Soccer Match Outcome Prediction

Gaurav Derasaria, Sharad Ghule, Aniket Shenoy, Prathamesh Jangam
School of Informatics, Computing and Engineering, Indiana University
Bloomington, USA, 47401

ABSTRACT

Soccer is a sport widely played and followed throughout Europe. We take data of 380 matches of English Premier League for the season of 2014 across 20 teams and try to build a multinomial logistic regression model that would predict the outcome of any match which can be win, loss or a draw. We use team attributes related to the play styles of both teams, select relevant features through exploratory data analysis, use feature engineering to build new features and try different models that would give us the highest accuracy. We are able to predict the outcome with 59.65% accuracy using a *Proportional Odds Logistic Regression* model which is higher than the accuracy with which bookies who take bets on the matches can predict.

Introduction

Soccer is one of the most followed sports in the world. Especially in Europe and South American countries, more than a game, soccer is a religion. Among the many European leagues, the English Premier League (EPL) is the most popular. In fact, the EPL is the most-watched sports league in the world, thereby generating millions in revenue. Betting on the outcome of matches is legal in Europe and is a billion dollar industry.

Goals:
The goal of this project is to predict the outcome of a match based on records of previous performances. We want to explore the potential of exploratory data analysis to maximize the odds of winning a bet.

Data Description:

The dataset comprised of an SQLite database with tables of matches, players and team attributes. Below is a summary of the dataset:

- +25,000 matches
- +10,000 players
- 11 European Countries
- Seasons 2008 to 2016
- Players and Teams' attributes sourced from EA Sports' FIFA video game series

Below are the snapshots of the raw data before preprocessing:

Figure 1: Matches Table

id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_api_id	home_team_goal	away_team_goal
1	1	1	2008/2009	1	2008-08-17 00:00:00	492473	9987	9993	1	1
2	1	1	2008/2009	1	2008-08-16 00:00:00	492474	10000	9994	0	0
3	1	1	2008/2009	1	2008-08-16 00:00:00	492475	9984	8635	0	3
4	1	1	2008/2009	1	2008-08-17 00:00:00	492476	9991	9998	5	0
5	1	1	2008/2009	1	2008-08-16 00:00:00	492477	7947	9985	1	3
6	1	1	2008/2009	1	2008-09-24 00:00:00	492478	8203	8342	1	1

Figure 2: Team Attributes

id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUpPlayDribbling	buildUpPlayDribblingClass	buildUpPlayPassing	buildUpPlayPassingClass
1	434	9930	2010-02-22 00:00:00	60	Balanced		Little	50	Mixed
2	434	9930	2014-09-19 00:00:00	52	Balanced	48	Normal	56	Mixed
3	434	9930	2015-09-10 00:00:00	47	Balanced	41	Normal	54	Mixed
4	77	8485	2010-02-22 00:00:00	70	Fast		Little	70	Long
5	77	8485	2011-02-22 00:00:00	47	Balanced		Little	52	Mixed
6	77	8485	2012-02-	58	Balanced		Little	62	Mixed

Data preprocessing:

We are working on a subset of the data that consists of the Matches table joined with the Team Attributes Table and we are only considering the _English Premier League_. Below is a snapshot of the data we are working with:

- 380 observations: Since 20 teams, each playing 2 matches against every other team, we have records of 380 matches.
- 18 numerical variables (on a scale of 100) represent one attribute for each team: Since there would have been duplication of attributes, 1 for each team, we decided to take a ratio of these attributes.

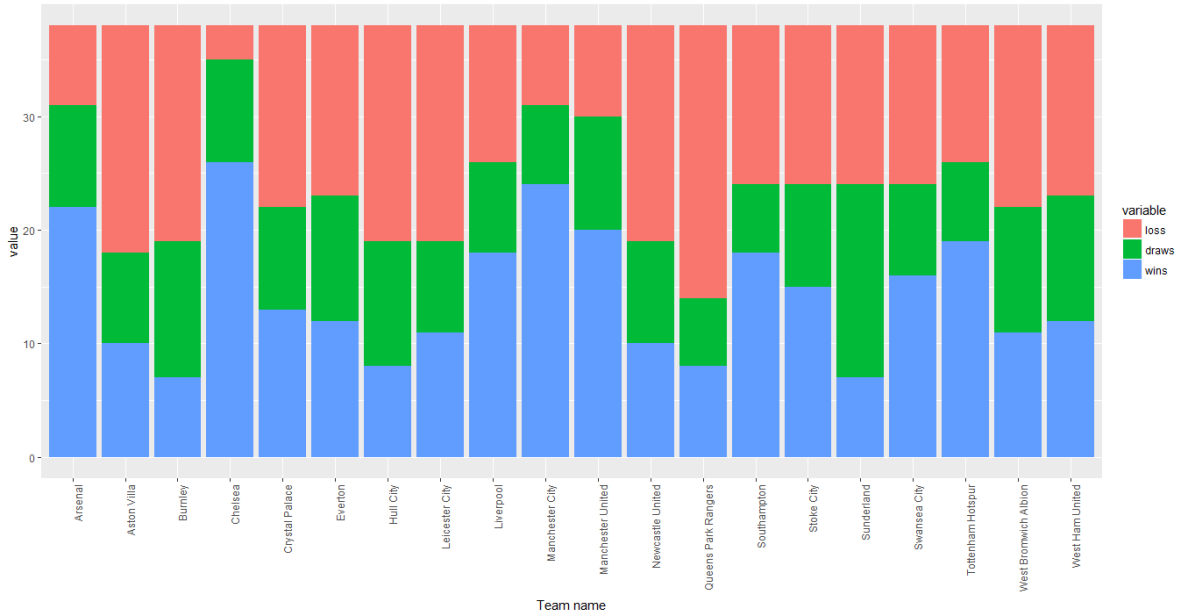
- 9 variables represent a ratio of an attribute for home vs. away team: After taking ratios of corresponding attributes, we ended up having 9 attributes of form (home_team_attribute/away_team_attribute)
- 1 multinomial predicted variable (win/loss/draw): Outcome of a match depends on the number of goals score by each team. We converted the number of goals by each team in 2 separate columns to a sinle column.
- Examples of attributes: buildUpPlaySpeed_ratio, buildUpPlayDribbling_ratio, defenceAggression_ratio, defenceTeamWidth_ratio

Below is a summary of the final dataset:

```
      id.x         season          home_team_api_id away_team_api_id result  buildUpPlaySpeed_ratio buildUpPlayDribbling_ratio
 Min.   :4009   Length:380         Min.   : 8191    Min.   : 8191    0:172   Min.   :0.5694         Min.   :0.4615
 1st Qu.:4104   Class :character   1st Qu.: 8470    1st Qu.: 8470    1: 93   1st Qu.:0.8571         1st Qu.:0.8953
 Median :4198   Mode  :character   Median : 8663    Median : 8663    2:115   Median :1.0000         Median :1.0000
 Mean   :4198                      Mean   : 9146    Mean   : 9146            Mean   :1.0238         Mean   :1.0313
 3rd Qu.:4293                      3rd Qu.:10045    3rd Qu.:10045            3rd Qu.:1.1667         3rd Qu.:1.1170
 Max.   :4388                      Max.   :10261    Max.   :10261            Max.   :1.7561         Max.   :2.1667
 buildUpPlayPassing_ratio chanceCreationPassing_ratio chanceCreationCrossing_ratio chanceCreationShooting_ratio defencePressure_ratio
 Min.   :0.3514           Min.   :0.3889              Min.   :0.5694               Min.   :0.4638               Min.   :0.4839
 1st Qu.:0.7258           1st Qu.:0.7640              1st Qu.:0.8644               1st Qu.:0.8276               1st Qu.:0.8039
 Median :1.0000           Median :1.0000              Median :1.0000               Median :1.0000               Median :1.0000
 Mean   :1.0998           Mean   :1.0719              Mean   :1.0201               Mean   :1.0489               Mean   :1.0389
 3rd Qu.:1.3778           3rd Qu.:1.3089              3rd Qu.:1.1569               3rd Qu.:1.2083               3rd Qu.:1.2439
 Max.   :2.8462           Max.   :2.5714              Max.   :1.7561               Max.   :2.1562               Max.   :2.0667
 defenceAggression_ratio defenceTeamWidth_ratio home_team_name     away_team_name
 Min.   :0.5312          Min.   :0.6613         Length:380         Length:380
 1st Qu.:0.8206          1st Qu.:0.8913         Class :character   Class :character
 Median :1.0000          Median :1.0000         Mode  :character   Mode  :character
 Mean   :1.0393          Mean   :1.0136
 3rd Qu.:1.2186          3rd Qu.:1.1220
 Max.   :1.8824          Max.   :1.5122
>
```

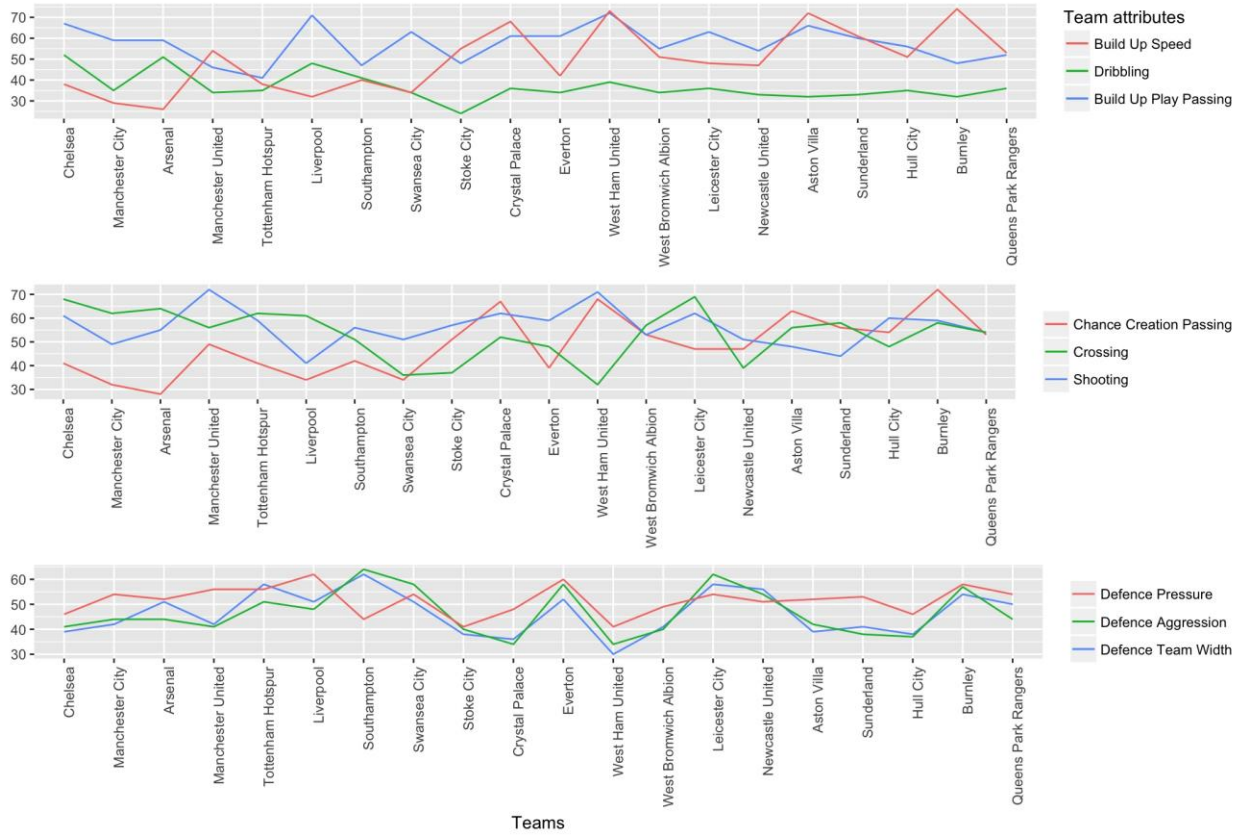
Exploring the dataset:

Figure 3. Wins/losses/draws



To get acquainted with the data, we try to plot the wins/draws/losses of all teams for the season. We see that every team plays 38 matches and there are 20 teams participating in the league. Thus, every team plays two matches with every other team in the league. After transforming the data so that it represents results for each team, we observe that the win/draw to loss ratio for team Chelsea seems to be the highest. We also know from our data that Chelsea won the league in that season. The team with the lowest wins/draws Queen Park Rangers have seemed to lose the season. Later we explore our data to see how the attributes of every team matter towards the result of a season.

Figure 4. Team Attribute Comparison

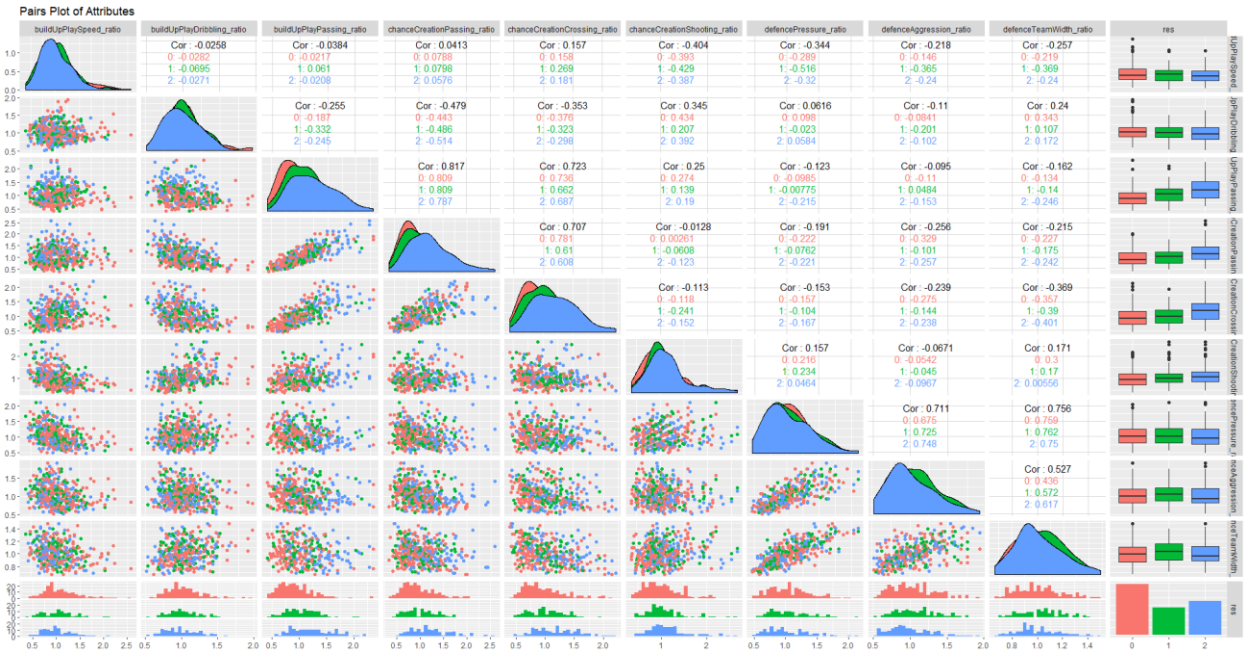


As we can see from above graph, the x-axis represents the teams in the league sorted on the total number of points in a descending order. The number points of any team is equal to their wins multiplied by three plus the number of their draws. It means that Chelsea score the highest points and Queen Park Rangers scoring the lowest points.

We facetted our plot to show three variables in each graph. We can argue that the winning team does not have higher attributes than the losing team or any other team. Majority attributes of teams do not actually seem to follow a pattern across the teams. On the other hand, we can also see that some attributes do follow a pattern. For example, we do see that dribbling of a team that has won the season seems to be higher and decreases as the points of teams go on

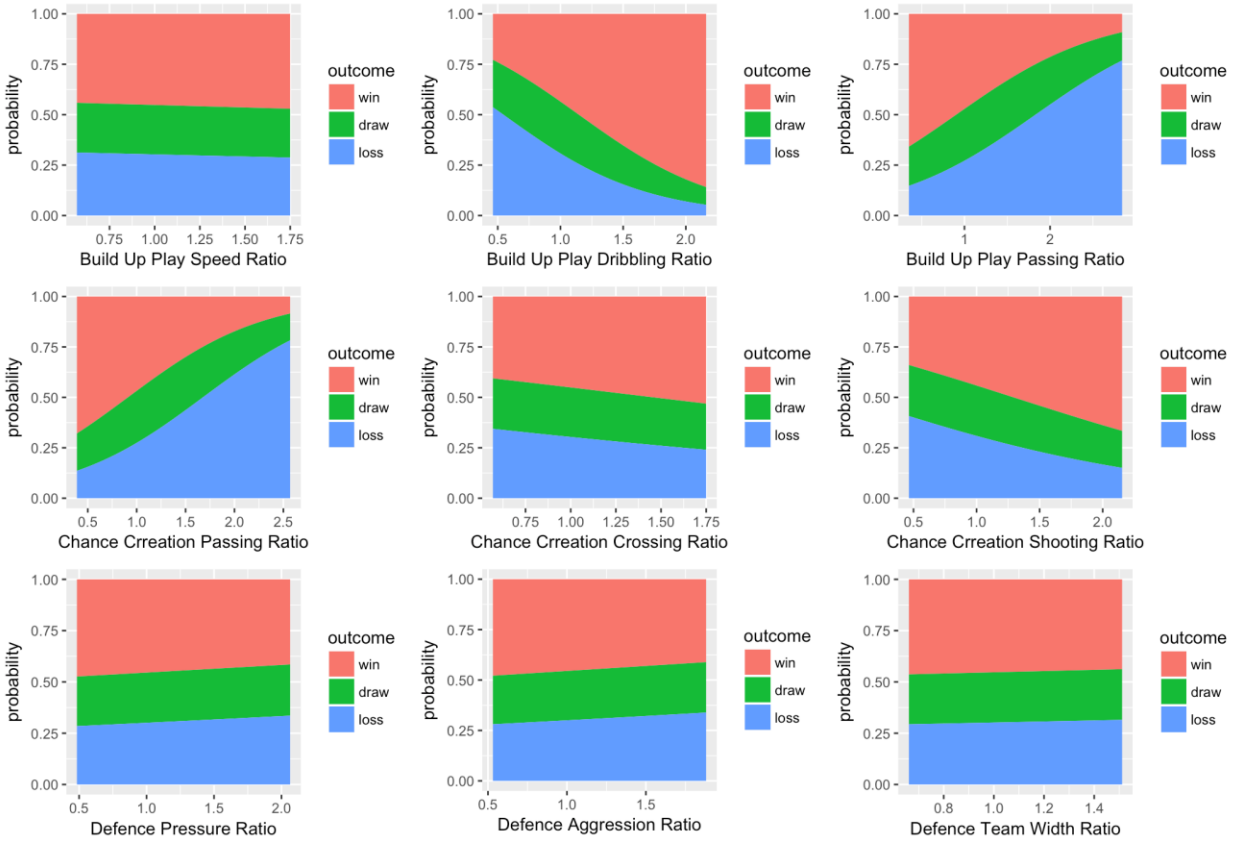
decreasing. Some attributes also actually seem to have a inverse relation. We can see that the chance creation passing seems to increase as the points scored by a team decreases.
Although the attributes do not seem to follow a pattern, we will still try to fit various models and continue our analysis to see if we can predict if a team wins, based on the ratio of its attributes to the attributes of the opposite team. In the next graph, we see how the ratios of attributes of different teams correlate with each other and the different classes they belong to.

Figure 5: Pairwise Correlation Among Attributes



We plotted the pairwise correlation between the ratios of attributes. The ratio of any attribute represents Home_Team_Attribute/Away_Team_Attribute and the prediction Win or Loss represents if the home team wins or home team losses respectively. We plot this graph to see which of our predictor variables have a high correlation. We can see that build up play passing ratio and the chance creation passing ratio seem to be highly correlated. We can also see that defense team width and defense pressure are highly correlated. Chance creation crossing and defense team width also seem to be highly correlated with other few attributes. We can thus see if dropping these variables can increase the accuracy of our model. We can also infer from the graph that no two of our variables together separate our result classes. We now try to perform a *Proportional Odds Logistic Regression* on our data and try to predict the outcome of the match. We first try to fit a *polr* model on our attributes individually and see how an individual attributes matter towards the predictions.

Figure 6: Attribute Selection



We decided to plot the probability of every outcome as a single attribute increases. The x-axis represents a pre-decided range of that attribute and the y axis represents the probability of an outcome. We can see that five out of 9 variables do not actually contribute to the outcome at all. Some attributes always give the highest probability of winning. Thus we can definitely say that we cannot use individual attributes to predict the outcome but we can also see that the graph of build up play passing and chance creation passing seems to be quite similar. We can see in both attributes as the attributes increase the probability of the team winning decreases. Thus we can conclude that dropping either variable will not affect our results much. In attributes, chance creation shooting and build play dribbling as the ratio increases, the probability of winning increases too.

Methods

POLR:

Since our response is an ordered categorical variable, we went ahead with ordered categorical regression using proportional odds logistic regression. The data was split into train and test sets with an 80:20 ratio.

1. **Model 1**

   As a preliminary model, we fit a polr model using all team attributes as dependent variables.

```
> m5.polr1
Call:
polr(formula = factor(result) ~ buildUpPlaySpeed_ratio + buildUpPlayDribbling_ratio +
    buildUpPlayPassing_ratio + chanceCreationPassing_ratio +
    chanceCreationCrossing_ratio + chanceCreationShooting_ratio +
    defencePressure_ratio + defenceAggression_ratio + defenceTeamWidth_ratio,
    data = m5.train)

Coefficients:
      buildUpPlaySpeed_ratio   buildUpPlayDribbling_ratio     buildUpPlayPassing_ratio  chanceCreationPassing_ratio
                   2.6967071                   -2.1357843                   -0.9516667                    2.6574128
chanceCreationCrossing_ratio chanceCreationShooting_ratio       defencePressure_ratio      defenceAggression_ratio
                   0.1330835                   -0.6296298                    4.8194513                   -2.7112242
      defenceTeamWidth_ratio
                  -0.2206415

Intercepts:
     0|1      1|2
3.584093 4.823948

Residual Deviance: 526.1071
AIC: 548.1071
>
```

   According to Occam's razor, a simpler model is a better model. Thus, we further analyse if we can reduce the complexity of the model by dropping some variables.

2. **Model 2**

   In the pairwise correlation plot in Figure 3, it can be seen that there is a high correlation between chanceCreationPassing_ratio and chanceCreationCrossing_ratio. Thus, we wanted to see if there would be a significant impact on the model when we drop any of these variables. In this model, we drop chanceCreationPassing_ratio.

```
> m5.polr2
Call:
polr(formula = factor(result) ~ buildUpPlaySpeed_ratio + buildUpPlayDribbling_ratio +
    buildUpPlayPassing_ratio + chanceCreationCrossing_ratio +
    chanceCreationShooting_ratio + defencePressure_ratio + defenceAggression_ratio +
    defenceTeamWidth_ratio, data = m5.train)

Coefficients:
      buildUpPlaySpeed_ratio   buildUpPlayDribbling_ratio     buildUpPlayPassing_ratio chanceCreationCrossing_ratio
                  2.45490440                  -1.84401913                   1.29024966                   0.07907531
chanceCreationShooting_ratio       defencePressure_ratio      defenceAggression_ratio      defenceTeamWidth_ratio
                 -0.48852067                   4.89892865                  -2.79591060                  -0.62316682

Intercepts:
     0|1      1|2
2.930679 4.163629

Residual Deviance: 528.1576
AIC: 548.1576
>
```

3. **Model 3**

   It can also be seen in Figure 3 that there is a high corelation between defenceTeamPressure_ratio and defenceTeamWidth_ratio. In Model 3, we drop defenceTeamWidth_ratio and chanceCreationCrossing_ratio.

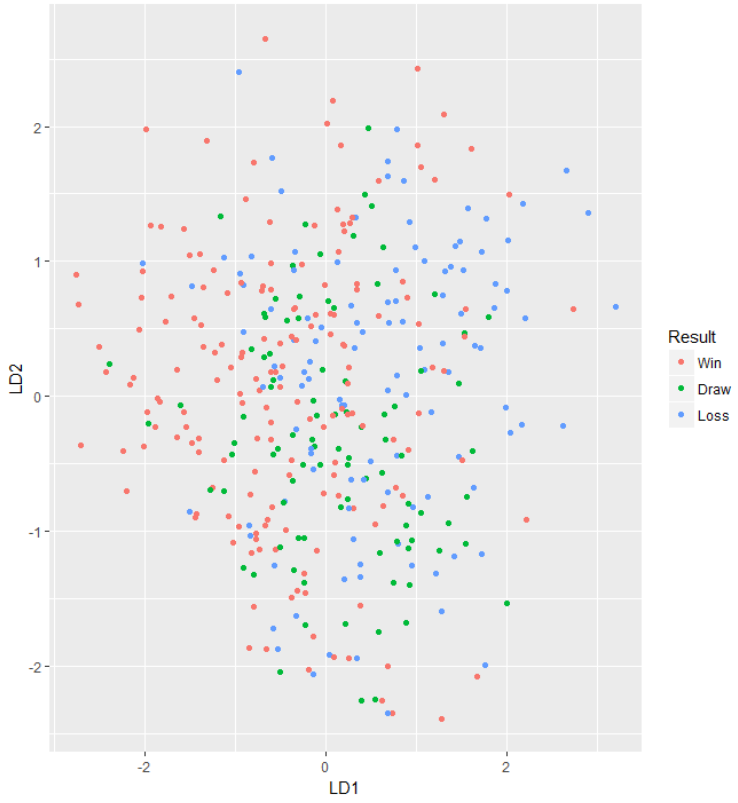
```
> m5.polr3
Call:
polr(formula = factor(result) ~ buildUpPlaySpeed_ratio + buildUpPlayDribbling_ratio +
    buildUpPlayPassing_ratio + chanceCreationPassing_ratio +
    chanceCreationShooting_ratio + defencePressure_ratio + defenceAggression_ratio,
    data = m5.train)

Coefficients:
      buildUpPlaySpeed_ratio   buildUpPlayDribbling_ratio     buildUpPlayPassing_ratio  chanceCreationPassing_ratio
                   2.5468408                   -2.0357646                   -1.0158987                    2.7566533
chanceCreationShooting_ratio        defencePressure_ratio       defenceAggression_ratio
                  -0.6905324                    4.5800576                   -2.5772568

Intercepts:
     0|1      1|2
3.482558 4.722224

Residual Deviance: 526.1882
AIC: 544.1882
>
```

LDA:



We performed a Linear Discriminant Analysis to find any linear combination between our predictor variables. The first plot describes the two generated discriminants. As we can see from the graph both our discriminants do no separate our classes at all. We still proceeded to fit the model and check the accuracy of our predictions. We split our data 80-20 for train and test respectively. We ran this 100 times and generated mean error and mean accuracy. We also tried to fit a Mixture Discriminant Analysis using the same method.

Results

1. **Model 1**

C	**0**	**2**
0	42	8
1	16	8
2	14	26

Accuracy: 59.649%

2. **Model 2**

C	**0**	**2**
0	41	9
1	15	9
2	17	23

Accuracy: 56.14%

3. **Model 3**

C	**0**	**2**
0	42	8
1	16	8
2	14	26

Accuracy: 59.649%

It can be seen that Models 1 and 3 give us the same results and Model 2 gives us a lower accuracy. Also, the AIC seems to be more for Model 2. This shows that the variable chanceCreationPassing_ratio is an important dependent variable whereas chanceCreationCrossing_ratio and defenceTeamWidth_ratio do not seem to contribute much. Thus, we go ahead with Model 3 as it is the least complex and still gives us the highest accuracy.

Conclusion and Discussion

When it comes to match outcome predictions, Bookies get it right about 53% of the times. As of now, our final model is slightly better than the benchmark. There is a bias towards giving a win or loss over a draw and we believe that it is difficult to remove this bias through a logistic regression model.

As mentioned earlier, we are currently only dealing with the English Premier League. So in our future work, we would like to expand our analysis across various other European leagues. We would also like to carry out time series analysis across seasons to see whether there is any trend fit or other time component involved that contributes to variation in match outcomes. Another thing we would like to do is consider individual player attributes as a team's playing squad can change from match to match and across seasons. To conclude, once a have a robust model, we would like to obtain a dataset which is sampled more frequently that covers real time statistics of matches (for example, weekly instead of yearly).

References

Dataset: https://www.kaggle.com/hugomathien/soccer