English Premier League Betting -- Refining Odds for Specific Scenarios

Final Paper

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Abstract

This document provides a detailed description of a model to predict outcomes of English Premier League football matches. It is outlined as follows: 1) Introduction, 2) Related Work and References, 3) Description of Datasets and Collection Methodology, 4) Method Description, 5) Evaluation, 6) Conclusion, 7) Contributions, and 8) Bibliography.

1. Introduction

<u>Context</u>

The English Premier League (EPL) is a competitive football (soccer) league based in the United Kingdom. Each year, 20 teams play in the league, and each team plays every other team twice (once at home, and once away), for a total of 380 matches per season. For each match, the name listed first is the home team and the name listed second is the away team. Ex: Chelsea vs Liverpool, indicates Chelsea is home and Liverpool is away.

		P	W	D	L	PTS
1	Manchester United	7	5	1	1	16
2	Manchester City	7	5	0	2	15
3	West Ham United	7	4	1	2	13
4	Arsenal	7	4	1	2	13
5	Tottenham Hotspur	7	3	3	1	12
6	Leicester City	7	3	3	1	12
7	Liverpool	7	3	2	2	11
8	Everton	6	2	3	1	9
9	Southampton	7	2	3	2	9
10	Crystal Palace	6	3	0	3	9
11	Swansea City	7	2	3	2	9
12	Watford	6	2	3	1	9
13	Norwich City	7	2	3	2	9
14	West Bromwich	6	2	2	2	8
15	Chelsea	7	2	2	3	8
16	Bournemouth	7	2	1	4	7
17	Stoke City	7	1	3	3	6
18	Aston Villa	7	1	1	5	4
19	Newcastle	7	0	3	4	3
20	Sunderland	7	0	2	5	2

Figure 1: English Premier League Table during the 2015/2016 season. Table displays wins, draws, and losses per team.

As the table shows, each team receives points based on their performance in each match. 3 points for a win, 1 for a draw and none for a loss. The Premier League is the top league in the English football league system. Relegation is a major fear for all underperforming Premier League teams. At the end of the regular season, the three teams with the least amount of points are relegated to the second best league, called the Championship. The three teams with the most points in the Championship league are then promoted to the Premier League.

Before every game, betting agencies (or bookmakers) provide odds to customers. The odds are proportional to the payout customers receive if they win, and inversely proportional to a team's likelihood of winning a game. In other words, the lower the odds, the higher the likelihood of a team winning (the math of converting odds to probabilities is described in the Description of Dataset and Collection Methodology section).

Odds to Probabilities

Odds		*Probabilities*
Home Win: 1.25	→	65.93%
Draw: 6.5	→	28.57%
Away Win: 15	→	5.49%

Note that the Odds do not sum to any value in particular, whereas the probabilities sum to 1.

<u>Motivation</u>

Customers use bookmakers in part because they provide "reliable" odds to make betting a game fair. We believe that we can use historically available data to create a model which would provide better probabilities than the bookmakers themselves. In the event that the model is successful in predicting match outcomes, there is money to be made in investing in accordance with the predictions of the model.

<u>Hypothesis</u>

By aggregating historical data from various betting agencies, and combining them with actual match outcomes, we can create a model that provides better probabilities than individual betting agencies for games in the immediate future. One model does better than another if it provides probabilities for games that more accurately predict the outcome of the game, thereby maximizing the payout for customers.

<u>Goals</u>

- Create a model that provides probabilities to the predict match outcomes based on historical betting data, past outcomes and current season performance.
- Identify variables that facilitate match outcomes, such as: past betting odds from across 7 betting agencies, past match results (both home and away), and recent form (team's results in the 5 most recent matches before the current).
- Use data from 4 previous seasons (2013/14 - 2016/17 to train the model.
- Use matches from the current season (2017/18) to evaluate the model.
- Identify areas for improvement for future work.

Potential Applications

If our model proves to be successful, it can provide users a complement to betting odds provided by bookmakers, so that they can make more informed decisions and potentially receive a higher payout. In the future this logic can also be expanded to assist gamblers of other professional football leagues and other sports.

2. Related Work and References

Reading previous research guided us to chose this project and also helped inform how to build our model. Some of the papers used existing classifiers (Naive Bayes, Decision Trees, etc) to a minimal degree of success. In the pursuit of a better performing model, we navigated away from these existing classifiers.

Reference #1: Using Bookmaker Odds to Predict the Final Result of Football Matches [1]

This paper is what inspired the idea to pursue this project in the first place. Odachowski and Grekow were of the first academics who decided to look at the link between bookmaker odds and actual results in football. Their research concludes that it is possible to create a predictive model using bookmaker odds. This confirmation, suggested that our project could be viable. However, they had minimal success using some off-the-shelf classifiers including: Bayes, Decision trees, and Bagging. In their opinion this is because betting data was not very compatible with those classifiers. Learning from their results, future papers have decided to implement their own model.

Reference #2: Soccer Betting Analysis - How to use betting agencies odds to predict match results? [2]

In Chen Trilnik's Soccer Betting Analysis project, he concluded that 3 factors: the agencies' favored prediction, the stage of the season, and the location of the game could predict matches with 80% precision. Similar to Chen, our final program analyzes whether being home or away has an effect on the results of a match. Chen concluded that the location of the match noticeably affected the outcome and that the home team wins 46%, the away team 29%, and there is a draw 25% of the time. We used this data as a model to adjust our weightings in the final model.

Reference #3**:** "The Secret Betting Strategy That Beats Online Bookmakers" [3]

Researchers from the University of Tokyo aggregated soccer betting odds from across betting agencies. Using this information they built a web crawler that gathered the odds offered by online betting companies on soccer games around the world. They calculated the average odds, found any outliers, and then worked out whether a bet would favor them or not. We used their techniques to aggregate odds in order to build our own web crawler and preprocessing tool.

Reference #4: Predicting The Dutch Football Competition Using Public Data: A Machine Learning Approach [4]

A group at Eindhoven University of Technology looked at which team/match-specific factors play a big role in predicting specific performance for the Eredevisie — a Dutch Football League. Specifically they thought home advantage, performance in earlier encounters, streaks, recent performance, and managerial change were significant factors. This use of specific factors and encouraged us to use home advantage, historical performance as well as betting odds to as factors in our own model.

Reference #5 FiveThirtyEight- How Our Club Soccer Projections Work [5]

FiveThirtyEight is a a website that focuses on data forecasting. They have club soccer projections, which predict the outcome of matches around the world. This reference gives insight into the methodology behind the forecast, and evaluation model. It details the four metrics (goals, adjusted goals, shot-based expected goals and non-shot expected goals) to evaluate a team's performance after each match. Their model helped us understand how to weight different factors in making a prediction. We also get a sense of the statistical techniques used for forecasting (Poisson Model, and Monte Carlo Simulation).

Reference #6 Differentiating the Top English Premier League Football Clubs from the Rest of the Pack: Identifying the Keys to Success [6]

Oberstone, a researcher for the Journal of Quantitative Analysis in Sports, classifies performance as a function of goal attempts, passing, defending, crossing, and discipline (yellow and red card bookings). His analysis is spatio-temporal, in that it considers the time of each action and also the position in which it occurred on the pitch.

Given the time and location of each match event and goal, paired with match outcomes, Oberstone uses multiple linear regressions to investigate contributors to successes and failures in game settings. For example, intercepting an opposition pass in the final third of the pitch is one of the strongest indicators of an impending goal.

We incorporated this aspect of looking at contributing factors to match outcomes rather than match events. Rather than looking at indicators of goals, we look at indicators of wins and losses. To this end, we studied Oberstone's analysis of recent form and team developments for predicting matches in the immediate future.

3. Description of Datasets & Collection Methodology

Our model requires us to gather historical data to train on, as well as the current season's data to use for evaluation. We decided to use data from 4 previous seasons ('13/14 - '16/17) for training purposes, and the current season's matches ('17/18) for testing, to have roughly an 80-20 split.

The data was collected from the website www.football-data.co.uk, which contains data on every Premier League match over the past ten seasons including dates, final score, location, and betting odds from seven of the top betting agencies. We created a python web scraper which scrapes all of the information the website has on each match and outputs this data to a CSV file. The scraper outputs five CSV files, one for each season starting at the 13/14 season. This data is raw and needs to be further processed and standardized for training the model.

In Exhibit 1 there is a snapshot of five rows of the raw 13/14 Premier League season CSV file. As you can see from the data below, since the website contains so much information on each match, there are multiple columns that are irrelevant to our final project such as who was the referee for the game. In addition, the columns labeled B365H to SJA are seven agencies' 3-way odds for home win, draw, and away win. Our final program does not care about odds and instead, needs these odds to be converted to probabilities. Also, our final program does not need information from individual agencies' but instead, wants the average 3-way probabilities from the top seven betting agencies. In other words, across all seven agencies, we must calculate the average probability of a home win, draw, and away win, for each fixture.

In order to clean up the data, we wrote a pre-processing python program that displays only relevant information to our final program as well as cleans up and performs some basic calculations on the data. This program outputs five processed CSV files (one for each season) which contain relevant information for our final program. These CSV files contain nine columns of data: date of match, home team name, away team name, home team goals, away team goals, final result, average home probability, average draw probability, and average away probability.

For the date column, preprocessing makes sure that every date was represented in the same way.

We represented all dates in the European format DD/MM/YY.

In the home team name and away team name column, we lowercased every letter and removed all spaces. The home team goals, away team goals, and final result columns did not require any processing and were displayed as they were.

The average home, draw, and away probabilities columns are simply the probabilities of the home team winning, a draw, or the away team winning. In order to compute these averages, we took an average of all of the 3-way odds for the top 7 betting agencies. Once these averages were calculated, we needed to convert the odds into probabilities. Let's walk through this process using the example from the Introduction. We can see that for a certain Premier League match, a betting agency created the following odds:

Home Win: 1.25
Draw: 6.5
Away Win: 15

These odds are proportional to the payout customers receive if they win, and inversely proportional to a team's likelihood of winning a game. Our program needs probabilities as input, not odds. As a result we created the following equations to convert odds to probabilities (P stands for probability and O stands for odds):

$$P(Home) = \frac{O(Away)}{O(Home) + O(Draw) + O(Away)}$$

$$P(Away) = \frac{O(Home)}{O(Home) + O(Draw) + O(Away)}$$

$$P(Draw) = \frac{O(Draw)}{O(Home) + O(Draw) + O(Away)}$$

We used these equations to compute the 3-way probability for a given match, resulting in the creation of the average home, draw, and away probability columns. These calculations were particularly tricky because occasionally the website would only contain information from 6 out of the 7 top betting agencies. As a result, our preprocessing program handled these inconsistencies and made sure to adjust the calculations if data from all of the betting agencies was unavailable.

As you can see from the diagram in Exhibit 2, these processed CSV files only contains relevant information for our final program. Later, our model will open up these CSV files as input.

4. Method description, including evaluation methodology

There are two key Phases of our methodology: Phase 1 builds from past outcomes, while Phase 2 synthesizes the findings of Phase 1 and adds current context to predict the immediate future.
There are also three sets of coefficients that sum to one in the model:

1. The weight of historic analysis vs. current form.
2. The weight of each past season, from 2013 to 2017.
3. The weight of each of the two home-away and away-home matches in each season.

We used a backward-propagation-like strategy to manipulate each set of weights on the 2013 - 2017 training data. The set of weights that we decided to use was the set that maximized the predictive accuracy of our model on a subset of the training data.

<u>Phase 1:</u>

Similar to Reference #3 (MIT Technology Review)[3], we assume that the set of top betting agencies have collectively performed their due diligence in creating their odds. Given this, the first step of the model is to incorporate their odds to develop an algorithm that takes into account both the predictions for a match and it's actual outcome.

We begin by considering the average betting agency distribution for each game, using the seven most successful bookmakers in the UK. Next, we classify the profile of each game based on the disparity between the two teams; is it an even matchup, or is one team heavily favored to win? We have four such profile classifications, with the middle two accounting for 80% of matches. Thus, the common case is for the match to be quite even.

The profile of the match, in tandem with the actual outcome (win, draw, loss), determine which direction we move the probabilities. This process is mapped out in in Exhibit 3. The magnitudes, however, are determined by the convincingness of the result.

For example, if a home team were highly unlikely to win a match (say, Swansea City at home to Manchester City), and yet they manage a result, then we'd like to increase the probability of a future Man City home result, and decrease the probability of a future home loss- as this is a surprising outcome. The extent to which we increase and decrease each aspect of the distribution is a function of convincingness, which we proxy by using the goal difference of the match.

Convincingness is incorporated in the form of a coefficient that ranges from 0.10 to 0.40. A greater margin of a win results in a greater coefficient. This is because a narrow 1-0 win is less convincing than a 4-0 thrashing, since the latter indicates a greater likelihood of similar outcome in the future.

Using the coefficient and the profile of the match, the model now knows which direction to move each probability, and by how much (if at all).
We increase a given probability by the product of the convincingness coefficient and that corresponding probability. The value removed from the probability to-be-decreased is equal to the net gain in the other two probabilities.

$$P(Home_{New}) = P(Home_{Old}) + (Convincingness * (1 - P(Home_{old}))$$

probabilities in one direction, and the third probability in the opposite direction of the first two. This is done not only to ensure the sum-to-one integrity constraint, but also because football is not binary — an unlikely win means that the winner is more likely to not only win, but also draw in the next fixture. In other words, we do not just trade shift value between wins and losses.

The end result of Phase 1 is a data structure that contains the altered probability distribution for each match and season. This data structure, and the fixture list for matches to be played in the 2017/18 season are used as inputs for Phase 2.

Phase 2:

Once each match has been appropriately "learned" and altered, the next step is to summarize the findings into a unique prediction for each fixture. In order to avoid the pitfalls of Reference #2, we weigh match data by recency. Matches from last season hold more weight than matches from three seasons ago.

For each fixture, our models weighs its "opposite" as well. This means that for a Liverpool vs Leicester prediction, we consider previous matches where Liverpool was at home to Leicester, but also matches where Leicester were home to Liverpool. We weigh the "opposite" fixture with only a 10% weighting, and the identical fixture with the remaining 90% for each season. This is because the intangibles in football associated with match location (ie home vs away) have a direct influence on match result. The weighted average yields a season's contribution to the 2017/18 prediction.

The seasons are then weighted according to their recency. 2013/14 is given a 10% weight, and 2014/15, 2015/16, and 2016/17 are given 20%, 30% and 40% weights respectively.
The final component is home and away form for each team, thus capturing the momentum that each team carries into the game. In our model, a team on a 5-game winning streak would have improved chances of beating a team on a 5-game losing streak, even if they have historically struggled against them.

We incorporate recent form by assessing the 5 most recent matches from each team in the build-up to the match to-be-predicted. Each win earns 1 point, where draws and losses earn 0 and -1 points respectively. The result is a value between -5 and +5 that gauges the recent form of the home and away teams. This value is then standardized to be between -1 and +1. Each team's recent form value is then added to their respective probability of a win.

However, there are 2 edge cases that we must consider. The first is when the recent form of either team does not really illuminate the story of the game. As in, we've predicted a low probability of a team winning, and they're also in poor form. In this case, the form does not tell us anything new, and the coefficient we multiply by before adding form is 0.10.

The second, and more illuminating case, is when we predict a team to have a low probability of winning, and yet they're in sustainable form. In this case, the coefficient we multiply by before adding in their form value is 0.50.

5. Evaluation

Our model will be evaluated based on the accuracy and confidence with which it predicts each match of the 2017/18 season. Each betting agency will be scored identically, and at the end, we will rank our model among them.

The evaluating algorithm is quite simple. The official "prediction" is considered to be the maximum of the three probabilities (home win, draw, away win).

From there, a prediction is either correct or incorrect. On a correct prediction, the model's "score" is increased by the value of the probability of the correct prediction. For example, if a model correctly predicted a home win with probability 65%, then its' score is incremented by 0.65.

However, if wrong, then the score is decreased by the difference between the probability value of the official prediction and that of the actual outcome. For example, if a model predicted a home win with probability of 65%, and an away win probability of 10%, its' score would be decreased by 0.55 in the event of an away win.

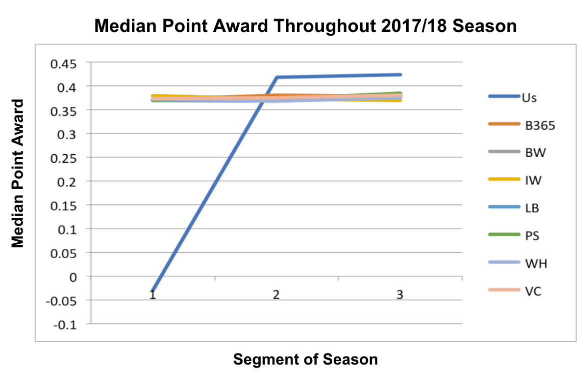
Thus, each match will provide a marginal increase or decrease in every model's total score. In order to assess the importance of team form in the performance of our model, we partitioned the 2017/18 season into equal thirds, and created a checkpoint and the end of each third of the season.

At each checkpoint, we considered the aggregate score, and median point allocation across matches in that third. We then benchmarked our model's performance against each of the seven competing agencies. While we lagged behind in the first third, our hypothesis was confirmed to be true in the remaining two thirds.

The recent-form calculations weighed heavier in the model later in the season, and this significantly swayed our performance. In terms of median point allocation and total point aggregation, we finished last among the seven competing agencies in the first third of the 2017/18 season, but finished first both of the remaining two checkpoints.

This data is displayed in our final output file, which lists each match of the 2017/18 season thus far. The file is also partitioned into thirds to reflect the shift in performance throughout the season, as recent form data became more complete. The last eight columns represent us and each of the seven competing agencies. The numerical values then represent the change in score as a result of that match. If the score is negative, then that means the agency (or us) mis-predicted the match. At the end of each third, we log the median point allocation (industry-standard metric from reference #1) and rank ourselves amongst the agencies.

The graph below summarizes the performance of our model against the agencies over the course of the season.



6. Conclusions and Future Considerations

One of the largest takeaways has been the importance of form in predicting match outcomes.

This can be deduced from the shift in our model's performance once enough form data was retrieved to weigh into our predictions.

A further finding was the importance of weighing identical home-away combinations from past seasons. The implication is that home-team advantage makes each match unique; although the same fixture occurs twice in each season, there is little that can be taken from the "reversed" home-away matchup due to the game taking place at a different ground.

An interesting future consideration would entail further investigating recent form and how it can defined outside of wins and losses in a 5-game window. One possibility is to monitor how the form of every team oscillates throughout each season, and assess any patterns that appear. For example, do teams like Arsenal and Tottenham tend to crumble every April just as they need to mount a challenge for the title? These questions can raise interesting team-specific insights.

7. Contributions

Team members included Abhimanyu Mucchal (abhimuch), Aklavya Kashyap (aklavyak), Colin Sullivan (colinmi), and Shayan Shafii (shafii).

- Everyone:
  - Conducted research to figure out the scope of the project, and cited relevant sources in the paper and the project
  - Participated in brainstorming sessions to develop an algorithm for pre-processing, classification, as well as evaluation
  - Proof-read the paper and the poster

- Abhi:
  - Worked on the scraper.py as well as code to incorporate recent form into the prediction (aggregate.py)
  - Helped Colin write the preprocess.py
  - Wrote the introduction to the paper
  - Wrote the context & introduction to the poster

- Colin:
  - Took the lead on creating an algorithm to preprocess the raw input and writing the preprocess.py file
  - He also helped Abhi with the logic for aggregation
  - Wrote the Goals and the Hypothesis for the Poster
  - Wrote the description of datasets in the paper

- Aklavya:
  - Worked with Shayan on creating the classification algorithm and the relevant code
  - Worked with Shayan to write the the calcprobs.py file which contains the predictive model
  - Wrote most of the Methods component for the poster
  - Wrote the method description for the paper

- Shayan:
  - Worked with Aklavya on creating the classification algorithm and the relevant code
  - Worked with Aklavya to write the the calcprobs.py file which contains the predictive model
  - Wrote the Evaluation & Results component of the poster
  - Wrote the Evaluation component of the paper

Footnotes:

1. Odachowski, Karol & Grekow, Jacek. (2012). Using Bookmaker Odds to Predict the Final Result of Football Matches. 7828. 196-205.

2. "Soccer Betting Analysis - How to Use Betting Agencies' Odds to Predict Match Results?" NYC Data Science Academy , 29 April 2017, https://nycdatascience.com/blog/student-works/r-shiny/soccer-betting-analysis-use-betting-agencies-odds-predict-match-results.

3. "The Secret Betting Strategy That Beats Online Bookmakers." MIT Technology Review , 19 Oct. 2017, www.technologyreview.com/s/609168/the-secret-betting-strategy-that-beats-online-bookmakers.

4. Tax, Niek & Joustra, Yme. (2015). Predicting The Dutch Football Competition Using Public Data: A Machine Learning Approach. 10.13140/RG.2.1.1383.4729.

5. Jayboice. "How Our Club Soccer Projections Work." FiveThirtyEight, FiveThirtyEight, 9 Aug. 2017, fivethirtyeight.com/features/how-our-club-soccer-projections-work/.

6. Obserstone. "Differentiating the Top English Premier League Football Clubs from the Rest of the Pack: Identifying the Keys to Success" University of San Francisco, Journal of Quantitative Analysis in Sports.

Exhibits:

1. Raw CSV snapshot

Div	Date	HomeTeam	AwayTeam	FTHG	FTAG	FTR	HTHG	HTAG	HTR	Referee	HS	AS	HST	AST	HF	AF	HC	AC	HY	AY	HR	AR	B365H	B365D	B365A	BWH	BWD	BWA	IWH	IWD	IWA	LBH	LBD	LBA	PSH	PSD	PSA	WHH	WHD	WHA	SJH	SJD	SJA
E0	17/08/13	Arsenal	Aston Villa	1	3	A	1	1	D	A Taylor	16	9	4	4	15	18	4	3	4	5	1	0	1.44	4.75	8	1.36	5	7.75	1.37	4.6	7.5	1.4	4.5	7.5	1.41	5.2	8.3	1.36	4.8	8.5	1.4	4.5	7.5
E0	17/08/13	Liverpool	Stoke	1	0	H	1	0	H	M Atkinson	26	10	11	4	11	11	12	6	1	1	0	0	1.4	5	9.5	1.4	4.33	8.25	1.4	4.4	7.3	1.44	4.2	7.5	1.41	4.88	9.35	1.36	4.6	9	1.36	4.5	9.5
E0	17/08/13	Norwich	Everton	2	2	D	0	0	D	M Oliver	8	19	2	6	13	10	6	8	2	0	0	0	3.2	3.4	2.4	3.1	3.25	2.3	2.9	3.3	2.3	3	3.3	2.3	3.32	3.41	2.35	3.1	3.3	2.3	3	3.4	2.3
E0	17/08/13	Sunderland	Fulham	0	1	A	0	0	D	N Swarbrick	20	5	3	1	14	14	6	1	0	3	0	0	2.3	3.4	3.4	2.25	3.2	3.25	2.2	3.2	3.2	2.2	3.25	3.3	2.25	3.37	3.58	2.2	3.3	3.3	2.25	3.3	3.3
E0	17/08/13	Swansea	Man United	1	4	A	0	2	A	P Dowd	17	15	6	7	13	10	7	4	1	3	0	0	4.2	3.5	2	4.1	3.5	1.87	4.2	3.5	1.8	4	3.5	1.9	4.1	3.52	2.03	4	3.4	1.91	4	3.6	1.9
E0	17/08/13	West Brom	Southampton	0	1	A	0	0	D	K Friend	11	7	1	2	14	24	4	8	4	0	0	0	2.4	3.4	3.2	2.3	3.25	3.1	2.2	3.3	3.1	2.2	3.3	3.25	2.42	3.38	3.21	2.25	3.3	3.2	2.25	3.4	3.2
E0	17/08/13	West Ham	Cardiff	2	0	H	1	0	H	H Webb	18	12	4	1	10	7	4	3	0	1	0	0	2	3.6	4	1.91	3.4	4	1.9	3.45	3.8	1.9	3.4	4	1.99	3.57	4.21	1.95	3.5	3.8	1.91	3.5	4
E0	18/08/13	Chelsea	Hull	2	0	H	2	0	H	J Moss	22	7	5	2	7	16	5	1	0	1	0	0	1.2	7	21	1.19	6.25	15	1.2	5.8	13	1.2	6.5	15	1.2	7.4	19.5	1.2	6	15	1.2	6.5	15
E0	18/08/13	Crystal Palace	Tottenham	0	1	A	0	0	D	M Clattenburg	5	17	3	2	6	9	3	7	1	0	0	0	4.75	3.75	1.83	4.75	3.7	1.72	4.2	3.5	1.8	4.5	3.5	1.8	5.16	3.69	1.8	4.75	3.6	1.75	4.8	3.8	1.73
E0	19/08/13	Man City	Newcastle	4	0	H	2	0	H	A Marriner	20	5	11	1	9	7	8	1	2	3	0	1	1.33	5.5	11	1.3	5.25	9.75	1.3	5	9	1.28	5.5	10	1.31	5.86	11.66	1.29	5.5	10	1.3	5.25	10

2. Processed CSV snapshot

Date	HomeTeam	AwayTeam	FTHG	FTAG	FTR	AVGHOMEPROB	AVGDRAWPROB	AVGAWAYPROB
17/08/13	Arsenal	Aston Villa	1	3	A	0.560933360505	0.339820664357	0.0992459751376
17/08/13	Liverpool	Stoke	1	0	H	0.591692789969	0.312597962382	0.0957092476489
17/08/13	Norwich	Everton	2	2	D	0.265392781316	0.381512330557	0.353094888127
17/08/13	Sunderland	Fulham	0	1	A	0.376290322581	0.371290322581	0.252419354839
17/08/13	Swansea	Man United	1	4	A	0.201563204569	0.368555538855	0.429881256576

3. Match Profiles

Results

Classification

	Home Team Win	Draw	Away Team Win
Unlikely	P(win) ↑ P(draw) ↑ P(loss) ↓	P(win) ↑ P(draw) ↑ P(loss) ↓	✗
Potential	P(win) ↑ P(draw) ↑ P(loss) ↓	✗	P(win) ↓ P(draw) ✗ P(loss) ↑
Likely	P(win) ↑ P(draw) ✗ P(loss) ↓	P(win) ↓ P(draw) ↑ P(loss) ↑	P(win) ↓ P(draw) ↑ P(loss) ↑
Guaranteed	✗	P(win) ↓ P(draw) ↑ P(loss) ↑	P(win) ↓ P(draw) ↑ P(loss) ↑