IPL EDA Project

March 22, 2025

#

IPL Data Analysis

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
```

[2]:
```python
matches=pd.read_csv("matches.csv")
```

[3]:
```python
matches.head()
```

[3]:
```
   id  season       city        date                        team1  \
0   1    2017  Hyderabad  2017-04-05          Sunrisers Hyderabad
1   2    2017       Pune  2017-04-06               Mumbai Indians
2   3    2017     Rajkot  2017-04-07                Gujarat Lions
3   4    2017     Indore  2017-04-08       Rising Pune Supergiant
4   5    2017  Bangalore  2017-04-08  Royal Challengers Bangalore

                         team2                  toss_winner toss_decision  \
0  Royal Challengers Bangalore  Royal Challengers Bangalore         field
1       Rising Pune Supergiant       Rising Pune Supergiant         field
2        Kolkata Knight Riders        Kolkata Knight Riders         field
3              Kings XI Punjab              Kings XI Punjab         field
4             Delhi Daredevils  Royal Challengers Bangalore           bat

   result  dl_applied                       winner  win_by_runs  \
0  normal           0          Sunrisers Hyderabad           35
1  normal           0       Rising Pune Supergiant            0
2  normal           0        Kolkata Knight Riders            0
3  normal           0              Kings XI Punjab            0
4  normal           0  Royal Challengers Bangalore           15

   win_by_wickets player_of_match                                      venue  \
0               0    Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal
1               7       SPD Smith    Maharashtra Cricket Association Stadium
2              10         CA Lynn     Saurashtra Cricket Association Stadium
```

```
3              6      GJ Maxwell                     Holkar Cricket Stadium
4              0       KM Jadhav                      M Chinnaswamy Stadium

         umpire1        umpire2  umpire3
0     AY Dandekar       NJ Llong      NaN
1  A Nand Kishore         S Ravi      NaN
2     Nitin Menon      CK Nandan      NaN
3    AK Chaudhary  C Shamshuddin      NaN
4             NaN            NaN      NaN
```

[4]:
```
matches.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 636 entries, 0 to 635
Data columns (total 18 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   id               636 non-null    int64
 1   season           636 non-null    int64
 2   city             629 non-null    object
 3   date             636 non-null    object
 4   team1            636 non-null    object
 5   team2            636 non-null    object
 6   toss_winner      636 non-null    object
 7   toss_decision    636 non-null    object
 8   result           636 non-null    object
 9   dl_applied       636 non-null    int64
 10  winner           633 non-null    object
 11  win_by_runs      636 non-null    int64
 12  win_by_wickets   636 non-null    int64
 13  player_of_match  633 non-null    object
 14  venue            636 non-null    object
 15  umpire1          635 non-null    object
 16  umpire2          635 non-null    object
 17  umpire3          0 non-null      float64
dtypes: float64(1), int64(5), object(12)
memory usage: 89.6+ KB
```

[5]:
```
matches.drop("umpire3",axis=1,inplace=True)
```

[6]:
```
matches.rename(columns={'id': 'match_id'}, inplace=True)
```

[7]:
```
matches["date"]=pd.to_datetime(matches["date"])
```

[8]:
```
matches.date.dtype
```

[8]:
```
dtype('<M8[ns]')
```

[9]:
```
matches.describe()
```

[9]:

	match_id	season	date	dl_applied
count	636.000000	636.000000	636	636.000000
mean	318.500000	2012.490566	2012-10-24 20:52:04.528302080	0.025157
min	1.000000	2008.000000	2008-04-18 00:00:00	0.000000
25%	159.750000	2010.000000	2010-04-11 00:00:00	0.000000
50%	318.500000	2012.000000	2012-05-21 00:00:00	0.000000
75%	477.250000	2015.000000	2015-04-22 00:00:00	0.000000
max	636.000000	2017.000000	2017-05-21 00:00:00	1.000000
std	183.741666	2.773026	NaN	0.156726

	win_by_runs	win_by_wickets
count	636.000000	636.000000
mean	13.682390	3.372642
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	4.000000
75%	20.000000	7.000000
max	146.000000	10.000000
std	23.908877	3.420338

[10]:
```
deliveries=pd.read_csv("deliveries.csv")
```

[11]:
```
deliveries.head()
```

[11]:

	match_id	inning	batting_team	bowling_team	over
0	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1
1	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1
2	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1
3	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1
4	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1

	ball	batsman	non_striker	bowler	is_super_over	…	bye_runs
0	1	DA Warner	S Dhawan	TS Mills	0	…	0
1	2	DA Warner	S Dhawan	TS Mills	0	…	0
2	3	DA Warner	S Dhawan	TS Mills	0	…	0
3	4	DA Warner	S Dhawan	TS Mills	0	…	0
4	5	DA Warner	S Dhawan	TS Mills	0	…	0

	legbye_runs	noball_runs	penalty_runs	batsman_runs	extra_runs
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	4	0
3	0	0	0	0	0
4	0	0	0	0	2

```
   total_runs  player_dismissed dismissal_kind fielder
0           0               NaN            NaN     NaN
1           0               NaN            NaN     NaN
2           4               NaN            NaN     NaN
3           0               NaN            NaN     NaN
4           2               NaN            NaN     NaN

[5 rows x 21 columns]
```

[12]:
```
deliveries.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150460 entries, 0 to 150459
Data columns (total 21 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   match_id          150460 non-null  int64
 1   inning            150460 non-null  int64
 2   batting_team      150460 non-null  object
 3   bowling_team      150460 non-null  object
 4   over              150460 non-null  int64
 5   ball              150460 non-null  int64
 6   batsman           150460 non-null  object
 7   non_striker       150460 non-null  object
 8   bowler            150460 non-null  object
 9   is_super_over     150460 non-null  int64
 10  wide_runs         150460 non-null  int64
 11  bye_runs          150460 non-null  int64
 12  legbye_runs       150460 non-null  int64
 13  noball_runs       150460 non-null  int64
 14  penalty_runs      150460 non-null  int64
 15  batsman_runs      150460 non-null  int64
 16  extra_runs        150460 non-null  int64
 17  total_runs        150460 non-null  int64
 18  player_dismissed  7438 non-null    object
 19  dismissal_kind    7438 non-null    object
 20  fielder           5369 non-null    object
dtypes: int64(13), object(8)
memory usage: 24.1+ MB
```

[13]:
```
deliveries.describe()
```

[13]:
```
            match_id         inning           over           ball  \
count  150460.000000  150460.000000  150460.000000  150460.000000
mean      318.281317       1.482188      10.142649       3.616483
std       182.955531       0.501768       5.674338       1.807698
min         1.000000       1.000000       1.000000       1.000000
25%       161.000000       1.000000       5.000000       2.000000
```

```
50%       319.000000       1.000000      10.000000       4.000000
75%       476.000000       2.000000      15.000000       5.000000
max       636.000000       4.000000      20.000000       9.000000

       is_super_over     wide_runs       bye_runs    legbye_runs  \
count  150460.000000  150460.000000  150460.000000  150460.000000
mean        0.000538       0.037498       0.004885       0.022232
std         0.023196       0.257398       0.114234       0.200104
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         1.000000       5.000000       4.000000       5.000000

         noball_runs   penalty_runs   batsman_runs     extra_runs  \
count  150460.000000  150460.000000  150460.000000  150460.000000
mean        0.004340       0.000066       1.222445       0.069022
std         0.072652       0.018229       1.594509       0.349667
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       1.000000       0.000000
75%         0.000000       0.000000       1.000000       0.000000
max         5.000000       5.000000       6.000000       7.000000

          total_runs
count  150460.000000
mean        1.291466
std         1.583240
min         0.000000
25%         0.000000
50%         1.000000
75%         1.000000
max         7.000000
```

[14]:
```
deliveries.shape
```

[14]: (150460, 21)

[15]:
```
df=pd.merge(deliveries, matches, on='match_id', how='inner')
```

[16]:
```
df.shape
```

[16]: (150460, 37)

[17]:
```
df.head()
```

[17]:
```
   match_id  inning         batting_team                  bowling_team  over  \
0         1       1  Sunrisers Hyderabad  Royal Challengers Bangalore     1
1         1       1  Sunrisers Hyderabad  Royal Challengers Bangalore     1
2         1       1  Sunrisers Hyderabad  Royal Challengers Bangalore     1
3         1       1  Sunrisers Hyderabad  Royal Challengers Bangalore     1
4         1       1  Sunrisers Hyderabad  Royal Challengers Bangalore     1

   ball    batman non_striker    bowler  is_super_over  …  toss_decision  \
0     1  DA Warner    S Dhawan  TS Mills              0  …          field
1     2  DA Warner    S Dhawan  TS Mills              0  …          field
2     3  DA Warner    S Dhawan  TS Mills              0  …          field
3     4  DA Warner    S Dhawan  TS Mills              0  …          field
4     5  DA Warner    S Dhawan  TS Mills              0  …          field

   result  dl_applied               winner  win_by_runs  win_by_wickets  \
0  normal           0  Sunrisers Hyderabad           35               0
1  normal           0  Sunrisers Hyderabad           35               0
2  normal           0  Sunrisers Hyderabad           35               0
3  normal           0  Sunrisers Hyderabad           35               0
4  normal           0  Sunrisers Hyderabad           35               0

   player_of_match                                      venue      umpire1  \
0     Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal  AY Dandekar
1     Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal  AY Dandekar
2     Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal  AY Dandekar
3     Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal  AY Dandekar
4     Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal  AY Dandekar

    umpire2
0  NJ Llong
1  NJ Llong
2  NJ Llong
3  NJ Llong
4  NJ Llong

[5 rows x 37 columns]
```

[18]:
```
df.columns
```

[18]:
```
Index(['match_id', 'inning', 'batting_team', 'bowling_team', 'over', 'ball',
       'batsman', 'non_striker', 'bowler', 'is_super_over', 'wide_runs',
       'bye_runs', 'legbye_runs', 'noball_runs', 'penalty_runs',
       'batsman_runs', 'extra_runs', 'total_runs', 'player_dismissed',
       'dismissal_kind', 'fielder', 'season', 'city', 'date', 'team1', 'team2',
       'toss_winner', 'toss_decision', 'result', 'dl_applied', 'winner',
       'win_by_runs', 'win_by_wickets', 'player_of_match', 'venue', 'umpire1',
       'umpire2'],
```

```
      dtype='object')
```

0.1 1. How are total runs distributed per over across all matches? Are there specific overs with higher or lower scoring tendencies?

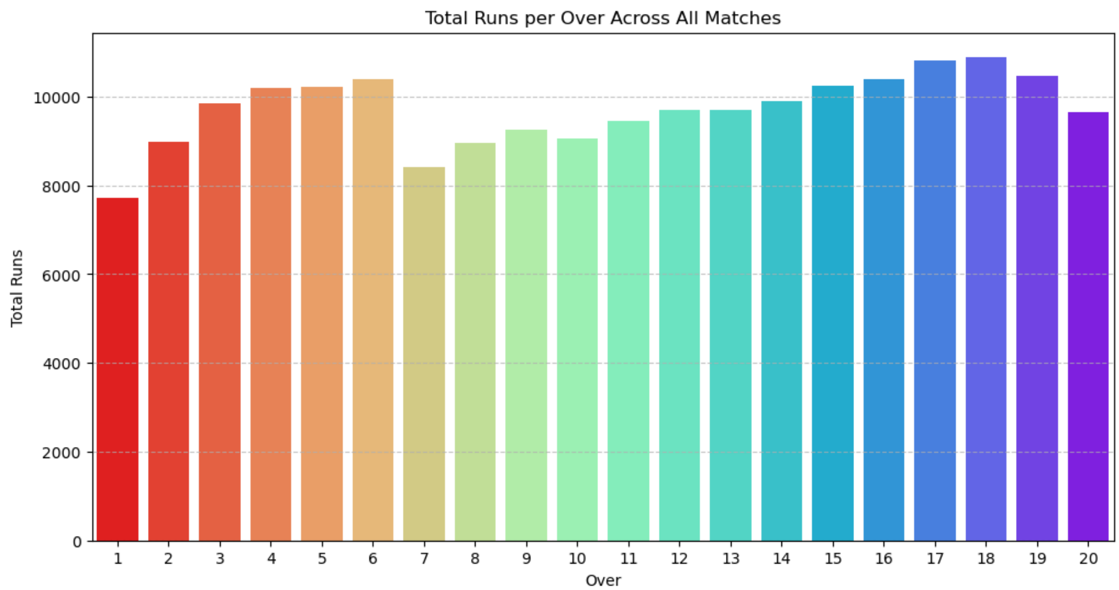
[20]:
```python
runs_per_over = df.groupby('over')['total_runs'].sum().reset_index()
```

[21]:
```python
runs_per_over
```

[21]:

	over	total_runs
0	1	7733
1	2	8993
2	3	9852
3	4	10207
4	5	10227
5	6	10397
6	7	8413
7	8	8966
8	9	9247
9	10	9047
10	11	9456
11	12	9694
12	13	9713
13	14	9900
14	15	10240
15	16	10397
16	17	10817
17	18	10899
18	19	10469
19	20	9647

[22]:
```python
plt.figure(figsize=(12, 6))
sns.barplot(x='over', y='total_runs', data=runs_per_over,␣
 ↪palette='rainbow_r',hue="over",legend=False)
plt.title('Total Runs per Over Across All Matches')
plt.xlabel('Over')
plt.ylabel('Total Runs')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



0.1.1 Insights:

Powerplay Overs (1-6): These overs have high flow of runs because of field restrictions as only 2 fielders are allowed outside the 30 yard circle

Middle Overs (7-15): The scoring rate might stabilize as batsmen settle in.

Death Overs (16-20): These overs often see a spike in average runs as batsmen aim to maximize the score.

0.2 2. How frequently do different batting teams hit boundaries (fours and sixes)? Do some teams rely more heavily on boundaries for scoring?

[23]:
```
boundaries = df[df['batsman_runs'].isin([4, 6])]
```

[24]:
```
boundaries[['batsman_runs']].head()
```

[24]:

	batsman_runs
2	4
8	4
10	6
13	4
30	4

[25]:
```
boundary_counts = boundaries.groupby(['batting_team', 'batsman_runs']).size().
    ↪unstack(fill_value=0)
boundary_counts.columns = ['Fours', 'Sixes']
```

[26]:
```
boundary_counts
```

[26]:

```
                             Fours  Sixes
batting_team
Chennai Super Kings           1770    742
Deccan Chargers                957    400
Delhi Daredevils              1970    686
Gujarat Lions                  460    155
Kings XI Punjab               2083    762
Kochi Tuskers Kerala           170     53
Kolkata Knight Riders         1978    659
Mumbai Indians                2145    876
Pune Warriors                  525    196
Rajasthan Royals              1630    538
Rising Pune Supergiant         197     89
Rising Pune Supergiants        171     68
Royal Challengers Bangalore   1978    935
Sunrisers Hyderabad            999    364
```

[27]:
```
boundary_counts['Total Boundary Runs'] = boundary_counts['Fours'] * 4 +␣
↪boundary_counts['Sixes'] * 6
```

[28]:
```
total_runs = df.groupby('batting_team')['total_runs'].sum()
```

[29]:
```
boundary_counts['Boundary Run Percentage'] = round((boundary_counts['Total␣
↪Boundary Runs'] / total_runs) * 100,2)
```

[30]:
```
boundary_counts
```

[30]:

```
                             Fours  Sixes  Total Boundary Runs  \
batting_team
Chennai Super Kings           1770    742                11532
Deccan Chargers                957    400                 6228
Delhi Daredevils              1970    686                11996
Gujarat Lions                  460    155                 2770
Kings XI Punjab               2083    762                12904
Kochi Tuskers Kerala           170     53                  998
Kolkata Knight Riders         1978    659                11866
Mumbai Indians                2145    876                13836
Pune Warriors                  525    196                 3276
Rajasthan Royals              1630    538                 9748
Rising Pune Supergiant         197     89                 1322
Rising Pune Supergiants        171     68                 1092
Royal Challengers Bangalore   1978    935                13522
Sunrisers Hyderabad            999    364                 6180

                             Boundary Run Percentage
```

```
batting_team
Chennai Super Kings                             55.18
Deccan Chargers                                 54.33
Delhi Daredevils                                54.64
Gujarat Lions                                   56.97
Kings XI Punjab                                 55.94
Kochi Tuskers Kerala                            52.50
Kolkata Knight Riders                           54.02
Mumbai Indians                                  56.43
Pune Warriors                                   51.53
Rajasthan Royals                                55.06
Rising Pune Supergiant                          53.52
Rising Pune Supergiants                         52.93
Royal Challengers Bangalore                     57.70
Sunrisers Hyderabad                             53.04
```

[31]:
```
boundary_counts.reset_index(inplace=True)
```

[32]:
```
boundary_counts
```

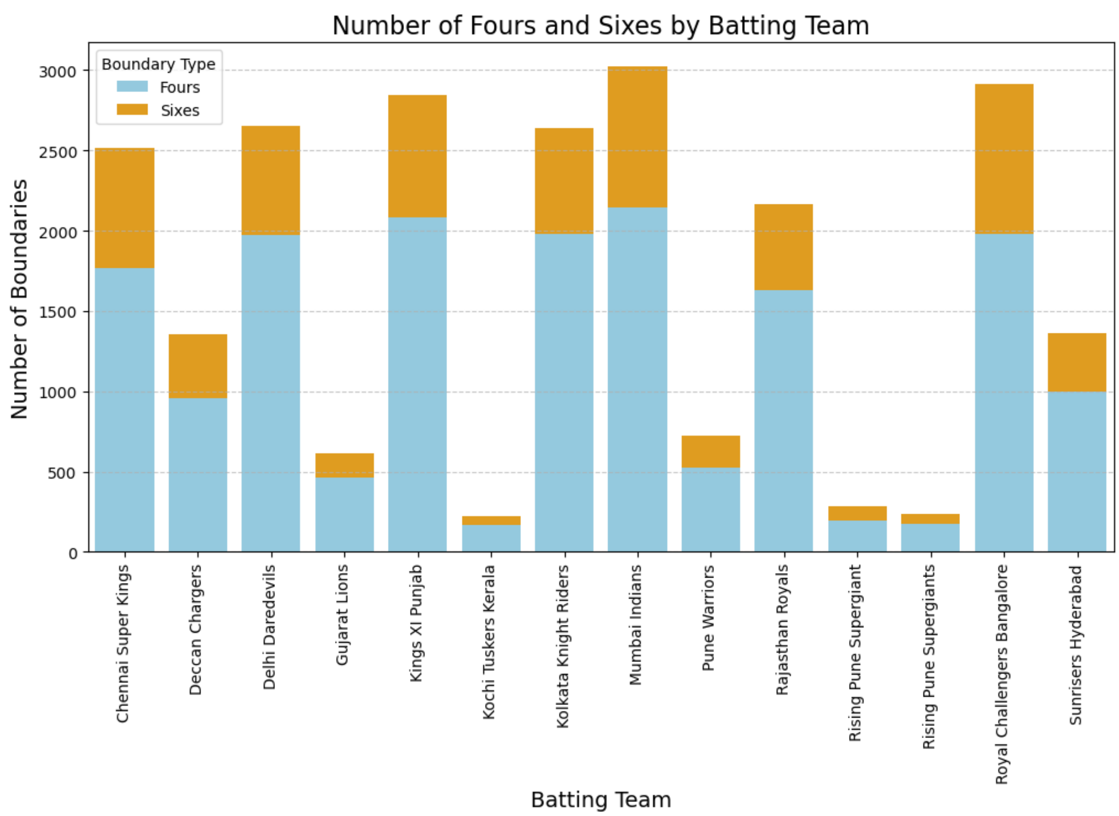
[32]:
```
                   batting_team  Fours  Sixes  Total Boundary Runs  \
0           Chennai Super Kings   1770    742                11532
1               Deccan Chargers    957    400                 6228
2              Delhi Daredevils   1970    686                11996
3                 Gujarat Lions    460    155                 2770
4               Kings XI Punjab   2083    762                12904
5           Kochi Tuskers Kerala   170     53                  998
6          Kolkata Knight Riders  1978    659                11866
7                Mumbai Indians   2145    876                13836
8                 Pune Warriors    525    196                 3276
9              Rajasthan Royals   1630    538                 9748
10       Rising Pune Supergiant    197     89                 1322
11      Rising Pune Supergiants    171     68                 1092
12  Royal Challengers Bangalore   1978    935                13522
13          Sunrisers Hyderabad    999    364                 6180

    Boundary Run Percentage
0                     55.18
1                     54.33
2                     54.64
3                     56.97
4                     55.94
5                     52.50
6                     54.02
7                     56.43
8                     51.53
9                     55.06
```

```
10                      53.52
11                      52.93
12                      57.70
13                      53.04
```

[33]:

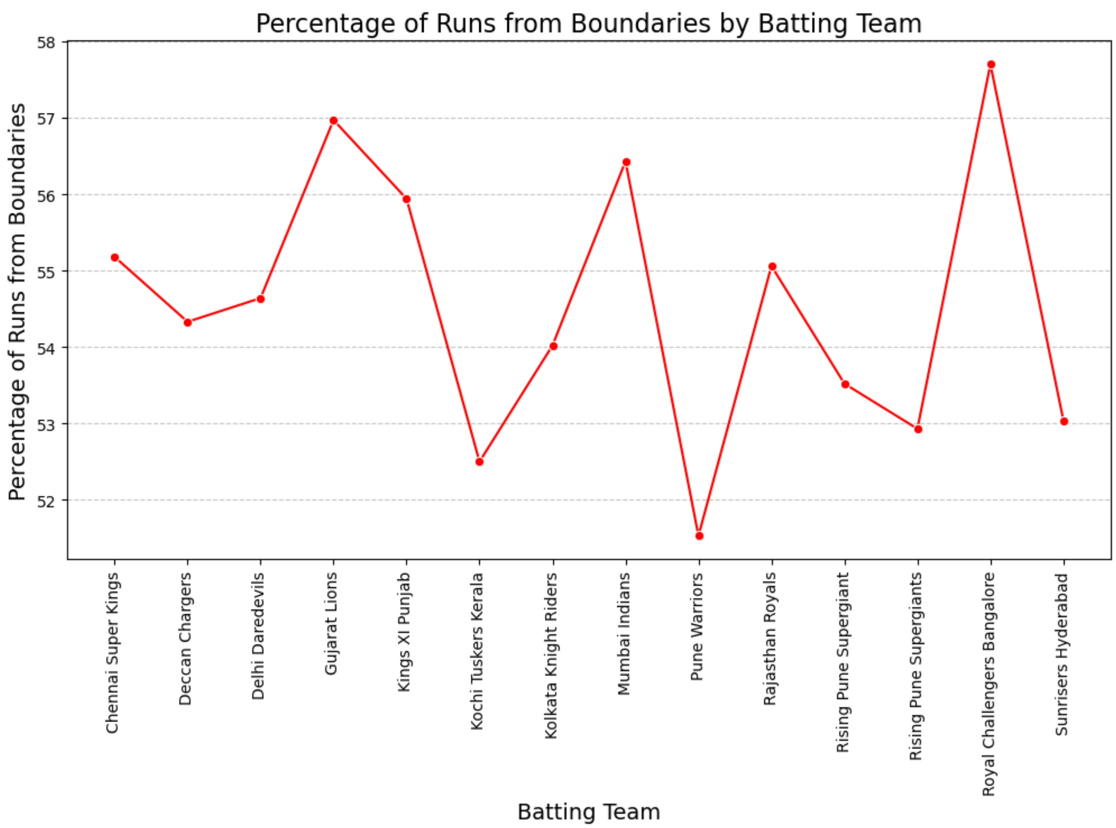
```python
plt.figure(figsize=(12, 6))
sns.barplot(data=boundary_counts, x='batting_team', y='Fours', color='skyblue', label='Fours')
sns.barplot(data=boundary_counts, x='batting_team', y='Sixes', color='orange', label='Sixes', bottom=boundary_counts['Fours'])
plt.title('Number of Fours and Sixes by Batting Team', fontsize=16)
plt.xlabel('Batting Team', fontsize=14)
plt.ylabel('Number of Boundaries', fontsize=14)
plt.xticks(rotation=90)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.legend(title='Boundary Type')
plt.show()
```



0.2.1 Insights:

The most number of boundaries scored by top 3 teams are: 1. Mumbai Indian 2. Royal Challenngers Banglore 3. Mumbai Indians

[34]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(data=boundary_counts, x='batting_team', y='Boundary Run␣
 ↪Percentage',marker='o',color='red')
plt.title('Percentage of Runs from Boundaries by Batting Team', fontsize=16)
plt.xlabel('Batting Team', fontsize=14)
plt.ylabel('Percentage of Runs from Boundaries', fontsize=14)
plt.xticks(rotation=90)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



0.2.2 Insights:

The team which is mostly dependent on boundaries id Royal Challengers Banglore which scored 58% of its total runs fom boundaries

0.3 3. Is there a difference in the distribution and types of extra runs conceded by various bowling teams?

[35]:
```
df.columns
```

[35]:
```
Index(['match_id', 'inning', 'batting_team', 'bowling_team', 'over', 'ball',
       'batsman', 'non_striker', 'bowler', 'is_super_over', 'wide_runs',
       'bye_runs', 'legbye_runs', 'noball_runs', 'penalty_runs',
       'batsman_runs', 'extra_runs', 'total_runs', 'player_dismissed',
       'dismissal_kind', 'fielder', 'season', 'city', 'date', 'team1', 'team2',
       'toss_winner', 'toss_decision', 'result', 'dl_applied', 'winner',
       'win_by_runs', 'win_by_wickets', 'player_of_match', 'venue', 'umpire1',
       'umpire2'],
      dtype='object')
```

[36]:
```
extra_runs_by_team = df.groupby('bowling_team')[['wide_runs', 'bye_runs',␣
↪'legbye_runs', 'noball_runs', 'penalty_runs']].sum()
```

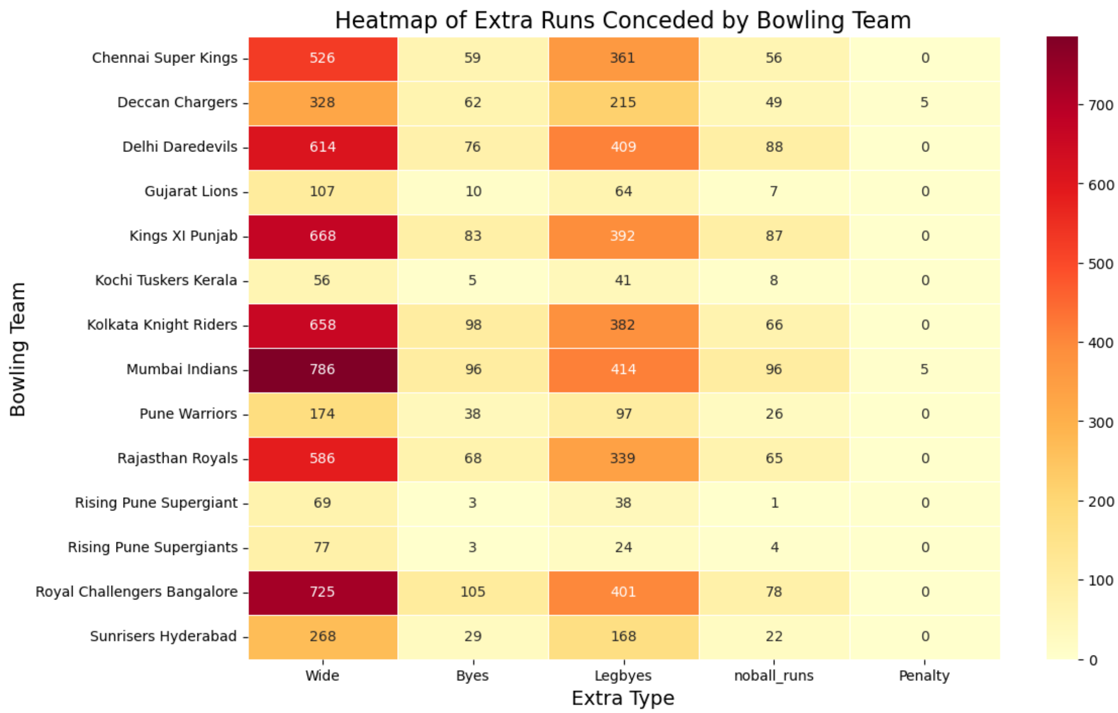
[37]:
```
extra_runs_by_team.rename(columns = {'wide_runs':'Wide','bye_runs':
↪'Byes','legbye_runs':'Legbyes','penalty_runs':'Penalty'},inplace=True)
```

[38]:
```
extra_runs_by_team
```

[38]:

bowling_team	Wide	Byes	Legbyes	noball_runs	Penalty
Chennai Super Kings	526	59	361	56	0
Deccan Chargers	328	62	215	49	5
Delhi Daredevils	614	76	409	88	0
Gujarat Lions	107	10	64	7	0
Kings XI Punjab	668	83	392	87	0
Kochi Tuskers Kerala	56	5	41	8	0
Kolkata Knight Riders	658	98	382	66	0
Mumbai Indians	786	96	414	96	5
Pune Warriors	174	38	97	26	0
Rajasthan Royals	586	68	339	65	0
Rising Pune Supergiant	69	3	38	1	0
Rising Pune Supergiants	77	3	24	4	0
Royal Challengers Bangalore	725	105	401	78	0
Sunrisers Hyderabad	268	29	168	22	0

[39]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(extra_runs_by_team, annot=True, fmt='d', cmap='YlOrRd',␣
↪linewidths=0.5)
plt.title('Heatmap of Extra Runs Conceded by Bowling Team', fontsize=16)
plt.xlabel('Extra Type', fontsize=14)
plt.ylabel('Bowling Team', fontsize=14)
plt.xticks(rotation=0)
plt.show()
```



0.3.1 Insights:

Teams which play on flat tracks like Delhi Dare Devils,Kings XI Punjab,Kolkata knight Riders, Mumbai Indians, Royal Challengers Banglore have conceded more extra runs compared to other teams

Teams which have good bowling lineups like Sunrisers Hyderabad and Chennai Super Kings have conceded low extra runs

0.4 4. How do run rates change across different phases of the innings (e.g., powerplay, middle overs, death overs) for different teams?

[40]:
```
def get_phase(over):
    if over <= 6:
        return 'Powerplay'
    elif 7 <= over <= 15:
        return 'Middle Overs'
    else:
        return 'Death Overs'
```

[41]:
```
df['phase'] = df['over'].apply(get_phase)
```

[42]:
```
df['phase'].head()
```

[42]:
```
0    Powerplay
1    Powerplay
2    Powerplay
3    Powerplay
4    Powerplay
Name: phase, dtype: object
```

[43]:
```python
phase_stats = df.groupby(['batting_team', 'phase']).agg(
    total_runs=('total_runs', 'sum'),
    total_balls=('ball', 'count')
).reset_index()
```

[44]:
```python
phase_stats['run_rate'] = (phase_stats['total_runs'] /␣
↪phase_stats['total_balls']) * 6
```

[45]:
```python
phase_stats
```

[45]:
```
                  batting_team         phase  total_runs  total_balls  \
0          Chennai Super Kings   Death Overs        5926         3665
1          Chennai Super Kings  Middle Overs        8952         7179
2          Chennai Super Kings     Powerplay        6021         4910
3              Deccan Chargers   Death Overs        3133         2103
4              Deccan Chargers  Middle Overs        4913         4112
5              Deccan Chargers     Powerplay        3417         2819
6             Delhi Daredevils   Death Overs        5606         3696
7             Delhi Daredevils  Middle Overs        9682         7985
8             Delhi Daredevils     Powerplay        6665         5504
9               Gujarat Lions   Death Overs        1159          787
10              Gujarat Lions  Middle Overs        2144         1654
11              Gujarat Lions     Powerplay        1559         1125
12             Kings XI Punjab   Death Overs        6033         3990
13             Kings XI Punjab  Middle Overs       10181         8035
14             Kings XI Punjab     Powerplay        6854         5569
15         Kochi Tuskers Kerala   Death Overs         390          305
16         Kochi Tuskers Kerala  Middle Overs         831          744
17         Kochi Tuskers Kerala     Powerplay         680          533
18        Kolkata Knight Riders   Death Overs        5648         3702
19        Kolkata Knight Riders  Middle Overs        9562         7944
20        Kolkata Knight Riders     Powerplay        6755         5583
21               Mumbai Indians   Death Overs        7097         4384
22               Mumbai Indians  Middle Overs       10478         8607
23               Mumbai Indians     Powerplay        6946         5952
24               Pune Warriors   Death Overs        1733         1282
25               Pune Warriors  Middle Overs        2730         2481
26               Pune Warriors     Powerplay        1895         1680
27            Rajasthan Royals   Death Overs        4520         3053
28            Rajasthan Royals  Middle Overs        8118         6479
```

29	Rajasthan Royals	Powerplay	5065	4382
30	Rising Pune Supergiant	Death Overs	681	440
31	Rising Pune Supergiant	Middle Overs	1004	862
32	Rising Pune Supergiant	Powerplay	785	598
33	Rising Pune Supergiants	Death Overs	530	324
34	Rising Pune Supergiants	Middle Overs	895	734
35	Rising Pune Supergiants	Powerplay	638	522
36	Royal Challengers Bangalore	Death Overs	6535	3900
37	Royal Challengers Bangalore	Middle Overs	10273	8110
38	Royal Challengers Bangalore	Powerplay	6628	5668
39	Sunrisers Hyderabad	Death Overs	3238	2106
40	Sunrisers Hyderabad	Middle Overs	4913	4114
41	Sunrisers Hyderabad	Powerplay	3501	2838

	run_rate
0	9.701501
1	7.481822
2	7.357637
3	8.938659
4	7.168774
5	7.272792
6	9.100649
7	7.275141
8	7.265625
9	8.836086
10	7.777509
11	8.314667
12	9.072180
13	7.602489
14	7.384450
15	7.672131
16	6.701613
17	7.654784
18	9.153971
19	7.222054
20	7.259538
21	9.713047
22	7.304287
23	7.002016
24	8.110764
25	6.602177
26	6.767857
27	8.883066
28	7.517827
29	6.935189
30	9.286364
31	6.988399

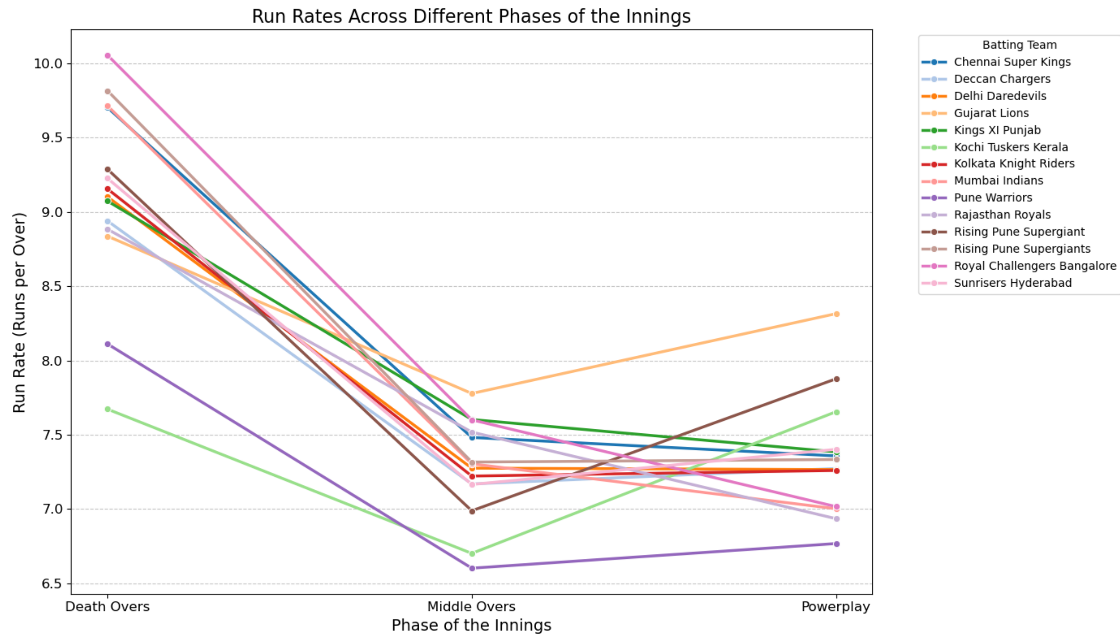
```
32     7.876254
33     9.814815
34     7.316076
35     7.333333
36    10.053846
37     7.600247
38     7.016231
39     9.225071
40     7.165289
41     7.401691
```

[46]:
```python
phase_stats_pivot = phase_stats.pivot(index='batting_team', columns='phase',
    values='run_rate')
```

[47]:
```python
phase_stats_pivot
```

[47]:
```
phase                        Death Overs  Middle Overs  Powerplay
batting_team
Chennai Super Kings             9.701501      7.481822   7.357637
Deccan Chargers                 8.938659      7.168774   7.272792
Delhi Daredevils                9.100649      7.275141   7.265625
Gujarat Lions                   8.836086      7.777509   8.314667
Kings XI Punjab                 9.072180      7.602489   7.384450
Kochi Tuskers Kerala            7.672131      6.701613   7.654784
Kolkata Knight Riders           9.153971      7.222054   7.259538
Mumbai Indians                  9.713047      7.304287   7.002016
Pune Warriors                   8.110764      6.602177   6.767857
Rajasthan Royals                8.883066      7.517827   6.935189
Rising Pune Supergiant          9.286364      6.988399   7.876254
Rising Pune Supergiants         9.814815      7.316076   7.333333
Royal Challengers Bangalore    10.053846      7.600247   7.016231
Sunrisers Hyderabad             9.225071      7.165289   7.401691
```

[48]:
```python
plt.figure(figsize=(14, 8))
sns.lineplot(data=phase_stats, x='phase', y='run_rate', hue='batting_team',
    marker='o', palette='tab20', linewidth=2.5)
plt.title('Run Rates Across Different Phases of the Innings', fontsize=16)
plt.xlabel('Phase of the Innings', fontsize=14)
plt.ylabel('Run Rate (Runs per Over)', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.legend(title='Batting Team', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



0.4.1 Insights:

Powerplay : Hihghest(Gujrat Lions) Lowest(Pune warriors)

Middle Overs : Hihghest(Gujrat Lions) Lowest(Pune warriors)

Middle Overs : Hihghest(Royal Challengers Banglore) Lowest(Kochi Tuskers kerela)

0.5 5. How do scoring patterns and run rates differ in super overs compared to regular overs?

[49]:
```
regular_overs = df[df['is_super_over'] == 0]
super_overs = df[df['is_super_over'] == 1]
```

[50]:
```
regular_overs.head(1)
```

[50]:
```
   match_id  inning         batting_team                  bowling_team  over  \
0         1       1  Sunrisers Hyderabad  Royal Challengers Bangalore     1

   ball    batsman non_striker    bowler  is_super_over  …  result  \
0     1  DA Warner    S Dhawan  TS Mills              0  …  normal

   dl_applied               winner  win_by_runs  win_by_wickets  \
0           0  Sunrisers Hyderabad           35               0

   player_of_match                                       venue      umpire1  \
```

```
0     Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal  AY Dandekar

    umpire2      phase
0  NJ Llong  Powerplay

[1 rows x 38 columns]
```

[51]:
```
super_overs.head(1)
```

[51]:
```
      match_id  inning    batting_team   bowling_team  over  ball     batsman  \
8092        34       3  Mumbai Indians  Gujarat Lions     1     1  JC Buttler

     non_striker       bowler  is_super_over  …  result  dl_applied  \
8092  KA Pollard  JP Faulkner              1  …     tie           0

              winner  win_by_runs  win_by_wickets  player_of_match  \
8092  Mumbai Indians            0               0        KH Pandya

                                       venue       umpire1      umpire2  \
8092  Saurashtra Cricket Association Stadium  AK Chaudhary  CB Gaffaney

          phase
8092  Powerplay

[1 rows x 38 columns]
```

[52]:
```
regular_run_rates = regular_overs.groupby('over')['total_runs'].mean() * 6
```

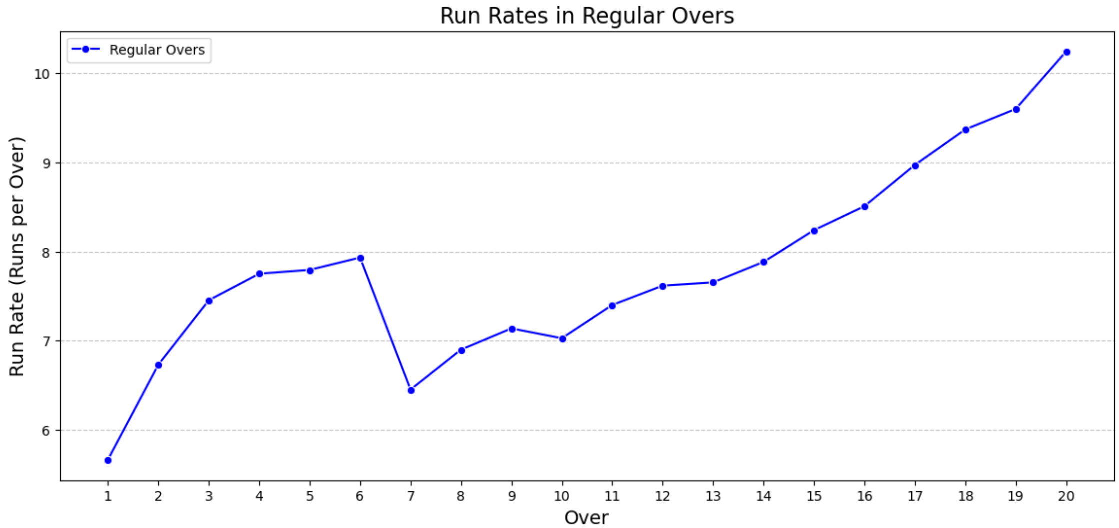
[53]:
```
regular_run_rates.head()
```

[53]:
```
over
1    5.662214
2    6.729608
3    7.452345
4    7.750190
5    7.792990
Name: total_runs, dtype: float64
```

[54]:
```
super_run_rates = super_overs.groupby('match_id')['total_runs'].sum()
```

[55]:
```
# Plot run rates for regular overs
plt.figure(figsize=(14, 6))
sns.lineplot(x=regular_run_rates.index, y=regular_run_rates.values, marker='o',␣
↪color='blue', label='Regular Overs')
plt.title('Run Rates in Regular Overs', fontsize=16)
plt.xlabel('Over', fontsize=14)
plt.ylabel('Run Rate (Runs per Over)', fontsize=14)
```

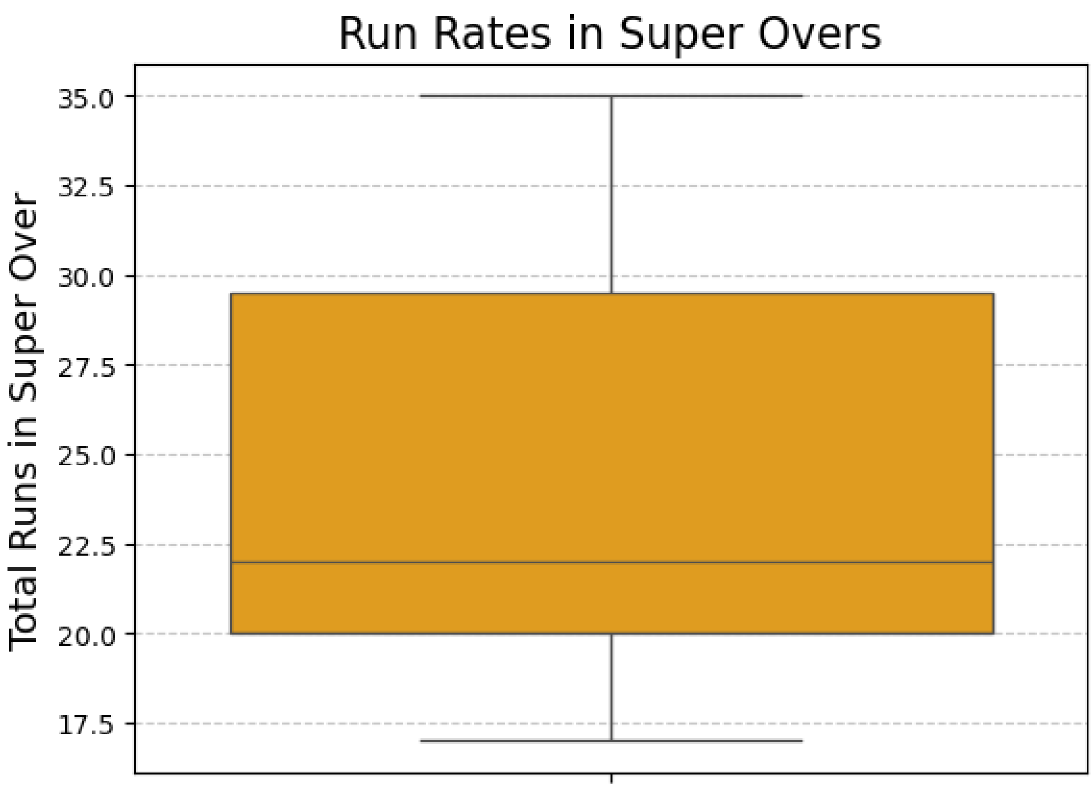
```
plt.xticks(range(1, 21))
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.legend()
plt.show()
```



[56]:
```
super_run_rates.head()
```

[56]:
```
match_id
34     17
126    33
190    19
388    35
401    26
Name: total_runs, dtype: int64
```

[57]:
```
# Plot run rates for super overs
sns.boxplot(y=super_run_rates.values, color='orange')
plt.title('Run Rates in Super Overs', fontsize=16)
plt.ylabel('Total Runs in Super Over', fontsize=14)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



0.5.1 Insights:

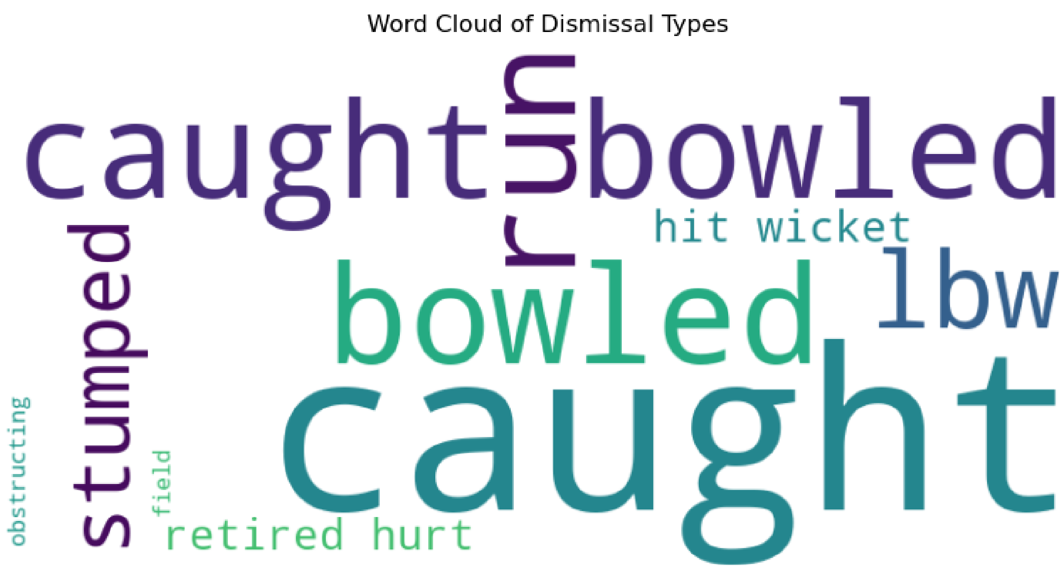
Runrate between regular overs ranges between 5-11 Runrate in super overs range mostly ranges between 20-29

0.6 6. What is the distribution of different dismissal types (caught, bowled, LBW, etc.)? Are there any trends in how batsmen are getting out?

[58]:
```
dismissals = df[df['player_dismissed'].notna()]
```

[60]:
```
dismissal_text = ' '.join(dismissals['dismissal_kind'].dropna())
wordcloud = WordCloud(width=800, height=400, background_color='white').
  ↪generate(dismissal_text)
```

[61]:
```
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Dismissal Types')
plt.show()
```



0.7 7. Which bowlers have the best performance in terms of wickets taken, economy rate, and bowling strike rate? What are their preferred dismissal methods?

[62]:
```
wickets_taken = df[df['player_dismissed'].notna()].groupby('bowler').size().
↪reset_index(name='wickets')
```

[63]:
```
wickets_taken
```

[63]:

	bowler	wickets
0	A Ashish Reddy	19
1	A Chandila	11
2	A Choudhary	5
3	A Flintoff	2
4	A Kumble	49
..	…	…
309	YA Abdulla	15
310	YK Pathan	45
311	YS Chahal	72
312	Yuvraj Singh	39
313	Z Khan	119

[314 rows x 2 columns]

[64]:
```
runs_conceded = df.groupby('bowler')['total_runs'].sum().
↪reset_index(name='runs_conceded')
balls_bowled = df.groupby('bowler').size().reset_index(name='balls_bowled')
```

```python
# Merge wickets, runs, and balls data
bowler_stats = pd.merge(wickets_taken, runs_conceded, on='bowler')
bowler_stats = pd.merge(bowler_stats, balls_bowled, on='bowler')

# Calculate economy rate
bowler_stats['economy_rate'] = round((bowler_stats['runs_conceded'] /
 ↪bowler_stats['balls_bowled']) * 6,2)
```

[65]:
```python
bowler_stats['bowling_strike_rate'] = round(bowler_stats['balls_bowled'] /
 ↪bowler_stats['wickets'],2)
```

[66]:
```python
bowler_stats
```

[66]:
```
              bowler  wickets  runs_conceded  balls_bowled  economy_rate  \
0     A Ashish Reddy       19            400           270          8.89
1         A Chandila       11            245           234          6.28
2        A Choudhary        5            144           108          8.00
3          A Flintoff        2            106            66          9.64
4            A Kumble       49           1089           983          6.65
..               ...      ...            ...           ...           ...
309       YA Abdulla       15            311           222          8.41
310        YK Pathan       45           1421          1166          7.31
311        YS Chahal       72           1600          1219          7.88
312     Yuvraj Singh       39           1068           869          7.37
313          Z Khan      119           2860          2276          7.54

     bowling_strike_rate
0                  14.21
1                  21.27
2                  21.60
3                  33.00
4                  20.06
..                   ...
309                14.80
310                25.91
311                16.93
312                22.28
313                19.13

[314 rows x 6 columns]
```

[67]:
```python
# Sort by wickets taken (descending), economy rate (ascending), and strike rate
 ↪(ascending)
top_bowlers = bowler_stats.sort_values(by=['wickets', 'economy_rate',
 ↪'bowling_strike_rate'], ascending=[False, True, True])
top_bowlers.head(10) # Display top 10 bowlers
```

[67]:

	bowler	wickets	runs_conceded	balls_bowled	economy_rate
259	SL Malinga	170	3034	2694	6.76
5	A Mishra	142	3305	2703	7.34
80	DJ Bravo	137	2815	2110	8.00
107	Harbhajan Singh	136	3453	2989	6.93
204	PP Chawla	133	3315	2594	7.67
219	R Vinay Kumar	125	2976	2161	8.26
7	A Nehra	121	2537	1974	7.71
313	Z Khan	119	2860	2276	7.54
46	B Kumar	117	2410	2054	7.04
209	R Ashwin	110	2552	2359	6.49

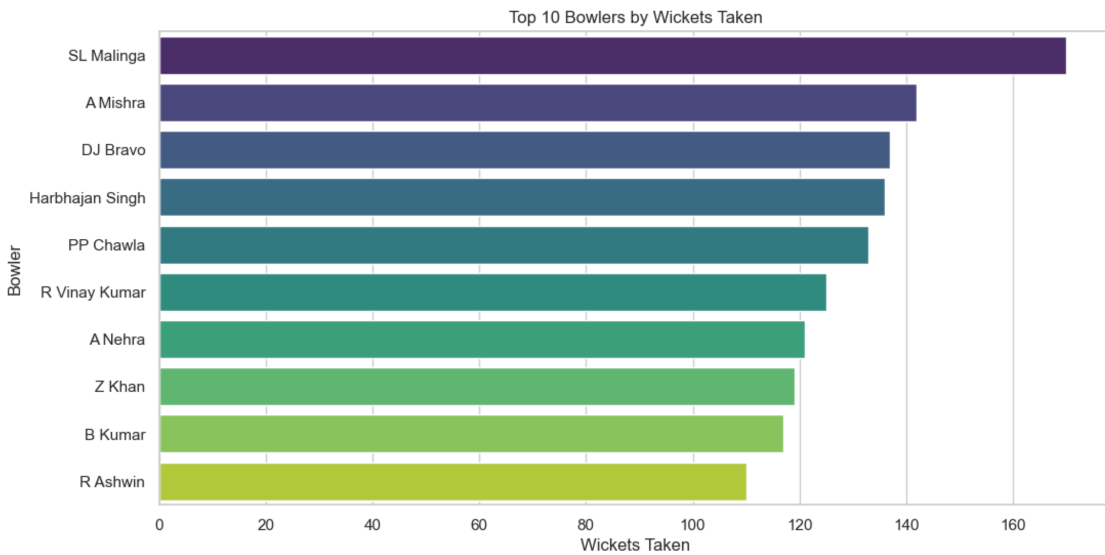
	bowling_strike_rate
259	15.85
5	19.04
80	15.40
107	21.98
204	19.50
219	17.29
7	16.31
313	19.13
46	17.56
209	21.45

[68]:
```
dismissals = df[df['player_dismissed'].notna()]
```

[69]:
```
dismissal_methods = dismissals.groupby(['bowler', 'dismissal_kind']).size().
 ↪unstack().fillna(0)
```

[70]:
```
sns.set(style="whitegrid")

# Plot top 10 bowlers by wickets taken
plt.figure(figsize=(12, 6))
sns.barplot(x='wickets', y='bowler', data=top_bowlers.head(10),␣
 ↪palette='viridis',hue='bowler',legend=False)
plt.title('Top 10 Bowlers by Wickets Taken')
plt.xlabel('Wickets Taken')
plt.ylabel('Bowler')
plt.show()
```



[71]:
```python
dismissal_methods
```

[71]:
```
dismissal_kind  bowled  caught  caught and bowled  hit wicket  lbw  \
bowler
A Ashish Reddy     6.0     8.0                1.0         0.0  3.0
A Chandila         0.0     4.0                5.0         0.0  0.0
A Choudhary        0.0     5.0                0.0         0.0  0.0
A Flintoff         0.0     1.0                1.0         0.0  0.0
A Kumble           8.0    24.0                1.0         0.0  4.0
…                 …       …                 …          …  …
YA Abdulla         4.0    10.0                0.0         0.0  1.0
YK Pathan          9.0    21.0                2.0         0.0  5.0
YS Chahal          9.0    49.0                1.0         0.0  3.0
Yuvraj Singh       9.0    19.0                2.0         0.0  2.0
Z Khan            22.0    70.0                1.0         0.0  9.0

dismissal_kind  obstructing the field  retired hurt  run out  stumped
bowler
A Ashish Reddy                    0.0           0.0      1.0      0.0
A Chandila                        0.0           0.0      0.0      2.0
A Choudhary                       0.0           0.0      0.0      0.0
A Flintoff                        0.0           0.0      0.0      0.0
A Kumble                          0.0           0.0      4.0      8.0
…                                …            …       …       …
YA Abdulla                        0.0           0.0      0.0      0.0
YK Pathan                         0.0           0.0      4.0      4.0
YS Chahal                         0.0           0.0      2.0      8.0
Yuvraj Singh                      0.0           0.0      3.0      4.0
```

```
Z Khan                              0.0          1.0     16.0      0.0

[314 rows x 9 columns]
```

[72]:
```python
bowler_stats_with_dismissals = pd.merge(bowler_stats, dismissal_methods,␣
 ↪on='bowler')
```

[73]:
```python
bowler_stats_with_dismissals
```

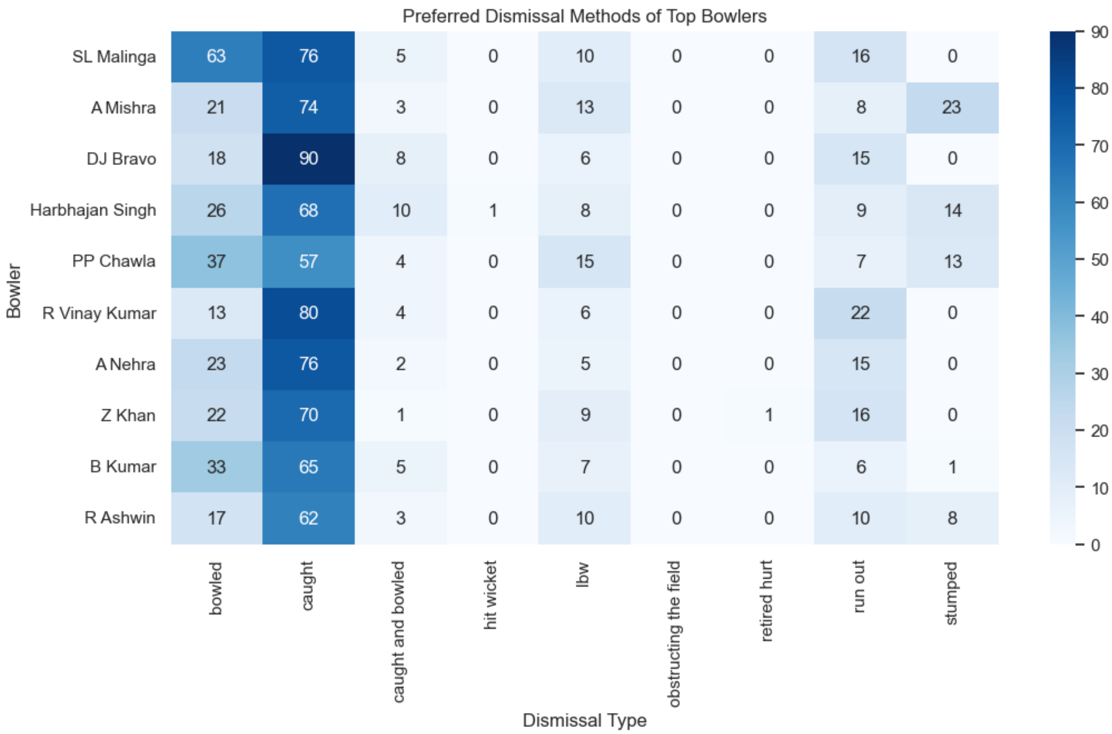
[73]:
```
             bowler  wickets  runs_conceded  balls_bowled  economy_rate  \
0     A Ashish Reddy       19            400           270          8.89
1        A Chandila       11            245           234          6.28
2       A Choudhary        5            144           108          8.00
3        A Flintoff        2            106            66          9.64
4          A Kumble       49           1089           983          6.65
..              …      …            …           …            …
309      YA Abdulla       15            311           222          8.41
310       YK Pathan       45           1421          1166          7.31
311       YS Chahal       72           1600          1219          7.88
312    Yuvraj Singh       39           1068           869          7.37
313          Z Khan      119           2860          2276          7.54

     bowling_strike_rate  bowled  caught  caught and bowled  hit wicket  lbw  \
0                  14.21     6.0     8.0                1.0         0.0  3.0
1                  21.27     0.0     4.0                5.0         0.0  0.0
2                  21.60     0.0     5.0                0.0         0.0  0.0
3                  33.00     0.0     1.0                1.0         0.0  0.0
4                  20.06     8.0    24.0                1.0         0.0  4.0
..                   …     …     …                 …         …  …
309                14.80     4.0    10.0                0.0         0.0  1.0
310                25.91     9.0    21.0                2.0         0.0  5.0
311                16.93     9.0    49.0                1.0         0.0  3.0
312                22.28     9.0    19.0                2.0         0.0  2.0
313                19.13    22.0    70.0                1.0         0.0  9.0

     obstructing the field  retired hurt  run out  stumped
0                      0.0           0.0      1.0      0.0
1                      0.0           0.0      0.0      2.0
2                      0.0           0.0      0.0      0.0
3                      0.0           0.0      0.0      0.0
4                      0.0           0.0      4.0      8.0
..                     …           …      …      …
309                    0.0           0.0      0.0      0.0
310                    0.0           0.0      4.0      4.0
311                    0.0           0.0      2.0      8.0
312                    0.0           0.0      3.0      4.0
313                    0.0           1.0     16.0      0.0
```

[314 rows x 15 columns]

[74]:
```python
# Heatmap for top bowlers and their dismissal methods
top_bowlers_dismissals = bowler_stats_with_dismissals.sort_values(by='wickets',␣
    ↪ascending=False).head(10)
plt.figure(figsize=(12, 6))
sns.heatmap(top_bowlers_dismissals.set_index('bowler').iloc[:, 5:], annot=True,␣
    ↪fmt='g', cmap='Blues')
plt.title('Preferred Dismissal Methods of Top Bowlers')
plt.xlabel('Dismissal Type')
plt.ylabel('Bowler')
plt.show()
```



0.7.1 Insights:

L Malinga : Bowled and caught are preferred dismissal methods A Mishra : Caught and stumped are preferred dismissal methods Dj Bravo : Catches is most preferred dismissal method

0.8 8. Analyze the win-loss trends of each team across different seasons. Are there teams that have shown consistent improvement or decline?

[75]:
```python
# Filter relevant columns
matches = df[['season', 'team1', 'team2', 'winner']].drop_duplicates()
```

[76]:
```python
wins = matches.groupby(['season', 'winner']).size().reset_index(name='wins')
wins = wins.rename(columns={'winner': 'team'})
```

[77]:
```python
wins
```

[77]:
```
    season                         team  wins
0     2008          Chennai Super Kings     7
1     2008              Deccan Chargers     2
2     2008             Delhi Daredevils     7
3     2008              Kings XI Punjab     6
4     2008        Kolkata Knight Riders     5
..     …                            …   …
79    2017        Kolkata Knight Riders     8
80    2017               Mumbai Indians     8
81    2017       Rising Pune Supergiant     8
82    2017  Royal Challengers Bangalore     2
83    2017          Sunrisers Hyderabad     6

[84 rows x 3 columns]
```

[78]:
```python
# Combine team1 and team2 to get all matches played by each team
team1_matches = matches[['season', 'team1']].rename(columns={'team1': 'team'})
team2_matches = matches[['season', 'team2']].rename(columns={'team2': 'team'})
total_matches = pd.concat([team1_matches, team2_matches]).groupby(['season',␣
↪'team']).size().reset_index(name='total_matches')
```

[79]:
```python
total_matches
```

[79]:
```
    season                         team  total_matches
0     2008          Chennai Super Kings             13
1     2008              Deccan Chargers             12
2     2008             Delhi Daredevils             13
3     2008              Kings XI Punjab             10
4     2008        Kolkata Knight Riders             10
..     …                            …             …
79    2017        Kolkata Knight Riders             14
80    2017               Mumbai Indians             12
81    2017       Rising Pune Supergiant             13
82    2017  Royal Challengers Bangalore             10
83    2017          Sunrisers Hyderabad             12

[84 rows x 3 columns]
```

[80]:
```
win_loss = pd.merge(total_matches, wins, on=['season', 'team'], how='left').
  ↪fillna(0)
win_loss['losses'] = win_loss['total_matches'] - win_loss['wins']
```

[81]:
```
win_loss['win_percentage'] = round((win_loss['wins'] /␣
  ↪win_loss['total_matches']) * 100,2)
```

[82]:
```
win_loss = win_loss.sort_values(by=['team', 'season'])
```

[83]:
```
win_loss
```

[83]:
```
    season                 team  total_matches  wins  losses  win_percentage
0     2008  Chennai Super Kings             13     7       6           53.85
8     2009  Chennai Super Kings             12     7       5           58.33
16    2010  Chennai Super Kings             15     8       7           53.33
24    2011  Chennai Super Kings             15    10       5           66.67
34    2012  Chennai Super Kings             14     8       6           57.14
..     …                   …             …     …     …               …
51    2013  Sunrisers Hyderabad             14     8       6           57.14
59    2014  Sunrisers Hyderabad             13     6       7           46.15
67    2015  Sunrisers Hyderabad             13     6       7           46.15
75    2016  Sunrisers Hyderabad             12     7       5           58.33
83    2017  Sunrisers Hyderabad             12     6       6           50.00

[84 rows x 6 columns]
```

[84]:
```
win_loss
```

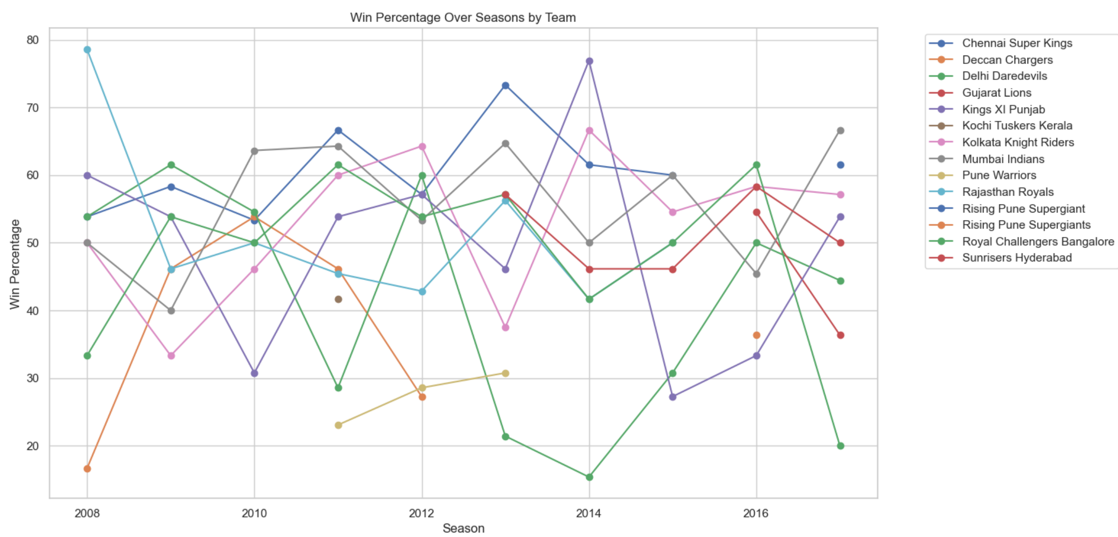
[84]:
```
    season                 team  total_matches  wins  losses  win_percentage
0     2008  Chennai Super Kings             13     7       6           53.85
8     2009  Chennai Super Kings             12     7       5           58.33
16    2010  Chennai Super Kings             15     8       7           53.33
24    2011  Chennai Super Kings             15    10       5           66.67
34    2012  Chennai Super Kings             14     8       6           57.14
..     …                   …             …     …     …               …
51    2013  Sunrisers Hyderabad             14     8       6           57.14
59    2014  Sunrisers Hyderabad             13     6       7           46.15
67    2015  Sunrisers Hyderabad             13     6       7           46.15
75    2016  Sunrisers Hyderabad             12     7       5           58.33
83    2017  Sunrisers Hyderabad             12     6       6           50.00

[84 rows x 6 columns]
```

[85]:
```
plt.figure(figsize=(14, 8))
for team in win_loss['team'].unique():
    team_data = win_loss[win_loss['team'] == team]
```

```
    plt.plot(team_data['season'], team_data['win_percentage'], label=team,␣
 ↪marker='o')

plt.title('Win Percentage Over Seasons by Team')
plt.xlabel('Season')
plt.ylabel('Win Percentage')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



0.9 Insights:

Teams like Mumbai Indians, Chennai Super Kings, Kolkata Knight Riders have consistent win percentage across seasons. Teams like Royal Challengers banglore, Kings XI Punjab have inconsistent win percentage across seasons.

0.10 9. Which fielders contribute the most to dismissals through catches and run-outs?

[86]:
```
dismissals = df[df['player_dismissed'].notna()]
catches_and_runouts = dismissals[dismissals['dismissal_kind'].isin(['caught',␣
 ↪'run out'])]
```

[87]:
```
catches = catches_and_runouts[catches_and_runouts['dismissal_kind'] == 'caught']
catches_by_fielder = catches.groupby('fielder').size().
 ↪reset_index(name='catches')
```

[88]:
```
catches_by_fielder
```

[88]:

```
             fielder  catches
0     A Ashish Reddy        8
1         A Chandila        2
2           A Chopra        2
3         A Flintoff        3
4           A Kumble        9
..               ...      ...
435      YV Takawale       13
436    Yashpal Singh        3
437      Younis Khan        1
438     Yuvraj Singh       28
439           Z Khan       20

[440 rows x 2 columns]
```

[89]:

```
run_outs = catches_and_runouts[catches_and_runouts['dismissal_kind'] == 'run␣
 ↪out']
run_outs_by_fielder = run_outs.groupby('fielder').size().
 ↪reset_index(name='run_outs')
```

[90]:

```
run_outs_by_fielder
```

[90]:

```
             fielder  run_outs
0     A Ashish Reddy         2
1           A Chopra         1
2           A Mishra         8
3           A Mithun         1
4     A Mukund (sub)         1
..               ...       ...
234        YK Pathan         9
235        YS Chahal         3
236      YV Takawale         4
237     Yuvraj Singh         8
238           Z Khan         4

[239 rows x 2 columns]
```

[91]:

```
fielder_contributions = pd.merge(catches_by_fielder, run_outs_by_fielder,␣
 ↪on='fielder', how='outer').fillna(0)
fielder_contributions['total_contributions'] = fielder_contributions['catches']␣
 ↪+ fielder_contributions['run_outs']
```

[92]:

```
fielder_contributions
```

[92]:

```
             fielder  catches  run_outs  total_contributions
0     A Ashish Reddy      8.0       2.0                 10.0
1         A Chandila      2.0       0.0                  2.0
```

```
2           A Chopra     2.0       1.0                    3.0
3         A Flintoff     3.0       0.0                    3.0
4           A Kumble     9.0       0.0                    9.0
..               …        …        …                   …
444      YV Takawale    13.0       4.0                   17.0
445    Yashpal Singh     3.0       0.0                    3.0
446      Younis Khan     1.0       0.0                    1.0
447     Yuvraj Singh    28.0       8.0                   36.0
448           Z Khan    20.0       4.0                   24.0

[449 rows x 4 columns]
```

[93]:

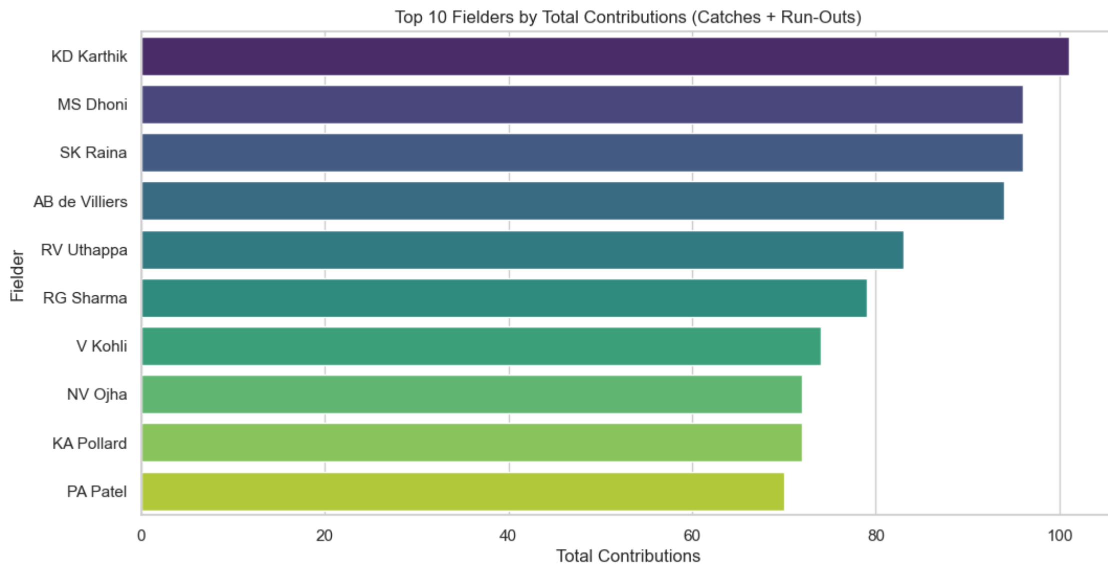
```
top_fielders = fielder_contributions.sort_values(by='total_contributions',␣
↪ascending=False)
top_fielders.head(10)  # Display top 10 fielders
```

[93]:

```
            fielder  catches  run_outs  total_contributions
189      KD Karthik     88.0      13.0                101.0
251        MS Dhoni     76.0      20.0                 96.0
364        SK Raina     83.0      13.0                 96.0
17   AB de Villiers     81.0      13.0                 94.0
336      RV Uthappa     75.0       8.0                 83.0
319       RG Sharma     70.0       9.0                 79.0
421         V Kohli     60.0      14.0                 74.0
270         NV Ojha     65.0       7.0                 72.0
183      KA Pollard     64.0       8.0                 72.0
280        PA Patel     60.0      10.0                 70.0
```

[94]:

```
# Plot top 10 fielders by total contributions
plt.figure(figsize=(12, 6))
sns.barplot(x='total_contributions', y='fielder', data=top_fielders.head(10),␣
↪palette='viridis',hue='fielder',legend=False)
plt.title('Top 10 Fielders by Total Contributions (Catches + Run-Outs)')
plt.xlabel('Total Contributions')
plt.ylabel('Fielder')
plt.show()
```



0.10.1 Insights:

Dinesh Karthik and MS Dhoni have maxmium dismissals in terms of catches and run outs

0.11 10. How are wickets distributed across overs in the matches? Are there specific overs where bowlers tend to be more successful?

[95]:
```
dismissals = df[df['player_dismissed'].notna()]
```

[96]:
```
wickets_by_over = dismissals.groupby('over').size().reset_index(name='wickets')
```

[97]:
```
wickets_by_over
```

[97]:

	over	wickets
0	1	266
1	2	299
2	3	321
3	4	308
4	5	331
5	6	327
6	7	264
7	8	268
8	9	307
9	10	299
10	11	320
11	12	317
12	13	314
13	14	358

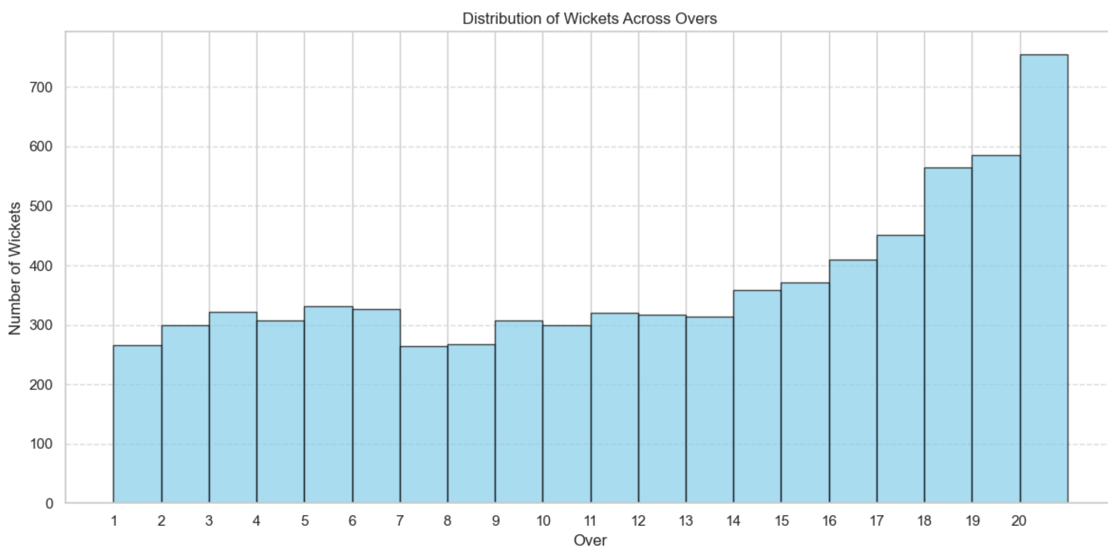
```
14    15       372
15    16       410
16    17       451
17    18       565
18    19       586
19    20       755
```

[98]:
```
overs=dismissals['over']
```

[99]:
```
# Plot the histogram
plt.figure(figsize=(12, 6))
plt.hist(overs, bins=20, range=(1, 21), edgecolor='black', color='skyblue',␣
 ↪alpha=0.7)

# Add labels and title
plt.title('Distribution of Wickets Across Overs')
plt.xlabel('Over')
plt.ylabel('Number of Wickets')
plt.xticks(range(1, 21))  # Assuming 20 overs in a match
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Show the plot
plt.tight_layout()
plt.show()
```



[100]:
```
average_wickets_per_over = wickets_by_over['wickets'].mean()
print(f'Average wickets per over: {average_wickets_per_over:.2f}')
```

```
Average wickets per over: 371.90
```

[101]:
```
high_wicket_overs = wickets_by_over[wickets_by_over['wickets'] >␣
 ↪average_wickets_per_over]
print('Overs with above-average wickets:')
print(high_wicket_overs)
```

```
Overs with above-average wickets:
    over  wickets
14    15      372
15    16      410
16    17      451
17    18      565
18    19      586
19    20      755
```

0.11.1 Insights:

The most successful overs are between 18-20 overs.

0.12 11. Analyze the bowling strength of teams based on metrics like economy rate, bowling strike rate, and performance in different phases of the match.

[102]:
```
# Filter relevant columns
bowling_data = df[['match_id', 'inning', 'bowling_team', 'bowler', 'over',␣
 ↪'ball', 'total_runs', 'player_dismissed']]
```

[108]:
```
# Define match phases
def match_phase(over):
    if over <= 6:
        return 'Powerplay'
    elif over <= 15:
        return 'Middle Overs'
    else:
        return 'Death Overs'

bowling_data.loc[:, 'phase'] = bowling_data['over'].apply(match_phase)
```

[109]:
```
bowling_data.head()
```

[109]:
```
   match_id  inning                 bowling_team    bowler  over  ball  \
0         1       1  Royal Challengers Bangalore  TS Mills     1     1
1         1       1  Royal Challengers Bangalore  TS Mills     1     2
2         1       1  Royal Challengers Bangalore  TS Mills     1     3
3         1       1  Royal Challengers Bangalore  TS Mills     1     4
4         1       1  Royal Challengers Bangalore  TS Mills     1     5

   total_runs player_dismissed      phase
0           0              NaN  Powerplay
1           0              NaN  Powerplay
```

```
2           4              NaN  Powerplay
3           0              NaN  Powerplay
4           2              NaN  Powerplay
```

[110]:
```python
# Calculate runs conceded and balls bowled by each team in each phase
bowling_stats = bowling_data.groupby(['bowling_team', 'phase']).agg(
    runs_conceded=('total_runs', 'sum'),
    balls_bowled=('ball', 'count'),
    wickets_taken=('player_dismissed', lambda x: x.notna().sum())
).reset_index()
```

[111]:
```python
bowling_stats
```

[111]:

	bowling_team	phase	runs_conceded	balls_bowled	\
0	Chennai Super Kings	Death Overs	5173	3490	
1	Chennai Super Kings	Middle Overs	8644	7181	
2	Chennai Super Kings	Powerplay	5973	4891	
3	Deccan Chargers	Death Overs	3451	2062	
4	Deccan Chargers	Middle Overs	4939	4154	
5	Deccan Chargers	Powerplay	3228	2823	
6	Delhi Daredevils	Death Overs	5993	3834	
7	Delhi Daredevils	Middle Overs	9673	7804	
8	Delhi Daredevils	Powerplay	6677	5461	
9	Gujarat Lions	Death Overs	1354	768	
10	Gujarat Lions	Middle Overs	2235	1657	
11	Gujarat Lions	Powerplay	1501	1120	
12	Kings XI Punjab	Death Overs	6113	3815	
13	Kings XI Punjab	Middle Overs	10203	8018	
14	Kings XI Punjab	Powerplay	6954	5559	
15	Kochi Tuskers Kerala	Death Overs	479	324	
16	Kochi Tuskers Kerala	Middle Overs	914	759	
17	Kochi Tuskers Kerala	Powerplay	593	531	
18	Kolkata Knight Riders	Death Overs	5837	3905	
19	Kolkata Knight Riders	Middle Overs	9518	7935	
20	Kolkata Knight Riders	Powerplay	6680	5571	
21	Mumbai Indians	Death Overs	6331	4271	
22	Mumbai Indians	Middle Overs	10753	8724	
23	Mumbai Indians	Powerplay	6751	5884	
24	Pune Warriors	Death Overs	1934	1252	
25	Pune Warriors	Middle Overs	2937	2487	
26	Pune Warriors	Powerplay	1986	1718	
27	Rajasthan Royals	Death Overs	4891	3165	
28	Rajasthan Royals	Middle Overs	7638	6479	
29	Rajasthan Royals	Powerplay	5325	4467	
30	Rising Pune Supergiant	Death Overs	660	439	
31	Rising Pune Supergiant	Middle Overs	1018	894	
32	Rising Pune Supergiant	Powerplay	758	595	

33	Rising Pune Supergiants	Death Overs	616	377
34	Rising Pune Supergiants	Middle Overs	821	711
35	Rising Pune Supergiants	Powerplay	676	527
36	Royal Challengers Bangalore	Death Overs	6350	4002
37	Royal Challengers Bangalore	Middle Overs	10328	8215
38	Royal Challengers Bangalore	Powerplay	6944	5703
39	Sunrisers Hyderabad	Death Overs	3047	2033
40	Sunrisers Hyderabad	Middle Overs	5055	4022
41	Sunrisers Hyderabad	Powerplay	3363	2833

	wickets_taken
0	315
1	304
2	201
3	166
4	161
5	119
6	316
7	311
8	205
9	51
10	51
11	49
12	301
13	330
14	203
15	24
16	28
17	22
18	316
19	337
20	205
21	346
22	367
23	236
24	91
25	90
26	57
27	256
28	255
29	193
30	40
31	45
32	28
33	34
34	24
35	18

```
36            332
37            337
38            214
39            179
40            179
41            102
```

[112]:
```
# Calculate economy rate (runs conceded per over)
bowling_stats['economy_rate'] = round((bowling_stats['runs_conceded'] /
↪bowling_stats['balls_bowled']) * 6,2)

# Calculate bowling strike rate (balls bowled per wicket)
bowling_stats['bowling_strike_rate'] = round(bowling_stats['balls_bowled'] /
↪bowling_stats['wickets_taken'],2)
```

[113]:
```
bowling_stats
```

[113]:
```
                  bowling_team          phase  runs_conceded  balls_bowled  \
0          Chennai Super Kings    Death Overs           5173          3490
1          Chennai Super Kings   Middle Overs           8644          7181
2          Chennai Super Kings      Powerplay           5973          4891
3              Deccan Chargers    Death Overs           3451          2062
4              Deccan Chargers   Middle Overs           4939          4154
5              Deccan Chargers      Powerplay           3228          2823
6             Delhi Daredevils    Death Overs           5993          3834
7             Delhi Daredevils   Middle Overs           9673          7804
8             Delhi Daredevils      Powerplay           6677          5461
9                Gujarat Lions    Death Overs           1354           768
10               Gujarat Lions   Middle Overs           2235          1657
11               Gujarat Lions      Powerplay           1501          1120
12             Kings XI Punjab    Death Overs           6113          3815
13             Kings XI Punjab   Middle Overs          10203          8018
14             Kings XI Punjab      Powerplay           6954          5559
15         Kochi Tuskers Kerala    Death Overs            479           324
16         Kochi Tuskers Kerala   Middle Overs            914           759
17         Kochi Tuskers Kerala      Powerplay            593           531
18       Kolkata Knight Riders    Death Overs           5837          3905
19       Kolkata Knight Riders   Middle Overs           9518          7935
20       Kolkata Knight Riders      Powerplay           6680          5571
21              Mumbai Indians    Death Overs           6331          4271
22              Mumbai Indians   Middle Overs          10753          8724
23              Mumbai Indians      Powerplay           6751          5884
24               Pune Warriors    Death Overs           1934          1252
25               Pune Warriors   Middle Overs           2937          2487
26               Pune Warriors      Powerplay           1986          1718
27            Rajasthan Royals    Death Overs           4891          3165
28            Rajasthan Royals   Middle Overs           7638          6479
```

29	Rajasthan Royals	Powerplay	5325	4467
30	Rising Pune Supergiant	Death Overs	660	439
31	Rising Pune Supergiant	Middle Overs	1018	894
32	Rising Pune Supergiant	Powerplay	758	595
33	Rising Pune Supergiants	Death Overs	616	377
34	Rising Pune Supergiants	Middle Overs	821	711
35	Rising Pune Supergiants	Powerplay	676	527
36	Royal Challengers Bangalore	Death Overs	6350	4002
37	Royal Challengers Bangalore	Middle Overs	10328	8215
38	Royal Challengers Bangalore	Powerplay	6944	5703
39	Sunrisers Hyderabad	Death Overs	3047	2033
40	Sunrisers Hyderabad	Middle Overs	5055	4022
41	Sunrisers Hyderabad	Powerplay	3363	2833

	wickets_taken	economy_rate	bowling_strike_rate
0	315	8.89	11.08
1	304	7.22	23.62
2	201	7.33	24.33
3	166	10.04	12.42
4	161	7.13	25.80
5	119	6.86	23.72
6	316	9.38	12.13
7	311	7.44	25.09
8	205	7.34	26.64
9	51	10.58	15.06
10	51	8.09	32.49
11	49	8.04	22.86
12	301	9.61	12.67
13	330	7.64	24.30
14	203	7.51	27.38
15	24	8.87	13.50
16	28	7.23	27.11
17	22	6.70	24.14
18	316	8.97	12.36
19	337	7.20	23.55
20	205	7.19	27.18
21	346	8.89	12.34
22	367	7.40	23.77
23	236	6.88	24.93
24	91	9.27	13.76
25	90	7.09	27.63
26	57	6.94	30.14
27	256	9.27	12.36
28	255	7.07	25.41
29	193	7.15	23.15
30	40	9.02	10.98
31	45	6.83	19.87

```
32              28          7.64                21.25
33              34          9.80                11.09
34              24          6.93                29.62
35              18          7.70                29.28
36             332          9.52                12.05
37             337          7.54                24.38
38             214          7.31                26.65
39             179          8.99                11.36
40             179          7.54                22.47
41             102          7.12                27.77
```

[114]:

```python
# Sort by economy rate (lower is better)
economy_rate_sorted = bowling_stats.sort_values(by=['phase', 'economy_rate'])

# Sort by bowling strike rate (lower is better)
strike_rate_sorted = bowling_stats.sort_values(by=['phase',␣
↪'bowling_strike_rate'])

# Sort by wickets taken (higher is better)
wickets_sorted = bowling_stats.sort_values(by=['phase', 'wickets_taken'],␣
↪ascending=[True, False])
```

[115]:

```python
economy_rate_sorted.head()
```

[115]:

```
             bowling_team        phase  runs_conceded  balls_bowled  \
15    Kochi Tuskers Kerala  Death Overs            479           324
0      Chennai Super Kings  Death Overs           5173          3490
21          Mumbai Indians  Death Overs           6331          4271
18   Kolkata Knight Riders  Death Overs           5837          3905
39     Sunrisers Hyderabad  Death Overs           3047          2033

    wickets_taken  economy_rate  bowling_strike_rate
15             24          8.87                13.50
0             315          8.89                11.08
21            346          8.89                12.34
18            316          8.97                12.36
39            179          8.99                11.36
```

[116]:

```python
strike_rate_sorted.head()
```

[116]:

```
                   bowling_team        phase  runs_conceded  balls_bowled  \
30        Rising Pune Supergiant  Death Overs            660           439
0            Chennai Super Kings  Death Overs           5173          3490
33       Rising Pune Supergiants  Death Overs            616           377
39           Sunrisers Hyderabad  Death Overs           3047          2033
36   Royal Challengers Bangalore  Death Overs           6350          4002
```

```
    wickets_taken  economy_rate  bowling_strike_rate
30             40          9.02                10.98
0             315          8.89                11.08
33             34          9.80                11.09
39            179          8.99                11.36
36            332          9.52                12.05
```

[117]:

```
wickets_sorted.head()
```

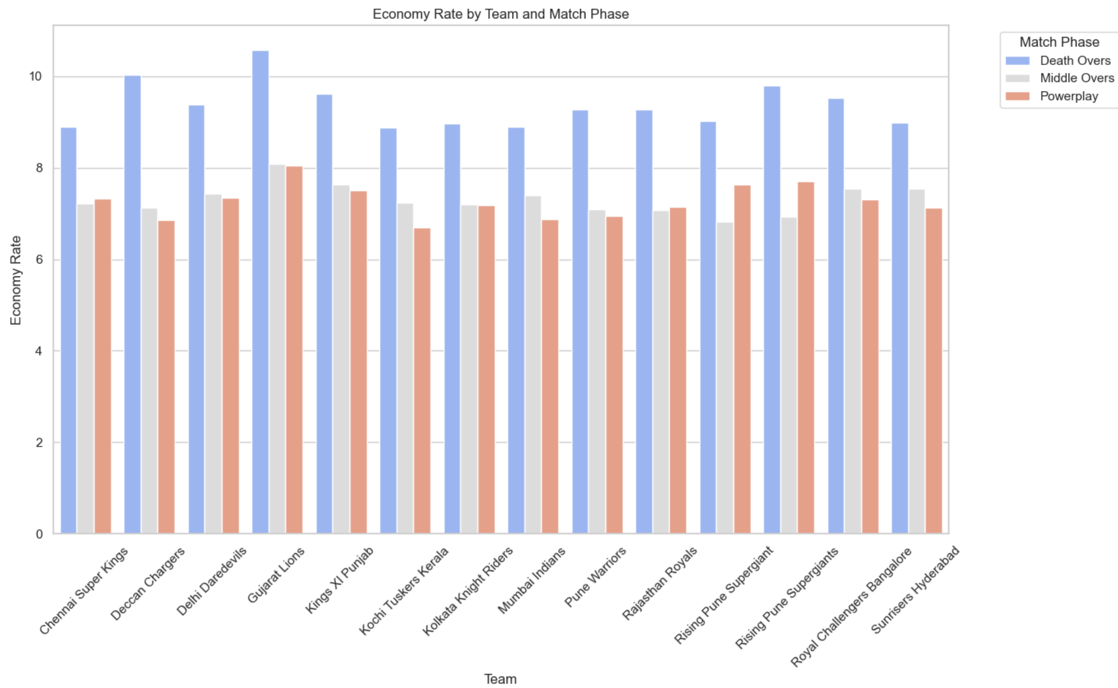
[117]:

```
                   bowling_team         phase  runs_conceded  balls_bowled  \
21               Mumbai Indians  Death Overs           6331          4271
36  Royal Challengers Bangalore  Death Overs           6350          4002
6              Delhi Daredevils  Death Overs           5993          3834
18        Kolkata Knight Riders  Death Overs           5837          3905
0           Chennai Super Kings  Death Overs           5173          3490

    wickets_taken  economy_rate  bowling_strike_rate
21            346          8.89                12.34
36            332          9.52                12.05
6             316          9.38                12.13
18            316          8.97                12.36
0             315          8.89                11.08
```

[118]:

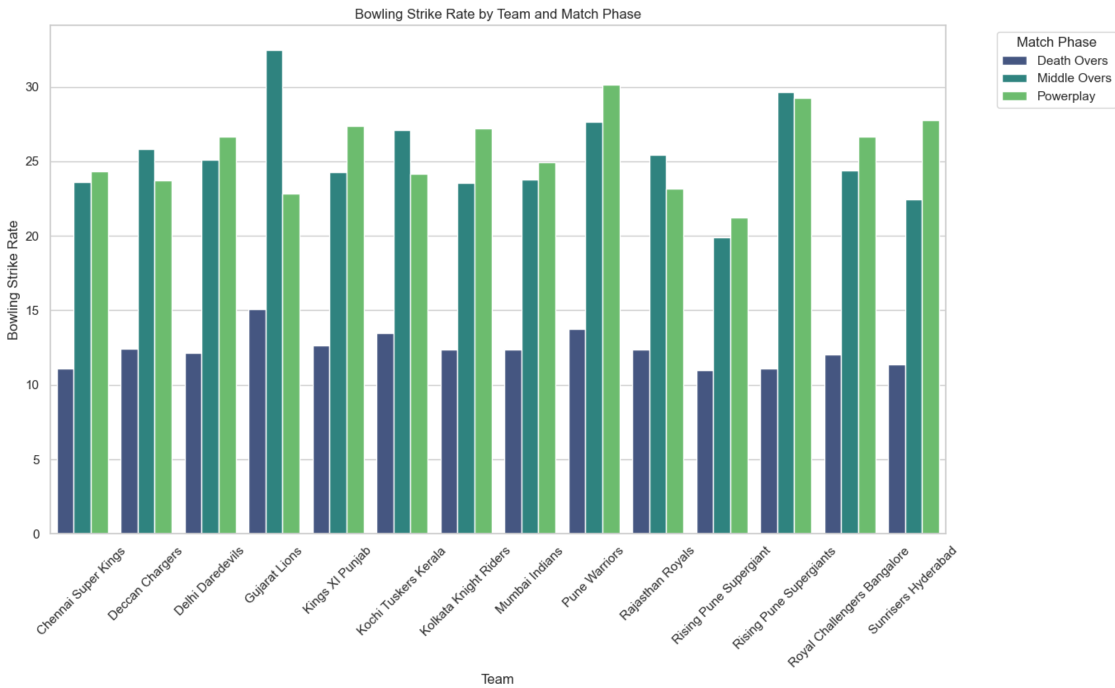
```
# Plot economy rate by phase
plt.figure(figsize=(14, 8))
sns.barplot(x='bowling_team', y='economy_rate', hue='phase',␣
↪data=bowling_stats, palette='coolwarm')
plt.title('Economy Rate by Team and Match Phase')
plt.xlabel('Team')
plt.ylabel('Economy Rate')
plt.legend(title='Match Phase', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45)
plt.show()
```



0.12.1 Insights:

Chennai Super Kings has the best Economy Rate in Match phases

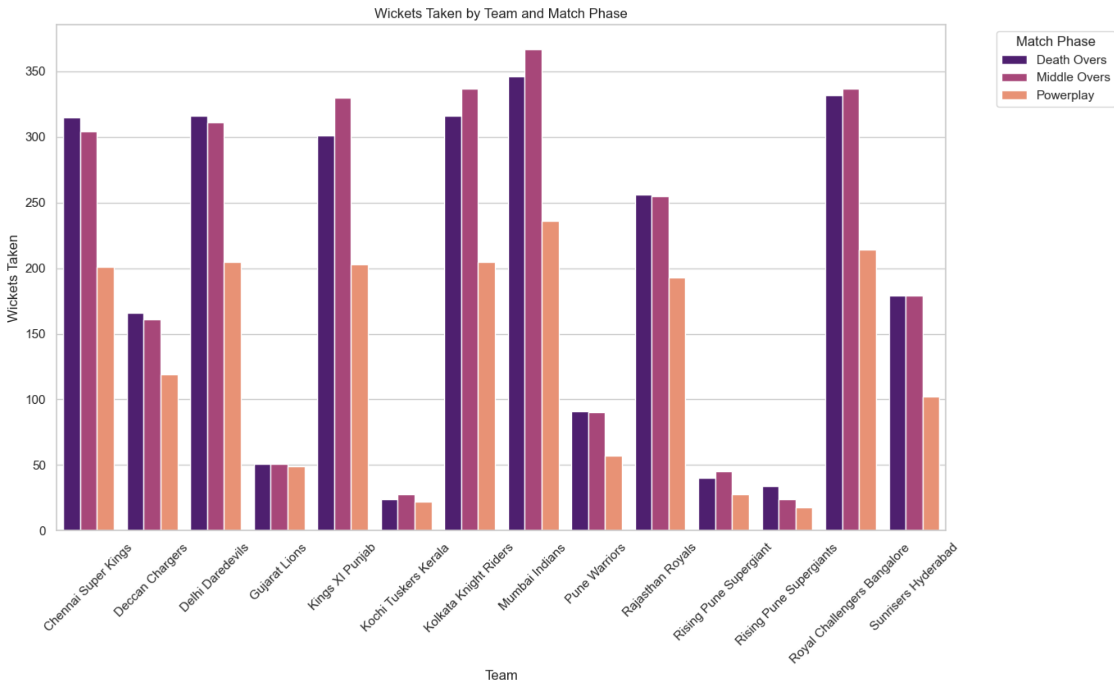
[119]:
```
# Plot bowling strike rate by phase
plt.figure(figsize=(14, 8))
sns.barplot(x='bowling_team', y='bowling_strike_rate', hue='phase',␣
 ↪data=bowling_stats, palette='viridis')
plt.title('Bowling Strike Rate by Team and Match Phase')
plt.xlabel('Team')
plt.ylabel('Bowling Strike Rate')
plt.legend(title='Match Phase', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45)
plt.show()
```



0.12.2 Insights:

Chennai Super Kings has better Bowling Strike rate compared to ther teams in match phase

[120]:
```
# Plot wickets taken by phase
plt.figure(figsize=(14, 8))
sns.barplot(x='bowling_team', y='wickets_taken', hue='phase',␣
↪data=bowling_stats, palette='magma')
plt.title('Wickets Taken by Team and Match Phase')
plt.xlabel('Team')
plt.ylabel('Wickets Taken')
plt.legend(title='Match Phase', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45)
plt.show()
```



0.12.3 Insights:

Mumbai Indians has taken most wickets comapred to other teams in different match phases

0.13 12. What are the characteristics of successful batting partnerships in terms of runs scored and duration

[121]:
```
# Group by match_id and batting partnership (batsman & non-striker)
partnership_df = df.groupby(['match_id', 'batsman', 'non_striker']).agg(
    total_runs=('total_runs', 'sum'),  # Total runs scored by the partnership
    balls_faced=('ball', 'count')  # Number of balls faced by the partnership
).reset_index()
```

[122]:
```
partnership_df
```

[122]:

	match_id	batsman	non_striker	total_runs	balls_faced
0	1	A Choudhary	YS Chahal	6	2
1	1	BCJ Cutting	DJ Hooda	16	6
2	1	CH Gayle	Mandeep Singh	28	20
3	1	CH Gayle	TM Head	6	3
4	1	DA Warner	S Dhawan	17	9
…	…	…	…	…	…
15830	636	V Kohli	AB de Villiers	22	10
15831	636	V Kohli	CH Gayle	33	26
15832	636	Yuvraj Singh	BCJ Cutting	1	2

```
15833       636  Yuvraj Singh       DA Warner          19            13
15834       636  Yuvraj Singh        DJ Hooda          19             9

[15835 rows x 5 columns]
```

[123]:
```
# Calculate the strike rate for each partnership
partnership_df['strike_rate'] = round((partnership_df['total_runs'] /␣
 ↪partnership_df['balls_faced']) * 100,2)
```

[124]:
```
# Sort partnerships by total runs scored in descending order
successful_partnerships = partnership_df.sort_values(by='total_runs',␣
 ↪ascending=False)
```

[125]:
```
top_partnerships=successful_partnerships.head(10)
```

[126]:
```
top_partnerships
```

[126]:
```
       match_id         batsman non_striker  total_runs  balls_faced  \
14028       562  AB de Villiers      V Kohli         138           61
15400       620  AB de Villiers      V Kohli         132           53
10324       411        CH Gayle  TM Dilshan         130           49
9300        372        CH Gayle      V Kohli         128           55
7447        296    AC Gilchrist    SE Marsh         126           51
8328        331       DA Warner     NV Ojha         119           55
1807         72    AC Gilchrist  VVS Laxman         116           50
9091        363       RG Sharma    HH Gibbs         113           62
891          36       DA Warner    S Dhawan         105           47
57            3         CA Lynn   G Gambhir         102           46

       strike_rate
14028       226.23
15400       249.06
10324       265.31
9300        232.73
7447        247.06
8328        216.36
1807        232.00
9091        182.26
891         223.40
57          221.74
```

0.14 13. How do individual batsmen perform against specific bowlers? Are there any notable batsman-bowler matchups?

[127]:
```
# Filter data to focus on batsman-bowler interactions
df_batsman_bowler = df[df['batsman'].notna() & df['bowler'].notna()]
```

[128]:
```
df_batsman_bowler[['batsman','bowler']].head()
```

[128]:
```
     batsman    bowler
0  DA Warner  TS Mills
1  DA Warner  TS Mills
2  DA Warner  TS Mills
3  DA Warner  TS Mills
4  DA Warner  TS Mills
```

[129]:
```
# Group by batsman and bowler to calculate performance metrics
batsman_bowler_performance = df_batsman_bowler.groupby(['batsman', 'bowler']).
 ↪agg(
    runs_scored=('batsman_runs', 'sum'),
    balls_faced=('ball', 'count'),
    dismissals=('player_dismissed', lambda x: x.notna().sum())
).reset_index()
```

[130]:
```
# Calculate strike rate
batsman_bowler_performance['strike_rate'] =␣
 ↪round((batsman_bowler_performance['runs_scored'] /
                                                    ␣
 ↪batsman_bowler_performance['balls_faced']) * 100,2)
```

[131]:
```
batsman_bowler_performance.head()
```

[131]:
```
          batsman         bowler  runs_scored  balls_faced  dismissals  \
0  A Ashish Reddy        A Nehra            7            9           1
1  A Ashish Reddy       AB Dinda            9            7           0
2  A Ashish Reddy     AD Mathews           25           12           0
3  A Ashish Reddy     AD Russell            4            3           1
4  A Ashish Reddy  Anureet Singh            2            2           0

   strike_rate
0        77.78
1       128.57
2       208.33
3       133.33
4       100.00
```

[132]:
```
# Top 10 batsman-bowler pairs by runs scored
top_runs = batsman_bowler_performance.sort_values(by='runs_scored',␣
 ↪ascending=False).head(10)

# Top 10 batsman-bowler pairs by strike rate (minimum 30 balls faced)
top_strike_rate =␣
 ↪batsman_bowler_performance[batsman_bowler_performance['balls_faced'] >= 30].
 ↪sort_values(by='strike_rate',
```

```
↪                          ascending=False).head(10)

# Top 10 bowlers by dismissals of a specific batsman
top_dismissals = batsman_bowler_performance.sort_values(by='dismissals',␣
↪ascending=False).head(10)
```

[133]:
```
top_runs
```

[133]:

	batsman	bowler	runs_scored	balls_faced	dismissals	\
14007	SK Raina	PP Chawla	152	90	4	
15913	V Kohli	A Mishra	149	95	1	
16085	V Kohli	UT Yadav	141	83	4	
12238	RG Sharma	PP Chawla	136	103	1	
13936	SK Raina	Harbhajan Singh	132	125	5	
6744	KA Pollard	A Mishra	131	79	1	
15954	V Kohli	DJ Bravo	130	91	1	
16042	V Kohli	R Ashwin	127	101	0	
3370	DA Warner	P Kumar	124	92	3	
12212	RG Sharma	M Morkel	119	69	2	

	strike_rate
14007	168.89
15913	156.84
16085	169.88
12238	132.04
13936	105.60
6744	165.82
15954	142.86
16042	125.74
3370	134.78
12212	172.46

[134]:
```
top_strike_rate
```

[134]:

	batsman	bowler	runs_scored	balls_faced	dismissals	\
5974	JA Morkel	SK Warne	89	39	0	
5666	IK Pathan	RP Singh	68	31	1	
15998	V Kohli	KV Sharma	79	37	0	
6455	JP Duminy	JJ Bumrah	70	33	1	
628	AB de Villiers	Sandeep Sharma	69	33	2	
6856	KA Pollard	RA Jadeja	77	37	2	
6505	JP Duminy	R Vinay Kumar	62	30	0	
547	AB de Villiers	JP Faulkner	62	30	1	
2182	BB McCullum	JA Morkel	63	31	0	
14052	SK Raina	Sandeep Sharma	65	32	1	

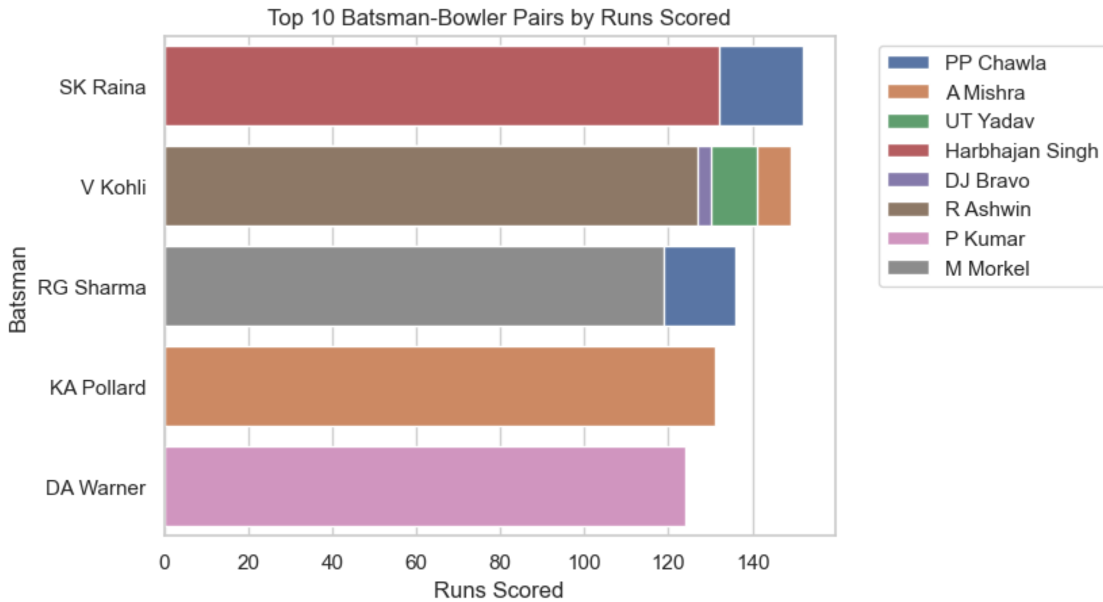
```
       strike_rate
5974        228.21
5666        219.35
15998       213.51
6455        212.12
628         209.09
6856        208.11
6505        206.67
547         206.67
2182        203.23
14052       203.12
```

[135]:
```
top_dismissals
```

[135]:
```
          batsman         bowler  runs_scored  balls_faced  dismissals  \
9985     MS Dhoni         Z Khan           74           43           7
9917     MS Dhoni        PP Ojha           98          100           7
4887   G Gambhir          Z Khan          109           85           6
1313   AM Rahane         B Kumar           69           75           6
15914    V Kohli         A Nehra           60           57           6
12272  RG Sharma      SK Trivedi           45           38           6
10853   PA Patel         B Kumar           50           59           6
12251  RG Sharma  R Vinay Kumar           22           34           6
12162  RG Sharma        DJ Bravo           66           60           5
14672  SR Watson        AR Patel           25           29           5

       strike_rate
9985        172.09
9917         98.00
4887        128.24
1313         92.00
15914       105.26
12272       118.42
10853        84.75
12251        64.71
12162       110.00
14672        86.21
```

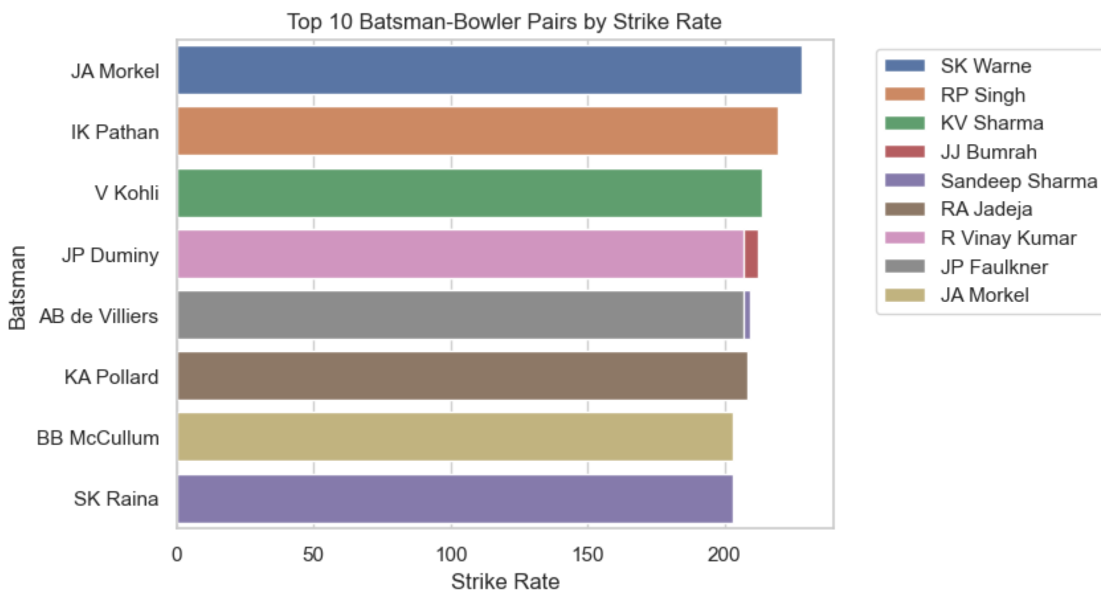
[136]:
```
sns.barplot(data=top_runs, x='runs_scored', y='batsman',␣
 ↪hue='bowler',dodge=False)
plt.title('Top 10 Batsman-Bowler Pairs by Runs Scored')
plt.xlabel('Runs Scored')
plt.ylabel('Batsman')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



0.14.1 Insights:

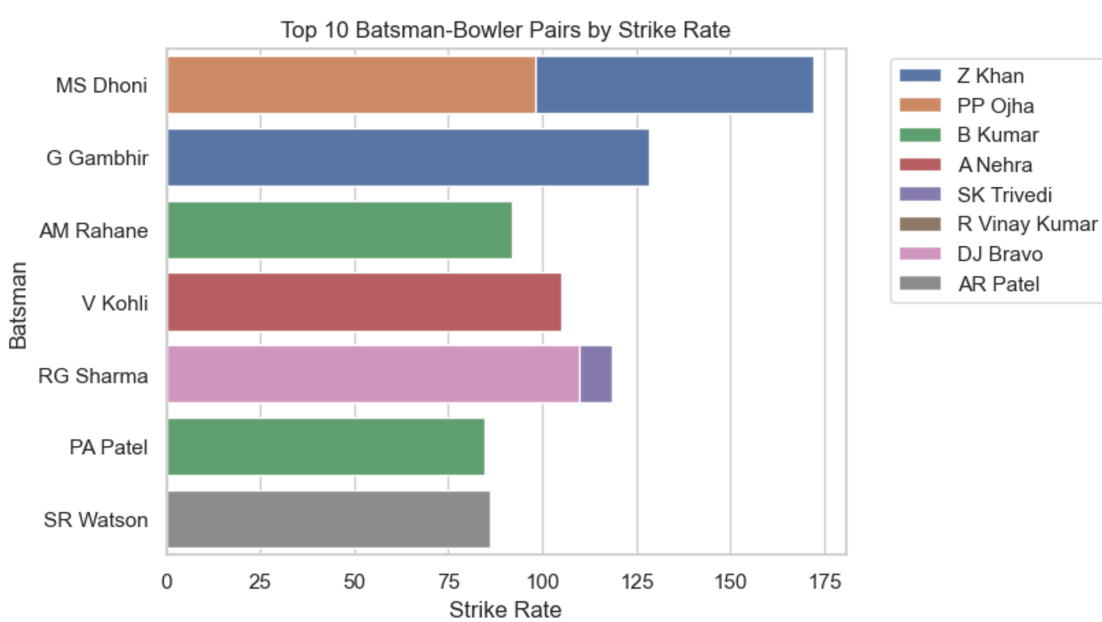
Virat Kohli has scored runs against bowlers like R Ashwin, DJ Bravo,Umesh Yadav, Amit Mishra

[137]:
```
# Bar chart of top 10 batsman-bowler pairs by strike rate
sns.barplot(data=top_strike_rate, x='strike_rate', y='batsman', hue='bowler',␣
↪dodge=False)
plt.title('Top 10 Batsman-Bowler Pairs by Strike Rate')
plt.xlabel('Strike Rate')
plt.ylabel('Batsman')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



[138]:

```
# Bar chart of top 10 batsman-bowler pairs by strike rate
sns.barplot(data=top_dismissals, x='strike_rate', y='batsman',␣
 ↪hue='bowler',dodge=False)
plt.title('Top 10 Batsman-Bowler Pairs by Strike Rate')
plt.xlabel('Strike Rate')
plt.ylabel('Batsman')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



0.14.2 Insights:

MS Dhoni has been dismissed by bowlers like Zaheer Khan, PP Ojha Gambhir has been dismissed by bowlers like Zaheer Khan

0.15 14. Do certain batsmen have a higher tendency to get dismissed in specific ways?

[139]:
```
# Remove NaN values in 'dismissal_kind' as they indicate not out cases
dismissal_counts = df.dropna(subset=['dismissal_kind'])

# Count dismissals per batsman and dismissal type
batsman_dismissals = dismissal_counts.groupby(['batsman', 'dismissal_kind']).
 ↪size().reset_index(name='count')

# Sort to show the most common dismissals per batsman
batsman_dismissals_sorted = batsman_dismissals.sort_values(by=['count'],␣
 ↪ascending=[False])

# Display the top 10 most common dismissals
batsman_dismissals_sorted.head(10)
```

[139]:

	batsman	dismissal_kind	count
1114	SK Raina	caught	94
1022	RV Uthappa	caught	87
971	RG Sharma	caught	83
390	G Gambhir	caught	77
1275	V Kohli	caught	76
1347	Yuvraj Singh	caught	76
561	KD Karthik	caught	71
1282	V Sehwag	caught	70
1333	YK Pathan	caught	68
778	MS Dhoni	caught	65

0.16 15. How does the presence of specific batsmen at the crease impact the batting team's run rate?

[140]:
```
# Calculate total runs and total balls faced per batsman
batsman_run_rate = df.groupby('batsman').agg(
    total_runs=('total_runs', 'sum'),
    total_balls=('ball', 'count')
).reset_index()

# Convert balls to overs (1 over = 6 balls)
batsman_run_rate['overs_faced'] = round(batsman_run_rate['total_balls'] / 6,2)
```

```
# Calculate run rate (Runs per over)
batsman_run_rate['run_rate'] = round(batsman_run_rate['total_runs'] /␣
↪batsman_run_rate['overs_faced'],2)

batsman_run_rate = batsman_run_rate[batsman_run_rate['total_balls']>=100]

# Sort by highest run rate
batsman_run_rate_sorted = batsman_run_rate.sort_values(by='run_rate',␣
↪ascending=False)
```

[141]:
```
# Display top 10 batsmen with the highest impact on run rate
batsman_run_rate_sorted.head(10)
```

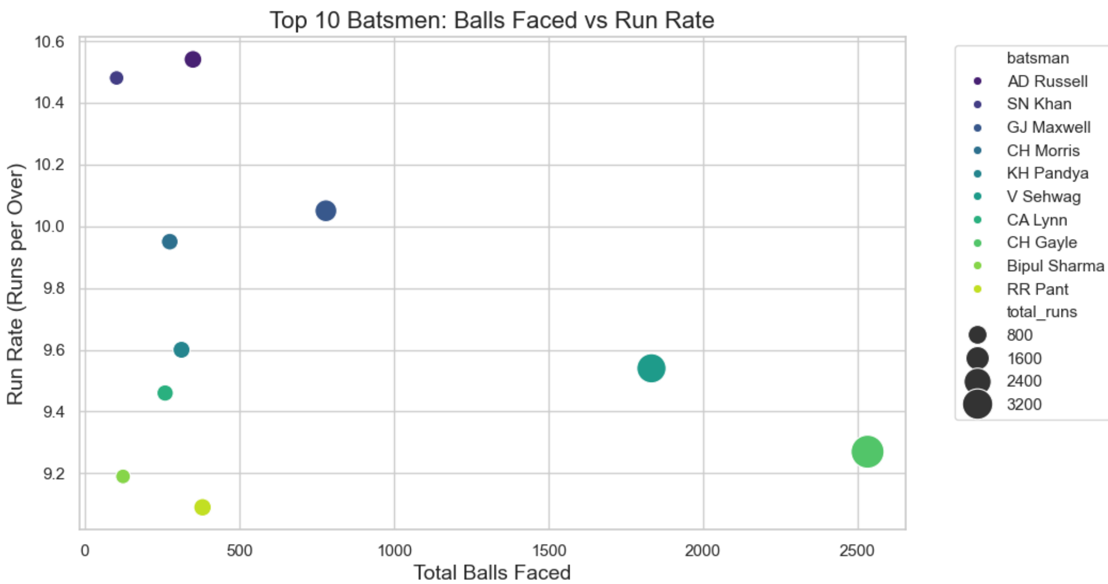
[141]:

	batsman	total_runs	total_balls	overs_faced	run_rate
30	AD Russell	615	350	58.33	10.54
382	SN Khan	180	103	17.17	10.48
143	GJ Maxwell	1306	780	130.00	10.05
86	CH Morris	456	275	45.83	9.95
196	KH Pandya	501	313	52.17	9.60
433	V Sehwag	2915	1833	305.50	9.54
83	CA Lynn	410	260	43.33	9.46
85	CH Gayle	3914	2532	422.00	9.27
77	Bipul Sharma	190	124	20.67	9.19
330	RR Pant	577	381	63.50	9.09

[142]:
```
# Scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x='total_balls',
    y='run_rate',
    size='total_runs',
    hue='batsman',
    data=batsman_run_rate_sorted.head(10),
    palette='viridis',
    sizes=(100, 500)
)

# Add labels and title
plt.title('Top 10 Batsmen: Balls Faced vs Run Rate', fontsize=16)
plt.xlabel('Total Balls Faced', fontsize=14)
plt.ylabel('Run Rate (Runs per Over)', fontsize=14)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

plt.show()
```



0.16.1 Insights:

Batsman like Andre Russel,Glenn Maxwell can significantly impact batting teams runrate.

0.17 16. How have average run rates and scoring patterns evolved across different IPL seasons?

[143]:
```
df_analysis = df[['season', 'total_runs', 'ball']].copy()

# Group by season and calculate the average run rate
seasonal_run_rates = df_analysis.groupby('season').agg(
    total_runs=("total_runs",'sum'),
    total_balls=('ball','count')
)
```

[144]:
```
seasonal_run_rates['run_rate'] = (seasonal_run_rates['total_runs']/
↪seasonal_run_rates['total_balls'])*6
```

[145]:
```
seasonal_run_rates
```

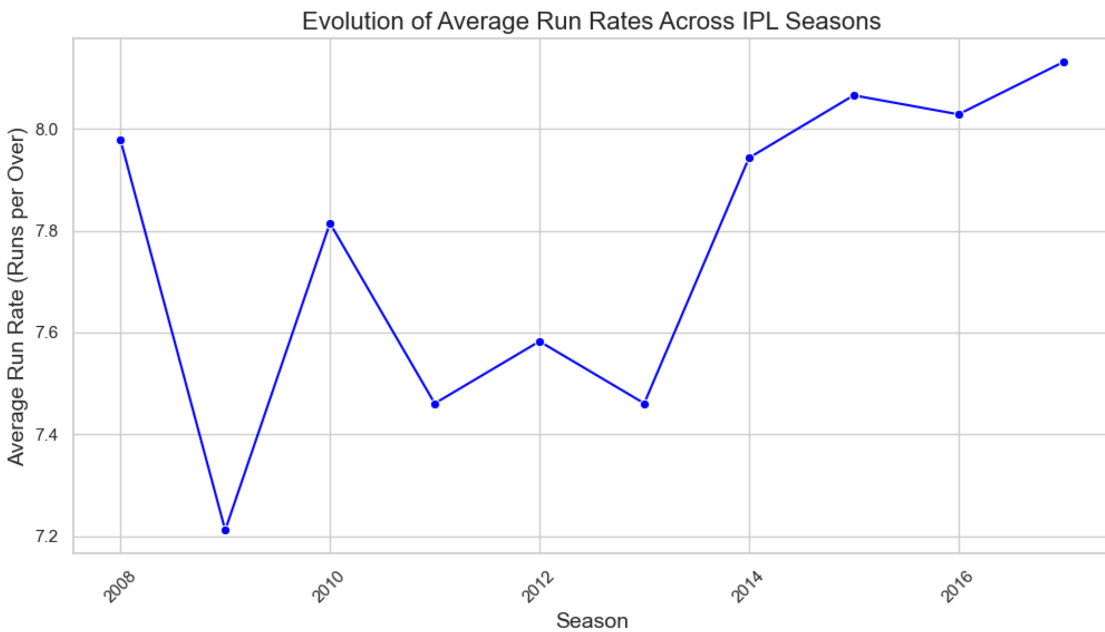
[145]:

season	total_runs	total_balls	run_rate
2008	17937	13489	7.978501
2009	16353	13606	7.211377
2010	18883	14498	7.814733
2011	21154	17013	7.460413
2012	22453	17767	7.582484
2013	22602	18177	7.460637

```
2014          18931         14300   7.943077
2015          18353         13652   8.066071
2016          18862         14096   8.028661
2017          18786         13862   8.131294
```

[146]:

```
# Visualization
plt.figure(figsize=(12, 6))
sns.lineplot(x='season', y='run_rate', data=seasonal_run_rates, marker='o',␣
 ↪color='blue')
plt.title('Evolution of Average Run Rates Across IPL Seasons', fontsize=16)
plt.xlabel('Season', fontsize=14)
plt.ylabel('Average Run Rate (Runs per Over)', fontsize=14)
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



0.17.1 Insights:

Runrate has gradually increased from season to season it ranged from 7.5 and now it is going above 8

0.18 17. Has the distribution of different dismissal types changed over the seasons?

[147]:
```
# Create a new dataframe with necessary columns
df_dismissals = df[['season', 'dismissal_kind']].copy()

# Filter rows where dismissal_kind is not null
df_dismissals = df_dismissals[df_dismissals['dismissal_kind'].notnull()]

# Group by season and dismissal_kind and count the occurrences
dismissal_counts = df_dismissals.groupby(['season', 'dismissal_kind']).size().
↪reset_index(name='count')

# Calculate the total dismissals for each season
total_dismissals = dismissal_counts.groupby('season')['count'].sum().
↪reset_index(name='total_dismissals')

# Merge the total dismissals back to the dismissal_counts dataframe
dismissal_counts = dismissal_counts.merge(total_dismissals, on='season')

# Calculate the percentage of each dismissal type for each season
dismissal_counts['percentage'] = (dismissal_counts['count'] /␣
↪dismissal_counts['total_dismissals']) * 100

# Pivot the data for visualization
dismissal_pivot = dismissal_counts.pivot(index='season',␣
↪columns='dismissal_kind', values='percentage')
```

[148]:
```
dismissal_pivot
```

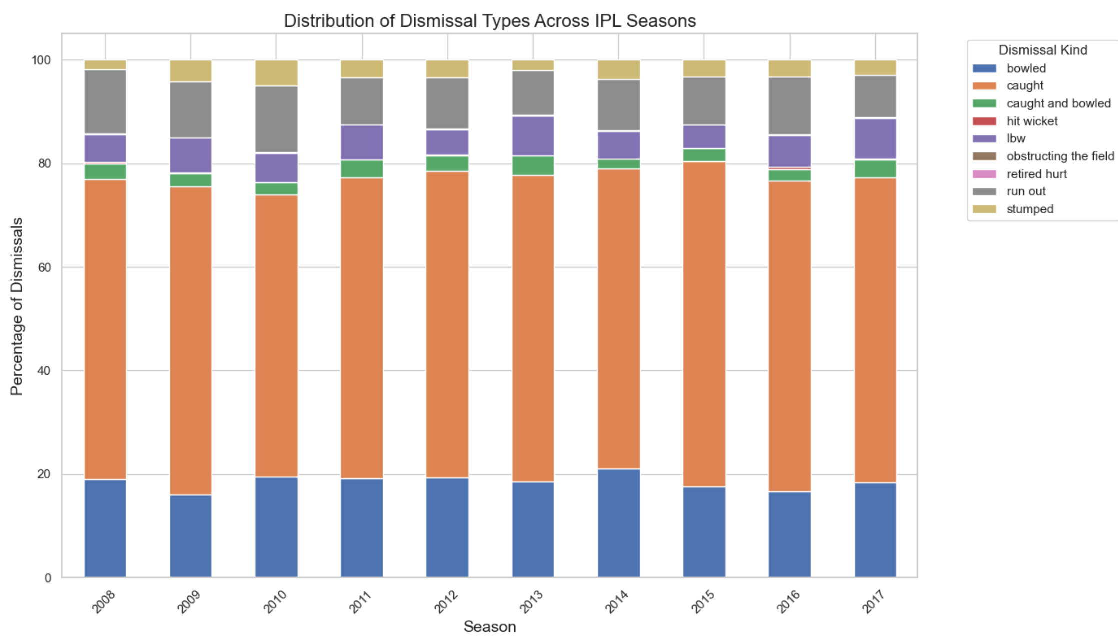
[148]:
```
dismissal_kind     bowled     caught  caught and bowled  hit wicket       lbw  \
season
2008            18.985507  57.971014           3.043478    0.289855  5.362319
2009            16.045845  59.455587           2.578797    0.143266  6.733524
2010            19.448276  54.482759           2.344828         NaN  5.655172
2011            19.188192  58.056581           3.567036         NaN  6.642066
2012            19.347319  59.207459           2.913753    0.233100  4.895105
2013            18.640351  59.100877           3.728070         NaN  7.675439
2014            21.068249  58.011869           1.780415         NaN  5.341246
2015            17.655572  62.807525           2.460203         NaN  4.486252
2016            16.666667  60.060060           2.102102    0.450450  6.156156
2017            18.424754  58.931083           3.375527    0.140647  7.876231

dismissal_kind  obstructing the field  retired hurt    run out   stumped
season
2008                              NaN      0.144928  12.318841  1.884058
2009                              NaN           NaN  10.888252  4.154728
```

```
2010                        NaN   0.275862  12.827586  4.965517
2011                        NaN        NaN   9.102091  3.444034
2012                        NaN   0.116550   9.906760  3.379953
2013                   0.109649   0.109649   8.662281  1.973684
2014                        NaN   0.148368   9.940653  3.709199
2015                        NaN   0.144718   9.261939  3.183792
2016                        NaN   0.150150  11.111111  3.303303
2017                        NaN   0.140647   8.157525  2.953586
```

[149]:

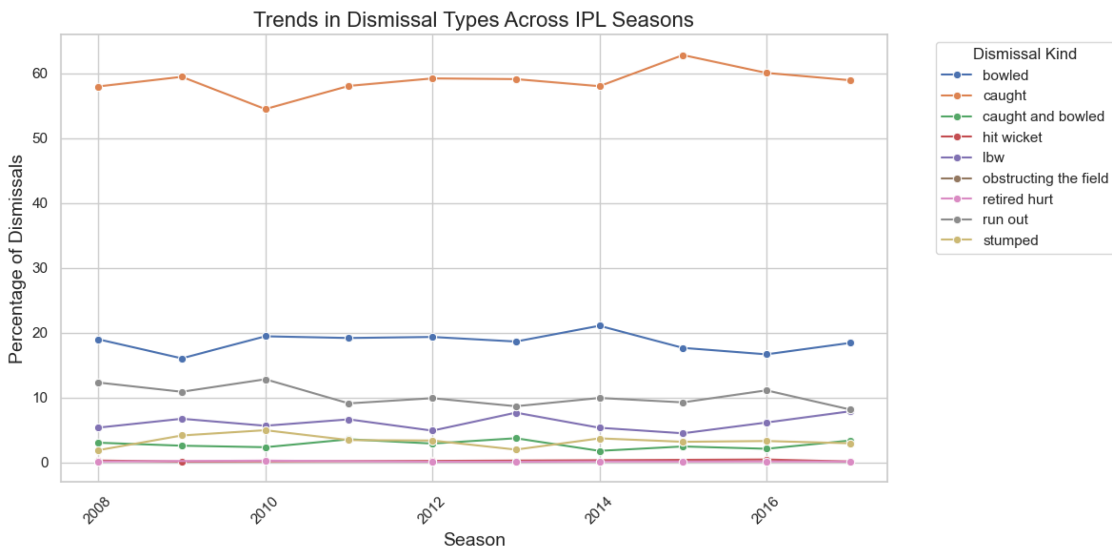
```
# Visualization: Stacked Bar Plot
dismissal_pivot.plot(kind='bar', stacked=True, figsize=(14, 8))
plt.title('Distribution of Dismissal Types Across IPL Seasons', fontsize=16)
plt.xlabel('Season', fontsize=14)
plt.ylabel('Percentage of Dismissals', fontsize=14)
plt.xticks(rotation=45)
plt.legend(title='Dismissal Kind', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



[150]:

```
# Visualization: Line Plot for Specific Dismissal Types
plt.figure(figsize=(12, 6))
for dismissal in dismissal_pivot.columns:
    sns.lineplot(x=dismissal_pivot.index, y=dismissal_pivot[dismissal],␣
 ↪label=dismissal, marker='o')
plt.title('Trends in Dismissal Types Across IPL Seasons', fontsize=16)
plt.xlabel('Season', fontsize=14)
```

```
plt.ylabel('Percentage of Dismissals', fontsize=14)
plt.xticks(rotation=45)
plt.legend(title='Dismissal Kind', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
plt.tight_layout()
plt.show()
```



0.18.1 Insights:

From the visualization we can say that the dismissal types across seasons is similar

0.19 18. How do average runs scored and wickets taken per match differ across various venues?

[151]:
```
df_analysis = df[['venue', 'total_runs', 'player_dismissed', 'match_id']].copy()

# Calculate total runs and total wickets per match for each venue
venue_stats = df_analysis.groupby(['venue', 'match_id']).agg(
    total_runs=('total_runs', 'sum'),
    total_wickets=('player_dismissed', 'count')
).reset_index()

# Calculate average runs and average wickets per match for each venue
venue_avg_stats = venue_stats.groupby('venue').agg(
    avg_runs_per_match=('total_runs', 'mean'),
    avg_wickets_per_match=('total_wickets', 'mean')
).reset_index()
```

[152]:
```
venue_avg_stats
```

[152]:

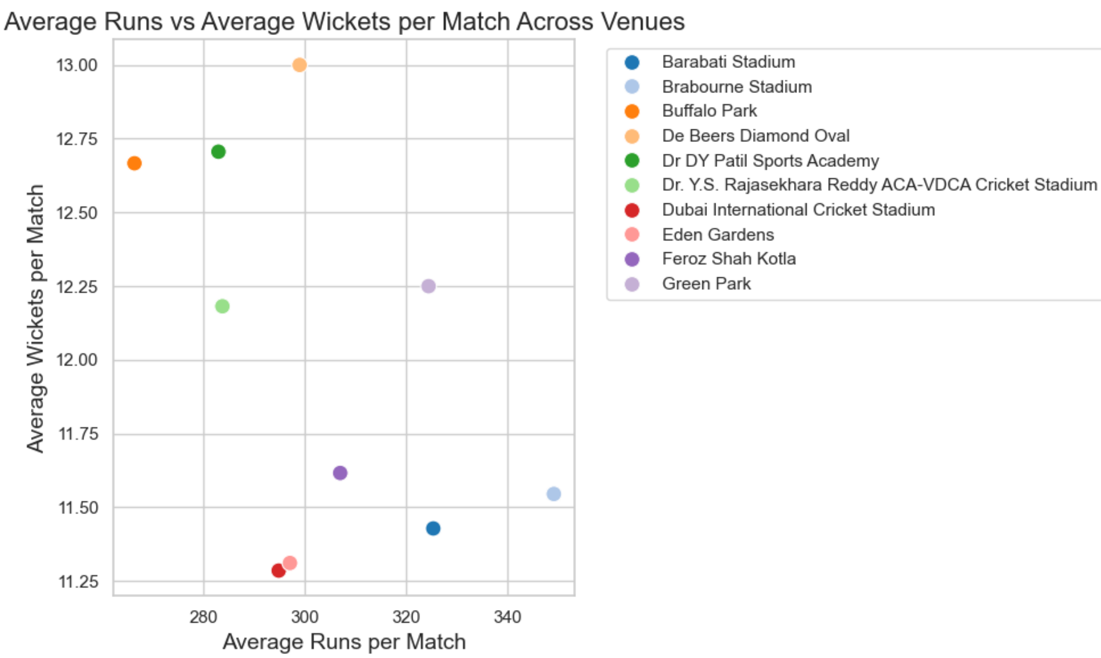
```
                                               venue  avg_runs_per_match  \
0                                   Barabati Stadium          325.428571
1                                  Brabourne Stadium          349.272727
2                                       Buffalo Park          266.333333
3                              De Beers Diamond Oval          299.000000
4                         Dr DY Patil Sports Academy          282.941176
5   Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket St…          283.727273
6                 Dubai International Cricket Stadium          294.857143
7                                       Eden Gardens          297.081967
8                                   Feroz Shah Kotla          307.016667
9                                         Green Park          324.500000
10       Himachal Pradesh Cricket Association Stadium          321.888889
11                              Holkar Cricket Stadium          315.200000
12                 JSCA International Stadium Complex          293.714286
13                                          Kingsmead          290.200000
14                             M Chinnaswamy Stadium          311.545455
15                  MA Chidambaram Stadium, Chepauk          318.270833
16            Maharashtra Cricket Association Stadium          317.466667
17                                      Nehru Stadium          272.600000
18                              New Wanderers Stadium          286.500000
19                                           Newlands          256.714286
20                                     OUTsurance Oval          264.500000
21  Punjab Cricket Association IS Bindra Stadium, …          322.272727
22          Punjab Cricket Association Stadium, Mohali          313.914286
23           Rajiv Gandhi International Stadium, Uppal          303.836735
24                        Sardar Patel Stadium, Motera          313.916667
25            Saurashtra Cricket Association Stadium          333.300000
26                             Sawai Mansingh Stadium          298.818182
27   Shaheed Veer Narayan Singh International Stadium          290.166667
28                             Sharjah Cricket Stadium          304.833333
29                                Sheikh Zayed Stadium          276.142857
30                                    St George's Park          290.428571
31                            Subrata Roy Sahara Stadium          279.705882
32                                     SuperSport Park          304.416667
33      Vidarbha Cricket Association Stadium, Jamtha          294.000000
34                                     Wankhede Stadium          315.631579

    avg_wickets_per_match
0               11.428571
1               11.545455
2               12.666667
3               13.000000
4               12.705882
5               12.181818
6               11.285714
7               11.311475
8               11.616667
```

```
9               12.250000
10              11.555556
11               9.000000
12              11.571429
13              13.400000
14              11.515152
15              11.791667
16              11.733333
17              12.400000
18              11.500000
19              13.285714
20              12.500000
21              10.454545
22              11.742857
23              11.530612
24              12.083333
25              10.900000
26              10.969697
27              10.000000
28              10.500000
29              13.714286
30              11.000000
31              11.823529
32              11.083333
33              16.000000
34              12.263158
```

[153]:

```python
# Visualization: Scatter Plot for Average Runs vs Average Wickets
plt.figure(figsize=(10, 6))
sns.scatterplot(x='avg_runs_per_match', y='avg_wickets_per_match', hue='venue',␣
    ↪data=venue_avg_stats.head(10), palette='tab20', s=100)
plt.title('Average Runs vs Average Wickets per Match Across Venues',␣
    ↪fontsize=16)
plt.xlabel('Average Runs per Match', fontsize=14)
plt.ylabel('Average Wickets per Match', fontsize=14)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



0.19.1 Insights:

From the graph we can see that Diamond Oval Stadium has an average runs per match of 300 and average wickets per match is around 13

0.20 19. Is there a significant difference in batting team performance between the first and second innings?

[154]:
```
df_analysis = df[['inning', 'total_runs', 'over', 'ball', 'match_id']].copy()


df_analysis = df_analysis.groupby('inning').agg(
    total_runs=('total_runs', 'sum'),
    total_balls=('ball', 'count')
).reset_index()

df_analysis['runrate'] = round((df_analysis['total_runs']/
 ↪df_analysis['total_balls'])*6,2)
```

[155]:
```
# Separate the data into first and second innings
first_innings = df_analysis[df_analysis['inning'] == 1]
second_innings = df_analysis[df_analysis['inning'] == 2]

# Calculate total runs for each innings
total_runs_first = first_innings['total_runs']
total_runs_second = second_innings['total_runs']
```

```
# Display the average run rates and total runs
print(f'Average Run Rate - First Innings: {first_innings['runrate'].values}')
print(f'Average Run Rate - Second Innings: {second_innings['runrate'].values}')
print(f'Total Runs - First Innings: {total_runs_first.values}')
print(f'Total Runs - Second Innings: {total_runs_second.values}')
```

```
Average Run Rate - First Innings: [7.81]
Average Run Rate - Second Innings: [7.68]
Total Runs - First Innings: [101547]
Total Runs - Second Innings: [92594]
```

0.20.1 Insights:

There is no much significant change in first and second innings scorings

0.21 20. Analyze how the average win by runs has changed across seasons. Is there a trend towards higher or lower scoring matches?

[156]:
```
df_analysis = df[['season', 'win_by_runs', 'result']].copy()

# Filter matches where the result is a win by runs (win_by_runs > 0)
df_analysis = df_analysis[df_analysis['win_by_runs'] > 0]

# Group by season and calculate the average win by runs
seasonal_avg_win_by_runs = df_analysis.groupby('season')['win_by_runs'].mean().
    reset_index(name='avg_win_by_runs')
```

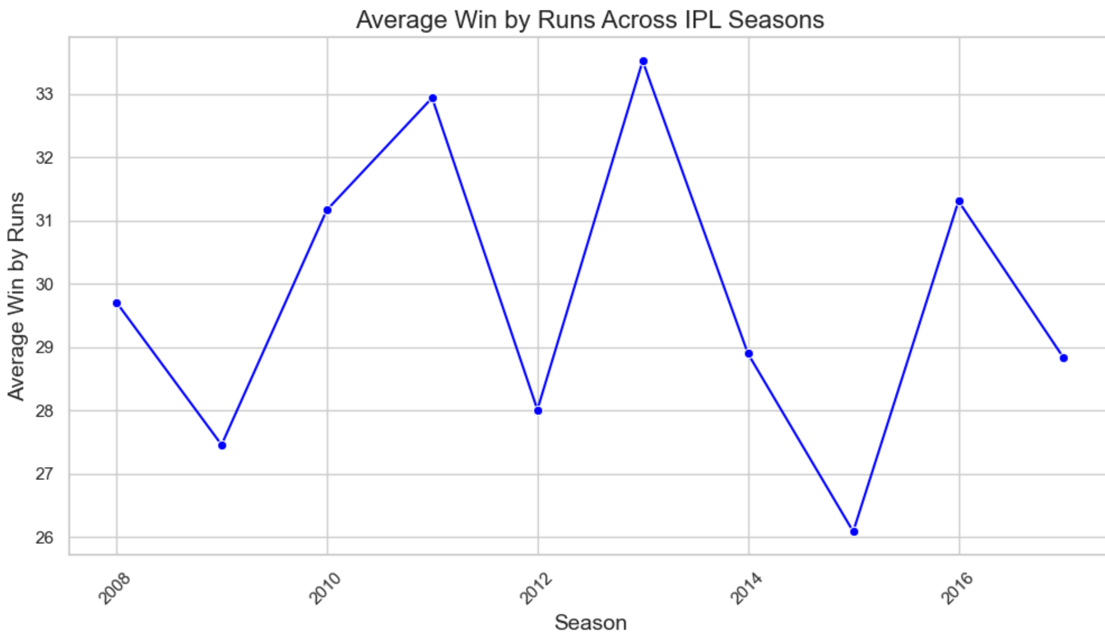
[157]:
```
seasonal_avg_win_by_runs
```

[157]:

	season	avg_win_by_runs
0	2008	29.711351
1	2009	27.459077
2	2010	31.167037
3	2011	32.937461
4	2012	28.013867
5	2013	33.519537
6	2014	28.899108
7	2015	26.089247
8	2016	31.306348
9	2017	28.828192

[158]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(x='season', y='avg_win_by_runs', data=seasonal_avg_win_by_runs,
    marker='o', color='blue')
plt.title('Average Win by Runs Across IPL Seasons', fontsize=16)
plt.xlabel('Season', fontsize=14)
plt.ylabel('Average Win by Runs', fontsize=14)
```

```
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



0.21.1 Insights :

Trend Over Time: The average win margin by runs has fluctuated over the seasons. It peaked at 31 runs in one season and dropped to 20 runs in another.

```
[ ]:
```