IPL Match Win Predictor: Final Report

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Introduction

The Indian Premier League (IPL) is a professional cricket league in India, which is held during April and May each year. Each team plays all other teams twice in a round-robin format.At the conclusion of the first stage, the top four teams will qualify for the Playoffs. The top two teams from the league phase will play against each other and the winner goes straight to the IPL final. The losing team plays the winner of the second match between the third and fourth team.

The Question Phase and some insights

The question which I will answer by the end of this project is "Given the previous data of IPL matches, who will win the next match?". There are various features which would contribute to predicting this outcome. This report shows the importance of some features which may prove significant for prediction and also identifies other features which will be calculated from the data sets. The importance of all these features will be confirmed with help of t-values and Beta constants determined by the prediction model. The model will predict a winner- team1 or team2. The team number will then be mapped to the name of the team for meaningful inference.

The Model

There are many machine learning models which can predict a categorical output. The most frequently used are logistic regression, Decision Trees and SVMs.I will be using decision trees for modelling my training set and applying the model to predict values on a test data set. The same procedure will be done for logistic regression. A comparison of the two models' accuracy will be ascertained. The plan also involves working with SVM's as they handle prediction well when the training dataset has limited number of observations.

Data Sanity / Tidying

The data is procured from a trusted source yet there are some sanity checks which are required to locate errors if any. I will start with reading the two csv files "matches.csv" and "deliveries.csv".

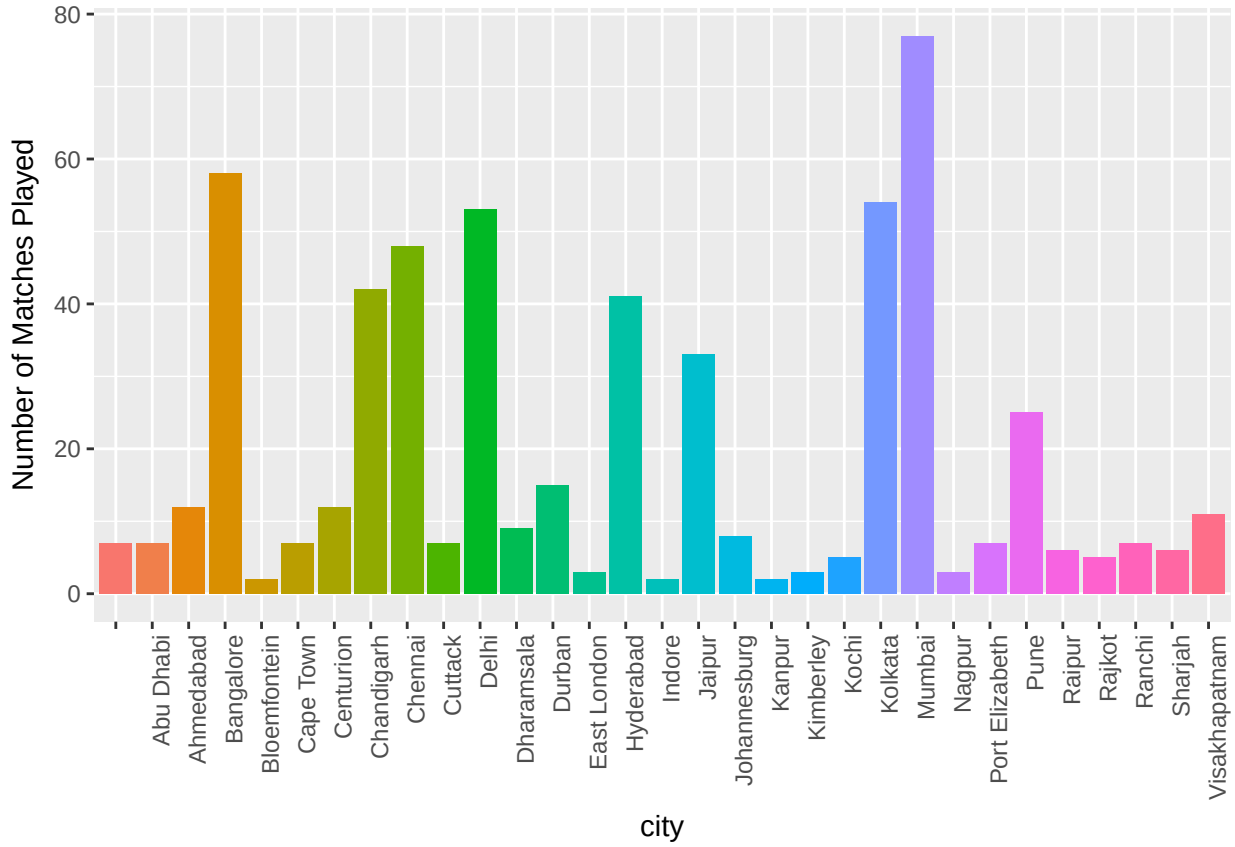
```
## 'data.frame':    577 obs. of  18 variables:
##  $ id              : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ season          : int  2008 2008 2008 2008 2008 2008 2008 2008 2008 2008 ...
##  $ city            : Factor w/ 31 levels "","Abu Dhabi",..: 4 8 11 23 22 17 15 9 15 8 ...
##  $ date            : Factor w/ 407 levels "2008-04-18","2008-04-19",..: 1 2 2 3 3 4 5 6 7 8 ...
##  $ team1           : Factor w/ 13 levels "Chennai Super Kings",..: 7 1 10 8 2 5 2 1 2 5 ...
##  $ team2           : Factor w/ 13 levels "Chennai Super Kings",..: 12 5 3 12 7 10 3 8 10 8 ...
##  $ toss_winner     : Factor w/ 13 levels "Chennai Super Kings",..: 12 1 10 8 2 5 2 8 10 8 ...
##  $ toss_decision   : Factor w/ 2 levels "bat","field": 2 1 1 1 1 1 1 2 2 2 ...
##  $ result          : Factor w/ 3 levels "no result","normal",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ dl_applied      : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ winner          : Factor w/ 14 levels "","Chennai Super Kings",..: 8 2 4 13 8 11 4 2 11 6 ...
##  $ win_by_runs     : int  140 33 0 0 0 0 0 6 0 66 ...
##  $ win_by_wickets  : int  0 0 9 5 5 6 9 0 3 0 ...
##  $ player_of_match: Factor w/ 188 levels "","A Chandila",..: 26 100 101 117 42 171 181 107 185 76 ..
##  $ venue           : Factor w/ 35 levels "Barabati Stadium",..: 15 23 9 35 8 27 24 16 24 23 ...
##  $ umpire1         : Factor w/ 43 levels "A Nand Kishore",..: 6 26 4 38 9 4 19 16 6 4 ...
##  $ umpire2         : Factor w/ 45 levels "A Nand Kishore",..: 29 40 14 13 19 28 5 14 23 5 ...
##  $ umpire3         : logi  NA NA NA NA NA NA ...
```

```
## 'data.frame':    136598 obs. of  21 variables:
##  $ match_id        : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ inning          : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ batting_team    : Factor w/ 13 levels "Chennai Super Kings",..: 7 7 7 7 7 7 7 7 7 7 ...
##  $ bowling_team    : Factor w/ 13 levels "Chennai Super Kings",..: 12 12 12 12 12 12 12 12 12 12 ...
##  $ over            : int  1 1 1 1 1 1 1 2 2 2 ...
##  $ ball            : int  1 2 3 4 5 6 7 1 2 3 ...
##  $ batsman         : Factor w/ 436 levels "A Ashish Reddy",..: 354 61 61 61 61 61 61 61 61 61 ...
##  $ non_striker     : Factor w/ 431 levels "A Ashish Reddy",..: 61 352 352 352 352 352 352 352 352 351
##  $ bowler          : Factor w/ 334 levels "A Ashish Reddy",..: 204 204 204 204 204 204 204 334 334 33
##  $ is_super_over   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ wide_runs       : int  0 0 1 0 0 0 0 0 0 0 ...
##  $ bye_runs        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ legbye_runs     : int  1 0 0 0 0 0 1 0 0 0 ...
##  $ noball_runs     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ penalty_runs    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ batsman_runs    : int  0 0 0 0 0 0 0 0 4 4 ...
##  $ extra_runs      : int  1 0 1 0 0 0 1 0 0 0 ...
##  $ total_runs      : int  1 0 1 0 0 0 1 0 4 4 ...
##  $ player_dismissed: Factor w/ 413 levels "","A Ashish Reddy",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ dismissal_kind  : Factor w/ 10 levels "","bowled","caught",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ fielder         : Factor w/ 422 levels "","A Ashish Reddy",..: 1 1 1 1 1 1 1 1 1 1 ...
```

In the "season" variable, the dataset contains data for 9 seasons. There should be 9 distinct values for season in the data set and values should range from 2008 to 2016. The following snippet is the output of the unique command.

```
## [1] 2008 2009 2010 2011 2012 2013 2014 2015 2016
```

Moving forward plotting the value of the "city" variable will show if there are any anomalies.



The plot shows that there are some blank observations in the "city" variable. On further exploration, it was found that the "city" variable was empty for matches in Dubai in the year 2014. This is rectified in the tidying phase of the project. There are less number of matches in venues located in South Africa. This is because IPL was held in South Africa instead of India in 2009.

Moving on,the "team" variables should have 13 unique values. Till date 13 teams have participated in IPL over 9 years. This is confirmed by the following unique command on "team1" and "team2" variables.

```
##  [1] Kolkata Knight Riders       Chennai Super Kings
##  [3] Rajasthan Royals            Mumbai Indians
##  [5] Deccan Chargers             Kings XI Punjab
##  [7] Royal Challengers Bangalore Delhi Daredevils
##  [9] Kochi Tuskers Kerala        Pune Warriors
## [11] Sunrisers Hyderabad         Rising Pune Supergiants
## [13] Gujarat Lions
## 13 Levels: Chennai Super Kings Deccan Chargers ... Sunrisers Hyderabad
```

```
##  [1] Royal Challengers Bangalore Kings XI Punjab
##  [3] Delhi Daredevils            Kolkata Knight Riders
##  [5] Rajasthan Royals            Mumbai Indians
##  [7] Chennai Super Kings         Deccan Chargers
##  [9] Pune Warriors               Kochi Tuskers Kerala
## [11] Sunrisers Hyderabad         Rising Pune Supergiants
## [13] Gujarat Lions
## 13 Levels: Chennai Super Kings Deccan Chargers ... Sunrisers Hyderabad
```

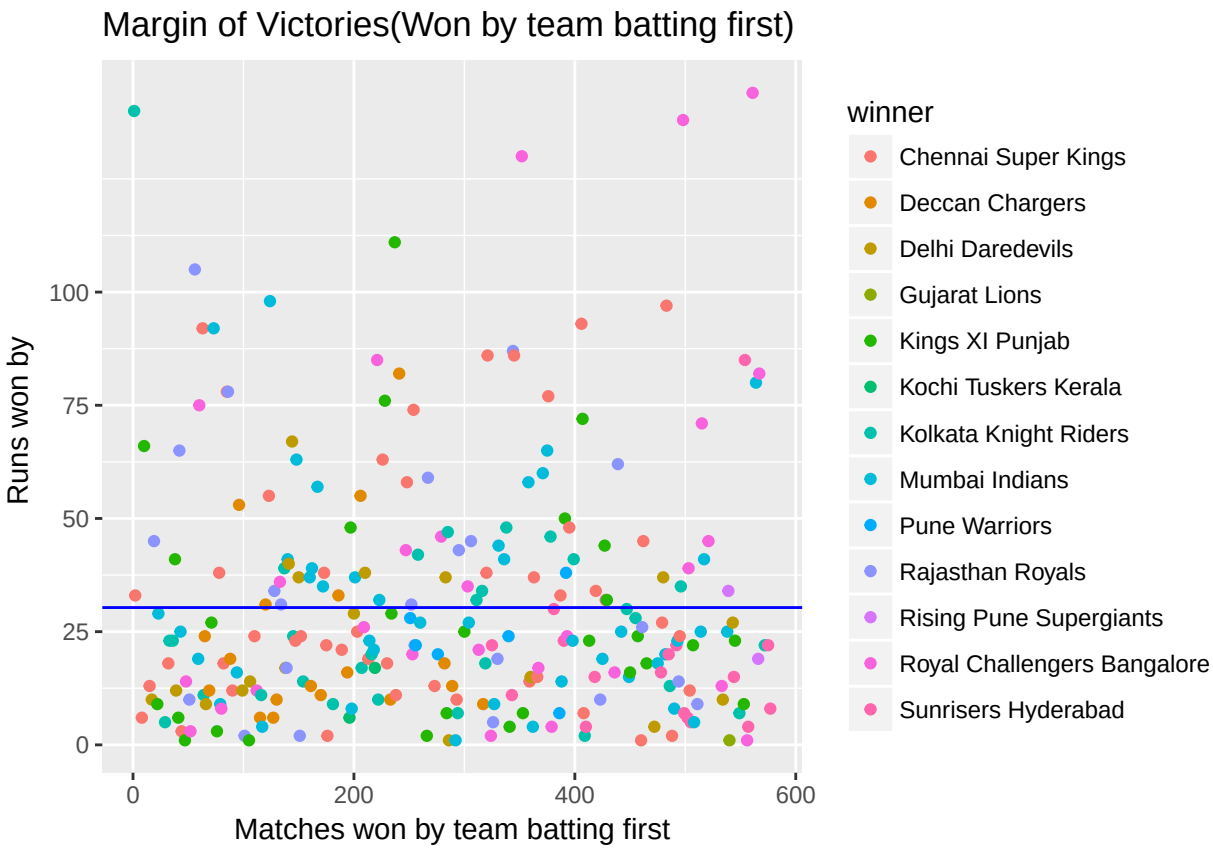
Similary the "toss decision" variable should have a binary value of field or bat.

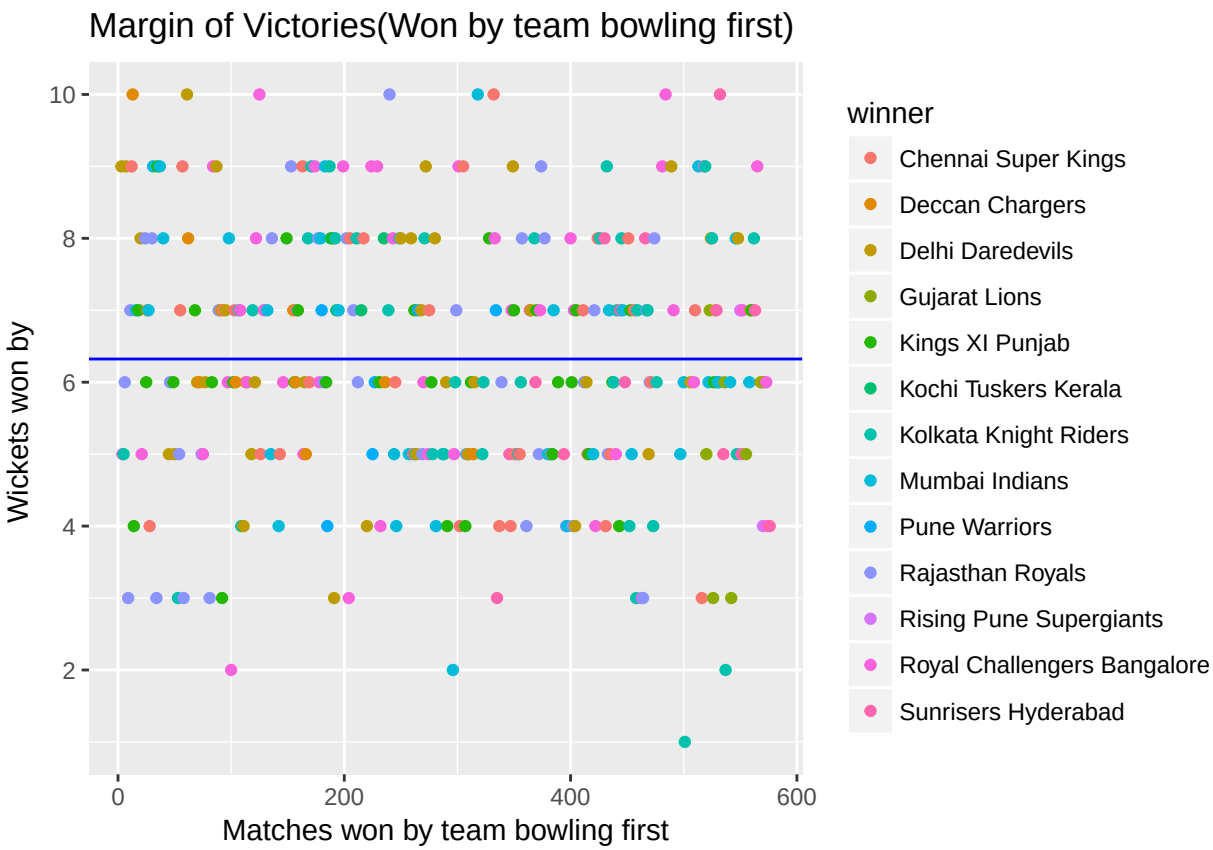
```
## [1] field bat
## Levels: bat field
```

"Winner"" variable should have 14 distinct values i.e 13 for the team names and 1 value for when the match is tied.

```
##  [1] Kolkata Knight Riders       Chennai Super Kings
##  [3] Delhi Daredevils            Royal Challengers Bangalore
##  [5] Rajasthan Royals            Kings XI Punjab
##  [7] Deccan Chargers             Mumbai Indians
##  [9] Pune Warriors               Kochi Tuskers Kerala
## [11]                             Sunrisers Hyderabad
## [13] Rising Pune Supergiants     Gujarat Lions
## 14 Levels:  Chennai Super Kings Deccan Chargers ... Sunrisers Hyderabad
```

To find the number of outliers for the "win_by_runs" and "win_by_wickets", a plot is generated to map these variables against number of matches.



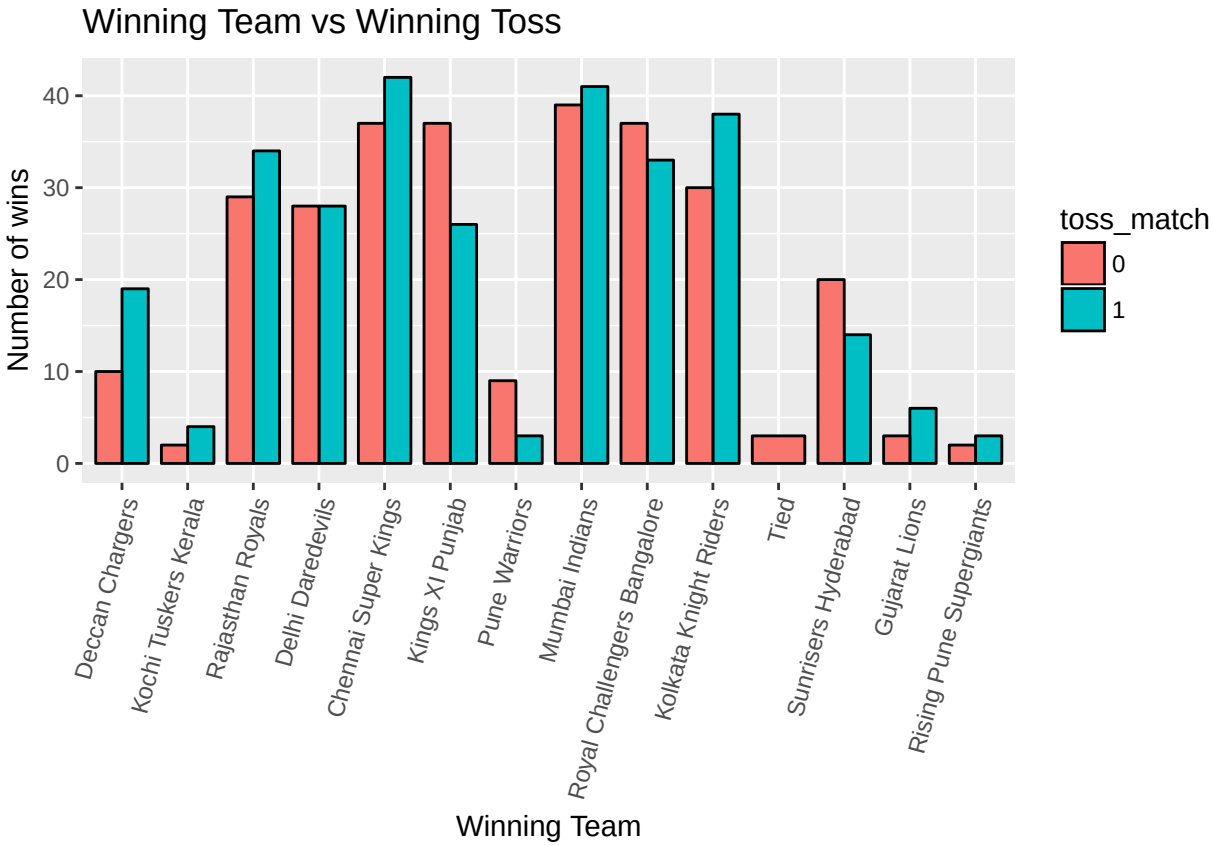


There are not more than 5 matches out of 577 which can be caetgorized as unusual. This is possible and hence no tidying or exploration is required.

Exploration

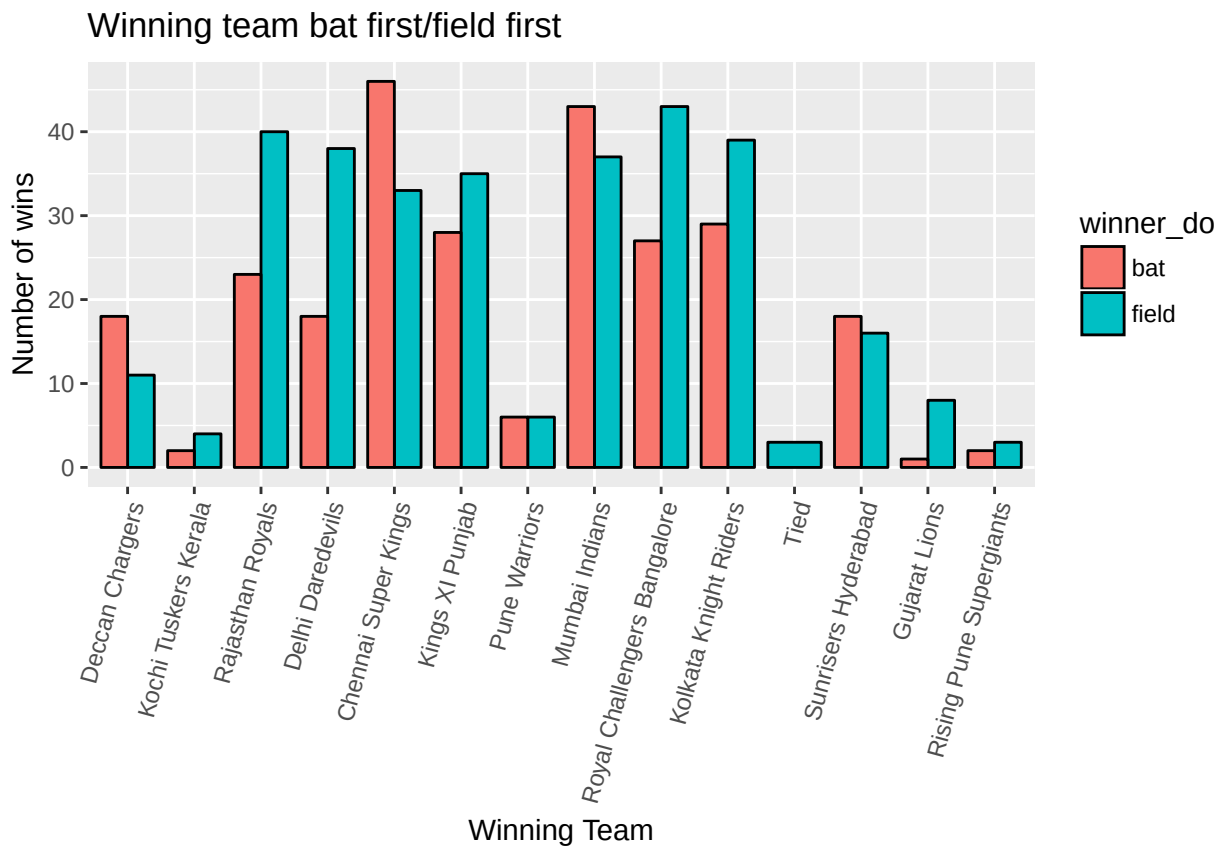
I will start exploring the most basic features which contributes to the sentiments of the winning team. Once these features are generated the machine learning model (Decision Trees) will make necessary inferences about the performance of each team.

The first feature which I explore is toss statistics. I have plotted a graph to depict the outcomes of each team on winning or losing a toss. For that we add two more variables namely "toss_match" and "winner_do". "toss_match"" variable shows that the team who won the toss won the match, and "winner_do" variable will indicate what the winning team opted for, i.e bat or field first.



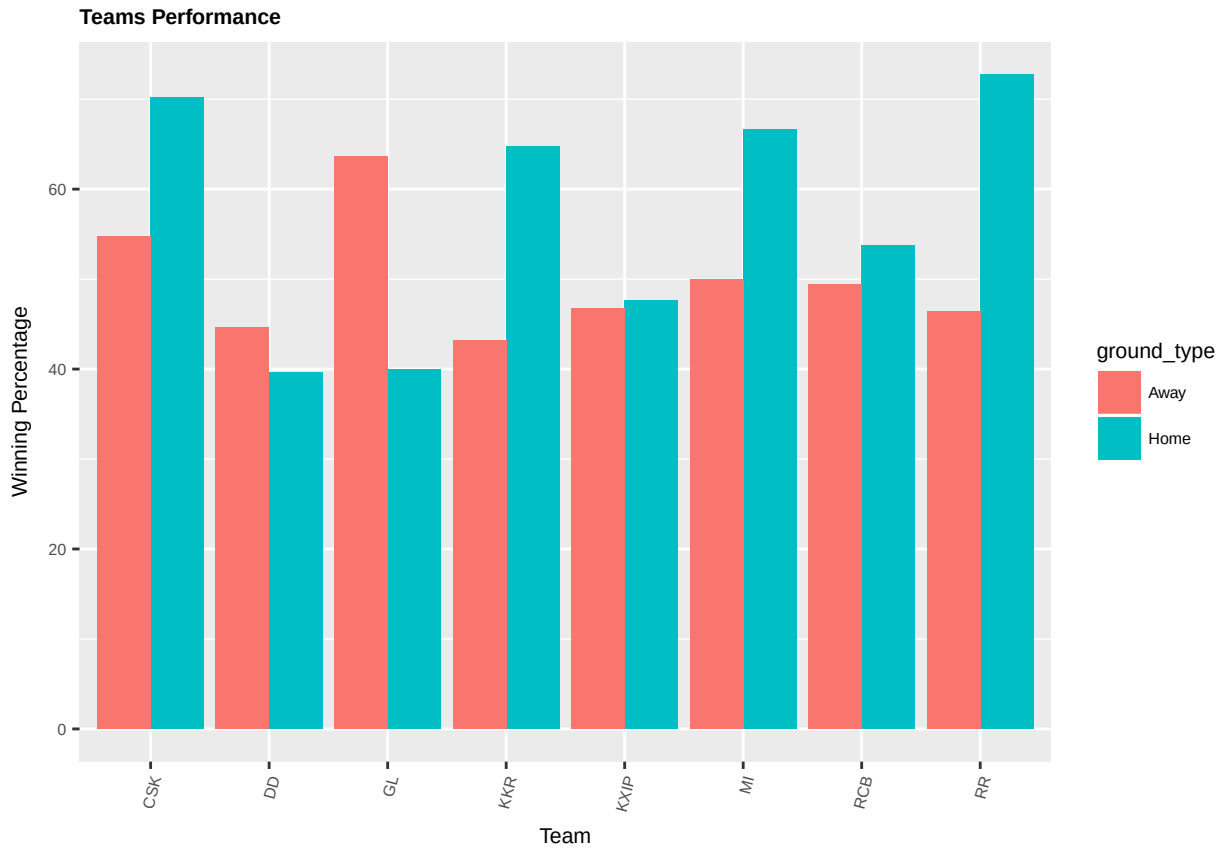
The plot shows that most teams have a higher winning percentage when they win the toss.

The next feature which I will explore is "what does a winning team elect for: Bat or Field first". This is to determine if there is a significant relevance of winning teams opting to bat or field.



There are some very interesting inferences in this graph. The team Gujarat Lions performs betterwhen it elects to field first. On the other hand, teams like Chennai Superkings and Deccan chargers do well when they elect to bat first. These inferences will help make deductions about the strength of each team.

Another imporant feature is the performance of teams on home and away grounds. It is a common notion that teams playing on their home grounds would perform better. The graph depicts the winning percentage of teams depending upon the location i.e “Home” or “Away”



Most teams perform well on their home ground, with the exception of Gujarat Lions and Delhi Daredevils. However,Gujarat Lions has played only 16 matches as it is a new team. This is the reason for the anomaly in the graph. The data is too small to make a generalized statement about the team's performance on home/ away grounds. Eventually, this data will be normalized against a fixed number of matches to reduce the skew in the plot. The following table shows the total number of matches played by each team on their home ground and away ground and their winning percentages.

```
##    team ground_type total_match_played total_win winning_perc
## 1   CSK        Away                 84        46     54.76190
## 2   CSK        Home                 47        33     70.21277
## 3    DD        Away                 83        37     44.57831
## 4    DD        Home                 48        19     39.58333
## 5   KKR        Away                 81        35     43.20988
## 6   KKR        Home                 51        33     64.70588
## 7    MI        Away                 80        40     50.00000
## 8    MI        Home                 60        40     66.66667
## 9  KXIP        Away                 92        43     46.73913
## 10 KXIP        Home                 42        20     47.61905
## 11  RCB        Away                 83        41     49.39759
## 12  RCB        Home                 54        29     53.70370
## 13   RR        Away                 84        39     46.42857
## 14   RR        Home                 33        24     72.72727
## 15   GL        Away                 11         7     63.63636
## 16   GL        Home                  5         2     40.00000
```

The above performance metrics may help in predicting wins in the future. The next section is about identifying a feature vector to be provided to the model for prediction.

Feature Engineering

The following are the suggested features which are known to directly contribute to the performance of a team. These features will be calculated and provided as input to the machine learning model which can then be used to predict future matches.

Season

Depicts the year of the match Data type: int (to be converted to factor if needed)

city

Data type: factor

team1 toss win

Data type: binary int Possible outcomes : 1 if team1 won thte toss and 0 if it lost the toss

team2 toss win

Data type: binary int Possible outcomes : 1 if team2 won thte toss and 0 if it lost the toss

team1 bat/field first

Data type: binary int Possible outcomes: 1 if team1 fields first and 0 if it bats first

team2 bat/field first

Data type: binary int Possible outcomes: 1 if team2 fields first and 0 if it bats first

Percentage of matches won by team 1

Data type: float

Number of matches won by team 1

Data type: int

Winning record of team 1(Number of matches won - number of matches lost)

Data type: ternary int
positive value = 1
equal value = 0
negative value = -1

Percentage of matches won by team 2

Data type: float

Number of matches won by team 2

Data type: int

Winning record team 2 (Number of matches won - number of matches lost)

Data type: ternary int
positive value = 1
equal value = 0
negative value = -1

Team1 home/away

Data type: Binary int
home = 1
away = 0

Team2 home/away

Data type: Binary int
home = 1
away = 0

Average run rate of team1

Data type: float

Average run rate of team2

Data type: float

Difference of run rate team1 - team2

Data type: ternary int positive = 1 zero = 0 negative = -1

Average wicket rate per over team1

Data type: int (rounded)

Average wicket rate per over team2

Data type: int (rounded)

Applying Machine Learning

After normalizing variables such as "number of runs scored by a team" and "number of wickets taken by a team", I started applying machine learning models such as Logistic Regression, Decision Trees, and Random Forests. With a limited number of observations, the accuracy of the models may be affected. To summarize, we have plotted features with respect to the performance of team1 and team2. We are predicting which team will win from team1 and team2.

Logistic Regression

Logistic Regression is the simplest and fastest when it comes to predicting categorical variables. I created a model using 90% of the dataset as training and rest as testing. In the first iteration, I used all the features listed in the previous section. The summary of the model is shown below.

```
##
## Call:
## glm(formula = winner ~ t1ha + t1tw + t1twbf + t1twff + team1tm +
##     team1mw + team1wp + team1wr + team1rs + team1rspi + team1w +
##     team1wpi + t2ha + t2tw + t2twbf + t2twff + team2tm + team2mw +
##     team2wp + team2wr + team2rs + team2rspi + team2w + team2wpi,
##     family = "binomial", data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9222  -1.1936   0.7728   1.0271   1.7375
##
## Coefficients: (7 not defined because of singularities)
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.3374422  7.8655556   0.170   0.8650
## t1ha         0.0628625  0.2302539   0.273   0.7848
## t1tw         0.0743503  0.1925637   0.386   0.6994
## t1twbf              NA         NA      NA       NA
## t1twff              NA         NA      NA       NA
## team1tm      0.9106240  3.7671109   0.242   0.8090
## team1mw     -0.0042965  0.0638604  -0.067   0.9464
## team1wp     -0.0240996  0.0518556  -0.465   0.6421
## team1wr             NA         NA      NA       NA
## team1rs     -0.0001639  0.0006345  -0.258   0.7961
## team1rspi    0.0096247  0.0767363   0.125   0.9002
## team1w      -0.1288033  2.1283464  -0.061   0.9517
## team1wpi    -0.2041296  0.4919545  -0.415   0.6782
## t2ha         0.5299254  0.2446857   2.166   0.0303 *
## t2tw                NA         NA      NA       NA
## t2twbf              NA         NA      NA       NA
## t2twff              NA         NA      NA       NA
## team2tm      0.8787716  3.8237503   0.230   0.8182
## team2mw     -0.0312569  0.0567723  -0.551   0.5819
## team2wp      0.0689226  0.0476545   1.446   0.1481
## team2wr             NA         NA      NA       NA
## team2rs     -0.0001683  0.0006267  -0.269   0.7883
## team2rspi    0.0330493  0.0761013   0.434   0.6641
## team2w       0.3738558  2.1598847   0.173   0.8626
## team2wpi    -0.1054877  0.4873163  -0.216   0.8286
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 694.08  on 504  degrees of freedom
## Residual deviance: 656.88  on 487  degrees of freedom
## AIC: 692.88
##
## Number of Fisher Scoring iterations: 4
```

The model shows extreme collinearity in the features of teams batting or fielding first after winning or losing the toss. This is attributed to the original arrangement of data. Depending on the toss win, the data is arranged in such a way that team1 always bats first and team2 fields first. Removing these features from the model also increases the accuracy of predictions.

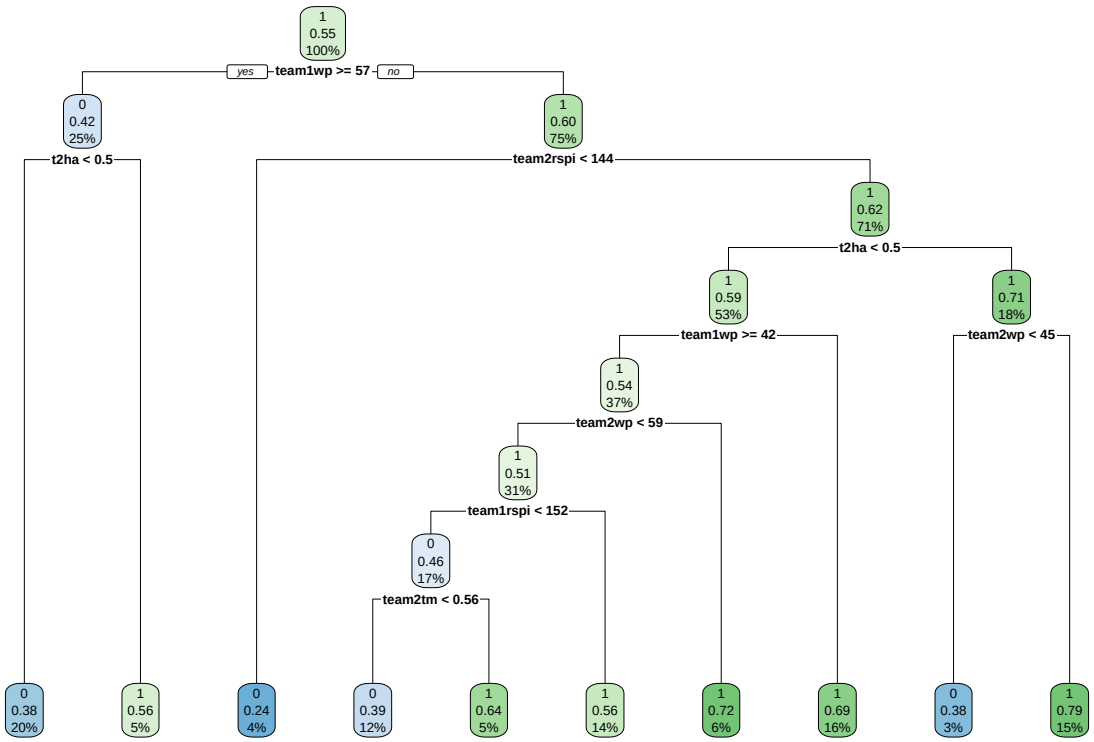
After trying various combinations of features, the final model predicts match wins with an accuracy of 62.5% which is an improvement from the first model which had an accuracy of about 55%. The model takes home advantage, total matches, toss win, winning percentage, runs per inning and total wickets of a team as features. The model also shows the significance of team1 and team2 home advantage. Home advantage is a thing, was also proved in our EDA section.

The confusion matrix of the model is shown below.

```
##
##     FALSE TRUE
##   0    19   17
##   1    10   26
```

Decision Trees

A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. In this case, the performance of decision trees is inferior to that of logistic regression. The tree and its accuracy are shown below.



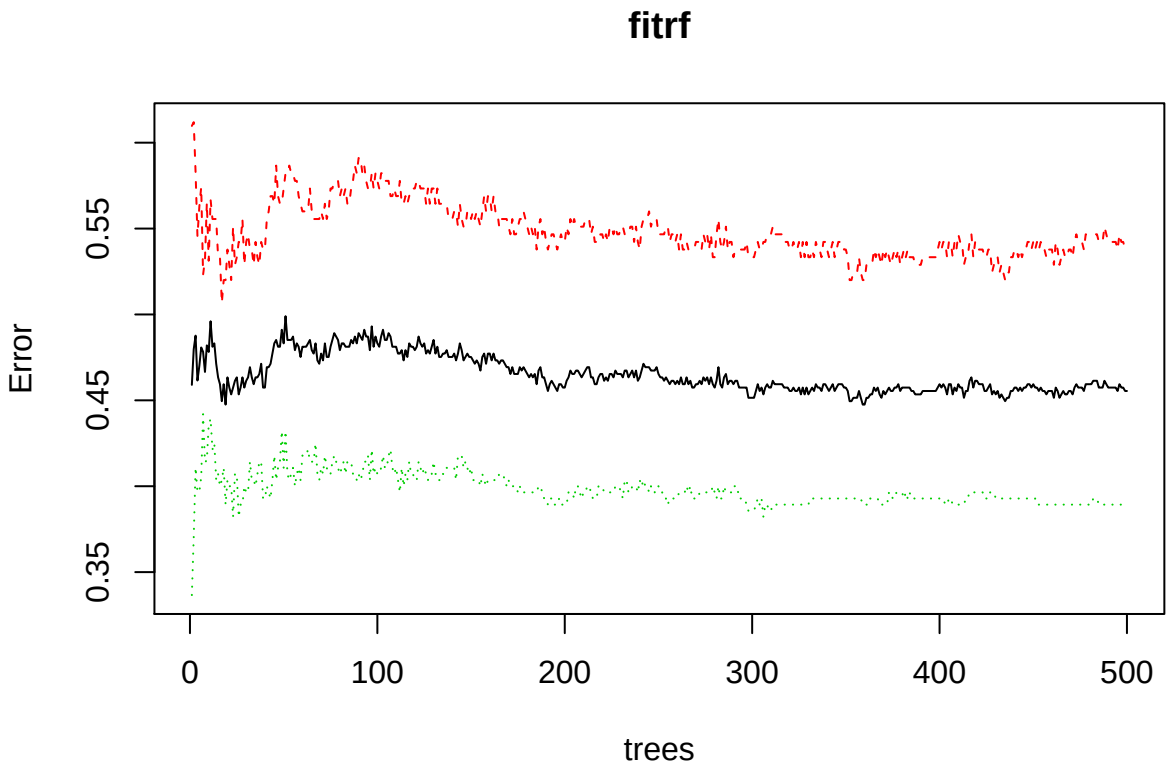

```
## [1] 58.33333
```

Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

In our case the performance of random forests is even lower than that of decision trees i.e 51.33% accuracy. This can be attributed to the fact that we have limited number of observation in our data set. This also proves that in some cases, logistic regression performs better than other machine learning models when the dataset is small.

```
##
## predictionrf  0  1
##            0 16 17
##            1 20 19
```



Conclusion and Future updates

It is evident that match win predictions highly rely on teams playing on home ground. Another important feature is the runs scored per innings by each team. The next iteration of the project would include calculating the strength of players of each team. The player strength index can then help build team strength index. This could be an important feature for predicting match outcomes. he predictor has to be combined with other staking strategies for increased accuracy.