['strike_rate'] = (batting_stats['batsman_runs'] / batting_stats['ball']) * 100

thresholds = [250, 500, 750, 1000]

fig, axes = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle("Top 5 Batters by Strike Rate at Different Ball-Faced Thresholds", fontsize=16)

for ax, threshold in zip(axes.flat, thresholds):
    filtered = batting_stats[batting_stats['ball'] >= threshold]
    top_sr = filtered.sort_values(by='strike_rate', ascending=False).head(5)
    colors = cm.Paired.colors[:len(top_sr)]
    bars = ax.bar(top_sr['batter'], top_sr['strike_rate'], color=colors)
    ax.set_title(f"Min {threshold} Balls Faced")
    ax.set_xlabel("Batter")
    ax.set_ylabel("Strike Rate")
    ax.set_xticklabels(top_sr['batter'], rotation=45)

    for bar in bars:
        ax.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 1,
                round(bar.get_height(), 1), ha='center', va='bottom')

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```


Top 5 Batters by Strike Rate at Different Ball-Faced Thresholds
Min 250 Balls Faced
Strike Rate
Batter
TH David
Mohammad Haris
L Ronchi
D Wiese
KA Pollard
172.4
166.6
161.6
156.1
155.9
Min 500 Balls Faced
Strike Rate
Batter
L Ronchi
KA Pollard
Asif Ali
C Munro
Saim Ayub
161.6
155.9
151.5
145.6
143.6
Min 750 Balls Faced
Strike Rate
Batter
Asif Ali
C Munro
JJ Roy
Azam Khan
RR Rossouw
151.5
145.6
141.3
140.4
139.0
Min 1000 Balls Faced
Strike Rate
Batter
RR Rossouw
Fakhar Zaman
Kamran Akmal
Shan Masood
Shoaib Malik
139.0
136.9
133.7
127.8
124.5

- Tim David showcased an exceptional strike rate despite facing less than 250 balls, highlighting his explosive impact in limited opportunities.
- Luke Ronchi, with less than 500 balls faced, maintained an outstanding strike rate, making him one of the most efficient hitters in that range.
- Asif Ali, within the 500–750 ball range, stood out with a high strike rate, reinforcing his role as a powerful finisher.
- Rilee Rossouw, with under 1000 balls faced, maintained a consistently aggressive approach, reflected in his top-tier strike rate.

In [236…

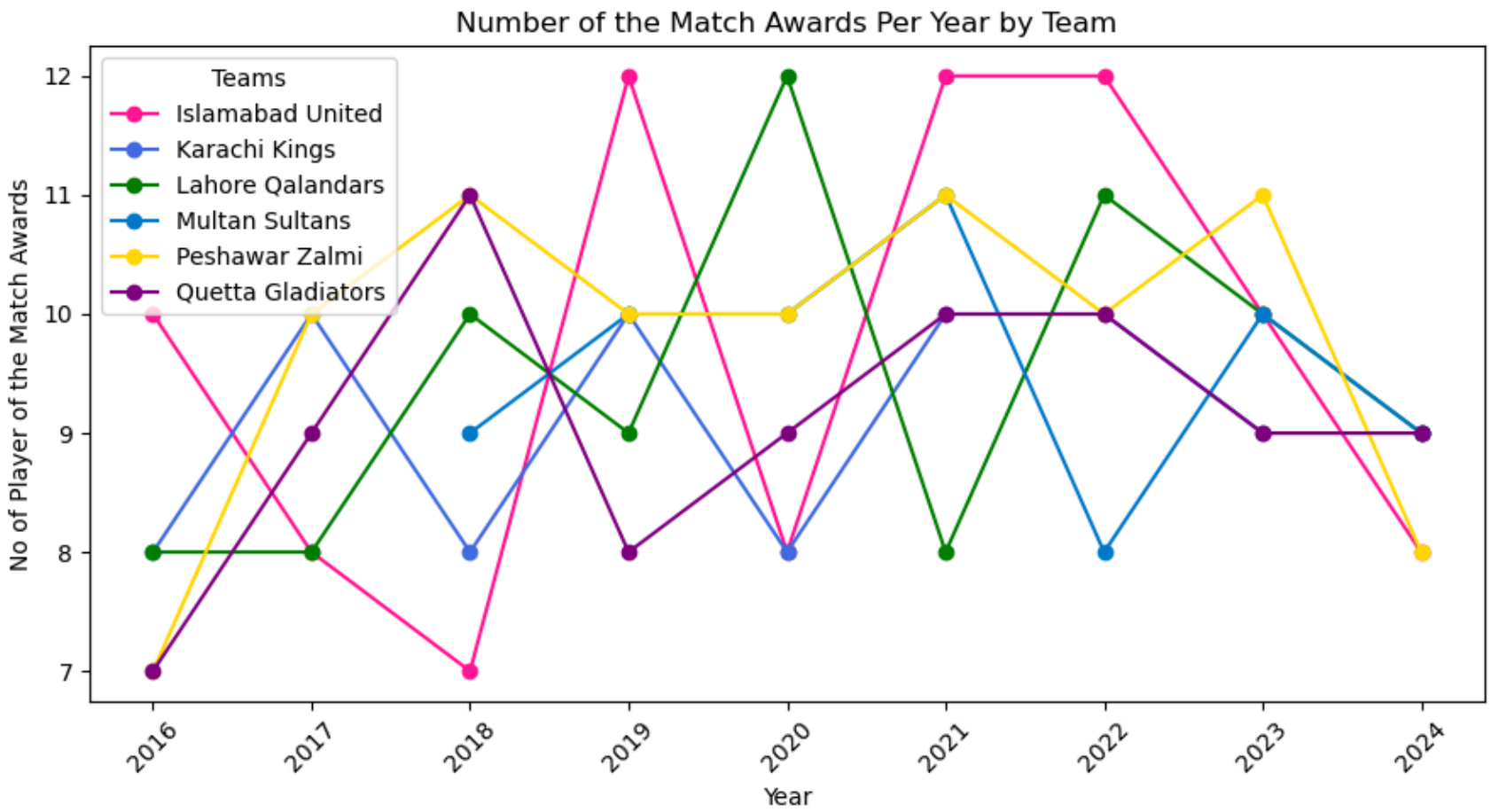
```
valid_deliveries = df[(df['extra_runs'] == 0)]

bowling_stats = valid_deliveries.groupby('bowler').agg({'ball': 'count','total_runs': 'sum','extra_runs': 'sum'}).so
bowling_stats['runs_conceded'] = bowling_stats['total_runs'] - bowling_stats['extra_runs']
bowling_stats['economy_rate'] = (bowling_stats['runs_conceded'] / (bowling_stats['ball'] / 6))

thresholds = [250, 500, 750, 1000]

fig, axes = plt.subplots(2, 2, figsize=(12, 10))
fig.suptitle("Top 5 Bowlers by Economy Rate at Different Thresholds", fontsize=13)

for ax, threshold in zip(axes.flat, thresholds):
    filtered = bowling_stats[bowling_stats['ball'] >= threshold]
    top_economy = filtered.sort_values(by='economy_rate', ascending=True).head(5)
    bars = ax.bar(top_economy['bowler'], top_economy['economy_rate'], color=colors)
    ax.set_title(f"Min {threshold} Balls Bowled")
    ax.set_xlabel("Bowler")
    ax.set_ylabel("Economy Rate")
    ax.set_xticklabels(top_economy['bowler'], rotation=45)

    for bar in bars:
        ax.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.05,
                round(bar.get_height(), 2), ha='center', va='bottom')

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```


Top 5 Bowlers by Economy Rate at Different Thresholds
Min 250 Balls Bowled
Economy Rate
Bowler
Rashid Khan
SP Narine
Shoaib Malik
Zulfiqar Babar
Mohammad Sami
6.0
6.09
6.67
6.74
6.82
Min 500 Balls Bowled
Economy Rate
Bowler
Rashid Khan
Shoaib Malik
Mohammad Sami
Mohammad Irfan
Imran Tahir
6.0
6.67
6.82
6.88
6.96
Min 750 Balls Bowled
Economy Rate
Bowler
Mohammad Irfan
Imran Tahir
Imad Wasim
Mohammad Nawaz (3)
Shahid Afridi
6.88
6.96
7.11
7.13
7.16
Min 1000 Balls Bowled
Economy Rate
Bowler
Mohammad Irfan
Imad Wasim
Mohammad Nawaz (3)
Mohammad Amir
Wahab Riaz
6.88
7.11
7.13
7.49
7.57

- Rashid Khan stands out with the best economy rate when bowling at least 250 balls, showcasing his exceptional ability to control the game over multiple overs.
- Rashid Khan continues to dominate with the best economy rate for bowlers who have bowled at least 500 balls, cementing his reputation as one of the most economical bowlers.
- Mohammad Irfan, with 750 balls bowled or more, holds the best economy rate, demonstrating his consistency and skill in restricting runs across extended spells.
- Mohammad Irfan maintains his dominance in economy rate, having bowled 1000 balls or more, proving his efficiency and effectiveness as a bowler in long spells.

In [237…

```
player_of_match_stats = df.groupby(['batting_team', 'year'])['player_of_match'].nunique().reset_index()
player_of_match_stats.rename(columns={'player_of_match': 'unique_pom_awards'}, inplace=True)

plt.figure(figsize=(9, 5))

for team in player_of_match_stats['batting_team'].unique():
    team_data = player_of_match_stats[player_of_match_stats['batting_team'] == team]
    team_color = team_colors.get(team, 'gray')
    plt.plot(team_data['year'], team_data['unique_pom_awards'], marker='o', label=team, color=team_color)

plt.xlabel('Year')
plt.ylabel('No of Player of the Match Awards')
plt.title('Number of the Match Awards Per Year by Team')
plt.xticks(rotation=45)
plt.legend(title='Teams')
plt.tight_layout()
plt.show()
```

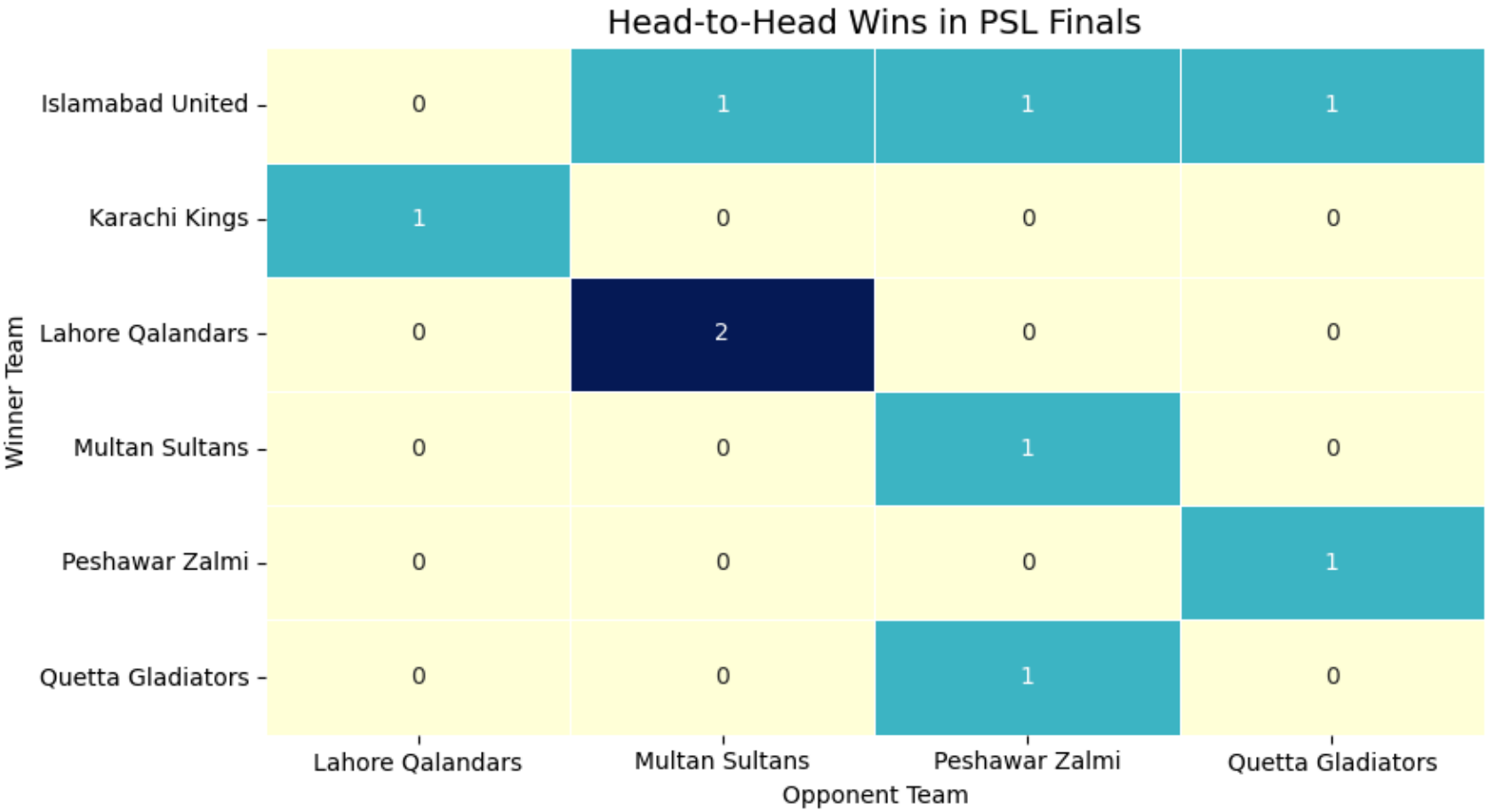


Islamabad United has consistently outperformed other teams in terms of the number of Player of the Match (POM) awards in the following years: 2016, 2019, 2021, and 2022. In these seasons, Islamabad United had a higher number of POM awards compared to other teams, highlighting their dominant performances in crucial matches.

In [238…

```
finals_df = df[df['match_type'].str.lower() == 'final'].copy()
unique_finals = finals_df.drop_duplicates(subset=['season', 'venue'])

unique_finals['opponent'] = unique_finals.apply(lambda row: row['batting_team'] if row['batting_team'] != row['winner
win_loss_matrix = unique_finals.groupby(['winner', 'opponent']).size().unstack(fill_value=0)

plt.figure(figsize=(9, 5))
sns.heatmap(win_loss_matrix, annot=True, fmt='d', cmap='YlGnBu', linewidths=0.5, cbar=False)
```

```
plt.title("Head-to-Head Wins in PSL Finals", fontsize=14)
plt.xlabel("Opponent Team")
plt.ylabel("Winner Team")
plt.tight_layout()
plt.show()
```



- Multan Sultans and Peshawar Zalmi have both reached the finals multiple times but faced tough luck each has lost 3 finals and managed to secure the title only once.
- Islamabad United, on the other hand, has a remarkable record in finals they've never lost a PSL final they played in.

Feature Engineering

First of all i create a copy of data, so every feature engineering and feature selection is done on copy of data.

In [239…

```
feature_df = df.copy()
```

Remove the No result from the data so that the model can predict accurately

In [240…

```
feature_df = feature_df[feature_df['winner'] != 'No result']
```

We correct inning values, where 3 = 1 and 4 = 2.

In [241…

```
feature_df['inning'] = feature_df['inning'].replace({3: 1, 4: 2})
```

Change venue as City, rename to it as the Cities name

In [242…

```
venue_to_city = {
    'Dubai International Cricket Stadium': 'Dubai',
    'Sharjah Cricket Stadium': 'Sharjah',
    'Sheikh Zayed Stadium, Abu Dhabi': 'Abu Dhabi',
    'Sheikh Zayed Stadium': 'Abu Dhabi',
    'Gaddafi Stadium, Lahore': 'Lahore',
    'Gaddafi Stadium': 'Lahore',
    'National Stadium, Karachi': 'Karachi',
    'National Stadium': 'Karachi',
    'Rawalpindi Cricket Stadium': 'Rawalpindi',
    'Multan Cricket Stadium': 'Multan'}

feature_df['city'] = feature_df['venue'].map(venue_to_city)
```

Change is_wicket values to True = 1 and False = 0

In [243…

```
feature_df['is_wicket'] = feature_df['is_wicket'].replace({True : 1 , False : 0})
```

Lets remove the irrelevent columns that didn't help us in prediction

In [244…

```
feature_df.drop(columns=['date', 'venue',  'year', 'win_by', 'player_of_match' , 'non_striker', 'umpire_1', 'umpire_2
```

Now i make of copy of that dataframe to new dataframe where i apply the feature engineering techniques like creating new features that helps in the prediction of the winner of the PSL 2025.

In [245…

```
new_df = feature_df.copy()
```

I created a new data frame overall_oerformance, where it contains

- matched_played by team in each season
- matched_won by team in each season
- win_percentage by team in each season

In [246…

```
overall_performance = new_df.groupby(['season', 'batting_team'])['match_id'].nunique().reset_index(name='matches_play

overall_performance['matches_won'] = new_df[new_df['winner'] == new_df['batting_team']].groupby(['season', 'batting_t

overall_performance['win_percentage'] = overall_performance['matches_won'] / overall_performance['matches_played']
```

Now i created a new dataframe called batting_strength

- total_runs_scored by team in each season
- avg_runs_per_match by team in each season

In [247…

```
batting_strength = new_df.groupby(['season', 'batting_team'])['total_runs'].sum().reset_index(name='total_runs_scored
```

In [248…

```
batting_strength = batting_strength.merge(overall_performance[['season', 'batting_team', 'matches_played']],
                                          on=['season', 'batting_team'],
                                          how='left')
batting_strength['avg_runs_per_match'] = batting_strength['total_runs_scored'] / batting_strength['matches_played']
```

Now i created a new dataframe called bowling_strength

- total_runs_conceded by the team in each season
- avg_runs_conceded by the team in each season
- wickets_taken by each team in each season

In [249…

```
bowling_strength = new_df[new_df['bowling_team'] == new_df['bowling_team']].groupby(['season', 'bowling_team'])['tota
```

In [250…

```
bowling_strength['avg_runs_conceded'] = bowling_strength['total_runs_conceded'] / overall_performance['matches_playe
```

In [251…

```
bowling_strength['wickets_taken'] = new_df[(new_df['is_wicket'] == 1) & (new_df['bowling_team'] == new_df['bowling_te
```

Now i created a new dataframe called city_win_rate

- city_win_count winning count of each team on each city
- city_total_matches total matches played by team on that city
- city_win_rate winning rate of each team on each city

In [252…

```
city_win_rate = new_df.groupby(['season', 'city', 'winner']).size().reset_index(name='city_win_count')
city_total_matches = new_df.groupby(['season', 'city']).size().reset_index(name='city_total_matches')

city_win_rate = city_win_rate.merge(city_total_matches, on=['season', 'city'], how='left')
city_win_rate['city_win_rate'] = city_win_rate['city_win_count'] / city_win_rate['city_total_matches']
```

Now i created a new dataframe called chasing_win_rate

- chasing_wins each season how many team chasing teams wins
- chasing_total how many times teams chasing in each season
- chasing_win_rate the chasing winning percentage

In [253…

```
chasing_wins = new_df[(new_df['inning'] == 2) & (new_df['batting_team'] == new_df['winner'])]
chasing_wins = chasing_wins.groupby('season')['winner'].nunique().reset_index(name='chasing_wins')
chasing_total = new_df[new_df['inning'] == 2].groupby('season')['batting_team'].nunique().reset_index(name='chasing_t

chasing_win_rate = chasing_wins.merge(chasing_total, on='season', how='left')
chasing_win_rate['chasing_win_rate'] = chasing_win_rate['chasing_wins'] / chasing_win_rate['chasing_total']
```

Now merge all dataframes with the new dataframe called features_df1

In [254…

```
overall_performance = overall_performance.rename(columns={'batting_team': 'team'})
bowling_strength = bowling_strength.rename(columns={'bowling_team': 'team'})
city_win_rate = city_win_rate.rename(columns={'winner': 'team'})
```

In [255…

```
features_df1 = pd.merge(overall_performance, bowling_strength, on=['season', 'team'], how='outer')

features_df1 = pd.merge(features_df1, city_win_rate, on=['season', 'team'], how='left')

features_df1 = pd.merge(features_df1, chasing_win_rate, on='season', how='left')
```

Correct data as every season every team record

In [256…

```
features_df1 = features_df1.groupby(['season', 'team']).agg({'matches_played': 'first',  'matches_won': 'first',
                                                              'win_percentage': 'first','total_runs_conceded': 'sum
                                                              'avg_runs_conceded': 'mean','wickets_taken': 'sum',
                                                              'city_win_rate': 'mean','chasing_win_rate': 'mean'}).r
```

Add is_winner feature in data, for those team who wins that particular season

In [257…

```
winners = {2016: 'Islamabad United',2017: 'Peshawar Zalmi',
           2018: 'Islamabad United',2019: 'Quetta Gladiators',
           2020: 'Karachi Kings',2021: 'Multan Sultans',
           2022: 'Lahore Qalandars',2023: 'Lahore Qalandars',2024: 'Islamabad United'}

features_df1['season_winner'] = features_df1['season'].map(winners)
features_df1['is_winner'] = (features_df1['team'] == features_df1['season_winner']).astype(int)
```

Model Training

Drop irrelevrnt features that didn't help for prediction

In [258…

```
X = features_df1.drop(columns=["season_winner", "is_winner"])
y = features_df1["is_winner"]
```

In [259…

```
X_train = X.copy()
y_train = y.copy()

X_predict = X.copy()
teams_2024 = X_predict['team'].values
```

Encode categorical feature team

In [260…

```
encoder = OneHotEncoder(handle_unknown="ignore", sparse_output=False)
encoded_teams_train = encoder.fit_transform(X_train[['team']])
encoded_teams_predict = encoder.transform(X_predict[['team']])

X_train = X_train.drop(columns=["team", "season"])
X_predict = X_predict.drop(columns=["team", "season"])
```

Combine encoded categorical features with numerical features

In [261…

```
X_train = np.hstack((encoded_teams_train, X_train.values))
X_predict = np.hstack((encoded_teams_predict, X_predict.values))
```

Train Logistic Regression

In [262…

```
lr = LogisticRegression(max_iter=70, penalty='l2', solver='liblinear')
lr.fit(X_train, y_train)
```

Out[262…

```
LogisticRegression
LogisticRegression(max_iter=70, solver='liblinear')
```

Model Evaluation

In [263…

```
y_pred = lr.predict(X_train)

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

```
Accuracy: 0.8846153846153846

Confusion Matrix:
 [[41  2]
 [ 4  5]]

Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.95      0.93        43
           1       0.71      0.56      0.62         9

    accuracy                           0.88        52
   macro avg       0.81      0.75      0.78        52
weighted avg       0.88      0.88      0.88        52
```

Predict the probability of a team winning the PSL 2025

In [264…

```
prob = lr.predict_proba(X_predict)[:, 1]
```

In [265…

```
pred_df = pd.DataFrame({'team': teams_2024,'win_probability_2025': prob })

team_win_probs = pred_df.groupby('team', as_index=False)['win_probability_2025'].mean()

team_win_probs = team_win_probs.sort_values(by='win_probability_2025', ascending=False)
team_win_probs
```

Out[265…

	team	win_probability_2025
0	Islamabad United	0.283922
3	Multan Sultans	0.228850
2	Lahore Qalandars	0.181031
5	Quetta Gladiators	0.142159
4	Peshawar Zalmi	0.136829
1	Karachi Kings	0.072377

In [266…

```
plt.figure(figsize=(7, 5))
sns.barplot(x='win_probability_2025', y='team', data=team_win_probs, palette=team_colors)
plt.title('Team Win Probabilities for PSL 2025', fontsize=16)
plt.xlabel('Winning Probability', fontsize=12)
plt.ylabel('Team', fontsize=12)
plt.show()
```