IPL_Predictor

November 19, 2018

1 An Accurate Calculation of Over-by-Over odds of winning an IPL Cricket Match

1.1 Overview

Often the Odds for a Cricket Team to win a match are swayed by the consensus of the general populus. This results in inaccurate and highly variable match predictions(odds calculations) often caused by speclators and spot-betters.

We aim to build a model that will help us identify, in most cases, the outcome of an IPL Match so that we can stay ahead of the curve and remain unfazed by the randomness of the match.

1.1.1 We have selected a very special match to infer from in the history of IPL from this dataset. It is the 2017 IPL finals between Mumbai Indians and Rising Pune Super-Giants

While Mumbai posed a paltry 129/8 in 20 Overs, they somehow managed to snatch the win out of Rising Pune's mouths as Pune went on to lose 3 wickets in the last over and failed to score 11 runs to win the match, 10 to draw, scoring only 9 and thereby losing by 1 single run.

We have taken our dataset from Kaggle Link: https://www.kaggle.com/manasgarg/ipl

This data set contains 2 csv sheets. One is the Ball-by-Ball Data and another is the overall outcome of a match. We combine both these data to create an over-by-over data with outcome of the match while adding several more features like required run-rate, current runrate, total wickets that fell in a single over to arrive to our inferences.

We train our Machine Learning Model with all the Over-by-Over data of all the matches in IPL. Assuming that all IPL teams start off on the same footing with equal budgets and such, each team must have some special team players like Pinch Hitters, Death-Over Specialist in Batting as well as fielding, all-rounders who come at 8 down or 9 down and still possess enough quality to win you a match.

Importing All the Relevant Package in one cell:

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

```
pd.set_option('display.max_columns', 50)
```

Importing Ball By Ball Data and Match Outcome Data

```
In [2]: deliveries_df = pd.read_csv("deliveries.csv")
        matches_df = pd.read_csv("matches.csv")

In [3]: deliveries_df.head()
```

Out[3]:

	match_id	inning	batting_team	bowling_team	over	ball	batsman	non_striker	bowler	is_super_over	wide_runs	bye_runs	legbye_runs	noball_runs	penalty_runs	batsman_runs	extra_runs	total_runs	player_dismissed	dismissal_kind	fielder
0	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1	1	DA Warner	S Dhawan	TS Mills	0	0	0	0	0	0	0	0	0	NaN	NaN	NaN
1	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1	2	DA Warner	S Dhawan	TS Mills	0	0	0	0	0	0	0	0	0	NaN	NaN	NaN
2	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1	3	DA Warner	S Dhawan	TS Mills	0	0	0	0	0	0	4	0	4	NaN	NaN	NaN
3	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1	4	DA Warner	S Dhawan	TS Mills	0	0	0	0	0	0	0	0	0	NaN	NaN	NaN
4	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	1	5	DA Warner	S Dhawan	TS Mills	0	0	2	0	0	0	0	2	2	NaN	NaN	NaN

```
In [4]: matches_df.head()
```

Out[4]:

	id	season	city	date	team1	team2	toss_winner	toss_decision
0	1	2017	Hyderabad	2017-04-05	Sunrisers Hyderabad	Royal Challengers Bangalore	Royal Challengers Bangalore	field
1	2	2017	Pune	2017-04-06	Mumbai Indians			
2	3	2017	Rajkot	2017-04-07	Gujarat Lions			
3	4	2017	Indore	2017-04-08	Rising Pune Supergiant			
4	5	2017	Bangalore	2017-04-08	Royal Challengers Bangalore			

```
1       Rising Pune Supergiant       Rising Pune Supergiant         field
2        Kolkata Knight Riders        Kolkata Knight Riders         field
3              Kings XI Punjab              Kings XI Punjab         field
4             Delhi Daredevils  Royal Challengers Bangalore           bat

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

   win_by_wickets player_of_match                                      venue  \
0               0    Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal
1               7       SPD Smith    Maharashtra Cricket Association Stadium
2              10         CA Lynn     Saurashtra Cricket Association Stadium
3               6      GJ Maxwell                     Holkar Cricket Stadium
4               0       KM Jadhav                      M Chinnaswamy Stadium

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

As mentioned above, since we are analysing for a particular season, we will take the matches taking place in **2017** only into consideration.

Also, since anomalies like D/L methods are highly irregular and random in nature and also dependent on external factors like rain, umpire's call etc, we clean those data out of our dataset.

In [5]:
```
# Let us take only the matches played in 2017 for this analysis #
matches_df = matches_df.loc[matches_df.season==2017,:]
matches_df = matches_df.loc[matches_df.dl_applied == 0,:]
matches_df.head()
```

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

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

```
4            Delhi Daredevils  Royal Challengers Bangalore           bat

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

   win_by_wickets player_of_match                                      venue  \
0               0    Yuvraj Singh  Rajiv Gandhi International Stadium, Uppal
1               7       SPD Smith    Maharashtra Cricket Association Stadium
2              10         CA Lynn     Saurashtra Cricket Association Stadium
3               6      GJ Maxwell                     Holkar Cricket Stadium
4               0       KM Jadhav                      M Chinnaswamy Stadium

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

Now that we are done with Data Cleaning, we can now create certain variables(stats) which will be helpful while inferring from our data.

Some of the important variables which I could think of are the following:

1. Total runs scored by each team
2. Total wickets remaining/total wickets fallen
3. Runs required/to be chased
4. Total target the team is chasing
5. Run Rate
6. Required Run Rate
7. Runs scored in last over
8. Wickets taken in last over
9. Difference between current run rate and required run rate
10. Binary variable representing the team for which we are predicting the win probability.

There are variables which can be created like:

1. Name of the Team
2. Name of the Opponent Team

3. Runs scored by the batting team in the last 'n' overs
4. Batsman
5. Bowler

However, we figured, while analysing for a team, minute interactions between two players does not matter much and usually the better team always wins.

```
In [6]: # runs and wickets per over #
        deliveries_df = pd.merge(deliveries_df, matches_df[['id','season', 'winner', 'result', '
        deliveries_df.player_dismissed.fillna(0, inplace=True)
        deliveries_df['player_dismissed'].loc[deliveries_df['player_dismissed'] != 0] = 1
        train_df = deliveries_df.groupby(['match_id', 'inning', 'over', 'team1', 'team2', 'batti
        train_df.columns = train_df.columns.get_level_values(0)
```

```
In [7]: # innings score and wickets #
        train_df['innings_wickets'] = train_df.groupby(['match_id', 'inning'])['player_dismissed
        train_df['innings_score'] = train_df.groupby(['match_id', 'inning'])['total_runs'].cumsu
        train_df.head()
```

Out[7]:

	match_id	inning	over	team1	team2	batting_team	winner	total_runs	player_dismissed	innings_wickets	innings_score
0	1	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	7	0	0	7
1	1	1	2	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	16	1	1	23
2	1	1	3	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	6	0	1	29
3	1	1	4	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	4	0	1	33
4	1	1	5	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	9	0	1	42

```
In [8]: # Get the target column #
        temp_df = train_df.groupby(['match_id', 'inning'])['total_runs'].sum().reset_index()
        temp_df = temp_df.ix[temp_df['inning']==1,:]
        temp_df['inning'] = 2
        # temp_df
        temp_df.columns = ['match_id', 'inning', 'score_target']
        train_df = train_df.merge(temp_df, how='left', on = ['match_id', 'inning'])
        train_df['score_target'].fillna(-1, inplace=True)
        train_df.head()
```

Out[8]:

	match_id	inning	over	team1	team2	batting_team	winner	total_runs	player_dismissed	innings_wickets	innings_score	score_target
0	1	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	7	0	0	7	-1.0
1	1	1	2	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	16	1	1	23	-1.0
2	1	1	3	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	6	0	1	29	-1.0
3	1	1	4	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	4	0	1	33	-1.0
4	1	1	5	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	9	0	1	42	-1.0

In [9]:
```
# get the remaining target #
def get_remaining_target(row):
    if row['score_target'] == -1.:
        return -1
    else:
        return row['score_target'] - row['innings_score']

train_df['remaining_target'] = train_df.apply(lambda row: get_remaining_target(row),axis
```

In [10]:
```
# get the run rate #
train_df['run_rate'] = train_df['innings_score'] / train_df['over']
```

In [11]:
```
# get the remaining run rate #
def get_required_rr(row):
    if row['remaining_target'] == -1:
        return -1.
    else:
        return row['remaining_target'] / (21-row['over'])

train_df['required_run_rate'] = train_df.apply(lambda row: get_required_rr(row), axis=1

def get_rr_diff(row):
    if row['inning'] == 1:
        return -1
    else:
        return row['run_rate'] - row['required_run_rate']
```

```
train_df['runrate_diff'] = train_df.apply(lambda row: get_rr_diff(row), axis=1)
train_df['is_batting_team'] = (train_df['team1'] == train_df['batting_team']).astype('i
train_df['target'] = (train_df['team1'] == train_df['winner']).astype('int')
```

In [12]:
```
train_df.head()
```

Out[12]:

	match_id	inning	over	team1	team2	batting_team	winner	total_runs	player_dismissed
0	1	1	1	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	7	0
1	1	1	2	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	16	1
2	1	1	3	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	6	0
3	1	1	4	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	4	0
4	1	1	5	Sunrisers Hyderabad	Royal Challengers Bangalore	Sunrisers Hyderabad	Sunrisers Hyderabad	9	0

	innings_wickets	innings_score	score_target	remaining_target	run_rate	required_run_rate	runrate_diff	is_batting_team	target
0	0	7	-1.0	-1.0	7.000000	-1.0	-1.0	1	1
1	1	23	-1.0	-1.0	11.500000	-1.0	-1.0	1	1
2	1	29	-1.0	-1.0	9.666667	-1.0	-1.0	1	1
3	1	33	-1.0	-1.0	8.250000	-1.0	-1.0	1	1
4	1	42	-1.0	-1.0	8.400000	-1.0	-1.0	1	1

Now let us split the data and keep the final match as our validation sample.

In [13]:
```
x_cols = ['inning', 'over', 'total_runs', 'player_dismissed', 'innings_wickets', 'innin

# let us take all the matches but for the final as development sample and final as val
final_df = train_df.ix[train_df.match_id == 59,:]
model_df = train_df.ix[train_df.match_id != 59,:]
final_df.head()
```

Out[13]:

	match_id	inning	over	team1	team2
2185	59	1	1	Mumbai Indians	Rising Pune Supergiant
2186	59	1	2	Mumbai Indians	Rising Pune Supergiant
2187	59	1	3	Mumbai Indians	Rising Pune Supergiant
2188	59	1	4	Mumbai Indians	Rising Pune Supergiant
2189	59	1	5	Mumbai Indians	Rising Pune Supergiant

```
        batting_team          winner  total_runs  player_dismissed  \
2185  Mumbai Indians  Mumbai Indians           3                 0
2186  Mumbai Indians  Mumbai Indians           4                 0
2187  Mumbai Indians  Mumbai Indians           2                 2
2188  Mumbai Indians  Mumbai Indians           2                 0
2189  Mumbai Indians  Mumbai Indians           5                 0

      innings_wickets  innings_score  score_target  remaining_target  \
2185                0              3          -1.0              -1.0
2186                0              7          -1.0              -1.0
2187                2              9          -1.0              -1.0
2188                2             11          -1.0              -1.0
2189                2             16          -1.0              -1.0

      run_rate  required_run_rate  runrate_diff  is_batting_team  target
2185      3.00               -1.0          -1.0                1       1
2186      3.50               -1.0          -1.0                1       1
2187      3.00               -1.0          -1.0                1       1
2188      2.75               -1.0          -1.0                1       1
2189      3.20               -1.0          -1.0                1       1
```

In [14]:
```
# create the input and target variables #
model_X = np.array(model_df[x_cols[:]])
model_y = np.array(model_df['target'])
final_X = np.array(final_df[x_cols[:]])[:,:]
final_y = np.array(final_df['target'])[:]
print(model_X.shape, model_y.shape)
print(final_X.shape, final_y.shape)
```

```
(2185, 12) (2185,)
(40, 12) (40,)
```

We are using Extra Trees Regressor from the Sci-Kit Learn Ensemble. We create a function for the same and run it.

The Reason for us using Extra Trees Regressor stems through the primary characteristics of our data. We explored some more classifiers but could not generate good results because of the following reasons: 1. k-Nearest Neighbours is rote learner and a lazy classifier such sort of classifiers work for small amount of data however fail for the large volume of features (classes) and data. Also, k-NN is very sensitive to noise. 2. Support Vector Machine based Regressors didn't lend ideal results for our project because intrinsically, SVMs are good for 2-dimensional i.e 2 class data. When we increase the dimensionality of the feature set, it becomes difficult for the machine to compute good values and it becomes tough for us to visualize the working of SVM past 3 dimensions. Whilst it's quite known that Tree based algorithm usually do better than SVMs in structured data. 3. Logistic Regression, similar to SVM has computational problems with multiclass data(features>2) but it lended results better than k-NN since it functions a bit better at handling noise/outliers and less usefull features. 4. We finally arrived to Tree based algorithms and Ensemble based learners and we had 2 more options:

4.1 Gradient Boosting Trees: Gradient Boosting Trees are good classifiers, however they use averaging from their decision(regression trees) rather than the Bootstrap and Bias method used by Random Forest and Random Forest Based Classifiers. This results in them filtering out all the outliers better than Random Forest. However, we, in IPL Data require more sensitivity towards outliers since some of the exciting nail-bitimg matches are decided in death overs and while boosting dictates to declare this as an outlier, we know that matches like IPL Finals should ideally belong to such outliers, being a competition between 2 very good teams.

4.2 Random Forest Classifiers: Within Random Forest Classifiers and Regressors, which uses Decision Trees is good enough as such, however Extra Trees was better because it uses an aggregation algorithm for its Decision Trees which is even more better and less biased to outliers than Random Forests. Random Forest assigns a default bias to poorly performing Decision Trees(also known as weak learners), however, Extra Trees uses feature selection on a case-by-case randomized basis instead of Random Forest's bias based selection process. This, being more robust and more sensitive to outliers performs the best for our project.

```
In [15]: # define the function to create the model #
         def ETRegr(train_X, train_y, seed_val=0):
             clf = ExtraTreesRegressor(n_estimators = 15, criterion='mae',min_samples_split=2)
             model = clf.fit(train_X,train_y)
             return model
```

We now are all set to build our predictive model.

```
In [16]: model = ETRegr(model_X, model_y)
         preds = model.predict(final_X)
```

```
In [17]: out_df = pd.DataFrame({'Team1':final_df.team1.values})
         out_df['is_batting_team'] = final_df.is_batting_team.values
         out_df['innings_over'] = np.array(final_df.apply(lambda row: str(row['inning']) + "_" +
         out_df['innings_score'] = final_df.innings_score.values
         out_df['innings_wickets'] = final_df.innings_wickets.values
         out_df['score_target'] = final_df.score_target.values
         out_df['total_runs'] = final_df.total_runs.values
         out_df['player_dismissed'] = final_df.player_dismissed.values
         out_df['run_rate'] = final_df.run_rate.values
         out_df['runrate_diff'] = final_df.runrate_diff.values
         out_df['predictions'] = list(preds)
         out_df.head()
```

Out[17]:

	Team1	is_batting_team	innings_over	innings_score	innings_wickets	score_target	total_runs	player_dismissed	run_rate	runrate_diff	predictions
0	Mumbai Indians	1	1_1	3	0	-1.0	3	0	3.00	0.0	0.0
1	Mumbai Indians	1	1_2	7	0	-1.0	4	0	3.50	0.0	0.0
2	Mumbai Indians	1	1_3	9							
3	Mumbai Indians	1	1_4	11							
4	Mumbai Indians	1	1_5	16							

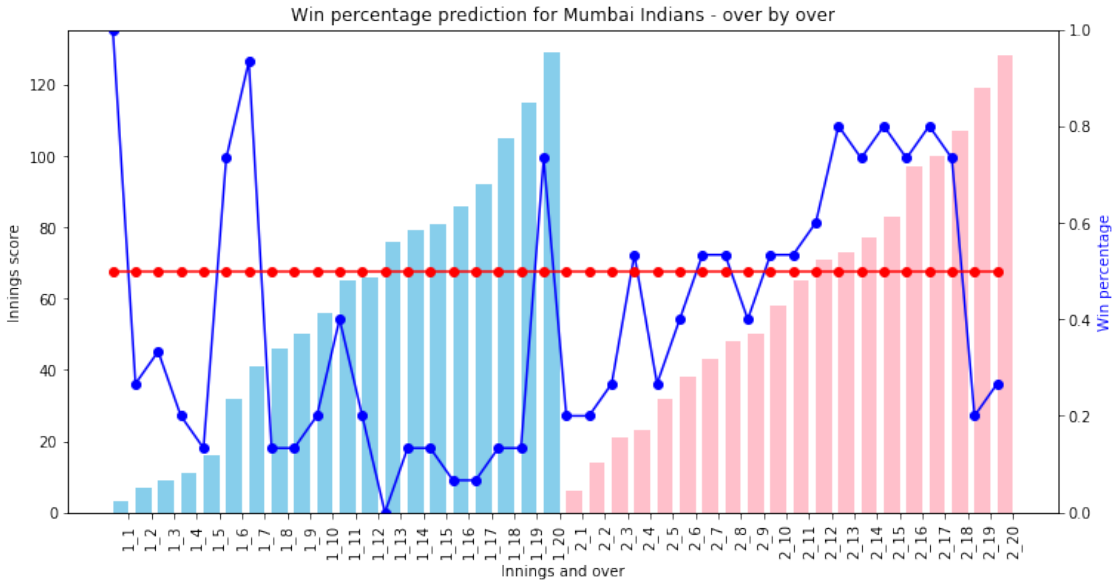
```
2                2          -1.0          2                2       3.00
3                2          -1.0          2                0       2.75
4                2          -1.0          5                0       3.20
```

```
   runrate_diff  predictions
0          -1.0     1.000000
1          -1.0     0.266667
2          -1.0     0.333333
3          -1.0     0.200000
4          -1.0     0.133333
```

In [18]:
```
fig, ax1 = plt.subplots(figsize=(12,6))
ax2 = ax1.twinx()
labels = np.array(out_df['innings_over'])
ind = np.arange(len(labels))
width = 0.7
rects = ax1.bar(ind, np.array(out_df['innings_score']), width=width, color=['skyblue']*
ax1.set_xticks(ind+((width)/2.))
ax1.set_xticklabels(labels, rotation='vertical')
ax1.set_ylabel("Innings score")
ax1.set_xlabel("Innings and over")
ax1.set_title("Win percentage prediction for Mumbai Indians - over by over")

ax2.plot(ind-0.35, np.array(out_df['predictions']), color='b', marker='o')

ax2.plot(ind-0.35, np.array([0.5]*40), color='red', marker='o')
ax2.set_ylabel("Win percentage", color='b')
ax2.set_ylim([0,1])
ax2.grid(b=False)
plt.show()
```



Light Blue Bars denote the overs played by Mumbai Indians. Baby Pink Bars denote the overs batted by Rising Pune Super-Giants.

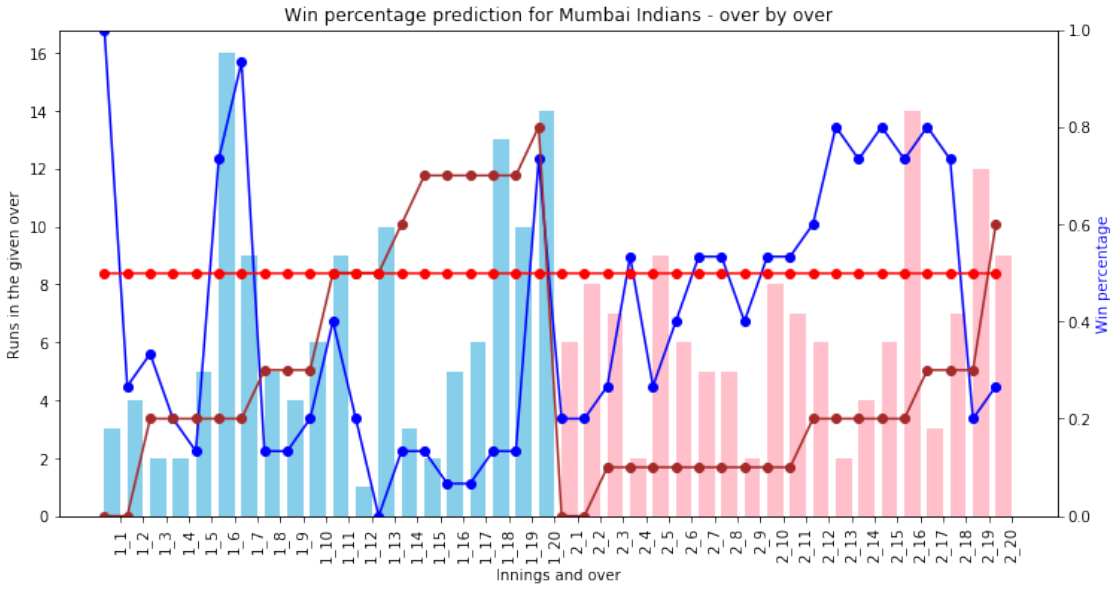
Red line represents the equal win probability and dark blue line represents the win probability of MI at the end of each over.

While an overall trend can be seen while plotting our win probability v/s cumulative runs scored by both the teams, it's nothing too profound and probably poor data visualisation. So we look to runs scored in each over where the inferences get more exciting.

So let us look at the same graph by using the number of runs scored in that over in place of overall runs.

```
In [19]: fig, ax1 = plt.subplots(figsize=(12,6))
         ax2 = ax1.twinx()
         labels = np.array(out_df['innings_over'])
         ind = np.arange(len(labels))
         width = 0.7
         rects = ax1.bar(ind, np.array(out_df['total_runs']), width=width, color=['skyblue']*20
         ax1.set_xticks(ind+((width)/2.))
         ax1.set_xticklabels(labels, rotation='vertical')
         ax1.set_ylabel("Runs in the given over")
         ax1.set_xlabel("Innings and over")
         ax1.set_title("Win percentage prediction for Mumbai Indians - over by over")

         ax2.plot(ind-0.35, np.array(out_df['predictions']), color='b', marker='o')
         ax2.plot(ind-0.35, np.array(out_df['innings_wickets']/10), color='brown', marker='o')
         ax2.plot(ind-0.35, np.array([0.5]*40), color='red', marker='o')
         ax2.set_ylabel("Win percentage", color='b')
         ax2.set_ylim([0,1])
         ax2.grid(b=False)
         plt.show()
```



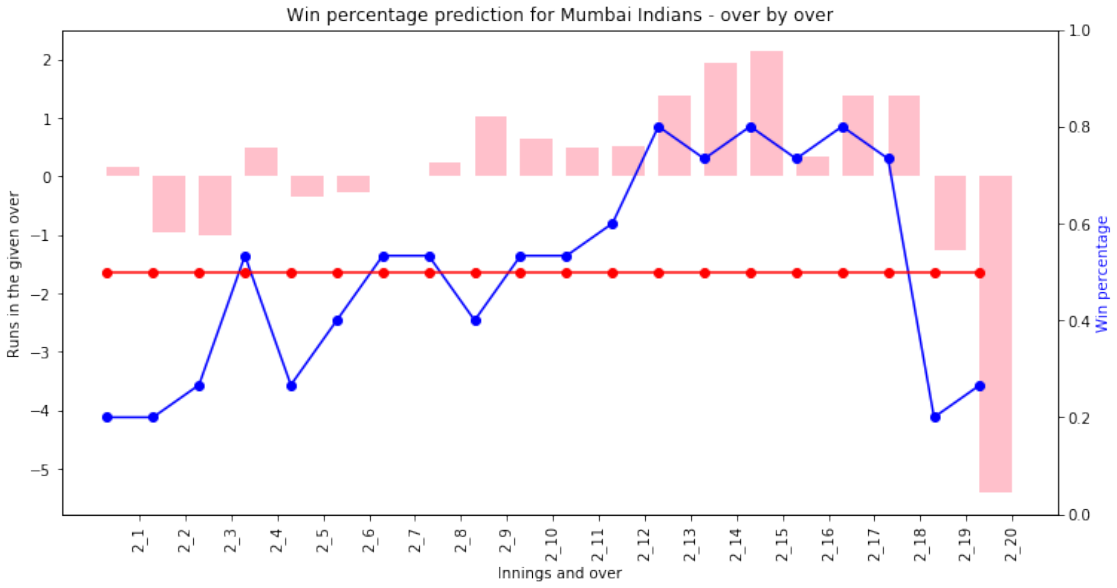
We have also added the wicket plot to better analyse the win probability variation while the runs scored per over varies.

We can see a direct correlation between the run scored in an over and the affect it has on the odds. We make predictions right untill the beginning of the 20th Over since there's no point in predicting the outcome after the match has finished.

Analysing win probability of Mumbai while Mumbai were batting from a microscope is probably moot because, while an increasing or decreasing trend for win probability can be noted for a good or a bad over for MI respectively, the value doesn't signify that much, hence we require to put the SRH innings through the microscope.

```
In [20]: fig, ax1 = plt.subplots(figsize=(12,6))
         ax2 = ax1.twinx()
         labels = np.array(out_df[20:]['innings_over'])
         ind = np.arange(len(labels))
         width = 0.7
         rects = ax1.bar(ind, np.array(out_df[20:]['runrate_diff']*(-1)), width=width, color=['p
         ax1.set_xticks(ind+((width)/2.))
         ax1.set_xticklabels(labels, rotation='vertical')
         ax1.set_ylabel("Runs in the given over")
         ax1.set_xlabel("Innings and over")
         ax1.set_title("Win percentage prediction for Mumbai Indians - over by over")

         ax2.plot(ind-0.35, np.array(out_df[20:]['predictions']), color='b', marker='o')
         #ax2.plot(ind-0.35, np.array(out_df['innings_wickets']/10), color='brown', marker='o')
         ax2.plot(ind-0.35, np.array([0.5]*20), color='red', marker='o')
         ax2.set_ylabel("Win percentage", color='b')
         ax2.set_ylim([0,1])
         ax2.grid(b=False)
         plt.show()
```



Now this is the best visualization we have come up with. This figure plots difference in run-rates between MI and RPS while we can visibly see the clear cause & effect relationship between the said parameter and the winning probability of Mumbai.

Note: Our model is not wrong to predict a meagre 0.4 win probability for Mumbai in the beginning of 20th Over. RPS had 7 wickets in hand going into the second last over. While 23 runs were required in the last 2 overs, RPS scored a whopping 12 runs which slid Mumbai's winning probability down too low. While Mumbai had the momentum from 10th Over onwards, RPS had it now and coudl've clearly taken the game home. However, 9 runs and 3 wickets and 6 balls later, Mumbai were declared winners in a historic nail-biting 1-run win

We can Infer from this the following things: 1. It's the safest to bet on the team that's on the upper foot during 2nd Innings Mid-Overs. 2. The Death Overs are highly unpredictable and it's safer to not bet on the basis of those results. 3. While wickets are important parameter throughout the match, the winning probability over 20-overs is more dependant on run-rate than anything else.