Title: G13ODI

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This is project report for the subject 'CS1305: Business Intelligence' at JK Lakshmipat University, Jaipur

ABSTRACT

Cricket is a facinating and a very popular game. There have been many analysis conducted on this game. This project is about analysing a sample of International One Day matches and also predict the runs scored by Virat Kohli. I have analysed certain hypothesis by preparing their statistical models in the project. The sample has a scorecard of roughly 1700 ODI matches. The crude data is ball-by-ball performance of player in these matches which is then subjected to data processing to obtain the scorecard of these matches. The descriptive analysis of this data provide some insights in the ODI matches. This data is then subjectd to t-test statistical model which concludes that the mean wickets fallen in the first 35.3 overs of the first inning is equal to the wickets fallen in the last 25.3 overs. In the end the runs scored by one of the best batsman in ODI have been predicted using linear regression.

1 Introduction

Cricket is one of the most popular game in the world. This project analysis ODI matches dataset and propose some hypothesis. The hypothesis considered in the project is about the dismissals in the game of the cricket. This project also tries and predict the runs score by one batsman. The dataset lacks the data of all the players that played in a match which would have result to better analysis.

2 Background

2.1 The Game of Cricket

'Cricket' also known as 'Gentlemen's game' is a bat and ball team sport played between two teams of eleven players each. The game is played on a ground at the centre of which is a 22-yard pitch with three wooden stumps at both the ends known as wickets. The wickets has also has two bails balanced on them. The game has fixed pitch size and variable ground size. One of the team act as a batting side in what is called as a inning while the other team at the same time act as the bowline or fielding side. The batting side score runs by striking the ball bowled to them using bat, and the fielding side tries to catch and stop the ball. Team scoring more runs in the specified balls wins the game. The possible scoring options in cricket include runs ranging from one to six and the possible dissmisal options include clean bowled, run out, caught, leg before wickets and stumped. The fielding side tries to restrict the batting side to minimum runs by taking wickets and exhausting the specified balls. A cluster of six such balls is known as an over. The batting side always plays in pair, in which one of the batsman known as striker stands at the further side of the pitch to the bowler and other known as non striker stand near the bowler.When ten players have been dismissed, the innings ends and the teams swap roles. The game has three umpires, two on the ground and one in a room with the ability of giving decision with the help of cameras. There is also a match refree in a cricket match.

The game has three popular formats the Twenety20, the One Day International and Test comprising of 20, 50 and unlimited overs respectiverly. Test matches are played for a duration of five days, where each team gets batting twice. The ball is a hard, solid spheroid made of compressed leather with a slightly raised sewn seam enclosing a cork core which is layered with tightly wound string. The bat is a piece of wooden crafted for hitting the ball. The size of bat has some restrictions, exact size depends on the comfort of the player.

Cricket's origins are uncertain, but the earlies reference is in South-East England in the middle of 16th century. Cricket is a highly popular sport in the British Colonies.

2.2 The Cricket Dataset

The dataset has been obtained from cricsheet.org. The data has ball by ball data of nearly 4000 matches played between 2006-2019. This data has been then processed to create scorecard file and match information file. We are using 1,788 ODI matches dataset for this project. The dataset provides various parameters for each match divided in two files. Match information file comprises of 1788 rows and 25 columns and the scorcard file has 37,963 rows and 23 columns. This dataset comprises of parameters such as match date, venue umpire, winner, winning runs/wickets etc alongwith scorecard of each match. The scorecard provides each player's performance in every match. The players who have contributed either through bowling or batting have been included in the dataset.

2.3 Cricket Betting

Cricket betting works in two ways, first one is to bet on the outcome of the match and the other one is betting on the outcome of six-overs. In the case of six-over betting, bets are placed on how many runs can be scored by a team. In betting one needs to analyse the situation and make an educated guess about the outcome and earn money from it. In a cricket match, there are several factors that are considered before betting, these factors include weather,pitch report,team combination,strengths and weakness of players,spin and pace combination,past records,player form etc. Betting is all mathematics. The ratios or odds offered depend on the situation of the match at a particular instance and the amount of money put on that team.

2.4 Statistical Models

Paired Sample T-Test: The paired sample t-test, sometimes called the dependent sample t-test, is a statistical procedure used to determine whether the mean difference between two sets of observations is zero. In a paired sample t-test, each subject or entity is measured twice, resulting in pairs of observations. Common applications of the paired sample t-test include case-control studies or repeated-measures designs. Suppose you are interested in evaluating the effectiveness of a company training program. One approach you might consider would be to measure the performance of a sample of employees before and after completing the program, and analyze the differences using a paired sample t-test.

2.5 Machine Learning Models

In statistics, linear regression is a linear approach to modeling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables). The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, the process is called multiple linear regression.This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable. In linear regression, the relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models. Most commonly, the conditional mean of the response given the values of the explanatory variables (or predictors) is assumed to be an affine function of those values; less commonly, the conditional median or some other quantile is used. Like all forms of regression analysis, linear regression focuses on the conditional probability distribution of the response given the values of the predictors, rather than on the joint probability distribution of all of these variables, which is the domain of multivariate analysis.

3 Past Work/Related work/Motivation

With the onset of the era of data and better computing systems, data from practically any field can be used for analysis and improve the performance or increase the efficiency of humans in that field. Similarly several studies have already been conducted to prove some popular hypothesis or analyse performance of the players. These analysis can actively predict the rising star in the field of cricket or can predict the future performance of a player. Such studies also act as an aid for team selection procedure by creating mathematical models for selection of players. These models can also help us in fantasy cricket. On similar lines we are trying to dismissal method in a match by away team which can again come handy in fantasy cricket and also team selection for a match.

4 Evaluation

4.1 Methodology

4.1.1 Objective of this work

The objective is to read the provided dataset and analyse the dismissal methods and dismissals of the players.

4.1.2 Followed Methodology

- Identified the objective and prepared scorecard and match information files accordingly.
- Descriptive Analysis of the thus generated data.
- Statistical Analysis of the data.
- Either accept the null hypothesis or suggest alternate hypothesis also predict the future outcome.

4.2 Descriptive Data Analysis

The dataset comprises of 1,788 ODI matches data collected from the ODI match held between 03/01/2006-11/7/2019 around the globe. The dataset describes player wise statistics of each match. This data is further accumulated to find out the method of dismissal method of the player by away team. The dataset also has each match's essential data including its venue, city, umpires, teams etc. The interactive visualizations cannot be shown in LaTex therefore, here is the link for all the Jupyter notebook: vis-cricket.ipynb.

- According to the figure 1 KC Sangakara is the batsman who has scored most runs and played most balls in the period of Jan 2006-July 2019.

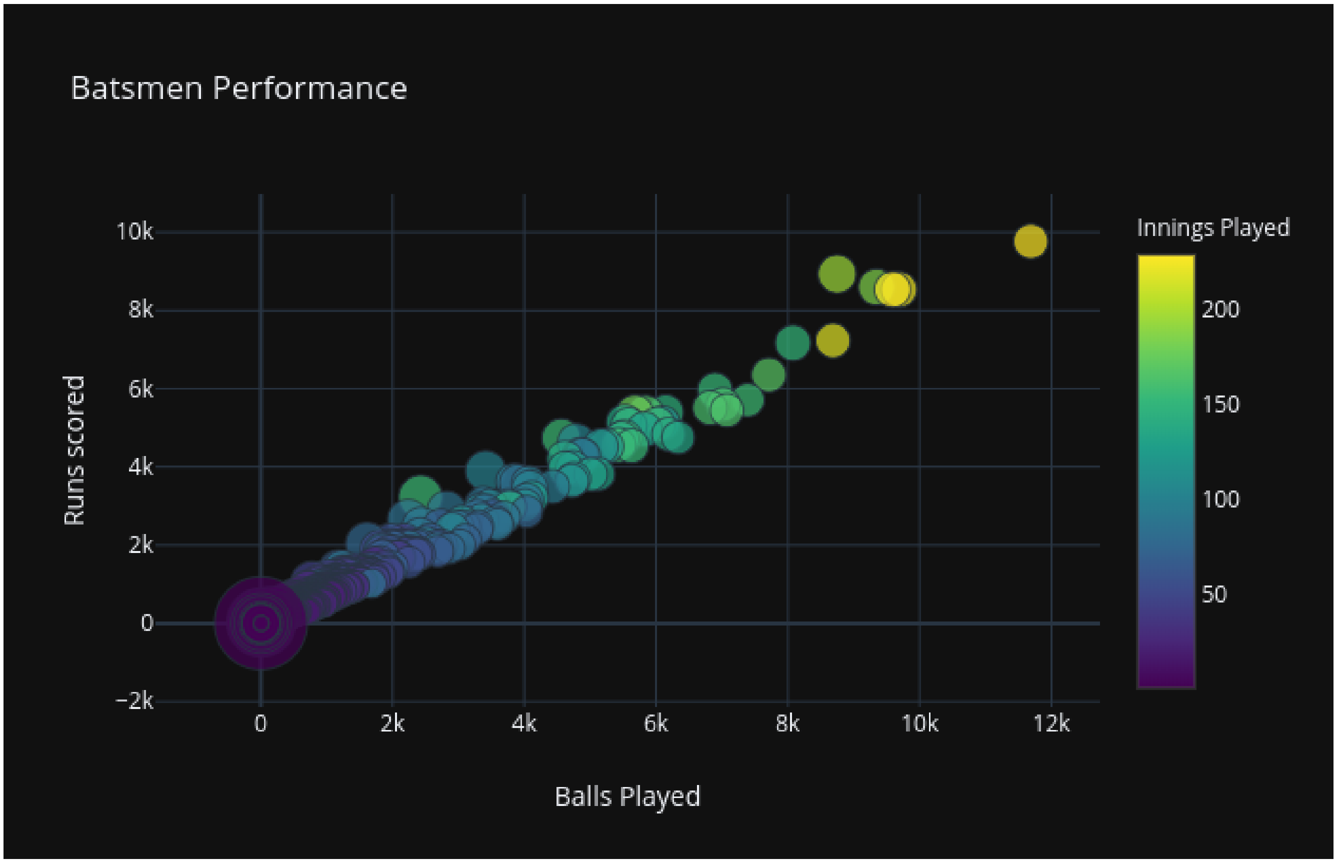

Figure 1. Batsmen performance analysis based on runs scored, balls played and innings played

- According to the Figure 2 KC Sangakara was the highest run scorer in 2006 and Rohit Sharma in in 2019(till July)
- According to Figure 3 all the grounds have nearly 7 wickets fallen in every match.
- According to Figure 4 many teams have perfect trackrecord in certain grounds and some teams didn't manage to win even a single match in some grounds.
- According to Figure 5, Australia was the best team in ODI in 2006 and they have been replaced by India in 2019 (till July).
- According to the Figure 6, the median and mean runs scored within the period of 1/2006 and 7/2019 is highest in Sydney Cricket Ground.
- According to Figure 7, Mashrafe Mortaza was the best bowler in 2006 and have been replace by Malinga (The figure only includes top 10 wicket takers in the period of 1/2006-7/2019)
- According to Figure 8, West Indies gives most extras with the mean extras given equal to 8.18 among the prominent cricket playing nations.

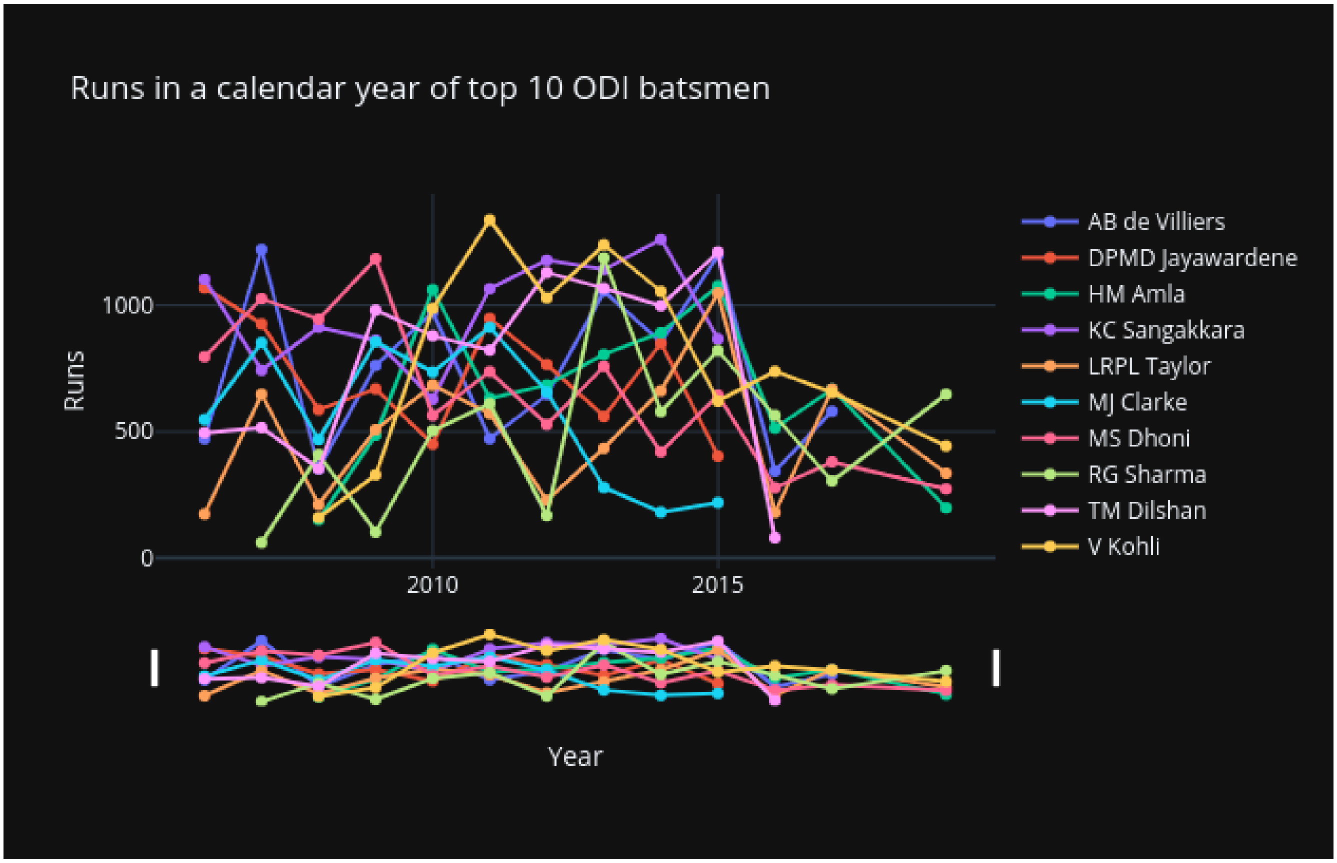

Figure 2. Runs in calendar year by top 10 batsmen in ODI

- According to Figure 9,Australia is the higest runs scorer in every match with the mean of 235 and median 238, closely followed by team India.
- According to Figure 10, Australia has taken the most number of average wickets per match.

4.3 Statistical Modelling

Paried sample T-test model has been developed for the statistical analysis of the project.

1. - H(0):Mean value of batsman bowled is equal to mean value of batsman dismissed by lbw in ODI
   - H(A):Mean value of batsman bowled is not equal to mean value batsman dismissed by lbw

   The data for the first hypothesis lead to following statistics: Figure 1

   The first null hypothesis is rejected as the p value is less than the significance value. Figure 2

2. - H(0):Wickets fallen in the first 70% of the first innings is equal to the wickets fallen in the last 30% of the first innings
   - H(A):Wickets fallen in the first 70% of the first innings is not equal to the wickets fallen in the last 30% of the first innings

   The second null hypothesis is rejected as the p value is less than the significance value. Figure 3

3. - H(0):Wickets fallen in the first 71% of the first innings is equal to the wickets fallen in the last 29% of the first innings
   - H(A):Wickets fallen in the first 71% of the first innings is not equal to the wickets fallen in the last 29% of the first innings

   The third null hypothesis is accepted as the p value is greater than the significance value. Figure 4

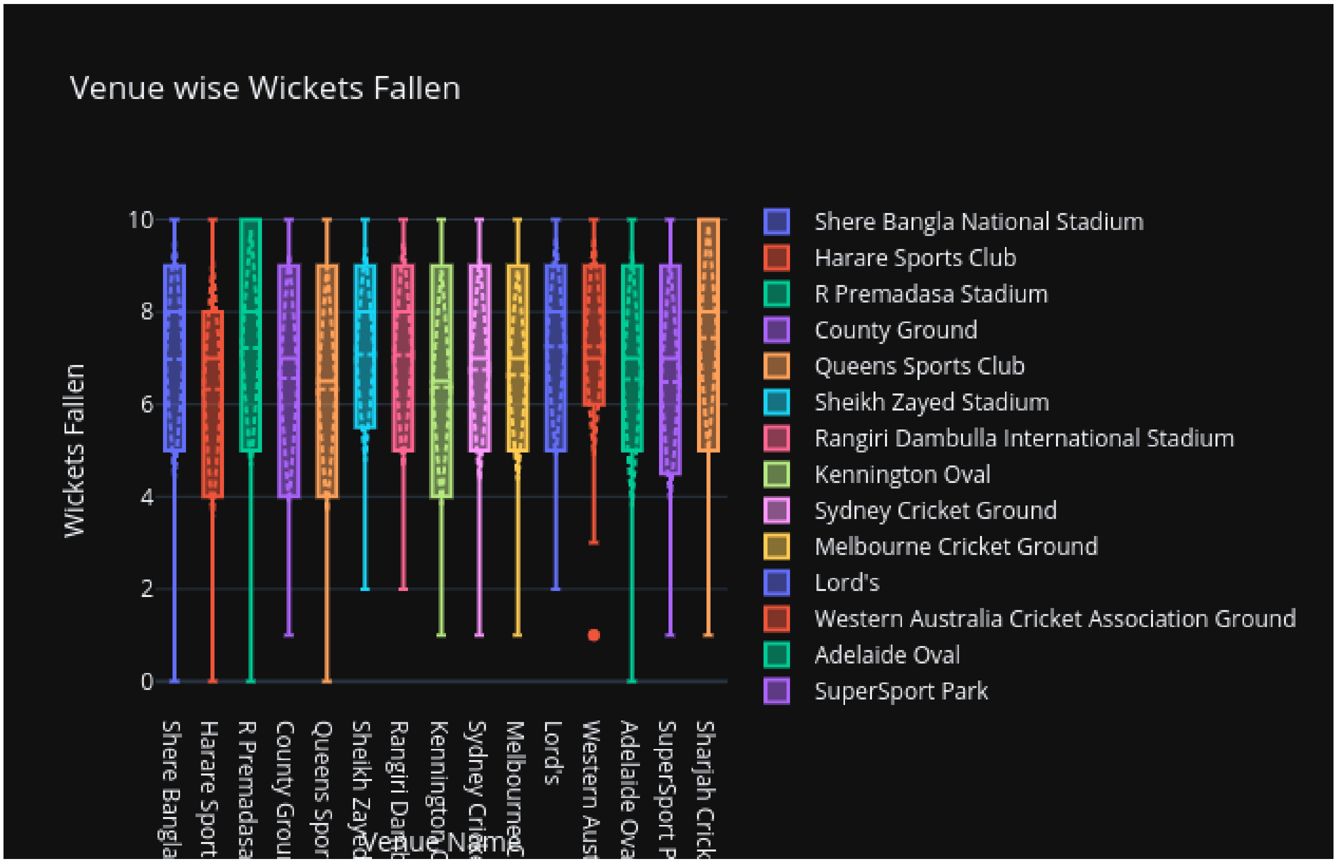

Figure 3. Venue wise wickets fallen.

4. • H(0):Wickets fallen in the first 50% of the first innings is equal to the wickets fallen in the last 50% of the first innings
   • H(A):Wickets fallen in the first 50% of the first innings is not equal to the wickets fallen in the last 50% of the first innings

   The fourth null hypothesis is rejected as the p value is less than the significance value. Figure 5

5. • H(0):Wickets fallen in the first 10 overs of the first innings is equal to the wickets fallen in the last 10 overs of the first innings
   • H(A):Wickets fallen in the first 10 overs of the first innings is not equal to the wickets fallen in the last 10 overs of the first innings

   The fifth null hypothesis is rejected as the p value is less than the significance value. Figure 6

   The data for the second, third, fourth and fifth hypothesis lead to following statistics: Figure 7

6. • H(0):There is an equal probability of wicket by the first category of dismissal and second category of dismissal
   • H(A):There is an equal probability of wicket by the first category of dismissal and second category of dismissal

   The data for the sixth hypothesis lead to following statistics: Figure 8

   The sixth null hypothesis is rejected as the p value is less than the significance value. Figure 9

The level of significance for the hypothesis have been set to 5%. The above hypothesis have been tested using statistics.
For first hypothesis the batsman dismissed by lbw and bowled in the provided matches have been conted and then the values in both the methods have been compared using paired t-test statistical model.
For second hypothesis first the 70% overs have been calculated and then the number of dismissals have been calculated. These wickets have been then compared to the number of wickets that have fallen in the last 30% overs of the match.

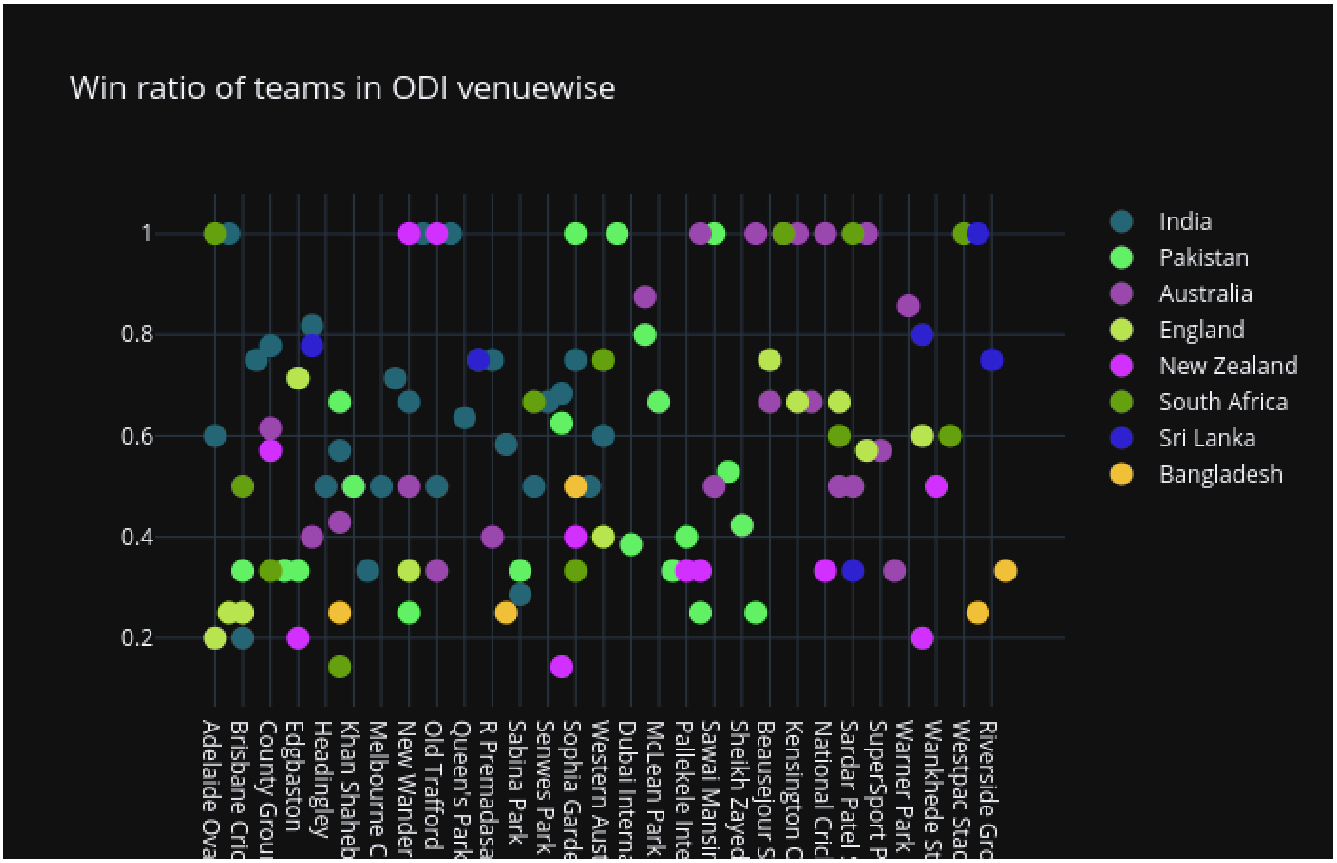

Figure 4. Win ratio of best performing teams venue wise in ODI.

The same procedure have been followed for the third, fourth and the fifth hypothesis.
In the last hypothesis the dismissal method have been divided into the following two categories:

- first category =['run out','hit wicket','obstructing the field','retired out','stumped']
- Second category= ['caught','bowled','lbw','caught and bowled']

then the number of wickets for each category have been calculated and compared using paired t-test.

4.4 Machine Learning Model

Machine learning model has been created for the data of Virat Kohli. The runs scored by him has been predicted. The correlation matrix for the scorecard is shown in Figure 10. According to which the runs scored by Virat Kohli majorly depends on the number of balls he faced and the runs he scored on these balls. The balls he played has been used to predict the runs he will score using Linear Regression.

5 Result and Discussion

After performing the statistical analysis we can suggest following:

- The mean wickets fallen in the first 71% overs (that translates to 35.3 overs) is equal to the mean wickets fallen in the rest of the first inning (i.e. 24.3 overs).

6 Future Work

This cricket analysis can be further extended by analyzing data more closely and generating player wise insights. Also machine learing models can be created using this dataset. It can be further extended to find the attributes that contribute to the result obtained of the statistical analysis.

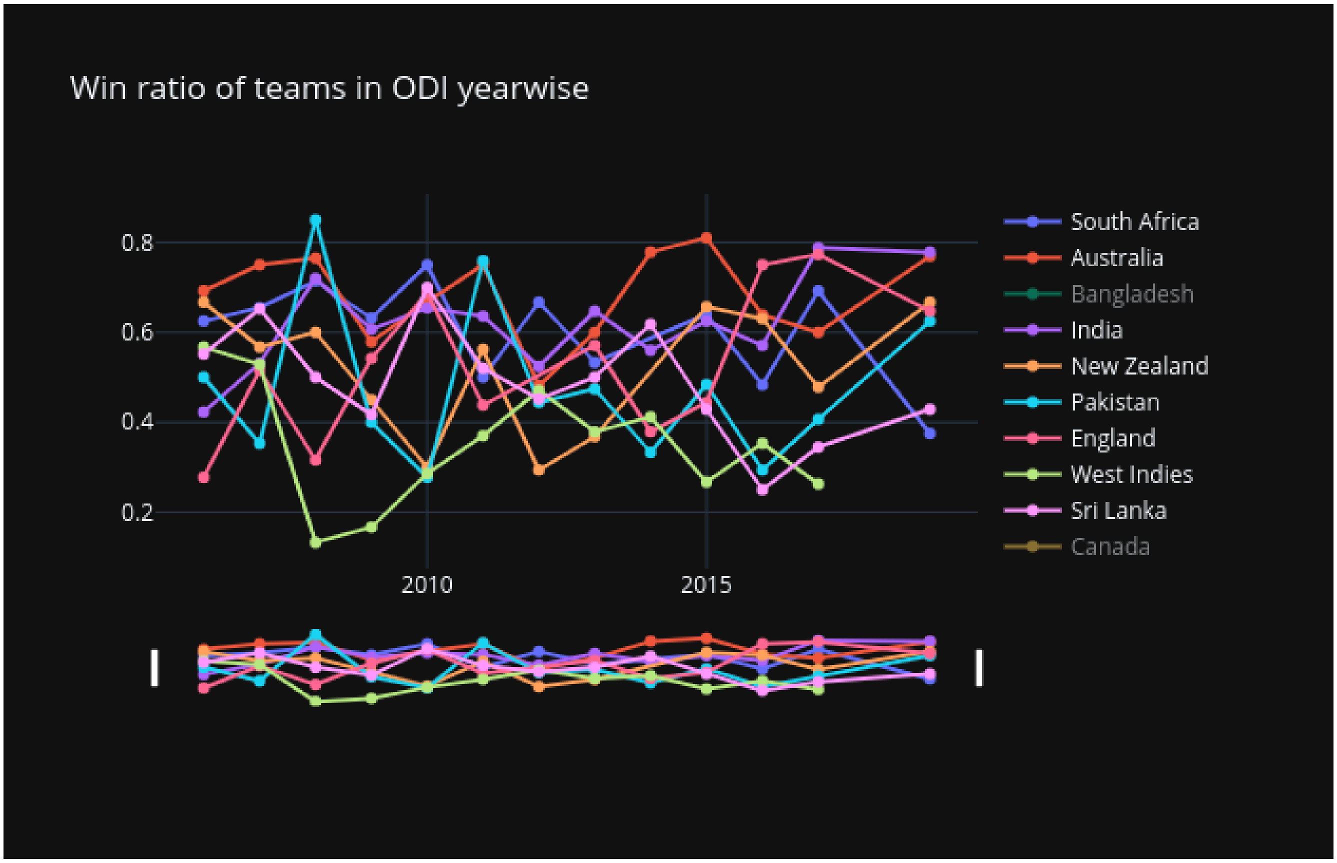

Figure 5. Win ratio of best performing teams yearwise in ODI

A Information of Dataset

The dataset comprises of two files, one file comprises of each ODI match description and the other file has the scorecard of every ODI match. These matches can be uniquely identified using match id. Attributes in both the files are as follows:

- Scorecard:

    1. match-id: Unique id of each match, that can uniquely identify a match between scorecard and match information file.
    2. innings: Innings number (Can be 0 or 1)
    3. name: Name of the player
    4. batting-position: Batting position of the player (0 if the player didn't bat)
    5. over-batsman: Over at which said batsman came out to play
    6. runs-scored: Runs scored by the player
    7. balls-played: Number of balls played by the player as a batsman.
    8. dots: Number of dot balls played by the player.
    9. ones: Number of balls when the player scored a single run.
    10. twos: Number of balls when the player scored two runs.
    11. threes: Number of balls when the player scored three runs.

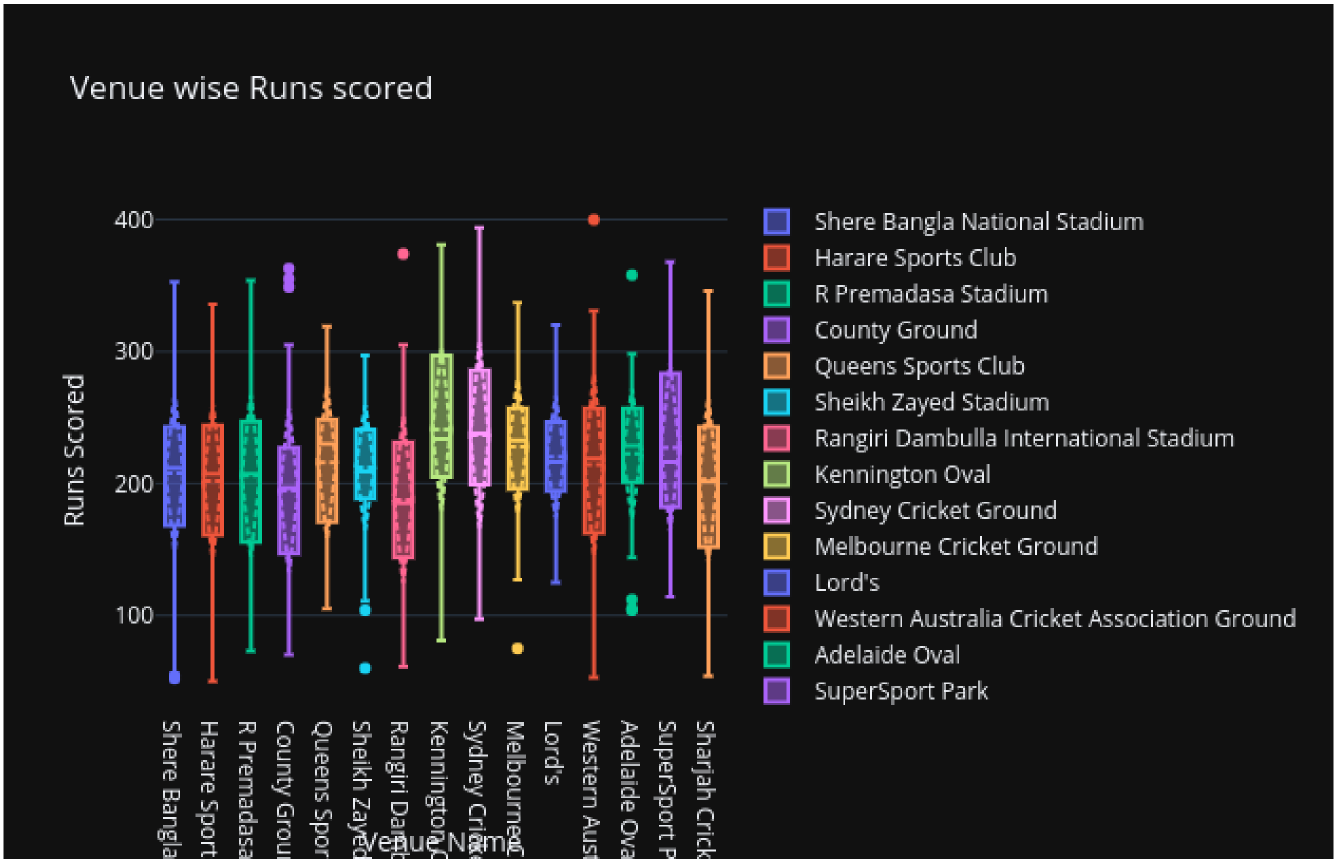

Figure 6. Venue wise runs scored.

12. fours: Number of balls when the player scored four runs.
13. sixes: Number of balls when the player scored six runs.
14. wicket-method: Dismissal method of the player (0 if player remained not out or didn't come out to bat)
15. balls-bowled: Number of balls that the player bowled as a bowler (0 if the player didn't bowled at all)
16. maiden-overs: Number of overs in which the player didn't give a single run as a bowler.
17. runs-given: Number of runs that the batsman scored on the said player's balls
18. wickets: Wickets taken by the player
19. extras: Extras given by the player as a bowler.
20. fall-of-wicket-score: Score at which the player got out.
21. fall-of-wicket-over: Over at which the player got out.
22. fall-of-wicket-no: Wicket number at which the player got out.
23. fall-of-wicket-bowler: Bowler who got the wicket (0 in case of run out).

- Match Information:

1. city: City in which match was held
2. competition: Competition name

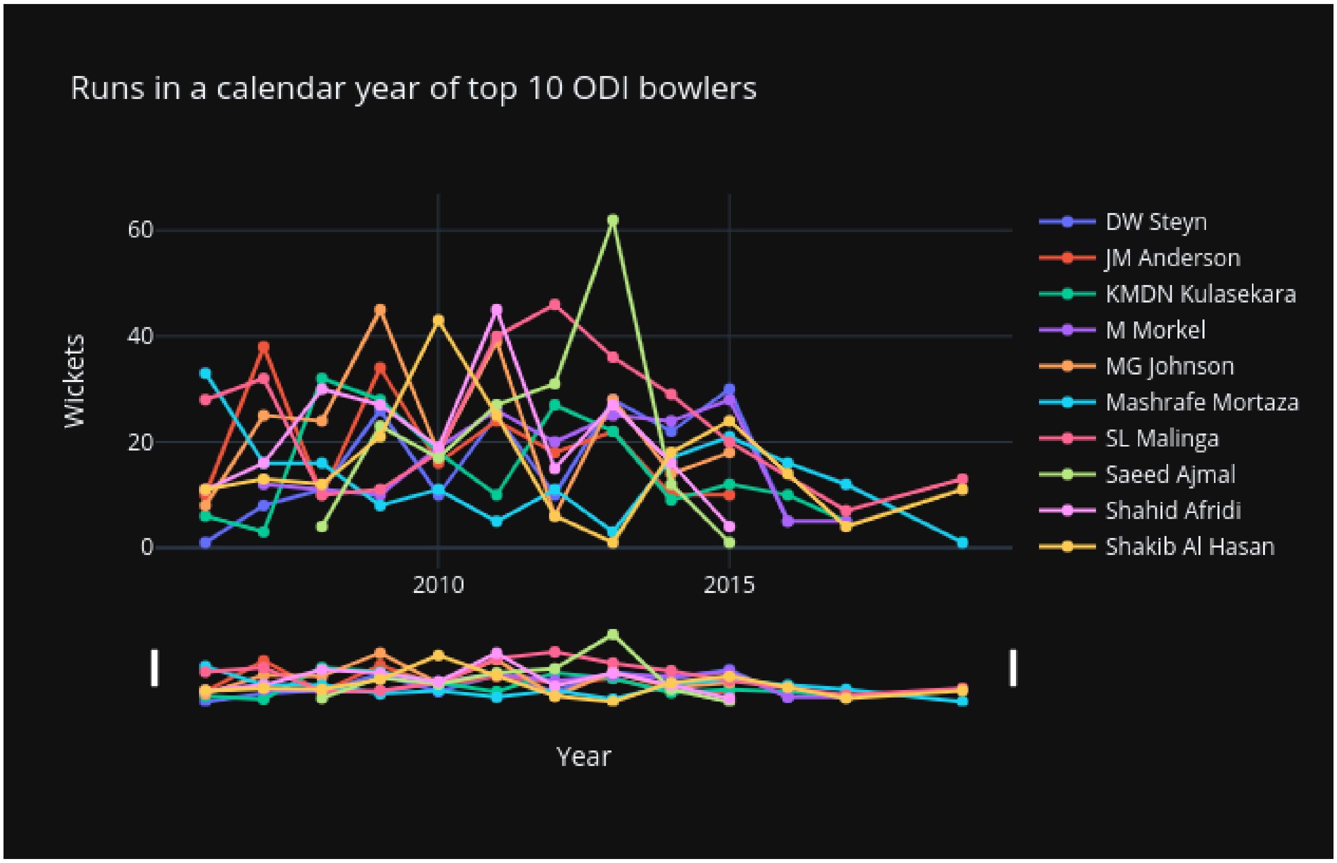

Figure 7. Wickets in a calendar year by top 10 ODI bowlers.

3. date: Date of match
4. match-id: Unique id of each match, that can uniquely identify a match between scorecard and match information file.
5. gender: Gender of the teams playing the match. (Either male or female)
6. match-number: Number of the match in the respective series or competition
7. match-referee: Match refree name
8. method: D/L if match ended by D/L rule
9. neutralvenue: true or false based upon the home venue of both the teams
10. outcome: (No result or tie), if none of the two team win the match
11. player-of-match: Name of the player of the match
12. reserve-umpire: Name of reserved umpire of the match
13. season: Year in which match was played
14. series: Series name of which the match was a part
15. team-0: First team name
16. team-1: Second team name
17. toss-decision: (Fielding or batting) Toss decision by toss winner team

18. toss-winner: Toss winner team name
19. tv-umpire: TV umpire name
20. umpire-0: First umpire name
21. umpire-1: Second umpire name
22. venue: Ground name where match is being held
23. winner: Winner of the match
24. winner-runs: Winner score difference
25. winner-wickets: Winner wicket difference

B Source Code of Implementation

bi_cricket (1)

November 24, 2019

[ ]:
```
# from google.colab import drive
# drive.mount('/gdrive')
# %cd /gdrive
```

[282]:
```
import pandas as pd
import os
```

[283]:
```
files = [file for dirpath, directory, file in os.walk('./all_csv/')][0]
# files=[file for dirpath,directory,file in os.walk(r'/gdrive/My Drive/all_csv/
 ↪')][0]
```

[284]:
```
match_data = pd.DataFrame(data=None)
odi_scorecard = pd.DataFrame(data=None)
ttwenty_scorecard = pd.DataFrame(data=None)
odi_info = pd.DataFrame(data=None)
ttwenty_info = pd.DataFrame(data=None)
```

[285]:
```
def rename_date_umpire(index_list):
    n = 0
    for i in range(index_list.__len__()):
        if str.lower(index_list[i]).strip() == 'date':
            index_list[i] += '_'+str(n)
            n += 1
    n = 0
    for i in range(index_list.__len__()):
        if str.lower(index_list[i]).strip() == 'umpire':
            index_list[i] += '_'+str(n)
            n += 1
    n = 0
    for i in range(index_list.__len__()):
        if str.lower(index_list[i]).strip() == 'team':
            index_list[i] += '_'+str(n)
            n += 1
    return index_list
```

[286]:
```
def find_game(df_game,df_info):
    if 'series' in df_info.columns:
        if 'odi' in str.lower(df_info.iloc[0]['series']):
            return 'odi'
```

```
        if 't20i' in str.lower(df_info.iloc[0]['series']) or 't20' in str.
↪lower(df_info.iloc[0]['series']) or 'indian premier league' in str.
↪lower(df_info.iloc[0]['series'])  or 'indian premier league' in str.
↪lower(df_info.iloc[0]['competition']):
            return 'twenty'
    if max(df_game['balls-bowled'])<=24:
        return 'twenty'
    if 24<max(df_game['balls-bowled'])<=60:
        return 'odi'
    return
```

[287]:
```
def append_file(temp_df, temp_info_df, type_game):
    global odi_scorecard
    global ttwenty_scorecard
    global odi_info
    global ttwenty_info
    if type_game == 'odi':
        odi_scorecard = odi_scorecard.append(temp_df, ignore_index=True)
        odi_info = odi_info.append(temp_info_df, ignore_index=True)
    elif type_game == 'twenty':
        ttwenty_scorecard = ttwenty_scorecard.append(
            temp_df, ignore_index=True)
        ttwenty_info = ttwenty_info.append(temp_info_df, ignore_index=True)
```

[288]:
```
def get_extras_type(match_data):
    list_extras = []
    for index, row in match_data.iterrows():
        ov = str(row['over'])
        if '.' in ov:
            ov = str(row['over']).split('.')
            ball_no = int(ov[1])
            over_no = int(ov[0])
        else:
            continue
        if row['extras'] != 0:
            if row['runs'] != 0:
                match_data.loc[index, 'extras_type'] = 'w'
            list_extras.append(index)
        if ball_no > 6:
            if len(list_extras) > 0:
                match_data.loc[list_extras.pop(-1), 'extras_type'] = 'w'
    for i in list_extras:
        match_data.loc[i, 'extras_type'] = 'b'
    return match_data
```

[289]:
```
def prepare_scorecard(match_data,team_0,team_1):
    match_data = get_extras_type(match_data)
#     print(match_data[match_data['bowler']==        'Mashrafe Mortaza'])
```

```
    teams=['','']
    players = list((match_data['striker'].append(
        match_data['non-striker']).append(match_data['bowler'])).unique())
    #     to make 22 players if any player has not played
#     for i in range(len(players),22):
#         players.append('p_'+str(i))
#         fow
#    ␣
↪player_stats=['match-id','innings','name','batting-position','over-batsman','runs-scored','
    player_stats = ['match-id', 'team-name', 'innings', 'name',␣
↪'batting-position', 'over-batsman', 'runs-scored', 'balls-played', 'dots',␣
↪'ones', 'twos', 'threes', 'fours', 'sixes',
                    'wicket-method', 'balls-bowled', 'maiden-overs',␣
↪'runs-given', 'wickets', 'extras', 'fall-of-wicket-score',␣
↪'fall-of-wicket-overs', 'fall-of-wicket-no', 'fall-of-wicket-bowler']
    player_data = {key: {key_type: 0 for key_type in player_stats}
                   for key in players}
    for p in players:
        player_data[p]['match-id'] = match_data.loc[0, 'file_no']
        player_data[p]['name'] = p
    team_score = 0
    balls = 0
    pos = 1
    inning = False
    w = 1
    p_no = 1
    w_no = 1
    extras_over = 0
    for index, row in match_data.iterrows():
        ov = str(row['over'])
        if '.' in ov:
            ov = ov.split('.')
            ball_no = int(ov[1])
            over_no = int(ov[0])
        else:
            continue
        if over_no > 50:
            player_data = [value for key, value in player_data.items()]
            scorecard = pd.DataFrame(data=player_data)
            scorecard = scorecard[player_stats]
            return scorecard
        if ball_no == 1 and over_no == 0:
            pos = 1
            w = 1
            team_score = 0
            w_no = 1
            runs_over = 0
```

```
            if row['innings']==1 and teams[0]=='':
                teams[0]=row['batting-team']
                if teams[0]==team_0:
                    teams[1]=team_1
                elif teams[0]==team_1:
                    teams[1]=team_0
            # if row['innings']!=1:
            #     p_no=12
        if ball_no == 1:
            extras_over = 0
        if row['runs'] == 1:
            player_data[row['striker']]['ones'] += 1
        elif row['runs'] == 2:
            player_data[row['striker']]['twos'] += 1
        elif row['runs'] == 3:
            player_data[row['striker']]['threes'] += 1
        elif row['runs'] == 4:
            player_data[row['striker']]['fours'] += 1
        elif row['runs'] == 6:
            player_data[row['striker']]['sixes'] += 1
        elif row['extras'] == 0:
            player_data[row['striker']]['dots'] += 1
        if player_data[row['striker']]['batting-position'] == 0:
            player_data[row['striker']]['batting-position'] = pos
#             print(type(row['over']),type(extras_over))
#             print(row['over'])
            player_data[row['striker']
                        ]['over-batsman'] = float(row['over'])-extras_over
            pos += 1
        if player_data[row['non-striker']]['batting-position'] == 0:
            player_data[row['non-striker']]['batting-position'] = pos
            player_data[row['non-striker']
                        ]['over-batsman'] = float(row['over'])-extras_over
            pos += 1
    # wicket
#         print(row['out-player'])
        if not pd.isna(row['out-player']):
            player_data[row['out-player']]['wicket-method'] = row['out']
#             fow
#             player_data[players[p_no-1]]['fow']=w
#             player_data[players[p_no-1]]['fow_runs']=team_score
#             player_data[players[p_no-1]]['fow_overs']=row['over']
#             player_data[players[p_no-1]]['fow_batsman']=row['out-player']
#             player_data[players[p_no-1]]['fow_bowler']=row['bowler']
            p_no += 1
            w += 1
            if row['out'] != 'run out':
```

```
                player_data[row['bowler']]['wickets'] += 1
            player_data[row['out-player']]['fall-of-wicket-score'] = team_score
            player_data[row['out-player']
                        ]['fall-of-wicket-overs'] =␣
 ↪float(row['over'])-extras_over
            player_data[row['out-player']]['fall-of-wicket-no'] = w_no
            player_data[row['out-player']
                        ]['fall-of-wicket-bowler'] = row['bowler']
            w_no += 1
        team_score += row['runs']+row['extras']
        runs_over += row['runs']
        if row['extras'] != 0 and row['extras_type'] == 'w':
            runs_over += 1
            player_data[row['bowler']]['extras'] += 1
            player_data[row['striker']]['runs-scored'] += row['extras']-1
            player_data[row['bowler']]['runs-given'] += row['extras']-1
            extras_over += 0.1
        elif row['extras'] != 0:
            #             print(row)
            player_data[row['bowler']]['balls-bowled'] += 1
            player_data[row['striker']]['balls-played'] += 1
        else:
            player_data[row['striker']]['balls-played'] += 1
            player_data[row['bowler']]['balls-bowled'] += 1
            player_data[row['bowler']]['runs-given'] += row['runs']
        player_data[row['striker']]['runs-scored'] += row['runs']
        if ball_no >= 6:
            if ball_no == 6 and runs_over == 0:
                player_data[row['bowler']]['maiden-overs'] += 1
            runs_over = 0
        player_data[row['striker']]['innings'] = row['innings']
        player_data[row['striker']]['team-name']=row['batting-team']
        player_data[row['non-striker']]['team-name']=row['batting-team']
        if row['innings'] == 1:
            player_data[row['bowler']]['innings'] = 2
            player_data[row['bowler']]['team-name']=teams[1]
#             print(teams,row['bowler'])
        elif row['innings']==2:
            player_data[row['bowler']]['innings'] = 1
            player_data[row['bowler']]['team-name']=teams[0]
#             print(teams,row['bowler'])
#     print(player_data)

    player_data = [value for key, value in player_data.items()]
    scorecard = pd.DataFrame(data=player_data)
    scorecard = scorecard[player_stats]
    return scorecard
```

[290]:
```python
i = 0
for file in files[:5]:
    print(i, '--', file)
    i += 1
    count = 0
    df_index = []
    df_row = []
    add = r'./all_csv/'+file
#     add=r'/gdrive/My Drive/all_csv/'+file
    df_index = ['file_no']
    file_no = file.split('.')[0]
    df_row = [file_no]
    with open(add) as f:
        new_f = f.readlines()
        for line in new_f:
            if 'version' in line:
                count += 1
            elif 'info' in line:
                count += 1
                line = line.strip().split(',')
                df_index.append(line[1])
                df_row.append(line[2])
            else:
                df_index = rename_date_umpire(df_index)
                df_dic = dict(zip(df_index, df_row), index=[0])
                temp_info_df = pd.DataFrame(df_dic)
#                 df_info=df_info.append(temp_info_df,ignore_index=True)
                # gender=df_info['gender'].iloc[0]
                # gender=str.lower(gender.strip())
                break
    temp_df = pd.read_csv(add, skiprows=count, names=[
                            0, 'innings', 'over', 'batting-team', 'striker',␣
 ↪'non-striker', 'bowler', 'runs', 'extras', 'out', 'out-player'])
    temp_df = temp_df.drop([0], axis=1)
    temp_df['file_no'] = [file_no]*(temp_df.shape[0])
    temp_sc = prepare_scorecard(temp_df,temp_info_df['team_0'].
 ↪values[0],temp_info_df['team_1'].values[0])
    # print(temp_sc)
#     append_file(temp_df,gender,type_game)
    append_file(temp_sc, temp_info_df, find_game(temp_sc, temp_info_df))
```

```
0 -- 1019975.csv
1 -- 682919.csv
2 -- 952191.csv
3 -- 1043961.csv
4 -- 565820.csv
```

[291]:
```
odi_info.columns
```

[291]:
```
Index(['city', 'competition', 'date_0', 'file_no', 'gender', 'index',
       'match_number', 'match_referee', 'player_of_match', 'reserve_umpire',
       'season', 'series', 'team_0', 'team_1', 'toss_decision', 'toss_winner',
       'tv_umpire', 'umpire_0', 'umpire_1', 'venue', 'winner', 'winner_runs'],
      dtype='object')
```

[292]:
```
ttwenty_info.columns
```

[292]:
```
Index(['city', 'competition', 'date_0', 'file_no', 'gender', 'index',
       'match_number', 'match_referee', 'neutralvenue', 'player_of_match',
       'reserve_umpire', 'season', 'series', 'team_0', 'team_1',
       'toss_decision', 'toss_winner', 'tv_umpire', 'umpire_0', 'umpire_1',
       'venue', 'winner', 'winner_runs', 'winner_wickets'],
      dtype='object')
```

[280]:
```
odi_info.to_csv('./odi_info.csv', index=False)
ttwenty_info.to_csv('./ttwenty_info.csv', index=False)
odi_scorecard.to_csv('./odi_scorecard.csv', index=False)
ttwenty_scorecard.to_csv('./ttwenty_scorecard.csv', index=False)
```

cricket-data-modification

November 24, 2019

[ ]:
```
import pandas as pd
```

[ ]:
```
df_info=pd.read_csv(r'./full/odi_info.csv')
```

[ ]:
```
df_scorecard=pd.read_csv(r'./full/odi_scorecard.csv')
```

[ ]:
```
df_scorecard = df_scorecard.astype({"match-id": str,'innings':str})
```

0.0.1 Delete Attributes

[ ]:
```
df_info=df_info.drop(['eliminator','date-1','date-2','date-3','date-4'],axis=1)
```

[ ]:
```
df_info=df_info.drop(['winner-innings'],axis=1)
```

[ ]:
```
df_info=df_info.drop(['index'],axis=1)
```

0.0.2 Delete matches

[ ]:
```
for i in df_info['match-id'].index:
    if '(' in df_info['match-id'][i]:
        print(i)
```

[ ]:
```
df_info.drop(df_info[df_info['match-id']=='300438 (1)'].index,inplace=True)
df_info.drop(df_info[df_info['match-id']=='812777 (1)'].index,inplace=True)
```

[ ]:
```
df_info.drop(df_info[df_info['match-id']=='1050229'].index,inplace=True)
```

[ ]:
```
df_info.drop(df_info[df_info['match-id']=='1022599'].index,inplace=True)
```

[ ]:
```
df_info.drop(df_info[df_info['match-id']=='426423'].index,inplace=True)
```

[ ]:
```
df_info.drop(df_info[df_info['match-id']=='915773'].index,inplace=True)
```

[ ]:
```
df_scorecard.drop(df_scorecard[df_scorecard['match-id']=='1050229'].
↪index,inplace=True)
```

[ ]:
```
df_scorecard.drop(df_scorecard[df_scorecard['match-id']=='1022599'].
↪index,inplace=True)
```

[ ]:
```
df_scorecard.drop(df_scorecard[df_scorecard['match-id']=='426423'].
↪index,inplace=True)
```

```
[ ]: df_scorecard.drop(df_scorecard[df_scorecard['match-id']=='915773'].
     ↪index,inplace=True)
```

```
[ ]: df_scorecard.drop(df_scorecard[df_scorecard['match-id']=='300438 (1)'].
     ↪index,inplace=True)
     df_scorecard.drop(df_scorecard[df_scorecard['match-id']=='812777 (1)'].
     ↪index,inplace=True)
```

```
[ ]: match_id=df_info[(df_info['competition']=='Indian Premier League') |␣
     ↪(df_info['competition']=='ICC World Twenty20') |␣
     ↪(df_info['competition']=='Big Bash League')]['match-id']
     for i in match_id:
         df_scorecard.drop(df_scorecard[df_scorecard['match-id']==i].
     ↪index,inplace=True)
         df_info.drop(df_info[df_info['match-id']==i].index,inplace=True)
```

```
[ ]: for i in match_id:
         df_scorecard.drop(df_scorecard[df_scorecard['match-id']==i].
     ↪index,inplace=True)
         df_info.drop(df_info[df_info['match-id']==i].index,inplace=True)
```

```
[ ]: # df_scorecard.drop(['Unnamed: 0','Unnamed: 0.1'],axis=1,inplace=True)
```

0.0.3 Additional Formatting

```
[ ]: df_zero=df_scorecard[df_scorecard['innings']=='0']
     for i, v in df_zero.iterrows():
         print(v['match-id'])
```

```
[ ]: df_info['competition']=df_info['competition'].apply(lambda x: str(x).
     ↪replace(r'"',''))
```

```
[ ]: df_info['venue']=df_info['venue'].apply(lambda x: str(x).replace(r'"',''))
```

```
[ ]: df_info['year']=df_info['date'].apply(lambda x: str(x).split(r'/')[0])
```

0.0.4 Aggregate scorecard

```
[ ]: df_scorecard_agg=df_scorecard.groupby(['match-id','team-name'],as_index=False).
     ↪sum()
```

```
[ ]: match_id=df_scorecard_agg[df_scorecard_agg['runs-scored']==0]['match-id']
```

```
[ ]: cancelled_matches=df_scorecard_agg[(df_scorecard_agg['runs-scored']<=50) &␣
     ↪(df_scorecard_agg['batting-position']<66) &␣
     ↪(df_scorecard_agg['balls-played']<300)]
     match_id=match_id.
     ↪append(cancelled_matches[cancelled_matches['runs-scored']<cancelled_matches['runs-given']][
```

[ ]:
```
for i in match_id:
    df_scorecard.drop(df_scorecard[df_scorecard['match-id']==i].
 ↪index,inplace=True)
    df_info.drop(df_info[df_info['match-id']==i].index,inplace=True)
    df_scorecard_agg.drop(df_scorecard_agg[df_scorecard_agg['match-id']==i].
 ↪index,inplace=True)
```

0.0.5 Save files

[ ]:
```
df_info.sort_values(['match-id'],inplace=True)
df_info.to_csv(r'./full/odi_info.csv',index=False)
```

[ ]:
```
df_scorecard.sort_values(['match-id'],inplace=True)
df_scorecard.to_csv(r'./full/odi_scorecard.csv',index=False)
```

[ ]:
```
df_scorecard_agg.sort_values(['match-id'],inplace=True)
df_scorecard_agg.to_csv(r'./full/odi_scorecard_agg.csv',index=False)
```

The interactive visualizations cannot be shown in LaTex therefore, here is the link for all the Jupyter notebook: vis-cricket.ipynb.

vis-cricket

November 24, 2019

[3]:
```python
import pandas as pd
import plotly.figure_factory as ff
import plotly.graph_objects as go
import plotly.io as pio
import math
# renderer for jupyter notebook
pio.renderers.default='notebook'
%%latex
```

```
UsageError: Line magic function `%%latex` not found.
```

[17]:
```python
pio.templates.default = "plotly_dark"
```

[18]:
```python
df_scorecard=pd.read_csv(r'./full/odi_scorecard.csv')
```

[19]:
```python
df_info=pd.read_csv(r'./full/odi_info.csv')
```

[20]:
```python
df_scorecard_agg=pd.read_csv(r'./full/odi_scorecard_agg.csv')
```

[21]:
```python
df_total=pd.merge(df_info,df_scorecard,on='match-id')
```

[22]:
```python
df_total_agg=pd.merge(df_info,df_scorecard_agg,on='match-id')
```

[23]:
```python
df_info.columns
```

[23]:
```
Index(['city', 'competition', 'date', 'match-id', 'gender', 'match-number',
       'match-referee', 'method', 'neutralvenue', 'outcome', 'player-of-match',
       'reserve-umpire', 'season', 'series', 'team-0', 'team-1',
       'toss-decision', 'toss-winner', 'tv-umpire', 'umpire-0', 'umpire-1',
       'venue', 'winner', 'winner-runs', 'winner-wickets', 'year'],
      dtype='object')
```

[24]:
```python
df_scorecard_agg.columns
```

[24]:
```
Index(['match-id', 'team-name', 'batting-position', 'over-batsman',
       'runs-scored', 'balls-played', 'dots', 'ones', 'twos', 'threes',
       'fours', 'sixes', 'balls-bowled', 'maiden-overs', 'runs-given',
       'wickets', 'extras', 'fall-of-wicket-score', 'fall-of-wicket-overs',
       'fall-of-wicket-no'],
      dtype='object')
```

[25]:
```python
df_scorecard.columns
```

[25]:
```
Index(['match-id', 'team-name', 'innings', 'name', 'batting-position',
       'over-batsman', 'runs-scored', 'balls-played', 'dots', 'ones', 'twos',
       'threes', 'fours', 'sixes', 'wicket-method', 'balls-bowled',
       'maiden-overs', 'runs-given', 'wickets', 'extras',
       'fall-of-wicket-score', 'fall-of-wicket-overs', 'fall-of-wicket-no',
       'fall-of-wicket-bowler'],
      dtype='object')
```

0.1 Visualizations

0.1.1 Wickets

Wickets Methods

[175]:
```
wickets_method=df_scorecard[df_scorecard['wicket-method']!='0']['wicket-method']
```

[176]:
```
wicket_method=wickets_method.value_counts().index
wicket_method_value=wickets_method.value_counts().values
fig=go.Figure(data=[go.
 ↪Bar(x=wicket_method,y=wicket_method_value,text=wicket_method_value,textposition='auto')],la
 ↪of wickets per dismissal method")
fig.update_layout(xaxis_title='Dismissal Method',yaxis_title='Count')
fig.show()
```

Dismissal Method Distribution

[177]:
```
fig=go.Figure()
fig.add_trace(go.Pie(labels=wicket_method,values=wicket_method_value))
fig.update_layout(title='Dismissal method distribution')
fig.show()
```

Fall of Wicket by Runs

[27]:
```
fow_score=df_scorecard[(df_scorecard['fall-of-wicket-score']!
 ↪=0)]['fall-of-wicket-score'].
 ↪append(df_scorecard[(df_scorecard['fall-of-wicket-score']==0) &␣
 ↪df_scorecard['fall-of-wicket-no']!=0]['fall-of-wicket-score'])
```

[28]:
```
fig = go.Figure(data=[go.Histogram(x=fow_score)])
fig.update_layout(title='Fall of wicket by␣
 ↪runs',xaxis_title='Runs',yaxis_title='Wickets Fallen')
fig.show()
```

Probability Distribution of fall of wicket by runs

[29]:
```
fig=ff.create_distplot([fow_score],group_labels=['Fall of wicket Runs'])
fig.update_layout(title='Probability Distribution of wickets fall by␣
 ↪runs',xaxis_title='runs',yaxis_title='Probability')
fig.show()
```

Fall of Wickets by overs

[143]:
```
fow_overs=df_scorecard[df_scorecard['fall-of-wicket-overs']>0.
 ↪0]['fall-of-wicket-overs'].apply(lambda x:str(x).split('.')[0])
```

[144]:
```
fig = go.Figure(data=[go.Histogram(x=fow_overs)])
fig.show()
```

Probability distribution of Fall of wickets by overs

[145]:
```
fow_overs=fow_overs.astype('int64')
```

[146]:
```
fig=ff.create_distplot([fow_overs],group_labels=['Fall of wicket Overs'])
fig.update_layout(title='Probability Distribution of wickets fall by␣
 ↪over',xaxis_title='Over',yaxis_title='Probability')
fig.show()
```

0.1.2 Team Statistics

Teamwise runs scored

[147]:
```
team_scores={team:[] for team in df_scorecard_agg['team-name']}
for index,row in df_scorecard_agg.iterrows():
    team_scores[row['team-name']].append(row['runs-scored'])
fig=go.Figure()
for index, value in team_scores.items():
    fig.add_trace(go.Box(y=value,name=index,boxmean='sd'))
fig.update_layout(title='Teamwise Runs scored',xaxis_title='Team␣
 ↪Name',yaxis_title='Runs Scored')
fig.show()
```

Teamwise Wickets Taken

[148]:
```
team_scores={team:[] for team in df_scorecard_agg['team-name']}
for index,row in df_scorecard_agg.iterrows():
    team_scores[row['team-name']].append(row['wickets'])
fig=go.Figure()
for index, value in team_scores.items():
    fig.add_trace(go.Box(y=value,name=index,boxmean='sd'))
fig.update_layout(title='Teamwise Wickets Taken',xaxis_title='Team␣
 ↪Name',yaxis_title='Wickets Taken Scored')
fig.show()
```

Teamwise Extras Given

[14]:
```
team_scores={team:[] for team in df_scorecard_agg['team-name']}
for index,row in df_scorecard_agg.iterrows():
    team_scores[row['team-name']].append(row['extras'])
fig=go.Figure()
for index, value in team_scores.items():
```

```
    fig.add_trace(go.Box(y=value,name=index,boxmean='sd'))
fig.update_layout(title='Teamwise Extras Given',xaxis_title='Team␣
↪Name',yaxis_title='Wickets Taken Scored')
fig.show()
```

Team performance over the years

[20]:
```
year=[]
team=[]
matches=[]
team_year_wise_total=df_info.groupby('year')['team-0'].value_counts()
for index,value in team_year_wise_total.iteritems():
    year.append(index[0])
    team.append(index[1])
    matches.append(value)
temp1=pd.DataFrame({'year':year,'team':team,'matches0':matches})
year=[]
team=[]
matches=[]
team_year_wise_total=df_info.groupby('year')['team-1'].value_counts()
for index,value in team_year_wise_total.iteritems():
    year.append(index[0])
    team.append(index[1])
    matches.append(value)
temp2=pd.DataFrame({'year':year,'team':team,'matches1':matches})
year=[]
team=[]
wins=[]
team_year_wise_wins=df_info.groupby('year')['winner'].value_counts()
for index,value in team_year_wise_wins.iteritems():
    year.append(index[0])
    team.append(index[1])
    wins.append(value)
temp3=pd.DataFrame({'year':year,'team':team,'wins':wins})
df_matches_year=pd.merge(temp1,temp2,on=['year','team'])
df_matches_year=pd.merge(df_matches_year,temp3,on=['year','team'])
```

[12]:
```
df_matches_year['matches']=df_matches_year['matches0']+df_matches_year['matches1']
df_matches_year['win-ratio']=round(df_matches_year['wins']/
↪df_matches_year['matches'],3)
```

[13]:
```
df_matches_year_dict={i:{'year':[],'ratio':[]} for i in df_matches_year['team'].
↪unique()}
for index,row in df_matches_year.iterrows():
    df_matches_year_dict[row['team']]['year'].append(row['year'])
    df_matches_year_dict[row['team']]['ratio'].append(row['win-ratio'])
```

[14]:
```
fig=go.Figure()
for i in df_matches_year['team'].unique():
    fig.add_trace(go.
 ↪Scatter(x=df_matches_year_dict[i]['year'],y=df_matches_year_dict[i]['ratio'],name=i))
fig.update_layout(
    title_text='Win ratio of teams in ODI yearwise',
    xaxis_rangeslider_visible=True
)
fig.show()
```

Team wise performance over different venues

[76]:
```
venue=[]
team=[]
matches=[]
team_year_wise_total=df_info.groupby('venue')['team-0'].value_counts()
for index,value in team_year_wise_total.iteritems():
    venue.append(index[0])
    team.append(index[1])
    matches.append(value)
temp1=pd.DataFrame({'venue':venue,'team':team,'matches0':matches})
venue=[]
team=[]
matches=[]
team_year_wise_total=df_info.groupby('venue')['team-1'].value_counts()
for index,value in team_year_wise_total.iteritems():
    venue.append(index[0])
    team.append(index[1])
    matches.append(value)
temp2=pd.DataFrame({'venue':venue,'team':team,'matches1':matches})
venue=[]
team=[]
wins=[]
team_year_wise_wins=df_info.groupby('venue')['winner'].value_counts()
for index,value in team_year_wise_wins.iteritems():
    venue.append(index[0])
    team.append(index[1])
    wins.append(value)
temp3=pd.DataFrame({'venue':venue,'team':team,'wins':wins})
df_matches_venue=pd.merge(temp1,temp2,on=['venue','team'])
df_matches_venue=pd.merge(df_matches_venue,temp3,on=['venue','team'])
```

[77]:
```
df_matches_venue['matches']=df_matches_venue['matches0']+df_matches_venue['matches1']
df_matches_venue['win-ratio']=round(df_matches_venue['wins']/
 ↪df_matches_venue['matches'],3)
```

[78]:
```
matches_count=df_matches_venue.groupby('team',as_index=False).sum()
matches_count=matches_count.sort_values(by='matches',ascending=False)
```

```
matches_count=matches_count.iloc[:8,:]
```

[79]:
```
df_matches_venue_dict={i:{'venue':[],'ratio':[]} for i in␣
 ↪df_matches_venue['team'].unique()}
for index,row in df_matches_venue.iterrows():
    df_matches_venue_dict[row['team']]['venue'].append(row['venue'])
    df_matches_venue_dict[row['team']]['ratio'].append(row['win-ratio'])
```

[80]:
```
fig=go.Figure()
color_v=["rgb(37,102,118)", "rgb(98,240,101)", "rgb(154,72,174)",␣
 ↪"rgb(184,228,80)", "rgb(209,48,255)", "rgb(101,161,14)", "rgb(46,33,208)",␣
 ↪"rgb(241,192,57)"]
j=0
for i in matches_count['team'].unique():
#     print(i)
    fig.add_trace(go.Scatter(
        x=df_matches_venue_dict[i]['venue'],
        y=df_matches_venue_dict[i]['ratio'],
        marker=dict(color=color_v[j],size=12),
        mode='markers',
        name=i))
    j+=1
fig.update_layout(
    title_text='Win ratio of teams in ODI yearwise',
    xaxis_rangeslider_visible=True
)
fig.show()
```

0.1.3 Venue Statistics

Venue wise Runs Scored

[150]:
```
venues=df_total_agg['venue'].value_counts()
venue_scores={venue:[] for venue in venues.index[:15]}
for index,row in df_total_agg.iterrows():
#     print(venue_scores.get(row['venue'],-1),row['venue'])
    if venue_scores.get(row['venue'],-1)!=-1:
        venue_scores[row['venue']].append(row['runs-scored'])
fig=go.Figure()
for index, value in venue_scores.items():
    fig.add_trace(go.Box(y=value,name=index,boxmean='sd'))
fig.update_layout(title='Venue wise Runs scored',xaxis_title='Venue␣
 ↪Name',yaxis_title='Runs Scored')
fig.show()
```

Venue wise Wickets Fallen

[151]:
```
venues=df_total_agg['venue'].value_counts()
venue_scores={venue:[] for venue in venues.index[:15]}
for index,row in df_total_agg.iterrows():
#     print(venue_scores.get(row['venue'],-1),row['venue'])
    if venue_scores.get(row['venue'],-1)!=-1:
        venue_scores[row['venue']].append(row['wickets'])
fig=go.Figure()
for index, value in venue_scores.items():
    fig.add_trace(go.Box(y=value,name=index,boxmean='sd'))
fig.update_layout(title='Venue wise Wickets Fallen',xaxis_title='Venue␣
↪Name',yaxis_title='Wickets Fallen')
fig.show()
```

ODI matches distribution among grounds

[152]:
```
venues=df_total_agg['venue'].value_counts().iloc[:50]
fig=go.Figure()
fig.add_trace(go.Pie(labels=venues.index,values=venues.values))
fig.update_layout(title='ODI matches distribution among top 50 grounds'
                  ,margin=dict(l=20,r=20,t=40,b=20),
                  autosize=False,
                  width=1000,
                  height=1000)
fig.show()
```

0.1.4 Player Statistics

Matches distibution between genders

[153]:
```
gender=df_info['gender'].value_counts()
fig=go.Figure()
fig.add_trace(go.Pie(labels=gender.index.unique(),values=gender.values))
fig.update_layout(title='Gender wise matches distribution')
fig.show()
```

Top 10 Batsmen

[109]:
```
df_scorecard_batsman_agg=df_scorecard.groupby(['name'],as_index=False).sum()
df_scorecard_batsman_agg=df_scorecard_batsman_agg.
↪sort_values(by=['runs-scored'],ascending=False)
df_scorecard_batsman_agg=df_scorecard_batsman_agg.reset_index(drop=True)
```

[110]:
```
df_scorecard_batsman_agg=df_scorecard_batsman_agg.drop(['batting-position',
       'over-batsman','extras',
       'fall-of-wicket-score', 'fall-of-wicket-overs',␣
↪'fall-of-wicket-no'],axis=1)
```

```
[111]: batsman_innings=df_scorecard[df_scorecard['over-batsman']>0.0]['name']
batsman_innings=batsman_innings.value_counts().to_dict()
df_scorecard_batsman_agg['innings']=df_scorecard_batsman_agg['name'].
 ↪map(batsman_innings)
df_scorecard_batsman_agg['strike-rate']=df_scorecard_batsman_agg.apply(lambda␣
 ↪row: round((row['runs-scored']/row['balls-played'])*100,3) if␣
 ↪row['balls-played']>0 else 0 ,axis=1)
df_scorecard_batsman_agg['avg']=df_scorecard_batsman_agg.apply(lambda row:␣
 ↪round(row['runs-scored']/row['innings'],3) if row['innings']>0 else 0,axis=1)
```

```
[112]: df_scorecard_batsman_agg_sub=df_scorecard_batsman_agg.iloc[:10]
fig=go.Figure()
fig.add_trace(go.Table(
    header=dict(
        values=['Batsman Name','Innings','Runs Scored','Balls␣
 ↪Played','Fours','Sixes','Batting Strike Rate','Batting Average'],
        fill_color='paleturquoise',
        align='left',
        font=dict(color='black',size=14)
    ),
    cells=dict(values=
              ␣
 ↪[df_scorecard_batsman_agg_sub['name'],df_scorecard_batsman_agg_sub['innings'],df_scorecard_
               ␣
 ↪df_scorecard_batsman_agg_sub['balls-played'],df_scorecard_batsman_agg_sub['fours'],df_score
              ␣
 ↪df_scorecard_batsman_agg_sub['strike-rate'],df_scorecard_batsman_agg_sub['avg']],
               align='left'
    )
))
fig.update_layout(title='Top 10 Batsmen')
fig.show()
```

Batsmen Performance

```
[113]: df_scorecard_batsman_agg_sub=df_scorecard_batsman_agg.iloc[:]
hover_text=[]
bubble_size=[]
for index,row in df_scorecard_batsman_agg_sub.iterrows():
    hover_text.append(
        ('Name: {name}<br>'+'Balls Played: {balls}<br>'+'Average:␣
 ↪{avg}<br>'+'Strike Rate: {strike}<br>').format(
            ␣
 ↪name=row['name'],avg=row['avg'],strike=row['strike-rate'],balls=row['balls-played']))
    bubble_size.append(math.sqrt(row['strike-rate'])*2)
fig=go.Figure()
fig.add_trace(
```

```
    go.Scatter(
    x=df_scorecard_batsman_agg_sub['balls-played'],
    y=df_scorecard_batsman_agg_sub['runs-scored'],
    text=hover_text,
        mode='markers',
        marker=dict(
        color=df_scorecard_batsman_agg_sub['innings'],
        colorbar=dict(
        title='Innings Played'
        ),
            colorscale='Viridis',
        size=bubble_size,
            showscale=True
        )
    )
)
fig.update_layout(title='Batsmen Performance',xaxis_title='Balls␣
↪Played',yaxis_title='Runs scored')
fig.show()
```

Top 10 Bowlers

[158]:
```
df_scorecard_bowler_agg=df_scorecard.groupby(['name'],as_index=False).sum()
df_scorecard_bowler_agg=df_scorecard_bowler_agg.
↪sort_values(by=['wickets'],ascending=False)
df_scorecard_bowler_agg=df_scorecard_bowler_agg.reset_index(drop=True)
```

[159]:
```
df_scorecard_bowler_agg=df_scorecard_bowler_agg.drop(['batting-position',␣
↪'over-batsman', 'runs-scored',
       'balls-played', 'dots', 'ones', 'twos', 'threes', 'fours', 'sixes',␣
↪'extras',
       'fall-of-wicket-score', 'fall-of-wicket-overs',␣
↪'fall-of-wicket-no'],axis=1)
```

[160]:
```
bowler_innings=df_scorecard[df_scorecard['balls-bowled']>0]['name']
bowler_innings=bowler_innings.value_counts().to_dict()
df_scorecard_bowler_agg['innings']=df_scorecard_bowler_agg['name'].
↪map(bowler_innings)
df_scorecard_bowler_agg['strike-rate']=df_scorecard_bowler_agg.apply(lambda row:
↪ round((row['balls-bowled']/row['wickets']),3) if row['wickets']>0 else 0␣
↪,axis=1)
df_scorecard_bowler_agg['avg']=df_scorecard_bowler_agg.apply(lambda row:␣
↪round(row['runs-given']/row['wickets'],3) if row['wickets']>0 else 0,axis=1)
df_scorecard_bowler_agg['eco']=df_scorecard_bowler_agg.apply(lambda row:␣
↪round(row['runs-given']/(row['balls-bowled']/6),3) if row['balls-bowled']>0␣
↪else 0,axis=1)
```

[161]:
```
df_scorecard_bowler_agg_sub=df_scorecard_bowler_agg.iloc[:10]
fig=go.Figure()
fig.add_trace(go.Table(
    header=dict(
        values=['Bowler Name','Innings','Balls','Maiden Overs','Runs␣
↪Conceded','Wickets','Economy','Bowling Strike Rate','Bowling Average'],
        fill_color='paleturquoise',
        align='left',
        font=dict(color='black',size=14)
    ),
    cells=dict(values=
            ␣
↪[df_scorecard_bowler_agg_sub['name'],df_scorecard_bowler_agg_sub['innings'],df_scorecard_bo
             ␣
↪df_scorecard_bowler_agg_sub['maiden-overs'],df_scorecard_bowler_agg_sub['runs-given'],df_sc
                df_scorecard_bowler_agg_sub['eco'],
            ␣
↪df_scorecard_bowler_agg_sub['strike-rate'],df_scorecard_bowler_agg_sub['avg']],
               align='left'
    )
))
fig.update_layout(title='Top 10 Bowlers')
fig.show()
```

Bowlers Performance

[162]:
```
df_scorecard_bowler_agg_sub=df_scorecard_bowler_agg.iloc[:]
hover_text=[]
bubble_size=[]

for index,row in df_scorecard_bowler_agg_sub.iterrows():
    hover_text.append(
        ('Name: {name}<br>'+'Economy: {eco}<br>'+'Average: {avg}<br>'+'Strike␣
↪Rate: {strike}<br>').format(
         ␣
↪name=row['name'],avg=row['avg'],strike=row['strike-rate'],eco=row['eco']))
    bubble_size.append(math.sqrt(row['eco'])*6)
fig=go.Figure()
fig.add_trace(
    go.Scatter(
    x=df_scorecard_batsman_agg_sub['balls-bowled'],
    y=df_scorecard_batsman_agg_sub['wickets'],
    text=hover_text,
        mode='markers',
        marker=dict(
        color=df_scorecard_batsman_agg_sub['innings'],
        colorbar=dict(
```

```
        title='Innings Played'
        ),
            colorscale='Viridis',
        size=bubble_size,
            showscale=True
        )
    )
)
fig.update_layout(title='Bowlers Performance',xaxis_title='Balls␣
↪Bowled',yaxis_title='Wickets')
fig.show()
```

Batsmen performance over the years: Runs scored

[183]:
```
df_player_year=df_total.groupby(by=['year','name'],as_index=False).sum()
```

[164]:
```
top_batsmen=df_scorecard_batsman_agg.iloc[:10]['name'].tolist()
df_batsmen_year=df_player_year[df_player_year['name'].isin(top_batsmen)]
df_batsman_year_grouped=df_batsmen_year.groupby('name')
```

[151]:
```
fig=go.Figure()
for name,group in df_batsman_year_grouped:
    fig.add_trace(go.Scatter(x=group['year'],y=group['runs-scored'],name=name))
fig.update_layout(
    title_text='Runs in a calendar year of top 10 ODI batsmen',
    xaxis_rangeslider_visible=True,
    xaxis_title='Year',
    yaxis_title='Runs'
)
fig.show()
```

Batsmen performance over the years: Strike rate

[152]:
```
df_batsmen_year['strike-rate']=round(df_batsmen_year['runs-scored']/
↪df_batsmen_year['balls-played'],4)*100
df_batsman_year_grouped=df_batsmen_year.groupby('name')
```

[153]:
```
fig=go.Figure()
for name,group in df_batsman_year_grouped:
    fig.add_trace(go.Scatter(x=group['year'],y=group['strike-rate'],name=name))
fig.update_layout(
    title_text='Strike rate of top 10 batsmen in ODI yearwise',
    xaxis_rangeslider_visible=True,
    xaxis_title='Year',
    yaxis_title='Strike Rate'
)
fig.show()
```

Bowlers performance over the years: Wickets taken

[171]:
```
top_bowlers=df_scorecard_bowler_agg.iloc[:10]['name'].tolist()
df_bowlers_year=df_player_year[df_player_year['name'].isin(top_bowlers)]
df_bowlers_year_grouped=df_bowlers_year.groupby('name')
```

[172]:
```
fig=go.Figure()
for name,group in df_bowlers_year_grouped:
    fig.add_trace(go.Scatter(x=group['year'],y=group['wickets'],name=name))
fig.update_layout(
    title_text='Runs in a calendar year of top 10 ODI bowlers',
    xaxis_rangeslider_visible=True,
    xaxis_title='Year',
    yaxis_title='Wickets'
)
fig.show()
```

Bowlers performance over the years: Economy

[181]:
```
df_bowlers_year['economy']=round(df_bowlers_year['runs-given']/
 ↪(df_bowlers_year['balls-bowled']/6),2)
df_bowlers_year_grouped=df_bowlers_year.groupby('name')
```

[182]:
```
fig=go.Figure()
for name,group in df_bowlers_year_grouped:
    fig.add_trace(go.Scatter(x=group['year'],y=group['economy'],name=name))
fig.update_layout(
    title_text='Economy of top 10 bowlers in ODI yearwise',
    xaxis_rangeslider_visible=True,
    xaxis_title='Year',
    yaxis_title='Strike Rate'
)
fig.show()
```

The interactive visualizations cannot be shown in LaTex therefore, here is the link for all the Jupyter notebook: hypothesis.ipynb.

hypothesis

November 24, 2019

[108]:
```
import pandas as pd
import plotly.figure_factory as ff
import plotly.graph_objects as go
import plotly.io as pio
import math
from scipy import stats
# renderer for jupyter notebook
from sklearn.metrics import mean_absolute_error
pio.renderers.default='notebook'
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

[109]:
```
pio.templates.default = "plotly_dark"
```

[110]:
```
df_scorecard=pd.read_csv(r'./full/odi_scorecard.csv')
df_info=pd.read_csv(r'./full/odi_info.csv')
```

0.0.1 Hypothesis

1

- H(0):Mean value of batsman bowled is equal to mean value of batsman dismissed by lbw in ODI
- H(A):Mean value of batsman bowled is not equal to mean value batsman dismissed by lbw

Data

[111]:
```
df_first=df_scorecard[(df_scorecard['wicket-method']=='bowled')|(df_scorecard['wicket-method']
```

[112]:
```
df_first['lbw']=df_first['wicket-method'].apply(lambda x: 0 if x=='bowled' else␣
↪1 )
df_first['bowled']=df_first['wicket-method'].apply(lambda x: 1 if x=='bowled'␣
↪else 0 )
```

[113]:
```
df_first=df_first.groupby(['match-id'],as_index=False).sum()
```

[114]:
```
df_first=df_first[['lbw','bowled']]
```

Visualizations

[116]:
```
fig = go.Figure()
fig.add_trace(go.Histogram(x=df_first['lbw'], histnorm='probability',␣
 ↪name='lbw'))
fig.add_trace(go.Histogram(x=df_first['bowled'],␣
 ↪histnorm='probability',name='bowled'))
fig.update_layout(title='Probability distribution for lbw and␣
 ↪bowled',xaxis_title='Number of wickets',yaxis_title='Probability')
fig.show()
```

[117]:
```
fig=ff.
 ↪create_distplot([df_first['lbw'],df_first['bowled']],['LBW','Bowled'],bin_size=1,curve_type
fig.update_layout(title_text='Distribution of dimissal␣
 ↪methods',xaxis_title='Number of wickets',yaxis_title='Density')
fig.show()
```

Hypothesis Testing

Paired T test

[118]:
```
df_first[['lbw','bowled']].describe()
```

[118]:

	lbw	bowled
count	1677.000000	1677.000000
mean	1.679785	2.774001
std	1.386744	1.684788
min	0.000000	0.000000
25%	1.000000	2.000000
50%	1.000000	3.000000
75%	2.000000	4.000000
max	8.000000	9.000000

[119]:
```
ttest,pval=stats.ttest_rel(df_first['lbw'],df_first['bowled'])
```

[120]:
```
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
8.855848765261422e-83
reject null hypothesis
```

2

- H(0):Wickets fallen in the first 70% of the first innings is equal to the wickets fallen in the last 30% of the first innings
- H(A):Wickets fallen in the first 70% of the first innings is not equal to the wickets fallen in the last 30% of the first innings

- H(0):Wickets fallen in the first 71% of the first innings is equal to the wickets fallen in the last 29% of the first innings
- H(A):Wickets fallen in the first 71% of the first innings is not equal to the wickets fallen in the last 29% of the first innings
- H(0):Wickets fallen in the first 50% of the first innings is equal to the wickets fallen in the last 50% of the first innings
- H(A):Wickets fallen in the first 50% of the first innings is not equal to the wickets fallen in the last 50% of the first innings
- H(0):Wickets fallen in the first 10 overs of the first innings is equal to the wickets fallen in the last 10 overs of the first innings
- H(A):Wickets fallen in the first 10 overs of the first innings is not equal to the wickets fallen in the last 10 overs of the first innings

Data

[121]:
```
temp=pd.DataFrame(data=None)
temp=df_scorecard[df_scorecard['innings']==1]
temp=temp.groupby('match-id',as_index=False).sum()
temp['total-overs']=round(temp['balls-played']/6)
temp=temp[['match-id','total-overs']]
temp['first-seventy']=round(temp['total-overs']*0.70)
temp['first-seventyone']=round(temp['total-overs']*0.71)
temp['first-fifty']=round(temp['total-overs']*0.5)
temp['last-ten']=round(temp['total-overs']-10)
temp=temp.merge(df_scorecard[(df_scorecard['innings']==1)␣
 ↪&(df_scorecard['fall-of-wicket-overs']>0.0)],on=['match-id'])
temp['fall-of-wicket-overs']=temp['fall-of-wicket-overs'].apply(lambda x:␣
 ↪int(x)+1)
```

[122]:
```
df_second=pd.DataFrame({'match-id':temp['match-id']})
df_second['first-seventy-wickets']=temp[(temp['fall-of-wicket-overs']<=temp['first-seventy'])␣
 ↪& (temp['fall-of-wicket-overs']>0)]['fall-of-wicket-overs']
df_second['last-thirty-wickets']=temp[temp['fall-of-wicket-overs']>temp['first-seventy']]['fal
df_second['first-seventy-wickets']=df_second['first-seventy-wickets'].
 ↪apply(lambda x:1 if x>0 else 0)
df_second['last-thirty-wickets']=df_second['last-thirty-wickets'].apply(lambda␣
 ↪x:1 if x>0 else 0)

df_second['first-seventyone-wickets']=temp[(temp['fall-of-wicket-overs']<=temp['first-seventyo
 ↪& (temp['fall-of-wicket-overs']>0)]['fall-of-wicket-overs']
df_second['last-twentynine-wickets']=temp[temp['fall-of-wicket-overs']>temp['first-seventyone'
df_second['first-seventyone-wickets']=df_second['first-seventyone-wickets'].
 ↪apply(lambda x:1 if x>0 else 0)
df_second['last-twentynine-wickets']=df_second['last-twentynine-wickets'].
 ↪apply(lambda x:1 if x>0 else 0)

df_second['first-fifty-wickets']=temp[(temp['fall-of-wicket-overs']<=temp['first-fifty'])␣
 ↪& (temp['fall-of-wicket-overs']>0)]['fall-of-wicket-overs']
```

```
df_second['last-fifty-wickets']=temp[temp['fall-of-wicket-overs']>temp['first-fifty']]['fall-o
df_second['first-fifty-wickets']=df_second['first-fifty-wickets'].apply(lambda␣
 ↪x:1 if x>0 else 0)
df_second['last-fifty-wickets']=df_second['last-fifty-wickets'].apply(lambda x:
 ↪1 if x>0 else 0)

df_second['first-ten-overs-wickets']=temp[(temp['fall-of-wicket-overs']<=10) &␣
 ↪(temp['fall-of-wicket-overs']>0)]['fall-of-wicket-overs']
df_second['last-ten-overs-wickets']=temp[temp['fall-of-wicket-overs']>temp['last-ten']]['fall-
df_second['first-ten-overs-wickets']=df_second['first-ten-overs-wickets'].
 ↪apply(lambda x:1 if x>0 else 0)
df_second['last-ten-overs-wickets']=df_second['last-ten-overs-wickets'].
 ↪apply(lambda x:1 if x>0 else 0)

df_second=df_second.groupby(['match-id'],as_index=False).sum()
df_second=df_second.drop(['match-id'],axis=1)
```

Visualizations

[124]:
```
fig = go.Figure()
fig.add_trace(go.Histogram(x=df_second['first-seventy-wickets'],␣
 ↪histnorm='probability', name='First 70%'))
fig.add_trace(go.Histogram(x=df_second['last-thirty-wickets'],␣
 ↪histnorm='probability',name='Last 30%'))
fig.update_layout(title='Probability distribution for wickets fallen in first␣
 ↪70% and last 30% of first innings',xaxis_title='Number of␣
 ↪wickets',yaxis_title='Probability')
fig.show()
```

[125]:
```
fig = go.Figure()
fig.add_trace(go.Histogram(x=df_second['first-seventyone-wickets'],␣
 ↪histnorm='probability', name='First 71%'))
fig.add_trace(go.Histogram(x=df_second['last-twentynine-wickets'],␣
 ↪histnorm='probability',name='Last 29%'))
fig.update_layout(title='Probability distribution for wickets fallen in first␣
 ↪71% and last 29% of first innings',xaxis_title='Number of␣
 ↪wickets',yaxis_title='Probability')
fig.show()
```

[126]:
```
fig = go.Figure()
fig.add_trace(go.Histogram(x=df_second['first-fifty-wickets'],␣
 ↪histnorm='probability', name='First 50%'))
fig.add_trace(go.Histogram(x=df_second['last-fifty-wickets'],␣
 ↪histnorm='probability',name='Last 50%'))
fig.update_layout(title='Probability distribution for wickets fallen in first␣
 ↪50% and last 50% of first innings',xaxis_title='Number of␣
 ↪wickets',yaxis_title='Probability')
```

```
fig.show()
```

[127]:
```
fig = go.Figure()
fig.add_trace(go.Histogram(x=df_second['first-ten-overs-wickets'],␣
↪histnorm='probability', name='First 10'))
fig.add_trace(go.Histogram(x=df_second['last-ten-overs-wickets'],␣
↪histnorm='probability',name='Last 10'))
fig.update_layout(title='Probability distribution for wickets fallen in first␣
↪10 overs and last 10 oversof first innings',xaxis_title='Number of␣
↪wickets',yaxis_title='Probability')
fig.show()
```

[128]:
```
fig=ff.
↪create_distplot([df_second['first-seventy-wickets'],df_second['last-thirty-wickets']],['Fir
↪70%','Last 30%'],curve_type='normal')
fig.update_layout(title='Distribution for wickets fallen in first 70% and last␣
↪30% of first innings',xaxis_title='Number of wickets',yaxis_title='Density')
fig.show()
```

[129]:
```
fig=ff.
↪create_distplot([df_second['first-fifty-wickets'],df_second['last-fifty-wickets']],['First␣
↪50%','Last 50%'],curve_type='normal')
fig.update_layout(title='Distribution for wickets fallen in first 50% and last␣
↪50% of first innings',xaxis_title='Number of wickets',yaxis_title='Density')
fig.show()
```

[130]:
```
fig=ff.
↪create_distplot([df_second['first-ten-overs-wickets'],df_second['last-ten-overs-wickets']],
↪10 overs','Last 10 overs'],curve_type='normal')
fig.update_layout(title='Distribution for wickets fallen in first 10 overs and␣
↪last 10 overs of first innings',xaxis_title='Number of␣
↪wickets',yaxis_title='Density')
fig.show()
```

Hypothesis Testing

Paired T Test

[131]:
```
df_second.describe()
```

[131]:

	first-seventy-wickets	last-thirty-wickets	first-seventyone-wickets	\
count	1707.000000	1707.000000	1707.000000	
mean	3.950791	4.100762	4.062097	
std	1.650583	1.652500	1.655468	
min	0.000000	0.000000	0.000000	
25%	3.000000	3.000000	3.000000	
50%	4.000000	4.000000	4.000000	
75%	5.000000	5.000000	5.000000	
max	9.000000	9.000000	9.000000	

```
       last-twentynine-wickets  first-fifty-wickets  last-fifty-wickets  \
count              1707.000000          1707.000000         1707.000000
mean                  3.989455             2.844757            5.206796
std                   1.647374             1.447369            1.790623
min                   0.000000             0.000000            0.000000
25%                   3.000000             2.000000            4.000000
50%                   4.000000             3.000000            5.000000
75%                   5.000000             4.000000            6.000000
max                   9.000000             8.000000           10.000000

       first-ten-overs-wickets  last-ten-overs-wickets
count              1707.000000             1707.000000
mean                  1.325718                3.445226
std                   1.113937                1.594545
min                   0.000000                0.000000
25%                   0.000000                2.000000
50%                   1.000000                3.000000
75%                   2.000000                5.000000
max                   6.000000                9.000000
```

[132]:
```
ttest,pval=stats.
 ↪ttest_rel(df_second['first-seventy-wickets'],df_second['last-thirty-wickets'])
```

[133]:
```
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
0.020019531021699132
reject null hypothesis
```

[134]:
```
ttest,pval=stats.
 ↪ttest_rel(df_second['first-seventyone-wickets'],df_second['last-twentynine-wickets'])
```

[135]:
```
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
0.25955086942355377
accept null hypothesis
```

[136]:
```
ttest,pval=stats.
 ↪ttest_rel(df_second['first-fifty-wickets'],df_second['last-fifty-wickets'])
```

[137]:
```
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
6.436197034363128e-225
reject null hypothesis
```

[138]:
```
ttest,pval=stats.
 ↪ttest_rel(df_second['first-ten-overs-wickets'],df_second['last-ten-overs-wickets'])
```

[139]:
```
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
8.92620766849228e-289
reject null hypothesis
```

3

- H(0):There is an equal probability of wicket by the first category of dismissal and second category of dismissal
- H(A):There is an equal probability of wicket by the first category of dismissal and second category of dismissal

Data

[140]:
```
df_third=df_scorecard[df_scorecard['wicket-method']!='0']
```

[141]:
```
first_cat=['run out','hit wicket','obstructing the field','retired␣
 ↪out','stumped']
second_cat=['caught','bowled','lbw','caught and bowled']
```

[142]:
```
df_third['first-category']=df_third['wicket-method'].apply(lambda x: 1 if x in␣
 ↪first_cat else 0 )
df_third['sec-category']=df_third['wicket-method'].apply(lambda x: 1 if x in␣
 ↪second_cat else 0 )
```

[143]:
```
df_third=df_third[['match-id','first-category','sec-category']]
df_third=df_third.groupby(['match-id'],as_index=False).sum()
df_third['wickets']=df_third['first-category']+df_third['sec-category']
```

[144]:
```
# df_third.loc[:,'wic_batsman']=round(df_third['wic_batsman']/
 ↪df_third['wickets'],3)
# df_third.loc[:,'wic_bowler']=round(df_third['wic_bowler']/
 ↪df_third['wickets'],3)
df_third=df_third[['first-category','sec-category']]
```

Visualizations

[146]:
```
fig = go.Figure()
fig.add_trace(go.Histogram(x=df_third['first-category'],␣
 ↪histnorm='probability', name='First Category'))
fig.add_trace(go.Histogram(x=df_third['sec-category'],␣
 ↪histnorm='probability',name='Second Category'))
fig.update_layout(title='Probability distribution for wickets fallen by First␣
 ↪category of dismissal methods and second category',xaxis_title='Number of␣
 ↪wickets',yaxis_title='Probability')
fig.show()
```

[147]:
```
fig=ff.
 ↪create_distplot([df_third['first-category'],df_third['sec-category']],['First␣
 ↪Category','Second Category'],curve_type='normal')
fig.update_layout(title='Density of wickets fallen by first and second category␣
 ↪of dismissal methods',xaxis_title='Number of wickets',yaxis_title='Density')
fig.show()
```

Hypothesis Testing

Paired T Test

[148]:
```
df_third.describe()
```

[148]:

	first-category	sec-category
count	1707.000000	1707.000000
mean	1.647920	13.127709
std	1.351782	2.980216
min	0.000000	4.000000
25%	1.000000	11.000000
50%	1.000000	13.000000
75%	2.000000	15.000000
max	7.000000	20.000000

[149]:
```
ttest,pval=stats.ttest_rel(df_third['first-category'],df_third['sec-category'])
```

[150]:
```
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
0.0
reject null hypothesis
```

Current

0.0.2 ML

Correlation

[151]:
```
df_kohli=df_scorecard[df_scorecard['name']=='V Kohli']
```

[152]:
```
corr_val=df_kohli.drop(['match-id'],axis=1).corr()
corr_list=[]
for i in range(corr_val.shape[0]):
    corr_list.append(corr_val.iloc[:,i])
fig = go.Figure(data=go.Heatmap(
                   z=corr_list,
                   x=corr_val.columns,
                   y=corr_val.columns))
fig.show()
```

[153]:
```
columns = np.full((corr_val.shape[0],), True, dtype=bool)
for i in range(corr_val.shape[0]):
    for j in range(i+1, corr_val.shape[0]):
        if corr_val.iloc[i,j] >= 0.9:
            if columns[j]:
                columns[j] = False
```

[154]:
```
selected_columns = corr_val.columns[columns]
data = df_scorecard[selected_columns]
```

[156]:
```
x = df_kohli.loc[:,'balls-played'].values
y = df_kohli.loc[:, 'runs-scored'].values
```

[157]:
```
xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size = 1/3,␣
 ↪random_state = 0)
```

[158]:
```
linearRegressor = LinearRegression()
```

[159]:
```
yTrain = yTrain.reshape(1, -1)
xTrain = xTrain.reshape(1, -1)
yTest = yTest.reshape(1, -1)
xTest = xTest.reshape(1, -1)
```

[160]:
```
linearRegressor.fit(xTrain, yTrain)
```

[160]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[ ]:
```
yPrediction = linearRegressor.predict(xTest)
```

[ ]:
```

```

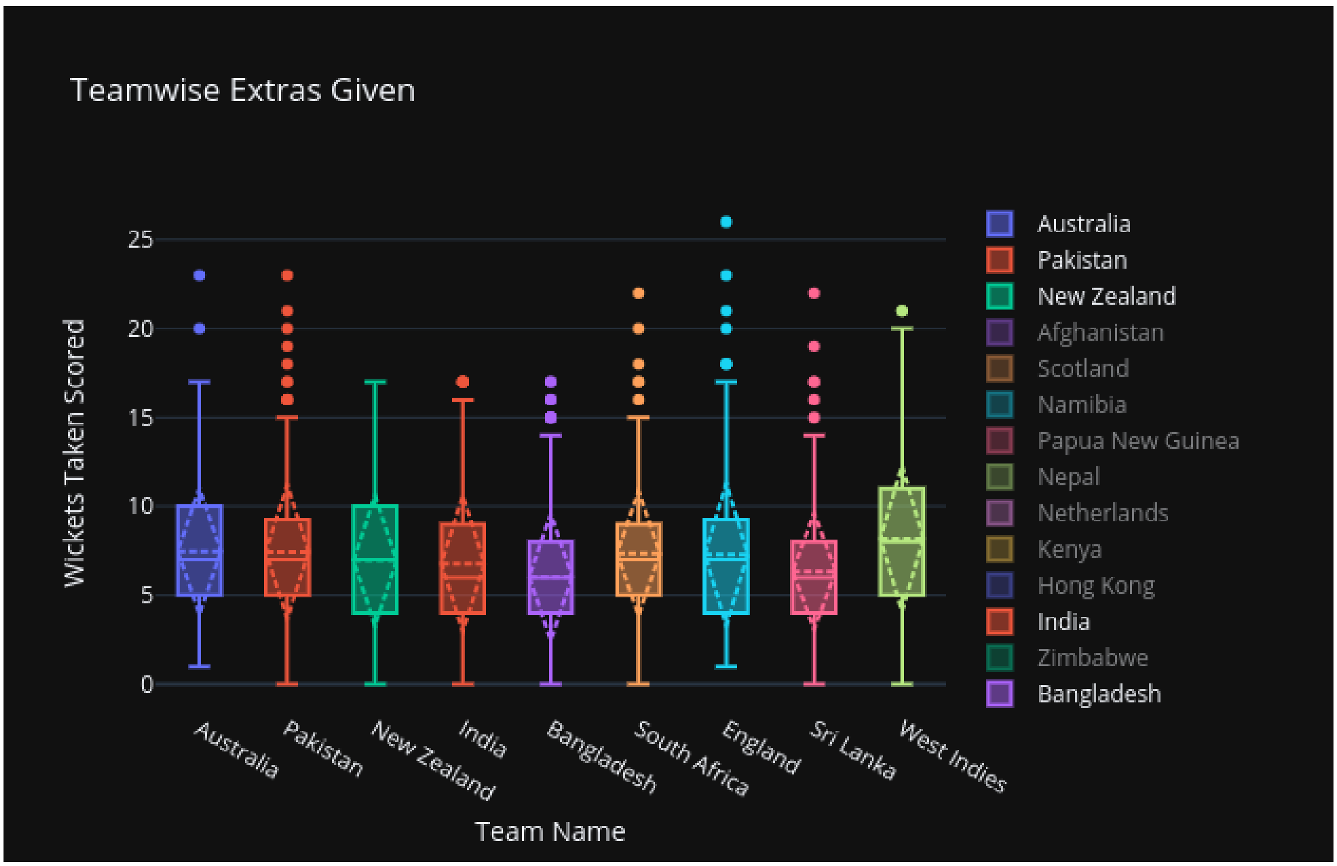

Figure 8. Teamwise extras given.

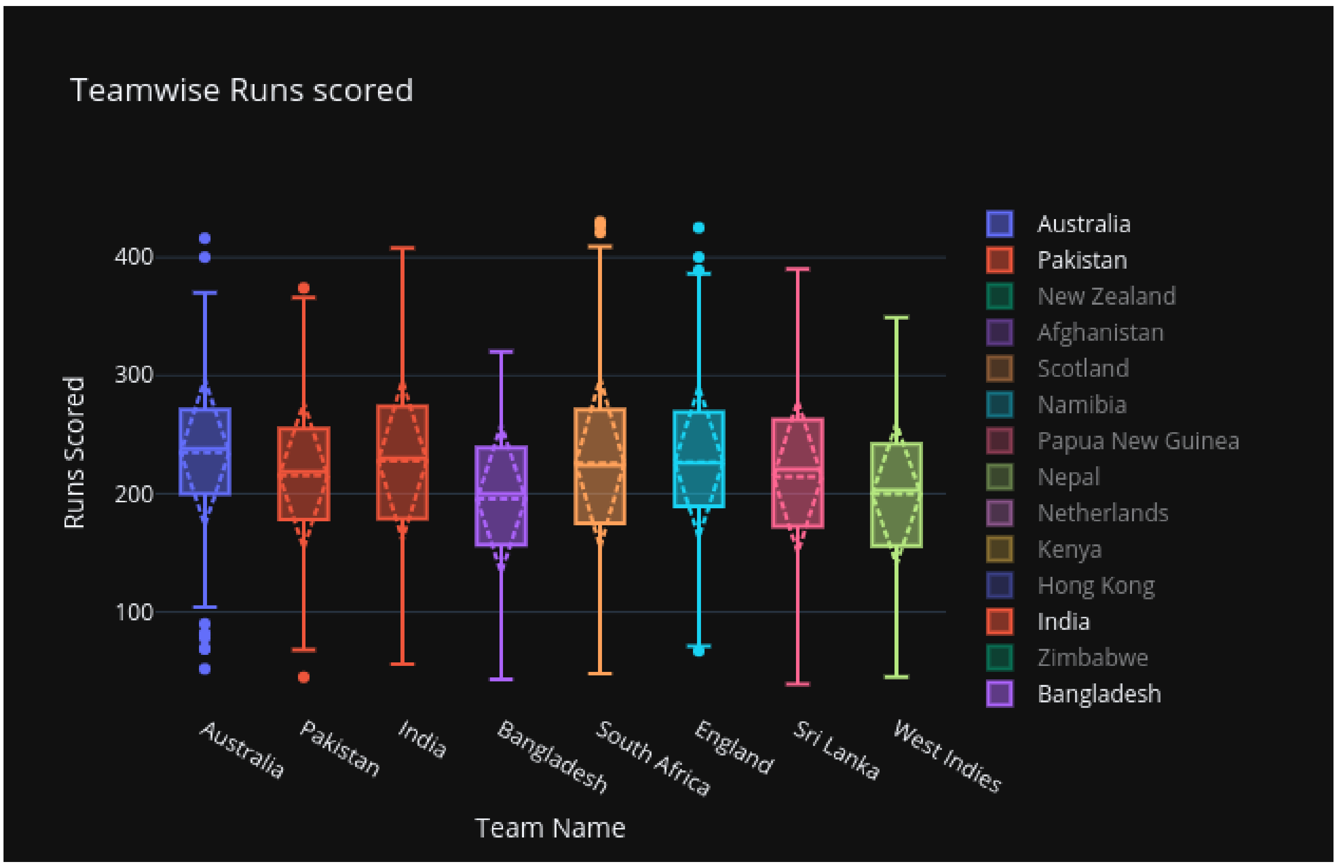

Figure 9. Teamwise runs scored.

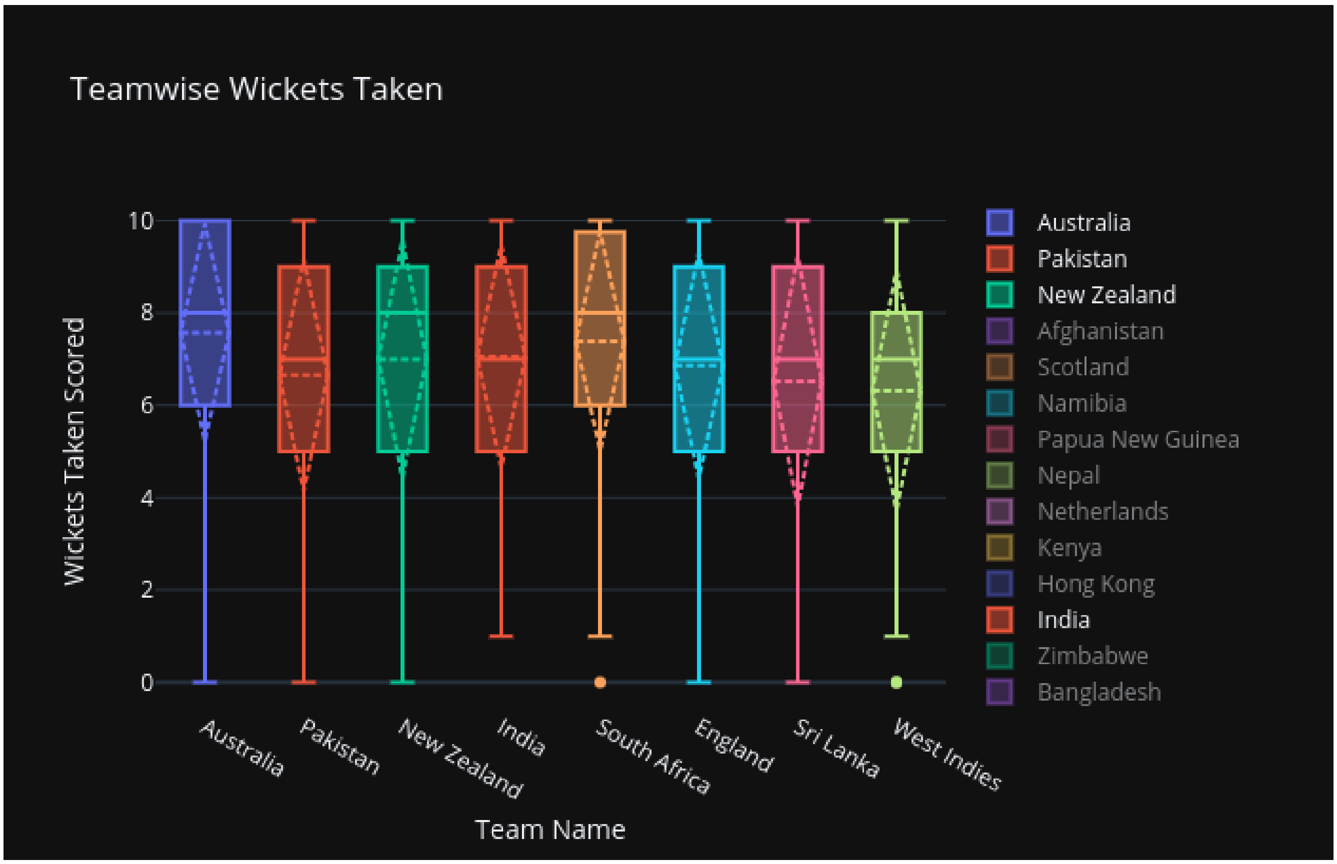

Figure 10. Teamwise wickets taken.

	lbw	bowled
count	1677.000000	1677.000000
mean	1.679785	2.774001
std	1.386744	1.684788
min	0.000000	0.000000
25%	1.000000	2.000000
50%	1.000000	3.000000
75%	2.000000	4.000000
max	8.000000	9.000000

Figure 11. Statistical analysis for data for first hypothesis.

```
8.855848765261422e-83
reject null hypothesis
```

Figure 12. First hypothesis result.

```
0.020019531021699132
reject null hypothesis
```

Figure 13. Second hypothesis result

```
0.25955086942355377
accept null hypothesis
```

Figure 14. Third hypothesis result

```
6.436197034363128e-225
reject null hypothesis
```

Figure 15. Fourth hypothesis result

```
8.92620766849228e-289
reject null hypothesis
```

Figure 16. Fifth hypothesis result

	first-seventy-wickets	last-thirty-wickets	first-seventyone-wickets	last-twentynine-wickets	first-fifty-wickets	last-fifty-wickets	first-ten-overs-wickets	last-ten-overs-wickets
count	1707.000000	1707.000000	1707.000000	1707.000000	1707.000000	1707.000000	1707.000000	1707.000000
mean	3.950791	4.100762	4.062097	3.989455	2.844757	5.206796	1.325718	3.445226
std	1.650583	1.652500	1.655468	1.647374	1.447369	1.790623	1.113937	1.594545
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.000000	3.000000	3.000000	3.000000	2.000000	4.000000	0.000000	2.000000
50%	4.000000	4.000000	4.000000	4.000000	3.000000	5.000000	1.000000	3.000000
75%	5.000000	5.000000	5.000000	5.000000	4.000000	6.000000	2.000000	5.000000
max	9.000000	9.000000	9.000000	9.000000	8.000000	10.000000	6.000000	9.000000

Figure 17. Statistical analysis for data for second, third, fourth and fifth hypothesis.

	first-category	sec-category
count	1707.000000	1707.000000
mean	1.647920	13.127709
std	1.351782	2.980216
min	0.000000	4.000000
25%	1.000000	11.000000
50%	1.000000	13.000000
75%	2.000000	15.000000
max	7.000000	20.000000

Figure 18. Statistical analysis for data for sixth hypothesis.

```
0.0
reject null hypothesis
```

Figure 19. Sixth hypothesis result

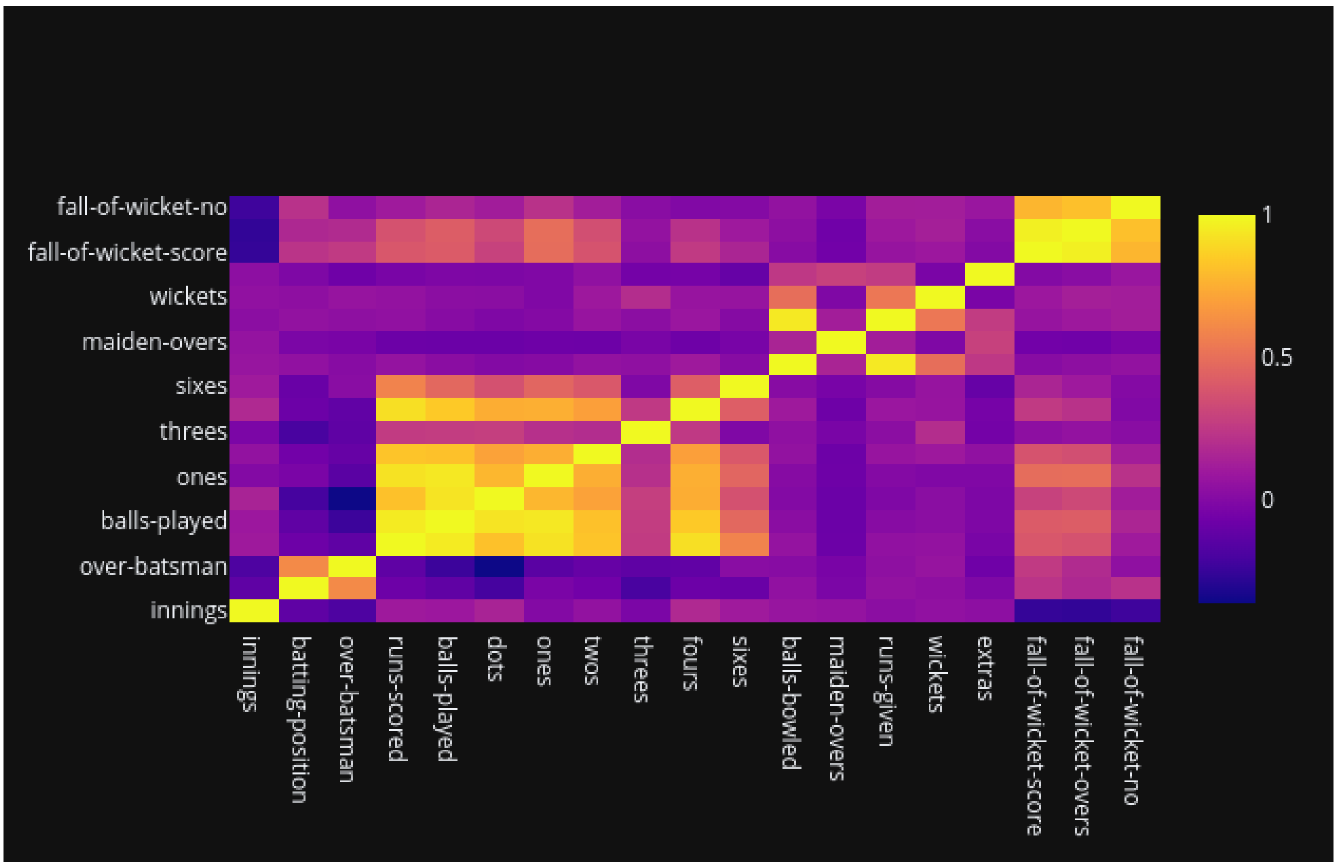

Figure 20. Correlation matrix of the scorecard for Virat Kohli