# Soccer Predictions - ISyE 7406 Data Mining Project

*Group C9*

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## Team

Parit Burintrathikul - 48129 - paritb@gatech.edu

Spencer Collins - 92822 - scollins46@gatech.edu

Johnny Humphrey - 15569 - johnny.humphrey@gatech.edu

Shoili Pal - 43987 - spal41@gatech.edu

Steven Yeh - 28005 - syeh35@gatech.edu

## Abstract

The goal of this project is to predict soccer match outcomes. Using non-statistical heuristic models as baselines, we develop predictive models based on data mining techniques. We try to determine the factors having the greatest impact on outcomes. We compare our results to professional gambling websites' odds. Finally, we suggest ways that could possibly lead to improving our predictions further.

## Introduction

### Motivation and Description

Sports are a popular form of entertainment. A form of entertainment parallel to the playing or watching matches themselves is to predict the outcomes. Much time, effort, and money are spent trying to make accurate predictions, especially at a rate better than everyone else. With this project we enter that highly competitive parallel stream. The sport we chose to model was soccer, with some general statistics coming from European soccer and our predictive models built based on data from the English Premier League (EPL). We decided to concentrate on one league since we had more data for it and since different leagues tend to have different styles of play which could affect the accuracy of our models.

### Challenges

The variability in sporting outcomes, and the fact that it is hard to quantify the variability given that athletes have good days and bad days, is what adds novelty to sporting events, and what helps make them so entertaining. However, it makes modeling sports with a high degree of accuracy much more difficult.

While we decided to model the outcome of a match instead of the scores, soccer has three possible outcomes, not just win and loss but also ties. In the English Premier League there are no tie-breakers. This makes the task of prediction more complex since the outcome is not binary. We tried several different model types and features to see which did the best job of accounting for the variation in outcomes, as measured by the accuracy of our predictions.

## Data

### Data Source and Description

The data we are using is a dataset obtainable at https://www.kaggle.com/hugomathien/soccer in the form of a SQL database. It was originally created by scraping several websites and crowdsourcing. It contains information about soccer matches in the top tier leagues from 11 different European countries. The following are the tables in the database and a description of the data that they hold.

- Country: Country name and ID for 11 European countries.
- League: League name, country, and ID for the top league in the 11 different countries.
- Team: Team name, league, IDs for this database, for the match information web site, and for the FIFA video game from Electronic Arts (EA). 299 records total, 34 in the EPL.
- Match: Season, match IDs, home and away team goals, home and away player starting position and IDs, match events(goal types, possession, shots on/off, penalty cards, fouls committed, corner kicks), betting odds from up to 10 providers. 25979 matches total, 3040 total for the EPL spread across 8 seasons.
- Player: ID, name, FIFA ID, birthday, height, and weight for 11060 total players.
- Player Attributes: Player ID and FIFA ID, date updated, 38 FIFA attributes (overall rating, potential, attacking and defensive work rate, crossing, finishing, reactions, shot power, etc.). Each row represents an updated FIFA profile for a given player, so multiple rows per player are possible.
- Team Attributes: Team ID and FIFA ID, date updated, 21 FIFA team attributes (build-up classes and values, chance creation classes and values, defense classes and values)

## Data Pre-processing

In our initial exploration of the database, we quickly realized that many of the variables in the dataset had a lot of missing values, mostly in the betting data and players in each match variables. Many of the player's data were crowdsourced by individuals and thus were only filled in haphazardly. This may lead to being biased towards players who are popular and outstanding. Therefore, we decided to remove all player data and focused solely on the team data like overall style of play and match related data like goal differentials, specifically in the English Premier League as we had more data for that.

We joined all the separate tables except the players table into one aggregated dataset, cleaning out N/A values as well as removing all the duplicated identifiers. We built two separate datasets, one including and one excluding betting data. Our assumption was that since the betting data were modelled and calculated by betting companies, they would be highly correlated to the match outcomes and since our objective is to predict match outcomes, building our predictions using other prediction data would not be ideal. However, we also decided to include them in separate models to compare the performances of models with and without the betting data. The dataset ultimately contains each match as one row, with predictor variables pertaining to the teams and the response variable being win, loss, or draw for the home team.

While the Match database table had the home and away goal totals, it did not explicitly have the goal differential, which we were interested in. We created a custom table to hold the results of a team's home or away goal differential going into each match, with the time horizons for calculating the differential of 1, 2, 3, 5, and 10 games, as well as season-to-date.

## Exploratory Data Analysis

Looking at each league across all of their seasons in the database, we can find the average percentage outcomes of a home win, an away win, or a draw for the league. We found that there was some variation. [Appendix Tables 1 & 2]

| x | Home Win % | Away Win % | Draw % |
|---|---|---|---|
| High | 48.8 | 33.8 | 28.3 |
| Low | 41.7 | 27.0 | 23.2 |
| Average | 45.9 | 28.7 | 25.4 |

Looking specifically at the EPL, and looking at per-season statistics, we notice that the average EPL season is a lot like the average across all European leagues, but there is still some fluctuation in the home-win/away-win/draw percentages across years. [Appendix Tables 3 & 4]

| x | Home Win % | Away Win % | Draw % |
|---|---|---|---|
| High | 50.8 | 32.4 | 29.2 |
| Low | 41.3 | 23.7 | 20.5 |
| Average | 45.7 | 28.5 | 25.8 |

Finally, as a reference for a good prediction accuracy, we note that the professional oddsmakers correctly predict home-win/away-win/draw for a match in the EPL 53% of the time. [Appendix Table 5]

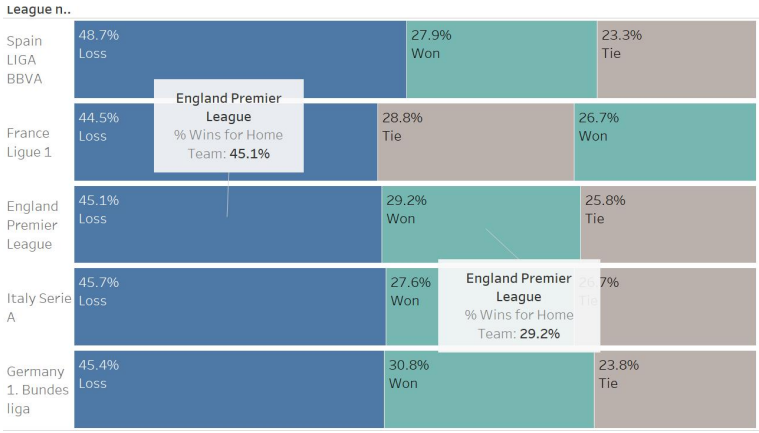
# Methods

## Baseline

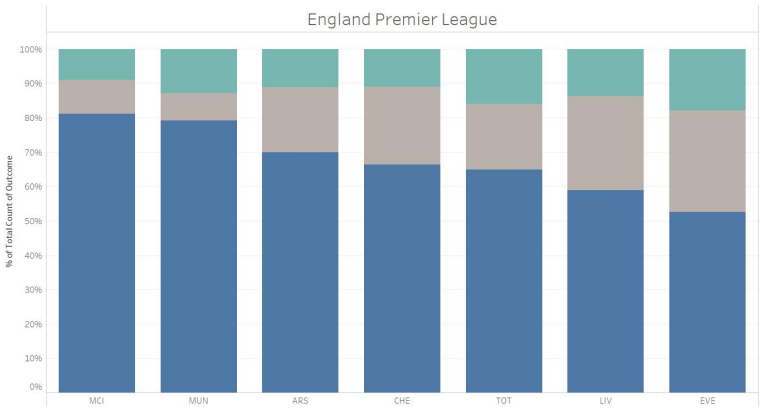
First we establish a baseline against which we will compare our models. We used a couple of prediction heuristics for this.

### Home Wins

This heuristic for predicting winning outcomes is correct 46% of the time, as we see from the data distribution tables. That is better than random picks based on the 46% - 28% - 26% distribution of home-win/away-win/draw, which would be about 36%, but it is still significantly behind the oddsmakers' accuracy at 53%, so we hope to do better with a statistical model.




This heuristic works well for the English Premier League as well with home teams winning 45% of the time in our data. It is interesting to note that the home advantage is more pronounced for the top teams.




**Goal Differential**

The Home Wins rule for picking the winner is a good heuristic only for predicting home team wins. For a simple way to pick between the three outcomes goal differential is a good model.

The correlation of goal differential with wins is common knowledge in the sport community. It is obvious that, when wins are determined by scoring more than your opponent, something that measures that ability should correlate well with wins. For this reason, web sites like ESPN list goal differentials along with the other statistics they provide in their standings. Once again, soccer has draws as an outcome, and they are not as good as a win but are better than a loss, the English Premier League weighs wins as 3 points and draws as 1 point when calculating total points to determine a team's position in the league table.

As an example, when we use that metric for points and compare a team's point total with their goal differential for the 2015 - 2016 EPL season, we find a correlation between points and goal differential of 0.961, which is very strong.

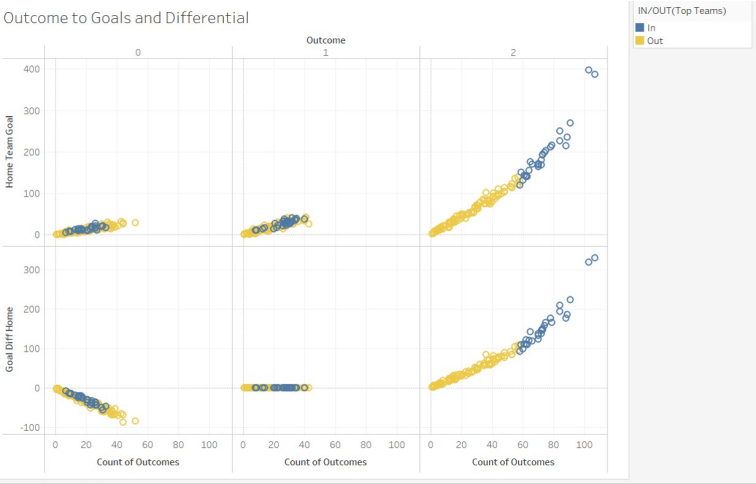
While we have seen a strong correlation between a season-long cumulative goal differential and total points, these are both aggregate measures, and so we still needed to determine how well goal differential helps predict individual match outcomes. To make those predictions we need to decide upon rules for mapping goal differential information into a match outcome. We use the following:

1. As we've seen in the outcome distributions, having the home field is an advantage, so we keep track of home goal differential and away goal differential for teams separately.
2. We treat seasons separately. It is possible that there could be some carry-over from season to season, but we don't try to determine this. For our calculations, goal differential starts back at 0 at the start of every season.
3. It's possible that goal differential is a stronger predictor over some number of the most recent games than season-to date. We checked results using goal differentials calculated from the most recent single game, and the most recent 2, 3, 5, and 10 games.
4. We need to compare average per-game goal differentials even if the total is determined over some number of games. For example, if the home team has played 3 home games but the away team has only played 1 away game, it wouldn't be a fair comparison to use a 3-game home total against a 1-game away total.
5. The rule we use to determine a draw is if the home team's home goal differential average is within a half game of the away team's away goal differential average, then we predict a tie. If the difference is greater than a half point, then the team with the greatest goal differential is picked as the predicted winner.

We note that these rules are not a Data Mining or Machine Learning model. We aren't estimating any parameters to minimize error. For example, it is possible that we would have greater accuracy if we used some number higher or lower than 0.5 as the cutoff for draws. We did not seek to find out what that number

might be. We are only trying to see if we can improve on our baseline Home Wins rule. Also, even if goal differential isn't enough by itself for predictions, we may find that it is a useful feature to have in a model.

After calculating the goal differentials and then the predicted outcomes, we compared the actual outcomes and found that the accuracy in the EPL of the goal differential predictions was about 43%. [Appendix Table 7] This is actually slightly less than simply predicting that Home Wins.




## Models

We tackle the problem in two ways -

- as a 3-class classification problem into wins, losses and draws for the home team.
- as a 2-class classification problem where the response is home win or not.

We use both parametric and non-parametric methods to model the problem. While the parametric models of logistic regression and SVM will give us a clear idea of the relation between the predictor variables and the response, sometimes non-parametric models like random forests can learn patterns that are not obvious to the human eye and give good results, especially in an area as unpredictable as sports. Hence we try both.

We use the same models for the binary classification and the 3-class classification.

Hundred fold validation is used on the regression and SVM models to establish the testing error.

## Parametric

### Logistic and Multinomial Regression

Logistic regression was used in the two-class prediction problem and Multinomial regression for the 3-class problem. Relying on the logit function as the link function between the calculated probability and the linear regression function, the model fits coefficients for each predictor variable. Logistic regression does not make any assumptions about common variance, and can be used as a robust estimator in this problem.

### Support Vector Machines

Support Vector Machines was chosen as a model for predicting both the two-class (Win/Not) and three-class (Win/Loss/Draw) problems. SVMs are useful in high dimensional space and can be tuned using different kernel functions for the decision function and different decision boundaries 'gamma'. A grid search was performed to find the best value of gamma and several kernels were tried like the radial and sigmoid kernels.

#### Ensemble of Regression and SVM

#### Bradley Terry Model

Bradley Terry has been used to estimate sports outcome because of it's ability to consider both teams attributes and records. It incorporates the Bayesian distributions of the home and away records of each team as well as attributes. For this model we trained the model including the records and goal differential.

### Non-Parametric

#### Random Forest

Random Forest was chosen as one of the models to try as it is known to give good accuracy in many cases and is not too computationally intense. It was used for both Win/Not Win and Win/Draw/Loss prediction.

## Results

The following table contains the mean accuracy and variance for each method when the calculations were run 100 times. The SVM model without betting data displayed the highest testing accuracy mean for the 2-class with ~64.5%. Random Forests with betting data had the highest accuracy for 3-class predictions, with respective accuracies of ~50.9%.

For Binary Classification

| Name | Mean Error |
|---|---|
| Bradley Terry Model | 0.536428 |
| Logistic Regression (with Betting data) | 0.6342500 |
| Logistic Regression (without Betting data) | 0.6235833 |
| SVM (with Betting data) | 0.5041667 |
| SVM (without Betting data) | 0.6447500 |
| Random Forest (with Betting data) | 0.5263779 |
| Random Forest (without Betting data) | 0.5325261 |

For 3-Class Classification

| Name | Testing Error |
|---|---|
| Multinomial Regression (with Betting data) | 0.5005000 |
| Multinomial Regression (without Betting data) | 0.4871667 |
| SVM (with Betting data) | 0.5065833 |
| SVM (without Betting data) | 0.5046667 |
| Random Forest (with Betting data) | 0.5277557 |
| Random Forest (without Betting data) | 0.5095616 |
| Ensemble Method (with Betting data) | 0.4471786 |
| Ensemble Method (without Betting data) | 0.4614107 |

#### Statistical Tests

We performed a statistical test (the t-test) to examine whether the mean accuracies are statistically significantly higher than the accuracies of other models.

For Binary Classification

Best Model: *SVM without Betting Data*

| Compared Model | T-test P-value |
|---|---|
| Logistic Regression (with Betting data) | 0.0504 |
| Logistic Regression (without Betting data) | 0.001147 |
| SVM (with Betting data) | <2.2e-16 |
| Random Forest (with Betting data) | <2.2e-16 |
| Random Forest (without Betting data) | <2.2e-16 |

For 3-Class Classification

Best Model: *Random Forest with Betting Data*

| Compared Model | T-test P-value |
|---|---|
| Multinomial Regression (with Betting data) | 3.793e-07 |
| Multinomial Regression (without Betting data) | 1.148e-12 |
| SVM (with Betting data) | 9.504e-07 |
| SVM (without Betting data) | 4.868e-08 |
| Random Forest (without Betting data) | <2.2e-16 |
| Ensemble Method (with Betting data) | <2.2e-16 |
| Ensemble Method (without Betting data) | <2.2e-16 |

For the 2-Class classification problem, the SVM model without the betting data had a statistically significantly better accuracy than the other models at the 5% significance level, except for the Logistic Regression model with betting data (p-value: 0.0504).

For the 3-Class classification problem, the Random Forest model with the betting data performed statistically significantly better than all the other models predicting outcome. All p-values were very small, with the largest p-value amongst the comparisons being 9.504e-07.

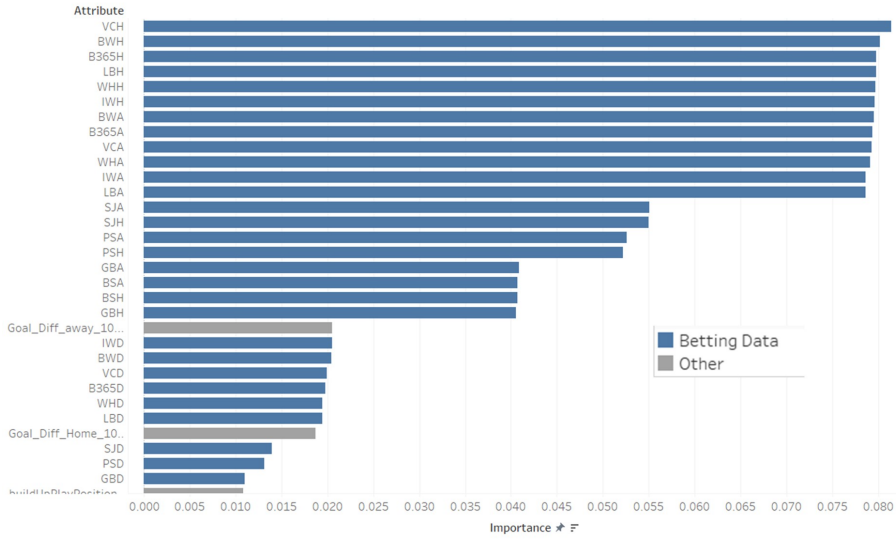
## Discussion

The best models for both the binary and the 3-class classification were tuned using appropriate methods.

For the binary classification, the SVM model's decision boundary was tuned using grid search. Different kernels were tried. The radial kernel gave us the best results.

For the logistic regression model some interaction terms were created and feature selection done. It is interesting to note that goal differentials were consistently features that seemed to have a lot of signal in all the models. Style of play variables seemed to matter less which is interesting because chances created or attacking play are not as good predictors as one might expect, conversion of chances and not conceding goals being equally important in soccer.

The random forest prediction result on the binary classification was quite surprising as it did barely better than the home win baseline on the out of sample prediction while doing very well on the in sample error. Our initial thought was that since it is entirely possible that several of the variables are highly correlated amongst each other, and thus would make each decision tree less effective since they may split on similar information several times, i.e. splitting on correlated variables. In order to try and improve our prediction, we selected a subset of variables through looking at each variable's' correlation against each other and its information gain ratio/entropy.




The variables with the highest information gain ratio were the betting odds data, as these were most likely fine-tuned by the betting companies. Amongst the non betting data, as shown in the figure above, the highest were actually the goal differential of the past 10 games. While this may sound logical, since the more goals you score the better chance you have of winning, one may expect certain variables such as shots on goal or shots creation would be more relevant.

However even with the trimming of the variables and the tuning of different random forests parameters e.g. number of trees or minimum leaf node size, we were only able to marginally improve the prediction by a few points.

For the 3-class classification however the random forest performed the best.

It is interesting to note that parametric models performed better on the binary classification but a non-parametric method did better on the multi-class problem.

## Conclusions

Our model outperforms our baseline analysis by a good margin and provides insights into important team attributes. Our model does not beat the professional betting companies odds, but our 3 class model had results comparable to the top voted Kaggle project (using all leagues + betting data) that saw results of 0.5538.

Competitive sports are a notoriously difficult area to model. The day to day variation of a players performance cannot be taken into account. The models here also do not take into account player data which could make a difference to our accuracy. In soccer it is also interesting to see not just the line up but also the specific strategy teams use against other teams. The data we have here was the overall team style of play related since it was from gaming data. In reality, teams adjust to the other teams strength and differences and vary the number of forwards or defenders they play on a given day. Substitutions during the match as well as red cards, corners and penalties awarded make a big difference to the match outcome. These are all factors which can be taken into account to advance this project's effort further.

# Appendices

## Tables

**Table 1: Win/Away/Draw All Leagues**

| League | Home | Away | Draw | Total | Home Fraction | Away Fraction | Draw Fraction |
|---|---|---|---|---|---|---|---|
| Belgium Jupiler League | 810 | 493 | 425 | 1728 | 0.469 | 0.285 | 0.246 |
| England Premier League | 1390 | 867 | 783 | 3040 | 0.457 | 0.285 | 0.258 |
| France Ligue 1 | 1359 | 822 | 859 | 3040 | 0.447 | 0.27 | 0.283 |
| Germany 1. Bundesliga | 1107 | 744 | 597 | 2448 | 0.452 | 0.304 | 0.244 |
| Italy Serie A | 1407 | 814 | 796 | 3017 | 0.466 | 0.27 | 0.264 |
| Netherlands Eredivisie | 1171 | 696 | 581 | 2448 | 0.478 | 0.284 | 0.237 |
| Poland Ekstraklasa | 870 | 525 | 525 | 1920 | 0.453 | 0.273 | 0.273 |
| Portugal Liga ZON Sagres | 908 | 611 | 533 | 2052 | 0.442 | 0.298 | 0.26 |
| Scotland Premier League | 760 | 617 | 447 | 1824 | 0.417 | 0.338 | 0.245 |
| Spain LIGA BBVA | 1485 | 851 | 704 | 3040 | 0.488 | 0.28 | 0.232 |
| Switzerland Super League | 650 | 426 | 346 | 1422 | 0.457 | 0.3 | 0.243 |

**Table 2: Win/Away/Draw Stats All Leagues**

| Home Fraction | Away Fraction | Draw Fraction | |
|---|---|---|---|
| High | 0.488 | 0.338 | 0.283 |
| Low | 0.417 | 0.27 | 0.232 |
| Average | 0.459 | 0.287 | 0.254 |

**Table 3: Win/Away/Draw EPL All Seasons**

| Season | Home | Away | Draw | Total | Home Fraction | Away Fraction | Draw Fraction |
|---|---|---|---|---|---|---|---|
| 2008/2009 | 173 | 110 | 97 | 380 | 0.455 | 0.289 | 0.255 |
| 2009/2010 | 193 | 91 | 96 | 380 | 0.508 | 0.239 | 0.253 |
| 2010/2011 | 179 | 90 | 111 | 380 | 0.471 | 0.237 | 0.292 |
| 2011/2012 | 171 | 116 | 93 | 380 | 0.45 | 0.305 | 0.245 |
| 2012/2013 | 166 | 106 | 108 | 380 | 0.437 | 0.279 | 0.284 |
| 2013/2014 | 179 | 123 | 78 | 380 | 0.471 | 0.324 | 0.205 |
| 2014/2015 | 172 | 115 | 93 | 380 | 0.453 | 0.303 | 0.245 |
| 2015/2016 | 157 | 116 | 107 | 380 | 0.413 | 0.305 | 0.282 |

**Table 4: Win/Away/Draw Stats EPL All Seasons**

| Home Fraction | Away Fraction | Draw Fraction | |
|---|---|---|---|
| High | 0.508 | 0.324 | 0.292 |
| Low | 0.413 | 0.237 | 0.205 |
| Average | 0.457 | 0.285 | 0.258 |

**Table 5: Oddsmakers EPL Prediction Accuracy**

| Correct Predictions | Total Predictions | Accuracy |
|---|---|---|
| 13676 | 25874 | 0.52856 |

**Table 6: 2016 EPL Final League Table**

| Team | Wins | Losses | Draws | Goal Differential | Points |
|---|---|---|---|---|---|
| LEI | 23 | 3 | 12 | 32 | 81 |
| ARS | 20 | 7 | 11 | 29 | 71 |
| TOT | 19 | 6 | 13 | 34 | 70 |
| MCI | 19 | 10 | 9 | 30 | 66 |
| MUN | 19 | 10 | 9 | 14 | 66 |
| SOU | 18 | 11 | 9 | 18 | 63 |
| WHU | 16 | 8 | 14 | 14 | 62 |
| LIV | 16 | 10 | 12 | 13 | 60 |
| STK | 14 | 15 | 9 | -14 | 51 |
| CHE | 12 | 12 | 14 | 6 | 50 |
| SWA | 12 | 15 | 11 | -10 | 47 |
| WAT | 12 | 17 | 9 | -10 | 45 |
| EVE | 11 | 13 | 14 | 4 | 47 |
| BOU | 11 | 18 | 9 | -22 | 42 |
| CRY | 11 | 18 | 9 | -12 | 42 |
| WBA | 10 | 15 | 13 | -14 | 43 |
| SUN | 9 | 17 | 12 | -14 | 39 |
| NEW | 9 | 19 | 10 | -21 | 37 |
| NOR | 9 | 22 | 7 | -28 | 34 |
| AVL | 3 | 27 | 8 | -49 | 17 |

**Table 7: Goal Diffferential EPL Prediction Accuracy**

| Season | 1 Game | 2 Game | 3 Game | 5 Game | 10 Game |
|---|---|---|---|---|---|
| 2008/09 | 0.46 | 0.45 | 0.48 | 0.46 | 0.45 |
| 2009/10 | 0.46 | 0.44 | 0.45 | 0.49 | 0.48 |
| 2010/11 | 0.41 | 0.39 | 0.46 | 0.45 | 0.46 |
| 2011/12 | 0.4 | 0.43 | 0.43 | 0.41 | 0.44 |
| 2012/13 | 0.38 | 0.4 | 0.42 | 0.43 | 0.42 |
| 2013/14 | 0.43 | 0.43 | 0.43 | 0.43 | 0.42 |
| 2014/15 | 0.37 | 0.44 | 0.46 | 0.43 | 0.41 |
| 2015/16 | 0.36 | 0.39 | 0.39 | 0.41 | 0.42 |
| Average | 0.41 | 0.42 | 0.44 | 0.44 | 0.44 |

## Visualizations

## SQL

### Table 1

```
SELECT league,
       sum(hm)  AS home_total,
       sum(awy) AS away_total,
       sum(drw) AS draw_total
  FROM (SELECT l.name AS league,
               CASE WHEN m.home_team_goal > m.away_team_goal THEN 1 ELSE 0 END AS hm,
               CASE WHEN m.home_team_goal < m.away_team_goal THEN 1 ELSE 0 END AS awy,
               CASE WHEN m.home_team_goal = m.away_team_goal THEN 1 ELSE 0 END AS drw
          FROM Match   m,
               League  l
         WHERE m.league_id = l.id)
 GROUP BY league
 ORDER BY league;
```

### Table 3

```
SELECT season,
       sum(hm)  AS home_total,
       sum(awy) AS away_total,
       sum(drw) AS draw_total
  FROM (SELECT m.season,
               CASE WHEN m.home_team_goal > m.away_team_goal THEN 1 ELSE 0 END AS hm,
               CASE WHEN m.home_team_goal < m.away_team_goal THEN 1 ELSE 0 END AS awy,
               CASE WHEN m.home_team_goal = m.away_team_goal THEN 1 ELSE 0 END AS drw
          FROM Match m
         WHERE m.league_id  = 1729)
 GROUP BY season
 ORDER BY season;
```

### Table 5

```
SELECT sum(correct),
       count(*)
  FROM (SELECT CASE WHEN ((B365H < B365D) AND (B365H < B365A) AND
                          (home_team_goal > away_team_goal)) OR
                         ((B365A < B365D) AND (B365A < B365H) AND
                          (away_team_goal > home_team_goal)) OR
                         ((B365D < B365A) AND (B365D < B365H) AND
                          (home_team_goal = away_team_goal))
                    THEN 1 ELSE 0 END AS correct
          FROM Match
         WHERE league_id = 1729
           AND B365H IS NOT NULL AND B365A IS NOT NULL AND B365D IS NOT NULL
         UNION ALL
```

```
SELECT CASE WHEN ((BWH < BWD) AND (BWH < BWA) AND
                  (home_team_goal > away_team_goal)) OR
                 ((BWA < BWD) AND (BWA < BWH) AND
                  (away_team_goal > home_team_goal)) OR
                 ((BWD < BWA) AND (BWD < BWH) AND
                  (home_team_goal = away_team_goal))
            THEN 1 ELSE 0 END AS correct
  FROM Match
 WHERE league_id = 1729
   AND BWH IS NOT NULL AND BWA IS NOT NULL AND BWD IS NOT NULL
 UNION ALL
SELECT CASE WHEN ((IWH < IWD) AND (IWH < IWA) AND
                  (home_team_goal > away_team_goal)) OR
                 ((IWA < IWD) AND (IWA < IWH) AND
                  (away_team_goal > home_team_goal)) OR
                 ((IWD < IWA) AND (IWD < IWH) AND
                  (home_team_goal = away_team_goal))
            THEN 1 ELSE 0 END AS correct
  FROM Match
 WHERE league_id = 1729
   AND IWH IS NOT NULL AND IWA IS NOT NULL AND IWD IS NOT NULL
 UNION ALL
SELECT CASE WHEN ((LBH < LBD) AND (LBH < LBA) AND
                  (home_team_goal > away_team_goal)) OR
                 ((LBA < LBD) AND (LBA < LBH) AND
                  (away_team_goal > home_team_goal)) OR
                 ((LBD < LBA) AND (LBD < LBH) AND
                  (home_team_goal = away_team_goal))
            THEN 1 ELSE 0 END AS correct
  FROM Match
 WHERE league_id = 1729
   AND LBH IS NOT NULL AND LBA IS NOT NULL AND LBD IS NOT NULL
 UNION ALL
SELECT CASE WHEN ((PSH < PSD) AND (PSH < PSA) AND
                  (home_team_goal > away_team_goal)) OR
                 ((PSA < PSD) AND (PSA < PSH) AND
                  (away_team_goal > home_team_goal)) OR
                 ((PSD < PSA) AND (PSD < PSH) AND
                  (home_team_goal = away_team_goal))
            THEN 1 ELSE 0 END AS correct
  FROM Match
 WHERE league_id = 1729
   AND PSH IS NOT NULL AND PSA IS NOT NULL AND PSD IS NOT NULL
 UNION ALL
SELECT CASE WHEN ((WHH < WHD) AND (WHH < WHA) AND
                  (home_team_goal > away_team_goal)) OR
                 ((WHA < WHD) AND (WHA < WHH) AND
                  (away_team_goal > home_team_goal)) OR
                 ((WHD < WHA) AND (WHD < WHH) AND
                  (home_team_goal = away_team_goal))
            THEN 1 ELSE 0 END AS correct
  FROM Match
 WHERE league_id = 1729
```

```
          AND WHH IS NOT NULL AND WHA IS NOT NULL AND WHD IS NOT NULL
        UNION ALL
       SELECT CASE WHEN ((SJH < SJD) AND (SJH < SJA) AND
                         (home_team_goal > away_team_goal)) OR
                        ((SJA < SJD) AND (SJA < SJH) AND
                         (away_team_goal > home_team_goal)) OR
                        ((SJD < SJA) AND (SJD < SJH) AND
                         (home_team_goal = away_team_goal))
                   THEN 1 ELSE 0 END AS correct
         FROM Match
        WHERE league_id = 1729
          AND SJH IS NOT NULL AND SJA IS NOT NULL AND SJD IS NOT NULL
        UNION ALL
       SELECT CASE WHEN ((VCH < VCD) AND (VCH < VCA) AND
                         (home_team_goal > away_team_goal)) OR
                        ((VCA < VCD) AND (VCA < VCH) AND
                         (away_team_goal > home_team_goal)) OR
                        ((VCD < VCA) AND (VCD < VCH) AND
                         (home_team_goal = away_team_goal))
                   THEN 1 ELSE 0 END AS correct
         FROM Match
        WHERE league_id = 1729
          AND VCH IS NOT NULL AND VCA IS NOT NULL AND VCD IS NOT NULL
        UNION ALL
       SELECT CASE WHEN ((GBH < GBD) AND (GBH < GBA) AND
                         (home_team_goal > away_team_goal)) OR
                        ((GBA < GBD) AND (GBA < GBH) AND
                         (away_team_goal > home_team_goal)) OR
                        ((GBD < GBA) AND (GBD < GBH) AND
                         (home_team_goal = away_team_goal))
                   THEN 1 ELSE 0 END AS correct
         FROM Match
        WHERE league_id = 1729
          AND GBH IS NOT NULL AND GBA IS NOT NULL AND GBD IS NOT NULL
        UNION ALL
       SELECT CASE WHEN ((BSH < BSD) AND (BSH < BSA) AND
                         (home_team_goal > away_team_goal)) OR
                        ((BSA < BSD) AND (BSA < BSH) AND
                         (away_team_goal > home_team_goal)) OR
                        ((BSD < BSA) AND (BSD < BSH) AND
                         (home_team_goal = away_team_goal))
                   THEN 1 ELSE 0 END AS correct
         FROM Match
        WHERE league_id = 1729
          AND BSH IS NOT NULL AND BSA IS NOT NULL AND BSD IS NOT NULL);
```

**Table 6**

```
SELECT t.team_short_name,
       sum(msq.win)        AS wins,
       sum(msq.loss)       AS losses,
       sum(msq.draw)       AS draws,
```

```
      sum(msq.goal_diff)  AS goal_diff_total
  FROM (SELECT m.home_team_api_id                    AS team_id,
               CASE WHEN (m.home_team_goal > m.away_team_goal)
                    THEN 1 ELSE 0 END                AS win,
               CASE WHEN (m.home_team_goal < m.away_team_goal)
                    THEN 1 ELSE 0 END                AS loss,
               CASE WHEN (m.home_team_goal = m.away_team_goal)
                    THEN 1 ELSE 0 END                AS draw,
               m.home_team_goal - m.away_team_goal  AS goal_diff
          FROM Match             m
         WHERE m.league_id   =   1729
           AND m.season      =   '2015/2016'
         UNION ALL
        SELECT m.away_team_api_id                    AS team_id,
               CASE WHEN (m.away_team_goal > m.home_team_goal)
                    THEN 1 ELSE 0 END                AS win,
               CASE WHEN (m.away_team_goal < m.home_team_goal)
                    THEN 1 ELSE 0 END                AS loss,
               CASE WHEN (m.away_team_goal = m.home_team_goal)
                    THEN 1 ELSE 0 END                AS draw,
               m.away_team_goal - m.home_team_goal  AS goal_diff
          FROM Match             m
         WHERE m.league_id   =   1729
           AND m.season      =   '2015/2016') msq,
       Team  t
 WHERE msq.team_id = t.team_api_id
 GROUP BY t.team_short_name
 ORDER BY 2 DESC, 4 DESC;
```

### Goal Differential

```
-- Create a table like the Match table, but having
-- calculated information about wins, losses,
-- and goal differential at various time horizons.
--
CREATE TABLE Match_Goal_Differential (
  league_id        INTEGER,
  season           TEXT,
  stage            INTEGER,
  timeline_id      INTEGER,
  match_api_id     INTEGER,
  home_team_api_id    INTEGER,
  home_team_short_name  TEXT,
  away_team_api_id    INTEGER,
  away_team_short_name  TEXT,
  home_team_goal    INTEGER,
  away_team_goal    INTEGER,
  home_win         INTEGER,
  home_loss        INTEGER,
  home_draw        INTEGER,
  away_win         INTEGER,
  away_loss        INTEGER,
```

```
  away_draw        INTEGER,
  home_goal_diff_0  INTEGER,
  away_goal_diff_0  INTEGER,
  home_goal_diff_1  INTEGER,
  away_goal_diff_1  INTEGER,
  home_goal_diff_2  INTEGER,
  away_goal_diff_2  INTEGER,
  home_goal_diff_3  INTEGER,
  away_goal_diff_3  INTEGER,
  home_goal_diff_5  INTEGER,
  away_goal_diff_5  INTEGER,
  home_goal_diff_10  INTEGER,
  away_goal_diff_10  INTEGER,
  home_goal_diff_total  INTEGER,
  away_goal_diff_total  INTEGER
);

--
-- Create our data.
--
INSERT INTO Match_Goal_Differential
            (league_id,
             season,
             stage,
             timeline_id,
             match_api_id,
             home_team_api_id,
             home_team_short_name,
             away_team_api_id,
             away_team_short_name,
             home_team_goal,
             away_team_goal,
             home_win,
             home_loss,
             home_draw,
             away_win,
             away_loss,
             away_draw,
             home_goal_diff_0,
             away_goal_diff_0,
             home_goal_diff_1,
             away_goal_diff_1,
             home_goal_diff_2,
             away_goal_diff_2,
             home_goal_diff_3,
             away_goal_diff_3,
             home_goal_diff_5,
             away_goal_diff_5,
             home_goal_diff_10,
             away_goal_diff_10,
             home_goal_diff_total,
             away_goal_diff_total)
      SELECT m.league_id,
```

```
            m.season,
            m.stage,
            tl.id,
            m.match_api_id,
            m.home_team_api_id,
            hm.team_short_name,
            m.away_team_api_id,
            aw.team_short_name,
            m.home_team_goal,
            m.away_team_goal,
            CASE WHEN m.home_team_goal > m.away_team_goal THEN 1 ELSE 0 END,
            CASE WHEN m.home_team_goal < m.away_team_goal THEN 1 ELSE 0 END,
            CASE WHEN m.home_team_goal = m.away_team_goal THEN 1 ELSE 0 END,
            CASE WHEN m.away_team_goal > m.home_team_goal THEN 1 ELSE 0 END,
            CASE WHEN m.away_team_goal < m.home_team_goal THEN 1 ELSE 0 END,
            CASE WHEN m.away_team_goal = m.home_team_goal THEN 1 ELSE 0 END,
            m.home_team_goal - m.away_team_goal,
            m.away_team_goal - m.home_team_goal,
            null,
            null,
            null,
            null,
            null,
            null,
            null,
            null,
            null,
            null,
            null,
            null
        FROM Match          m,
            Time_Line_EPL  tl,
            Team           hm,
            Team           aw
       WHERE m.league_id  = 1729
         AND m.season     = tl.season
         AND m.stage      = tl.stage
         AND m.home_team_api_id = hm.team_api_id
         AND m.away_team_api_id = aw.team_api_id;

--
-- Output of the new table data
--
.headers on
.mode csv
.output match_goal_differential.csv

SELECT league_id,
       season,
       stage,
       timeline_id,
       match_api_id,
       home_team_api_id,
       home_team_short_name,
```

```
       away_team_api_id,
       away_team_short_name,
       home_team_goal,
       away_team_goal,
       home_win,
       home_loss,
       home_draw,
       away_win,
       away_loss,
       away_draw,
       home_goal_diff_0,
       away_goal_diff_0,
       home_goal_diff_1,
       away_goal_diff_1,
       home_goal_diff_2,
       away_goal_diff_2,
       home_goal_diff_3,
       away_goal_diff_3,
       home_goal_diff_5,
       away_goal_diff_5,
       home_goal_diff_10,
       away_goal_diff_10,
       home_goal_diff_total,
       away_goal_diff_total
  FROM Match_Goal_Differential
 WHERE league_id = 1729
 ORDER BY timeline_id, match_api_id;
```

## R Code

### Goal Differential

```
# This code uses as input the goal differential file output from the SQLite database.
goal_diff <- read.table(file="match_goal_differential.csv",sep = ",",header=TRUE);

seasons <- goal_diff$season
s08 <- which( seasons == "2008/2009" )
s09 <- which( seasons == "2009/2010" )
s10 <- which( seasons == "2010/2011" )
s11 <- which( seasons == "2011/2012" )
s12 <- which( seasons == "2012/2013" )
s13 <- which( seasons == "2013/2014" )
s14 <- which( seasons == "2014/2015" )
s15 <- which( seasons == "2015/2016" )

gd08 <- goal_diff[s08,]
gd09 <- goal_diff[s09,]
gd10 <- goal_diff[s10,]
gd11 <- goal_diff[s11,]
gd12 <- goal_diff[s12,]
gd13 <- goal_diff[s13,]
gd14 <- goal_diff[s14,]
```

```
gd15 <- goal_diff[s15,]

#
# Information from the database
# Teams by season
#
t08 <- c("ARS","AVL","BLB","BOL","CHE","EVE","FUL","HUL","LIV","MCI","MID","MUN","NEW","POR",
"STK","SUN","TOT","WBA","WHU","WIG")
t09 <- c("ARS","AVL","BIR","BLB","BOL","BUR","CHE","EVE","FUL","HUL","LIV","MCI","MUN","POR",
"STK","SUN","TOT","WHU","WIG","WOL")
t10 <- c("ARS","AVL","BIR","BLA","BLB","BOL","CHE","EVE","FUL","LIV","MCI","MUN","NEW","STK",
"SUN","TOT","WBA","WHU","WIG","WOL")
t11 <- c("ARS","AVL","BLB","BOL","CHE","EVE","FUL","LIV","MCI","MUN","NEW","NOR","QPR","STK",
"SUN","SWA","TOT","WBA","WIG","WOL")
t12 <- c("ARS","AVL","CHE","EVE","FUL","LIV","MCI","MUN","NEW","NOR","QPR","REA","SOU","STK",
"SUN","SWA","TOT","WBA","WHU","WIG")
t13 <- c("ARS","AVL","CAR","CHE","CRY","EVE","FUL","HUL","LIV","MCI","MUN","NEW","NOR","SOU",
"STK","SUN","SWA","TOT","WBA","WHU")
t14 <- c("ARS","AVL","BUR","CHE","CRY","EVE","HUL","LEI","LIV","MCI","MUN","NEW","QPR","SOU",
"STK","SUN","SWA","TOT","WBA","WHU")
t15 <- c("ARS","AVL","BOU","CHE","CRY","EVE","LEI","LIV","MCI","MUN","NEW","NOR","SOU","STK",
"SUN","SWA","TOT","WAT","WBA","WHU")

# Since we are doing cumulative counts within a season
# it is easier to process the seasons individually.

#
# 2008/2009 season
#
for ( t in t08 ) {

   #
   # Home games for this team
   #
   htsn <- gd08$home_team_short_name
   gmh <- which( htsn == t )

   #
   # Single-game home-team goal differential
   #
   hgd0 <- gd08[gmh,]$home_goal_diff_0

   #
   # Goal diff for last previous game only
   #
   gd08[gmh[2:19],]$home_goal_diff_1 <- hgd0[1:18]

   #
   # Goal diff for last 2 previous games
   #
   gd08[gmh[2],]$home_goal_diff_2 <- hgd0[1]
   for ( i in 1:17 ) {
      gd08[gmh[i+2],]$home_goal_diff_2 <- sum( hgd0[i:(i+1)] )
```

```
}

#
# Goal diff for last 3 previous games
#
gd08[gmh[2],]$home_goal_diff_3 <- hgd0[1]
gd08[gmh[3],]$home_goal_diff_3 <- sum( hgd0[1:2] )
for ( i in 1:16 ) {
   gd08[gmh[i+3],]$home_goal_diff_3 <- sum( hgd0[i:(i+2)] )
}

#
# Goal diff for last 5 previous games
#
gd08[gmh[2],]$home_goal_diff_5 <- hgd0[1]
gd08[gmh[3],]$home_goal_diff_5 <- sum( hgd0[1:2] )
gd08[gmh[4],]$home_goal_diff_5 <- sum( hgd0[1:3] )
gd08[gmh[5],]$home_goal_diff_5 <- sum( hgd0[1:4] )
for ( i in 1:14 ) {
   gd08[gmh[i+5],]$home_goal_diff_5 <- sum( hgd0[i:(i+4)] )
}

#
# Goal diff for last 10 previous games
#
gd08[gmh[2],]$home_goal_diff_10 <- hgd0[1]
for ( i in 2:9 ) {
   gd08[gmh[i+1],]$home_goal_diff_10 <- sum( hgd0[1:i] )
}
for ( i in 1:9 ) {
   gd08[gmh[i+10],]$home_goal_diff_10 <- sum( hgd0[i:(i+9)] )
}

#
# Cumulative season goal diff
#
for ( i in 1:18 ) {
   gd08[gmh[i+1],]$home_goal_diff_total <- sum( hgd0[1:i] )
}


#
# Same for this team when away
#
atsn <- gd08$away_team_short_name
gma <- which( atsn == t )
agd0 <- gd08[gma,]$away_goal_diff_0

#
# Goal diff for last previous game only
#
gd08[gma[2:19],]$away_goal_diff_1 <- agd0[1:18]
```

```
   #
   # Goal diff for last 2 previous games
   #
   gd08[gma[2],]$away_goal_diff_2 <- agd0[1]
   for ( i in 1:17 ) {
      gd08[gma[i+2],]$away_goal_diff_2 <- sum( agd0[i:(i+1)] )
   }

   #
   # Goal diff for last 3 previous games
   #
   gd08[gma[2],]$away_goal_diff_3 <- agd0[1]
   gd08[gma[3],]$away_goal_diff_3 <- sum( agd0[1:2] )
   for ( i in 1:16 ) {
      gd08[gma[i+3],]$away_goal_diff_3 <- sum( agd0[i:(i+2)] )
   }

   #
   # Goal diff for last 5 previous games
   #
   gd08[gma[2],]$away_goal_diff_5 <- agd0[1]
   gd08[gma[3],]$away_goal_diff_5 <- sum( agd0[1:2] )
   gd08[gma[4],]$away_goal_diff_5 <- sum( agd0[1:3] )
   gd08[gma[5],]$away_goal_diff_5 <- sum( agd0[1:4] )
   for ( i in 1:14 ) {
      gd08[gma[i+5],]$away_goal_diff_5 <- sum( agd0[i:(i+4)] )
   }

   #
   # Goal diff for last 10 previous games
   #
   gd08[gma[2],]$away_goal_diff_10 <- agd0[1]
   for ( i in 2:9 ) {
      gd08[gma[i+1],]$away_goal_diff_10 <- sum( agd0[1:i] )
   }
   for ( i in 1:9 ) {
      gd08[gma[i+10],]$away_goal_diff_10 <- sum( agd0[i:(i+9)] )
   }

   #
   # Cumulative season goal diff
   #
   for ( i in 1:18 ) {
      gd08[gma[i+1],]$away_goal_diff_total <- sum( agd0[1:i] )
   }
}

#
# A similar code was used to process the remaining seasons. There were only 2
# changes/substitutions:
#    1) The main loop variable would represent the teams for a different season.
#       For example, instead of using the teams in t08 for the 2008/2009 season,
#       we would use the teams in t12 for the 2012/2013 season.
```

```
#    2) The goal differential season information changes. This is held in the
#       data frame variables named gdXX. So instead of using gd08 as shown in
#       the R code above for the 2008/2009 season, we would use gd12 for the
#       calculations for the 2012/2013 season.
#

# Save calculations
write.table( gd08, "goal_differential_info.csv", append = FALSE, sep = ",",
             row.names=FALSE, col.names=TRUE );
write.table( gd09, "goal_differential_info.csv", append = TRUE, sep = ",",
             row.names=FALSE, col.names=FALSE );
write.table( gd10, "goal_differential_info.csv", append = TRUE, sep = ",",
             row.names=FALSE, col.names=FALSE );
write.table( gd11, "goal_differential_info.csv", append = TRUE, sep = ",",
             row.names=FALSE, col.names=FALSE );
write.table( gd12, "goal_differential_info.csv", append = TRUE, sep = ",",
             row.names=FALSE, col.names=FALSE );
write.table( gd13, "goal_differential_info.csv", append = TRUE, sep = ",",
             row.names=FALSE, col.names=FALSE );
write.table( gd14, "goal_differential_info.csv", append = TRUE, sep = ",",
             row.names=FALSE, col.names=FALSE );
write.table( gd15, "goal_differential_info.csv", append = TRUE, sep = ",",
             row.names=FALSE, col.names=FALSE );
```

**SVM and Logistic/Multinomial Regression**

```
setwd('/Users/Stevenstuff/Downloads')
#setwd("/Users/Stevenstuff/soccerdatamining")
soccer <- read.csv('Soccerdata.csv')

# fill in blanks with NA's
soccer[soccer==""] <- NA

# betting data as numeric instead of factor
for(i in rep(20:49)) {
  soccer[,i] <- as.numeric(soccer[,i])
}

# remove "diff" columns: time since last update
soccer <- subset(soccer, select=-c(rank_Update_diff1, rank_Update_diff11,
                                   Update_diff1, Update_diff11))

# buildUpPlayDribbling_home and buildUpPlayDribbling1_away has 19088 NA's
soccer <- subset(soccer, select=-c(buildUpPlayDribbling_home, buildUpPlayDribbling1_away))

# remove duplicate columns
soccer <- subset(soccer, select=-c(country_id1, league_id, team_api_id,
                                   team_api_id1, team_api_id1_away_away,
                                   id3_home, id4, team_fifa_api_id2_home,
                                   team_api_id2_home, team_fifa_api_id3_away,
                                   team_api_id3_away))
```

```r
# multinomial regression: 1 if home wins, 2 if home loses, 3 if tie
soccer$outcome <- ifelse(soccer$home_team_goal-soccer$away_team_goal > 0, 1,
                         ifelse(soccer$home_team_goal-soccer$away_team_goal<0, 2, 3))
soccer$outcome <- as.factor(soccer$outcome)
soccer$win <- as.factor(ifelse(soccer$home_team_goal-soccer$away_team_goal > 0, 1, 0))
soccer$lose <- as.factor(ifelse(soccer$home_team_goal-soccer$away_team_goal < 0, 1, 0))
soccer$tie <- as.factor(ifelse(soccer$home_team_goal-soccer$away_team_goal == 0, 1, 0))

# remove useless columns
soccer <- subset(soccer, select=-c(id, date, match_api_id, home_team_goal,
                                   away_team_goal, Goal_Diff_Home,
                                   Goal_Diff_away, id1_home_home, team_fifa_api_id_home_home,
                                   team_long_name_home_home, team_short_name_home_home,
                                   id2_away_away,team_fifa_api_id1_away_away,team_long_name1_away_away,
                                   team_short_name1_away_away,Country_Name_home,League_name,id5,date1_h
                                   id6_away,date2_away))

# remove columns with too many factors (messes up classification)
soccer <- subset(soccer, select=-c(home_team_api_id, away_team_api_id))

# factorize columns
names<-c("country_id", "season", "stage")
soccer[,names] <- lapply(soccer[,names], factor)

# dataset with betting data removed
library(dplyr)
nan_columns = colnames(soccer)[colSums(is.na(soccer)) > 0]
soccer_nobet <- soccer[, !colnames(soccer) %in% nan_columns]
write.csv(soccer_nobet, 'soccer_nobet.csv', row.names=FALSE)

# dataset with NA rows removed
soccer_nona <- na.omit(soccer)
write.csv(soccer_nona, 'soccer_nona.csv', row.names=FALSE)

write.csv(soccer, 'soccer_clean.csv', row.names=FALSE)


library(nnet)
# doesn't work
test <- multinom(outcome ~ country_id+season+stage+Goal_Diff_Home_10.Games+Goal_Diff_away_10.Games+
                   B365H+B365D+B365A+BWH+BWD+BWA+IWH+IWD+IWA+LBH+LBD+LBA+PSH+PSD+PSA+
                   WHH+WHD+WHA+SJH+SJD+SJA+VCH+VCD+VCA+GBH+GBD+GBA+BSH+BSD+BSA+
                   buildUpPlaySpeed_home+buildUpPlaySpeedClass_home+
                   buildUpPlayDribblingClass_home+buildUpPlayPassing_home+buildUpPlayPassingClass_home+
                   buildUpPlayPositioningClass_home+chanceCreationPassing_home+chanceCreationPassingCla
                   chanceCreationCrossing_home+chanceCreationCrossingClass_home+chanceCreationShooting_
                   chanceCreationShootingClass_home+chanceCreationPositioningClass_home+defencePressure
                   defencePressureClass_home+defenceAggression_home+defenceAggressionClass_home+
                   defenceTeamWidth_home+defenceTeamWidthClass_home+defenceDefenderLineClass_home+
                   buildUpPlaySpeed1_away+buildUpPlaySpeedClass1_away+
                   buildUpPlayDribblingClass1_away+buildUpPlayPassing1_away+buildUpPlayPassingClass1_aw
                   buildUpPlayPositioningClass1_away+chanceCreationPassing1_away+chanceCreationPassingC
                   chanceCreationCrossing1_away+chanceCreationCrossingClass1_away+chanceCreationShootin
```

```
                  chanceCreationShootingClass1_away+chanceCreationPositioningClass1_away+defencePressu
                  defencePressureClass1_away+defenceAggression1_away+defenceAggressionClass1_away+
                  defenceTeamWidth1_away+defenceTeamWidthClass1_away+defenceDefenderLineClass1_away, da
# multinomial model
model <- multinom(outcome ~ country_id+season+stage+Goal_Diff_Home_10.Games+Goal_Diff_away_10.Games+
          buildUpPlaySpeed_home+buildUpPlaySpeedClass_home+
          buildUpPlayDribblingClass_home+buildUpPlayPassing_home+buildUpPlayPassingClass_home+
          buildUpPlayPositioningClass_home+chanceCreationPassing_home+chanceCreationPassingClass_home+
          chanceCreationCrossing_home+chanceCreationCrossingClass_home+chanceCreationShooting_home+
          chanceCreationShootingClass_home+chanceCreationPositioningClass_home+defencePressure_home+
          defencePressureClass_home+defenceAggression_home+defenceAggressionClass_home+
          defenceTeamWidth_home+defenceTeamWidthClass_home+defenceDefenderLineClass_home+
          buildUpPlaySpeed1_away+buildUpPlaySpeedClass1_away+
          buildUpPlayDribblingClass1_away+buildUpPlayPassing1_away+buildUpPlayPassingClass1_away+
          buildUpPlayPositioningClass1_away+chanceCreationPassing1_away+chanceCreationPassingClass1_away
          chanceCreationCrossing1_away+chanceCreationCrossingClass1_away+chanceCreationShooting1_away+
          chanceCreationShootingClass1_away+chanceCreationPositioningClass1_away+defencePressure1_away+
          defencePressureClass1_away+defenceAggression1_away+defenceAggressionClass1_away+
          defenceTeamWidth1_away+defenceTeamWidthClass1_away+defenceDefenderLineClass1_away, data=socce


###    save the TE values for all models in all $B=100$ loops
B= 100;            ### number of loops
TEALL = NULL;      ### Final TE values
n = dim(soccer_nobet)[1]
n1 = round(n/10)

for (b in 1:B){
  ### randomly select 25 observations as testing data in each loop
  flag <- sort(sample(1:n, n1));
  train <- soccer_nobet[-flag,];
  test  <- soccer_nobet[flag,];
  wins <- glm(win ~ country_id+season+stage+Goal_Diff_Home_10.Games+Goal_Diff_away_10.Games+
                    buildUpPlaySpeed_home+buildUpPlaySpeedClass_home+
                    buildUpPlayDribblingClass_home+buildUpPlayPassing_home+buildUpPlayPassingClass_hom
                    buildUpPlayPositioningClass_home+chanceCreationPassing_home+chanceCreationPassingC
                    chanceCreationCrossing_home+chanceCreationCrossingClass_home+chanceCreationShootin
                    chanceCreationShootingClass_home+chanceCreationPositioningClass_home+defencePressu
                    defencePressureClass_home+defenceAggression_home+defenceAggressionClass_home+
                    defenceTeamWidth_home+defenceTeamWidthClass_home+defenceDefenderLineClass_home+
                    buildUpPlaySpeed1_away+buildUpPlaySpeedClass1_away+
                    buildUpPlayDribblingClass1_away+buildUpPlayPassing1_away+buildUpPlayPassingClass1_a
                    buildUpPlayPositioningClass1_away+chanceCreationPassing1_away+chanceCreationPassing
                    chanceCreationCrossing1_away+chanceCreationCrossingClass1_away+chanceCreationShoot
                    chanceCreationShootingClass1_away+chanceCreationPositioningClass1_away+defencePres
                    defencePressureClass1_away+defenceAggression1_away+defenceAggressionClass1_away+
                    defenceTeamWidth1_away+defenceTeamWidthClass1_away+defenceDefenderLineClass1_away,
              family = binomial(link="logit"))
  loss <- glm(lose ~ country_id+season+stage+Goal_Diff_Home_10.Games+Goal_Diff_away_10.Games+
                buildUpPlaySpeed_home+buildUpPlaySpeedClass_home+
                buildUpPlayDribblingClass_home+buildUpPlayPassing_home+buildUpPlayPassingClass_home+
                buildUpPlayPositioningClass_home+chanceCreationPassing_home+chanceCreationPassingClass_
                chanceCreationCrossing_home+chanceCreationCrossingClass_home+chanceCreationShooting_hom
```

```
                chanceCreationShootingClass_home+chanceCreationPositioningClass_home+defencePressure_hom
                defencePressureClass_home+defenceAggression_home+defenceAggressionClass_home+
                defenceTeamWidth_home+defenceTeamWidthClass_home+defenceDefenderLineClass_home+
                buildUpPlaySpeed1_away+buildUpPlaySpeedClass1_away+
                buildUpPlayDribblingClass1_away+buildUpPlayPassing1_away+buildUpPlayPassingClass1_away+
                buildUpPlayPositioningClass1_away+chanceCreationPassing1_away+chanceCreationPassingClass
                chanceCreationCrossing1_away+chanceCreationCrossingClass1_away+chanceCreationShooting1_a
                chanceCreationShootingClass1_away+chanceCreationPositioningClass1_away+defencePressure1_
                defencePressureClass1_away+defenceAggression1_away+defenceAggressionClass1_away+
                defenceTeamWidth1_away+defenceTeamWidthClass1_away+defenceDefenderLineClass1_away, data=
              family = binomial(link="logit"))
  tie <- glm(tie ~ country_id+season+stage+Goal_Diff_Home_10.Games+Goal_Diff_away_10.Games+
                buildUpPlaySpeed_home+buildUpPlaySpeedClass_home+
                buildUpPlayDribblingClass_home+buildUpPlayPassing_home+buildUpPlayPassingClass_home+
                buildUpPlayPositioningClass_home+chanceCreationPassing_home+chanceCreationPassingClass_h
                chanceCreationCrossing_home+chanceCreationCrossingClass_home+chanceCreationShooting_home
                chanceCreationShootingClass_home+chanceCreationPositioningClass_home+defencePressure_hom
                defencePressureClass_home+defenceAggression_home+defenceAggressionClass_home+
                defenceTeamWidth_home+defenceTeamWidthClass_home+defenceDefenderLineClass_home+
                buildUpPlaySpeed1_away+buildUpPlaySpeedClass1_away+
                buildUpPlayDribblingClass1_away+buildUpPlayPassing1_away+buildUpPlayPassingClass1_away+
                buildUpPlayPositioningClass1_away+chanceCreationPassing1_away+chanceCreationPassingClass
                chanceCreationCrossing1_away+chanceCreationCrossingClass1_away+chanceCreationShooting1_a
                chanceCreationShootingClass1_away+chanceCreationPositioningClass1_away+defencePressure1_
                defencePressureClass1_away+defenceAggression1_away+defenceAggressionClass1_away+
                defenceTeamWidth1_away+defenceTeamWidthClass1_away+defenceDefenderLineClass1_away, data=
              family = binomial(link="logit"))
  #Testmod <- mean(predict(model,test[,1:8]) != test$outcome)
  predict_wins <- predict(wins,test[,1:45], type="response")
  predict_wins <- ifelse(predict_wins > win_thresh,1,0)
  Testwins <- mean(predict_wins == test$outcome)
  # losses
  predict_losses <- predict(loss,test[,1:45], type="response")
  predict_losses <- ifelse(predict_losses > loss_thresh,1,0)
  Testlosses_bench <- mean(predict_losses == test$outcome)
  # ties
  predict_ties <- predict(tie,test[,1:45], type="response")
  predict_ties <- ifelse(predict_ties > tie_thresh,1,0)
  Test_tie <- mean(predict_ties == test$outcome)
  TEALL = rbind(TEALL, cbind(Testmod))
}
# decision boundary for wins
summary(soccer_nobet$win)
perc = 8835/(10515+8835) #~0.2899225
win_thresh <- quantile(predict(wins,test[,1:45], type="response"), perc)

# determining decision boundary for loss
summary(soccer_nobet$lose)
perc = 5610/(5610+13740) #~0.2899225
loss_thresh <- quantile(predict(loss,test[,1:45], type="response"), perc)

# decision boundary for ties
summary(soccer_nobet$tie)
```

```
perc = 4905/(4905+14445) #~0.253
tie_thresh <- quantile(predict(tie,test[,1:45], type="response"), perc)
```

There is no code for our Bradley Terry Model since we used XLSTAT in Microsoft Excel for that analysis.

## Bibliography and Credits


- European Soccer Database

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- SQLite

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- R

https://www.r-project.org/

https://cran.r-project.org/doc/manuals/r-patched/R-intro.pdf