

Task 3

August 17, 2023

1 Task 3 - Cricket Player Performance Prediction using machine learning

2 Problem Statement

The data is scraped from ESPN Cricinfo, matches till 18th May 2019 are only counted. We need to analyze the performance of all the players playing in CWC 2019.

2.1 Import Data and Required Packages

```
[1]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

```
[2]: batter_df = pd.read_csv("Batsman_Data.csv")
bowler_df = pd.read_csv("Bowler_data.csv")
grnd_avg_df = pd.read_csv("Ground_Averages.csv")
odi_res_df = pd.read_csv("ODI_Match_Results.csv")
odi_tot_df = pd.read_csv("ODI_Match_Totals.csv")
wc_players_df = pd.read_csv("WC_players.csv")
```

```
[3]: batter_df.sample(5)
```

```
[3]:      Unnamed: 0  Bat1  Runs  BF      SR  4s  6s  Opposition  Ground \
6831      6832    38    38  48   79.16   4   0    v Zimbabwe  Auckland
2555      2556    31    31  49   63.26   3   0    v England   Johannesburg
7999      8000    59    59  65   90.76   6   1    v Ireland    Dublin
1937      1938     7     7  10   70.00   1   0    v Australia  Colombo (RPS)
7292      7293   104   104  78  133.33  13   2    v New Zealand  Birmingham

      Start Date  Match_ID      Batsman  Player_ID
6831  14 Mar 2015  ODI # 3636    Virat Kohli    253802
2555  12 Feb 2016  ODI # 3737      JP Duminy    44932
```

7999	25 Aug 2011	ODI # 3185	Eoin Morgan	24598
1937	24 Aug 2016	ODI # 3769	Dhananjaya de Silva	465793
7292	9 Jun 2015	ODI # 3654	Joe Root	303669

```
[4]: bowler_df.sample(5)
```

```
[4]:      Unnamed: 0  Overs  Mdns  Runs  Wkts  Econ    Ave    SR    Opposition \
8069      8070      -      -      -      -      -      -      -      v South Africa
5463      5464    10.0      0     35      1    3.50   35.00   60.0      v Australia
324       325      -      -      -      -      -      -      -      v Afghanistan
1477      1478      -      -      -      -      -      -      -      v Pakistan
2850      2851      -      -      -      -      -      -      -      v West Indies
```

	Ground	Start Date	Match_ID	Bowler	Player_ID
8069	Johannesburg	12 Feb 2016	ODI # 3737	Eoin Morgan	24598
5463	Pune	13 Oct 2013	ODI # 3419	Ravindra Jadeja	234675
324	Gros Islet	11 Jun 2017	ODI # 3887	Shai Hope	581379
1477	Abu Dhabi	25 Dec 2013	ODI # 3448	Kusal Perera	300631
2850	Durban	16 Jan 2015	ODI # 3579	Hashim Amla	43906

```
[5]: grnd_avg_df.sample(5)
```

```
[5]:      Ground      Span  Mat  Won \
1      Feroz Shah Kotla, Delhi - India  2013-2019      4      4
91  Greater Noida Sports Complex Ground, Greater N...  2017-2017      5      5
41      Mannofield Park, Aberdeen - Scotland  2013-2014      3      3
98      Old Hararians, Harare - Zimbabwe  2018-2018      5      5
6  Brisbane Cricket Ground, Woolloongabba, Brisba...  2013-2018      8      8

      Tied  NR  Runs  Wkts  Balls    Ave  RPO
1      0   0  1789    75   2331  23.85  4.60
91      0   0  2629    79   2918  33.27  5.40
41      0   0  1094    45   1316  24.31  4.98
98      0   0  2156    75   2522  28.74  5.12
6      0   0  3671   123   4189  29.84  5.25
```

```
[6]: odi_res_df.sample(5)
```

```
[6]:      Unnamed: 0  Result    Margin    BR Toss  Bat    Opposition \
409      1024    won      21 runs    NaN  won  1st      v Zimbabwe
421      464    won      3 wickets    3.0  won  2nd     v New Zealand
692      634   lost      4 wickets   21.0  won  1st      v Australia
646      205    won      19 runs     NaN  won  2nd     v West Indies
1128     1073    won      48 runs     NaN  won  1st     v West Indies

      Ground  Start Date  Match_ID  Country  Country_ID
409      Dhaka  28 Nov 2014  ODI # 3555  Bangladesh      25
```

421	Dubai (DSC)	8 Dec 2014	ODI # 3564	Pakistan	7
692	Wellington	6 Feb 2016	ODI # 3733	Newzealad	5
646	Pallekele	7 Nov 2015	ODI # 3704	SriLanka	8
1128	Providence	22 Jul 2018	ODI # 4022	Bangladesh	25

```
[7]: odi_tot_df.sample(5)
```

```
[7]:      Unnamed: 0  Score  Overs  RPO  Target  Inns Result  Opposition \
175      1098  350/6   50.0  7.00    NaN    1  lost      v India
785      772   241   48.4  4.95  261.0    2  lost  v New Zealand
1090     1189  310/8   50.0  6.20    NaN    1  lost      v England
359      731  263/7   50.0  5.26    NaN    1  won   v West Indies
1290     1075  213/5   22.5  9.32  210.0    2  won   v West Indies

      Ground  Start Date  Match_ID  Country  Country_ID
175      Nagpur  30 Oct 2013  ODI # 3424  Australia      2
785      Ranchi  26 Oct 2016  ODI # 3799    India      6
1090  Chester-le-Street  21 Jun 2018  ODI # 4012  Australia      2
359      Delhi  11 Oct 2014  ODI # 3533    India      6
1290  Dublin (Malahide)  17 May 2019  ODI # 4137  Bangladesh     25
```

```
[8]: wc_players_df.sample(5)
```

```
[8]:      Player      ID  Country
133  Milinda Siriwardana  222354  SriLanka
67    Kedar Jadhav    290716    India
73    Hardik Pandya   625371    India
89    Ish Sodhi     559066  NewZealand
52    Alex Hales    249866    England
```

```
[9]: common = set.intersection(set(odi_res_df['Start Date']), set(odi_tot_df['Start_
↳Date']))
```

```
[10]: df = pd.concat([
odi_res_df[odi_res_df['Start Date'].isin(common)],
odi_tot_df[odi_tot_df['Start Date'].isin(common)]).sort_values(by='Start_
↳Date')
```

```
[11]: c = set.intersection(set(odi_res_df['Start Date']), set(odi_tot_df['Start_
↳Date']),set(batter_df['Start Date']), set(bowler_df['Start Date']))

bat_boll_res_tot = pd.concat([
odi_res_df[odi_res_df['Start Date'].isin(c)],
odi_tot_df[odi_tot_df['Start Date'].isin(c)],
batter_df[batter_df['Start Date'].isin(c)],
bowler_df[bowler_df['Start Date'].isin(c)]).sort_values(by='Start Date')
```

```
[12]: bat_boll_res_tot.sample(5)
```

```
[12]:      Unnamed: 0  Result  Margin  BR  Toss  Bat  Opposition  \
669          621    won      NaN NaN   NaN   NaN    v Pakistan
5728         5729   NaN      NaN NaN   NaN   NaN    v New Zealand
1291          552  lost    80 runs NaN  lost  2nd    v Australia
8606         8607   NaN      NaN NaN   NaN   NaN    v West Indies
432           899  lost    87 runs NaN  lost  2nd    v Sri Lanka

      Ground  Start Date  Match_ID  ...  SR  4s  6s  Batsman  \
669      Auckland  31 Jan 2016  ODI # 3730  ...  NaN  NaN  NaN    NaN
5728  Mount Maunganui  28 Jan 2019  ODI # 4088  ...  30.0  NaN  NaN    NaN
1291      Abu Dhabi  27 Mar 2019  ODI # 4118  ...  NaN  NaN  NaN    NaN
8606      Sylhet  14 Dec 2018  ODI # 4073  ...  -  NaN  NaN    NaN
432    Colombo (RPS)  16 Dec 2014  ODI # 3569  ...  NaN  NaN  NaN    NaN

      Player_ID  Mdns  Wkts  Econ  Ave  Bowler
669          NaN  NaN  NaN  NaN  NaN      NaN
5728  326016.0    1    2  4.60  23.00  Bhuvneshwar Kumar
1291          NaN  NaN  NaN  NaN  NaN      NaN
8606  56025.0    0    0  4.66    -  Mahmudullah
432          NaN  NaN  NaN  NaN  NaN      NaN
```

[5 rows x 30 columns]

```
[13]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2597 entries, 891 to 790
Data columns (total 17 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Unnamed: 0      2597 non-null  int64
1   Result          2597 non-null  object
2   Margin          1301 non-null  object
3   BR              606 non-null   float64
4   Toss            1301 non-null  object
5   Bat             1301 non-null  object
6   Opposition      2597 non-null  object
7   Ground          2597 non-null  object
8   Start Date      2597 non-null  object
9   Match_ID        2597 non-null  object
10  Country          2597 non-null  object
11  Country_ID       2597 non-null  int64
12  Score            1296 non-null  object
13  Overs            1296 non-null  float64
14  RPO              1296 non-null  object
15  Target          620 non-null   float64
```

```

16  Inns          1296 non-null   float64
dtypes: float64(4), int64(2), object(11)
memory usage: 365.2+ KB

```

2.2 Converting 'Start Date' into date/time data type

```
[14]: df['Start Date'] = pd.to_datetime(df['Start Date'])
```

```
[15]: df['Start Date'].info()
```

```

<class 'pandas.core.series.Series'>
Int64Index: 2597 entries, 891 to 790
Series name: Start Date
Non-Null Count  Dtype
-----
2597 non-null   datetime64[ns]
dtypes: datetime64[ns](1)
memory usage: 40.6 KB

```

```
[16]: df.sample(5)
```

```

[16]:      Unnamed: 0  Result  Margin  BR  Toss  Bat  Opposition  Ground \
339      453    lost      NaN  NaN  NaN  NaN    v Sri Lanka  Dambulla
1151     965    n/r      NaN  NaN  NaN  NaN    v Sri Lanka  Dambulla
7        836    won      NaN  NaN  NaN  NaN          v India  Rajkot
606      622    lost    20 runs  NaN  won  2nd  v South Africa  Centurion
318      312    won    75 runs  NaN  won  1st    v Sri Lanka  Colombo (RPS)

```

```

      Start Date  Match_ID  Country  Country_ID  Score  Overs  RPO \
339  2014-08-30  ODI # 3519  Pakistan          7    102   32.1  3.17
1151 2018-10-10  ODI # 4052   England          1    92/2   15.0  6.13
7    2013-01-11  ODI # 3318   England          1   325/4   50.0  6.50
606  2015-08-19  ODI # 3676  Newzealad          5     NaN     NaN  NaN
318  2014-07-06  ODI # 3500  SouthAfrica          3     NaN     NaN  NaN

```

```

      Target  Inns
339     NaN    1.0
1151     NaN    1.0
7      NaN    1.0
606     NaN    NaN
318     NaN    NaN

```

2.3 Things we can do with df: Gather data induvidually based on Opposition, Ground

- Result vs Toss
- Margin vs Bat
- Target, result, ground - Lowest and Highest

- How many times has ‘Country’ won against ‘Opposition’ and for what score, RPO, Target

```
[17]: res_toss = df[['Result', 'Toss', 'Opposition', 'Ground']]
```

```
[18]: res_toss.sample(5)
```

```
[18]:
```

	Result	Toss		Opposition	Ground
96	tied	NaN	v	South Africa	Cardiff
381	lost	NaN	v	South Africa	Perth
1279	n/r	NaN		v Pakistan	The Oval
996	won	NaN		v Ireland	Sharjah
1049	lost	won		v England	Brisbane

```
[19]: res_toss.isna().sum()
```

```
[19]: Result          0
      Toss          1296
      Opposition      0
      Ground         0
      dtype: int64
```

```
[20]: res_toss.dropna(inplace=True)
```

2.4 VENUES - GROUNDS LIST

- The Oval, London
- Trent Bridge, Nottingham
- Sophia Gardens, Cardiff
- County Ground, Bristol
- Rose Bowl, Southampton
- County Ground, Taunton
- Old Trafford, Manchester
- Edgbaston, Birmingham
- Headingley, Leeds
- Lord's, London
- Riverside Ground, Chester-le-Street

2.5 We are playing in the england so we will analyse only england grounds

```
[21]: WC_venue_pitches = ["The Oval, London", "Trent Bridge, Nottingham", "Sophia_
↪Gardens, Cardiff", "County Ground, Bristol", "Rose Bowl, Southampton", "County_
↪Ground, Taunton", "Old Trafford, Manchester", "Edgbaston, _
↪Birmingham", "Headingley, Leeds", "Lord's, London", "Riverside Ground, _
↪Chester-le-Street"]
```

2.6 Total Grounds

```
[22]: wc_ground_state = []
      ODI_grounds = odi_res_df.Ground

      for grnd in ODI_grounds:
          for grnds in WC_venue_pitches:
              if grnd in grnds:
                  wc_ground_state.append((grnd, grnds))
```

```
[23]: Ground_names = dict(set(wc_ground_state))
      def Full_Ground_names(value):
          return Ground_names[value]
      Ground_names
```

```
[23]: {'The Oval': 'The Oval, London',
      'Nottingham': 'Trent Bridge, Nottingham',
      'Bristol': 'County Ground, Bristol',
      'Manchester': 'Old Trafford, Manchester',
      "Lord's": "Lord's, London",
      'Leeds': 'Headingley, Leeds',
      'Chester-le-Street': 'Riverside Ground, Chester-le-Street',
      'Cardiff': 'Sophia Gardens, Cardiff',
      'Birmingham': 'Edgbaston, Birmingham',
      'Southampton': 'Rose Bowl, Southampton'}
```

2.7 Gathering the data of all ODI's in these WC Venues

```
[24]: WC_Grounds_History = odi_res_df[odi_res_df.Ground.isin([Ground[0] for Ground in_
      ↪wc_ground_state])]
      WC_Grounds_History["Ground"] = WC_Grounds_History.Ground.
      ↪apply(Full_Ground_names)
      WC_Grounds_History.head()
```

```
[24]:
```

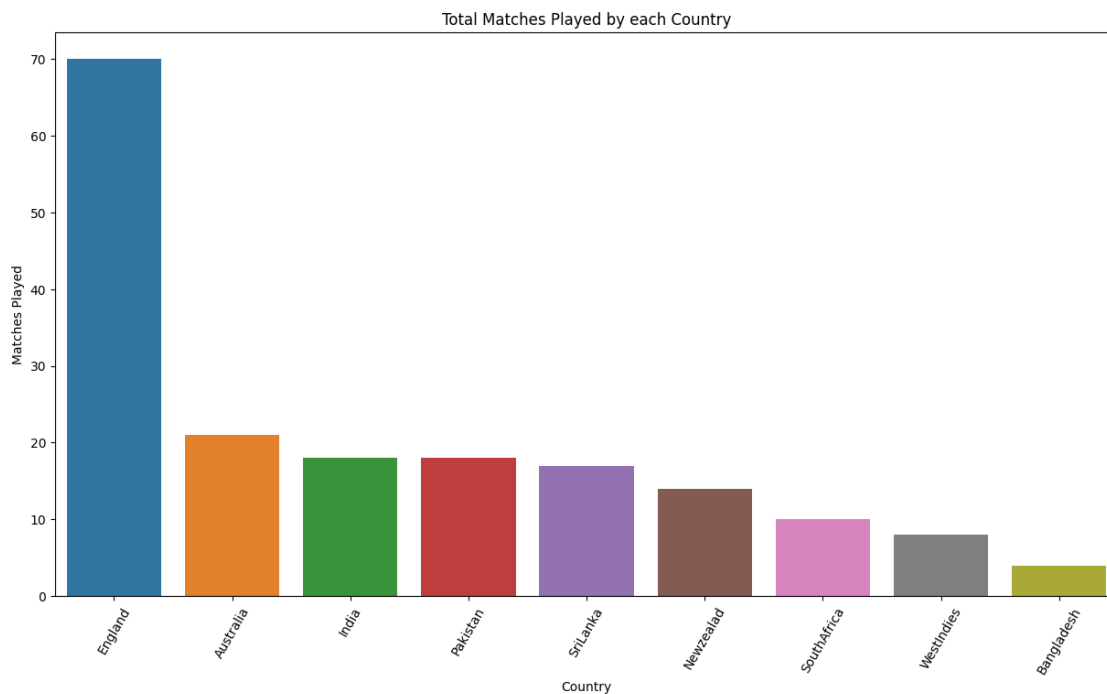
	Unnamed: 0	Result	Margin	BR	Toss	Bat	Opposition	\
75	566	won	5 wickets	19.0	won	2nd	v England	
76	860	lost	5 wickets	19.0	lost	1st	v New Zealand	
77	567	won	86 runs	NaN	won	1st	v England	
78	861	lost	86 runs	NaN	lost	2nd	v New Zealand	
79	568	lost	34 runs	NaN	won	2nd	v England	

	Ground	Start Date	Match_ID	Country	Country_ID
75	Lord's, London	31 May 2013	ODI # 3360	Newzealad	5
76	Lord's, London	31 May 2013	ODI # 3360	England	1
77	Rose Bowl, Southampton	2 Jun 2013	ODI # 3361	Newzealad	5
78	Rose Bowl, Southampton	2 Jun 2013	ODI # 3361	England	1
79	Trent Bridge, Nottingham	5 Jun 2013	ODI # 3362	Newzealad	5

So, now we have the data of matches that were played in WC venues. Now let's analyze the following things,

- How many WC teams have played in these venues before and what are they?
- Which Team has more Win Percentage in these Venues?
- Does Batting First helps winning in these Pitches?
- What should the captain opt for, when he wins the Toss?

```
[25]: Team_Matches = WC_Grounds_History.Country.value_counts().reset_index()
plt.figure(figsize=(15,8))
sns.barplot(x = "index", y = "Country", data = Team_Matches).set_title("Total_
↳Matches Played by each Country")
plt.xlabel("Country")
plt.ylabel("Matches Played")
plt.xticks(rotation = 60)
plt.show()
```



- So, England has the benifit of Home conditions and even playing many matches over there, they will get used to those pitches and can understand the conditions of pitches very well.
- After England, it's Aussies which played many mathces in those conditions.

2.8 Team wise winning percentage in england piches

```
[26]: WC_Grounds_History.sample(5)
```



```
[26]:
```

	Unnamed: 0	Result	Margin	BR	Toss	Bat	Opposition	\
927	386	lost	19 runs	NaN	won	1st	v Pakistan	
620	921	lost	8 wickets	154.0	won	1st	v Australia	
928	518	won	19 runs	NaN	lost	2nd	v South Africa	
1122	827	lost	8 wickets	33.0	lost	1st	v England	
102	865	won	10 runs	NaN	lost	1st	v New Zealand	

	Ground	Start Date	Match_ID	Country	\
927	Edgbaston, Birmingham	7 Jun 2017	ODI # 3881	SouthAfrica	
620	Old Trafford, Manchester	13 Sep 2015	ODI # 3684	England	
928	Edgbaston, Birmingham	7 Jun 2017	ODI # 3881	Pakistan	
1122	Headingley, Leeds	17 Jul 2018	ODI # 4018	India	
102	Sophia Gardens, Cardiff	16 Jun 2013	ODI # 3373	England	

	Country_ID
927	3
620	1
928	7
1122	6
102	1

```
[27]: WC_Grounds_History.Result.value_counts()
```

```
[27]: won      79
lost      77
n/r       14
tied       4
aban       4
-          2
Name: Result, dtype: int64
```

- Seems like there are some unwanted datas in the dataset, removing those data.

```
[28]: WC_Grounds_History = WC_Grounds_History[~ WC_Grounds_History.Result.isin(["-"])
WC_Grounds_History.Result.value_counts()
```

```
[28]: won      79
lost      77
n/r       14
tied       4
aban       4
Name: Result, dtype: int64
```

```
[29]: winnings = WC_Grounds_History[["Country","Result"]]
winnings["count"] = 1
Ground_Results_Per_Team = winnings.groupby(["Country","Result"]).
↳ aggregate(["sum"])
```

```

Ground_Results_Per_Team = Ground_Results_Per_Team.groupby(level=0).apply(lambda
    ↪x:100 * x / float(x.sum())).reset_index()
Ground_Results_Per_Team.columns = ["Country", "Result", "Count"]
Ground_Results_Per_Team.head()

```

```

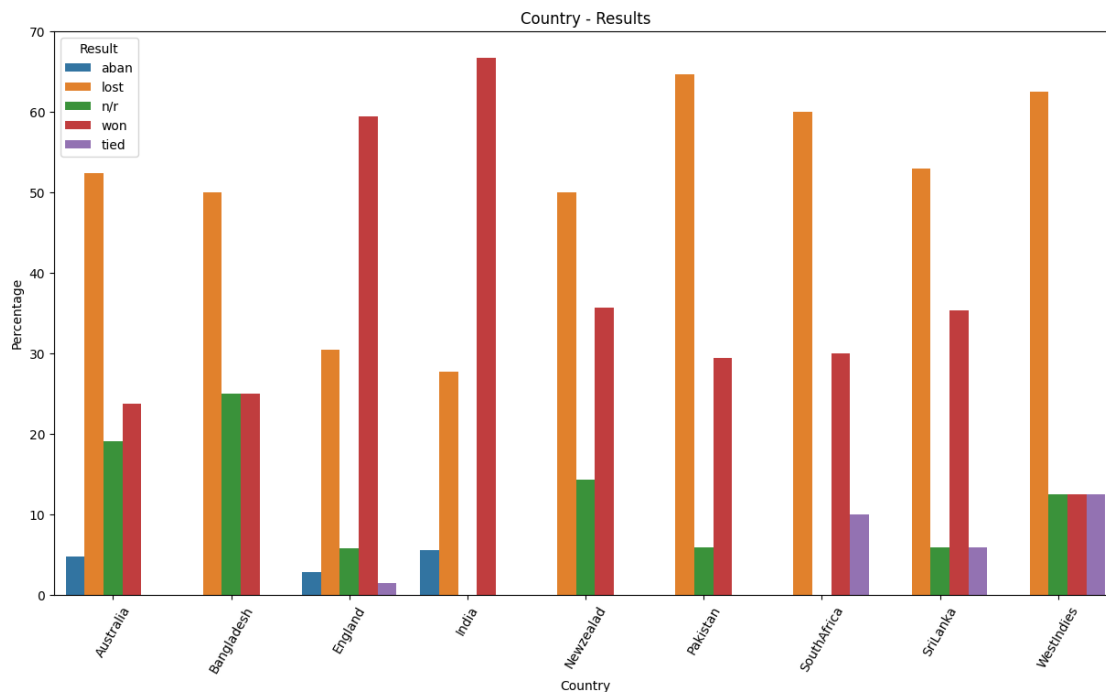
[29]:
   Country Result      Count
0  Australia  aban    4.761905
1  Australia  lost   52.380952
2  Australia   n/r   19.047619
3  Australia   won   23.809524
4  Bangladesh  lost   50.000000

```

```

[30]: plt.figure(figsize=(15,8))
sns.barplot(x = "Country", y = "Count", hue = "Result", data =
    ↪Ground_Results_Per_Team)
plt.ylabel("Percentage")
plt.title("Country - Results")
plt.xticks(rotation = 60)
plt.show()

```

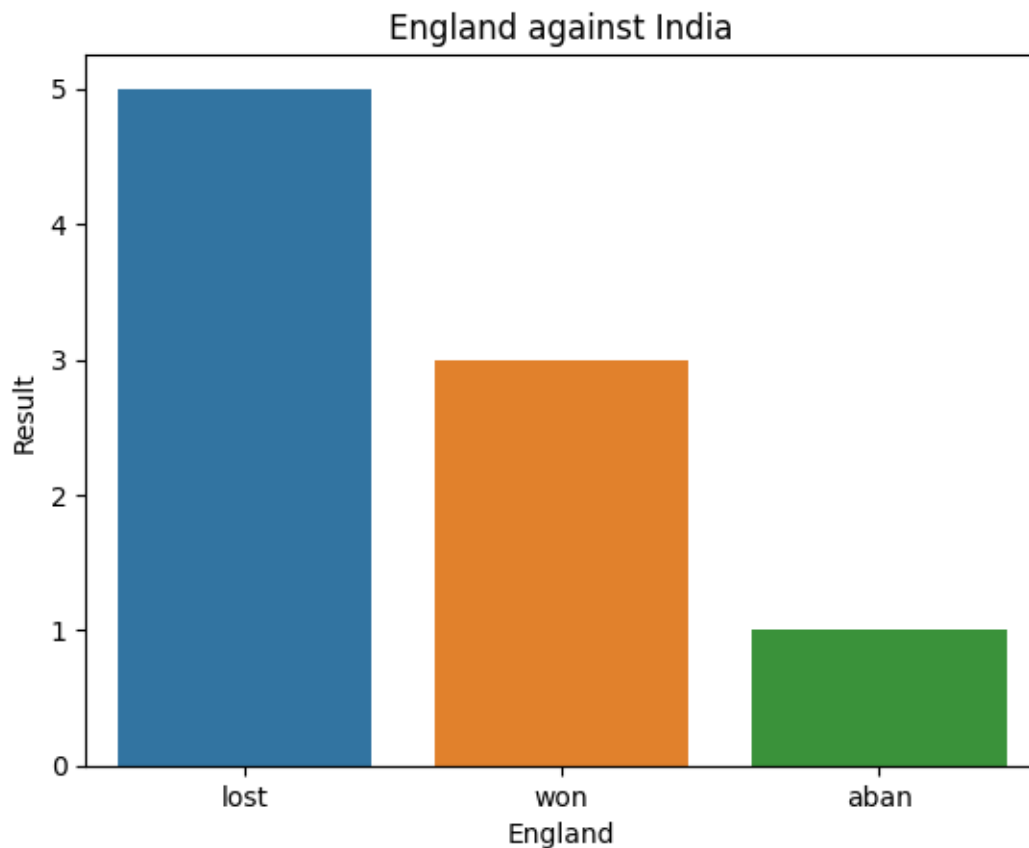


From the above figure, we can understand that,

- India and England have the highest winning percentage compared to that of other Nations
- Pakistan, South Africa, West Indies have the Highest Losing Percentage.

Let's see what happens when the Top Two Teams face?

```
[31]: India_vs_England = WC_Grounds_History[WC_Grounds_History.Country == "England"]\
[WC_Grounds_History.Opposition.str.contains("India")]
India_vs_England = India_vs_England.Result.value_counts().reset_index()
sns.barplot(x = "index", y = "Result", data = India_vs_England).
    set_title("England against India")
plt.xlabel("England")
plt.show()
```



```
[32]: WC_Grounds_History.sample(5)
```

```
[32]: Unnamed: 0 Result      Margin      BR Toss Bat Opposition \
915      955      won  8 wickets  16.0  won  2nd  v Bangladesh
724      931      tied      -      NaN  won  2nd  v Sri Lanka
356      891      lost  9 wickets 117.0 lost  1st      v India
987       87      lost 124 runs   NaN  won  2nd      v England
308      886      lost   7 runs   NaN  won  2nd  v Sri Lanka

      Ground      Start Date      Match_ID      Country      Country_ID
915      The Oval, London  1 Jun 2017  ODI # 3875      England      1
```

724	Trent Bridge, Nottingham	21 Jun 2016	ODI # 3751	England	1
356	Edgbaston, Birmingham	2 Sep 2014	ODI # 3523	England	1
987	County Ground, Bristol	24 Sep 2017	ODI # 3915	WestIndies	4
308	Lord's, London	31 May 2014	ODI # 3495	England	1

```
[33]: batter_df.sample(5)
```

```
[33]:
```

	Unnamed: 0	Bat1	Runs	BF	SR	4s	6s	Opposition	Ground	\
5250	5251	15	15	22	68.18	1	0	v Sri Lanka	Christchurch	
5213	5214	13	13	18	72.22	0	0	v South Africa	Napier	
2750	2751	46	46	59	77.96	6	0	v England	The Oval	
975	976	0	0	1	0.00	0	0	v Bangladesh	Dambulla	
7927	7928	110*	110	55	200.00	6	9	v Pakistan	Southampton	

	Start Date	Match_ID	Batsman	Player_ID
5250	11 Jan 2015	ODI # 3574	Kane Williamson	277906
5213	29 Feb 2012	ODI # 3252	Kane Williamson	277906
2750	29 Aug 2008	ODI # 2757	Hashim Amla	43906
975	28 Mar 2017	ODI # 3856	Nuwan Pradeep	324358
7927	11 May 2019	ODI # 4133	Jos Buttler	308967

```
[34]: batter_df.isnull().sum()
```

```
[34]:
```

Unnamed: 0	0
Bat1	0
Runs	0
BF	0
SR	0
4s	0
6s	0
Opposition	0
Ground	0
Start Date	0
Match_ID	0
Batsman	0
Player_ID	0
dtype:	int64

```
[35]: batter_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11149 entries, 0 to 11148
Data columns (total 13 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Unnamed: 0   11149 non-null  int64
1   Bat1         11149 non-null  object
2   Runs         11149 non-null  object
```

```

3   BF          11149 non-null object
4   SR          11149 non-null object
5   4s          11149 non-null object
6   6s          11149 non-null object
7   Opposition  11149 non-null object
8   Ground      11149 non-null object
9   Start Date  11149 non-null object
10  Match_ID    11149 non-null object
11  Batsman     11149 non-null object
12  Player_ID   11149 non-null int64
dtypes: int64(2), object(11)
memory usage: 1.1+ MB

```

```

[36]: batter_df['Runs'] = pd.to_numeric(batter_df['Runs'], errors='coerce').fillna(0).
      ↪astype(int)
batter_df['SR'] = pd.to_numeric(batter_df['SR'], errors='coerce').fillna(0).
      ↪astype(int)
batter_df['4s'] = pd.to_numeric(batter_df['4s'], errors='coerce').fillna(0).
      ↪astype(int)
batter_df['6s'] = pd.to_numeric(batter_df['6s'], errors='coerce').fillna(0).
      ↪astype(int)

```

```

[37]: batter_df.info()

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11149 entries, 0 to 11148
Data columns (total 13 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Unnamed: 0      11149 non-null  int64
1   Bat1            11149 non-null  object
2   Runs            11149 non-null  int32
3   BF              11149 non-null  object
4   SR              11149 non-null  int32
5   4s              11149 non-null  int32
6   6s              11149 non-null  int32
7   Opposition      11149 non-null  object
8   Ground          11149 non-null  object
9   Start Date      11149 non-null  object
10  Match_ID        11149 non-null  object
11  Batsman         11149 non-null  object
12  Player_ID       11149 non-null  int64
dtypes: int32(4), int64(2), object(7)
memory usage: 958.2+ KB

```

```

[38]: batter_df.describe()

```

```
[38]:
```

	Unnamed: 0	Runs	SR	4s	6s \
count	11149.00000	11149.000000	11149.000000	11149.000000	11149.000000
mean	5575.00000	22.964391	62.098125	2.080635	0.431788
std	3218.58341	30.694241	54.666471	3.072333	1.077853
min	1.00000	0.000000	0.000000	0.000000	0.000000
25%	2788.00000	0.000000	0.000000	0.000000	0.000000
50%	5575.00000	10.000000	63.000000	1.000000	0.000000
75%	8362.00000	34.000000	94.000000	3.000000	0.000000
max	11149.00000	264.000000	600.000000	33.000000	16.000000

```

Player_ID
count  1.114900e+04
mean   2.259088e+05
std    1.942613e+05
min    5.334000e+03
25%    4.749200e+04
50%    2.335140e+05
75%    3.217770e+05
max    1.158100e+06

```

```
[39]: batter_df["Runs"].isnull().sum()
```

```
[39]: 0
```

```
[40]: batter_df.sample(5)
```

```
[40]:
```

	Unnamed: 0	Bat1	Runs	BF	SR	4s	6s	Opposition	Ground \
9800	9801	74	74	95	77	5	2	v West Indies	Basseterre
9411	9412	0	0	9	0	0	0	v India	Dhaka
8790	8791	21	21	28	75	3	0	v Zimbabwe	Dhaka
5890	5891	8*	8	15	53	1	0	v Zimbabwe	Harare
10988	10989	2	2	22	9	0	0	v Ireland	Sharjah

```

Start Date    Match_ID      Batsman  Player_ID
9800  13 Jun 2016  ODI # 3745      Steve Smith    267192
9411  24 Jun 2015  ODI # 3661  Mashrafe Mortaza    56007
8790   9 Nov 2015  ODI # 3705  Mushfiqur Rahim    56029
5890  24 Jul 2013  ODI # 3395      Dinesh Karthik    30045
10988  5 Dec 2017  ODI # 3935      Asghar Afghan    320652

```

```
[41]: batter_df.drop(batter_df[batter_df.Bat1 == 'DNB'].index, inplace=True)
batter_df.head()
```

```
[41]:
```

	Unnamed: 0	Bat1	Runs	BF	SR	4s	6s	Opposition	Ground \
5	6	0*	0	8	0	0	0	v India	Dhaka
6	7	0*	0	0	0	0	0	v England	The Oval
9	10	1*	1	3	33	0	0	v England	Nottingham
10	11	0*	0	2	0	0	0	v Australia	Pallekele

```
11          12      0      0  2      0      0      0      v Pakistan  Dubai (DSC)
```

	Start Date	Match_ID	Batsman	Player_ID
5	10 Jan 2010	ODI # 2941	Oshane Thomas	49619
6	28 Jun 2011	ODI # 3165	Oshane Thomas	49619
9	6 Jul 2011	ODI # 3169	Oshane Thomas	49619
10	10 Aug 2011	ODI # 3175	Oshane Thomas	49619
11	11 Nov 2011	ODI # 3212	Oshane Thomas	49619

```
[42]: batter_df.shape
```

```
[42]: (9106, 13)
```

```
[43]: batter_df['Bat1'] = batter_df['Bat1'].str.replace('*', '.')
batter_df['SR'] = batter_df['SR'].replace('-', '0')
batter_df['Runs'] = batter_df['Runs'].replace('-', '0')
batter_df['4s'] = batter_df['4s'].replace('-', '0')
batter_df['6s'] = batter_df['6s'].replace('-', '0')
batter_df.head()
```

```
[43]:      Unnamed: 0  Bat1  Runs BF  SR  4s  6s  Opposition      Ground \
5          6      0.    0  8   0   0   0      v India      Dhaka
6          7      0.    0  0   0   0   0      v England    The Oval
9         10      1.    1  3  33   0   0      v England  Nottingham
10         11      0.    0  2   0   0   0      v Australia  Pallekele
11         12      0    0  2   0   0   0      v Pakistan  Dubai (DSC)
```

	Start Date	Match_ID	Batsman	Player_ID
5	10 Jan 2010	ODI # 2941	Oshane Thomas	49619
6	28 Jun 2011	ODI # 3165	Oshane Thomas	49619
9	6 Jul 2011	ODI # 3169	Oshane Thomas	49619
10	10 Aug 2011	ODI # 3175	Oshane Thomas	49619
11	11 Nov 2011	ODI # 3212	Oshane Thomas	49619

```
[44]: batter_df['SR']=batter_df['SR'].astype(float)
batter_df['Runs']=batter_df['Runs'].astype(float)
batter_df['4s']=batter_df['4s'].astype(float)
batter_df['6s']=batter_df['6s'].astype(float)
```

```
[45]: batter_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9106 entries, 5 to 11148
Data columns (total 13 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Unnamed: 0   9106 non-null   int64
1   Bat1        9106 non-null   object
```

```

2   Runs          9106 non-null  float64
3   BF            9106 non-null  object
4   SR            9106 non-null  float64
5   4s            9106 non-null  float64
6   6s            9106 non-null  float64
7   Opposition    9106 non-null  object
8   Ground        9106 non-null  object
9   Start Date    9106 non-null  object
10  Match_ID      9106 non-null  object
11  Batsman        9106 non-null  object
12  Player_ID     9106 non-null  int64
dtypes: float64(4), int64(2), object(7)
memory usage: 996.0+ KB

```

```
[46]: Top_10_batters = batter_df['Batsman'].value_counts()[:10]
Top_10_batters
```

```
[46]: MS Dhoni          294
Chris Gayle         288
Shoaib Malik        255
Virat Kohli         222
Ross Taylor         209
Mohammad Hafeez     208
Eoin Morgan         208
Rohit Sharma        202
Mushfiqur Rahim     194
Tamim Iqbal         193
Name: Batsman, dtype: int64
```

```
[47]: induvidual_player = batter_df.query('Batsman == "Virat Kohli "')
induvdual_player
```

```
[47]:
```

	Unnamed: 0	Bat1	Runs	BF	SR	4s	6s	Opposition	\
6676	6677	12	12.0	22	54.0	1.0	0.0	v Sri Lanka	
6677	6678	37	37.0	67	55.0	6.0	0.0	v Sri Lanka	
6678	6679	25	25.0	38	65.0	4.0	0.0	v Sri Lanka	
6679	6680	54	54.0	66	81.0	7.0	0.0	v Sri Lanka	
6680	6681	31	31.0	46	67.0	3.0	1.0	v Sri Lanka	
...
6898	6899	44	44.0	45	97.0	6.0	1.0	v Australia	
6899	6900	116	116.0	120	96.0	10.0	0.0	v Australia	
6900	6901	123	123.0	95	129.0	16.0	1.0	v Australia	
6901	6902	7	7.0	6	116.0	1.0	0.0	v Australia	
6902	6903	20	20.0	22	90.0	2.0	0.0	v Australia	

	Ground	Start Date	Match_ID	Batsman	Player_ID
6676	Dambulla	18 Aug 2008	ODI # 2742	Virat Kohli	253802
6677	Dambulla	20 Aug 2008	ODI # 2745	Virat Kohli	253802

6678	Colombo (RPS)	24 Aug 2008	ODI # 2750	Virat Kohli	253802
6679	Colombo (RPS)	27 Aug 2008	ODI # 2755	Virat Kohli	253802
6680	Colombo (RPS)	29 Aug 2008	ODI # 2756	Virat Kohli	253802
...
6898	Hyderabad (Deccan)	2 Mar 2019	ODI # 4102	Virat Kohli	253802
6899	Nagpur	5 Mar 2019	ODI # 4106	Virat Kohli	253802
6900	Ranchi	8 Mar 2019	ODI # 4109	Virat Kohli	253802
6901	Mohali	10 Mar 2019	ODI # 4111	Virat Kohli	253802
6902	Delhi	13 Mar 2019	ODI # 4113	Virat Kohli	253802

[222 rows x 13 columns]

```
[48]: print("The highest number of score for this batsman is: ")
print(individual_player['Runs'].max())
print("The highest Strike Rate for this batsman is: ")
print(individual_player['SR'].max())
print("The most number of 4s for this batsman is: ")
print(individual_player['4s'].max())
print("The most number of 6s score for this batsman is: ")
print(individual_player['6s'].max())
```

The highest number of score for this batsman is:

183.0

The highest Strike Rate for this batsman is:

209.0

The most number of 4s for this batsman is:

22.0

The most number of 6s score for this batsman is:

7.0

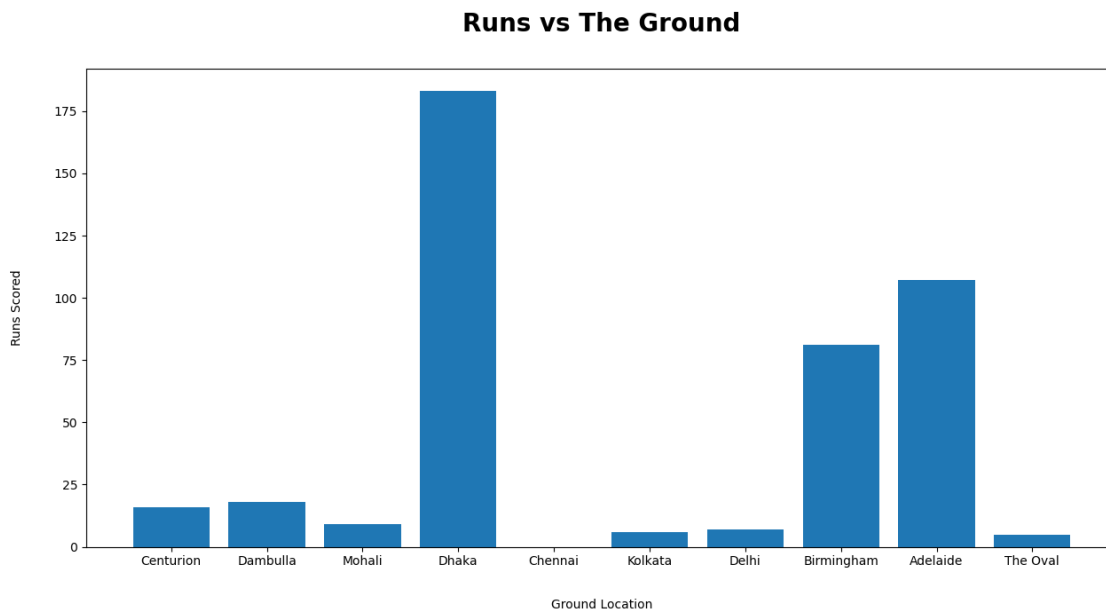
```
[49]: against_pak = individual_player.query('Opposition == "v Pakistan"')
against_pak
```

	Unnamed: 0	Bat1	Runs	BF	SR	4s	6s	Opposition	Ground \
6682	6683	16	16.0	24	66.0	1.0	0.0	v Pakistan	Centurion
6704	6705	18	18.0	27	66.0	1.0	0.0	v Pakistan	Dambulla
6728	6729	9	9.0	21	42.0	0.0	0.0	v Pakistan	Mohali
6760	6761	183	183.0	148	123.0	22.0	1.0	v Pakistan	Dhaka
6766	6767	0	0.0	5	0.0	0.0	0.0	v Pakistan	Chennai
6767	6768	6	6.0	9	66.0	1.0	0.0	v Pakistan	Kolkata
6768	6769	7	7.0	17	41.0	1.0	0.0	v Pakistan	Delhi
6776	6777	22.	22.0	27	81.0	3.0	0.0	v Pakistan	Birmingham
6808	6809	5	5.0	11	45.0	0.0	0.0	v Pakistan	Dhaka
6826	6827	107	107.0	126	84.0	8.0	0.0	v Pakistan	Adelaide
6855	6856	81.	81.0	68	119.0	6.0	3.0	v Pakistan	Birmingham
6859	6860	5	5.0	9	55.0	0.0	0.0	v Pakistan	The Oval

Start Date	Match_ID	Batsman	Player_ID
------------	----------	---------	-----------

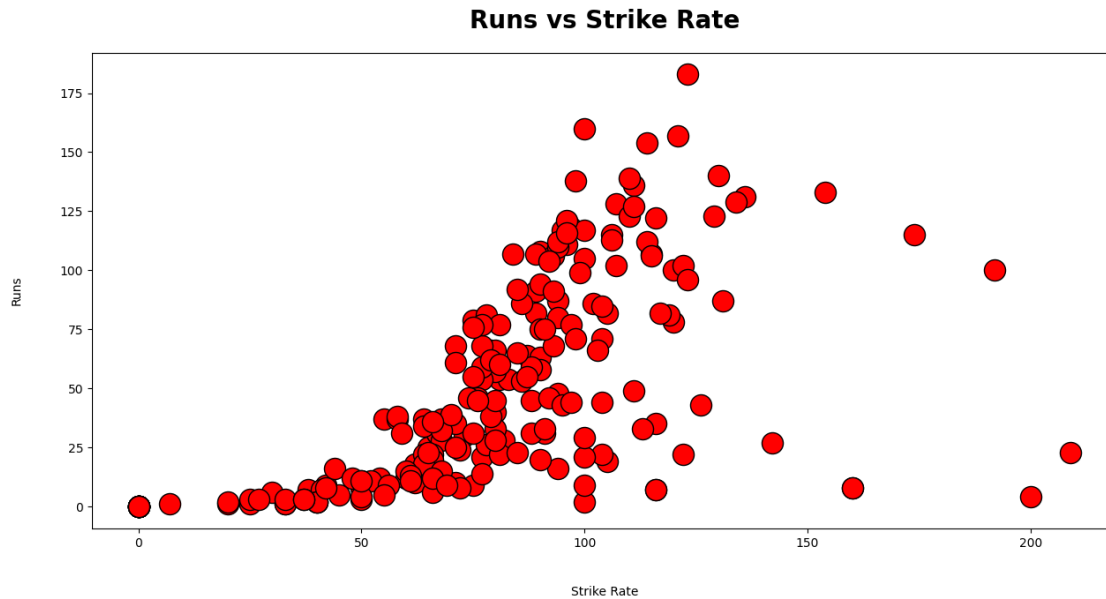
6682	26 Sep 2009	ODI # 2898	Virat Kohli	253802
6704	19 Jun 2010	ODI # 2996	Virat Kohli	253802
6728	30 Mar 2011	ODI # 3147	Virat Kohli	253802
6760	18 Mar 2012	ODI # 3263	Virat Kohli	253802
6766	30 Dec 2012	ODI # 3314	Virat Kohli	253802
6767	3 Jan 2013	ODI # 3315	Virat Kohli	253802
6768	6 Jan 2013	ODI # 3316	Virat Kohli	253802
6776	15 Jun 2013	ODI # 3372	Virat Kohli	253802
6808	2 Mar 2014	ODI # 3479	Virat Kohli	253802
6826	15 Feb 2015	ODI # 3602	Virat Kohli	253802
6855	4 Jun 2017	ODI # 3878	Virat Kohli	253802
6859	18 Jun 2017	ODI # 3894	Virat Kohli	253802

```
[50]: plt.figure(figsize=(15,7))
x = against_pak['Ground']
y = against_pak['Runs']
plt.xlabel('Ground Location', labelpad=25)
plt.ylabel('Runs Scored', labelpad=25)
plt.title('Runs vs The Ground', fontweight='bold', pad=30, fontsize=20)
plt.bar(x, y)
plt.show()
```



```
[51]: #strike rate vs the score of player in each match
plt.figure(figsize=(15,7))
x = individual_player['SR']
y = individual_player['Runs']
plt.xlabel('Strike Rate', labelpad=30)
```

```
plt.ylabel('Runs', labelpad=30)
plt.title('Runs vs Strike Rate', fontweight='bold', pad=20, fontsize=20)
plt.scatter(x, y, color='red', s=300, edgecolor='black')
plt.show()
```



```
[52]: bowler_df.sample(5)
```

```
[52]:      Unnamed: 0  Overs  Mdns  Runs  Wkts  Econ  Ave  SR  Opposition \
5514      5515   10.0    0   39    1  3.90  39.00  60.0  v South Africa
1363      1364    2.0    0    4    0  2.00    -    -    v New Zealand
9777      9778    -    -    -    -    -    -    -    v West Indies
6522      6523    -    -    -    -    -    -    -    v West Indies
1236      1237    -    -    -    -    -    -    -    v Pakistan
```

	Ground	Start Date	Match_ID	Bowler	Player_ID
5514	The Oval	11 Jun 2017	ODI # 3886	Ravindra Jadeja	234675
1363	Cardiff	9 Jun 2013	ODI # 3366	Thisara Perera	233514
9777	Providence	5 Jun 2016	ODI # 3740	Steve Smith	267192
6522	Port of Spain	8 Jun 2011	ODI # 3160	Rohit Sharma	34102
1236	Sharjah	23 Oct 2017	ODI # 3930	Milinda Siriwardana	222354

```
[53]: bowler_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11118 entries, 0 to 11117
Data columns (total 14 columns):
#   Column          Non-Null Count  Dtype
---

```

```

0   Unnamed: 0   11118 non-null   int64
1   Overs       11118 non-null   object
2   Mdns        11118 non-null   object
3   Runs        11118 non-null   object
4   Wkts        11118 non-null   object
5   Econ        11118 non-null   object
6   Ave         11118 non-null   object
7   SR          11118 non-null   object
8   Opposition  11118 non-null   object
9   Ground      11118 non-null   object
10  Start Date  11118 non-null   object
11  Match_ID    11118 non-null   object
12  Bowler      11118 non-null   object
13  Player_ID   11118 non-null   int64
dtypes: int64(2), object(12)
memory usage: 1.2+ MB

```

```
[54]: bowler_df.drop(bowler_df[bowler_df.Overs == '-'].index, inplace=True)
      bowler_df.head()
```

```
[54]:
```

	Unnamed: 0	Overs	Mdns	Runs	Wkts	Econ	Ave	SR	Opposition	Ground	\
0	1	8.0	0	57	0	7.12	-	-	v India	Nagpur	
1	2	10.0	0	55	2	5.50	27.50	30.0	v India	Kolkata	
3	4	9.0	1	63	2	7.00	31.50	27.0	v Bangladesh	Dhaka	
4	5	8.0	1	48	0	6.00	-	-	v India	Dhaka	
5	6	10.0	0	75	0	7.50	-	-	v India	Dhaka	

	Start Date	Match_ID	Bowler	Player_ID
0	18 Dec 2009	ODI # 2933	Suranga Lakmal	49619
1	24 Dec 2009	ODI # 2935	Suranga Lakmal	49619
3	4 Jan 2010	ODI # 2937	Suranga Lakmal	49619
4	5 Jan 2010	ODI # 2938	Suranga Lakmal	49619
5	10 Jan 2010	ODI # 2941	Suranga Lakmal	49619

```
[55]: bowler_df.shape
```

```
[55]: (5848, 14)
```

```
[56]: bowler_df['Mdns'] = bowler_df['Mdns'].str.replace('-', '0')
      bowler_df['Runs'] = bowler_df['Runs'].str.replace('-', '0')
      bowler_df['Wkts'] = bowler_df['Wkts'].str.replace('-', '0')
      bowler_df['Econ'] = bowler_df['Econ'].str.replace('-', '0')
      bowler_df['Ave'] = bowler_df['Ave'].str.replace('-', '0')
      bowler_df['SR'] = bowler_df['SR'].str.replace('-', '0')
```

```
[57]: bowler_df['Overs'] = bowler_df['Overs'].astype(float)
      bowler_df['Mdns'] = bowler_df['Mdns'].astype(float)
      bowler_df['Runs'] = bowler_df['Runs'].astype(float)
```

```

bowler_df['Wkts'] = bowler_df['Wkts'].astype(float)
bowler_df['Econ'] = bowler_df['Econ'].astype(float)
bowler_df['Ave'] = bowler_df['Ave'].astype(float)
bowler_df['SR'] = bowler_df['SR'].astype(float)
bowler_df.dtypes

```

```

[57]: Unnamed: 0      int64
      Overs        float64
      Mdns         float64
      Runs         float64
      Wkts         float64
      Econ         float64
      Ave          float64
      SR           float64
      Opposition    object
      Ground        object
      Start Date    object
      Match_ID      object
      Bowler        object
      Player_ID     int64
      dtype: object

```

2.9 Highest Number of Wickets

```

[58]: bowler_df.loc[bowler_df['Wkts']==bowler_df['Wkts'].max()]

```

```

[58]:      Unnamed: 0  Overs  Mdns  Runs  Wkts  Econ   Ave   SR  Opposition \
2056      2057    9.0    0.0  45.0    7.0  5.00  6.42  7.7  v West Indies
4933      4934   10.0    3.0  34.0    7.0  3.40  4.85  8.5  v West Indies
5044      5045    9.0    0.0  33.0    7.0  3.66  4.71  7.7      v England
11034     11035    8.4    1.0  18.0    7.0  2.07  2.57  7.4  v West Indies

      Ground  Start Date  Match_ID  Bowler  Player_ID
2056  Basseterre  15 Jun 2016  ODI # 3747  Imran Tahir      40618
4933  Christchurch  23 Dec 2017  ODI # 3944  Trent Boult     277912
5044  Wellington  20 Feb 2015  ODI # 3607  Tim Southee     232364
11034  Gros Islet   9 Jun 2017  ODI # 3884  Rashid Khan     793463

```

2.10 Highest Number of Madiens

```

[59]: bowler_df.loc[bowler_df['Mdns']==bowler_df['Mdns'].max()]

```

```

[59]:      Unnamed: 0  Overs  Mdns  Runs  Wkts  Econ   Ave   SR  Opposition \
67      68    10.0    4.0  13.0    4.0  1.30  3.25  15.0      v India
193     194    10.0    4.0  28.0    3.0  2.80  9.33  20.0  v Pakistan
200     201     6.0    4.0  14.0    1.0  2.33  14.00  36.0  v Pakistan
867     868    10.0    4.0  13.0    4.0  1.30  3.25  15.0  v Pakistan

```

982	983	10.0	4.0	37.0	2.0	3.70	18.50	30.0	v India
2231	2232	8.0	4.0	19.0	0.0	2.37	0.00	0.0	v Bangladesh
4952	4953	10.0	4.0	21.0	5.0	2.10	4.20	12.0	v India
5320	5321	9.0	4.0	23.0	1.0	2.55	23.00	54.0	v Pakistan
5644	5645	8.0	4.0	24.0	2.0	3.00	12.00	24.0	v Sri Lanka
9052	9053	10.0	4.0	13.0	1.0	1.30	13.00	60.0	v Scotland
9099	9100	10.0	4.0	11.0	3.0	1.10	3.66	20.0	v Zimbabwe
9101	9102	8.0	4.0	15.0	3.0	1.87	5.00	16.0	v Zimbabwe
9276	9277	10.0	4.0	25.0	3.0	2.50	8.33	20.0	v Kenya
9312	9313	10.0	4.0	22.0	3.0	2.20	7.33	20.0	v Ireland
10657	10658	8.3	4.0	10.0	2.0	1.17	5.00	25.5	v Kenya
10789	10790	8.2	4.0	26.0	4.0	3.12	6.50	12.5	v Kenya

	Ground	Start Date	Match_ID	Bowler	Player_ID
67	Dharamsala	10 Dec 2017	ODI # 3939	Suranga Lakmal	49619
193	The Oval	7 Jun 2013	ODI # 3364	Kemar Roach	230553
200	Providence	16 Jul 2013	ODI # 3390	Kemar Roach	230553
867	Providence	14 Jul 2013	ODI # 3389	Jason Holder	391485
982	Dharamsala	10 Dec 2017	ODI # 3939	Nuwan Pradeep	324358
2231	Dhaka	14 Mar 2008	ODI # 2692	Dale Steyn	47492
4952	Hamilton	31 Jan 2019	ODI # 4091	Trent Boult	277912
5320	Delhi	6 Jan 2013	ODI # 3316	Mohammed Shami	481896
5644	Port of Spain	11 Jul 2013	ODI # 3388	Bhuvneshwar Kumar	326016
9052	Chattogram	15 Dec 2006	ODI # 2465	Shakib Al Hasan	56143
9099	Dhaka	19 Jan 2009	ODI # 2797	Shakib Al Hasan	56143
9101	Dhaka	23 Jan 2009	ODI # 2801	Shakib Al Hasan	56143
9276	Nairobi (Gym)	12 Aug 2006	ODI # 2402	Mashrafe Mortaza	56007
9312	Dhaka	18 Mar 2008	ODI # 2693	Mashrafe Mortaza	56007
10657	Sharjah	4 Oct 2013	ODI # 3418	Mohammad Nabi	25913
10789	Nairobi (Gym)	7 Oct 2010	ODI # 3052	Hamid Hassan	311427

2.11 Gathering Data of one opponent individually

```
[60]: opponent = bowler_df.query('Opposition == "v India"')
opponent
```

```
[60]:
```

	Unnamed: 0	Overs	Mdns	Runs	Wkts	Econ	Ave	SR	Opposition	\
0	1	8.0	0.0	57.0	0.0	7.12	0.0	0.0	v India	
1	2	10.0	0.0	55.0	2.0	5.50	27.5	30.0	v India	
4	5	8.0	1.0	48.0	0.0	6.00	0.0	0.0	v India	
5	6	10.0	0.0	75.0	0.0	7.50	0.0	0.0	v India	
12	13	10.0	1.0	67.0	1.0	6.70	67.0	60.0	v India	
...	
10736	10737	10.0	0.0	40.0	2.0	4.00	20.0	30.0	v India	
10821	10822	5.0	0.0	25.0	0.0	5.00	0.0	0.0	v India	
11005	11006	10.0	0.0	53.0	2.0	5.30	26.5	30.0	v India	
11059	11060	9.5	0.0	41.0	2.0	4.16	20.5	29.5	v India	

11113	11114	4.0	0.0	41.0	0.0	10.25	0.0	0.0	v India
-------	-------	-----	-----	------	-----	-------	-----	-----	---------

	Ground	Start Date	Match_ID	Bowler	Player_ID
0	Nagpur	18 Dec 2009	ODI # 2933	Suranga Lakmal	49619
1	Kolkata	24 Dec 2009	ODI # 2935	Suranga Lakmal	49619
4	Dhaka	5 Jan 2010	ODI # 2938	Suranga Lakmal	49619
5	Dhaka	10 Jan 2010	ODI # 2941	Suranga Lakmal	49619
12	Dhaka	13 Mar 2012	ODI # 3259	Suranga Lakmal	49619
...
10736	Dubai (DSC)	25 Sep 2018	ODI # 4046	Mohammad Nabi	25913
10821	Dhaka	5 Mar 2014	ODI # 3483	Dawlat Zadran	516561
11005	Dubai (DSC)	25 Sep 2018	ODI # 4046	Aftab Alam	440963
11059	Dubai (DSC)	25 Sep 2018	ODI # 4046	Rashid Khan	793463
11113	Dubai (DSC)	25 Sep 2018	ODI # 4046	Gulbadin Naib	352048

[680 rows x 14 columns]

```
[61]: print("The maximum runs conceded against this team is: ")
print(bowler_df.loc[bowler_df['Runs'].max()])
print("-----")
print("The maximum maidens conceded against this team is: ")
print(bowler_df.loc[bowler_df['Mdns'].max()])
print("-----")
print("The maximum Wickets taken against this team is: ")
print(bowler_df.loc[bowler_df['Wkts'].max()])
print("-----")
print("The maximum Economy maintained against this team is: ")
print(bowler_df.loc[bowler_df['Econ'].max()])
```

The maximum runs conceded against this team is:

Unnamed: 0	107
Overs	4.0
Mdns	0.0
Runs	21.0
Wkts	0.0
Econ	5.25
Ave	0.0
SR	0.0
Opposition	v Australia
Ground	Kingstown
Start Date	16 Mar 2012
Match_ID	ODI # 3262
Bowler	Andre Russell
Player_ID	276298

Name: 106, dtype: object

The maximum maidens conceded against this team is:

Unnamed: 0	5
------------	---

Overs	8.0
Mdns	1.0
Runs	48.0
Wkts	0.0
Econ	6.0
Ave	0.0
SR	0.0
Opposition	v India
Ground	Dhaka
Start Date	5 Jan 2010
Match_ID	ODI # 2938
Bowler	Suranga Lakmal
Player_ID	49619

Name: 4, dtype: object

The maximum Wickets taken against this team is:

Unnamed: 0	8
Overs	7.5
Mdns	0.0
Runs	43.0
Wkts	3.0
Econ	5.48
Ave	14.33
SR	15.6
Opposition	v England
Ground	Leeds
Start Date	1 Jul 2011
Match_ID	ODI # 3167
Bowler	Suranga Lakmal
Player_ID	49619

Name: 7, dtype: object

The maximum Economy maintained against this team is:

Unnamed: 0	37
Overs	8.0
Mdns	0.0
Runs	50.0
Wkts	1.0
Econ	6.25
Ave	50.0
SR	48.0
Opposition	v Pakistan
Ground	Colombo (RPS)
Start Date	22 Jul 2015
Match_ID	ODI # 3671
Bowler	Suranga Lakmal
Player_ID	49619

Name: 36, dtype: object

2.12 Top 20 ballers with highest machthes/data

```
[62]: new = bowler_df['Bowler'].value_counts()[:20]
new
```

```
[62]: Shoaib Malik          213
      Lasith Malinga       212
      Mashrafe Mortaza     209
      Shakib Al Hasan      195
      Chris Gayle          195
      Mohammad Hafeez      169
      Angelo Mathews       154
      Ravindra Jadeja      147
      Thisara Perera       144
      Tim Southee          137
      Mahmudullah          132
      JP Duminy            131
      Dale Steyn           124
      Mohammad Nabi        107
      Bhuvneshwar Kumar    104
      Imran Tahir           96
      Rubel Hossain         95
      Jason Holder         93
      Moeen Ali             89
      Kemar Roach           84
      Name: Bowler, dtype: int64
```

```
[63]: induvidual_bowler = bowler_df.query('Bowler == "Ravindra Jadeja"')
      induvidual_bowler
```

```
[63]:      Unnamed: 0  Overs  Mdns  Runs  Wkts  Econ   Ave   SR  Opposition \
5383      5384    6.0    0.0  40.0    0.0  6.66   0.00   0.0    v Sri Lanka
5384      5385    7.0    1.0  34.0    0.0  4.85   0.00   0.0    v West Indies
5385      5386    2.0    0.0  12.0    0.0  6.00   0.00   0.0    v West Indies
5386      5387    9.0    0.0  39.0    1.0  4.33  39.00  54.0    v Australia
5387      5388    6.3    0.0  35.0    3.0  5.38  11.66  13.0    v Australia
...      ...      ...      ...      ...      ...      ...      ...
5529      5530    9.0    0.0  53.0    0.0  5.88   0.00   0.0    v Australia
5530      5531   10.0    0.0  33.0    0.0  3.30   0.00   0.0    v Australia
5531      5532   10.0    0.0  48.0    1.0  4.80  48.00  60.0    v Australia
5532      5533   10.0    0.0  64.0    0.0  6.40   0.00   0.0    v Australia
5533      5534   10.0    0.0  45.0    2.0  4.50  22.50  30.0    v Australia

      Ground  Start Date  Match_ID  Bowler  Player_ID
5383  Colombo (RPS)    8 Feb 2009  ODI # 2818  Ravindra Jadeja    234675
5384  Kingston       26 Jun 2009  ODI # 2852  Ravindra Jadeja    234675
5385  Kingston       28 Jun 2009  ODI # 2853  Ravindra Jadeja    234675
5386  Vadodara       25 Oct 2009  ODI # 2913  Ravindra Jadeja    234675
```

5387	Nagpur	28 Oct 2009	ODI # 2915	Ravindra Jadeja	234675
...
5529	Melbourne	18 Jan 2019	ODI # 4079	Ravindra Jadeja	234675
5530	Hyderabad (Deccan)	2 Mar 2019	ODI # 4102	Ravindra Jadeja	234675
5531	Nagpur	5 Mar 2019	ODI # 4106	Ravindra Jadeja	234675
5532	Ranchi	8 Mar 2019	ODI # 4109	Ravindra Jadeja	234675
5533	Delhi	13 Mar 2019	ODI # 4113	Ravindra Jadeja	234675

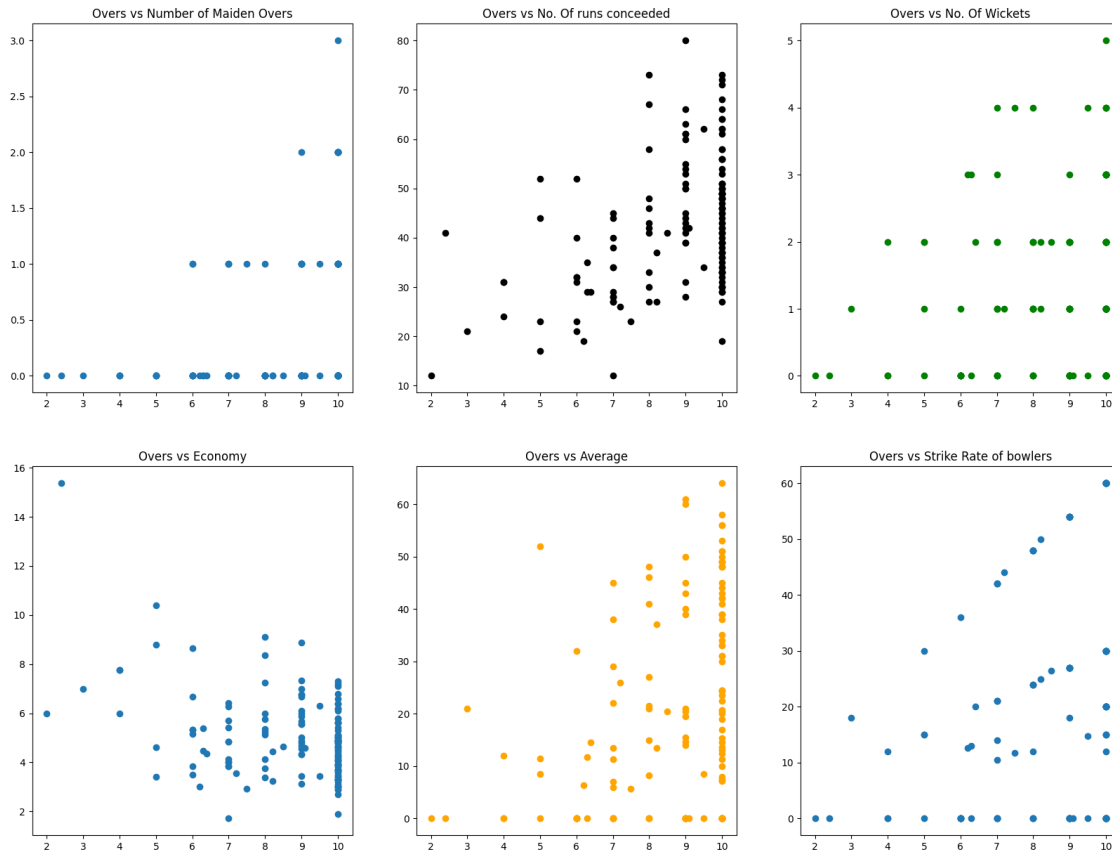
[147 rows x 14 columns]

2.13 Storing the data into variables

```
[64]: x = individual_bowler['Overs']
      y1 = individual_bowler['Mdns']
      y2 = individual_bowler['Runs']
      y3 = individual_bowler['Wkts']
      y4 = individual_bowler['Econ']
      y5 = individual_bowler['Ave']
      y6 = individual_bowler['SR']
```

2.14 Plotting the various graphs with Overs as X axis to understand the complete performance of a bowler

```
[65]: fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2, 3, figsize=(20, 15))
      ax1.scatter(x, y1)
      ax1.set_title('Overs vs Number of Maiden Overs')
      ax2.scatter(x, y2, color='black')
      ax2.set_title('Overs vs No. Of runs conceded')
      ax3.scatter(x, y3, color='green')
      ax3.set_title('Overs vs No. Of Wickets')
      ax4.scatter(x, y4)
      ax4.set_title('Overs vs Economy')
      ax5.scatter(x, y5, color='orange')
      ax5.set_title('Overs vs Average')
      ax6.scatter(x, y6)
      ax6.set_title('Overs vs Strike Rate of bowlers')
      plt.show()
```



2.15 Gathering Data of one opponent individually

```
[66]: bdf_induividual_opponence = induividual_bowler.query('Opposition == "v Pakistan"')
      bdf_induividual_opponence
```

```
[66]: Unnamed: 0  Overs  Mdns  Runs  Wkts  Econ   Ave   SR  Opposition  \
5410      5411   10.0   0.0  43.0    1.0  4.30  43.00  60.0  v Pakistan
5441      5442   10.0   1.0  41.0    3.0  4.10  13.66  20.0  v Pakistan
5442      5443   10.0   2.0  19.0    1.0  1.90  19.00  60.0  v Pakistan
5450      5451    8.0   1.0  30.0    2.0  3.75  15.00  24.0  v Pakistan
5482      5483   10.0   1.0  61.0    0.0  6.10    0.00   0.0  v Pakistan
5494      5495   10.0   0.0  56.0    1.0  5.60  56.00  60.0  v Pakistan
5512      5513    8.0   0.0  43.0    2.0  5.37  21.50  24.0  v Pakistan
5516      5517    8.0   0.0  67.0    0.0  8.37    0.00   0.0  v Pakistan
5520      5521    9.0   0.0  50.0    0.0  5.55    0.00   0.0  v Pakistan
```

```
      Ground  Start Date  Match_ID  Bowler  Player_ID
5410  Dambulla  19 Jun 2010  ODI # 2996  Ravindra Jadeja  234675
5441  Kolkata   3 Jan 2013  ODI # 3315  Ravindra Jadeja  234675
5442   Delhi   6 Jan 2013  ODI # 3316  Ravindra Jadeja  234675
```

5450	Birmingham	15 Jun 2013	ODI # 3372	Ravindra Jadeja	234675
5482	Dhaka	2 Mar 2014	ODI # 3479	Ravindra Jadeja	234675
5494	Adelaide	15 Feb 2015	ODI # 3602	Ravindra Jadeja	234675
5512	Birmingham	4 Jun 2017	ODI # 3878	Ravindra Jadeja	234675
5516	The Oval	18 Jun 2017	ODI # 3894	Ravindra Jadeja	234675
5520	Dubai (DSC)	23 Sep 2018	ODI # 4044	Ravindra Jadeja	234675