





CHALLENGERS

Tabular Data Visualization  
Interesting insights into  
Premier League cricket  
matches

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# Overview

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# Introduction

- The dataset contains information about Indian Premier League (IPL) matches from 2008 to 2019.
- IPL is a professional Twenty20 cricket league formed by the Board of Control for Cricket in India (BCCI).
- The league consists of eight clubs representing different states or cities in India.
- The dataset is in CSV format and has 756 rows and 18 columns.
- The rows signify games played, so there were 756 games played during the time period of the dataset.
- The columns provide information such as match ID, season, city, date, teams, toss winner and decision, match result, winner, margin of victory, outstanding player of the match, venue, and umpires.
- The dataset can be used for data visualization and cleaning to understand the statistics and trends of the IPL matches over the years.
- IPL is extremely popular, with the league's brand value estimated to reach \$475 billion (US\$6.7 billion) in 2019.
- The league consists of eight clubs, each representing one of India's eight states or cities. It is extremely popular, with the IPL's brand value estimated to reach \$475 billion (US\$6.7 billion) in 2019. So, let's look at the IPL in terms of statistics.





# Objectives - Finding Trends

- To determine Most successful teams.
- To determine Impact of toss decision.
- To determine Winning margin.
- To determine Player of the match.
- To determine Season-wise analysis.
- To determine Venue analysis and many more.





# Dataset

- Source is Data world.
- The dataset is in CSV format
- It has 756 rows and 18 columns
- Rows signify games played - so 756 games played.
- <https://data.world/coolboipranav/ipl-data/workspace/file?filename=matches.csv>



```
In [257]: import pandas as pd
df = pd.read_csv('C:/Users/rohit/Downloads/EDA Project Data/IPL.csv')
df
```

```
Out[257]:
```

|     | id    | Season   | city          | date       | team1                       | team2                       | toss_winner                 | toss_decision | result | dl_applied | winner                      | win_by_runs | win_by_wickets | p   |
|-----|-------|----------|---------------|------------|-----------------------------|-----------------------------|-----------------------------|---------------|--------|------------|-----------------------------|-------------|----------------|-----|
| 0   | 1     | IPL-2017 | Hyderabad     | 05-04-2017 | Sunrisers Hyderabad         | Royal Challengers Bangalore | Royal Challengers Bangalore | field         | normal | 0          | Sunrisers Hyderabad         | 35          | 0              |     |
| 1   | 2     | IPL-2017 | Pune          | 06-04-2017 | Mumbai Indians              | Rising Pune Supergiant      | Rising Pune Supergiant      | field         | normal | 0          | Rising Pune Supergiant      | 0           | 7              |     |
| 2   | 3     | IPL-2017 | Rajkot        | 07-04-2017 | Gujarat Lions               | Kolkata Knight Riders       | Kolkata Knight Riders       | field         | normal | 0          | Kolkata Knight Riders       | 0           | 10             |     |
| 3   | 4     | IPL-2017 | Indore        | 08-04-2017 | Rising Pune Supergiant      | Kings XI Punjab             | Kings XI Punjab             | field         | normal | 0          | Kings XI Punjab             | 0           | 6              |     |
| 4   | 5     | IPL-2017 | Bangalore     | 08-04-2017 | Royal Challengers Bangalore | Delhi Daredevils            | Royal Challengers Bangalore | bat           | normal | 0          | Royal Challengers Bangalore | 15          | 0              |     |
| ... | ...   | ...      | ...           | ...        | ...                         | ...                         | ...                         | ...           | ...    | ...        | ...                         | ...         | ...            | ... |
| 751 | 11347 | IPL-2019 | Mumbai        | 05-05-2019 | Kolkata Knight Riders       | Mumbai Indians              | Mumbai Indians              | field         | normal | 0          | Mumbai Indians              | 0           | 9              |     |
| 752 | 11412 | IPL-2019 | Chennai       | 07-05-2019 | Chennai Super Kings         | Mumbai Indians              | Chennai Super Kings         | bat           | normal | 0          | Mumbai Indians              | 0           | 6              |     |
| 753 | 11413 | IPL-2019 | Visakhapatnam | 08-05-2019 | Sunrisers Hyderabad         | Delhi Capitals              | Delhi Capitals              | field         | normal | 0          | Delhi Capitals              | 0           | 2              |     |
| 754 | 11414 | IPL-2019 | Visakhapatnam | 10-05-2019 | Delhi Capitals              | Chennai Super Kings         | Chennai Super Kings         | field         | normal | 0          | Chennai Super Kings         | 0           | 6              |     |
| 755 | 11415 | IPL-2019 | Hyderabad     | 12-05-2019 | Mumbai Indians              | Chennai Super Kings         | Mumbai Indians              | bat           | normal | 0          | Mumbai Indians              | 1           | 0              |     |

756 rows × 18 columns

# Data Loading

- Importing the Pandas library, which reads the CSV file "IPL.csv"

# IPL Dataset Information

- The dataset contains 756 entries with 18 columns
- Data types in the dataset include integers and objects
- Non-null values for each column range from 119 to 756
- 'id', 'Season', 'team1', 'team2', 'toss\_winner', 'toss\_decision', 'result', 'dl\_applied', 'win\_by\_runs', and 'win\_by\_wickets' columns have 756 non-null values
- 'city', 'winner', 'player\_of\_match', 'venue', 'umpire1', and 'umpire2' columns have non-null values ranging from 749 to 754
- The 'umpire3' column has only 119 non-null values.

```
In [258]: df.info()
# The columns in the dataset have non-null values ranging from 119 to 756.

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 756 entries, 0 to 755
Data columns (total 18 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                     756 non-null    int64
1   Season                756 non-null    object
2   city                  749 non-null    object
3   date                  756 non-null    object
4   team1                  756 non-null    object
5   team2                  756 non-null    object
6   toss_winner            756 non-null    object
7   toss_decision          756 non-null    object
8   result                 756 non-null    object
9   dl_applied             756 non-null    int64
10  winner                 752 non-null    object
11  win_by_runs            756 non-null    int64
12  win_by_wickets         756 non-null    int64
13  player_of_match        752 non-null    object
14  venue                  756 non-null    object
15  umpire1                754 non-null    object
16  umpire2                754 non-null    object
17  umpire3                119 non-null    object
dtypes: int64(4), object(14)
memory usage: 106.4+ KB
```



# IPL Dataset Column Description

- **id:** IPL match identification number
- **season:** The season of the IPL match
- **city:** The city where the IPL match was held
- **date:** The date on which the match was held
- **team1:** One of the teams participating in the IPL match
- **team2:** The other team participating in the IPL match
- **toss\_winner:** The team that won the toss
- **toss\_decision:** The decision taken by the team that won the toss to 'bat' or 'field'
- **result:** The result ('normal', 'tie', 'no result') of the match
- **dl\_applied:** A binary indicator of whether the Duckworth-Lewis rule was applied (1) or not (0)
- **winner:** The winning team of the match
- **win\_by\_runs:** The runs by which the team batting first won
- **win\_by\_wickets:** The number of wickets by which the team batting second won
- **player\_of\_match:** The outstanding player of the match
- **venue:** The venue where the match was hosted
- **umpire1:** One of the two on-field umpires who officiate the match
- **umpire2:** One of the two on-field umpires who officiate the match
- **umpire3:** The off-field umpire who officiates the match

```
In [259]: df.columns
```

```
Out[259]: Index(['id', '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',  
                'umpire3'],  
              dtype='object')
```

# Data Cleaning

## Displaying Unique Values of Each Column in a DataFrame

- using the `iteritems()` method to iterate through each column of a DataFrame, then utilizing the `unique()` method to extract the unique values present in each column.

```
In [426]: # Iterating over each column of a DataFrame and printing the unique values present in each column,  
# to understand the dataset better .  
for column_name, column_data in df.iteritems():  
    unique_values = column_data.unique()  
    print(unique_values)
```

```
[ 1  2  3  4  5  6  7  8  9 10 11 12  
13 14 15 16 17 18 19 20 21 22 23 24  
25 26 27 28 29 30 31 32 33 34 35 36  
37 38 39 40 41 42 43 44 45 46 47 48  
49 50 51 52 53 54 55 56 57 58 59 60  
61 62 63 64 65 66 67 68 69 70 71 72  
73 74 75 76 77 78 79 80 81 82 83 84  
85 86 87 88 89 90 91 92 93 94 95 96  
97 98 99 100 101 102 103 104 105 106 107 108  
109 110 111 112 113 114 115 116 117 118 119 120  
121 122 123 124 125 126 127 128 129 130 131 132  
133 134 135 136 137 138 139 140 141 142 143 144  
145 146 147 148 149 150 151 152 153 154 155 156  
157 158 159 160 161 162 163 164 165 166 167 168  
169 170 171 172 173 174 175 176 177 178 179 180  
181 182 183 184 185 186 187 188 189 190 191 192  
193 194 195 196 197 198 199 200 201 202 203 204]
```



# Finding all the NaN Values in Dataset

- Identifying all the NaN values present in the dataset, enabling us to locate and assign appropriate values to nullify the NaN values.

```
In [427]: finding_NaN_df = df.loc[df.isna().sum(axis=1) > 0]  
         finding_NaN_df.style.highlight_null(null_color='yellow')
```

|                             |                             |       |           |   |                             |    |   |              |                                     |             |             |     |
|-----------------------------|-----------------------------|-------|-----------|---|-----------------------------|----|---|--------------|-------------------------------------|-------------|-------------|-----|
| Kings XI Punjab             | Kings XI Punjab             | field | normal    | 0 | Deccan Chargers             | 82 | 0 | S Dhawan     | Pradesh Cricket Association Stadium | Asad Rauf   | AM Saheba   | nan |
| Pune Warriors               | Delhi Daredevils            | bat   | no result | 0 | nan                         | 0  | 0 | nan          | Feroz Shah Kotla                    | SS Hazare   | RJ Tucker   | nan |
| Royal Challengers Bangalore | Royal Challengers Bangalore | field | normal    | 0 | Royal Challengers Bangalore | 0  | 8 | CH Gayle     | M Chinnaswamy Stadium               | K Hariharan | RE Koertzen | nan |
| Mumbai Indians              | Mumbai Indians              | field | normal    | 0 | Mumbai Indians              | 0  | 5 | JEC Franklin | Eden Gardens                        | SK Tarapore | SJA Taufel  | nan |
| Chennai Super Kings         | Chennai Super Kings         | field | normal    | 0 | Chennai Super Kings         | 0  | 6 | SK Raina     | Wankhede Stadium                    | Asad Rauf   | SJA Taufel  | nan |
| Mumbai Indians              | Mumbai Indians              | field | normal    | 0 | Mumbai Indians              | 0  | 4 | MM Patel     | Wankhede Stadium                    | Asad Rauf   | SJA Taufel  | nan |

# Counting the number of NaN cells in the DataFrame

- Here we can observe that there are total of 656 NaN cells in the dataset we need to clear those to and get it to 0 to complete the Data cleaning operation

```
In [428]: # counting the number of NaN cells in the DataFrame
n_nans = df.isna().sum().sum()

print(f'The number of NaN cells in the dataset is {n_nans}')
```

The number of NaN cells in the dataset is 656



# The Column 'Umpire 3' has more 'NaN' values in them, so lets remove it.

- After removing the 'Umpire 3' column from the Pandas DataFrame, we can observe the change in the DataFrame shape using the df.shape attribute. The shape has been updated from 756 rows and 18 columns to 756 rows and 17 columns, providing evidence that the 'Umpire 3' column has been successfully removed.

```
In [429]: # Before removing column Umpire 3
df.shape
```

```
Out[429]: (756, 18)
```

```
In [430]: # Removing the column Umpire 3
df = df.loc[:, df.columns != 'umpire3']

# After removing the column Umpire 3
df.shape

# Here we can observe that number of columns has been changed to 17 from 18
```

```
Out[430]: (756, 17)
```

```
In [431]: df.head()
# The column umpire3 has been removed
```

```
Out[431]:
```

|    | 1 | team2                       | toss_winner                 | toss_decision | result | dl_applied | winner                 | win_by_runs | win_by_wickets | player_of_match | venue                                     | umpire1        | umpire2   |
|----|---|-----------------------------|-----------------------------|---------------|--------|------------|------------------------|-------------|----------------|-----------------|---|----------------|-----------|
| s  | 1 | Royal Challengers Bangalore | Royal Challengers Bangalore | field         | normal | 0          | Sunrisers Hyderabad    | 35          | 0              | Yuvraj Singh    | Rajiv Gandhi International Stadium, Uppal | AY Dandekar    | NJ Llong  |
| ii | s | Rising Pune Supergiant      | Rising Pune Supergiant      | field         | normal | 0          | Rising Pune Supergiant | 0           | 7              | SPD Smith       | Maharashtra Cricket Association Stadium   | A Nand Kishore | S Ravi    |
| it | s | Kolkata Knight Riders       | Kolkata Knight Riders       | field         | normal | 0          | Kolkata Knight Riders  | 0           | 10             | CA Lynn         | Saurashtra Cricket Association Stadium    | Nitin Menon    | CK Nandan |

# Handling of Missing Data

- The number of NaN values has decreased from 656 to 19.

```
In [432]: n_nans = df.isna().sum().sum()
```

```
print(f'The number of NaN cells in the dataset is {n_nans}')  
finding_NaN_df = df.loc[df.isna().sum(axis=1) > 0]  
finding_NaN_df.style.highlight_null(null_color='yellow')
```

The number of NaN cells in the dataset is 19

Out[432]:

|     | id  | Season   | city      | date       | team1                       | team2                       | toss_winner                 | toss_decision | result    | dl_applied | winner                      | win_by_runs | win_by_wickets | p |
|-----|-----|----------|-----------|------------|-----------------------------|-----------------------------|-----------------------------|---------------|-----------|------------|-----------------------------|-------------|----------------|---|
| 4   | 5   | IPL-2017 | Bangalore | 08-04-2017 | Royal Challengers Bangalore | Delhi Daredevils            | Royal Challengers Bangalore | bat           | normal    | 0          | Royal Challengers Bangalore | 15          | 0              |   |
| 300 | 301 | IPL-2011 | Delhi     | 21-05-2011 | Delhi Daredevils            | Pune Warriors               | Delhi Daredevils            | bat           | no result | 0          | nan                         | 0           | 0              |   |
| 461 | 462 | IPL-2014 | nan       | 19-04-2014 | Mumbai Indians              | Royal Challengers Bangalore | Royal Challengers Bangalore | field         | normal    | 0          | Royal Challengers Bangalore | 0           | 7              |   |
| 462 | 463 | IPL-2014 | nan       | 19-04-2014 | Kolkata Knight Riders       | Delhi Daredevils            | Kolkata Knight Riders       | bat           | normal    | 0          | Delhi Daredevils            | 0           | 4              |   |
| 466 | 467 | IPL-2014 | nan       | 23-04-2014 | Chennai Super Kings         | Rajasthan Royals            | Rajasthan Royals            | field         | normal    | 0          | Chennai Super Kings         | 7           | 0              |   |
| 468 | 469 | IPL-2014 | nan       | 25-04-2014 | Sunrisers Hyderabad         | Delhi Daredevils            | Sunrisers Hyderabad         | bat           | normal    | 0          | Sunrisers Hyderabad         | 4           | 0              |   |



# Highlighting Specific Data in a Pandas DataFrame

- Setting the values of the 'city' column to 'Dubai' for specific row indices with the venue as Dubai International Cricket Stadium
- Defining a function called "highlight\_data" that takes a DataFrame as an input and returns a copy of it with specific cells highlighted in pink.

```
In [433]: # Setting the values of the 'city' column to 'Dubai' for the below row indices.
indices = [461, 462, 466, 468, 469, 474, 476]
df.loc[indices, 'city'] = "Dubai"
```

```
In [434]: def highlight_data(df):
# Creating a copy of the DataFrame with all cells set to white
df_copy = df.copy().applymap(lambda x: 'background-color:white')

# Setting the background color of specific cells to light green
df_copy.loc[[461, 462, 466, 468, 469, 474, 476], 'city'] = 'background-color:pink'

return df_copy

# Selecting the rows 461 through 480 of the DataFrame, applying the "highlight_data" function, and format the result.
df_styled = df.loc[461:480].style
df_styled.apply(highlight_data, axis=None)
```

Out[434]:

|     | id  | Season   | city    | date       | team1                 | team2                       | toss_winner                 | toss_decision | result | dl_applied | winner                      | win_by_runs | win_by_wickets | player_o |
|-----|-----|----------|---------|------------|-----------------------|-----------------------------|-----------------------------|---------------|--------|------------|-----------------------------|-------------|----------------|----------|
| 461 | 462 | IPL-2014 | Dubai   | 19-04-2014 | Mumbai Indians        | Royal Challengers Bangalore | Royal Challengers Bangalore | field         | normal | 0          | Royal Challengers Bangalore | 0           | 7              |          |
| 462 | 463 | IPL-2014 | Dubai   | 19-04-2014 | Kolkata Knight Riders | Delhi Daredevils            | Kolkata Knight Riders       | bat           | normal | 0          | Delhi Daredevils            | 0           | 4              | JF       |
| 463 | 464 | IPL-2014 | Sharjah | 20-04-2014 | Rajasthan Royals      | Kings XI Punjab             | Kings XI Punjab             | field         | normal | 0          | Kings XI Punjab             | 0           | 7              | GJ       |

# Updating 'no result' Matches

- updating the 'winner' and 'player\_of\_match' columns in the dataframe 'df' for those rows where the 'result' column has the value 'no result'. It sets the value for both 'winner' and 'player\_of\_match' as 'No Result'. This is likely done to indicate that the match did not have a clear winner or standout player.

```
In [436]: df.loc[df['result'] == 'no result', ['winner', 'player_of_match']] = 'No Result'
```

Out[436]:

|   | id | Season   | city      | date       | team1                       | team2                       | toss_winner                 | toss_decision | result | dl_applied | winner                      | win_by_runs | win_by_wickets | p |
|---|----|----------|-----------|------------|-----------------------------|-----------------------------|-----------------------------|---------------|--------|------------|-----------------------------|-------------|----------------|---|
| 0 | 1  | IPL-2017 | Hyderabad | 05-04-2017 | Sunrisers Hyderabad         | Royal Challengers Bangalore | Royal Challengers Bangalore | field         | normal | 0          | Sunrisers Hyderabad         | 35          | 0              |   |
| 1 | 2  | IPL-2017 | Pune      | 06-04-2017 | Mumbai Indians              | Rising Pune Supergiant      | Rising Pune Supergiant      | field         | normal | 0          | Rising Pune Supergiant      | 0           | 7              |   |
| 2 | 3  | IPL-2017 | Rajkot    | 07-04-2017 | Gujarat Lions               | Kolkata Knight Riders       | Kolkata Knight Riders       | field         | normal | 0          | Kolkata Knight Riders       | 0           | 10             |   |
| 3 | 4  | IPL-2017 | Indore    | 08-04-2017 | Rising Pune Supergiant      | Kings XI Punjab             | Kings XI Punjab             | field         | normal | 0          | Kings XI Punjab             | 0           | 6              |   |
| 4 | 5  | IPL-2017 | Bangalore | 08-04-2017 | Royal Challengers Bangalore | Delhi Daredevils            | Royal Challengers Bangalore | bat           | normal | 0          | Royal Challengers Bangalore | 15          | 0              |   |



# Counting the number of NaN cells in the Dataframe.

- At this point the NaN values has been reduced to 4. After all trials we found removing these two rows with Nan vales will be the perfect solution

```
In [404]: # counting the number of NaN cells in the DataFrame
n_nans = df.isna().sum().sum()

print(f'The number of NaN cells in the dataset is {n_nans}')
```

The number of NaN cells in the dataset is 4

# Data Cleaning

- Setting the 'id' column as the index of the DataFrame, dropping two rows with specific target IDs, and resetting the index to a sequential integer index.

```
In [405]: df.shape
```

```
Out[405]: (756, 17)
```

```
In [437]: df = df.set_index('id') # set 'id' column as the DataFrame index  
df = df.drop([5, 11413], axis=0) # drop rows with the target_id1 and target_id2 values from the DataFrame  
df = df.reset_index() # reset the index to a sequential integer index
```

```
In [438]: df.shape
```

```
Out[438]: (754, 17)
```



# Finding all the NaN Values in Dataset

- Now that we have confirmed that our dataset has no null values, we can proceed to the next phase of our analysis after completing the data cleansing and preparation steps.

```
In [456]: n_nans = df.isna().sum().sum()
```

```
print(f'The number of NaN cells in the dataset is {n_nans}')
```

```
finding_NaN_df = df.loc[df.isna().sum(axis=1) > 0]
```

```
finding_NaN_df.style.highlight_null(null_color='yellow')
```

The number of NaN cells in the dataset is 0

```
Out[456]:
```

|  | id | Season | city | date | team1 | team2 | toss_winner | toss_decision | result | dl_applied | winner | win_by_runs | win_by_wickets | player_of_match | venue | umpire1 |
|--|----|--------|------|------|-------|-------|-------------|---------------|--------|------------|--------|-------------|----------------|-----------------|-------|---------|
|--|----|--------|------|------|-------|-------|-------------|---------------|--------|------------|--------|-------------|----------------|-----------------|-------|---------|

# Data Analysis using Descriptive Statistics



# 1. Statistics of Win Margin in IPL Matches

## Finding the statistics of a numerical column

- Describing the numerical column 'win\_by\_runs' using descriptive statistics to understand the average, variability, and range of win margins in IPL matches.
- Observation - # We can see that the average win margin in IPL matches is 13.29 runs, with a standard deviation of 23.49 runs. The minimum win margin is 0 runs (indicating a tie or a win by wickets), while the maximum win margin is 146 runs.

```
In [476]: win_by_runs_stats = df['win_by_runs'].describe()  
print(win_by_runs_stats)
```

```
count    754.000000  
mean      13.298408  
std       23.497220  
min        0.000000  
25%        0.000000  
50%        0.000000  
75%       19.000000  
max      146.000000  
Name: win_by_runs, dtype: float64
```



## 2. Counting the number of matches played in each city

- Visualizing the distribution of IPL matches across different cities using a bar chart or a map.
- Observation - We can see that Mumbai has hosted the most number of IPL matches (101), followed by Kolkata (77) and Delhi (74).

```
In [477]: # Counting the number of matches played in each city
city_counts = df['city'].value_counts()

print(city_counts)
|
```

|               |     |
|---------------|-----|
| Mumbai        | 101 |
| Kolkata       | 77  |
| Delhi         | 74  |
| Bangalore     | 65  |
| Hyderabad     | 64  |
| Chennai       | 57  |
| Jaipur        | 47  |
| Chandigarh    | 46  |
| Pune          | 38  |
| Durban        | 15  |
| Bengaluru     | 14  |
| Ahmedabad     | 12  |
| Centurion     | 12  |
| Visakhapatnam | 12  |

### 3. Proportions of Wins for Each Team in the IPL Matches Dataset

- shows the proportion of wins for each team in the IPL matches dataset, with Mumbai Indians having the highest proportion of wins at 14.46% and Kochi Tuskers Kerala having the lowest proportion of wins at 0.8%.

```
In [521]: # Calculating the proportion of matches won by each team
team_wins = df['winner'].value_counts(normalize=True)
print(team_wins)
```

|                             |          |
|-----------------------------|----------|
| Mumbai Indians              | 0.144562 |
| Chennai Super Kings         | 0.132626 |
| Kolkata Knight Riders       | 0.122016 |
| Royal Challengers Bangalore | 0.110080 |
| Kings XI Punjab             | 0.108753 |
| Rajasthan Royals            | 0.099469 |
| Delhi Daredevils            | 0.088859 |
| Sunrisers Hyderabad         | 0.076923 |
| Deccan Chargers             | 0.038462 |
| Gujarat Lions               | 0.017241 |
| Pune Warriors               | 0.015915 |
| Rising Pune Supergiant      | 0.013263 |
| Delhi Capitals              | 0.011936 |
| Kochi Tuskers Kerala        | 0.007958 |
| Rising Pune Supergiants     | 0.006631 |
| No Result                   | 0.005305 |

Name: winner, dtype: float64

# Summary statistics of IPL match data

- The total number of IPL matches played in the dataset is 754, with match ID ranging from 1 to 11415.
- The average value of the **dl\_applied** variable is 0.025, which means that the Duckworth-Lewis rule was applied in only a small proportion of matches.
- The average margin of victory for the team batting first (**win\_by\_runs**) is 13 runs, with a maximum of 146 runs and a minimum of 0 runs.
- The average number of wickets remaining when the team batting second wins (**win\_by\_wickets**) is 3, with a maximum of 10 wickets and a minimum of 0 wickets.

```
In [522]: df.describe()
```

```
Out[522]:
```

|       | id           | dl_applied | win_by_runs | win_by_wickets |
|-------|--------------|------------|-------------|----------------|
| count | 754.000000   | 754.000000 | 754.000000  | 754.000000     |
| mean  | 1781.789125  | 0.025199   | 13.298408   | 3.356764       |
| std   | 3450.683492  | 0.156833   | 23.497220   | 3.389898       |
| min   | 1.000000     | 0.000000   | 0.000000    | 0.000000       |
| 25%   | 190.250000   | 0.000000   | 0.000000    | 0.000000       |
| 50%   | 378.500000   | 0.000000   | 0.000000    | 4.000000       |
| 75%   | 566.750000   | 0.000000   | 19.000000   | 6.000000       |
| max   | 11415.000000 | 1.000000   | 146.000000  | 10.000000      |





# Using Data Aggregation Technique

## 1. Number of matches per season in IPL

- Grouping the data by season and counting the number of matches played in each season
- Observation: The number of matches played in each season is relatively consistent, with the exception of IPL 2011, which had the most number of matches played (73), and IPL 2013, which had the second-most number of matches played (76). The other seasons had between 57 to 60 matches played.

```
In [530]: matches_per_season = df.groupby('Season')['id'].count()
          print(matches_per_season)
```

| Season   |    |
|----------|----|
| IPL-2008 | 58 |
| IPL-2009 | 57 |
| IPL-2010 | 60 |
| IPL-2011 | 73 |
| IPL-2012 | 74 |
| IPL-2013 | 76 |
| IPL-2014 | 60 |
| IPL-2015 | 59 |
| IPL-2016 | 60 |
| IPL-2017 | 58 |
| IPL-2018 | 60 |

## 2. Grouping data by player\_of\_match and calculating the count of matches won.

- Calculating the number of times each player has won the "player of the match" award in IPL matches.
- Observation: The output shows the top 10 players who have won the most "player of the match" awards. We can see that Chris Gayle has won the most awards, followed by AB de Villiers, Rohit Sharma, MS Dhoni, DA Warner, YK Pathan, SR Watson, SK Raina, G Gambhir, and AM Rahane.

```
In [555]: player_wins = df.groupby('player_of_match')['winner'].count().sort_values(ascending=False)
          print(player_wins.head(10))
```

```
player_of_match
CH Gayle      21
AB de Villiers 20
RG Sharma     17
MS Dhoni      17
DA Warner     17
YK Pathan     16
SR Watson     15
SK Raina      14
G Gambhir     13
AM Rahane     12
Name: winner, dtype: int64
```

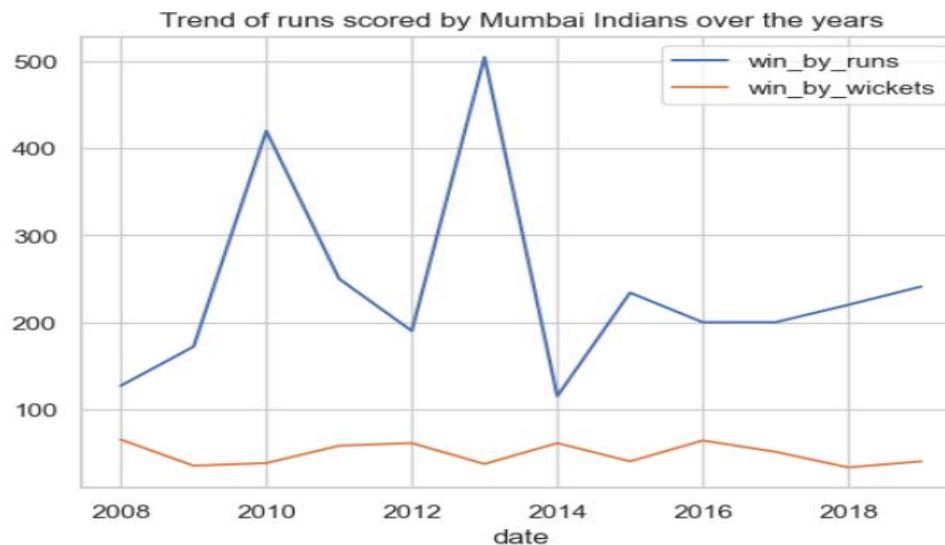


# Trend of runs scored by Mumbai Indians over the years in the IPL using time series techniques

- The line plot shows that Mumbai Indians have been consistently scoring more runs over the years with some fluctuations

```
In [556]: df['date'] = pd.to_datetime(df['date'], format='%d-%m-%Y')
df['date'] = pd.to_datetime(df['date'], format='%d-%m-%Y')
df.set_index('date', inplace=True)
team = 'Mumbai Indians'
df_team = df[(df['team1']==team) | (df['team2']==team)]
df_yearly = df_team.groupby(df_team.index.year)[['win_by_runs', 'win_by_wickets']].sum()
df_yearly.plot(kind='line', title='Trend of runs scored by Mumbai Indians over the years')

Out[556]: <AxesSubplot:title={'center':'Trend of runs scored by Mumbai Indians over the years'}, xlabel='date'>
```



The background is a dark teal color with a complex network of thin, glowing green lines and small green squares. These elements are scattered across the frame, creating a sense of depth and connectivity. Some lines are thicker and more prominent, while others are thin and faint. The squares are also of varying sizes and are often positioned at the intersections of the lines. The overall effect is a futuristic, data-driven aesthetic.

# Data Visualization

# Data Visualization

Data visualization is the representation of data in a visual format such as charts, graphs, and plots. In this context, we have used four different types of visualization techniques to represent data:

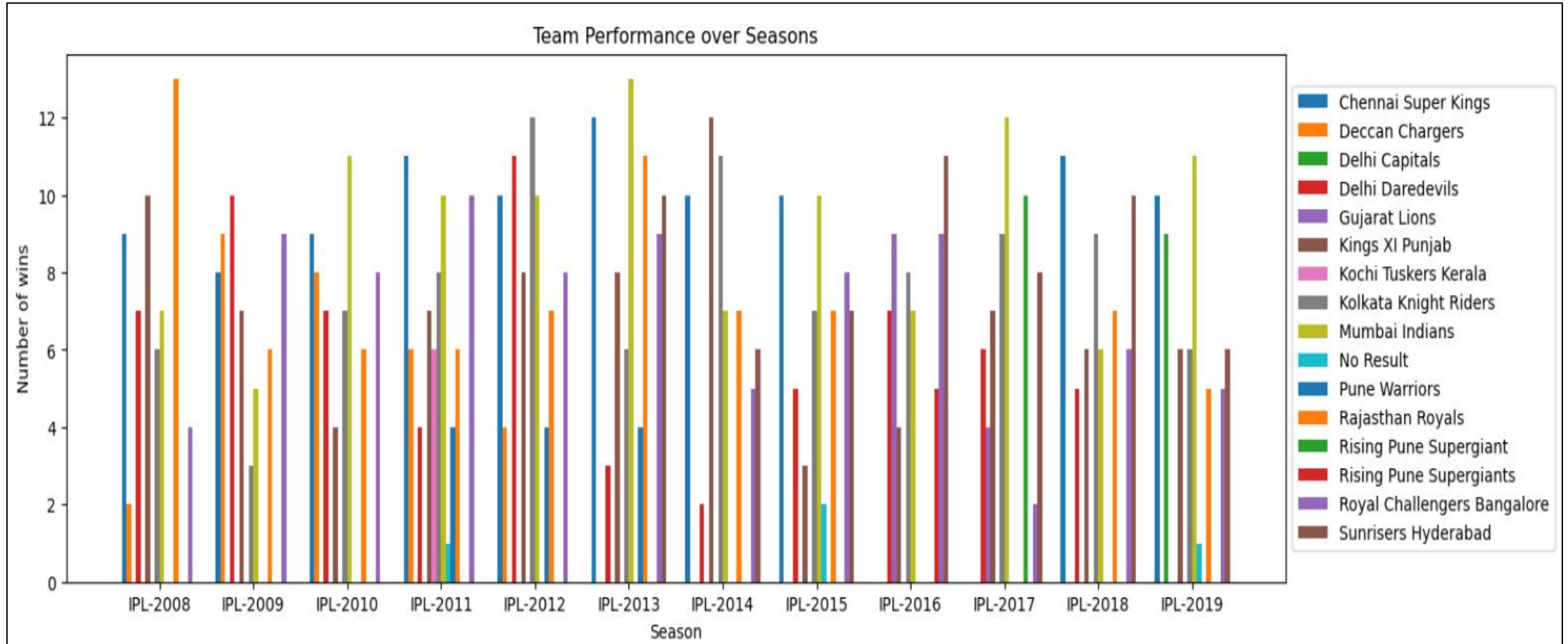
1. Clustered Bar Chart
2. Pie Chart
3. Stacked Bar Chart
4. Scatter Plot



# Comparing the Win/Loss Record of Each Team in IPL Seasons

- Grouping the data by season and team to get the number of wins per team per season. Then, it creates a clustered bar chart to visualize the win/loss record of each team in IPL seasons.
- The visualization shows the number of wins per team per season in a clustered bar chart. We can observe the performance of each team in different seasons and compare their win/loss records. The bar chart also shows a gradual increase in the total number of matches played per season.
- the chart can be used to track the overall trend of the league's competitiveness over time. By observing the number of matches played per season, one can identify the growth of the league and how it has evolved over time.

# Clustered Bar Chart

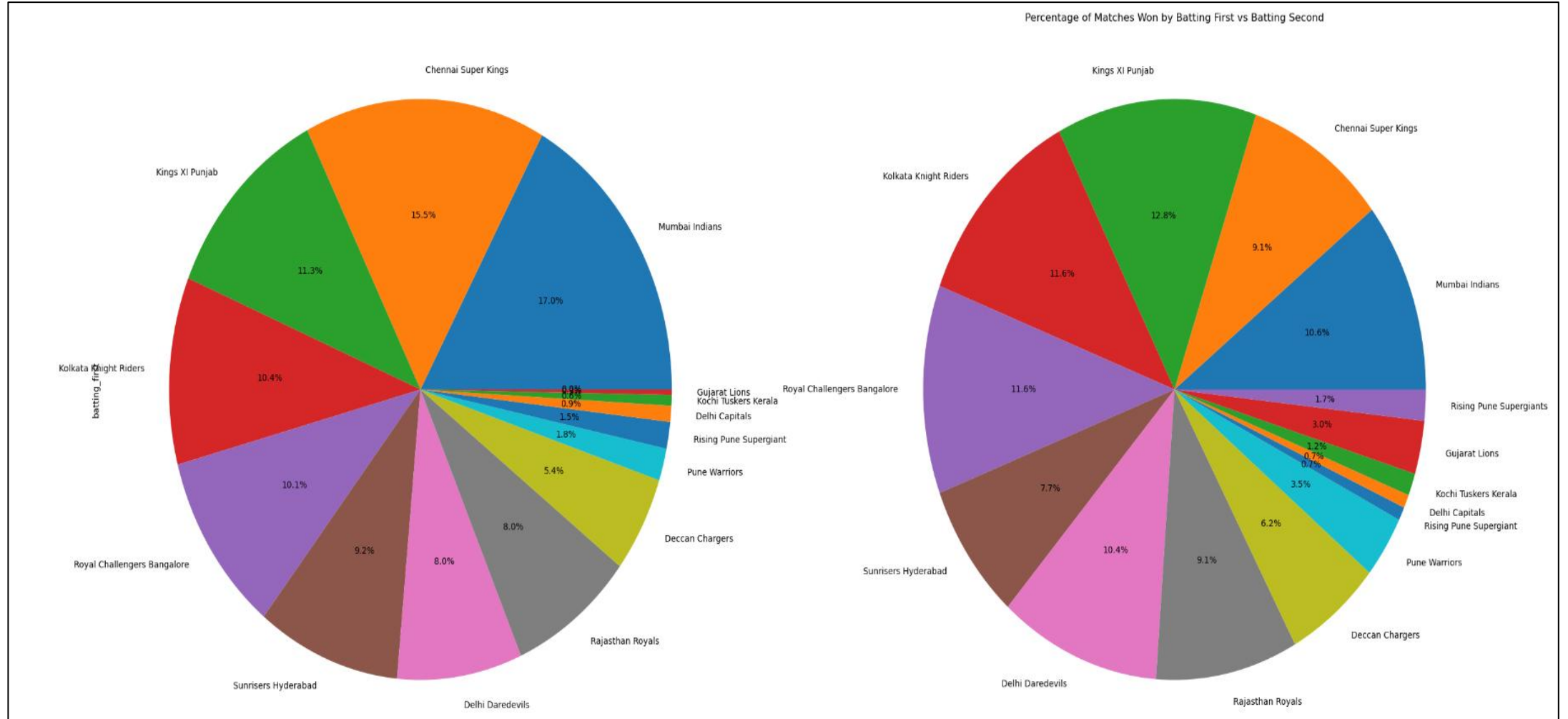


# Percentage of Matches Won by Batting First vs Batting Second

- A new column 'winning\_team' is created to identify the team that won (either team1 or team2). The number of matches won by each team batting first and the number of matches won by each team batting second are counted. The counts are combined into a single dataframe. A pie chart is plotted to show the percentage of matches won by teams batting first vs teams batting second.
- The pie chart shows that in the Indian Premier League, teams batting second have a higher percentage of wins than teams batting first.



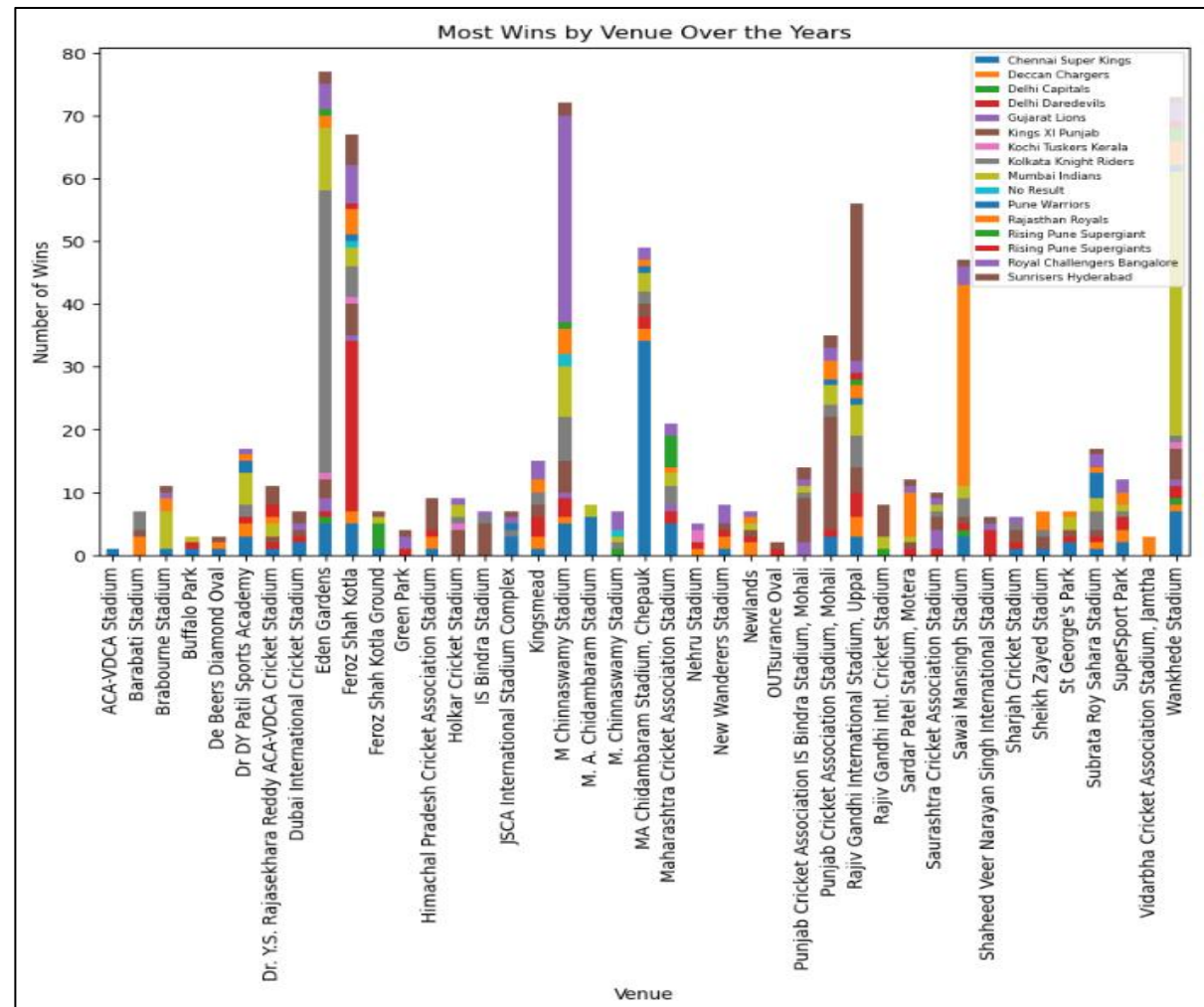
# Pie Chart



# Most Wins by Venue Over the Years

- Creating a bar chart showing the number of wins for each team at each venue by pivoting the data to create a table of wins for each team at each venue
- we can observe which teams have the most wins at each venue over the years. We can also identify which venues have been most favorable for each team. The chart helps to visualize the data and identify patterns in team performance across different venues.

# Stacked Bar Chart



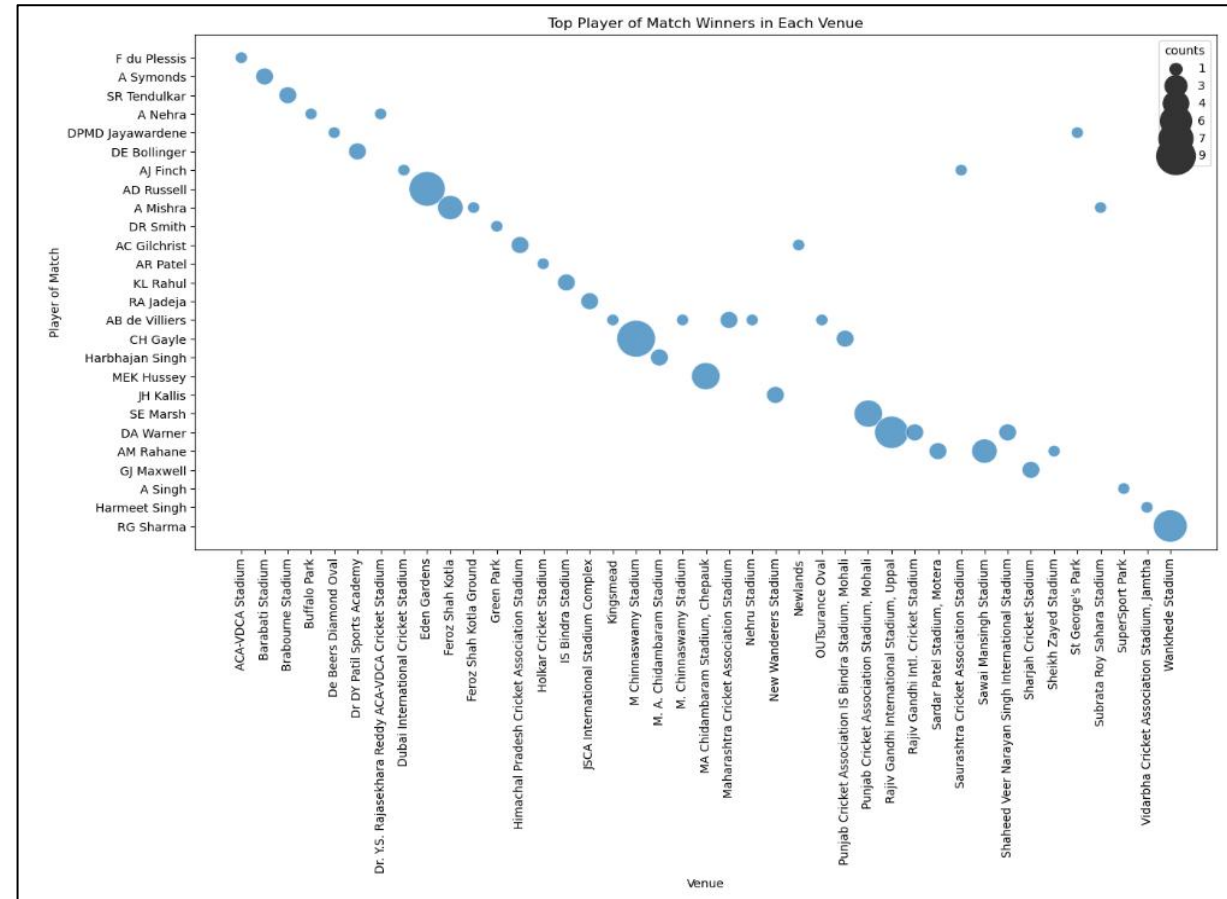




# Get the top player of match winner in each venue?

- The scatter plot reveals that Chris Gayle has won the player of the match award at the M Chinnaswamy Stadium in Bengaluru more times than any other player. Similarly, AB de Villiers has won the award at the same stadium on the second most occasions.

# Scatter Plot



**Q & A**  
time



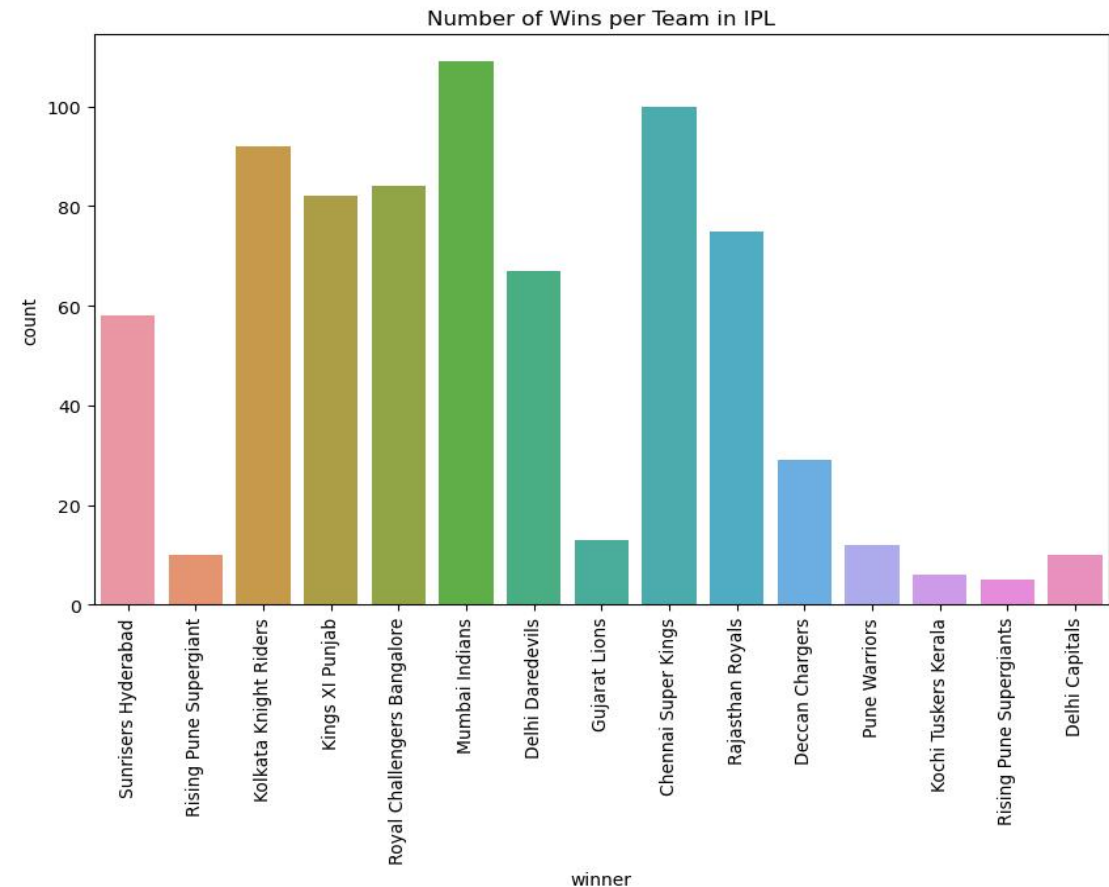
# Which team is the most successful team in IPL?

- Mumbai Indians hold the record for winning the most games in the Indian Premier League (IPL). They have won the IPL trophy four times and have secured the most wins in four seasons. This makes Mumbai Indians the most successful team in the history of IPL.

```
# Count the number of wins for each team
wins_by_team = df['winner'].value_counts()

# Print the team with the most wins
print('The most successful team in IPL is', wins_by_team.index[0])
```

The most successful team in IPL is Mumbai Indians



# Impact of Winning the Coin Toss on Winning the Match in IPL

- 51% in coin toss wins are favored. It is pretty close, so it is not certain that coin toss decides the winner

```
# creating a new column 'won_toss_and_won_match' to indicate if the team that won the toss also won the match
df['won_toss_and_won_match'] = (df['toss_winner'] == df['winner'])

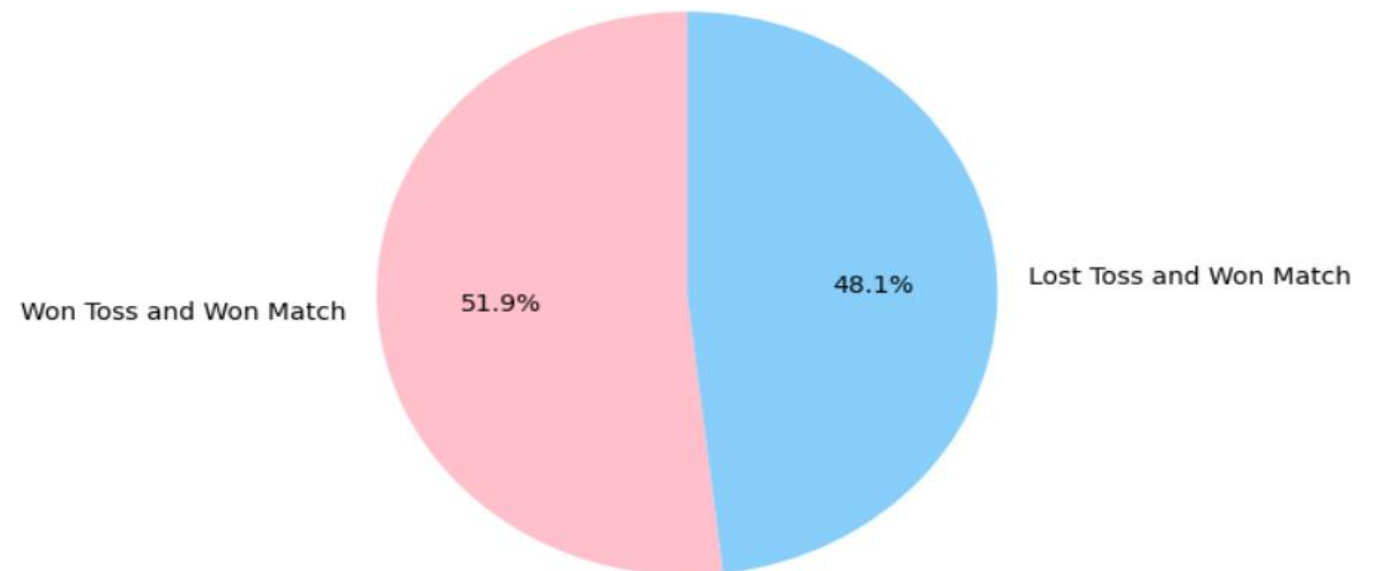
# calculating the percentage of matches won by teams who won the toss
toss_win_match_win_pct = df[df['toss_winner']==df['winner']]['winner'].count() / df['winner'].count()

# calculating the percentage of matches won by teams who lost the toss
toss_loss_match_win_pct = df[df['toss_winner']!=df['winner']]['winner'].count() / df['winner'].count()
print("Percentage of Matches Won by Teams Who Won the Toss: ", toss_win_match_win_pct)
print("Percentage of Matches Won by Teams Who Lost the Toss: ", toss_loss_match_win_pct)

labels = ['Won Toss and Won Match', 'Lost Toss and Won Match']
sizes = [toss_win_match_win_pct, toss_loss_match_win_pct]
colors = ['pink', 'lightskyblue']
plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=90)
plt.axis('equal')
plt.title('Percentage of Matches Won by Teams Who Won and Lost the Toss')
plt.show()
```

Percentage of Matches Won by Teams Who Won the Toss: 0.5185676392572944  
Percentage of Matches Won by Teams Who Lost the Toss: 0.48143236074270557

Percentage of Matches Won by Teams Who Won and Lost the Toss



# Inferences and Conclusion

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## Key findings from Exploratory Data Analysis:

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756 IPL matches were played in 40 venues in 2019.

---

Winning the toss can't decide winning of the match.

---

Mumbai Indians are the most successful IPL team with 4 winning seasons.

---

Eden Gardens hosted the most IPL matches.

---

Chris Gayle received the most player of the match awards.

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# References and Future work

- Indian Premier League official website - <https://www.iplt20.com/>
- "IPL Stats - IPLT20.com." IPLT20, 22 Mar. 2023, <https://www.iplt20.com/stats>.
- "IPL 2022: Full schedule, teams, venues, timings, live streaming, tickets, and all you need to know - Sports News." India Today, 22 Mar. 2023, <https://www.indiatoday.in/sports/cricket/story/ipl-2022-full-schedule-teams-venues-timings-live-streaming-tickets-and-all-you-need-to-know-1944097-2022-03-11>.

Thank  
you!