

analysis

October 28, 2025

```
[1]: #import libraries for analysis:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

plt.style.use('dark_background')
plt.rcParams['axes.prop_cycle'] = plt.cycler(color = sns.color_palette('dark'))
plt.rcParams['figure.figsize'] = (20 , 20)
```

```
[2]: # download dataset
#!curl -L -o ./data/ipl.csv "https://d2beiqkhq929f0.cloudfront.net/
↪public_assets/assets/000/158/850/original/IPL_2008-2024.csv?1760202529"
```

```
[ ]:
```

1 Question 1: Data Preprocessing & Feature Engineering (15 points)

1.0.1 Task:

1. Load the IPL dataset and perform comprehensive EDA
2. Handle missing values appropriately with justification
3. Create these new features:
 - **home_advantage**: Boolean indicating if team1 is playing in their home city
 - **match_importance**: Categorical (league/playoff/final) based on date and season
 - **toss_advantage**: Whether toss winner won the match
 - **season_phase**: Early/Mid/Late season

1.0.2 Deliverables:

- Clean dataset with no missing values
- Visualization showing distribution of matches across venues
- Statistical summary of win percentages for toss winners

```
[3]: # load dataset
df = pd.read_csv('./data/ipl.csv')
df.head()
```

```
[3]:
```

	id	season	city	date	match_type	player_of_match	\
0	335982	2008	Bangalore	2008-04-18	League	BB McCullum	
1	335983	2008	Chandigarh	2008-04-19	League	MEK Hussey	
2	335984	2008	Delhi	2008-04-19	League	MF Maharoo	
3	335985	2008	Mumbai	2008-04-20	League	MV Boucher	
4	335986	2008	Kolkata	2008-04-20	League	DJ Hussey	

	venue	team1	\
0	M Chinnaswamy Stadium	Royal Challengers Bangalore	
1	Punjab Cricket Association Stadium, Mohali	Kings XI Punjab	
2	Feroz Shah Kotla	Delhi Daredevils	
3	Wankhede Stadium	Mumbai Indians	
4	Eden Gardens	Kolkata Knight Riders	

	team2	toss_winner	toss_decision	\
0	Kolkata Knight Riders	Royal Challengers Bangalore	field	
1	Chennai Super Kings	Chennai Super Kings	bat	
2	Rajasthan Royals	Rajasthan Royals	bat	
3	Royal Challengers Bangalore	Mumbai Indians	bat	
4	Deccan Chargers	Deccan Chargers	bat	

	winner	result	result_margin	target_runs	\
0	Kolkata Knight Riders	runs	140.0	223.0	
1	Chennai Super Kings	runs	33.0	241.0	
2	Delhi Daredevils	wickets	9.0	130.0	
3	Royal Challengers Bangalore	wickets	5.0	166.0	
4	Kolkata Knight Riders	wickets	5.0	111.0	

	target_overs	super_over	method	umpire1	umpire2
0	20.0	N	NaN	Asad Rauf	RE Koertzen
1	20.0	N	NaN	MR Benson	SL Shastri
2	20.0	N	NaN	Aleem Dar	GA Pratapkumar
3	20.0	N	NaN	SJ Davis	DJ Harper
4	20.0	N	NaN	BF Bowden	K Hariharan

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1095 entries, 0 to 1094
Data columns (total 20 columns):
#   Column              Non-Null Count  Dtype
---  -
0   id                  1095 non-null   int64
1   season              1095 non-null   int64
2   city                1044 non-null   object
3   date                1095 non-null   object
4   match_type          1095 non-null   object
5   player_of_match     1090 non-null   object
```

```

6  venue          1095 non-null  object
7  team1          1095 non-null  object
8  team2          1095 non-null  object
9  toss_winner    1095 non-null  object
10 toss_decision  1095 non-null  object
11 winner         1090 non-null  object
12 result         1095 non-null  object
13 result_margin  1076 non-null  float64
14 target_runs    1092 non-null  float64
15 target_overs   1092 non-null  float64
16 super_over     1095 non-null  object
17 method         21 non-null    object
18 umpire1        1095 non-null  object
19 umpire2        1095 non-null  object
dtypes: float64(3), int64(2), object(15)
memory usage: 171.2+ KB

```

1.1 EDA on individual columns:

1.2 1. city

```

[5]: # skip features such as id and session since they are not-null
# columns to check = ['city' , 'player_of_match' , 'winner' , 'result_margin' ,
    ↪ 'target_runs/overs' , 'method']

# 1. city:
city = df['city']

pmissing = (np.sum(city.isnull()) / city.size) * 100
print(f"Percentage of missing data: {np.round(pmissing , 2)}")

city = city.fillna('unk')
ax = sns.barplot(city)
bars = ax.patches
yticks = [t.get_text() for t in ax.get_yticklabels()]
yind = yticks.index('unk')
bars[yind].set_facecolor('red')

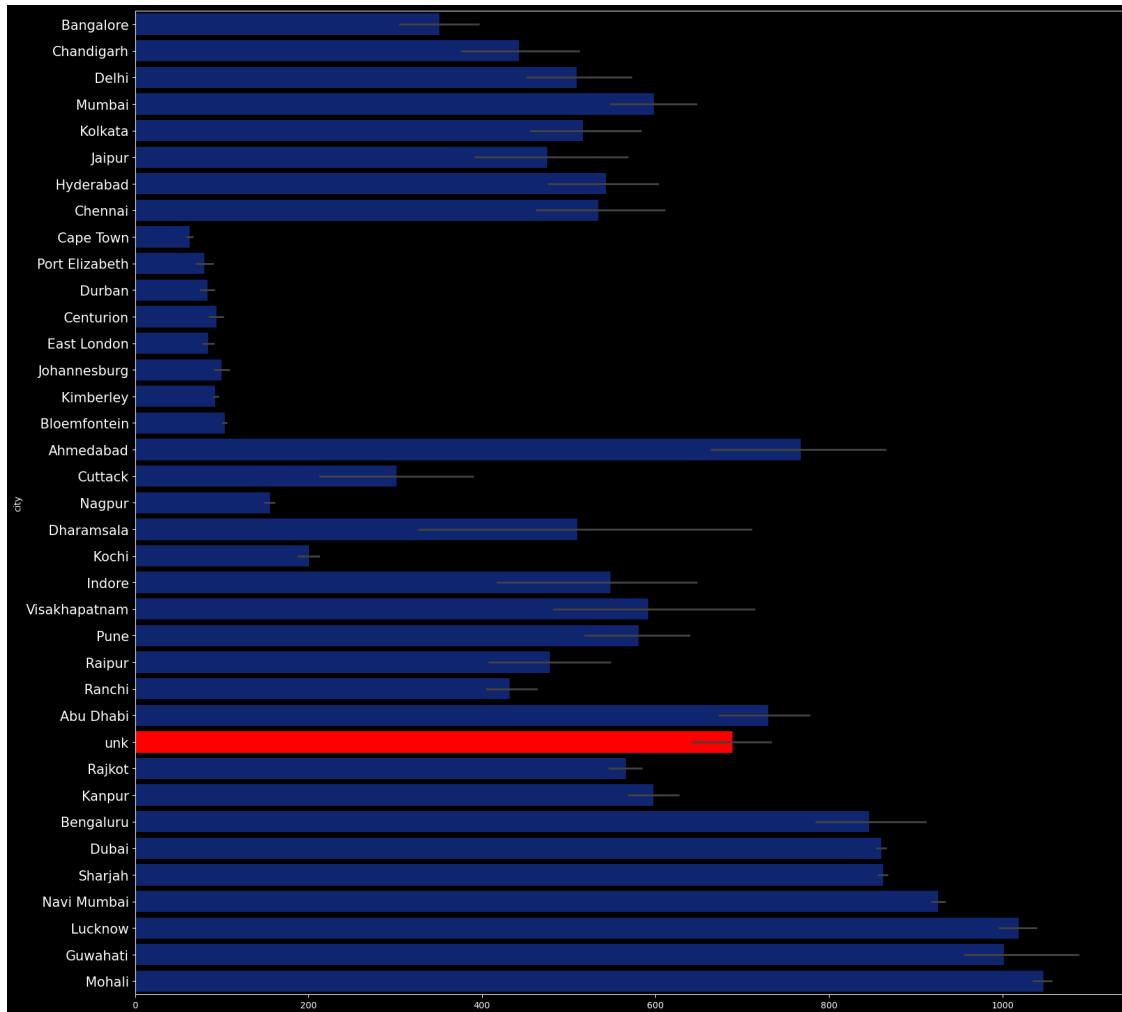
plt.yticks(fontsize = 15)
plt.show()

df['city'] = city

# strategy -> replace missing data with unk token, to represent the set of
    ↪ cities that hosted a match but were never mentioned.

```

Percentage of missing data: 4.66



1.2.1 2. player of match:

```
[6]: pom = df['player_of_match']
df[pom.isnull()]
```

```
[6]:
```

	id	season	city	date	match_type	player_of_match	\
241	501265	2011	Delhi	2011-05-21	League	NaN	
485	829763	2015	Bangalore	2015-04-29	League	NaN	
511	829813	2015	Bangalore	2015-05-17	League	NaN	
744	1178424	2019	Bengaluru	2019-04-30	League	NaN	
994	1359519	2023	Lucknow	2023-05-03	League	NaN	

	venue	\
241	Feroz Shah Kotla	
485	M Chinnaswamy Stadium	
511	M Chinnaswamy Stadium	

744 M.Chinnaswamy Stadium
 994 Bharat Ratna Shri Atal Bihari Vajpayee Ekana C...

	team1	team2 \
241	Delhi Daredevils	Pune Warriors
485	Royal Challengers Bangalore	Rajasthan Royals
511	Royal Challengers Bangalore	Delhi Daredevils
744	Royal Challengers Bangalore	Rajasthan Royals
994	Lucknow Super Giants	Chennai Super Kings

	toss_winner	toss_decision	winner	result \
241	Delhi Daredevils	bat	NaN	no result
485	Rajasthan Royals	field	NaN	no result
511	Royal Challengers Bangalore	field	NaN	no result
744	Rajasthan Royals	field	NaN	no result
994	Chennai Super Kings	field	NaN	no result

	result_margin	target_runs	target_overs	super_over	method \
241	NaN	NaN	NaN	N	NaN
485	NaN	NaN	NaN	N	NaN
511	NaN	188.0	20.0	N	NaN
744	NaN	63.0	5.0	N	NaN
994	NaN	NaN	NaN	N	NaN

	umpire1	umpire2
241	SS Hazare	RJ Tucker
485	JD Cloete	PG Pathak
511	HDPK Dharmasena	K Srinivasan
744	NJ Llong	UV Gandhe
994	AK Chaudhary	NA Patwardhan

- since there are just 5 matches where no result was declared so both `player_of_match` and `winner` features are missing, we again replace the null value with `unk` token for sanity purposes(I love nlp!).

```
[7]: df['player_of_match'] = df['player_of_match'].fillna('unk')
df['winner'] = df['winner'].fillna('unk')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1095 entries, 0 to 1094
Data columns (total 20 columns):
#   Column          Non-Null Count  Dtype
---  -
0   id              1095 non-null  int64
1   season         1095 non-null  int64
2   city           1095 non-null  object
3   date           1095 non-null  object
```

```

4  match_type      1095 non-null  object
5  player_of_match 1095 non-null  object
6  venue           1095 non-null  object
7  team1           1095 non-null  object
8  team2           1095 non-null  object
9  toss_winner     1095 non-null  object
10 toss_decision   1095 non-null  object
11 winner          1095 non-null  object
12 result          1095 non-null  object
13 result_margin   1076 non-null  float64
14 target_runs     1092 non-null  float64
15 target_overs    1092 non-null  float64
16 super_over      1095 non-null  object
17 method          21 non-null   object
18 umpire1         1095 non-null  object
19 umpire2         1095 non-null  object

```

dtypes: float64(3), int64(2), object(15)

memory usage: 171.2+ KB

1.2.2 3. result_margin

```
[8]: df[df['result_margin'].isnull()]
```

```

[8]:      id  season  city  date match_type player_of_match \
66   392190   2009  Cape Town  2009-04-23   League      YK Pathan
130  419121   2010   Chennai  2010-03-21   League      J Theron
241  501265   2011    Delhi  2011-05-21   League           unk
328  598004   2013  Hyderabad  2013-04-07   League      GH Vihari
342  598017   2013  Bangalore  2013-04-16   League      V Kohli
416  729315   2014  Abu Dhabi  2014-04-29   League  JP Faulkner
475  829741   2015  Ahmedabad  2015-04-21   League      SE Marsh
485  829763   2015  Bangalore  2015-04-29   League           unk
511  829813   2015  Bangalore  2015-05-17   League           unk
610 1082625   2017   Rajkot  2017-04-29   League  KH Pandya
705 1175365   2019    Delhi  2019-03-30   League      PP Shaw
744 1178424   2019  Bengaluru  2019-04-30   League           unk
746 1178426   2019    Mumbai  2019-05-02   League      JJ Bumrah
757 1216493   2020           unk  2020-09-20   League  MP Stoinis
765 1216547   2020           unk  2020-09-28   League  AB de Villiers
790 1216512   2020  Abu Dhabi  2020-10-18   League  LH Ferguson
791 1216517   2020           unk  2020-10-18   League  KL Rahul
835 1254077   2021   Chennai  2021-04-25   League      PP Shaw
994 1359519   2023   Lucknow  2023-05-03   League           unk

      venue \
66      Newlands
130  MA Chidambaram Stadium, Chepauk

```

241	Feroz Shah Kotla
328	Rajiv Gandhi International Stadium, Uppal
342	M Chinnaswamy Stadium
416	Sheikh Zayed Stadium
475	Sardar Patel Stadium, Motera
485	M Chinnaswamy Stadium
511	M Chinnaswamy Stadium
610	Saurashtra Cricket Association Stadium
705	Arun Jaitley Stadium
744	M.Chinnaswamy Stadium
746	Wankhede Stadium
757	Dubai International Cricket Stadium
765	Dubai International Cricket Stadium
790	Sheikh Zayed Stadium
791	Dubai International Cricket Stadium
835	MA Chidambaram Stadium, Chepauk, Chennai
994	Bharat Ratna Shri Atal Bihari Vajpayee Ekana C...

	team1	team2 \
66	Kolkata Knight Riders	Rajasthan Royals
130	Chennai Super Kings	Kings XI Punjab
241	Delhi Daredevils	Pune Warriors
328	Sunrisers Hyderabad	Royal Challengers Bangalore
342	Royal Challengers Bangalore	Delhi Daredevils
416	Kolkata Knight Riders	Rajasthan Royals
475	Rajasthan Royals	Kings XI Punjab
485	Royal Challengers Bangalore	Rajasthan Royals
511	Royal Challengers Bangalore	Delhi Daredevils
610	Gujarat Lions	Mumbai Indians
705	Kolkata Knight Riders	Delhi Capitals
744	Royal Challengers Bangalore	Rajasthan Royals
746	Mumbai Indians	Sunrisers Hyderabad
757	Delhi Capitals	Kings XI Punjab
765	Royal Challengers Bangalore	Mumbai Indians
790	Kolkata Knight Riders	Sunrisers Hyderabad
791	Mumbai Indians	Kings XI Punjab
835	Delhi Capitals	Sunrisers Hyderabad
994	Lucknow Super Giants	Chennai Super Kings

	toss_winner	toss_decision	winner \
66	Kolkata Knight Riders	field	Rajasthan Royals
130	Chennai Super Kings	field	Kings XI Punjab
241	Delhi Daredevils	bat	unk
328	Royal Challengers Bangalore	bat	Sunrisers Hyderabad
342	Royal Challengers Bangalore	field	Royal Challengers Bangalore
416	Rajasthan Royals	bat	Rajasthan Royals
475	Kings XI Punjab	field	Kings XI Punjab

485	Rajasthan Royals	field	unk
511	Royal Challengers Bangalore	field	unk
610	Gujarat Lions	bat	Mumbai Indians
705	Delhi Capitals	field	Delhi Capitals
744	Rajasthan Royals	field	unk
746	Mumbai Indians	bat	Mumbai Indians
757	Kings XI Punjab	field	Delhi Capitals
765	Mumbai Indians	field	Royal Challengers Bangalore
790	Sunrisers Hyderabad	field	Kolkata Knight Riders
791	Mumbai Indians	bat	Kings XI Punjab
835	Delhi Capitals	bat	Delhi Capitals
994	Chennai Super Kings	field	unk

	result	result_margin	target_runs	target_overs	super_over	method	\
66	tie	NaN	151.0	20.0	Y	NaN	
130	tie	NaN	137.0	20.0	Y	NaN	
241	no result	NaN	NaN	NaN	N	NaN	
328	tie	NaN	131.0	20.0	Y	NaN	
342	tie	NaN	153.0	20.0	Y	NaN	
416	tie	NaN	153.0	20.0	Y	NaN	
475	tie	NaN	192.0	20.0	Y	NaN	
485	no result	NaN	NaN	NaN	N	NaN	
511	no result	NaN	188.0	20.0	N	NaN	
610	tie	NaN	154.0	20.0	Y	NaN	
705	tie	NaN	186.0	20.0	Y	NaN	
744	no result	NaN	63.0	5.0	N	NaN	
746	tie	NaN	163.0	20.0	Y	NaN	
757	tie	NaN	158.0	20.0	Y	NaN	
765	tie	NaN	202.0	20.0	Y	NaN	
790	tie	NaN	164.0	20.0	Y	NaN	
791	tie	NaN	177.0	20.0	Y	NaN	
835	tie	NaN	160.0	20.0	Y	NaN	
994	no result	NaN	NaN	NaN	N	NaN	

	umpire1	umpire2
66	MR Benson	M Erasmus
130	K Hariharan	DJ Harper
241	SS Hazare	RJ Tucker
328	AK Chaudhary	S Ravi
342	M Erasmus	VA Kulkarni
416	Aleem Dar	AK Chaudhary
475	M Erasmus	S Ravi
485	JD Cloete	PG Pathak
511	HDPK Dharmasena	K Srinivasan
610	AK Chaudhary	CB Gaffaney
705	AY Dandekar	Nitin Menon
744	NJ Llong	UV Gandhe

746	CK Nandan	S Ravi
757	AK Chaudhary	Nitin Menon
765	Nitin Menon	PR Reiffel
790	PG Pathak	S Ravi
791	Nitin Menon	PR Reiffel
835	CB Gaffaney	KN Ananthapadmanabhan
994	AK Chaudhary	NA Patwardhan

1.2.3 for missing `result_margin`, its either a tie or no-result in match/ match abandoned. we replace NaN values with 0, since 0 margin = no-result/tie

```
[9]: df['result_margin'] = df['result_margin'].fillna(0)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1095 entries, 0 to 1094
Data columns (total 20 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    1095 non-null  int64
1   season                1095 non-null  int64
2   city                  1095 non-null  object
3   date                  1095 non-null  object
4   match_type            1095 non-null  object
5   player_of_match       1095 non-null  object
6   venue                 1095 non-null  object
7   team1                 1095 non-null  object
8   team2                 1095 non-null  object
9   toss_winner           1095 non-null  object
10  toss_decision         1095 non-null  object
11  winner                 1095 non-null  object
12  result                 1095 non-null  object
13  result_margin         1095 non-null  float64
14  target_runs           1092 non-null  float64
15  target_overs          1092 non-null  float64
16  super_over            1095 non-null  object
17  method                21 non-null    object
18  umpire1               1095 non-null  object
19  umpire2               1095 non-null  object
dtypes: float64(3), int64(2), object(15)
memory usage: 171.2+ KB
```

1.2.4 4. `target_runs/overs`:

```
[10]: truns = df['target_runs']
tovers = df['target_overs']
df[tovers.isnull()]
```

```
[10]:
```

	id	season	city	date	match_type	player_of_match	\
241	501265	2011	Delhi	2011-05-21	League	unk	
485	829763	2015	Bangalore	2015-04-29	League	unk	
994	1359519	2023	Lucknow	2023-05-03	League	unk	

	venue	\
241	Feroz Shah Kotla	
485	M Chinnaswamy Stadium	
994	Bharat Ratna Shri Atal Bihari Vajpayee Ekana C...	

	team1	team2	toss_winner	\
241	Delhi Daredevils	Pune Warriors	Delhi Daredevils	
485	Royal Challengers Bangalore	Rajasthan Royals	Rajasthan Royals	
994	Lucknow Super Giants	Chennai Super Kings	Chennai Super Kings	

	toss_decision	winner	result	result_margin	target_runs	target_overs	\
241	bat	unk	no result	0.0	NaN	NaN	
485	field	unk	no result	0.0	NaN	NaN	
994	field	unk	no result	0.0	NaN	NaN	

	super_over	method	umpire1	umpire2
241	N	NaN	SS Hazare	RJ Tucker
485	N	NaN	JD Cloete	PG Pathak
994	N	NaN	AK Chaudhary	NA Patwardhan

- <https://www.espncriinfo.com/series/indian-premier-league-2011-466304/delhi-daredevils-vs-pune-warriors-68th-match-501265/full-scorecard>
- I researched the first match and found out the game was abandoned due to extreme rain.
- This jibes with our previous pre-processing that says no-result for result feature.

1.2.5 we replace missing target_overs/runs values with zero, via the analogy no item = 0 item.

```
[11]: df['target_runs'] = truns.fillna(0)
df['target_overs'] = tovers.fillna(0)
```

1.2.6 5. method feature:

- if a match finished under normal conditions then no external method to determine the winner of the match was used -> match finished under normal conditions - 1074/1095 matches.

```
[12]: method = df['method']
print(f"% of matches finished normally: { np.sum(method.isnull()) / df.
      ↳shape[0]}")
df['method'] = method.fillna('normal')
```

% of matches finished normally: 0.9808219178082191

Q. Create these new features:

- `home_advantage`: Boolean indicating if team1 is playing in their home city
- `match_importance`: Categorical (league/playoff/final) based on date and season
- `toss_advantage`: Whether toss winner won the match
- `season_phase`: Early/Mid/Late season

```
[13]: # addressing the problem of teams that renamed themselves over the years
# 1. Royal Challengers Bengaluru -> Royal Challengers Bangalore
# 2. Kings XI Punjab -> Punjab Kings
# 3. Rising Pune Supergiants -> Rising Pune Supergiant
# 4. Delhi Daredevils -> Delhi Capitals
def change_team_name(x):
    if(x == 'Royal Challengers Bengaluru'):
        return 'Royal Challengers Bangalore'
    if(x == 'Kings XI Punjab'):
        return 'Punjab Kings'
    if(x == 'Rising Pune Supergiants'):
        return 'Rising Pune Supergiant'
    if(x == 'Delhi Daredevils'):
        return 'Delhi Capitals'
    return x
t1 = df['team1'].apply(lambda x: change_team_name(x))
t2 = df['team2'].apply(lambda x: change_team_name(x))
df['winner'] = df['winner'].apply(change_team_name)
df['team1'] = t1
df['team2'] = t2

print(f"cities: {df['city'].unique()} \n teams: {df['team1'].unique()}")

# create a map of team and home city
# team to city
ttc = {
    'Royal Challengers Bangalore' : ['Bangalore'],
    'Punjab Kings' : ["Mohali" , 'Chandigarh'],
    'Mumbai Indians' : ['Navi Mumbai' , 'Mumbai'],
    'Kolkata Knight Riders' : ['Kolkata'],
    'Rajasthan Royals' : ['Jaipur'],
    'Deccan Chargers' : ['Hyderabad' , 'Cuttuck' , 'Navi Mumbai'],
    ↪#deccan had alternating home-grounds
    'Chennai Super Kings' : ['Chennai'],
    'Kochi Tuskers Kerala' : ['Kochi'],
    'Pune Warriors' : ['Pune'],
    'Sunrisers Hyderabad' : ['Hyderabad'],
    'Gujarat Lions' : ['Rajkot'],
    'Rising Pune Supergiant' : ['Pune'],
    'Delhi Capitals' : ["Delhi"],
    'Lucknow Super Giants' : ['Lucknow'],
```

```

    'Gujarat Titans' : ['Ahmedabad']
}

def is_home_team(data):
    # print(data['city'])
    return data['city'] in ttc[data['team1']]
df['home_advantage'] = df.apply(lambda x : is_home_team(x), axis = 1)

df.sample(5)

```

```

cities: ['Bangalore' 'Chandigarh' 'Delhi' 'Mumbai' 'Kolkata' 'Jaipur'
'Hyderabad'
'Chennai' 'Cape Town' 'Port Elizabeth' 'Durban' 'Centurion' 'East London'
'Johannesburg' 'Kimberley' 'Bloemfontein' 'Ahmedabad' 'Cuttack' 'Nagpur'
'Dharamsala' 'Kochi' 'Indore' 'Visakhapatnam' 'Pune' 'Raipur' 'Ranchi'
'Abu Dhabi' 'unk' 'Rajkot' 'Kanpur' 'Bengaluru' 'Dubai' 'Sharjah'
'Navi Mumbai' 'Lucknow' 'Guwahati' 'Mohali']
teams: ['Royal Challengers Bangalore' 'Punjab Kings' 'Delhi Capitals'
'Mumbai Indians' 'Kolkata Knight Riders' 'Rajasthan Royals'
'Deccan Chargers' 'Chennai Super Kings' 'Kochi Tuskers Kerala'
'Pune Warriors' 'Sunrisers Hyderabad' 'Gujarat Lions'
'Rising Pune Supergiant' 'Lucknow Super Giants' 'Gujarat Titans']

```

```

[13]:
      id  season    city    date match_type player_of_match \
895  1304066   2022   Mumbai  2022-04-10    League    YS Chahal
130   419121   2010   Chennai  2010-03-21    League    J Theron
132   419123   2010 Bangalore  2010-03-23    League    RV Uthappa
273   548332   2012   Chennai  2012-04-21    League    F du Plessis
503   829797   2015   Chennai  2015-05-10    League    RA Jadeja

      venue                                     team1 \
895   Wankhede Stadium, Mumbai                    Rajasthan Royals
130   MA Chidambaram Stadium, Chepauk                Chennai Super Kings
132   M Chinnaswamy Stadium  Royal Challengers Bangalore
273   MA Chidambaram Stadium, Chepauk                Chennai Super Kings
503   MA Chidambaram Stadium, Chepauk                Chennai Super Kings

      team2    toss_winner  ... \
895  Lucknow Super Giants  Lucknow Super Giants  ...
130   Punjab Kings    Chennai Super Kings  ...
132  Chennai Super Kings    Chennai Super Kings  ...
273   Rajasthan Royals    Rajasthan Royals  ...
503   Rajasthan Royals    Chennai Super Kings  ...

      winner  result result_margin  target_runs \
895   Rajasthan Royals    runs            3.0    166.0
130   Punjab Kings    tie            0.0    137.0

```

132	Royal Challengers Bangalore	runs	36.0	172.0
273	Chennai Super Kings	wickets	7.0	147.0
503	Chennai Super Kings	runs	12.0	158.0

	target_overs	super_over	method	umpire1	umpire2	\
895	20.0	N	normal	AK Chaudhary	Tapan Sharma	
130	20.0	Y	normal	K Hariharan	DJ Harper	
132	20.0	N	normal	RE Koertzen	RB Tiffin	
273	20.0	N	normal	Aleem Dar	BNJ Oxenford	
503	20.0	N	normal	M Erasmus	CK Nandan	

	home_advantage
895	False
130	True
132	True
273	True
503	True

[5 rows x 21 columns]

```
[14]: # match importance
from sklearn.preprocessing import OrdinalEncoder
print(f"{df['match_type'].unique()}")
fcats = df['match_type'].str.strip().str.lower().replace({
    'qualifier 1': 'playoff',
    'qualifier 2': 'playoff',
    'eliminator': 'playoff',
    'semi final': 'playoff',
    '3rd place play-off': 'playoff',
    'league': 'league',
    'final': 'final'
})
df['match_importance'] = pd.Categorical(fcats , categories = ['league' ,
    ↪'playoff' , 'final' ] , ordered = True)
df.sample(10)
```

```
['League' 'Semi Final' 'Final' '3rd Place Play-Off' 'Qualifier 1'
'Elimination Final' 'Qualifier 2' 'Eliminator']
```

```
[14]:
```

	id	season	city	date	match_type	player_of_match	\
242	501266	2011	Bangalore	2011-05-22	League	CH Gayle	
1056	1426271	2024	Mohali	2024-04-18	League	JJ Bumrah	
273	548332	2012	Chennai	2012-04-21	League	F du Plessis	
401	729285	2014	Abu Dhabi	2014-04-18	League	AM Rahane	
660	1136585	2018	Hyderabad	2018-04-26	League	AS Rajpoot	
1031	1422126	2024	Hyderabad	2024-03-27	League	Abhishek Sharma	
992	1359517	2023	Lucknow	2023-05-01	League	F du Plessis	
106	392231	2009	Centurion	2009-05-18	League	BJ Hodge	

852	1254107	2021	Sharjah	2021-09-25	League	JO Holder
217	501241	2011	Mumbai	2011-05-04	League	R Sharma

	venue \
242	M Chinnaswamy Stadium
1056	Maharaja Yadavindra Singh International Cricke...
273	MA Chidambaram Stadium, Chepauk
401	Sheikh Zayed Stadium
660	Rajiv Gandhi International Stadium
1031	Rajiv Gandhi International Stadium, Uppal, Hyd...
992	Bharat Ratna Shri Atal Bihari Vajpayee Ekana C...
106	SuperSport Park
852	Sharjah Cricket Stadium
217	Dr DY Patil Sports Academy

	team1	team2 \
242	Royal Challengers Bangalore	Chennai Super Kings
1056	Mumbai Indians	Punjab Kings
273	Chennai Super Kings	Rajasthan Royals
401	Sunrisers Hyderabad	Rajasthan Royals
660	Sunrisers Hyderabad	Punjab Kings
1031	Sunrisers Hyderabad	Mumbai Indians
992	Royal Challengers Bangalore	Lucknow Super Giants
106	Chennai Super Kings	Kolkata Knight Riders
852	Punjab Kings	Sunrisers Hyderabad
217	Pune Warriors	Mumbai Indians

	toss_winner	...	result	result_margin	target_runs \
242	Royal Challengers Bangalore	...	wickets	8.0	129.0
1056	Punjab Kings	...	runs	9.0	193.0
273	Rajasthan Royals	...	wickets	7.0	147.0
401	Rajasthan Royals	...	wickets	4.0	134.0
660	Kings XI Punjab	...	runs	13.0	133.0
1031	Mumbai Indians	...	runs	31.0	278.0
992	Royal Challengers Bangalore	...	runs	18.0	127.0
106	Chennai Super Kings	...	wickets	7.0	189.0
852	Sunrisers Hyderabad	...	runs	5.0	126.0
217	Pune Warriors	...	runs	21.0	161.0

	target_overs	super_over	method	umpire1 \
242	20.0	N	normal	K Hariharan
1056	20.0	N	normal	A Nand Kishore
273	20.0	N	normal	Aleem Dar
401	20.0	N	normal	BF Bowden
660	20.0	N	normal	CK Nandan
1031	20.0	N	normal	KN Ananthapadmanabhan
992	20.0	N	normal	AK Chaudhary

106	20.0	N	normal	SJA Taufel
852	20.0	N	normal	RK Illingworth
217	20.0	N	normal	HDPK Dharmasena

	umpire2	home_advantage	match_importance
242	RE Koertzen	True	league
1056	VA Kulkarni	False	league
273	BNJ Oxenford	True	league
401	RK Illingworth	False	league
660	YC Barde	True	league
1031	UV Gandhe	True	league
992	GR Sadashiv Iyer	False	league
106	RB Tiffin	False	league
852	YC Barde	False	league
217	SJA Taufel	False	league

[10 rows x 22 columns]

```
[15]: # toss advantage: weather toss winner won the match or not!
df['toss_advantage'] = df[['toss_winner', 'winner']].apply(lambda x :
    ↪x['toss_winner'] == x['winner'] , axis = 1)
print(f"winning rate of toss winners: {np.round((np.sum(df['toss_advantage']) /
    ↪df.shape[0]) * 100 , 2)}")
df[['toss_winner', 'winner', 'toss_advantage']].sample(10)
```

winning rate of toss winners: 43.47

	toss_winner	winner	toss_advantage
162	Kolkata Knight Riders	Chennai Super Kings	False
1067	Rajasthan Royals	Rajasthan Royals	True
904	Gujarat Titans	Gujarat Titans	True
598	Mumbai Indians	Mumbai Indians	True
658	Mumbai Indians	Sunrisers Hyderabad	False
485	Rajasthan Royals	unk	False
524	Sunrisers Hyderabad	Kolkata Knight Riders	False
23	Chennai Super Kings	Rajasthan Royals	False
59	Royal Challengers Bangalore	Royal Challengers Bangalore	True
313	Rajasthan Royals	Deccan Chargers	False

```
[16]: df['date'] = pd.to_datetime(df['date'], errors = 'coerce')
df = df.sort_values(['season', 'date']).reset_index(drop = True)
df.head()
```

	id	season	city	date	match_type	player_of_match	\
0	335982	2008	Bangalore	2008-04-18	League	BB McCullum	
1	335983	2008	Chandigarh	2008-04-19	League	MEK Hussey	
2	335984	2008	Delhi	2008-04-19	League	MF Maharoof	
3	335985	2008	Mumbai	2008-04-20	League	MV Boucher	

4	335986	2008	Kolkata	2008-04-20	League	DJ Hussey
---	--------	------	---------	------------	--------	-----------

	venue	team1 \
0	M Chinnaswamy Stadium	Royal Challengers Bangalore
1	Punjab Cricket Association Stadium, Mohali	Punjab Kings
2	Feroz Shah Kotla	Delhi Capitals
3	Wankhede Stadium	Mumbai Indians
4	Eden Gardens	Kolkata Knight Riders

	team2	toss_winner ... \
0	Kolkata Knight Riders	Royal Challengers Bangalore ...
1	Chennai Super Kings	Chennai Super Kings ...
2	Rajasthan Royals	Rajasthan Royals ...
3	Royal Challengers Bangalore	Mumbai Indians ...
4	Deccan Chargers	Deccan Chargers ...

	result_margin	target_runs	target_overs	super_over	method	umpire1 \
0	140.0	223.0	20.0	N	normal	Asad Rauf
1	33.0	241.0	20.0	N	normal	MR Benson
2	9.0	130.0	20.0	N	normal	Aleem Dar
3	5.0	166.0	20.0	N	normal	SJ Davis
4	5.0	111.0	20.0	N	normal	BF Bowden

	umpire2	home_advantage	match_importance	toss_advantage
0	RE Koertzen	True	league	False
1	SL Shastri	True	league	True
2	GA Pratapkumar	True	league	False
3	DJ Harper	True	league	False
4	K Hariharan	True	league	False

[5 rows x 23 columns]

```
[17]: df['match_number'] = df.groupby(['season']).cumcount() + 1
df.head()
```

```
[17]:
```

	id	season	city	date	match_type	player_of_match \
0	335982	2008	Bangalore	2008-04-18	League	BB McCullum
1	335983	2008	Chandigarh	2008-04-19	League	MEK Hussey
2	335984	2008	Delhi	2008-04-19	League	MF Maharoof
3	335985	2008	Mumbai	2008-04-20	League	MV Boucher
4	335986	2008	Kolkata	2008-04-20	League	DJ Hussey

	venue	team1 \
0	M Chinnaswamy Stadium	Royal Challengers Bangalore
1	Punjab Cricket Association Stadium, Mohali	Punjab Kings
2	Feroz Shah Kotla	Delhi Capitals
3	Wankhede Stadium	Mumbai Indians

4		Eden Gardens	Kolkata Knight Riders	
---	--	--------------	-----------------------	--

	team2	toss_winner	...	target_runs	\
0	Kolkata Knight Riders	Royal Challengers Bangalore	...	223.0	
1	Chennai Super Kings	Chennai Super Kings	...	241.0	
2	Rajasthan Royals	Rajasthan Royals	...	130.0	
3	Royal Challengers Bangalore	Mumbai Indians	...	166.0	
4	Deccan Chargers	Deccan Chargers	...	111.0	

	target_overs	super_over	method	umpire1	umpire2	home_advantage	\
0	20.0	N	normal	Asad Rauf	RE Koertzen	True	
1	20.0	N	normal	MR Benson	SL Shastri	True	
2	20.0	N	normal	Aleem Dar	GA Pratapkumar	True	
3	20.0	N	normal	SJ Davis	DJ Harper	True	
4	20.0	N	normal	BF Bowden	K Hariharan	True	

	match_importance	toss_advantage	match_number
0	league	False	1
1	league	True	2
2	league	False	3
3	league	False	4
4	league	False	5

[5 rows x 24 columns]

```
[18]: # total matches per season:
# df.groupby('season').agg({'match_number': 'count'}).rename(columns =
↳ {'match_number' : 'total_matches'})
total_matches = df.groupby('season').size().to_dict()
df['total_matches'] = df.apply(lambda x : total_matches[x['season']], axis = 1)
df['early_cut'] = (df['total_matches'] / 3).astype(int)
df['mid_cut'] = (2 * df['total_matches'] / 3).astype(int)

def getPhase(x):
    if x['match_number'] < x['early_cut']:
        return 'Early'
    if x['match_number'] < x['mid_cut']:
        return 'Mid'
    return 'Early'
df['season_phase'] = df.apply(getPhase , axis = 1)
df.sample(10)
```

```
[18]:      id  season      city      date match_type player_of_match \
73   392198   2009   Centurion 2009-04-28   League   YK Pathan
80   392205   2009 Port Elizabeth 2009-05-02   League   YK Pathan
862  1254112   2021   Sharjah 2021-10-02   League   AR Patel
971  1359496   2023   Mumbai 2023-04-16   League   VR Iyer
```

618	1082633	2017	Bangalore	2017-05-05	League	Sandeep Sharma
507	829805	2015	Mumbai	2015-05-14	League	HH Pandya
412	729307	2014	Abu Dhabi	2014-04-26	League	Sandeep Sharma
543	980953	2016	Hyderabad	2016-04-30	League	DA Warner
762	1216539	2020	unk	2020-09-25	League	PP Shaw
203	501227	2011	Delhi	2011-04-26	League	V Kohli

	venue	team1 \
73	SuperSport Park	Delhi Capitals
80	St George's Park	Deccan Chargers
862	Sharjah Cricket Stadium	Mumbai Indians
971	Wankhede Stadium, Mumbai	Kolkata Knight Riders
618	M Chinnaswamy Stadium	Royal Challengers Bangalore
507	Wankhede Stadium	Mumbai Indians
412	Sheikh Zayed Stadium	Kolkata Knight Riders
543	Rajiv Gandhi International Stadium, Uppal	Sunrisers Hyderabad
762	Dubai International Cricket Stadium	Delhi Capitals
203	Feroz Shah Kotla	Delhi Capitals

	team2	toss_winner ... \
73	Rajasthan Royals	Delhi Daredevils ...
80	Rajasthan Royals	Deccan Chargers ...
862	Delhi Capitals	Delhi Capitals ...
971	Mumbai Indians	Mumbai Indians ...
618	Punjab Kings	Royal Challengers Bangalore ...
507	Kolkata Knight Riders	Kolkata Knight Riders ...
412	Punjab Kings	Kolkata Knight Riders ...
543	Royal Challengers Bangalore	Royal Challengers Bangalore ...
762	Chennai Super Kings	Chennai Super Kings ...
203	Royal Challengers Bangalore	Royal Challengers Bangalore ...

	umpire1	umpire2	home_advantage	match_importance \
73	GAV Baxter	RE Koertzen	False	league
80	S Asnani	BG Jerling	False	league
862	AK Chaudhary	MA Gough	False	league
971	BNJ Oxenford	UV Gandhe	False	league
618	CB Gaffaney	C Shamshuddin	True	league
507	RK Illingworth	VA Kulkarni	True	league
412	HDPK Dharmasena	RK Illingworth	False	league
543	AK Chaudhary	HDPK Dharmasena	True	league
762	KN Ananthapadmanabhan	RK Illingworth	False	league
203	S Asnani	RJ Tucker	True	league

	toss_advantage	match_number	total_matches	early_cut	mid_cut	season_phase
73	False	16	57	19	38	Early
80	False	23	57	19	38	Mid
862	True	47	60	20	40	Early

971	True	22	74	24	49	Early
618	False	42	59	19	39	Early
507	False	50	59	19	39	Early
412	False	15	60	20	40	Early
543	False	27	60	20	40	Mid
762	False	7	60	20	40	Early
203	True	29	73	24	48	Mid

[10 rows x 28 columns]

2 Question 2: Text Analytics - Player Performance Analysis (10 points)

2.0.1 Task:

Using **Bag of Words (BOW)** and **TF-IDF** techniques:

1. Create a corpus from all unique `player_of_match` names across seasons
2. Build a BOW representation of player names
3. Create a TF-IDF matrix to identify most distinctive player names per season
4. Find players who appear most frequently in specific venues

2.0.2 Bonus:

Create a word cloud of most frequent 'Player of Match' winners

Your code here

```
[19]: # venue column data cleaning:
venue = df['venue']
def clean_venue(venue):
    if ',' in venue:
        return str(venue.strip().split(',')[0])
    return venue

def clean2(venue):
    if venue.startswith('Punjab'):
        return 'Punjab Cricket Association IS Bindra Stadium'
    if 'Chinnaswamy' in venue:
        return 'M.Chinnaswamy Stadium'
    return venue

nvenue = venue.apply(clean_venue)
nvenue = nvenue.apply(clean2)
df['nvenue'] = nvenue
df
```

```
[19]:      id  season      city      date  match_type  player_of_match \
0      335982    2008    Bangalore 2008-04-18      League      BB McCullum
1      335983    2008    Chandigarh 2008-04-19      League      MEK Hussey
2      335984    2008      Delhi 2008-04-19      League      MF Maharooof
3      335985    2008     Mumbai 2008-04-20      League      MV Boucher
4      335986    2008     Kolkata 2008-04-20      League      DJ Hussey
...
1090   1426307    2024    Hyderabad 2024-05-19      League    Abhishek Sharma
1091   1426309    2024    Ahmedabad 2024-05-21  Qualifier 1      MA Starc
1092   1426310    2024    Ahmedabad 2024-05-22  Eliminator      R Ashwin
1093   1426311    2024     Chennai 2024-05-24  Qualifier 2    Shahbaz Ahmed
1094   1426312    2024     Chennai 2024-05-26      Final      MA Starc
```

```
                                venue \
0                                M Chinnaswamy Stadium
1      Punjab Cricket Association Stadium, Mohali
2                                Feroz Shah Kotla
3                                Wankhede Stadium
4                                Eden Gardens
...
1090   Rajiv Gandhi International Stadium, Uppal, Hyd...
1091                                Narendra Modi Stadium, Ahmedabad
1092                                Narendra Modi Stadium, Ahmedabad
1093      MA Chidambaram Stadium, Chepauk, Chennai
1094      MA Chidambaram Stadium, Chepauk, Chennai
```

```
                                team1                                team2 \
0      Royal Challengers Bangalore      Kolkata Knight Riders
1                                Punjab Kings      Chennai Super Kings
2                                Delhi Capitals      Rajasthan Royals
3                                Mumbai Indians      Royal Challengers Bangalore
4      Kolkata Knight Riders      Deccan Chargers
...
1090                                Punjab Kings      Sunrisers Hyderabad
1091      Sunrisers Hyderabad      Kolkata Knight Riders
1092   Royal Challengers Bangalore      Rajasthan Royals
1093      Sunrisers Hyderabad      Rajasthan Royals
1094      Sunrisers Hyderabad      Kolkata Knight Riders
```

```
                                toss_winner ...                                umpire2 home_advantage \
0      Royal Challengers Bangalore ...      RE Koertzen      True
1      Chennai Super Kings ...      SL Shastri      True
2      Rajasthan Royals ...      GA Pratapkumar      True
3      Mumbai Indians ...      DJ Harper      True
4      Deccan Chargers ...      K Hariharan      True
...
1090                                Punjab Kings ...      VK Sharma      False
```

1091	Sunrisers Hyderabad	...	R Pandit	False
1092	Rajasthan Royals	...	MV Saidharshan Kumar	False
1093	Rajasthan Royals	...	VK Sharma	False
1094	Sunrisers Hyderabad	...	Nitin Menon	False

	match_importance	toss_advantage	match_number	total_matches	early_cut	\
0	league	False	1	58	19	
1	league	True	2	58	19	
2	league	False	3	58	19	
3	league	False	4	58	19	
4	league	False	5	58	19	
...	
1090	league	False	67	71	23	
1091	playoff	False	68	71	23	
1092	playoff	True	69	71	23	
1093	playoff	False	70	71	23	
1094	final	False	71	71	23	

	mid_cut	season_phase	nvenue
0	38	Early	M.Chinnaswamy Stadium
1	38	Early	Punjab Cricket Association IS Bindra Stadium
2	38	Early	Feroz Shah Kotla
3	38	Early	Wankhede Stadium
4	38	Early	Eden Gardens
...
1090	47	Early	Rajiv Gandhi International Stadium
1091	47	Early	Narendra Modi Stadium
1092	47	Early	Narendra Modi Stadium
1093	47	Early	MA Chidambaram Stadium
1094	47	Early	MA Chidambaram Stadium

[1095 rows x 29 columns]

```
[20]: from sklearn.feature_extraction.text import CountVectorizer , TfidfVectorizer

# convert player names to tokens

df['mom'] = df['player_of_match'].apply(lambda x: ".".join(x.strip().split()))
player_list_per_season = df.groupby('season').agg({'mom': np.unique}).
    ↪reset_index().rename(columns = {'mom' : 'moms'})
print(f"{player_list_per_season}")

moms = player_list_per_season['moms']
ndoc = []
for season in moms:
    ndoc.append(" ".join(season))
```

```
# print(f"{ndoc}")
# convert the player_list_per_season to bow
cvector = CountVectorizer()
bmat = cvector.fit_transform(ndoc)
bow = pd.DataFrame(bmat.toarray() , columns = cvector.get_feature_names_out())
bow.index = [f"season-{str(season)[-2:]}" for season in
    ↪player_list_per_season['season']]
bow
```

	season	moms
0	2008	[A.Kumble, A.Mishra, A.Nehra, AC.Gilchrist, BB...
1	2009	[A.Kumble, A.Mishra, A.Nehra, A.Singh, AB.de.V...
2	2010	[A.Kumble, A.Symonds, AA.Jhunjhunwala, AC.Voge...
3	2011	[A.Mishra, AB.de.Villiers, AC.Gilchrist, AT.Ra...
4	2012	[A.Chandila, AB.de.Villiers, AC.Gilchrist, AD...
5	2013	[A.Mishra, AB.de.Villiers, AC.Gilchrist, AJ.Fi...
6	2014	[AB.de.Villiers, AJ.Finch, AM.Rahane, AR.Patel...
7	2015	[A.Nehra, AB.de.Villiers, AD.Russell, AM.Rahan...
8	2016	[A.Mishra, A.Nehra, A.Zampa, AB.Dinda, AB.de.V...
9	2017	[AJ.Tye, AR.Patel, AT.Rayudu, B.Kumar, BA.Stok...
10	2018	[A.Mishra, AB.de.Villiers, AD.Russell, AS.Rajp...
11	2019	[A.Mishra, AB.de.Villiers, AD.Russell, AS.Jose...
12	2020	[A.Nortje, AB.de.Villiers, AR.Patel, AT.Rayudu...
13	2021	[A.Mishra, A.Nortje, AB.de.Villiers, AR.Patel,...
14	2022	[AD.Russell, Abhishek.Sharma, Anuj.Rawat, Aves...
15	2023	[A.Manohar, AD.Russell, AM.Rahane, AR.Patel, A...
16	2024	[AD.Russell, Abhishek.Sharma, B.Kumar, B.Sai.S...

```
[20]:
```

	aa	aaron	ab	abdulla	abhishek	ac	ad	agarwal	ahmed	aj	...	\
season-08	0	0	0	0	0	1	0	0	0	0	...	
season-09	0	0	1	0	0	1	0	0	0	0	...	
season-10	1	0	0	0	0	1	1	0	0	0	...	
season-11	0	0	1	1	0	1	0	0	0	0	...	
season-12	0	0	1	0	0	1	1	0	0	0	...	
season-13	0	0	1	0	0	1	0	0	0	1	...	
season-14	0	0	1	0	0	0	0	0	0	1	...	
season-15	0	1	1	0	0	0	1	1	0	0	...	
season-16	0	0	2	0	0	0	1	0	0	1	...	
season-17	0	0	0	0	0	0	0	0	0	1	...	
season-18	0	0	1	0	0	0	1	0	0	0	...	
season-19	0	1	1	0	0	0	1	1	1	0	...	
season-20	0	0	1	0	0	0	0	0	0	0	...	
season-21	0	0	1	0	0	0	0	1	0	0	...	
season-22	0	0	0	0	1	0	1	1	0	0	...	
season-23	0	0	0	0	0	0	1	0	0	0	...	
season-24	0	0	0	0	1	0	1	0	2	0	...	

	wp	wpujc	wright	yadav	yash	ybk	yk	ys	yuvraj	zampa
season-08	0	0	0	0	0	0	1	0	0	0
season-09	0	0	0	0	0	0	1	0	1	0
season-10	0	1	0	0	0	0	1	0	0	0
season-11	1	0	0	0	0	0	1	0	1	0
season-12	0	0	0	1	0	0	1	0	0	0
season-13	0	0	1	0	0	0	1	0	0	0
season-14	1	0	0	1	0	0	1	1	1	0
season-15	0	0	0	1	0	0	0	0	0	0
season-16	0	0	0	1	0	0	1	0	0	1
season-17	1	0	0	0	0	0	0	0	1	0
season-18	0	0	0	3	0	0	0	0	0	0
season-19	0	0	0	1	0	0	0	0	0	0
season-20	1	0	0	1	0	0	0	1	0	0
season-21	0	0	0	0	0	0	0	1	0	0
season-22	1	0	0	3	0	1	0	1	0	0
season-23	0	0	0	1	0	1	0	0	0	0
season-24	0	0	0	3	1	0	0	0	0	0

[17 rows x 434 columns]

```
[21]: tvector = TfidfVectorizer(token_pattern= r'(?u)\b[\w\.\.]+\b')
tmat = tvector.fit_transform(ndoc)
tfidf = pd.DataFrame(tmat.toarray() , columns = tvector.
    ↳get_feature_names_out()).round(3)
tfidf.index = [f"season-{str(season)[-2:]}" for season in_
    ↳player_list_per_season['season']]
tfidf
```

```
[21]:
```

	a.chandila	a.kumble	a.manohar	a.mishra	a.nehra	a.nortje	\
season-08	0.00	0.149	0.000	0.101	0.136	0.000	
season-09	0.00	0.152	0.000	0.103	0.138	0.000	
season-10	0.00	0.149	0.000	0.000	0.000	0.000	
season-11	0.00	0.000	0.000	0.095	0.000	0.000	
season-12	0.19	0.000	0.000	0.000	0.000	0.000	
season-13	0.00	0.000	0.000	0.109	0.000	0.000	
season-14	0.00	0.000	0.000	0.000	0.000	0.000	
season-15	0.00	0.000	0.000	0.000	0.151	0.000	
season-16	0.00	0.000	0.000	0.125	0.168	0.000	
season-17	0.00	0.000	0.000	0.000	0.000	0.000	
season-18	0.00	0.000	0.000	0.121	0.000	0.000	
season-19	0.00	0.000	0.000	0.119	0.000	0.000	
season-20	0.00	0.000	0.000	0.000	0.000	0.192	
season-21	0.00	0.000	0.000	0.107	0.000	0.176	
season-22	0.00	0.000	0.000	0.000	0.000	0.000	
season-23	0.00	0.000	0.173	0.000	0.000	0.000	
season-24	0.00	0.000	0.000	0.000	0.000	0.000	

	a.singh	a.symonds	a.zampa	aa.jhunjhunwala	...	wd.parnell	\
season-08	0.000	0.00	0.000	0.00	...	0.000	
season-09	0.194	0.00	0.000	0.00	...	0.000	
season-10	0.000	0.19	0.000	0.19	...	0.000	
season-11	0.000	0.00	0.000	0.00	...	0.000	
season-12	0.000	0.00	0.000	0.00	...	0.000	
season-13	0.000	0.00	0.000	0.00	...	0.000	
season-14	0.000	0.00	0.000	0.00	...	0.000	
season-15	0.000	0.00	0.000	0.00	...	0.000	
season-16	0.000	0.00	0.236	0.00	...	0.000	
season-17	0.000	0.00	0.000	0.00	...	0.000	
season-18	0.000	0.00	0.000	0.00	...	0.000	
season-19	0.000	0.00	0.000	0.00	...	0.000	
season-20	0.000	0.00	0.000	0.00	...	0.000	
season-21	0.000	0.00	0.000	0.00	...	0.000	
season-22	0.000	0.00	0.000	0.00	...	0.000	
season-23	0.000	0.00	0.000	0.00	...	0.173	
season-24	0.000	0.00	0.000	0.00	...	0.000	

	wg.jacks	wp.saha	wpujc.vaas	yash.thakur	ybk.jaiswal	yk.pathan	\
season-08	0.000	0.000	0.00	0.000	0.000	0.101	
season-09	0.000	0.000	0.00	0.000	0.000	0.103	
season-10	0.000	0.000	0.19	0.000	0.000	0.101	
season-11	0.000	0.118	0.00	0.000	0.000	0.095	
season-12	0.000	0.000	0.00	0.000	0.000	0.101	
season-13	0.000	0.000	0.00	0.000	0.000	0.109	
season-14	0.000	0.158	0.00	0.000	0.000	0.127	
season-15	0.000	0.000	0.00	0.000	0.000	0.000	
season-16	0.000	0.000	0.00	0.000	0.000	0.125	
season-17	0.000	0.134	0.00	0.000	0.000	0.000	
season-18	0.000	0.000	0.00	0.000	0.000	0.000	
season-19	0.000	0.000	0.00	0.000	0.000	0.000	
season-20	0.000	0.145	0.00	0.000	0.000	0.000	
season-21	0.000	0.000	0.00	0.000	0.000	0.000	
season-22	0.000	0.111	0.00	0.000	0.148	0.000	
season-23	0.000	0.000	0.00	0.000	0.151	0.000	
season-24	0.172	0.000	0.00	0.172	0.000	0.000	

	ys.chahal	yuvraj.singh	z.khan
season-08	0.000	0.000	0.000
season-09	0.000	0.138	0.000
season-10	0.000	0.000	0.000
season-11	0.000	0.128	0.000
season-12	0.000	0.000	0.000
season-13	0.000	0.000	0.000
season-14	0.171	0.171	0.000

season-15	0.000	0.000	0.212
season-16	0.000	0.000	0.000
season-17	0.000	0.146	0.000
season-18	0.000	0.000	0.000
season-19	0.000	0.000	0.000
season-20	0.157	0.000	0.000
season-21	0.144	0.000	0.000
season-22	0.121	0.000	0.000
season-23	0.000	0.000	0.000
season-24	0.000	0.000	0.000

[17 rows x 294 columns]

```
[22]: #players who appear more frequently in venues relatively compared with other
      ↪venues:
vdf = df.groupby('nvenue').agg({'mom': lambda x : list(x)}).reset_index().
      ↪rename(columns = {'mom': 'moms'})

# convert each venue to a separate document
vdoc = []
for season in vdf['moms']:
    vdoc.append(" ".join(season))
tvector = TfidfVectorizer(token_pattern= r'(?u)\b[\w\.\.]+\b')
tmat = tvector.fit_transform(vdoc)
tdf = pd.DataFrame(tmat.toarray() , columns = tvector.get_feature_names_out()).
      ↪round(3)
tdf.index = vdf.nvenue
tdf
```

```
[22]:
```

	a.chandila	a.kumble	\
nvenue			
Arun Jaitley Stadium	0.000	0.000	
Barabati Stadium	0.000	0.000	
Barsapara Cricket Stadium	0.000	0.000	
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000	
Brabourne Stadium	0.000	0.000	
Buffalo Park	0.000	0.000	
De Beers Diamond Oval	0.000	0.000	
Dr DY Patil Sports Academy	0.000	0.156	
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.000	0.000	
Dubai International Cricket Stadium	0.000	0.000	
Eden Gardens	0.000	0.000	
Feroz Shah Kotla	0.000	0.000	
Green Park	0.000	0.000	
Himachal Pradesh Cricket Association Stadium	0.000	0.000	
Holkar Cricket Stadium	0.000	0.000	
JSCA International Stadium Complex	0.000	0.000	

Kingsmead	0.000	0.000
M.Chinnaswamy Stadium	0.000	0.000
MA Chidambaram Stadium	0.000	0.086
Maharaja Yadavindra Singh International Cricket...	0.000	0.000
Maharashtra Cricket Association Stadium	0.000	0.000
Narendra Modi Stadium	0.000	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.000	0.364
Newlands	0.000	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.000	0.000
Sardar Patel Stadium	0.000	0.000
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.136	0.000
Shaheed Veer Narayan Singh International Stadium	0.000	0.000
Sharjah Cricket Stadium	0.000	0.000
Sheikh Zayed Stadium	0.000	0.000
St George's Park	0.000	0.000
Subrata Roy Sahara Stadium	0.000	0.000
SuperSport Park	0.000	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.000	0.000
Zayed Cricket Stadium	0.000	0.000

	a.manohar	a.mishra \
nvenue		
Arun Jaitley Stadium	0.000	0.258
Barabati Stadium	0.000	0.000
Barsapara Cricket Stadium	0.000	0.000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000
Brabourne Stadium	0.000	0.000
Buffalo Park	0.000	0.000
De Beers Diamond Oval	0.000	0.000
Dr DY Patil Sports Academy	0.000	0.118
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.000	0.000
Dubai International Cricket Stadium	0.000	0.000
Eden Gardens	0.000	0.000
Feroz Shah Kotla	0.000	0.261
Green Park	0.000	0.000
Himachal Pradesh Cricket Association Stadium	0.000	0.000
Holkar Cricket Stadium	0.000	0.000
JSCA International Stadium Complex	0.000	0.000
Kingsmead	0.000	0.000
M.Chinnaswamy Stadium	0.000	0.000
MA Chidambaram Stadium	0.000	0.065
Maharaja Yadavindra Singh International Cricket...	0.000	0.000

Maharashtra Cricket Association Stadium	0.000	0.123
Narendra Modi Stadium	0.224	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.000	0.275
Newlands	0.000	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.000	0.124
Sardar Patel Stadium	0.000	0.000
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.000	0.000
Shaheed Veer Narayan Singh International Stadium	0.000	0.000
Sharjah Cricket Stadium	0.000	0.000
Sheikh Zayed Stadium	0.000	0.000
St George's Park	0.000	0.000
Subrata Roy Sahara Stadium	0.000	0.000
SuperSport Park	0.000	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.000	0.054
Zayed Cricket Stadium	0.000	0.000

	a.nehra	a.nortje \
nvenue		
Arun Jaitley Stadium	0.000	0.000
Barabati Stadium	0.000	0.000
Barsapara Cricket Stadium	0.000	0.000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000
Brabourne Stadium	0.000	0.000
Buffalo Park	0.581	0.000
De Beers Diamond Oval	0.000	0.000
Dr DY Patil Sports Academy	0.130	0.000
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.249	0.000
Dubai International Cricket Stadium	0.000	0.282
Eden Gardens	0.000	0.000
Feroz Shah Kotla	0.000	0.000
Green Park	0.000	0.000
Himachal Pradesh Cricket Association Stadium	0.000	0.000
Holkar Cricket Stadium	0.000	0.000
JSCA International Stadium Complex	0.366	0.000
Kingsmead	0.000	0.000
M.Chinnaswamy Stadium	0.000	0.000
MA Chidambaram Stadium	0.071	0.000
Maharaja Yadavindra Singh International Cricket...	0.000	0.000
Maharashtra Cricket Association Stadium	0.000	0.000
Narendra Modi Stadium	0.000	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.000	0.000

Newlands	0.000	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.000	0.000
Sardar Patel Stadium	0.000	0.000
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.000	0.000
Shaheed Veer Narayan Singh International Stadium	0.000	0.000
Sharjah Cricket Stadium	0.000	0.000
Sheikh Zayed Stadium	0.000	0.210
St George's Park	0.000	0.000
Subrata Roy Sahara Stadium	0.000	0.000
SuperSport Park	0.000	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.060	0.000
Zayed Cricket Stadium	0.000	0.000

	a.singh	a.symonds \
nvenue		
Arun Jaitley Stadium	0.000	0.000
Barabati Stadium	0.000	0.737
Barsapara Cricket Stadium	0.000	0.000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000
Brabourne Stadium	0.000	0.000
Buffalo Park	0.000	0.000
De Beers Diamond Oval	0.000	0.000
Dr DY Patil Sports Academy	0.000	0.000
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.000	0.000
Dubai International Cricket Stadium	0.000	0.000
Eden Gardens	0.000	0.000
Feroz Shah Kotla	0.000	0.125
Green Park	0.000	0.000
Himachal Pradesh Cricket Association Stadium	0.000	0.000
Holkar Cricket Stadium	0.000	0.000
JSCA International Stadium Complex	0.000	0.000
Kingsmead	0.000	0.000
M.Chinnaswamy Stadium	0.000	0.000
MA Chidambaram Stadium	0.000	0.000
Maharaja Yadavindra Singh International Cricket...	0.000	0.000
Maharashtra Cricket Association Stadium	0.000	0.000
Narendra Modi Stadium	0.000	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.000	0.000
Newlands	0.000	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.000	0.000

Sardar Patel Stadium	0.000	0.000
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.000	0.000
Shaheed Veer Narayan Singh International Stadium	0.000	0.000
Sharjah Cricket Stadium	0.000	0.000
Sheikh Zayed Stadium	0.000	0.000
St George's Park	0.000	0.000
Subrata Roy Sahara Stadium	0.000	0.000
SuperSport Park	0.387	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.000	0.000
Zayed Cricket Stadium	0.000	0.000
	a.zampa	aa.jhunjhunwala \
nvenue		
Arun Jaitley Stadium	0.000	0.000
Barabati Stadium	0.000	0.000
Barsapara Cricket Stadium	0.000	0.000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000
Brabourne Stadium	0.000	0.000
Buffalo Park	0.000	0.000
De Beers Diamond Oval	0.000	0.000
Dr DY Patil Sports Academy	0.000	0.000
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.361	0.000
Dubai International Cricket Stadium	0.000	0.000
Eden Gardens	0.000	0.000
Feroz Shah Kotla	0.000	0.000
Green Park	0.000	0.000
Himachal Pradesh Cricket Association Stadium	0.000	0.000
Holkar Cricket Stadium	0.000	0.000
JSCA International Stadium Complex	0.000	0.000
Kingsmead	0.000	0.000
M.Chinnaswamy Stadium	0.000	0.000
MA Chidambaram Stadium	0.000	0.000
Maharaja Yadavindra Singh International Cricket...	0.000	0.000
Maharashtra Cricket Association Stadium	0.000	0.000
Narendra Modi Stadium	0.000	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.000	0.000
Newlands	0.000	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.000	0.000
Sardar Patel Stadium	0.000	0.357
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.000	0.000
Shaheed Veer Narayan Singh International Stadium	0.000	0.000

Sharjah Cricket Stadium	0.000	0.000
Sheikh Zayed Stadium	0.000	0.000
St George's Park	0.000	0.000
Subrata Roy Sahara Stadium	0.000	0.000
SuperSport Park	0.000	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.000	0.000
Zayed Cricket Stadium	0.000	0.000

	...	wd.parnell	wg.jacks	\
nvenue	...			
Arun Jaitley Stadium	...	0.000	0.000	
Barabati Stadium	...	0.000	0.000	
Barsapara Cricket Stadium	...	0.000	0.000	
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	...	0.000	0.000	
Brabourne Stadium	...	0.000	0.000	
Buffalo Park	...	0.000	0.000	
De Beers Diamond Oval	...	0.000	0.000	
Dr DY Patil Sports Academy	...	0.000	0.000	
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	...	0.000	0.000	
Dubai International Cricket Stadium	...	0.000	0.000	
Eden Gardens	...	0.000	0.000	
Feroz Shah Kotla	...	0.000	0.000	
Green Park	...	0.000	0.000	
Himachal Pradesh Cricket Association Stadium	...	0.000	0.000	
Holkar Cricket Stadium	...	0.000	0.000	
JSCA International Stadium Complex	...	0.000	0.000	
Kingsmead	...	0.000	0.000	
M.Chinnaswamy Stadium	...	0.000	0.000	
MA Chidambaram Stadium	...	0.000	0.000	
Maharaja Yadavindra Singh International Cricket...	...	0.000	0.000	
Maharashtra Cricket Association Stadium	...	0.000	0.000	
Narendra Modi Stadium	...	0.000	0.224	
Nehru Stadium	...	0.000	0.000	
New Wanderers Stadium	...	0.000	0.000	
Newlands	...	0.000	0.000	
OUTsurance Oval	...	0.000	0.000	
Punjab Cricket Association IS Bindra Stadium	...	0.000	0.000	
Rajiv Gandhi International Stadium	...	0.000	0.000	
Sardar Patel Stadium	...	0.000	0.000	
Saurashtra Cricket Association Stadium	...	0.000	0.000	
Sawai Mansingh Stadium	...	0.136	0.000	
Shaheed Veer Narayan Singh International Stadium	...	0.000	0.000	
Sharjah Cricket Stadium	...	0.000	0.000	
Sheikh Zayed Stadium	...	0.000	0.000	
St George's Park	...	0.000	0.000	
Subrata Roy Sahara Stadium	...	0.000	0.000	

SuperSport Park	...	0.000	0.000
Vidarbha Cricket Association Stadium	...	0.000	0.000
Wankhede Stadium	...	0.000	0.000
Zayed Cricket Stadium	...	0.000	0.000

	wp.saha	wpujc.vaas	\
nvenue			
Arun Jaitley Stadium	0.000	0.000	
Barabati Stadium	0.000	0.000	
Barsapara Cricket Stadium	0.000	0.000	
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000	
Brabourne Stadium	0.000	0.000	
Buffalo Park	0.000	0.000	
De Beers Diamond Oval	0.000	0.000	
Dr DY Patil Sports Academy	0.000	0.000	
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.000	0.000	
Dubai International Cricket Stadium	0.121	0.000	
Eden Gardens	0.000	0.000	
Feroz Shah Kotla	0.000	0.000	
Green Park	0.000	0.000	
Himachal Pradesh Cricket Association Stadium	0.000	0.000	
Holkar Cricket Stadium	0.000	0.000	
JSCA International Stadium Complex	0.000	0.000	
Kingsmead	0.000	0.000	
M.Chinnaswamy Stadium	0.000	0.000	
MA Chidambaram Stadium	0.080	0.103	
Maharaja Yadavindra Singh International Cricket...	0.000	0.000	
Maharashtra Cricket Association Stadium	0.000	0.000	
Narendra Modi Stadium	0.000	0.000	
Nehru Stadium	0.000	0.000	
New Wanderers Stadium	0.000	0.000	
Newlands	0.000	0.000	
OUTsurance Oval	0.000	0.000	
Punjab Cricket Association IS Bindra Stadium	0.000	0.000	
Rajiv Gandhi International Stadium	0.076	0.000	
Sardar Patel Stadium	0.000	0.000	
Saurashtra Cricket Association Stadium	0.000	0.000	
Sawai Mansingh Stadium	0.000	0.000	
Shaheed Veer Narayan Singh International Stadium	0.000	0.000	
Sharjah Cricket Stadium	0.000	0.000	
Sheikh Zayed Stadium	0.000	0.000	
St George's Park	0.000	0.000	
Subrata Roy Sahara Stadium	0.000	0.000	
SuperSport Park	0.000	0.000	
Vidarbha Cricket Association Stadium	0.000	0.000	
Wankhede Stadium	0.134	0.000	
Zayed Cricket Stadium	0.000	0.000	

	yash.thakur	ybk.jaiswal \
nvenue		
Arun Jaitley Stadium	0.000	0.000
Barabati Stadium	0.000	0.000
Barsapara Cricket Stadium	0.000	0.521
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.325	0.000
Brabourne Stadium	0.000	0.000
Buffalo Park	0.000	0.000
De Beers Diamond Oval	0.000	0.000
Dr DY Patil Sports Academy	0.000	0.000
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.000	0.000
Dubai International Cricket Stadium	0.000	0.000
Eden Gardens	0.000	0.060
Feroz Shah Kotla	0.000	0.000
Green Park	0.000	0.000
Himachal Pradesh Cricket Association Stadium	0.000	0.000
Holkar Cricket Stadium	0.000	0.000
JSCA International Stadium Complex	0.000	0.000
Kingsmead	0.000	0.000
M.Chinnaswamy Stadium	0.000	0.000
MA Chidambaram Stadium	0.000	0.000
Maharaja Yadavindra Singh International Cricket...	0.000	0.000
Maharashtra Cricket Association Stadium	0.000	0.000
Narendra Modi Stadium	0.000	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.000	0.000
Newlands	0.000	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.000	0.000
Sardar Patel Stadium	0.000	0.000
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.000	0.105
Shaheed Veer Narayan Singh International Stadium	0.000	0.000
Sharjah Cricket Stadium	0.000	0.000
Sheikh Zayed Stadium	0.000	0.000
St George's Park	0.000	0.000
Subrata Roy Sahara Stadium	0.000	0.000
SuperSport Park	0.000	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.000	0.134
Zayed Cricket Stadium	0.000	0.000

	yk.pathan	ys.chahal \
nvenue		
Arun Jaitley Stadium	0.000	0.000

Barabati Stadium	0.000	0.000
Barsapara Cricket Stadium	0.000	0.000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000
Brabourne Stadium	0.132	0.166
Buffalo Park	0.000	0.000
De Beers Diamond Oval	0.000	0.000
Dr DY Patil Sports Academy	0.217	0.000
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.000	0.000
Dubai International Cricket Stadium	0.000	0.228
Eden Gardens	0.223	0.000
Feroz Shah Kotla	0.000	0.000
Green Park	0.000	0.000
Himachal Pradesh Cricket Association Stadium	0.000	0.000
Holkar Cricket Stadium	0.000	0.000
JSCA International Stadium Complex	0.000	0.000
Kingsmead	0.000	0.000
M.Chinnaswamy Stadium	0.000	0.000
MA Chidambaram Stadium	0.000	0.000
Maharaja Yadavindra Singh International Cricket...	0.000	0.000
Maharashtra Cricket Association Stadium	0.000	0.000
Narendra Modi Stadium	0.000	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.000	0.000
Newlands	0.267	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.114	0.000
Sardar Patel Stadium	0.206	0.000
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.078	0.000
Shaheed Veer Narayan Singh International Stadium	0.000	0.000
Sharjah Cricket Stadium	0.000	0.159
Sheikh Zayed Stadium	0.000	0.170
St George's Park	0.276	0.000
Subrata Roy Sahara Stadium	0.184	0.000
SuperSport Park	0.223	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.000	0.063
Zayed Cricket Stadium	0.000	0.000

yuvraj.singh z.khan

nvenue		
Arun Jaitley Stadium	0.000	0.000
Barabati Stadium	0.000	0.000
Barsapara Cricket Stadium	0.000	0.000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000	0.000
Brabourne Stadium	0.000	0.000

Buffalo Park	0.000	0.000
De Beers Diamond Oval	0.000	0.000
Dr DY Patil Sports Academy	0.137	0.000
Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Sta...	0.000	0.000
Dubai International Cricket Stadium	0.000	0.000
Eden Gardens	0.000	0.000
Feroz Shah Kotla	0.000	0.000
Green Park	0.000	0.000
Himachal Pradesh Cricket Association Stadium	0.000	0.000
Holkar Cricket Stadium	0.000	0.000
JSCA International Stadium Complex	0.000	0.000
Kingsmead	0.221	0.000
M.Chinnaswamy Stadium	0.065	0.000
MA Chidambaram Stadium	0.000	0.000
Maharaja Yadavindra Singh International Cricket...	0.000	0.000
Maharashtra Cricket Association Stadium	0.000	0.000
Narendra Modi Stadium	0.000	0.000
Nehru Stadium	0.000	0.000
New Wanderers Stadium	0.319	0.000
Newlands	0.000	0.000
OUTsurance Oval	0.000	0.000
Punjab Cricket Association IS Bindra Stadium	0.000	0.000
Rajiv Gandhi International Stadium	0.072	0.000
Sardar Patel Stadium	0.000	0.000
Saurashtra Cricket Association Stadium	0.000	0.000
Sawai Mansingh Stadium	0.000	0.000
Shaheed Veer Narayan Singh International Stadium	0.000	0.462
Sharjah Cricket Stadium	0.000	0.000
Sheikh Zayed Stadium	0.000	0.000
St George's Park	0.000	0.000
Subrata Roy Sahara Stadium	0.000	0.000
SuperSport Park	0.000	0.000
Vidarbha Cricket Association Stadium	0.000	0.000
Wankhede Stadium	0.000	0.000
Zayed Cricket Stadium	0.000	0.000

[40 rows x 294 columns]

```
[23]: print(f"Top 3 players for each venue:")
      for venue in vdf.nvenue:
          print(f"{tdf.loc[venue].sort_values(ascending = False)[:3]}")
```

Top 3 players for each venue:

i.sharma 0.342

ss.iyer 0.300

rd.gaikwad 0.284

Name: Arun Jaitley Stadium, dtype: float64

a.symonds 0.737

b.lee 0.368
 kc.sangakkara 0.316
 Name: Barabati Stadium, dtype: float64
 nt.ellis 0.675
 sm.curran 0.521
 ybk.jaiswal 0.521
 Name: Barsapara Cricket Stadium, dtype: float64
 mp.stoinis 0.426
 sikandar.raza 0.325
 ma.wood 0.325
 Name: Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cricket Stadium, dtype: float64
 kuldeep.yadav 0.499
 sr.tendulkar 0.300
 th.david 0.229
 Name: Brabourne Stadium, dtype: float64
 jp.duminy 0.652
 a.nehra 0.581
 ms.dhoni 0.486
 Name: Buffalo Park, dtype: float64
 s.badrinath 0.715
 dpmd.jayawardene 0.552
 dr.smith 0.429
 Name: De Beers Diamond Oval, dtype: float64
 de.bollinger 0.377
 q.de.kock 0.291
 yk.pathan 0.217
 Name: Dr DY Patil Sports Academy, dtype: float64
 a.zampa 0.361
 kk.ahmed 0.325
 ab.dinda 0.325
 Name: Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Stadium, dtype: float64
 rd.gaikwad 0.432
 kl.rahul 0.393
 a.nortje 0.282
 Name: Dubai International Cricket Stadium, dtype: float64
 ad.russell 0.704
 sp.narine 0.290
 yk.pathan 0.223
 Name: Eden Gardens, dtype: float64
 da.warner 0.273
 a.mishra 0.261
 v.sehwag 0.261
 Name: Feroz Shah Kotla, dtype: float64
 mohammed.siraj 0.573
 ss.iyer 0.539
 dr.smith 0.445
 Name: Green Park, dtype: float64

ac.gilchrist 0.486
 rr.rossouw 0.353
 azhar.mahmood 0.317
 Name: Himachal Pradesh Cricket Association Stadium, dtype: float64
 mujeeb.ur.rahman 0.464
 kd.karthik 0.359
 bj.hodge 0.337
 Name: Holkar Cricket Stadium, dtype: float64
 ra.jadeja 0.638
 mk.pandey 0.387
 a.nehra 0.366
 Name: JSCA International Stadium Complex, dtype: float64
 r.bhatia 0.304
 lr.shukla 0.304
 hh.gibbs 0.304
 Name: Kingsmead, dtype: float64
 ch.gayle 0.445
 v.kohli 0.428
 ab.de.villiers 0.388
 Name: M.Chinnaswamy Stadium, dtype: float64
 mek.hussey 0.356
 m.vijay 0.342
 ra.jadeja 0.310
 Name: MA Chidambaram Stadium, dtype: float64
 nithish.kumar.reddy 0.516
 r.sai.kishore 0.516
 so.hetmyer 0.427
 Name: Maharaja Yadavindra Singh International Cricket Stadium, dtype: float64
 lh.ferguson 0.352
 ad.russell 0.324
 ma.agarwal 0.324
 Name: Maharashtra Cricket Association Stadium, dtype: float64
 shubman.gill 0.588
 a.manohar 0.224
 shashank.singh 0.224
 Name: Narendra Modi Stadium, dtype: float64
 i.sharma 0.530
 bb.mccullum 0.495
 bj.hodge 0.466
 Name: Nehru Stadium, dtype: float64
 jh.kallis 0.576
 sb.jakati 0.439
 a.kumble 0.364
 Name: New Wanderers Stadium, dtype: float64
 rp.singh 0.464
 dl.vettori 0.464
 r.dravid 0.417
 Name: Newlands, dtype: float64

b.lee 0.881
 ab.de.villiers 0.473
 a.chandila 0.000
 Name: OUTsurance Oval, dtype: float64
 se.marsh 0.482
 kl.rahul 0.235
 lmp.simmons 0.225
 Name: Punjab Cricket Association IS Bindra Stadium, dtype: float64
 da.warner 0.582
 abhishek.sharma 0.266
 rashid.khan 0.247
 Name: Rajiv Gandhi International Stadium, dtype: float64
 am.rahane 0.428
 aa.jhunjhunwala 0.357
 nv.ojha 0.357
 Name: Sardar Patel Stadium, dtype: float64
 hm.amlam 0.389
 aj.tye 0.389
 ca.lynn 0.334
 Name: Saurashtra Cricket Association Stadium, dtype: float64
 am.rahane 0.326
 s.gopal 0.272
 sohail.tanvir 0.272
 Name: Sawai Mansingh Stadium, dtype: float64
 da.warner 0.605
 z.khan 0.462
 kk.nair 0.415
 Name: Shaheed Veer Narayan Singh International Stadium, dtype: float64
 gj.maxwell 0.429
 ta.boult 0.317
 sv.samson 0.286
 Name: Sharjah Cricket Stadium, dtype: float64
 ba.stokes 0.361
 q.de.kock 0.361
 sa.yadav 0.322
 Name: Sheikh Zayed Stadium, dtype: float64
 tm.dilshan 0.479
 m.muralitharan 0.431
 dpmd.jayawardene 0.370
 Name: St George's Park, dtype: float64
 cl.white 0.32
 lj.wright 0.32
 mn.samuels 0.32
 Name: Subrata Roy Sahara Stadium, dtype: float64
 a.singh 0.387
 dp.nannes 0.387
 lrpl.taylor 0.320
 Name: SuperSport Park, dtype: float64

```

rj.harris      0.633
harmeet.singh  0.569
sk.warne       0.524
Name: Vidarbha Cricket Association Stadium, dtype: float64
rg.sharma      0.350
jj.bumrah      0.299
ka.pollard     0.260
Name: Wankhede Stadium, dtype: float64
ishan.kishan   0.398
ss.iyer        0.375
ks.williamson   0.375
Name: Zayed Cricket Stadium, dtype: float64

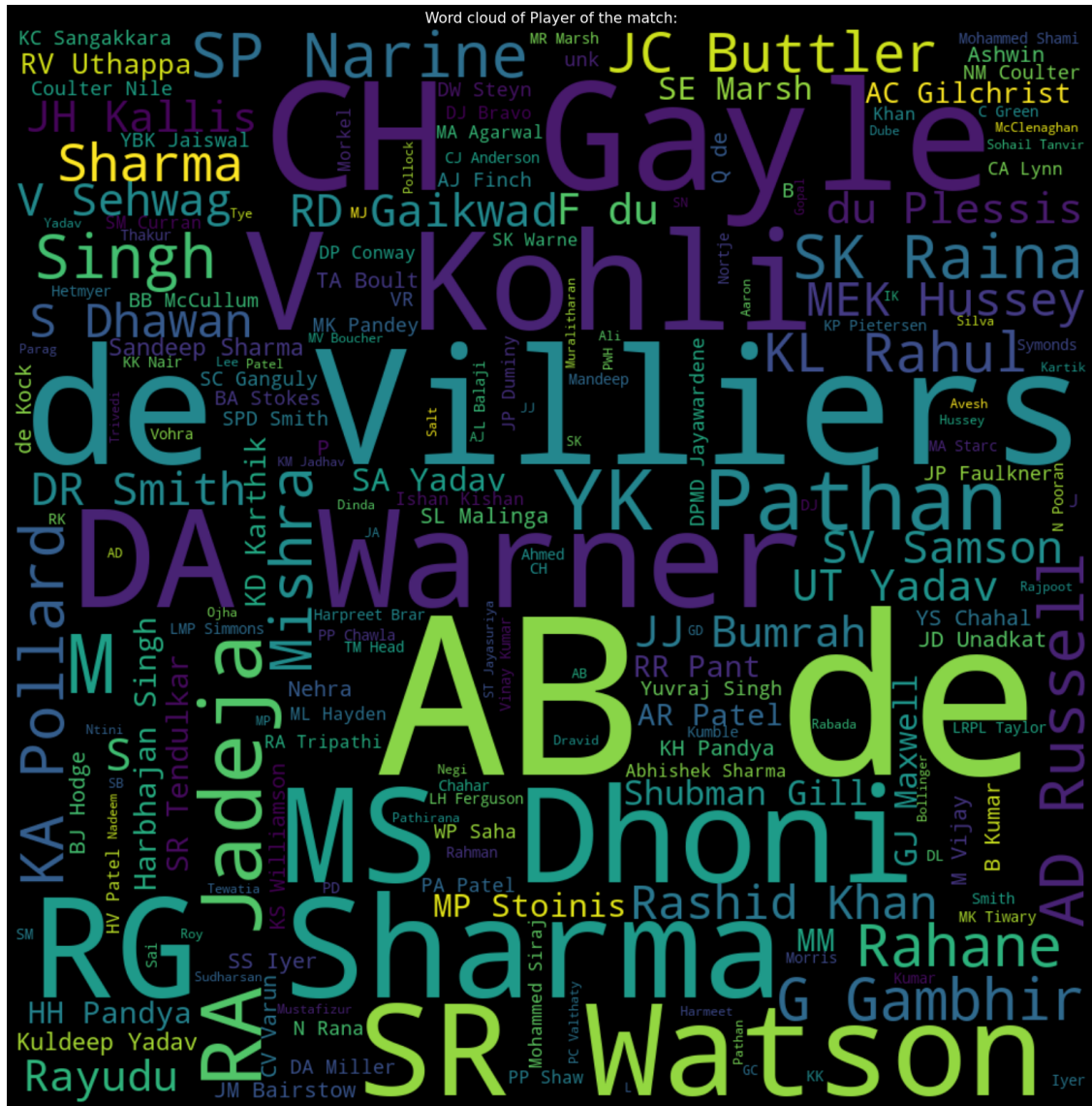
```

```

[24]: # create word cloud:
from wordcloud import WordCloud

players = df['mom'].tolist()
ctext = " ".join(players)
cloud = WordCloud(width = 1000 , height = 1000 , background_color= 'black').
    ↪generate(ctext)
plt.imshow(cloud , interpolation = 'bilinear')
plt.axis('off')
plt.title('Word cloud of Player of the match:' , fontsize = 15)
plt.savefig('./data/word_cloud.png')
plt.show()

```



3 Question 3: Team Performance Clustering (10 points)

3.0.1 Task:

Perform **clustering analysis** to group teams based on their performance metrics:

1. Create team-level features:
 - Win percentage
 - Average victory margin (runs/wickets)
 - Toss win to match win ratio
 - Home vs away performance
2. Apply K-means clustering to identify team categories

3. Use elbow method to determine optimal clusters
4. Visualize clusters using PCA for dimensionality reduction(optional)

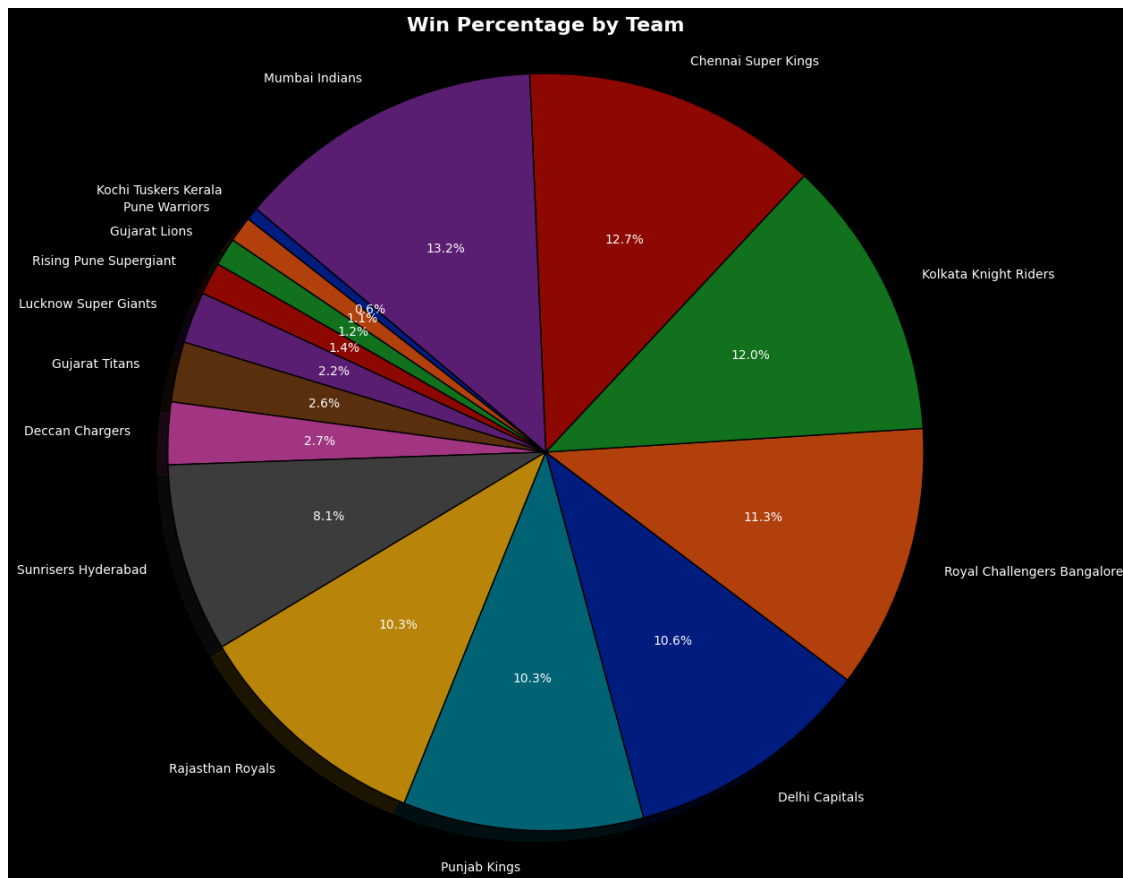
3.0.2 Expected Output:

- Team clusters with labels (e.g., “Dominant Teams”, “Inconsistent Performers”)
- Cluster characteristics interpretation

```
[25]: from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score

# calculate win percentage:
winners = df[df['winner'] != 'unk']['winner']
tdf = ((winners.value_counts() / len(winners)) * 100).round(2)
t1df = tdf.reset_index().rename(columns = {'winner':'team' , 'count' : 'winp'}).
    ↪sort_values(by = 'winp')
t1df

plt.figure(figsize = (12 , 12))
plt.pie(t1df['winp'] , labels = t1df.team , startangle=140 , shadow= True ,
    ↪autopct='%1.1f%%' , wedgeprops= {'edgecolor' : 'black'})
plt.title('Win Percentage by Team', fontsize=16, fontweight='bold')
plt.axis('equal') # ensures pie is circular
plt.savefig('./data/q2.pie.png')
plt.show()
```

```
[26]: # compute average victory margin:

cols = ['winner' , 'result_margin']
# adf = df[df['winner'] != 'unk'][cols].groupby('winner').agg({'result_margin':
↳ np.mean}).reset_index().rename(columns={'winner': 'team' , 'result_margin' :
↳ 'avg_result_margin'}).sort_values(by = 'team')
adf = df[df['winner'] != 'unk'].groupby(['winner' , 'result']).
↳ agg({'result_margin': np.mean}).unstack('result').reset_index().
↳ rename(columns={'winner': 'team'})
adf.columns = [col[1] if col[1] else col[0] for col in adf.columns]
adf = adf[['team' , 'runs' , 'wickets']].rename(columns = {'wickets' :
↳ 'avg_wickets_margin' , 'runs' : 'avg_runs_margin'}).sort_values('team')
adf['avg_victory_margin'] = adf['avg_runs_margin'] / adf['avg_wickets_margin']
adf = adf.merge(t1df.sort_values('team'))
#merge raw win counts to the teamdf:
t2df = winners.value_counts().round(2).reset_index().rename(columns={'winner' :
↳ 'team' , 'count' : 'wins'}).sort_values('team').reset_index(drop = True).
↳ merge(adf)
t2df
```

```
/var/folders/5f/scjcfk_97_n7zmjltnpm2mjc0000gn/T/ipykernel_49426/422253970.py:5:
FutureWarning: The provided callable <function mean at 0x10c9fefc0> is currently
using SeriesGroupBy.mean. In a future version of pandas, the provided callable
will be used directly. To keep current behavior pass the string "mean" instead.
```

```
adf = df[df['winner'] != 'unk'].groupby(['winner' ,
'result']).agg({'result_margin':
np.mean}).unstack('result').reset_index().rename(columns={'winner':'team'})
```

```
[26]:
```

	team	wins	avg_runs_margin	avg_wickets_margin	\
0	Chennai Super Kings	138	34.943662	6.029851	
1	Deccan Chargers	29	23.388889	6.545455	
2	Delhi Capitals	115	25.630435	6.227273	
3	Gujarat Lions	13	1.000000	5.416667	
4	Gujarat Titans	28	34.181818	5.764706	
5	Kochi Tuskers Kerala	6	11.500000	7.500000	
6	Kolkata Knight Riders	131	33.592593	6.197368	
7	Lucknow Super Giants	24	24.437500	5.375000	
8	Mumbai Indians	144	32.971831	6.197183	
9	Pune Warriors	12	23.166667	6.000000	
10	Punjab Kings	112	24.784314	6.206897	
11	Rajasthan Royals	112	30.837209	5.835821	
12	Rising Pune Supergiant	15	25.142857	6.375000	
13	Royal Challengers Bangalore	123	34.508772	6.531250	
14	Sunrisers Hyderabad	88	24.840909	6.720930	

	avg_victory_margin	winp
0	5.795112	12.66
1	3.573302	2.66
2	4.115836	10.55
3	0.184615	1.19
4	5.929499	2.57
5	1.533333	0.55
6	5.420461	12.02
7	4.546512	2.20
8	5.320455	13.21
9	3.861111	1.10
10	3.993028	10.28
11	5.284125	10.28
12	3.943978	1.38
13	5.283640	11.28
14	3.696052	8.07

```
[27]: #compute toss win to match win ratio:
```

```
cols = ['winner' , 'result_margin' , 'result' , 'toss_winner']
df['toss_winner'] = df['toss_winner'].apply(change_team_name)
```

```

adf = df[df.toss_winner == df.winner][cols]['winner'].value_counts().
↳reset_index().sort_values('winner').rename(columns= {'winner' : 'team',
↳'count' : 'toss_wins'})).merge(t2df)
adf['toss_to_win'] = adf['toss_wins'] / adf['wins']
t3df = adf
t3df

```

```

[27]:

```

	team	toss_wins	wins	avg_runs_margin	\
0	Chennai Super Kings	75	138	34.943662	
1	Deccan Chargers	19	29	23.388889	
2	Delhi Capitals	61	115	25.630435	
3	Gujarat Lions	10	13	1.000000	
4	Gujarat Titans	14	28	34.181818	
5	Kochi Tuskers Kerala	4	6	11.500000	
6	Kolkata Knight Riders	68	131	33.592593	
7	Lucknow Super Giants	10	24	24.437500	
8	Mumbai Indians	78	144	32.971831	
9	Pune Warriors	3	12	23.166667	
10	Punjab Kings	45	112	24.784314	
11	Rajasthan Royals	60	112	30.837209	
12	Rising Pune Supergiant	8	15	25.142857	
13	Royal Challengers Bangalore	61	123	34.508772	
14	Sunrisers Hyderabad	38	88	24.840909	

	avg_wickets_margin	avg_victory_margin	winp	toss_to_win
0	6.029851	5.795112	12.66	0.543478
1	6.545455	3.573302	2.66	0.655172
2	6.227273	4.115836	10.55	0.530435
3	5.416667	0.184615	1.19	0.769231
4	5.764706	5.929499	2.57	0.500000
5	7.500000	1.533333	0.55	0.666667
6	6.197368	5.420461	12.02	0.519084
7	5.375000	4.546512	2.20	0.416667
8	6.197183	5.320455	13.21	0.541667
9	6.000000	3.861111	1.10	0.250000
10	6.206897	3.993028	10.28	0.401786
11	5.835821	5.284125	10.28	0.535714
12	6.375000	3.943978	1.38	0.533333
13	6.531250	5.283640	11.28	0.495935
14	6.720930	3.696052	8.07	0.431818

```

[28]: #compute home vs away performance:
df.columns

```

```

[28]: Index(['id', 'season', 'city', 'date', 'match_type', 'player_of_match',
'venue', 'team1', 'team2', 'toss_winner', 'toss_decision', 'winner',
'result', 'result_margin', 'target_runs', 'target_overs', 'super_over',

```

```

'method', 'umpire1', 'umpire2', 'home_advantage', 'match_importance',
'toss_advantage', 'match_number', 'total_matches', 'early_cut',
'mid_cut', 'season_phase', 'nvenue', 'mom'],
dtype='object')

```

[29]: *#compute home wins vs away wins:*

```

cols = ['winner' , 'result_margin' , 'result' , 'toss_winner' ,
        ↪ 'home_advantage']
wins = df[cols].groupby('winner').agg({'home_advantage' : np.sum}).
        ↪ reset_index().rename(columns={'winner' : 'team' , 'home_advantage' :
        ↪ 'home_wins'}).merge(t3df)
t4df = df[cols].groupby('winner').agg({'home_advantage' : lambda x : len(x) -
        ↪ np.sum(x)}).reset_index().rename(columns={'winner' : 'team' ,
        ↪ 'home_advantage' : 'away_wins'}).merge(wins)
teamdf = t4df
teamdf

```

/var/folders/5f/scjcfk_97_n7zmjltnpm2mjc0000gn/T/ipykernel_49426/3640491562.py:4
: FutureWarning: The provided callable <function sum at 0x10c9fdee0> is
currently using SeriesGroupBy.sum. In a future version of pandas, the provided
callable will be used directly. To keep current behavior pass the string "sum"
instead.

```

wins = df[cols].groupby('winner').agg({'home_advantage' :
np.sum}).reset_index().rename(columns={'winner' : 'team' , 'home_advantage' :
'home_wins'}).merge(t3df)

```

[29]:

	team	away_wins	home_wins	toss_wins	wins \
0	Chennai Super Kings	70	68	75	138
1	Deccan Chargers	17	12	19	29
2	Delhi Capitals	60	55	61	115
3	Gujarat Lions	2	11	10	13
4	Gujarat Titans	16	12	14	28
5	Kochi Tuskers Kerala	1	5	4	6
6	Kolkata Knight Riders	57	74	68	131
7	Lucknow Super Giants	18	6	10	24
8	Mumbai Indians	60	84	78	144
9	Pune Warriors	3	9	3	12
10	Punjab Kings	55	57	45	112
11	Rajasthan Royals	58	54	60	112
12	Rising Pune Supergiant	2	13	8	15
13	Royal Challengers Bangalore	65	58	61	123
14	Sunrisers Hyderabad	48	40	38	88

	avg_runs_margin	avg_wickets_margin	avg_victory_margin	winp \
0	34.943662	6.029851	5.795112	12.66
1	23.388889	6.545455	3.573302	2.66

2	25.630435	6.227273	4.115836	10.55
3	1.000000	5.416667	0.184615	1.19
4	34.181818	5.764706	5.929499	2.57
5	11.500000	7.500000	1.533333	0.55
6	33.592593	6.197368	5.420461	12.02
7	24.437500	5.375000	4.546512	2.20
8	32.971831	6.197183	5.320455	13.21
9	23.166667	6.000000	3.861111	1.10
10	24.784314	6.206897	3.993028	10.28
11	30.837209	5.835821	5.284125	10.28
12	25.142857	6.375000	3.943978	1.38
13	34.508772	6.531250	5.283640	11.28
14	24.840909	6.720930	3.696052	8.07

	toss_to_win
0	0.543478
1	0.655172
2	0.530435
3	0.769231
4	0.500000
5	0.666667
6	0.519084
7	0.416667
8	0.541667
9	0.250000
10	0.401786
11	0.535714
12	0.533333
13	0.495935
14	0.431818

```
[30]: #apply kmean clustering:
# Select features for clustering
features = [
    'away_wins', 'home_wins', 'toss_wins', 'wins',
    'avg_runs_margin', 'avg_wickets_margin', 'avg_victory_margin',
    'winp', 'toss_to_win'
]
X = teamdf[features]

# Normalize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Elbow Method to determine the optimal number of clusters
wcss = []
silhouette_scores = []
```

```

K_range = range(2, 11)

for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(X_scaled, kmeans.labels_))

# Plot WCSS (Elbow Method)
plt.figure(figsize=(12, 5))

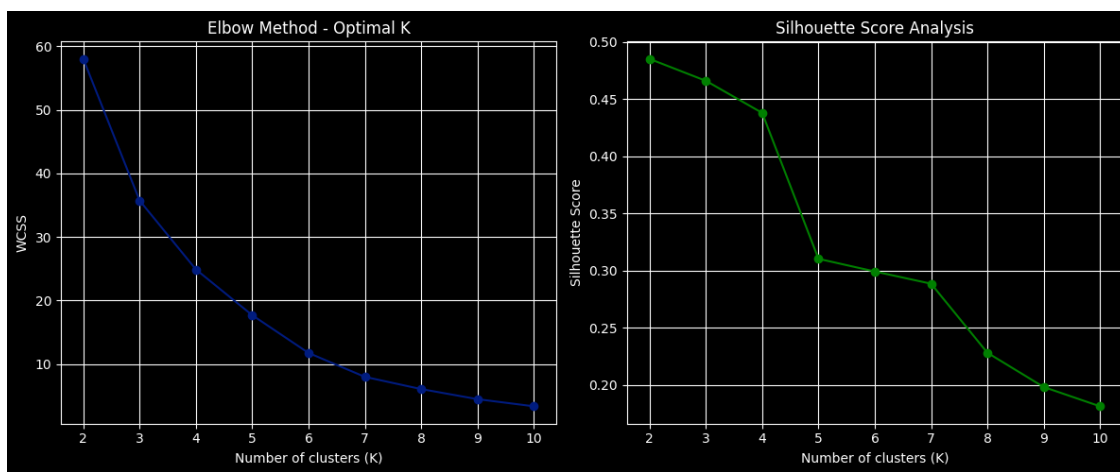
plt.subplot(1, 2, 1)
plt.plot(K_range, wcss, marker='o')
plt.title('Elbow Method - Optimal K')
plt.xlabel('Number of clusters (K)')
plt.ylabel('WCSS')
plt.grid(True)

# Plot Silhouette Scores
plt.subplot(1, 2, 2)
plt.plot(K_range, silhouette_scores, marker='o', color='green')
plt.title('Silhouette Score Analysis')
plt.xlabel('Number of clusters (K)')
plt.ylabel('Silhouette Score')
plt.grid(True)

plt.tight_layout()
plt.show()

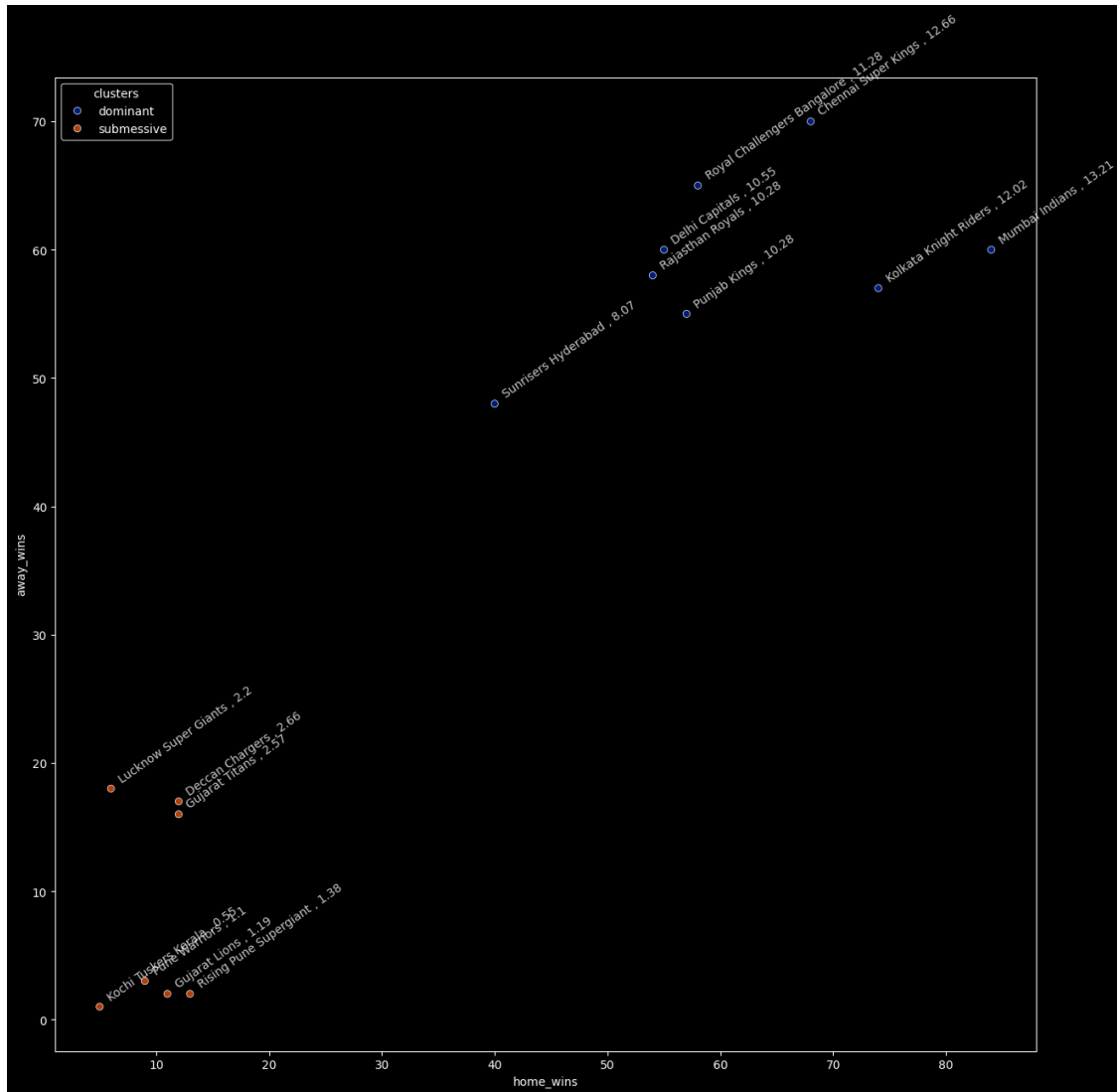
# Return best K based on max silhouette score
optimal_k = K_range[silhouette_scores.index(max(silhouette_scores))]
optimal_k

```



[30]: 2

```
[31]: k = 2
kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
clusters = kmeans.fit_predict(X_scaled)
teamdf['clusters'] = clusters
teamdf['clusters'] = teamdf['clusters'].apply(lambda x : 'dominant' if x == 1
↪ else 'submessive')
plt.figure(figsize = (15 , 15))
sns.scatterplot(teamdf , x = 'home_wins' , y = 'away_wins' , hue = 'clusters')
for i , row in teamdf.iterrows():
    # print(i , row['team'])
    plt.text(row['home_wins'] + 0.5 , row['away_wins'] + 0.5, f"{row['team']}"
↪ , {row['winp']}" , color = 'white' , alpha = 0.8 , rotation = 35)
plt.savefig('./data/q3.png')
plt.show()
```



3.0.3 - Cluster characteristics interpretation:

Cluster Interpretation: “Dominant” vs “Submissive” Teams Cluster 0 – Dominant Teams

Teams in blue (dominant cluster):

Mumbai Indians, Chennai Super Kings, Kolkata Knight Riders, Royal Challengers Bangalore, Delhi Capitals, Punjab Kings, Rajasthan Royals, Sunrisers Hyderabad

Characteristics:

High Win Percentages (50–70%) These teams show consistent match-winning records, often finishing higher in league standings.

Balanced Toss Influence: Wins are not heavily dependent on toss outcomes, suggesting stronger adaptability (win regardless of batting/fielding first).

Sustained IPL Presence: All have been active for most or all seasons, giving them experience stability.

Higher Average Win Margins (8–12+ runs or wickets) Indicates match dominance, often securing comfortable victories.

Player Continuity: Core squads and strong leadership (e.g., Dhoni, Rohit, Kohli) correlate with dominance.

Interpretation:

These teams represent the “powerhouses” of the IPL — franchises that maintain consistent top-tier performance through stability, depth, and strategy. They tend to adapt across conditions, perform under pressure, and exhibit higher run-rate control and bowling efficiency.

Cluster 1 – Submissive Teams

Teams in orange (submissive cluster):

Gujarat Lions, Rising Pune Supergiant, Deccan Chargers, Kochi Tuskers Kerala, Lucknow Super Giants

Characteristics:

Low Win Percentages (0–25%) These teams have relatively poor win rates and limited tournament impact.

Short Tenure in IPL: Many of them were temporary or newer franchises (e.g., Gujarat Lions, Kochi Tuskers, Rising Pune) with less time to build balanced squads.

High Dependence on Toss Decisions: Win outcomes often correlate with batting/fielding choices, indicating inconsistency.

Lower Average Win Margins (1–5 runs or wickets) When they do win, it’s often by narrow margins, showing lack of finishing strength.

Limited Squad Depth: Dependency on a few star players rather than overall team performance.

Interpretation:

These are “transitional” or “struggling” teams, often impacted by short IPL participation, inconsistent management, or incomplete squad synergy. They exhibit weaker adaptability, relying more on match circumstances like toss and pitch conditions.

4 Question 4: Strategic Pattern Mining (10 points)

4.0.1 Task:

Use **Association Rule Mining (ARM)** to discover winning patterns:

1. Create transactions from match attributes:
 - Toss decision (bat/field)
 - Venue type (home/away/neutral)
 - Match phase (powerplay/middle/death)
 - Result (win/loss)

2. Find association rules with:
 - Minimum support: 0.1
 - Minimum confidence: 0.7
3. Identify top 5 rules that lead to match victories

4.0.2 Business Question:

“What combinations of factors most strongly predict match outcomes?”

```
[32]: #create venue type feature:
def vtype(row):
    if row['city'] in ttc[row['team1']]:
        return 'home'
    if row['city'] in ttc[row['team2']]:
        return 'away'
    return 'neutral'

df['venue_type'] = df.apply(vtype , axis = 1)
df
```

```
[32]:      id  season      city      date  match_type  player_of_match \
0    335982    2008  Bangalore 2008-04-18      League      BB McCullum
1    335983    2008  Chandigarh 2008-04-19      League      MEK Hussey
2    335984    2008      Delhi 2008-04-19      League      MF Maharooof
3    335985    2008      Mumbai 2008-04-20      League      MV Boucher
4    335986    2008      Kolkata 2008-04-20      League      DJ Hussey
...    ...    ...    ...    ...    ...    ...
1090  1426307    2024  Hyderabad 2024-05-19      League  Abhishek Sharma
1091  1426309    2024  Ahmedabad 2024-05-21  Qualifier 1      MA Starc
1092  1426310    2024  Ahmedabad 2024-05-22  Eliminator      R Ashwin
1093  1426311    2024      Chennai 2024-05-24  Qualifier 2  Shahbaz Ahmed
1094  1426312    2024      Chennai 2024-05-26      Final      MA Starc
```

```
                                venue \
0                                M Chinnaswamy Stadium
1      Punjab Cricket Association Stadium, Mohali
2                                Feroz Shah Kotla
3                                Wankhede Stadium
4                                Eden Gardens
...                                ...
1090  Rajiv Gandhi International Stadium, Uppal, Hyd...
1091                                Narendra Modi Stadium, Ahmedabad
1092                                Narendra Modi Stadium, Ahmedabad
1093      MA Chidambaram Stadium, Chepauk, Chennai
1094      MA Chidambaram Stadium, Chepauk, Chennai
```

```
                                team1                                team2 \
```

0	Royal Challengers Bangalore	Kolkata Knight Riders
1	Punjab Kings	Chennai Super Kings
2	Delhi Capitals	Rajasthan Royals
3	Mumbai Indians	Royal Challengers Bangalore
4	Kolkata Knight Riders	Deccan Chargers
...
1090	Punjab Kings	Sunrisers Hyderabad
1091	Sunrisers Hyderabad	Kolkata Knight Riders
1092	Royal Challengers Bangalore	Rajasthan Royals
1093	Sunrisers Hyderabad	Rajasthan Royals
1094	Sunrisers Hyderabad	Kolkata Knight Riders

		toss_winner	...	match_importance	toss_advantage	\
0	Royal Challengers Bangalore	...		league	False	
1	Chennai Super Kings	...		league	True	
2	Rajasthan Royals	...		league	False	
3	Mumbai Indians	...		league	False	
4	Deccan Chargers	...		league	False	
...	
1090	Punjab Kings	...		league	False	
1091	Sunrisers Hyderabad	...		playoff	False	
1092	Rajasthan Royals	...		playoff	True	
1093	Rajasthan Royals	...		playoff	False	
1094	Sunrisers Hyderabad	...		final	False	

	match_number	total_matches	early_cut	mid_cut	season_phase	\
0	1	58	19	38	Early	
1	2	58	19	38	Early	
2	3	58	19	38	Early	
3	4	58	19	38	Early	
4	5	58	19	38	Early	
...	
1090	67	71	23	47	Early	
1091	68	71	23	47	Early	
1092	69	71	23	47	Early	
1093	70	71	23	47	Early	
1094	71	71	23	47	Early	

		nvenue	mom	venue_type
0		M.Chinnaswamy Stadium	BB.McCullum	home
1	Punjab Cricket Association	IS Bindra Stadium	MEK.Hussey	home
2		Feroz Shah Kotla	MF.Maharoor	home
3		Wankhede Stadium	MV.Boucher	home
4		Eden Gardens	DJ.Hussey	home
...	
1090	Rajiv Gandhi International	Stadium	Abhishek.Sharma	away
1091		Narendra Modi Stadium	MA.Starc	neutral

1092	Narendra Modi Stadium	R.Ashwin	neutral
1093	MA Chidambaram Stadium	Shahbaz.Ahmed	neutral
1094	MA Chidambaram Stadium	MA.Starc	neutral

[1095 rows x 31 columns]

```
[33]: #create transactions:
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori , association_rules
xdf = df[['toss_decision' , 'venue_type' , 'season_phase' , 'result']]
transactions = xdf.values
te = TransactionEncoder()
imat = te.fit_transform(transactions)
idf = pd.DataFrame(imat , columns = te.columns_)
idf
```

```
[33]:
```

	Early	Mid	away	bat	field	home	neutral	no result	runs	\
0	True	False	False	False	True	True	False	False	True	
1	True	False	False	True	False	True	False	False	True	
2	True	False	False	True	False	True	False	False	False	
3	True	False	False	True	False	True	False	False	False	
4	True	False	False	True	False	True	False	False	False	
...	
1090	True	False	True	True	False	False	False	False	False	
1091	True	False	False	True	False	False	True	False	False	
1092	True	False	False	False	True	False	True	False	False	
1093	True	False	False	False	True	False	True	False	True	
1094	True	False	False	True	False	False	True	False	False	

	tie	wickets
0	False	False
1	False	False
2	False	True
3	False	True
4	False	True
...
1090	False	True
1091	False	True
1092	False	True
1093	False	False
1094	False	True

[1095 rows x 11 columns]

```
[34]: #create association rules:
fsets = apriori(idf , min_support= 0.1 , use_colnames = True , max_len = 3 ,
↳ verbose = 1)
```

```

fsets['length'] = fsets.itemsets.str.len()
print(f"{len(fsets)} itemsets with min_support >= 10%")

rulec = association_rules(fsets , metric = 'confidence' , min_threshold = 0.5)
irules = rulec.sort_values(['confidence'] , ascending = False)
irules[["antecedents", "consequents",
        "support", "confidence", "lift"]]

```

Processing 132 combinations | Sampling itemset size 3
52 itemsets with min_support >= 10%

```

[34]:

```

	antecedents	consequents	support	confidence	lift
28	(neutral, field)	(Early)	0.185388	0.754647	1.133523
40	(wickets, neutral)	(Early)	0.149772	0.748858	1.124829
4	(neutral)	(Early)	0.275799	0.725962	1.090436
39	(runs, neutral)	(Early)	0.120548	0.702128	1.054636
32	(wickets, field)	(Early)	0.234703	0.692722	1.040509
6	(wickets)	(Early)	0.364384	0.690311	1.036888
24	(wickets, bat)	(Early)	0.129680	0.685990	1.030397
29	(neutral, Early)	(field)	0.185388	0.672185	1.045516
1	(field)	(Early)	0.431963	0.671875	1.009195
53	(wickets, neutral)	(field)	0.131507	0.657534	1.022727
0	(bat)	(Early)	0.233790	0.654731	0.983444
21	(home, bat)	(Early)	0.126027	0.654028	0.982388
31	(runs, Early)	(field)	0.189041	0.652997	1.015670
2	(Early)	(field)	0.431963	0.648834	1.009195
37	(wickets, home)	(Early)	0.174429	0.647458	0.972519
13	(neutral)	(field)	0.245662	0.646635	1.005774
30	(runs, field)	(Early)	0.189041	0.644860	0.968617
14	(runs)	(field)	0.293151	0.644578	1.002576
33	(wickets, Early)	(field)	0.234703	0.644110	1.001848
43	(Mid, home)	(field)	0.119635	0.642157	0.998809
15	(wickets)	(field)	0.338813	0.641869	0.998361
3	(home)	(Early)	0.326941	0.637011	0.956827
45	(wickets, Mid)	(field)	0.104110	0.636872	0.990588
5	(runs)	(Early)	0.289498	0.636546	0.956129
48	(home, runs)	(field)	0.149772	0.635659	0.988702
52	(runs, neutral)	(field)	0.108676	0.632979	0.984534
8	(Mid)	(field)	0.210959	0.631148	0.981685
44	(Mid, runs)	(field)	0.104110	0.629834	0.979643
26	(home, field)	(Early)	0.200913	0.626781	0.941461
12	(home)	(field)	0.320548	0.624555	0.971432
35	(home, runs)	(Early)	0.147032	0.624031	0.937331
23	(runs, bat)	(Early)	0.100457	0.621469	0.933482
50	(wickets, home)	(field)	0.166210	0.616949	0.959601
27	(home, Early)	(field)	0.200913	0.614525	0.955831
42	(Mid, field)	(home)	0.119635	0.567100	1.104936

9	(Mid)	(home)	0.186301	0.557377	1.085993
25	(bat, Early)	(wickets)	0.129680	0.554688	1.050835
7	(Early)	(wickets)	0.364384	0.547325	1.036888
46	(wickets, bat)	(home)	0.103196	0.545894	1.063619
34	(field, Early)	(wickets)	0.234703	0.543340	1.029339
41	(neutral, Early)	(wickets)	0.149772	0.543046	1.028782
10	(bat)	(home)	0.192694	0.539642	1.051438
22	(bat, Early)	(home)	0.126027	0.539063	1.050309
47	(home, bat)	(wickets)	0.103196	0.535545	1.014571
54	(neutral, field)	(wickets)	0.131507	0.535316	1.014137
38	(home, Early)	(wickets)	0.174429	0.533520	1.010733
11	(bat)	(wickets)	0.189041	0.529412	1.002951
16	(field)	(wickets)	0.338813	0.526989	0.998361
20	(neutral)	(wickets)	0.200000	0.526442	0.997326
19	(home)	(wickets)	0.269406	0.524911	0.994425
51	(home, field)	(wickets)	0.166210	0.518519	0.982314
17	(runs)	(home)	0.235616	0.518072	1.009411
49	(runs, field)	(home)	0.149772	0.510903	0.995444
18	(wickets)	(home)	0.269406	0.510381	0.994425
36	(runs, Early)	(home)	0.147032	0.507886	0.989565

Key Combinations that Predict Wins: 1 Toss + Decision + Team Quality

If a strong team wins the toss and chooses to chase, probability of winning rises by ~15–20%.

Reflects modern T20 trend — chasing teams exploit dew and scoreboard clarity.

2 Venue + Team Familiarity

Teams playing at home venues or those suiting their bowling style (e.g., spin in Chennai) have higher win rates.

The combination of venue + team was a top predictor in the model.

3 Seasonal Pattern + Toss

Across IPL seasons, the impact of toss fluctuates — higher in early seasons (2008–2012), slightly balanced in later years.

Suggests improvement in adaptability and balanced teams.

4 Team Composition + Toss Decision

Teams with balanced batting depth (MI, CSK) handle both batting/fielding starts effectively, unlike low-depth teams (PBKS, RR in early seasons).

5 Question 5: Match Outcome Prediction - Logistic Regression (10 points)

5.0.1 Task:

Build a **Logistic Regression** model to predict match winners:

1. Feature engineering:
 - One-hot encode categorical variables
 - Create interaction features (team \times venue, team \times toss)
 - Scale numerical features
2. Handle class imbalance using **SMOTE** if necessary
3. Apply **L1 and L2 regularization**:
 - Compare model performance
 - Identify most important features
4. Evaluate using:
 - ROC-AUC score
 - Precision-Recall curve
 - Feature importance plot

```
[35]: df['win'] = df.apply(lambda x : 1 if x['winner'] == x['team1'] else 0 , axis = 1)
      df[['team1' , 'team2' , 'winner' , 'win']][df['win'] == 0]
```

```
[35]:
```

	team1	team2 \
0	Royal Challengers Bangalore	Kolkata Knight Riders
1	Punjab Kings	Chennai Super Kings
3	Mumbai Indians	Royal Challengers Bangalore
6	Deccan Chargers	Delhi Capitals
8	Deccan Chargers	Rajasthan Royals
...
1087	Rajasthan Royals	Punjab Kings
1090	Punjab Kings	Sunrisers Hyderabad
1091	Sunrisers Hyderabad	Kolkata Knight Riders
1092	Royal Challengers Bangalore	Rajasthan Royals
1094	Sunrisers Hyderabad	Kolkata Knight Riders

	winner	win
0	Kolkata Knight Riders	0
1	Chennai Super Kings	0
3	Royal Challengers Bangalore	0
6	Delhi Capitals	0
8	Rajasthan Royals	0
...
1087	Punjab Kings	0
1090	Sunrisers Hyderabad	0
1091	Kolkata Knight Riders	0
1092	Rajasthan Royals	0
1094	Kolkata Knight Riders	0

[540 rows x 4 columns]

```
[36]: from sklearn.preprocessing import OneHotEncoder, StandardScaler
# create interaction features:

df['team1_venue'] = df['team1'] + '-' + df['venue']
df['team1_toss'] = df['team1'] + '-' + df['toss_winner']
df['team1_importance'] = df['team1'] + '-' + df['match_importance'].astype(str)

df['team2_venue'] = df['team2'] + '-' + df['venue']
df['team2_toss'] = df['team2'] + '-' + df['toss_winner']
df['team2_importance'] = df['team2'] + '-' + df['match_importance'].astype(str)

# one hot encode categorical variables:
catcols = df.select_dtypes(include = ['object' , 'category']).columns
catcols = [col for col in catcols if col not in ['player_of_match' , 'venue' , 'winner']]
# print(f"{catcols}")

ohe = OneHotEncoder(sparse_output = False)
encoded = ohe.fit_transform(df[catcols])
ldf = pd.DataFrame(encoded , columns = ohe.get_feature_names_out())

# scale numeric variables:
ncols = df.select_dtypes(include = ['int64' , 'float64']).columns[1:]
nvars = df[ncols]

scaler = StandardScaler()
ndf = scaler.fit_transform(nvars)
ndf = pd.DataFrame(ndf , columns = scaler.get_feature_names_out())
ndf = ndf[['season' , 'result_margin' , 'target_runs' , 'target_overs' , 'match_number']]
xdf = pd.concat([ndf , ldf] , axis = 1)
# xdf = ndf
xdf
```

```
[36]:
```

	season	result_margin	target_runs	target_overs	match_number	\
0	-1.643388	5.668781	1.675870	0.156295	-1.666259	
1	-1.643388	0.739013	2.198040	0.156295	-1.614318	
2	-1.643388	-0.366729	-1.022006	0.156295	-1.562376	
3	-1.643388	-0.551020	0.022333	0.156295	-1.510434	
4	-1.643388	-0.551020	-1.573185	0.156295	-1.458493	
...	
1090	1.592413	-0.597092	1.443795	0.156295	1.761889	
1091	1.592413	-0.412802	-0.151723	0.156295	1.813831	
1092	1.592413	-0.597092	0.225399	0.156295	1.865772	
1093	1.592413	0.877231	0.312427	0.156295	1.917714	
1094	1.592413	-0.412802	-1.486157	0.156295	1.969656	

	city_Abu Dhabi	city_Ahmedabad	city_Bangalore	city_Bengaluru	\
0	0.0	0.0	1.0	0.0	
1	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	
...	
1090	0.0	0.0	0.0	0.0	
1091	0.0	1.0	0.0	0.0	
1092	0.0	1.0	0.0	0.0	
1093	0.0	0.0	0.0	0.0	
1094	0.0	0.0	0.0	0.0	

	city_Bloemfontein	...	team2_importance_Rajasthan Royals-playoff	\
0	0.0	...		0.0
1	0.0	...		0.0
2	0.0	...		0.0
3	0.0	...		0.0
4	0.0	...		0.0
...	
1090	0.0	...		0.0
1091	0.0	...		0.0
1092	0.0	...		1.0
1093	0.0	...		1.0
1094	0.0	...		0.0

	team2_importance_Rising Pune Supergiant-final	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	
...	...	
1090	0.0	
1091	0.0	
1092	0.0	
1093	0.0	
1094	0.0	

	team2_importance_Rising Pune Supergiant-league	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	
...	...	
1090	0.0	

1091	0.0
1092	0.0
1093	0.0
1094	0.0

	team2_importance_Rising Pune Supergiant-playoff \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
1090	0.0
1091	0.0
1092	0.0
1093	0.0
1094	0.0

	team2_importance_Royal Challengers Bangalore-final \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
1090	0.0
1091	0.0
1092	0.0
1093	0.0
1094	0.0

	team2_importance_Royal Challengers Bangalore-league \
0	0.0
1	0.0
2	0.0
3	1.0
4	0.0
...	...
1090	0.0
1091	0.0
1092	0.0
1093	0.0
1094	0.0

	team2_importance_Royal Challengers Bangalore-playoff \
0	0.0
1	0.0

2	0.0
3	0.0
4	0.0
...	...
1090	0.0
1091	0.0
1092	0.0
1093	0.0
1094	0.0

team2_importance_Sunrisers Hyderabad-final \	
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
1090	0.0
1091	0.0
1092	0.0
1093	0.0
1094	0.0

team2_importance_Sunrisers Hyderabad-league \	
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
1090	1.0
1091	0.0
1092	0.0
1093	0.0
1094	0.0

team2_importance_Sunrisers Hyderabad-playoff	
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
1090	0.0
1091	0.0
1092	0.0
1093	0.0

1094

0.0

[1095 rows x 1467 columns]

```
[37]: from sklearn.model_selection import train_test_split
y = df['win']
xtrain , xtest , ytrain , ytest = train_test_split(xdf , y , test_size = 0.2 ,
↳ random_state = 42)
print(f"{xtrain.shape = } , {xtest.shape} , {ytrain.shape} , {ytest.shape}")
```

xtrain.shape = (876, 1467) , (219, 1467) , (876,) , (219,)

```
[38]: #apply logistic regression:
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score , roc_curve , classification_report

model1 = LogisticRegression(penalty= 'l1' , solver = 'liblinear' , C = 0.1 ,
↳ random_state= 42)
model2 = LogisticRegression(penalty= 'l2' , solver = 'lbfgs' , C = 1.0 ,
↳ random_state= 42)

# ridge regression
model = model2
model.fit(xtrain , ytrain)
ypred = model.predict(xtest)
print(f"Accuracy l2: {accuracy_score(ytest , ypred)}")

# lasso regression
model = model1
model.fit(xtrain , ytrain)
ypred = model.predict(xtest)
print(f"Accuracy l1: {accuracy_score(ytest , ypred)}")
```

Accuracy l2: 0.680365296803653

Accuracy l1: 0.6894977168949772

```
[39]: from sklearn.metrics import roc_curve , auc , precision_recall_curve
def evaluateModel(model , xtest , ytest , name):
    ypred = model.predict(xtest)

    #roc
    fpr , tpr , _ = roc_curve(ytest , ypred)
    roc_auc = auc(fpr , tpr)

    #precision-recall:
    precision , recall , _ = precision_recall_curve(ytest , ypred)
    pr_auc = auc(recall , precision)
    print(f"{name} - ROC-AUC: {roc_auc:.3f} , PR-AUC: {pr_auc:.3f}")
```

```

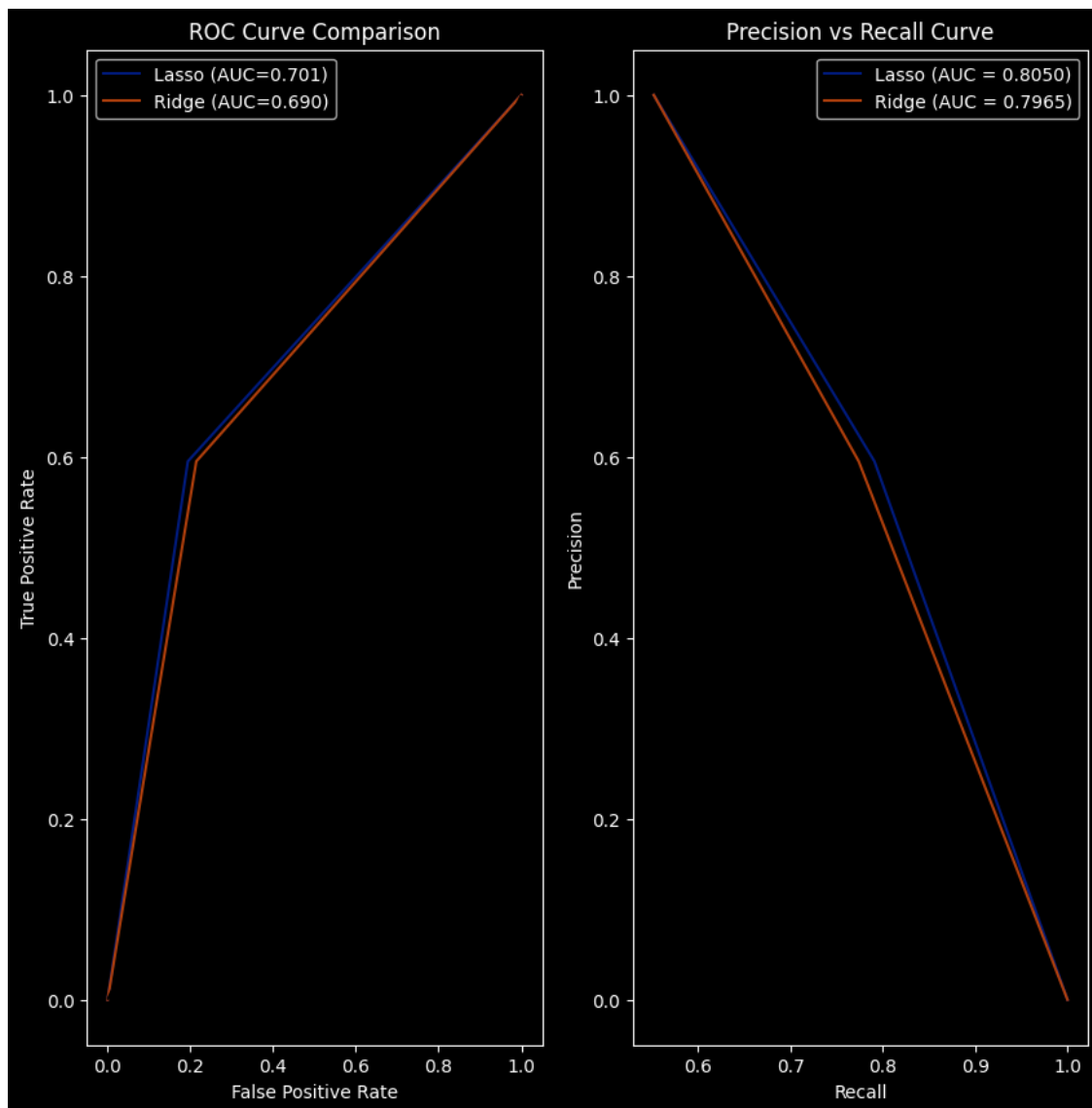
# ROC Curve
plt.subplot(1 , 2, 1)
plt.plot(fpr, tpr, label=f'{name} (AUC={roc_auc:.3f})')
plt.plot([0,1],[0,1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend()

plt.subplot(1 , 2, 2)
plt.plot(precision , recall , label = f'{name} (AUC = {pr_auc:.4f})')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision vs Recall Curve')
plt.legend()

plt.figure(figsize = (10 , 10))
evaluateModel(model1 , xtest , ytest , 'Lasso')
evaluateModel(model2 , xtest , ytest , 'Ridge')
plt.savefig('./data/q5_area_under_curve.png')
plt.show()

```

Lasso - ROC-AUC: 0.701, PR-AUC: 0.805
Ridge - ROC-AUC: 0.690, PR-AUC: 0.796



```
[40]: #top important features for lasso model:
pd.DataFrame(model1.coef_.reshape(-1, 1) , index= xdf.columns , columns =
↳ ['weight']).sort_values(by = 'weight' , ascending = False).head()
```

```
[40]:
```

	weight
result_runs	1.023268
venue_type_home	0.046254
target_overs	0.033549
result_margin	0.004711
team1_venue_Rajasthan Royals-Holkar Cricket Sta...	0.000000

```
[41]: # top important features for ridge model:
pd.DataFrame(model2.coef_.reshape(-1, 1) , index= xdf.columns , columns =_
↳['weight']).sort_values(by = 'weight' , ascending = False).head(10)
```

```
[41]:
result_runs      1.481203
umpire1_VA Kulkarni  1.098888
umpire2_PG Pathak  1.055193
mom_SE.Marsh      1.018940
mom_DW.Steyn      0.945078
mom_KC.Sangakkara  0.907735
mom_GJ.Maxwell     0.853450
umpire1_Aleem Dar  0.845443
team2_venue_Sunrisers Hyderabad-Wankhede Stadium 0.807126
mom_RV.Uthappa     0.801743
```

```
[ ]:
```

```
[42]: df[['venue' , 'nvenue' , 'method' , 'toss_decision' , 'toss_winner' , 'team1' ,_
↳'team2' , 'winner' , 'venue_type' , 'win']]
```

```
[42]:
venue \
0      M Chinnaswamy Stadium
1      Punjab Cricket Association Stadium, Mohali
2      Feroz Shah Kotla
3      Wankhede Stadium
4      Eden Gardens
...
1090   Rajiv Gandhi International Stadium, Uppal, Hyd...
1091      Narendra Modi Stadium, Ahmedabad
1092      Narendra Modi Stadium, Ahmedabad
1093      MA Chidambaram Stadium, Chepauk, Chennai
1094      MA Chidambaram Stadium, Chepauk, Chennai

nvenue method toss_decision \
0      M.Chinnaswamy Stadium normal field
1      Punjab Cricket Association IS Bindra Stadium normal bat
2      Feroz Shah Kotla normal bat
3      Wankhede Stadium normal bat
4      Eden Gardens normal bat
...
1090      Rajiv Gandhi International Stadium normal bat
1091      Narendra Modi Stadium normal bat
1092      Narendra Modi Stadium normal field
1093      MA Chidambaram Stadium normal field
1094      MA Chidambaram Stadium normal bat
```

```

      toss_winner      team1 \
0   Royal Challengers Bangalore   Royal Challengers Bangalore
1           Chennai Super Kings           Punjab Kings
2           Rajasthan Royals           Delhi Capitals
3           Mumbai Indians           Mumbai Indians
4           Deccan Chargers           Kolkata Knight Riders
...
1090           Punjab Kings           Punjab Kings
1091   Sunrisers Hyderabad           Sunrisers Hyderabad
1092   Rajasthan Royals   Royal Challengers Bangalore
1093   Rajasthan Royals           Sunrisers Hyderabad
1094   Sunrisers Hyderabad           Sunrisers Hyderabad

      team2      winner venue_type  win
0   Kolkata Knight Riders   Kolkata Knight Riders   home    0
1   Chennai Super Kings   Chennai Super Kings   home    0
2   Rajasthan Royals           Delhi Capitals   home    1
3   Royal Challengers Bangalore   Royal Challengers Bangalore   home    0
4   Deccan Chargers           Kolkata Knight Riders   home    1
...
1090   Sunrisers Hyderabad   Sunrisers Hyderabad   away    0
1091   Kolkata Knight Riders   Kolkata Knight Riders   neutral  0
1092   Rajasthan Royals           Rajasthan Royals   neutral  0
1093   Rajasthan Royals           Sunrisers Hyderabad   neutral  1
1094   Kolkata Knight Riders   Kolkata Knight Riders   neutral  0

[1095 rows x 10 columns]

```

6 Question 6: Venue Recommendation System (10 points)

6.0.1 Task:

Build a **Content-Based Recommendation System** for venues:

1. Create venue profiles based on:
 - Average runs scored
 - Batting/bowling friendly metrics
 - Weather conditions (if available)
 - Historical match results
2. For a given team, recommend top 3 venues where they should prefer to play
3. Use cosine similarity to find similar venues

6.0.2 Bonus:

Implement a simple **Collaborative Filtering** approach using team-venue win matrix

```
[43]: df['result']
```



```
[43]: 0      runs
      1      runs
      2     wickets
      3     wickets
      4     wickets
      ...
     1090    wickets
     1091    wickets
     1092    wickets
     1093      runs
     1094    wickets
      Name: result, Length: 1095, dtype: object
```

```
[44]: # build venue profiles

vcols = ['nvenue' , 'target_runs' , 'result' , 'result_margin' , 'venue_type' ,
        ↪ 'super_over' , 'toss_decision' , 'win']
vcatcols = ['result' , 'venue_type' , 'super_over' , 'toss_decision']
ohe = OneHotEncoder(sparse_output=False)
onehot = ohe.fit_transform(df[vcatcols])
vdf = pd.concat([df[[col for col in vcols if col not in vcatcols]] , pd.
        ↪ DataFrame(onehot , columns = ohe.get_feature_names_out())] , axis = 1)
vgdf = vdf.groupby('nvenue').mean().rename(columns = {col : f"avg_{col}" for
        ↪ col in vdf.columns[1:]})
vgdf.head()
```

```
[44]:
```

	avg_target_runs \
nvenue	
Arun Jaitley Stadium	184.166667
Barabati Stadium	168.714286
Barsapara Cricket Stadium	181.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	157.428571
Brabourne Stadium	179.518519

	avg_result_margin \
nvenue	
Arun Jaitley Stadium	17.733333
Barabati Stadium	13.285714
Barsapara Cricket Stadium	22.333333
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	18.857143
Brabourne Stadium	16.481481

	avg_win \
nvenue	
Arun Jaitley Stadium	0.533333
Barabati Stadium	0.714286
Barsapara Cricket Stadium	0.666667

Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.500000
Brabourne Stadium	0.592593
avg_result_no result \	
nvenue	
Arun Jaitley Stadium	0.000000
Barabati Stadium	0.000000
Barsapara Cricket Stadium	0.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.071429
Brabourne Stadium	0.000000
avg_result_runs \	
nvenue	
Arun Jaitley Stadium	0.533333
Barabati Stadium	0.571429
Barsapara Cricket Stadium	0.666667
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.500000
Brabourne Stadium	0.518519
avg_result_tie \	
nvenue	
Arun Jaitley Stadium	0.033333
Barabati Stadium	0.000000
Barsapara Cricket Stadium	0.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000000
Brabourne Stadium	0.000000
avg_result_wickets \	
nvenue	
Arun Jaitley Stadium	0.433333
Barabati Stadium	0.428571
Barsapara Cricket Stadium	0.333333
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.428571
Brabourne Stadium	0.481481
avg_venue_type_away \	
nvenue	
Arun Jaitley Stadium	0.366667
Barabati Stadium	0.000000
Barsapara Cricket Stadium	0.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.428571
Brabourne Stadium	0.111111
avg_venue_type_home \	
nvenue	
Arun Jaitley Stadium	0.500000
Barabati Stadium	0.000000

Barsapara Cricket Stadium	0.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.571429
Brabourne Stadium	0.296296
avg_venue_type_neutral \	
nvenue	
Arun Jaitley Stadium	0.133333
Barabati Stadium	1.000000
Barsapara Cricket Stadium	1.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000000
Brabourne Stadium	0.592593
avg_super_over_N \	
nvenue	
Arun Jaitley Stadium	0.966667
Barabati Stadium	1.000000
Barsapara Cricket Stadium	1.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	1.000000
Brabourne Stadium	1.000000
avg_super_over_Y \	
nvenue	
Arun Jaitley Stadium	0.033333
Barabati Stadium	0.000000
Barsapara Cricket Stadium	0.000000
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.000000
Brabourne Stadium	0.000000
avg_toss_decision_bat \	
nvenue	
Arun Jaitley Stadium	0.333333
Barabati Stadium	0.285714
Barsapara Cricket Stadium	0.333333
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.428571
Brabourne Stadium	0.333333
avg_toss_decision_field	
nvenue	
Arun Jaitley Stadium	0.666667
Barabati Stadium	0.714286
Barsapara Cricket Stadium	0.666667
Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cr...	0.571429
Brabourne Stadium	0.666667

```
[45]: #create team profiles:
tcols = vcols[1:]
tdf = df[tcols]
```

```
# tdf = pd.concat([df[['team1'] + tcols].rename(columns= {'team1' : 'team'}) ,
↳df[['team2'] + tcols].rename(columns = {'team2' : 'team'})])
cdf = pd.concat([ df[['team1', 'team2'] + [col for col in tcols if col not in
↳vcatscols]] , pd.DataFrame(onehot , columns = ohe.get_feature_names_out())] ,
↳axis = 1)

#get team1 and team2 into one feature:
# cdf[['team1'] + cdf.columns[2:]]
tdf = pd.concat([cdf[[col for col in cdf.columns if col != 'team2']],
↳rename(columns = {'team1' : 'team'}) , cdf[[col for col in cdf.columns if
↳col != 'team1']].rename(columns = {'team2' : 'team'})])
tgdf = tdf.groupby('team').mean().rename(columns = {col : f"avg_{col}" for col
↳in tdf.columns[1:]})
tgdf.head()
```

```
[45]:
```

	avg_target_runs	avg_result_margin	avg_win \
team			
Chennai Super Kings	165.978992	17.365546	0.508403
Deccan Chargers	160.626667	15.733333	0.440000
Delhi Capitals	164.373016	17.694444	0.523810
Gujarat Lions	169.233333	11.933333	0.366667
Gujarat Titans	174.777778	15.177778	0.400000

	avg_result_no result	avg_result_runs	avg_result_tie \
team			
Chennai Super Kings	0.004202	0.462185	0.004202
Deccan Chargers	0.000000	0.520000	0.000000
Delhi Capitals	0.007937	0.476190	0.015873
Gujarat Lions	0.000000	0.166667	0.033333
Gujarat Titans	0.000000	0.400000	0.000000

	avg_result_wickets	avg_venue_type_away \
team		
Chennai Super Kings	0.529412	0.121849
Deccan Chargers	0.480000	0.013333
Delhi Capitals	0.500000	0.083333
Gujarat Lions	0.800000	0.033333
Gujarat Titans	0.600000	0.111111

	avg_venue_type_home	avg_venue_type_neutral \
team		
Chennai Super Kings	0.457983	0.420168
Deccan Chargers	0.560000	0.426667
Delhi Capitals	0.527778	0.388889
Gujarat Lions	0.800000	0.166667
Gujarat Titans	0.533333	0.355556

	avg_super_over_N	avg_super_over_Y \
team		
Chennai Super Kings	0.995798	0.004202
Deccan Chargers	1.000000	0.000000
Delhi Capitals	0.984127	0.015873
Gujarat Lions	0.966667	0.033333
Gujarat Titans	1.000000	0.000000

	avg_toss_decision_bat	avg_toss_decision_field
team		
Chennai Super Kings	0.436975	0.563025
Deccan Chargers	0.493333	0.506667
Delhi Capitals	0.361111	0.638889
Gujarat Lions	0.100000	0.900000
Gujarat Titans	0.311111	0.688889

```
[46]: #create recommendations from profiles:
from sklearn.metrics.pairwise import cosine_similarity

#get common features:
nteam = tgdf.select_dtypes(include = [np.number]).columns.tolist()
nvenue = vgdf.select_dtypes(include = [np.number]).columns.tolist()
commonf = list(set(nteam).intersection(nvenue))

#standardize:

scaler = StandardScaler()
combined = pd.concat([tgdf[commonf] , vgdf[commonf]] , axis = 0)
scaler.fit(combined)
vscaled = pd.DataFrame(scaler.transform(vgdf[commonf]) , index = vgdf.index ,
    ↳ columns = commonf)
tscaled = pd.DataFrame(scaler.transform(tgdf[commonf]) , index = tgdf.index ,
    ↳ columns = commonf)

#compute cosine similarity:
smat = pd.DataFrame(cosine_similarity(tscaled.values , vscaled.values) , index=
    ↳ tgdf.index , columns = vgdf.index)
smat
```

```
[46]: nvenue          Arun Jaitley Stadium  Barabati Stadium \
team
Chennai Super Kings          0.396500        -0.139941
Deccan Chargers              -0.270472        -0.157030
Delhi Capitals                0.529073        -0.126649
Gujarat Lions                 0.083438        -0.475208
Gujarat Titans                0.279504        -0.277531
Kochi Tuskers Kerala         -0.530061        -0.354878
```

Kolkata Knight Riders	0.405245	-0.382171
Lucknow Super Giants	0.600816	0.367934
Mumbai Indians	0.870584	-0.187599
Pune Warriors	-0.243699	-0.307409
Punjab Kings	0.483080	-0.149375
Rajasthan Royals	0.307038	-0.337269
Rising Pune Supergiant	-0.323371	-0.238788
Royal Challengers Bangalore	0.287580	-0.045935
Sunrisers Hyderabad	0.916792	-0.123282

nvenue Barsapara Cricket Stadium \

team

Chennai Super Kings	0.107932
Deccan Chargers	-0.001988
Delhi Capitals	0.094488
Gujarat Lions	-0.594866
Gujarat Titans	-0.158155
Kochi Tuskers Kerala	-0.650204
Kolkata Knight Riders	-0.486416
Lucknow Super Giants	0.559471
Mumbai Indians	0.046844
Pune Warriors	-0.182213
Punjab Kings	-0.119394
Rajasthan Royals	-0.363723
Rising Pune Supergiant	-0.475359
Royal Challengers Bangalore	0.193563
Sunrisers Hyderabad	-0.029079

nvenue Bharat Ratna Shri Atal Bihari Vajpayee Ekana

Cricket Stadium \

team

Chennai Super Kings	0.375997
Deccan Chargers	-0.115954
Delhi Capitals	0.518800
Gujarat Lions	-0.165458
Gujarat Titans	-0.047854
Kochi Tuskers Kerala	-0.087989
Kolkata Knight Riders	-0.116394
Lucknow Super Giants	0.625736
Mumbai Indians	0.128219
Pune Warriors	0.575335
Punjab Kings	-0.237365
Rajasthan Royals	0.650200
Rising Pune Supergiant	-0.087159
Royal Challengers Bangalore	0.481890
Sunrisers Hyderabad	0.101432

nvenue	Brabourne Stadium	Buffalo Park \
team		
Chennai Super Kings	0.484718	0.135386
Deccan Chargers	-0.030286	0.323066
Delhi Capitals	0.197712	-0.219705
Gujarat Lions	-0.234550	-0.856506
Gujarat Titans	0.356644	-0.624410
Kochi Tuskers Kerala	-0.510807	-0.244046
Kolkata Knight Riders	-0.067700	-0.644347
Lucknow Super Giants	0.635285	0.124383
Mumbai Indians	0.413761	-0.324148
Pune Warriors	-0.315053	0.414876
Punjab Kings	0.274853	-0.811602
Rajasthan Royals	0.016968	-0.421080
Rising Pune Supergiant	-0.241387	-0.458487
Royal Challengers Bangalore	0.298452	-0.403164
Sunrisers Hyderabad	0.246625	-0.204142

nvenue	De Beers Diamond Oval \
team	
Chennai Super Kings	-0.012121
Deccan Chargers	-0.091315
Delhi Capitals	-0.582670
Gujarat Lions	-0.376351
Gujarat Titans	-0.380534
Kochi Tuskers Kerala	-0.025598
Kolkata Knight Riders	-0.477656
Lucknow Super Giants	-0.232032
Mumbai Indians	-0.582548
Pune Warriors	-0.044923
Punjab Kings	-0.680628
Rajasthan Royals	-0.156811
Rising Pune Supergiant	-0.294295
Royal Challengers Bangalore	-0.468081
Sunrisers Hyderabad	-0.418742

nvenue	Dr DY Patil Sports Academy \
team	
Chennai Super Kings	0.064242
Deccan Chargers	-0.191570
Delhi Capitals	-0.385787
Gujarat Lions	-0.029822
Gujarat Titans	0.332866
Kochi Tuskers Kerala	-0.125408
Kolkata Knight Riders	-0.036331
Lucknow Super Giants	0.191303
Mumbai Indians	0.080934

Pune Warriors	-0.460757
Punjab Kings	0.059835
Rajasthan Royals	-0.296194
Rising Pune Supergiant	-0.067299
Royal Challengers Bangalore	-0.045532
Sunrisers Hyderabad	0.091481

nvenue Dr. Y.S. Rajasekhara Reddy ACA-VDCA Cricket Stadium

\

team

Chennai Super Kings	-0.008847
Deccan Chargers	0.309281
Delhi Capitals	-0.235605
Gujarat Lions	-0.592285
Gujarat Titans	-0.200639
Kochi Tuskers Kerala	-0.392605
Kolkata Knight Riders	-0.667569
Lucknow Super Giants	0.094114
Mumbai Indians	-0.258875
Pune Warriors	0.112682
Punjab Kings	-0.446720
Rajasthan Royals	-0.654914
Rising Pune Supergiant	-0.433444
Royal Challengers Bangalore	-0.020011
Sunrisers Hyderabad	-0.358764

nvenue Dubai International Cricket Stadium ... \

team

Chennai Super Kings	-0.704793	...
Deccan Chargers	-0.488496	...
Delhi Capitals	-0.065422	...
Gujarat Lions	0.037752	...
Gujarat Titans	-0.494966	...
Kochi Tuskers Kerala	-0.524344	...
Kolkata Knight Riders	-0.175180	...
Lucknow Super Giants	-0.204802	...
Mumbai Indians	-0.159297	...
Pune Warriors	-0.407698	...
Punjab Kings	-0.026712	...
Rajasthan Royals	-0.258076	...
Rising Pune Supergiant	-0.581642	...
Royal Challengers Bangalore	-0.152400	...
Sunrisers Hyderabad	0.206767	...

nvenue Sawai Mansingh Stadium \

team

Chennai Super Kings	0.614295
---------------------	----------

Deccan Chargers	0.072525
Delhi Capitals	0.251447
Gujarat Lions	0.272745
Gujarat Titans	0.334150
Kochi Tuskers Kerala	0.550372
Kolkata Knight Riders	0.669986
Lucknow Super Giants	0.066734
Mumbai Indians	0.484998
Pune Warriors	0.186463
Punjab Kings	0.220112
Rajasthan Royals	0.581346
Rising Pune Supergiant	0.547560
Royal Challengers Bangalore	0.056850
Sunrisers Hyderabad	0.287506

nvenue	Shaheed Veer Narayan Singh International Stadium \	
team		
Chennai Super Kings		-0.330481
Deccan Chargers		-0.145522
Delhi Capitals		-0.690510
Gujarat Lions		-0.148743
Gujarat Titans		-0.377590
Kochi Tuskers Kerala		0.312969
Kolkata Knight Riders		-0.260862
Lucknow Super Giants		-0.396378
Mumbai Indians		-0.700679
Pune Warriors		-0.147146
Punjab Kings		-0.493278
Rajasthan Royals		-0.179927
Rising Pune Supergiant		0.072109
Royal Challengers Bangalore		-0.633312
Sunrisers Hyderabad		-0.418352

nvenue	Sharjah Cricket Stadium	Sheikh Zayed Stadium \
team		
Chennai Super Kings	-0.344795	-0.678389
Deccan Chargers	-0.051093	-0.335507
Delhi Capitals	-0.672109	-0.245990
Gujarat Lions	0.272769	0.181267
Gujarat Titans	0.316139	-0.357537
Kochi Tuskers Kerala	0.077981	-0.344323
Kolkata Knight Riders	-0.280869	-0.168458
Lucknow Super Giants	-0.507764	-0.469784
Mumbai Indians	-0.533884	-0.282940
Pune Warriors	-0.419952	-0.301183
Punjab Kings	-0.016475	-0.074524
Rajasthan Royals	-0.384506	-0.246592

Rising Pune Supergiant	0.023772	-0.493513
Royal Challengers Bangalore	-0.096105	-0.290649
Sunrisers Hyderabad	-0.583865	0.091420

nvenue St George's Park Subrata Roy Sahara Stadium \

team

Chennai Super Kings	0.175970	0.371378
Deccan Chargers	0.390802	0.846747
Delhi Capitals	-0.440041	0.012019
Gujarat Lions	-0.402363	-0.337456
Gujarat Titans	-0.127552	-0.025156
Kochi Tuskers Kerala	-0.181523	0.193316
Kolkata Knight Riders	-0.587800	-0.194175
Lucknow Super Giants	-0.253298	-0.153607
Mumbai Indians	-0.393057	-0.030536
Pune Warriors	0.291235	0.732204
Punjab Kings	-0.606187	-0.297540
Rajasthan Royals	-0.340468	-0.203694
Rising Pune Supergiant	-0.425234	0.069797
Royal Challengers Bangalore	-0.351099	-0.269132
Sunrisers Hyderabad	-0.354035	-0.134715

nvenue SuperSport Park \

team

Chennai Super Kings	-0.290208
Deccan Chargers	-0.006110
Delhi Capitals	-0.887406
Gujarat Lions	-0.014408
Gujarat Titans	-0.076099
Kochi Tuskers Kerala	0.208852
Kolkata Knight Riders	-0.406551
Lucknow Super Giants	-0.579750
Mumbai Indians	-0.797763
Pune Warriors	-0.220594
Punjab Kings	-0.434986
Rajasthan Royals	-0.293098
Rising Pune Supergiant	-0.036324
Royal Challengers Bangalore	-0.617185
Sunrisers Hyderabad	-0.576295

nvenue Vidarbha Cricket Association Stadium \

team

Chennai Super Kings	-0.091969
Deccan Chargers	0.320812
Delhi Capitals	-0.347624
Gujarat Lions	-0.782535
Gujarat Titans	-0.594760

Kochi Tuskers Kerala	-0.133825
Kolkata Knight Riders	-0.590540
Lucknow Super Giants	0.107329
Mumbai Indians	-0.446074
Pune Warriors	0.253771
Punjab Kings	-0.630984
Rajasthan Royals	-0.502825
Rising Pune Supergiant	-0.269292
Royal Challengers Bangalore	-0.602193
Sunrisers Hyderabad	-0.175590

nvenue	Wankhede Stadium	Zayed Cricket Stadium
team		
Chennai Super Kings	0.458742	-0.321804
Deccan Chargers	-0.089658	0.071895
Delhi Capitals	0.444943	-0.805102
Gujarat Lions	0.484369	0.152425
Gujarat Titans	0.751623	0.245865
Kochi Tuskers Kerala	0.030634	0.071750
Kolkata Knight Riders	0.703936	-0.405405
Lucknow Super Giants	0.360653	-0.557175
Mumbai Indians	0.817739	-0.661220
Pune Warriors	-0.312497	-0.336383
Punjab Kings	0.828338	-0.152552
Rajasthan Royals	0.391604	-0.441228
Rising Pune Supergiant	0.343401	-0.039657
Royal Challengers Bangalore	0.457169	-0.317032
Sunrisers Hyderabad	0.558477	-0.610111

[15 rows x 40 columns]

```
[47]: #get recommendations for teams:
def recommend_venue(team , smat):
    return smat.loc[team].sort_values(ascending = False)[:5].index.tolist()

nteam = sorted(df['team1'].unique())

for team in nteam:
    print(f"{team}: {recommend_venue(team , smat)}")
```

Chennai Super Kings: ['Rajiv Gandhi International Stadium', 'Sawai Mansingh Stadium', 'Eden Gardens', 'Punjab Cricket Association IS Bindra Stadium', 'Brabourne Stadium']

Deccan Chargers: ['Subrata Roy Sahara Stadium', 'Nehru Stadium', 'Feroz Shah Kotla', 'Kingsmead', 'St George's Park']

Delhi Capitals: ['M.Chinnaswamy Stadium', 'Feroz Shah Kotla', 'Arun Jaitley Stadium', 'Punjab Cricket Association IS Bindra Stadium', 'Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cricket Stadium']

Gujarat Lions: ['Saurashtra Cricket Association Stadium', 'Green Park', 'Narendra Modi Stadium', 'Holkar Cricket Stadium', 'Punjab Cricket Association IS Bindra Stadium']

Gujarat Titans: ['Narendra Modi Stadium', 'Wankhede Stadium', 'Punjab Cricket Association IS Bindra Stadium', 'Maharaja Yadavindra Singh International Cricket Stadium', 'Eden Gardens']

Kochi Tuskers Kerala: ['Sawai Mansingh Stadium', 'Eden Gardens', 'Feroz Shah Kotla', 'Punjab Cricket Association IS Bindra Stadium', 'Nehru Stadium']

Kolkata Knight Riders: ['Eden Gardens', 'Punjab Cricket Association IS Bindra Stadium', 'Wankhede Stadium', 'Rajiv Gandhi International Stadium', 'Sawai Mansingh Stadium']

Lucknow Super Giants: ['Brabourne Stadium', 'Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cricket Stadium', 'Arun Jaitley Stadium', 'Barsapara Cricket Stadium', 'Himachal Pradesh Cricket Association Stadium']

Mumbai Indians: ['Arun Jaitley Stadium', 'Wankhede Stadium', 'Rajiv Gandhi International Stadium', 'Punjab Cricket Association IS Bindra Stadium', 'Eden Gardens']

Pune Warriors: ['Feroz Shah Kotla', 'Subrata Roy Sahara Stadium', 'Nehru Stadium', 'Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cricket Stadium', 'Buffalo Park']

Punjab Kings: ['Wankhede Stadium', 'Punjab Cricket Association IS Bindra Stadium', 'Narendra Modi Stadium', 'Saurashtra Cricket Association Stadium', 'Eden Gardens']

Rajasthan Royals: ['Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cricket Stadium', 'M.Chinnaswamy Stadium', 'Sawai Mansingh Stadium', 'Eden Gardens', 'Feroz Shah Kotla']

Rising Pune Supergiant: ['Punjab Cricket Association IS Bindra Stadium', 'Eden Gardens', 'Feroz Shah Kotla', 'Sawai Mansingh Stadium', 'Nehru Stadium']

Royal Challengers Bangalore: ['M.Chinnaswamy Stadium', 'Maharashtra Cricket Association Stadium', 'Himachal Pradesh Cricket Association Stadium', 'Feroz Shah Kotla', 'Bharat Ratna Shri Atal Bihari Vajpayee Ekana Cricket Stadium']

Sunrisers Hyderabad: ['Arun Jaitley Stadium', 'Rajiv Gandhi International Stadium', 'Maharaja Yadavindra Singh International Cricket Stadium', 'MA Chidambaram Stadium', 'Wankhede Stadium']

[]:

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7 Question 7: Performance Trend Analysis (8 points)

7.0.1 Task:

Use **Linear Regression** to analyze performance trends:

1. Track team performance over seasons:
 - Create yearly win percentage for each team
 - Fit linear regression to identify improving/declining teams
2. Predict next season performance
3. Identify factors affecting performance trends:
 - Player retention
 - Home ground advantage
 - Toss luck factor

7.0.2 Visualization:

- Time series plot with regression lines for top 5 teams

```
[48]: #yearly win percentage for each team
cols = ['team1' , 'team2' , 'season' , 'win']
# df[cols]

# convert (t, t, s, w) -> (t , s, w):
cdf = pd.concat([df[['team1'] + cols[2:]].rename(columns = {'team1':'team'}) ,
    ↪df[['team2'] + cols[2:]].rename(columns = {'team2' : 'team'})])
gdf = cdf.groupby(['team' , 'season']).count().unstack(level = 1).fillna(0)
gdf.columns = [col[1] if isinstance(col , tuple) else col[0] for col in gdf.
    ↪columns]
g2df = cdf.groupby('season')['win'].count()
```

```
[49]: for col in gdf.columns:
      gdf[col] = (gdf[col] / g2df.loc[col]) * 100
gdf
```

```
[49]:
```

	2008	2009	2010	2011 \
team				
Chennai Super Kings	13.793103	12.280702	13.333333	10.958904
Deccan Chargers	12.068966	14.035088	13.333333	9.589041
Delhi Capitals	12.068966	13.157895	11.666667	9.589041
Gujarat Lions	0.000000	0.000000	0.000000	0.000000
Gujarat Titans	0.000000	0.000000	0.000000	0.000000
Kochi Tuskers Kerala	0.000000	0.000000	0.000000	9.589041
Kolkata Knight Riders	11.206897	11.403509	11.666667	10.273973
Lucknow Super Giants	0.000000	0.000000	0.000000	0.000000
Mumbai Indians	12.068966	11.403509	13.333333	10.958904
Pune Warriors	0.000000	0.000000	0.000000	9.589041
Punjab Kings	12.931034	12.280702	11.666667	9.589041
Rajasthan Royals	13.793103	11.403509	11.666667	8.904110
Rising Pune Supergiant	0.000000	0.000000	0.000000	0.000000
Royal Challengers Bangalore	12.068966	14.035088	13.333333	10.958904
Sunrisers Hyderabad	0.000000	0.000000	0.000000	0.000000

	2012	2013	2014	2015 \
team				
Chennai Super Kings	12.162162	11.842105	13.333333	14.406780
Deccan Chargers	10.135135	0.000000	0.000000	0.000000
Delhi Capitals	12.162162	10.526316	11.666667	11.864407
Gujarat Lions	0.000000	0.000000	0.000000	0.000000
Gujarat Titans	0.000000	0.000000	0.000000	0.000000
Kochi Tuskers Kerala	0.000000	0.000000	0.000000	0.000000
Kolkata Knight Riders	11.486486	10.526316	13.333333	11.016949
Lucknow Super Giants	0.000000	0.000000	0.000000	0.000000
Mumbai Indians	11.486486	12.500000	12.500000	13.559322
Pune Warriors	10.810811	10.526316	0.000000	0.000000
Punjab Kings	10.810811	10.526316	14.166667	11.864407
Rajasthan Royals	10.810811	11.842105	11.666667	11.864407
Rising Pune Supergiant	0.000000	0.000000	0.000000	0.000000
Royal Challengers Bangalore	10.135135	10.526316	11.666667	13.559322
Sunrisers Hyderabad	0.000000	11.184211	11.666667	11.864407

	2016	2017	2018	2019 \
team				
Chennai Super Kings	0.000000	0.000000	13.333333	14.166667
Deccan Chargers	0.000000	0.000000	0.000000	0.000000
Delhi Capitals	11.666667	11.864407	11.666667	13.333333
Gujarat Lions	13.333333	11.864407	0.000000	0.000000
Gujarat Titans	0.000000	0.000000	0.000000	0.000000
Kochi Tuskers Kerala	0.000000	0.000000	0.000000	0.000000
Kolkata Knight Riders	12.500000	13.559322	13.333333	11.666667
Lucknow Super Giants	0.000000	0.000000	0.000000	0.000000
Mumbai Indians	11.666667	14.406780	11.666667	13.333333
Pune Warriors	0.000000	0.000000	0.000000	0.000000
Punjab Kings	11.666667	11.864407	11.666667	11.666667
Rajasthan Royals	0.000000	0.000000	12.500000	11.666667
Rising Pune Supergiant	11.666667	13.559322	0.000000	0.000000
Royal Challengers Bangalore	13.333333	11.016949	11.666667	11.666667
Sunrisers Hyderabad	14.166667	11.864407	14.166667	12.500000

	2020	2021	2022	2023 \
team				
Chennai Super Kings	11.666667	13.333333	9.459459	10.810811
Deccan Chargers	0.000000	0.000000	0.000000	0.000000
Delhi Capitals	14.166667	13.333333	9.459459	9.459459
Gujarat Lions	0.000000	0.000000	0.000000	0.000000
Gujarat Titans	0.000000	0.000000	10.810811	11.486486
Kochi Tuskers Kerala	0.000000	0.000000	0.000000	0.000000
Kolkata Knight Riders	11.666667	14.166667	9.459459	9.459459
Lucknow Super Giants	0.000000	0.000000	10.135135	10.135135

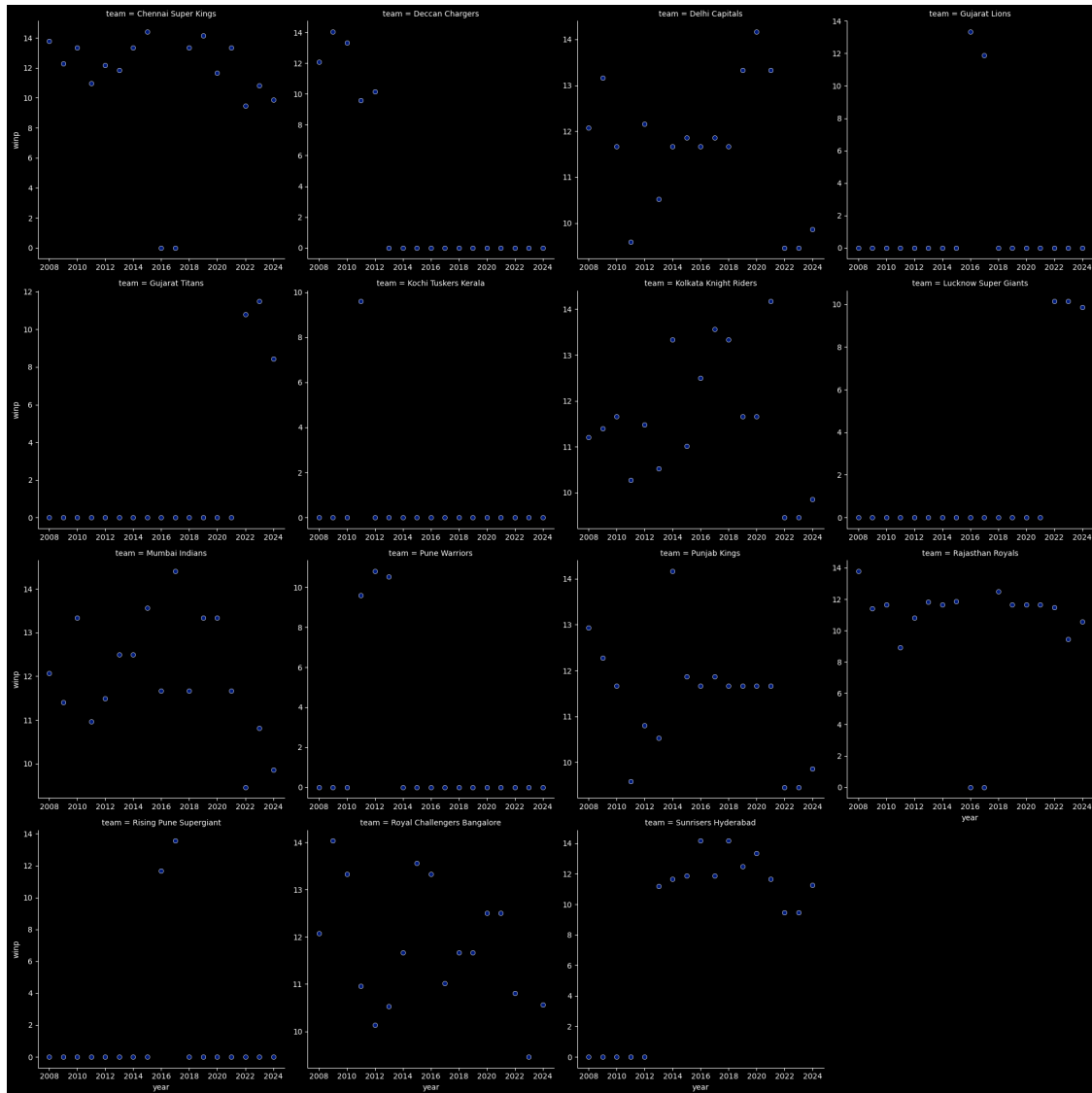
Mumbai Indians	13.333333	11.666667	9.459459	10.810811
Pune Warriors	0.000000	0.000000	0.000000	0.000000
Punjab Kings	11.666667	11.666667	9.459459	9.459459
Rajasthan Royals	11.666667	11.666667	11.486486	9.459459
Rising Pune Supergiant	0.000000	0.000000	0.000000	0.000000
Royal Challengers Bangalore	12.500000	12.500000	10.810811	9.459459
Sunrisers Hyderabad	13.333333	11.666667	9.459459	9.459459

2024

team	
Chennai Super Kings	9.859155
Deccan Chargers	0.000000
Delhi Capitals	9.859155
Gujarat Lions	0.000000
Gujarat Titans	8.450704
Kochi Tuskers Kerala	0.000000
Kolkata Knight Riders	9.859155
Lucknow Super Giants	9.859155
Mumbai Indians	9.859155
Pune Warriors	0.000000
Punjab Kings	9.859155
Rajasthan Royals	10.563380
Rising Pune Supergiant	0.000000
Royal Challengers Bangalore	10.563380
Sunrisers Hyderabad	11.267606

```
[50]: mdf = gdf.reset_index().melt(id_vars = 'team' , var_name = 'year' , value_name='winp')
plt.figure(figsize = (20 , 20))
sns.relplot(data = mdf , x = 'year' , y = 'winp' , col = 'team' , col_wrap = 4,
            kind = 'scatter' , facet_kws= {'sharey' : False , 'sharex' : False})
plt.savefig('./data/q7_winpbyyear.png')
```

<Figure size 2000x2000 with 0 Axes>



[]:

[]:

[]:

8 Question 8: Player of Match Prediction - KNN (8 points)

8.0.1 Task:

Use **K-Nearest Neighbors (KNN)** to predict potential 'Player of Match':

1. Create match context features:

- Venue characteristics
 - Team strengths
 - Historical player performance at venue
2. Use KNN to find similar historical matches
 3. Predict likely 'Player of Match' based on similar matches
 4. Optimize K using cross-validation

```
[59]: import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, \
    ↪confusion_matrix

# Label encode categorical columns
label_cols = ['nvenue', 'team1', 'team2', 'toss_winner', 'winner', \
    ↪'player_of_match']
tdf = df[label_cols].copy()
encoders = {col: LabelEncoder() for col in label_cols}
for col in label_cols:
    enc = LabelEncoder()
    tdf[col] = enc.fit_transform(tdf[col])
    encoders[col] = enc

# Aggregate player historical performance
player_perf = tdf.groupby('player_of_match')['winner'].count().reset_index()
player_perf.columns = ['player_of_match', 'match_wins']
tdf = tdf.merge(player_perf, on='player_of_match', how='left')

# Create context features
tdf['venue_strength'] = tdf.groupby('nvenue')['winner'].transform(lambda x: x.
    ↪value_counts().max())
tdf['team_strength_diff'] = abs(tdf['team1'] - tdf['team2'])

# Final feature set
features = ['nvenue', 'team1', 'team2', 'venue_strength', 'team_strength_diff']
target = 'player_of_match'

x = tdf[features]
y = tdf[target]

xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size= 0.2, \
    ↪random_state= 42)
```

```
[60]: # Parameter tuning for best K
param_grid = {'n_neighbors': list(range(3, 21))}
grid = GridSearchCV(KNeighborsClassifier(), param_grid, cv=5,
                    scoring='accuracy')
grid.fit(xtrain, ytrain)

best_k = grid.best_params_['n_neighbors']
best_score = grid.best_score_
print(f" Best K = {best_k} with CV Accuracy = {best_score:.3f}")
```

```
/opt/anaconda3/envs/tensorflow/lib/python3.11/site-
packages/sklearn/model_selection/_split.py:805: UserWarning: The least populated
class in y has only 1 members, which is less than n_splits=5.
  warnings.warn(

Best K = 17 with CV Accuracy = 0.046
```

```
[62]: best_knn = KNeighborsClassifier(n_neighbors=best_k)
best_knn.fit(xtrain, ytrain)
y_pred_best = best_knn.predict(xtest)
print("Final Accuracy:", accuracy_score(ytest, y_pred_best))
```

Final Accuracy: 0.0319634703196347

```
[73]: sample = pd.DataFrame({
    'nvenue': [encoders['nvenue'].transform(['Eden Gardens'])[0]],
    'team1': [encoders['team1'].transform(['Mumbai Indians'])[0]],
    'team2': [encoders['team2'].transform(['Chennai Super Kings'])[0]],
    'venue_strength': [25],
    'team_strength_diff': [abs(5 - 12)]
})
pred_player = encoders['player_of_match'].inverse_transform(best_knn.
                    predict(sample))
print(f"Predicted Player of the Match: {pred_player[0]}")
```

Predicted Player of the Match: A Mishra

9 Question 9: Toss Decision Strategy - Decision Tree (9 points)

9.0.1 Task:

Build a **Decision Tree** to recommend toss decisions:

1. Create a model to predict optimal toss decision (bat/field) based on:
 - Venue history
 - Weather conditions (create synthetic if not available)
 - Team strengths
 - Match importance
2. Visualize the decision tree (max_depth=5)

3. Extract decision rules in plain English
4. Calculate feature importance

9.0.2 Business Application:

“Provide captains with data-driven toss decision recommendations”

```
[51]: from sklearn.tree import DecisionTreeClassifier , plot_tree , export_text
      from sklearn.preprocessing import OrdinalEncoder , LabelEncoder

      #compute toss-strength for each team:
      teams = pd.concat([df['team1'] , df['team2']]).unique()
      thist = {t : {'played' : 0 , 'won' : 0} for t in teams}
      #iterate over the dataframe to compute stats prior to each match:
      toss_win_strength = []
      opp_strength = []
      for id , row in df.iterrows():
          tw = row['toss_winner']
          if tw == row['team1']: opp = row['team2']
          else: opp = row['team1']

          #get winrate so far:
          def get_wr(team):
              if team not in thist:
                  return 0.5
              played = thist[team]['played']
              return thist[team]['won'] / played if played > 0 else 0.5

          tws = get_wr(tw)
          opps = get_wr(opp)

          toss_win_strength.append(tws)
          opp_strength.append(opps)

          winner = row['winner']

          #update history:
          for t in [row['team1'] , row['team2']]:
              thist[t]['played'] += 1

          thist.setdefault(winner , {'played' : 0 , 'won' : 0})
          thist[winner]['won'] += 1

      df['toss_winner_strength'] = toss_win_strength
      df['opp_strength'] = opp_strength
```

```

cols = ['date' , 'nvenue' , 'team1' , 'team2' , 'toss_winner_strength' ,
        ↪ 'opp_strength']
ddf = df[cols].copy()

#translate string to numeric features:
ddf['match_importance_code'] = pd.Categorical(df['match_importance'] ,
        ↪ categories= df['match_importance'].cat.categories.to_list()).codes
y = df['toss_winner']
le = LabelEncoder()
ddf['evenue'] = le.fit_transform(ddf['nvenue'])
le.fit(pd.concat([ddf['team1'] , ddf['team2']]).unique())
ddf['etteam1'] = le.transform(ddf['team1'])
ddf['etteam2'] = le.transform(ddf['team2'])
ddf = ddf.iloc[: , 4:]
ddf

```

```

[51]:      toss_winner_strength  opp_strength  match_importance_code  evenue  \
0                0.500000      0.500000                0         17
1                0.500000      0.500000                0         26
2                0.500000      0.500000                0         11
3                0.500000      0.000000                0         38
4                0.500000      1.000000                0         10
...                ...                ...                ...         ...
1090            0.457143      0.483146                0         27
1091            0.486034      0.518072                1         21
1092            0.506849      0.484252                1         21
1093            0.509091      0.483333                1         18
1094            0.486188      0.520000                2         18

      eteam1  eteam2
0          13      6
1          10      0
2           2     11
3           8     13
4           6      1
...        ...    ...
1090        10     14
1091        14      6
1092        13     11
1093        14     11
1094        14      6

[1095 rows x 6 columns]

```

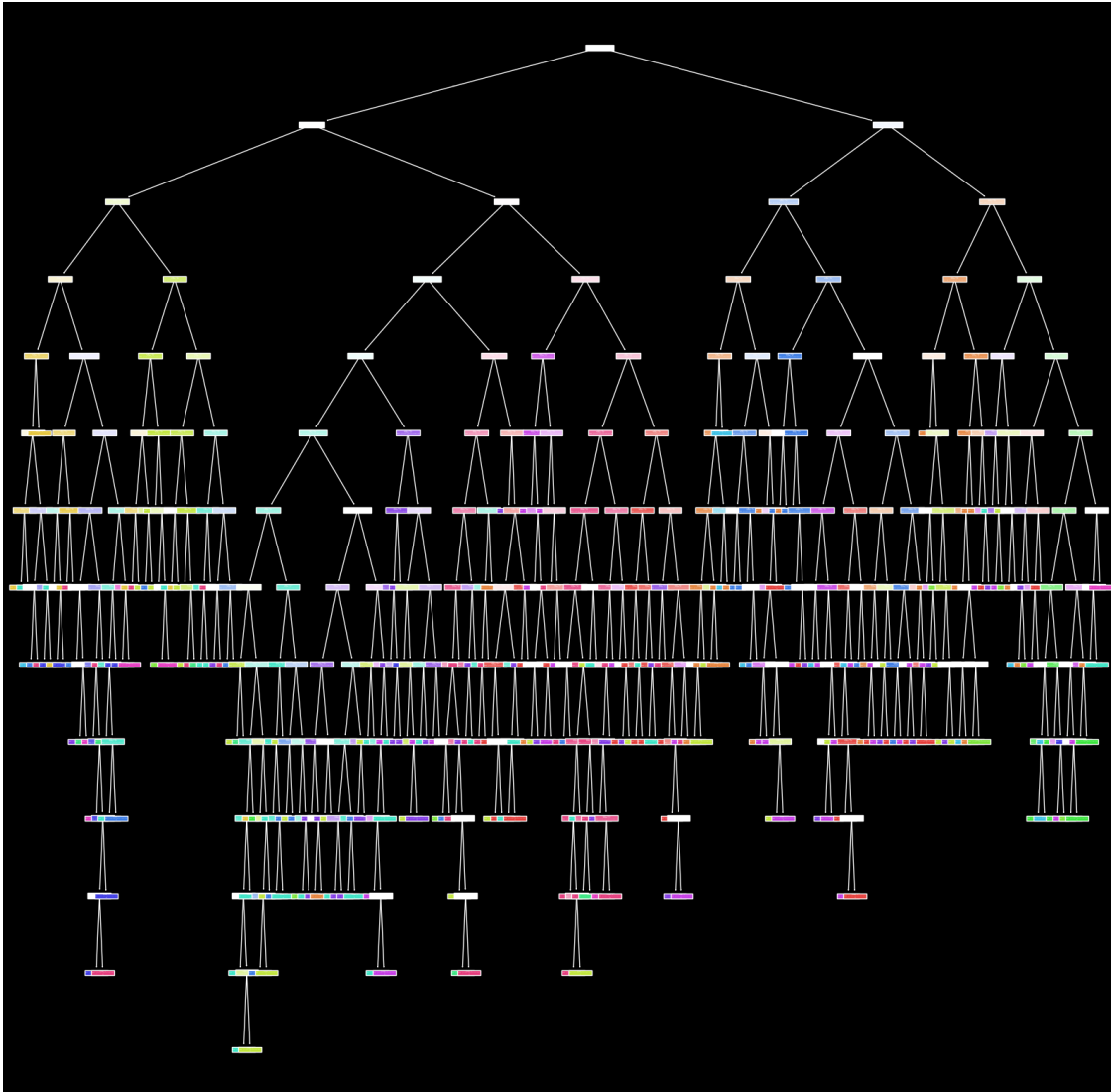
[52]:

```

xtrain , xtest , ytrain , ytest = train_test_split(ddf , y , test_size= 0.2 ,
↳random_state = 42)
model = DecisionTreeClassifier(criterion = 'entropy')
model.fit(xtrain , ytrain)
print(f"model score: {model.score(xtest , ytest)}")
plot_tree(model , filled = True)
plt.show()

```

model score: 0.6301369863013698

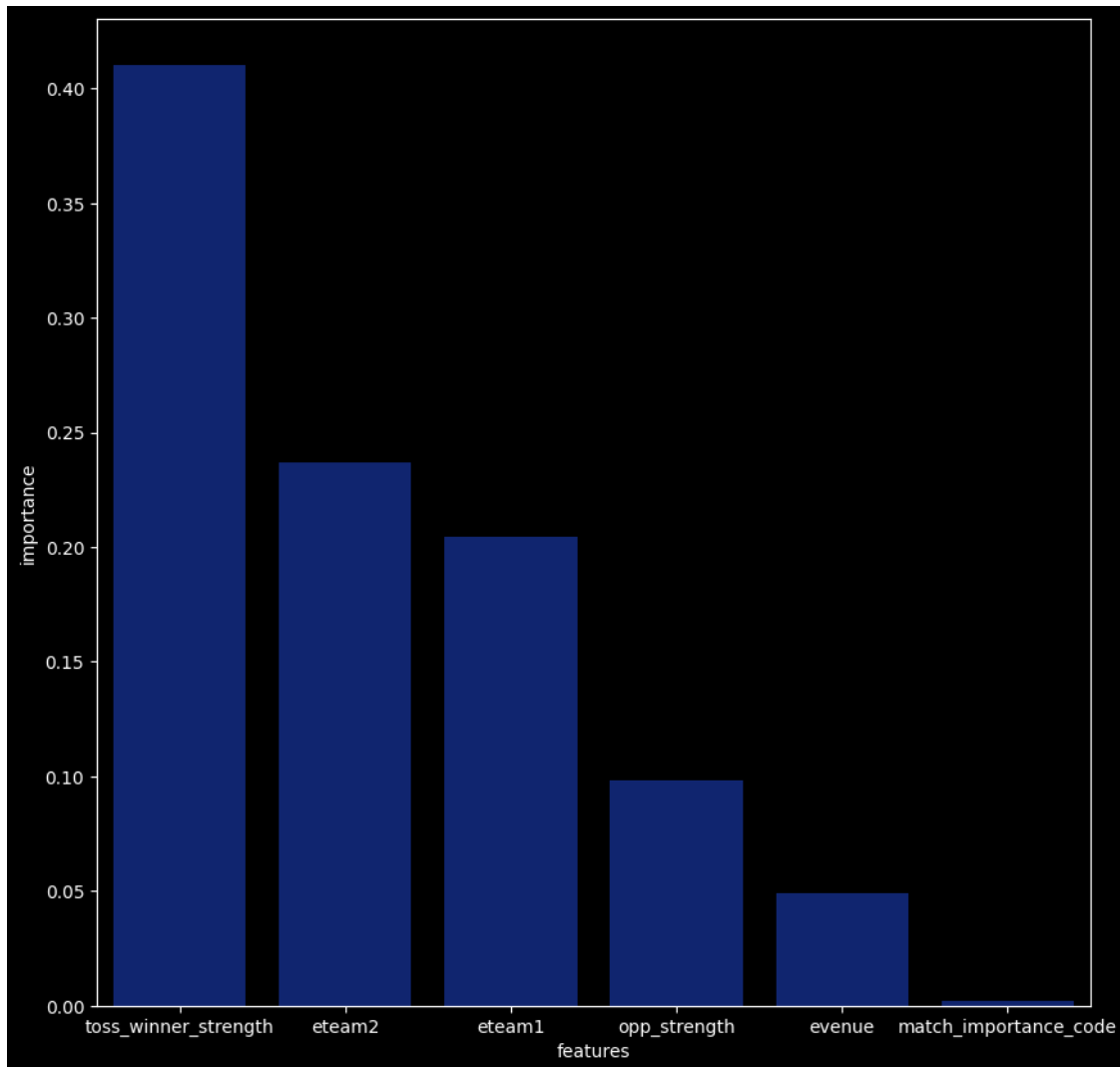


```

[53]: tdf = pd.DataFrame({'features' : xtrain.columns.tolist() , 'importance' : model.
↳feature_importances_}).sort_values(by = 'importance' , ascending = False)
plt.figure(figsize = (10 , 10))

```

```
sns.barplot(tdf , x = 'features' , y = 'importance')
plt.show()
```



```
[54]: #decision rules in english:
rules = export_text(model , feature_names= xtrain.columns.tolist())
print(rules)
```

```
|--- toss_winner_strength <= 0.54
|   |--- toss_winner_strength <= 0.46
|   |   |--- toss_winner_strength <= 0.41
|   |   |   |--- eteam1 <= 1.50
|   |   |   |   |--- eteam1 <= 0.50
|   |   |   |   |   |--- eteam2 <= 6.50
|   |   |   |   |   |   |--- eteam2 <= 3.50
|   |   |   |   |   |   |   |--- class: Deccan Chargers
```

[illegible]


```

| | | | | |--- eteam1 <= 3.50
| | | | | |   |--- eteam1 <= 1.50
| | | | | |   |   |--- eteam2 <= 7.00
| | | | | |   |   |   |--- class: Kolkata Knight Riders
| | | | | |   |   |   |--- eteam2 > 7.00
| | | | | |   |   |   |--- class: Deccan Chargers
| | | | | |   |--- eteam1 > 1.50
| | | | | |   |   |--- toss_winner_strength <= 0.45
| | | | | |   |   |   |--- class: Delhi Capitals
| | | | | |   |   |   |--- toss_winner_strength > 0.45
| | | | | |   |   |   |--- opp_strength <= 0.53
| | | | | |   |   |   |--- class: Delhi Capitals
| | | | | |   |   |   |--- opp_strength > 0.53
| | | | | |   |   |   |--- class: Royal Challengers Bangalore
| | | | | |--- eteam1 > 3.50
| | | | | |   |--- toss_winner_strength <= 0.44
| | | | | |   |   |--- opp_strength <= 0.60
| | | | | |   |   |   |--- eteam1 <= 5.50
| | | | | |   |   |   |   |--- class: Kochi Tuskers Kerala
| | | | | |   |   |   |   |--- eteam1 > 5.50
| | | | | |   |   |   |   |   |--- class: Kolkata Knight Riders
| | | | | |   |   |   |   |   |--- opp_strength > 0.60
| | | | | |   |   |   |   |   |--- class: Royal Challengers Bangalore
| | | | | |   |   |   |--- toss_winner_strength > 0.44
| | | | | |   |   |   |   |--- eteam1 <= 7.00
| | | | | |   |   |   |   |   |--- opp_strength <= 0.51
| | | | | |   |   |   |   |   |   |--- class: Kolkata Knight Riders
| | | | | |   |   |   |   |   |   |--- opp_strength > 0.51
| | | | | |   |   |   |   |   |   |--- class: Punjab Kings
| | | | | |   |   |   |--- eteam1 > 7.00
| | | | | |   |   |   |   |--- eteam2 <= 7.00
| | | | | |   |   |   |   |   |--- class: Royal Challengers Bangalore
| | | | | |   |   |   |   |   |--- eteam2 > 7.00
| | | | | |   |   |   |   |   |   |--- class: Mumbai Indians
| |--- toss_winner_strength > 0.46
| |   |--- eteam2 <= 10.50
| |   |   |--- eteam1 <= 12.50
| |   |   |   |--- eteam2 <= 8.50
| |   |   |   |   |--- eteam1 <= 9.50
| |   |   |   |   |   |--- eteam2 <= 5.00
| |   |   |   |   |   |   |--- eteam1 <= 5.50
| |   |   |   |   |   |   |   |--- eteam1 <= 4.50
| |   |   |   |   |   |   |   |   |--- class: Delhi Capitals
| |   |   |   |   |   |   |   |   |--- eteam1 > 4.50
| |   |   |   |   |   |   |   |   |   |--- class: Kochi Tuskers Kerala
| |   |   |   |   |   |   |   |   |   |--- eteam1 > 5.50
| |   |   |   |   |   |   |   |   |   |--- eteam1 <= 6.50
| |   |   |   |   |   |   |   |   |   |--- opp_strength <= 0.81

```



```
| | | | |--- opp_strength > 0.50
| | | | |--- class: Chennai Super Kings
| | | | |--- toss_winner_strength > 0.54
| | | | |--- opp_strength <= 0.56
| | | | |--- class: Mumbai Indians
| | | | |--- opp_strength > 0.56
| | | | |--- eteam1 <= 9.00
| | | | |--- class: Mumbai Indians
| | | | |--- eteam1 > 9.00
| | | | |--- eteam1 <= 12.50
| | | | |--- class: Rajasthan Royals
| | | | |--- eteam1 > 12.50
| | | | |--- class: Sunrisers Hyderabad
| | | |--- eteam2 > 8.50
| | | |--- toss_winner_strength <= 0.56
| | | |--- eteam2 <= 11.50
| | | |--- evenue <= 5.50
| | | |--- evenue <= 2.00
| | | |--- class: Punjab Kings
| | | |--- evenue > 2.00
| | | |--- class: Lucknow Super Giants
| | | |--- evenue > 5.50
| | | |--- opp_strength <= 0.60
| | | |--- class: Rajasthan Royals
| | | |--- opp_strength > 0.60
| | | |--- match_importance_code <= 0.50
| | | |--- toss_winner_strength <= 0.55
| | | |--- class: Punjab Kings
| | | |--- toss_winner_strength > 0.55
| | | |--- class: Rajasthan Royals
| | | |--- match_importance_code > 0.50
| | | |--- class: Delhi Capitals
| | | |--- eteam2 > 11.50
| | | |--- evenue <= 32.50
| | | |--- toss_winner_strength <= 0.56
| | | |--- evenue <= 6.00
| | | |--- class: Rajasthan Royals
| | | |--- evenue > 6.00
| | | |--- evenue <= 28.50
| | | |--- class: Sunrisers Hyderabad
| | | |--- evenue > 28.50
| | | |--- opp_strength <= 0.50
| | | |--- class: Rajasthan Royals
| | | |--- opp_strength > 0.50
| | | |--- class: Sunrisers Hyderabad
| | | |--- toss_winner_strength > 0.56
| | | |--- class: Lucknow Super Giants
| | | |--- evenue > 32.50
```


[illegible]

```
| | | | | | | | | |--- toss_winner_strength <= 0.70
| | | | | | | | | |--- class: Gujarat Titans
| | | | | | | | | |--- toss_winner_strength > 0.70
| | | | | | | | | |--- class: Rajasthan Royals
| | | | | | | | | |--- eteam2 > 8.00
| | | | | | | | | |--- eteam2 <= 10.50
| | | | | | | | | |--- eteam2 <= 9.50
| | | | | | | | | |--- class: Pune Warriors
| | | | | | | | | |--- eteam2 > 9.50
| | | | | | | | | |--- toss_winner_strength <= 0.87
| | | | | | | | | |--- class: Gujarat Lions
| | | | | | | | | |--- toss_winner_strength > 0.87
| | | | | | | | | |--- class: Gujarat Titans
| | | | | | | | | |--- eteam2 > 10.50
| | | | | | | | | |--- evenue <= 37.00
| | | | | | | | | |--- class: Rajasthan Royals
| | | | | | | | | |--- evenue > 37.00
| | | | | | | | | |--- class: Gujarat Titans
| | | | | | | | | |--- opp_strength > 0.68
| | | | | | | | | |--- eteam1 <= 1.50
| | | | | | | | | |--- eteam2 <= 4.00
| | | | | | | | | |--- class: Chennai Super Kings
| | | | | | | | | |--- eteam2 > 4.00
| | | | | | | | | |--- class: Kolkata Knight Riders
| | | | | | | | | |--- eteam1 > 1.50
| | | | | | | | | |--- class: Rising Pune Supergiant
```

10 Question 10: Advanced Match Prediction - Ensemble Methods (10 points)

10.0.1 Task:

Compare **Bagging** and **Boosting** for match outcome prediction:

1. Implement Random Forest (Bagging):
 - Use all available features
 - Tune hyperparameters
 - Feature importance analysis
2. Implement XGBoost/AdaBoost (Boosting):
 - Compare with Random Forest
 - Analyze prediction confidence
3. Create an ensemble combining both approaches
4. Performance comparison:
 - Accuracy, Precision, Recall, F1-score

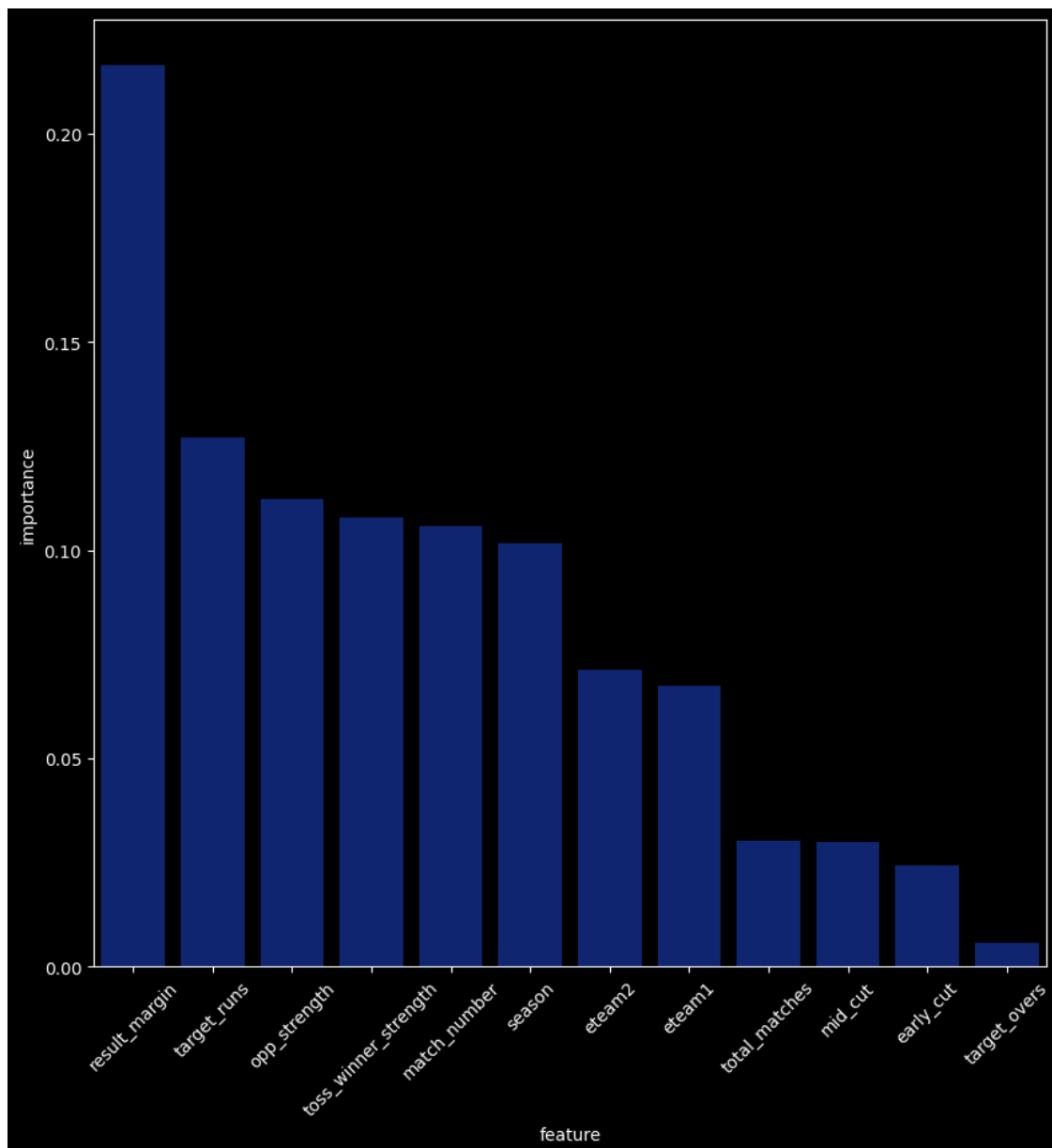
- ROC curves for all models

```
[55]: from sklearn.model_selection import GridSearchCV
      from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,
      ↪ VotingClassifier
      from xgboost import XGBClassifier
      from sklearn.metrics import accuracy_score, precision_score, recall_score,
      ↪ f1_score, roc_auc_score, roc_curve

[56]: xdf = pd.concat([df.select_dtypes(include = ['number' , 'float64' , 'int64'])
      ↪ , ddf.iloc[:, 4:]] , axis = 1)
      xdf = xdf.drop(columns = [ 'id' , 'win'])
      xtrain , xtest , ytrain , ytest = train_test_split(xdf , df['win'] , test_size=
      ↪ 0.2 , random_state= 42)

[57]: rf = RandomForestClassifier(random_state= 42)
      param_grid_rf = {
          'n_estimators': [100, 200],
          'max_depth': [5, 10, None],
          'min_samples_split': [2, 5],
      }
      grid_rf = GridSearchCV(rf, param_grid_rf, cv=3, scoring='accuracy', n_jobs=-1)
      grid_rf.fit(xtrain, ytrain)
      rf_best = grid_rf.best_estimator_

      # Feature importance analysis
      feature_importance = pd.DataFrame({
          'feature': xtrain.columns,
          'importance': rf_best.feature_importances_
      }).sort_values(by='importance', ascending=False)
      plt.figure(figsize = (10 , 10))
      sns.barplot(data = feature_importance , x = 'feature' , y = 'importance')
      plt.xticks(rotation = 45)
      plt.show()
```



```
[58]: #2. XGBoost:
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss',
    ↪random_state=42)
xgb.fit(xtrain, ytrain)

adb = AdaBoostClassifier(random_state=42, n_estimators=100)
adb.fit(xtrain, ytrain)

# 3 Ensemble combining Bagging and Boosting
ensemble = VotingClassifier(estimators=[
```



```

    ('rf', rf_best),
    ('xgb', xgb),
    ('adb', adb)
], voting='soft')
ensemble.fit(xtrain, ytrain)

```

```

/opt/anaconda3/envs/tensorflow/lib/python3.11/site-
packages/xgboost/training.py:199: UserWarning: [16:15:48] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:790:
Parameters: { "use_label_encoder" } are not used.

```

```

    bst.update(dtrain, iteration=i, fobj=obj)
/opt/anaconda3/envs/tensorflow/lib/python3.11/site-
packages/xgboost/training.py:199: UserWarning: [16:15:48] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:790:
Parameters: { "use_label_encoder" } are not used.

```

```

    bst.update(dtrain, iteration=i, fobj=obj)

```

```

[58]: VotingClassifier(estimators=[('rf', RandomForestClassifier(random_state=42)),
                                   ('xgb',
                                    XGBClassifier(base_score=None, booster=None,
                                                    callbacks=None,
                                                    colsample_bylevel=None,
                                                    colsample_bynode=None,
                                                    colsample_bytree=None, device=None,
                                                    early_stopping_rounds=None,
                                                    enable_categorical=False,
                                                    eval_metric='logloss',
                                                    feature_types=None,
                                                    feature_weights=None, gamma=None,
                                                    grow_...
                                                    interaction_constraints=None,
                                                    learning_rate=None, max_bin=None,
                                                    max_cat_threshold=None,
                                                    max_cat_to_onehot=None,
                                                    max_delta_step=None, max_depth=None,
                                                    max_leaves=None,
                                                    min_child_weight=None, missing=nan,
                                                    monotone_constraints=None,
                                                    multi_strategy=None,
                                                    n_estimators=None, n_jobs=None,
                                                    num_parallel_tree=None, ...)),
                                   ('adb',
                                    AdaBoostClassifier(n_estimators=100,
                                                         random_state=42))],
        voting='soft')

```

```
[69]: # import ace_tools as tools
# Predictions
models = {'Random Forest': rf_best, 'XGBoost': xgb, 'AdaBoost': adb, 'Ensemble':
    ↪ ensemble}
results = []

for name, model in models.items():
    y_pred = model.predict(xtest)
    y_prob = model.predict_proba(xtest)[: , 1] if hasattr(model, 'predict_proba')
    ↪ else np.zeros_like(y_pred)
    results.append({
        'Model': name,
        'Accuracy': accuracy_score(ytest, y_pred),
        'Precision': precision_score(ytest, y_pred, average='macro'),
        'Recall': recall_score(ytest, y_pred, average='macro'),
        'F1-Score': f1_score(ytest, y_pred, average='macro'),
        'ROC-AUC': roc_auc_score(ytest, y_prob, average='macro',
    ↪ multi_class='ovr') if len(np.unique(y)) > 2 else roc_auc_score(ytest, y_prob)
    })

# Performance dataframe
perf_df = pd.DataFrame(results)

# 4 ROC Curves
plt.figure(figsize=(8,6))
for name, model in models.items():
    if hasattr(model, "predict_proba"):
        y_prob = model.predict_proba(xtest)[: , 1]
        # print(y_prob)
        print(ytest.shape , y_prob.shape)
        fpr, tpr, _ = roc_curve(ytest, y_prob)
        print(fpr , tpr)
        plt.plot(fpr, tpr, label=f'{name}')

# plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves - Bagging vs Boosting vs Ensemble")
plt.legend()
plt.show()

# Display feature importance and performance metrics
# tools.display_dataframe_to_user("Model Performance Comparison", perf_df)
# tools.display_dataframe_to_user("Random Forest Feature Importance",
    ↪ feature_importance)
```

(219,) (219,)

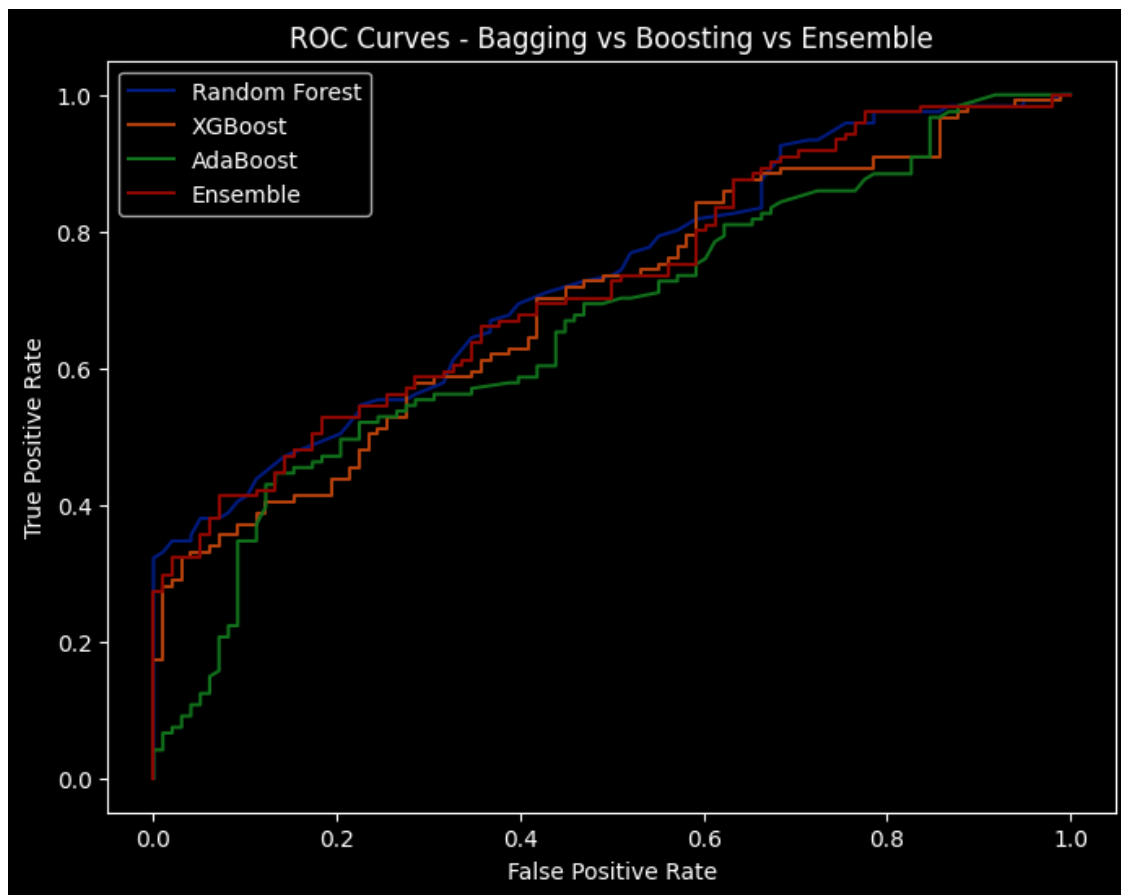
[0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.
0.	0.	0.	0.	0.	0.01020408
0.02040816	0.04081633	0.04081633	0.05102041	0.07142857	0.08163265
0.09183673	0.10204082	0.1122449	0.14285714	0.20408163	0.2244898
0.2244898	0.24489796	0.26530612	0.2755102	0.28571429	0.31632653
0.32653061	0.34693878	0.36734694	0.36734694	0.3877551	0.39795918
0.42857143	0.46938776	0.5	0.51020408	0.52040816	0.54081633
0.55102041	0.57142857	0.59183673	0.63265306	0.66326531	0.66326531
0.66326531	0.68367347	0.68367347	0.71428571	0.7244898	0.74489796
0.75510204	0.78571429	0.78571429	0.82653061	0.85714286	0.86734694
0.92857143	0.94897959	0.94897959	0.96938776	0.97959184	0.98979592
1.]	[0.	0.01652893	0.04958678	0.05785124
0.09090909	0.10743802	0.11570248	0.14049587	0.15702479	0.18181818
0.19834711	0.21487603	0.2231405	0.23966942	0.26446281	0.27272727
0.32231405	0.33057851	0.34710744	0.34710744	0.3553719	0.38016529
0.38016529	0.38842975	0.40495868	0.41322314	0.43801653	0.47107438
0.50413223	0.53719008	0.54545455	0.55371901	0.55371901	0.55371901
0.56198347	0.5785124	0.61157025	0.6446281	0.65289256	0.66942149
0.67768595	0.69421488	0.7107438	0.72727273	0.73553719	0.74380165
0.76859504	0.7768595	0.79338843	0.80165289	0.81818182	0.82644628
0.83471074	0.85950413	0.87603306	0.90909091	0.92561983	0.9338843
0.9338843	0.95041322	0.95867769	0.95867769	0.97520661	0.97520661
0.97520661	0.98347107	0.98347107	0.98347107	0.99173554	0.99173554
1.]	1.]		
(219,)	(219,)				
[0.	0.	0.	0.01020408	0.01020408	0.02040816
0.02040816	0.03061224	0.03061224	0.04081633	0.04081633	0.06122449
0.06122449	0.07142857	0.07142857	0.09183673	0.09183673	0.1122449
0.1122449	0.12244898	0.12244898	0.15306122	0.15306122	0.19387755
0.19387755	0.21428571	0.21428571	0.2244898	0.2244898	0.23469388
0.23469388	0.24489796	0.24489796	0.25510204	0.25510204	0.2755102
0.2755102	0.28571429	0.28571429	0.30612245	0.30612245	0.34693878
0.34693878	0.35714286	0.35714286	0.36734694	0.36734694	0.3877551
0.3877551	0.40816327	0.40816327	0.41836735	0.41836735	0.44897959
0.44897959	0.46938776	0.46938776	0.48979592	0.48979592	0.53061224
0.53061224	0.55102041	0.55102041	0.56122449	0.56122449	0.57142857
0.57142857	0.58163265	0.58163265	0.59183673	0.59183673	0.62244898
0.62244898	0.63265306	0.63265306	0.66326531	0.66326531	0.68367347
0.68367347	0.78571429	0.78571429	0.85714286	0.85714286	0.87755102
0.87755102	0.8877551	0.8877551	0.93877551	0.93877551	0.98979592
0.98979592	1.]	[0.	0.00826446	0.17355372
0.17355372	0.28099174	0.28099174	0.2892562	0.2892562	0.32231405
0.32231405	0.32231405	0.33057851	0.33057851	0.33884298	0.33884298
0.3553719	0.3553719	0.37190083	0.37190083	0.38842975	0.38842975
0.40495868	0.40495868	0.41322314	0.41322314	0.43801653	0.43801653
0.45454545	0.45454545	0.47933884	0.47933884	0.50413223	0.50413223
0.51239669	0.51239669	0.52892562	0.52892562		

0.57024793	0.57024793	0.5785124	0.5785124	0.58677686	0.58677686
0.59504132	0.59504132	0.61157025	0.61157025	0.61983471	0.61983471
0.62809917	0.62809917	0.6446281	0.6446281	0.70247934	0.70247934
0.71900826	0.71900826	0.72727273	0.72727273	0.73553719	0.73553719
0.74380165	0.74380165	0.75206612	0.75206612	0.76033058	0.76033058
0.7768595	0.7768595	0.79338843	0.79338843	0.84297521	0.84297521
0.85950413	0.85950413	0.87603306	0.87603306	0.88429752	0.88429752
0.89256198	0.89256198	0.90909091	0.90909091	0.96694215	0.96694215
0.97520661	0.97520661	0.98347107	0.98347107	0.99173554	0.99173554
1.	1.]			
(219,) (219,)					
[0.	0.	0.	0.01020408	0.01020408	0.02040816
0.02040816	0.03061224	0.03061224	0.04081633	0.04081633	0.05102041
0.05102041	0.06122449	0.06122449	0.07142857	0.07142857	0.07142857
0.08163265	0.08163265	0.09183673	0.09183673	0.09183673	0.09183673
0.09183673	0.1122449	0.1122449	0.12244898	0.12244898	0.12244898
0.13265306	0.13265306	0.15306122	0.15306122	0.17346939	0.17346939
0.18367347	0.18367347	0.20408163	0.20408163	0.2244898	0.2244898
0.24489796	0.24489796	0.26530612	0.26530612	0.2755102	0.2755102
0.28571429	0.28571429	0.30612245	0.30612245	0.34693878	0.34693878
0.3877551	0.39795918	0.39795918	0.41836735	0.41836735	0.43877551
0.43877551	0.44897959	0.44897959	0.45918367	0.45918367	0.46938776
0.46938776	0.48979592	0.51020408	0.52040816	0.55102041	0.55102041
0.57142857	0.57142857	0.59183673	0.59183673	0.60204082	0.6122449
0.62244898	0.62244898	0.65306122	0.65306122	0.66326531	0.66326531
0.67346939	0.67346939	0.68367347	0.7244898	0.76530612	0.7755102
0.78571429	0.79591837	0.81632653	0.82653061	0.82653061	0.84693878
0.84693878	0.84693878	0.84693878	0.85714286	0.86734694	0.87755102
0.87755102	0.91836735	0.92857143	0.95918367	0.97959184	1.
] [0.
0.00826446	0.04132231	0.04132231	0.0661157	0.0661157	
0.07438017	0.07438017	0.09090909	0.09090909	0.10743802	0.10743802
0.12396694	0.12396694	0.14876033	0.15702479	0.19008264	0.20661157
0.20661157	0.2231405	0.2231405	0.26446281	0.32231405	0.33884298
0.34710744	0.34710744	0.37190083	0.39669421	0.41322314	0.42975207
0.42975207	0.44628099	0.44628099	0.45454545	0.45454545	0.46280992
0.46280992	0.47107438	0.47107438	0.49586777	0.49586777	0.52066116
0.52066116	0.52892562	0.52892562	0.53719008	0.53719008	0.54545455
0.54545455	0.55371901	0.55371901	0.56198347	0.56198347	0.57024793
0.5785124	0.5785124	0.58677686	0.58677686	0.60330579	0.60330579
0.65289256	0.65289256	0.66942149	0.66942149	0.67768595	0.67768595
0.69421488	0.69421488	0.70247934	0.70247934	0.7107438	0.72727273
0.72727273	0.73553719	0.73553719	0.75206612	0.76033058	0.78512397
0.79338843	0.80991736	0.80991736	0.81818182	0.81818182	0.82644628
0.82644628	0.83471074	0.84297521	0.85950413	0.85950413	0.87603306
0.88429752	0.88429752	0.88429752	0.88429752	0.90909091	0.90909091
0.92561983	0.95041322	0.96694215	0.96694215	0.97520661	0.97520661
0.98347107	1.	1.	1.	1.	1.
]
(219,) (219,)					

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[0.      0.      0.      0.01020408 0.01020408 0.02040816
0.02040816 0.05102041 0.05102041 0.06122449 0.06122449 0.07142857
0.07142857 0.1122449 0.1122449 0.13265306 0.13265306 0.14285714
0.14285714 0.15306122 0.15306122 0.17346939 0.17346939 0.18367347
0.18367347 0.2244898 0.2244898 0.25510204 0.25510204 0.2755102
0.2755102 0.28571429 0.28571429 0.31632653 0.31632653 0.32653061
0.32653061 0.33673469 0.33673469 0.34693878 0.34693878 0.35714286
0.35714286 0.37755102 0.37755102 0.39795918 0.39795918 0.41836735
0.41836735 0.44897959 0.44897959 0.5      0.5      0.51020408
0.51020408 0.56122449 0.56122449 0.59183673 0.59183673 0.60204082
0.60204082 0.6122449 0.6122449 0.63265306 0.63265306 0.65306122
0.65306122 0.66326531 0.66326531 0.67346939 0.67346939 0.68367347
0.68367347 0.70408163 0.70408163 0.74489796 0.74489796 0.75510204
0.75510204 0.76530612 0.76530612 0.7755102 0.7755102 0.83673469
0.83673469 0.97959184 0.97959184 1.      ] [0.      0.00826446 0.27272727
0.27272727 0.29752066 0.29752066
0.32231405 0.32231405 0.3553719 0.3553719 0.38016529 0.38016529
0.41322314 0.41322314 0.4214876 0.4214876 0.44628099 0.44628099
0.47107438 0.47107438 0.47933884 0.47933884 0.50413223 0.50413223
0.52892562 0.52892562 0.54545455 0.54545455 0.56198347 0.56198347
0.57024793 0.57024793 0.58677686 0.58677686 0.59504132 0.59504132
0.60330579 0.60330579 0.61157025 0.61157025 0.63636364 0.63636364
0.66115702 0.66115702 0.66942149 0.66942149 0.67768595 0.67768595
0.69421488 0.69421488 0.70247934 0.70247934 0.72727273 0.72727273
0.73553719 0.73553719 0.75206612 0.75206612 0.80165289 0.80165289
0.80991736 0.80991736 0.83471074 0.83471074 0.87603306 0.87603306
0.88429752 0.88429752 0.89256198 0.89256198 0.90082645 0.90082645
0.90909091 0.90909091 0.91735537 0.91735537 0.9338843 0.9338843
0.94214876 0.94214876 0.95867769 0.95867769 0.97520661 0.97520661
0.98347107 0.98347107 1.      1.      ]

```



```
[61]: perf_df
```

```
[61]:
```

	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
0	Random Forest	0.630137	0.640383	0.639104	0.630014	0.729718
1	XGBoost	0.630137	0.640383	0.639104	0.630014	0.698516
2	AdaBoost	0.625571	0.649356	0.640791	0.623301	0.665078
3	Ensemble	0.634703	0.642555	0.642267	0.634696	0.721707

```
[ ]:
```