pi-football: A Bayesian network model for forecasting Association Football match outcomes

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pi-football: A Bayesian network model for forecasting Association Football match outcomes

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ABSTRACT

A Bayesian network is a graphical probabilistic belief network that represents the conditional dependencies among uncertain variables, which can be both objective and subjective. We present a Bayesian network model for forecasting Association Football matches in which the subjective variables represent the factors that are important for prediction but which historical data fails to capture. The model (pi-football) was used to generate forecasts about the outcomes of the English Premier League (EPL) matches during season 2010/11 (but is easily extended to any football league). Forecasts were published online at www.pi-football.com prior to the start of each match. In this paper, we demonstrate that

a) using an appropriate measure of forecast accuracy, the subjective information improved the model such that posterior forecasts were on par with bookmakers' performance;
b) using a standard profitability measure with discrepancy levels at ≥ 5%, the model generates profit under maximum, mean, and common bookmakers' odds, even allowing for the bookmakers' built-in profit margin.

Hence, compared with other published football forecast models, pi-football not only appears to be exceptionally accurate, but it can also be used to 'beat the bookies'.

Keywords: Bayesian probability, Bayesian reasoning, expert information, football predictions, soccer predictions, sports predictions, subjective information

1 INTRODUCTION

Association Football (hereafter referred to simply as 'football') is the world's most popular sport (Dunning & Joseph A. M., 1993; Mueller et al., 1996; Dunning E., 1999), and constitutes the fastest growing gambling market (Constantinou & Norman, 2012b). As a result, researchers continue to introduce a variety of football models which are formulated by diverse forecast methodologies. While some of these focus on predicting tournament outcomes (Kuonen, 1996; Buchner, et al., 1997; Koning et al., 2003; Halicioglu, 2005a; Halicioglu, 2005b) or league positions (Koning, 2000), our interest is in predicting outcomes of individual matches.

A common approach is the Poisson distribution goal-based data analysis whereby match results are generated by the attack and defence parameters of the two competing

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teams (Maher, 1982; Dixon & Coles, 1997, Lee 1997; Karlis & Ntzoufras, 2003). A similar version is also reported in (Dixon & Pope, 2004) where the authors demonstrate profitability against the market only at very high levels of discrepancy, but which relies on small quantities of bets against an unspecified bookmaker. A time-varying Poisson distribution version was proposed by (Rue & Salvesen, 2000) in which the authors demonstrate profitability against Intertops (a bookmaker located in Antigua, West Indies), and refinements of this technique were later proposed in (Crowder et al., 2002) which allow for a computationally less demanding model.

In contrast to the Poisson models that predict the number of goals scored and conceded, all other models restrict their predictions to match result, i.e. win, draw, or lose. Typically these are ordered probit regression models that consist of different explanatory variables. For example, (Kuypers, 2000) considered team performance data as well as published bookmakers' odds, whereas (Goddard & Asimakopoulos, 2004; Forrest et al, 2005) considered team quality, recent performance, match significance and geographical distance. (Goddard, 2005) compared goal-driven models with models that only consider match results and concluded that both versions generate similar predictions.

Techniques from the field of machine learning have also been proposed for prediction. In (Tsakonas et. al., 2002) the authors claimed that a genetic programming based technique was superior in predicting football outcomes to other two methods based on fuzzy models and neural networks. More recently, (Rotshtein et al., 2005) claimed that acceptable match simulation results can be obtained by tuning fuzzy rules using parameters of fuzzy-term membership functions and rule weights by a combination of genetic and neural optimisation techniques.

Models based on team quality ratings have also been considered, but they do not appear to have been extensively evaluated. Knorr-Held (2000) used a dynamic cumulative link model to generate ratings for top division football teams in Germany. The ELO rating that was initially developed for assessing the strength of chess players (Elo, 1978) has been adopted to football (Buchdahl, 2003). In (Hvattum & Arntzen, 2010) the authors used the ELO rating for match predictions and concluded that the ratings appeared to be useful in encoding the information of past results for measuring the strength of a team, but the forecasts generated were not on par with market odds. (Leitner et al., 2010) have also assessed an ELO rating based model along with the FIFA/Cocal Cola World rating model and concluded that both were inferior against bookmakers' forecasts for EURO 2008.

Numerous studies have considered the impact of specific factors on match outcome. These factors include: home advantage (Hirotsu & Wright, 2003), ball possession (Hirotsu & Wright, 2003), and red cards (Ridder et al., 1994; Vecer et al., 2009)[†]

Recently researchers have considered Bayesian networks and subjective information for football match predictions. In particular, (Joseph et. al., 2006) demonstrated the importance of supplementing data with expert judgement by showing that an expert constructed Bayesian network was more accurate in generating football match forecasts for matches involving Tottenham Hotspurt than machine learners of MC4, naive Bayes,

[†] While this work falls within the scope of our interest, other empirical forecasting studies such as attendance demand (Peel & Thomas, 1989; Peel & Thomas, 1992; Peel & Thomas, 1997; Falter & Perignnon, 2000; Forrest & Simmons, 2002), and the effectiveness of football tipsters (Forrest & Simmons, 2000) do not.

Bayesian learning and K-nearest neighbour. A model that combined a Bayesian network along with a rule-based reasoner appeared to provide reasonable World Cup forecasts in (Min et al., 2008) through simulating various predifined strategies along with subjective information, whereas in (Baio & Blangiardo, 2010) a hierarchical Bayesian network model that did not incorporate subjective judgments appeared to be inferior in predicting football results when compared to standard Poisson distribution models.

In this paper we present a new Bayesian network model for forecasting the outcomes of football matches in the distribution form of {p(H), p(D), p(A)}; corresponding to home win, draw and away win. We believe this study is important for the following reasons:

a) the model is profitable under maximum, mean and common bookmakers' odds, even by allowing for the bookmakers' introduced profit margin;
b) the model priors are dependent on statistics derived from predetermined scales of team-strength, rather than statistics derived from a particular team (hence enabling us to maximise historical data);
c) the model enables us to revise forecasts from objective data, by incorporating subjective information for important factors that are not captured in the historical data;
d) the significance of recent information (objective or subjective) is weighted using degrees of uncertainty resulting in a non-symmetric Bayesian parameter learning procedure;
e) forecasts were published online at www.pi-football.com before the start of each match;
f) although the model has so far been applied for one league (the English Premier League) it is easily applicable to any other football league.

The paper is organised as follows: section 2 describes the historical data and method used to inform the model priors, section 3 describes the Bayesian network model, section 4 describes the assessment methods and section 5 provides our concluding remarks and future work.

2 DATA

The basic data used to inform the priors for the model were the results (home, draw or away) of all English Premier League (EPL) matches from season 1993/94 to 2009/10 inclusive (a total of 6244 occurrences). This information is available online at (Football-Data). The forecasts generated by the model were for season 2010/11, a total of 380 EPL matches, and are all available online at www.pi-football.com.

In contrast to previous approaches we use the historical data to generate prior forecasts that are 'anonymous' by using predetermined levels of team-strength, rather than distinct team-names. We achieve this by replacing each team-name in each match in the database with a ranked number that represents the strength of that particular team for a particular season. The team-strength number is derived from the total number of points[‡] that the particular team achieved during that particular season as shown in Table 1.

Table 1. Predetermined levels of team strength

Total points	>84	80-84	75-79	70-74	65-69	...(intervals of 5 points)	30-34	25-29	<25
Strength	1	2	3	4	5	...	12	13	14

This implies that the same team may receive different ranks for different seasons and that different teams may receive identical ranks within the same season.

For example, the Manchester City at home to Aston Villa match in season 2006-07 is classified as ranked 10 versus a ranked 8 team (because in that season Manchester City totalled 42 points and Aston Villa 50 points), whereas in season 2009-10 the Manchester City at home to Aston Villa match is classified as a ranked 5 versus a ranked 6 team (because in that season Manchester City totalled 67 points and Aston Villa 64 points).

The granularity (of 14 levels of team strength) has been chosen to ensure that for any match combination (i.e. a team of strength x at home to a team of strength y) there are sufficient data points for a reasonably well informed prior for {p(H), p(D), p(A)}. This approach has a number of important advantages:

a) it enables us to make maximum use of limited data and be able to deal with the fact that every season the set of 20 teams changes (three are relegated and three new teams are promoted). For example, forecasts for teams which there is little or no historical data (such as those recently promoted) are based on data for different teams but of similar strength;
b) historical observations do not have to be ignored or weighted since the challenge here is to estimate a team's current strength and *learn* how such a team performed in the past given the specified ground (home/away) and opponent's strength. For example, consider the prior for the Manchester City at home to Aston Villa match in season 2010-11. Because the historical performances of Manchester City and Aston Villa prior to season 2010-11 were in no way representative of their strength in season 2010-11, what matters is not the results of previous matches between Manchester City and Aston Villa (which would be sparse as well as irrelevant), but the results of all previous matches where a rank 4 team played at home to a rank 9 team.
c) historical observations do not necessarily require weekly updating. The database already consists of thousands of historical match observations, and adding a few more matches every week will not make a major difference (this can be done once a year).
d) historical observations from one league can be used to predict match results for teams in another league (as long as the introduced ranking is redefined to

[‡] In EPL a total of 20 football teams participate and thus, a team can accumulate a minimum of 0 and a maximum of 114 points

accommodate potential discrepancies in the number of teams participating within that league);

3 THE MODEL

The model, which we call 'pi-football' (v1.32), generates predictions for a particular match by considering generic factors for both the home and away team, namely: 1) strength, 2) form, 3) psychology and 4) fatigue. There are model components corresponding to each of the four generic factors. In this sections we describe each of the model components (with further details regarding the assumptions and the different scenarios available for each of the Bayesian network nodes provided in Appendix A), but first we provide a brief overview.

Component 1 provides an estimate of each team's current strength (based on recent data) expressed as a distribution. Using historical outcomes between such ranked teams). We get a distribution for the predicted outcome as shown in Figure 1. Here we have a home team with mean strength 65-69 points (or rank 5) and an away team with mean strength 80-84 points (or rank 2). Component 1 is predominantly dependent on objective information for prediction and thus, we will refer to the resulting forecasts as 'objective forecasts'.

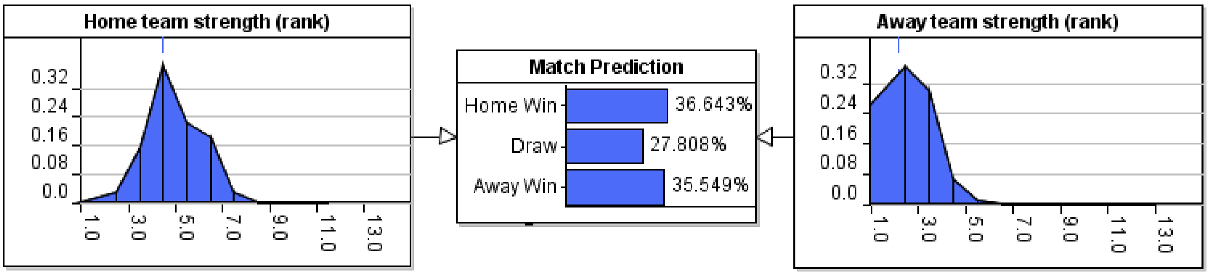


Figure 1. An example of an objective forecast generated at component 1,

Components 2, 3 and 4 are predominantly dependent on subjective information. They are used to revise the forecast from component 1. The outcome of each of the components is mutually summarised in a single value (considering both teams) which we describe as ‘subjective proximity’. The subjective proximity is measured on a scale from 0 to 1. A value equal to 0.5 indicates no advantage either of the teams; a value less than 0.5 indicates an advantage for the home team, while a value greater than 0.5 indicates an advantage for the away team. Since the forecast nodes are ranked in the sense of (Fenton et. al., 2007), the Bayesian Network software we have used (Agena, 2012) automatically updates the forecast taking account of the subjective proximity as shows for different examples in Figure 2. Figure 3 illustrates how the four components are linked. We will refer to the revised (and final) forecasts as 'subjective forecasts'.

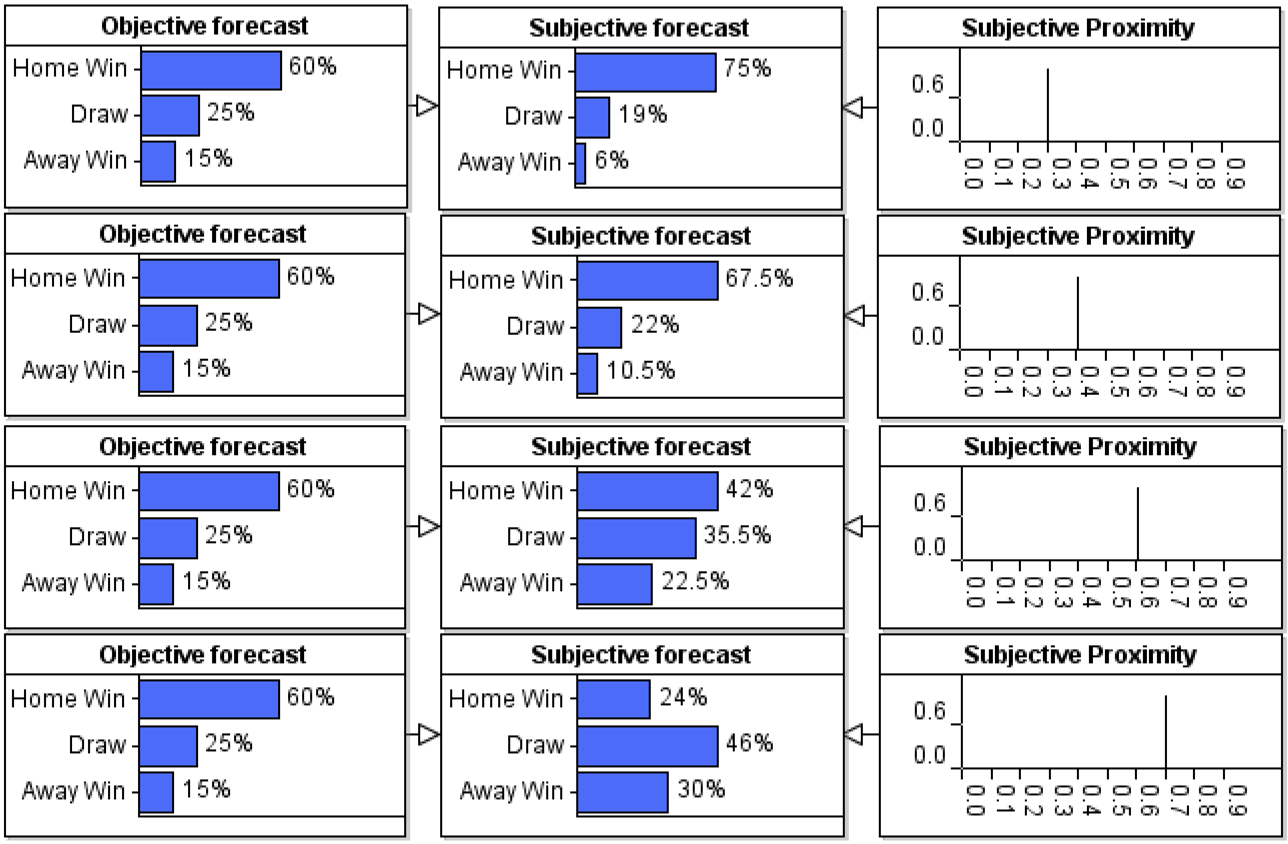


Figure 2. Forecast revision given different indications of subjective proximity

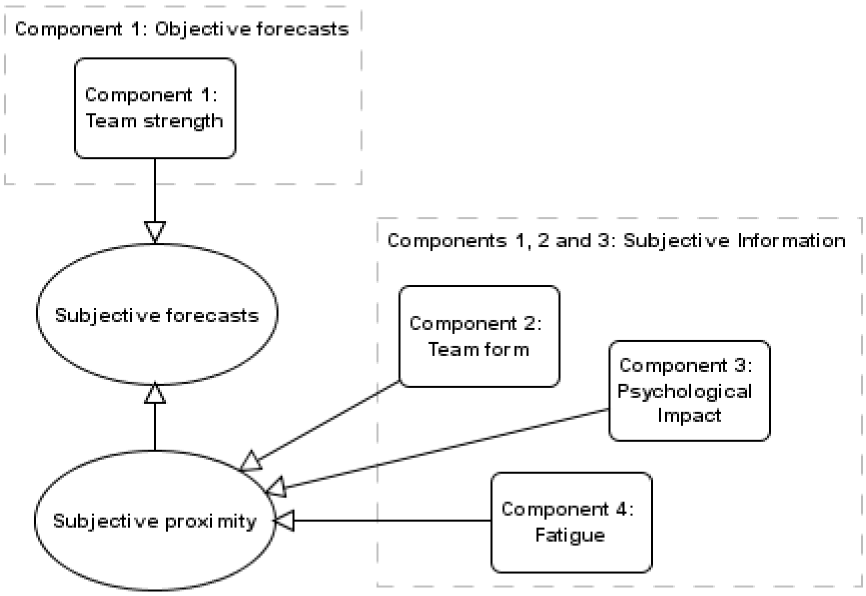


Figure 3. How components 1, 2, 3 and 4 are linked.

3.1. Component 1: team strength

The Bayesian network corresponding to the team strength component is shown in Figure 4 and it can be explained in terms of the following information:

a) *Previous information*: represented by five parameters (nodes 2, 3, 4, 5, and 6), each of which holds the number of total points accumulated in each of the five previous seasons with degrees of uncertainty (higher uncertainty for older seasons);
b) *Current information*: represented by a single parameter (node 9) that holds an estimate about the strength of the team in total points, and which is measured according to the total points accumulated during the current season and the points expected from residual matches[§] with degrees of uncertainty (lower uncertainty for higher number of matches played).
c) *Subjective information (optional):* represented by a single parameter (node 7) that holds the expert's subjective belief about the strength of the team in total points with degrees of uncertainty (reflects the expert's confidence). This information is used in cases where important changes happen before the start of the current season that cannot be captures by the historical data. A good example is Manchester City at the start of seasons 2009/10, 2010/11 and 2011/12, who dramatically improved their strength by spending £160m, £77m and £75m respectively signing some of the world's top players (Soccer Base, 2012).

The degree of uncertainty is modelled by exponential predetermined levels of variance in an attempt to achieve a limited memory process. This process produces a non-symmetric Bayesian parameter learning procedure. Accordingly,

a) *Previous information*: this indication receives increased rates of variance (and hence become less important) for each previous season, following the exponential growth illustrated in Figure 5a;
b) *Current information*: this indication receives decreased rates of variance (and hence become more important) after each subsequent gameweek[**], following the exponential decay illustrated in Figure 5b;
c) *Subjective Information:* this indication receives decreased or increased rates of variance according to the expert's confidence regarding his indication. The decreased/increased rates of variance follow those of the *previous information*[††] (Figure 5a).

Further information regarding the variables and available scenarios of this process is provided in table A1. An example with observations from the actual match between Man City and Man United dated 10th of November 2010 is illustrated in Appendix B.

[§] It is important to appreciate that the resulting parameter summarises a belief about the team's strength in points and not the points the team is expected to have by the end of the proceeding season.

[**] A complete EPL season consists of 38 gameweeks.

[††] For example, the degree of uncertainty when the expert's confidence is "Very Low" (fifth lowest out of five) is equal to the degree of uncertainty introduced for the points accumulated during the 5th preceding season.

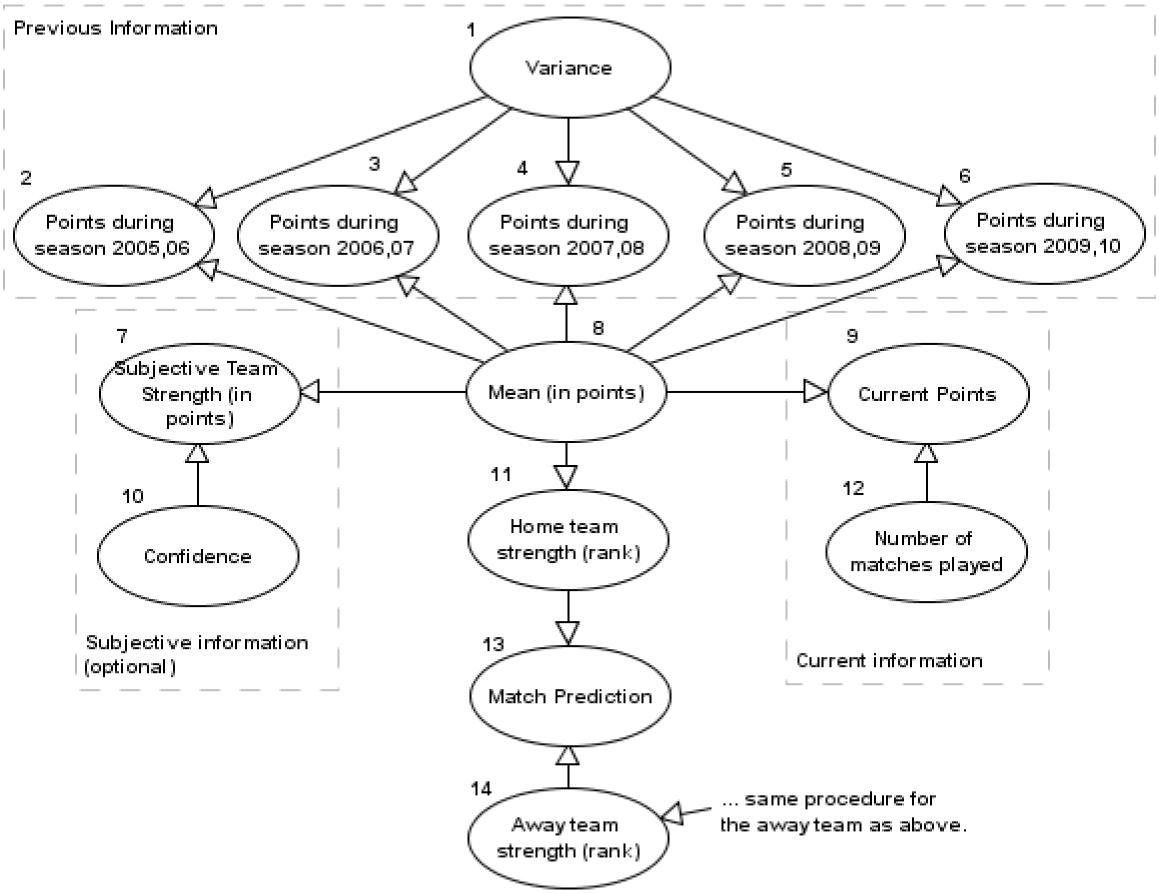
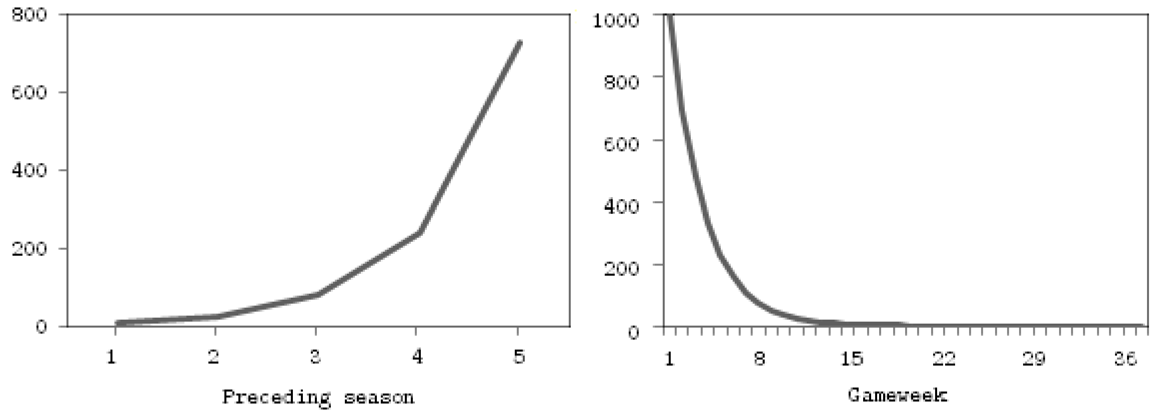


Figure 4. Component 1: Non-symmetric Bayesian parameter learning network for measuring the strength of the two teams and generating objective match predictions



(a) (b)

Figure 5. Limited memory process achieved by exponential growth/decay rates of uncertainty for (a) the previous seasons and (b) the gameweeks played under the current season.

3.2. Component 2: Team form

This Bayesian network component is shown in Figure 6. The 'form' of a team (node 10 for the home team and 12 for the away team) indicates the particular team's recent performance against expectations, and it is measured by comparing the team's expected performance[‡‡] against its observed performance during the five most recent gameweeks.

The form of a team is represented on a scale that goes from 0 to 1. When the value is close to 0.5 it suggests that the team is performing as expected; a higher value indicates that the team is performing better than expected. Further, if the particular team is playing at home, then the model will consider home form and away form with weights [2/3, 1/3] respectively (nodes 5, 6, 7; the reverse applies for the away team). The form is revised according to subjective indications about the availability of certain players (nodes 1, 2, 3, 4)[§§]. The expert constructed Bayesian network determines whether one team has an advantage over the other when comparing each other's form. Further information regarding the variables and available scenarios of this process is provided in table A2.

Figure 6. Component 2: Expert constructed Bayesian network for estimating potential advantages in form between the two teams.

[‡‡] Represented by what the model had initially forecasted.

[§§] Form decreases if the team has new first-team injuries and increases when important players return back to action.

3.3. Component 3: Psychological impact

This Bayesian network component is shown in Figure 7. The psychology of a team is determined by subjective indications regarding motivation, team spirit, managerial issues and potential head-to-head biases. The Bayesian network estimates the difference in psychological impact between the two teams. This process is divided into two levels; where the information assessed during level 1 (node 6) is updated at level 2 (node 7). This implies that the total information of level 1 (nodes 1, 2) shares identical impact with that of level 2 (node 4). Further information regarding the variables and available scenarios of this process is provided in table A3.

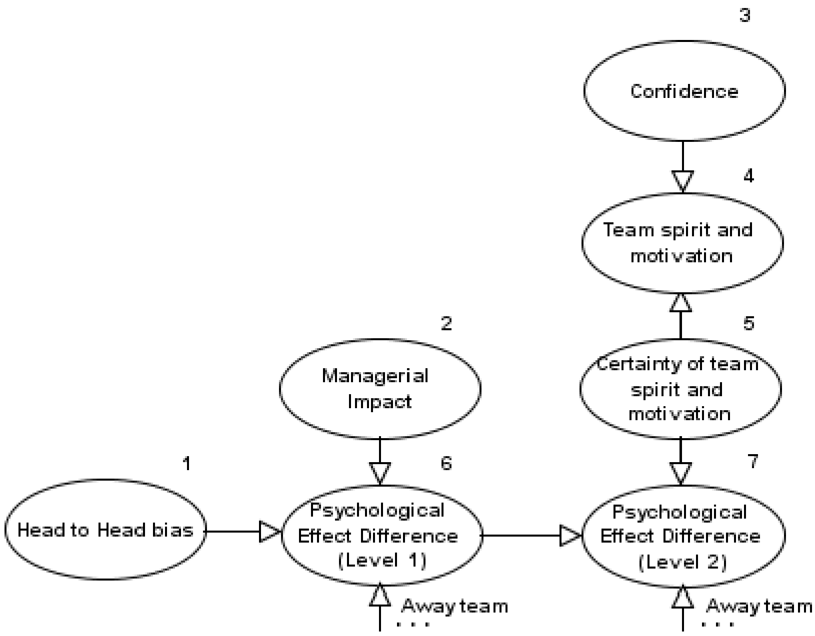


Figure 7. Component 3: Expert constructed Bayesian network for estimating potential advantages in psychological impact between the two teams.

3.4. Component 4: Fatigue

This Bayesian network component is shown in Figure 8. The fatigue of a team is determined by the toughness of the previous match, the number of days gap since that match, the number of first team players rested (if any), and the participation of first team players in national team matches (if any). The Bayesian network estimates the difference in the level of fatigue between the two teams. In particular, the resulting tiredness, which is determined according to the toughness of the previous match (node 5), is diminished according to a) the number of days gap since the last match (node 1), and b) the number of first-team players rested during that match[***] (node 2). Further, the indication of fatigue may increase up to 50% towards its maximum value depending on the level of participation of first team players in additional matches with their national team[†††] (nodes 6, 7). If there is no national team

[***] Where (a) is defined to be twice as important to (b) when calculating 'Restness' (node 3).

[†††] When football teams are given a break due to national matches, top level teams (e.g. Man United) might suffer greater levels of fatigue due to having many players who are first-team regulars with their national team.

participation the fatigue will receive no increase. Further information regarding the variables and available scenarios of this process is provided in table A4.

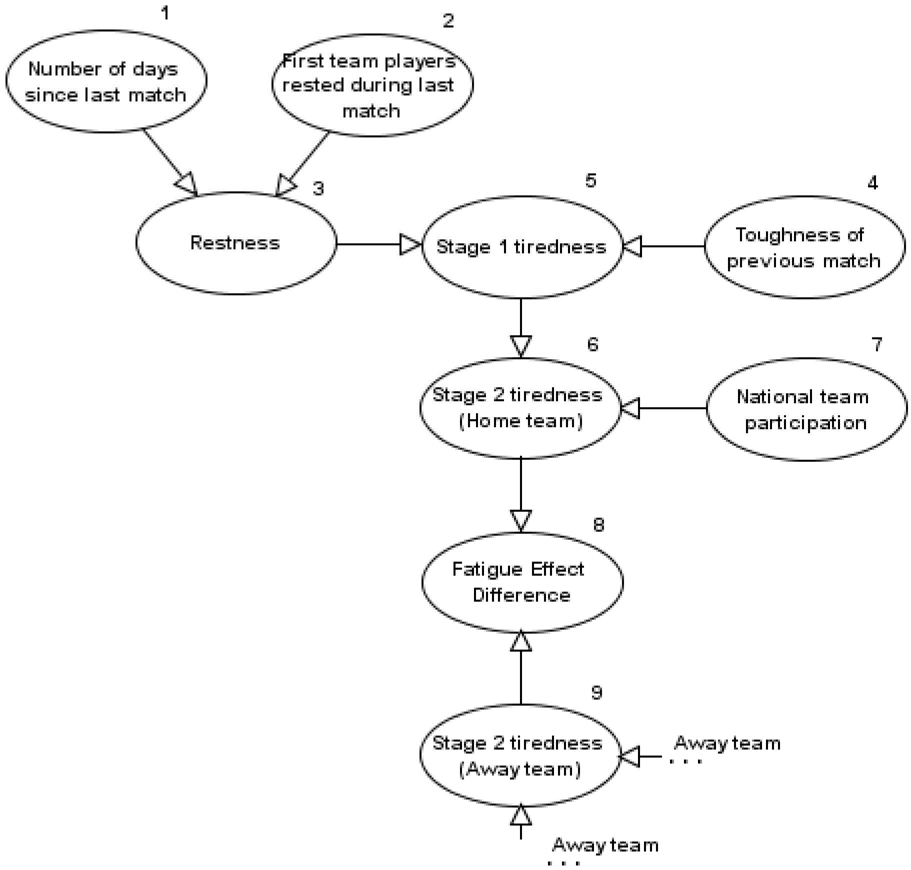


Figure 8. Component 4: Expert constructed Bayesian network for estimating potential advantages in fatigue between the two teams.

4 RESULTS & DISCUSSION

There are various ways in which the quality of a forecast model can be assessed. In particular, we can consider *accuracy* (how close the forecasts are to actual results) and *profitability* (how useful the forecasts are when used as the basis of a betting strategy). Researchers have already concluded that there is only a weak relationship between commonly used measures of accuracy and profitability (Leitch & Tanner, 1991) and that a combination of the two might be best (Wing et. al., 2007). Hence we use assessments of both accuracy (Section 4.1) and profitability (Section 4.2) in order to get a more informative picture about the performance of pi-football.

4.1. Accuracy Measurement

For assessing the accuracy of the forecasts we use of the Rank Probability Score (RPS), a scoring rule introduced in 1969 (Epstein), and which has been described to be particularly appropriate in assessing both interval and ordinal scale probabilistic variables (Murphy, 1970). We explained why it was the most rational scoring rule of those that have been proposed and used for football outcomes in (Constantinou & Fenton, 2012a). In general, this scoring rule represents the difference between the observed and forecasted cumulative distributions in which a higher difference leads to a higher penalty (Wilks, 1995), which is subject to a negative bias that is strongest for small ensemble size (Jolliffe & Stephenson, 2003). RPS is both strictly proper and sensitive to distance (Murphy, 1969; Murphy, 1970). For a single forecast the RPS is defined as

$$RPS = \frac{1}{r-1}\sum_{i=1}^{r-1}\left(\sum_{j=1}^{i}(p_j - e_j)\right)^2$$

where r is the number of potential outcomes, and p_j and e_j are the forecasts and observed outcomes at position j. A lower score indicates a more accurate forecast (lower error).

To determine the accuracy of our model we compute the RPS for the following three forecasts:

a) the objective forecasts generated at component 1; we will refer to these forecasts as f_O;
b) the subjective (revised) forecasts after considering components 2, 3 and 4; we will refer to these forecasts as f_S;
c) the respective normalised[‡‡‡] bookmakers' forecasts; we will refer to these forecasts as f_B.

Other studies have concluded that the normalised odds of one bookmaker are representative of any other bookmaker (Dixon & Pope, 2004; Forrest et al., 2005; Constantinou & Fenton, 2012b). However, instead of selecting a single bookmaker we make use of the mean[§§§] bookmakers' odds as provided by (Football-Data). Figure C1 demonstrates the RPS generated per forecast under the three datasets.

Figure 9 presents the cumulative RPS difference for a) f_B-f_O, b) f_B-f_S, and c) f_O-f_S. Since a higher RPS value indicates a higher error a cumulative difference for A-B below 0 indicates that A is more accurate than B. Accordingly, the graphs suggest that the accuracy of pi-football improves after considering subjective information. However, the bookmakers appear to have a higher overall accuracy even after the forecasts are revised. We performed 2-tailed paired t-tests to determine the importance of the above discrepancies. The null hypothesis is that the two datasets are represented by similar forecasts. The results are:

a) the dataset f_O is statistically significant to that of f_B at 99% confidence interval with a p-value of 0.0023; therefore, the null hypothesis is rejected;

‡‡‡ The bookmakers' odds are normalised such so that the sum of probabilities over the possible events is equal to 1 (the introduced profit margin is eliminated). For more information see (Constantinou & Fenton, 2012b).

§§§ The mean odds are measured by considering a minimum of 28 and a maximum of 40 different bookmakers per match instance (Football-Data).

b) the dataset f_S is not statistically significant to that of f_B at 99% (not even at 90%) confidence interval with a *p*-value of 0.1319; therefore, the null hypothesis is accepted.

We conclude that the accuracy of objective forecasts was significantly inferior to bookmakers' forecasts, and that subjective information improved the forecasts such that they were on par with bookmakers' performance. This also suggests that the bookmakers, as in the pi-football model, make use of information that is not captured by the standard statistical football data available to the public. Further, appendix D provides evidence of significant improvements in f_O by incorporating subjective information. Table D.1. presents match instances in which f_O and f_S generate the highest RPS discrepancies, along with indications whether f_S lead to a more accurate forecast.

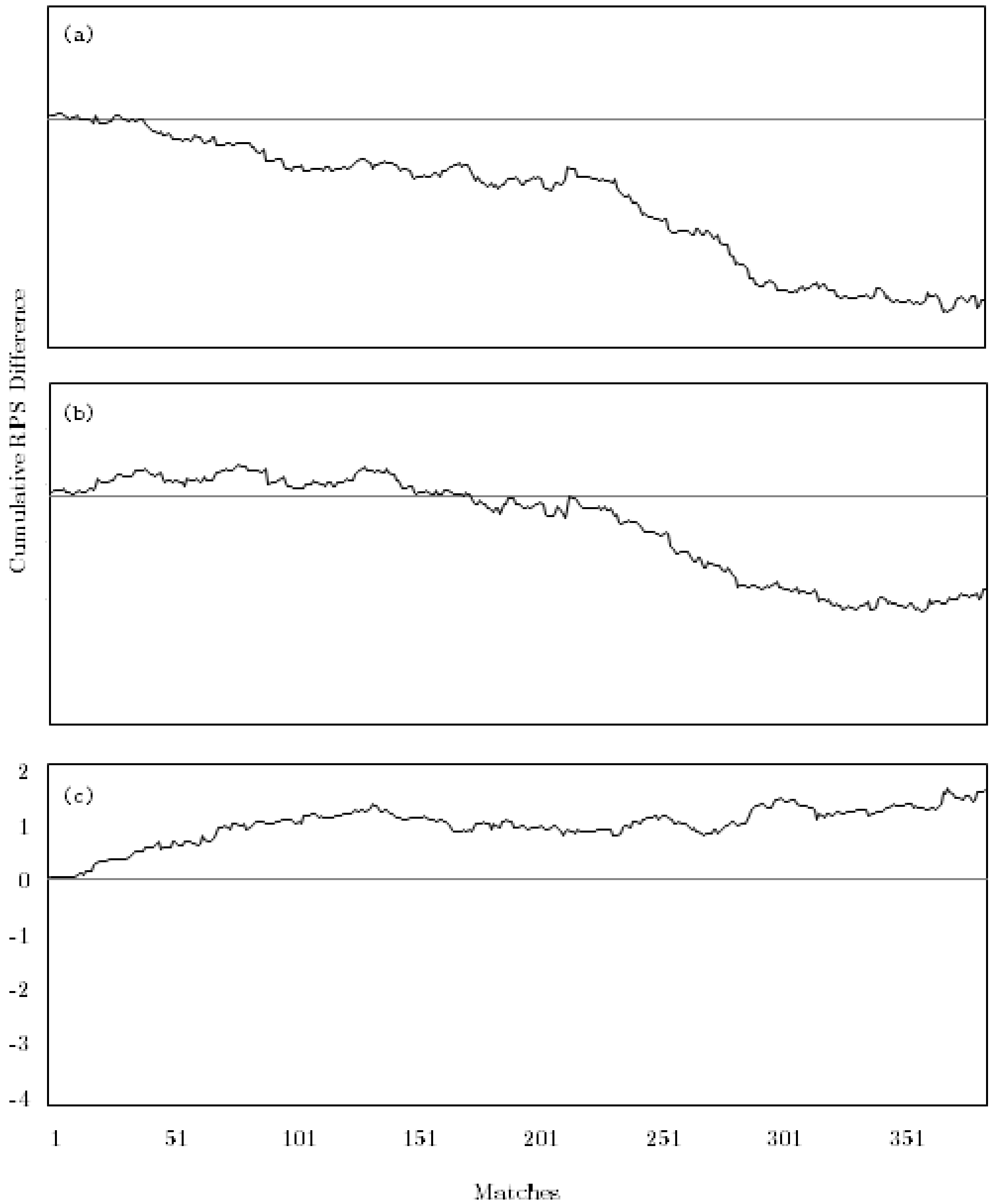


Figure 9. Cumulative RPS difference when (a) f_B-f_O, (b) f_B-f_S, (c) f_O-f_S.

4.2. Profitability Measurement

For assessing the profitability of the forecasts we perform a simple betting simulation which satisfies the following standard betting rule: *for each match instance, place a 1-pound bet on the outcome with the highest discrepancy, of which the pi-football model predicts with higher probability, if and only if the discrepancy is greater or equal to 5%.*

This assessment, of course, depends on the availability of an appropriate bookmaker's odds[****]. In contrast to previous papers (Forrest & Simmons, 2002; Forrest et al., 2005), the work in (Constantinou & Fenton, 2012b) shows that the published odds of a single bookmaker are not representative of the overall market. The profitability differs to accuracy because when one is interested in the profitability of the model has to consider the published odds; implying that such odds are not normalised and are considered with their introduced profit margins, hence the odds of one bookmaker can be significantly different to another (unlike in the case of accuracy - Section 4.1 - where published odds are normalised and hence the profit margin is eliminated). Accordingly, in determining pi-football's profitability we consider the following three different sets of bookmaker's odds[††††]:

a) the maximum (best available for the bettor) bookmakers' odds which we are going to refer to as f_{maxB}. This dataset is used to estimate how an informed bettor, who knows how to pick the best odds by comparing the different bookmakers' odds, could have performed;
b) the mean (average) bookmakers' odds which we are going to refer to as f_{meanB}. This dataset is used to estimate how an ignorant bettor could have performed, assuming he selects a bookmaker at random;
c) the William Hill (most common) bookmakers' odds which we are going to refer to as f_{WH}. This dataset is used to estimate how the common UK bettor could have performed. For this, we consider the odds provided by the leading UK bookmaker William Hill, who represents the 25% of the total market throughout the UK and Ireland (William Hill PLC, 2012).

Figure 10 demonstrates the cumulative profit/loss generated against a) f_{maxB}, b) f_{meanB} and c) f_{WH} after each subsequent match, assuming a 1-pound stake when the betting condition is met. The model generates a profit under all of the three scenarios and the imulation almost never leads into a negative cumulative loss; even by allowing for the in-built bookmakers' profit margin[‡‡‡‡]. Figure 11 illustrates the *Risk of Ruin* for up to a bankroll 100 times the value of a single bet. A bankroll of ~£55 (or 55 times the value of a single bet) and ~£45 is required to ensure that the probability to lose the specified bankroll

[****] See also the following studies on the football gambling market: (Pope & Peel, 1989; Dixon & Coles, 1997; Kuypers, 2000; Rue & Salvesen, 2000; Forrest & Simmons, 2001; Dixon & Pope, 2004; Goddard & Asimakopoulos, 2004; Forrest & Simmons, 2008; Graham & Stott, 2008).

[††††] The bookmaker's odds are also provided by (Football-Data).

[‡‡‡‡] We have also performed the identical betting simulation given f_O. Figure E1 demonstrates how the betting simulation results in losses of -13.98% against f_{maxB}, -19.92% against f_{meanB} and -12.84% against f_{WH}. This confirms the accuracy measurement results; that is, the significant improvements in f_O (which form f_S) by incorporating subjective information.

under infinite betting is ≤5% for f_{maxB} and f_{WH} respectively. In the case of f_{meanB} the profit rate is not high enough to ensure a risk of ruin ≤5% with a bankroll up to 100 times the value of a single bet. Table 2 summarises the statistics of the betting simulation for all of the three scenarios.

Overall, pi-football won approximately 35% of the bets simulated under all of the three scenarios, with the mean odds of winning bets at approximately 3.00. This suggests that the model was able to generate profit via longshot bets; what makes this especially interesting is that longshots are proven to be biased against the bettors (Cain et al., 2000, Forrest & Simmons, 2001; 2002; Forrest et al., 2005; Graham & Stott, 2008; Constantinou & Fenton, 2012b). This implies that the model would have generated even higher profits if the betting market was to provide unbiased odds. Additionally, profits are most likely to have been even higher under scenarios (b) and (c) if we were to eliminate the respective built-in profit margins of 6.09% and 6.50%.

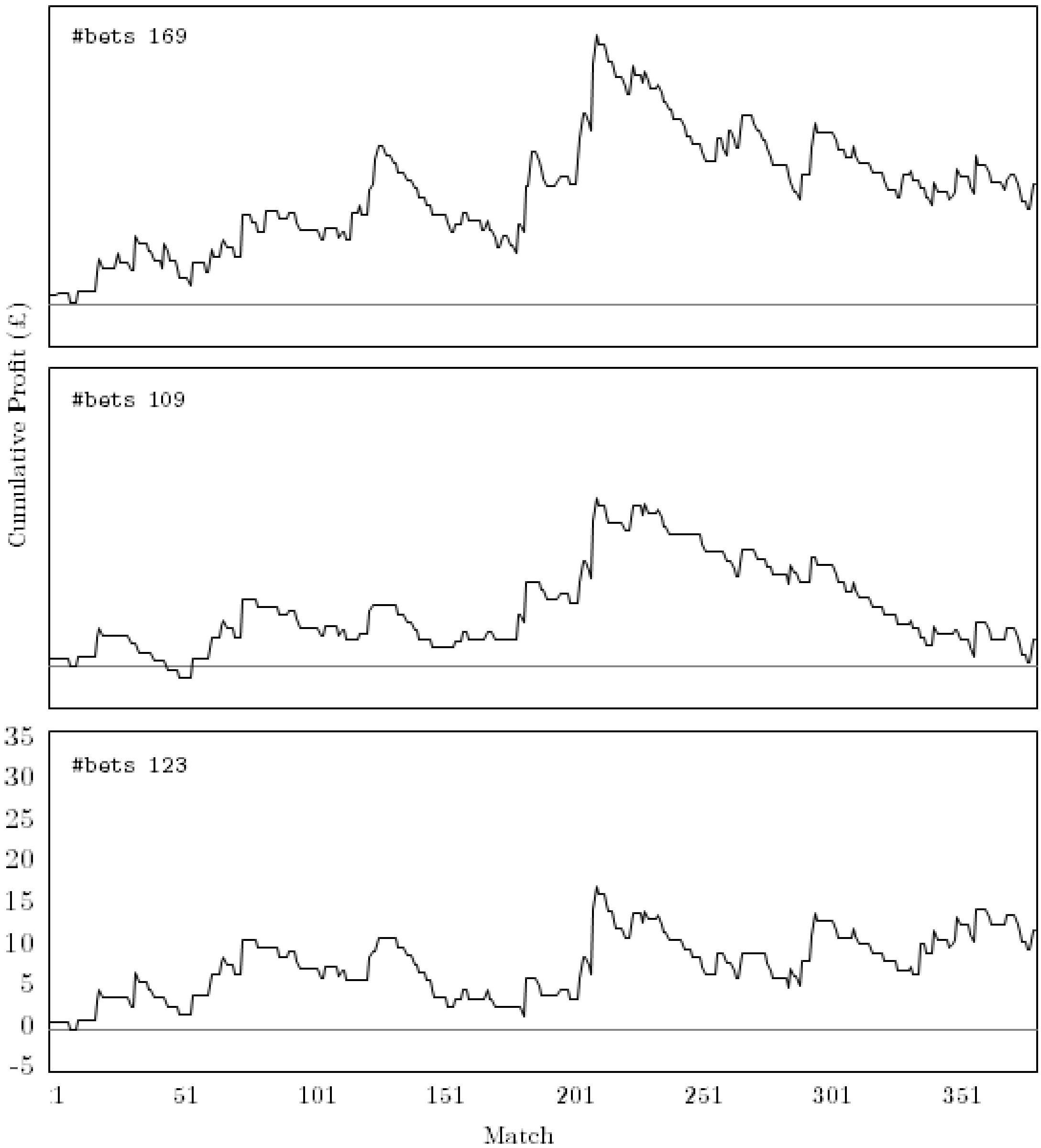


Figure 10. Cumulative profit/loss observed given fs when simulating the standard betting strategy at discrepancy levels of ≥ 5% against a) f_{maxB}, b) f_{meanB} and c) f_{WH}.

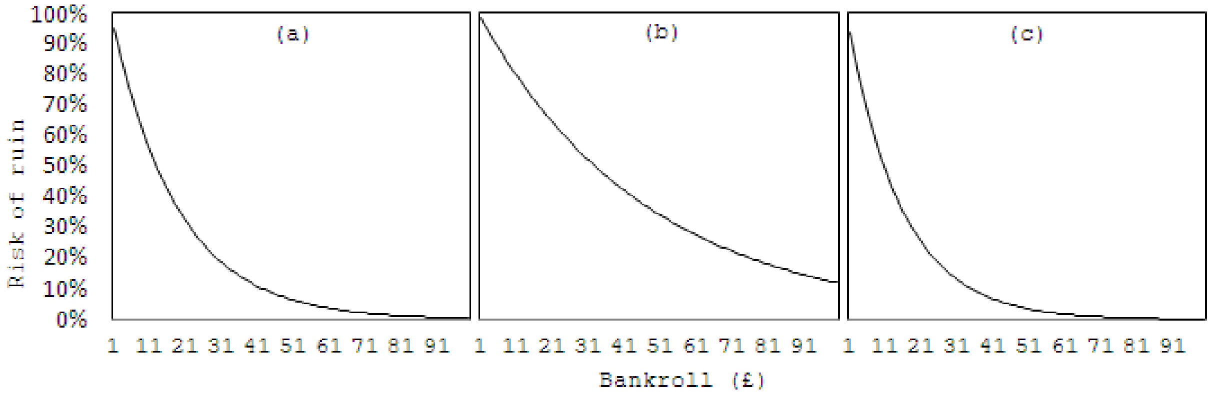


Figure 11. Risk of Ruin given the specified betting simulation against a) f_{maxB}, b) f_{meanB} and c) f_{WH}.

Table 2. Betting simulation stats given f_S against) f_{maxB}, b) f_{meanB} and c) f_{WH} at discrepancy levels of ≥ 5%

	f_{maxB}	f_{meanB}	f_{WH}
Total bets	169	109	123
Bets won	57 (33.72%)	38 (34.86%)	44 (35.77%)
Total returns	£183.19	£112.13	£134.66
Min. P/L balance observed	£0.28	-£0.04	-£0.09
Max. P/L balance observed	£30.67	£19.86	£16.86
Final P/L balance	£14.19	£3.13	£11.66
Profit/Loss (%)	8.40%	2.87%	9.48%
Max. bookmakers considered per instance	40	40	1
Min. bookmakers considered per instance	28	28	1
Mean bookmakers considered per instance	35.73	35.73	1
Max. odds won	9	7.73	8.5
Min. odds won	1.19	1.40	1.40
Mean odds won	3.21	2.95	3.06
Mean profit margin (for all 380 instances)	0.63%	6.09%	6.50%
Arbitrage instances (for all 380 instances)	62	0	0

Table F1 provides further statistics when performing this betting simulation given f_S against f_{maxB}, f_{meanB}, and f_{WH} using discrepancy levels that are different from the standard 5%. In general, pi-football appears to perform much worse at the lowest discrepancy levels (1%-3%) and much better at higher discrepancy levels (4%-11%). Considering a minimum of 30 simulated bets, the maximum profits are observed at discrepancy levels of 11% (35.63%), 9% (8.86%) and 8% (10.07%) against f_{maxB}, f_{meanB}, and f_{WH} respectively. At discrepancy levels above ~11% there were too few betting instances to be able to derive meaningful conclusions.

5 CONCLUDING REMARKS & FUTURE WORK

We have presented a novel Bayesian network model called pi-football (v1.32) that was used to generate the EPL match forecasts during season 2010/11. The model considers both objective and subjective information for prediction, in which time-dependent data is weighted using degrees of uncertainty. In particular, objective forecasts are generated first and revised afterwards according to subjective indicators; whereas uncertainty allows for a non-symmetric Bayesian parameter learning procedure. Because of the 'anonymous' underlying approach which generates predictions by only considering the strength of the two competing teams given results data and total points, the entire model is easily applicable to any other football league.

For assessing the performance of our model we have considered both accuracy and profitability measurements since earlier studies have shown conflicting conclusions between the two and suggested that both measurements should be considered. In (Dixon & Coles, 1997) authors claimed that for a football forecast model to generate profit against bookmakers' odds without eliminating the in-built profit margin it requires a determination of probabilities that is sufficiently more accurate from those obtained by published odds, and (Graham & Stott, 2008) suggested that if such a work was particularly successful, it would not have been published. Ours is the first study to demonstrate profitability against all of the (available) published odds. Previous studies have only considered a single bookmaker for that matter, since only recently it was proven that the published odds of a single bookmaker cannot be representative of the overall market (Constantinou & Fenton, 2012b). In fact, pi-football was able to generate profit against maximum, mean, and common bookmakers' odds, even by allowing for the bookmakers' in-built profit margin.

We conclude that subjective information improved the forecast capability of our model significantly. This also emphasises the importance of Bayesian networks, in which subjective information can both be represented and displayed without any particular effort. Because of the nature of subjective information, we have been publishing our forecasts online at www.pi-football.com prior to the start of each match (earlier studies which incorporated subjective information have not done so). Both the objective (f_O) and subjective (f_S) forecasts are provided in Appendix G, for all of the 380 EPL matches during season 2010/11. At standard discrepancy levels of 5% the profitability of this model ranges from 2.87% to 9.48%, whereas at higher discrepancy levels (8% to 11%) the maximum profit observed ranges from 8.86% to 35.63%, depending on the various bookmakers' odds considered. No other published work appears to be particularly successful at beating all of the various bookmakers' odds over a large period of time, which highlights the success of pi-football.

The next stage in research might be to determine whether revising the strength of the team (given subjective information) rather than the probability distribution itself would improve the performance of the model; since the former represents a natural causality whereas the latter does not. Further, we have not been able to assess the impact of time-dependent uncertainty for weighting the more recent information. It would be interesting to determine the degree of irrelevance to prediction per preceding information, as well as the degree of efficiency of the various time-series methodologies introduced throughout the sports academic literature (none of the previous football studies have attempted to measure their efficiency).

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APPENDIX A: Subjective scenarios and assumptions per specified variable (node)

Table A.1. Team Strength (as presented in Figure 2)

ID	Variable (node)	Description	Subjective Scenarios
I.	Subjective team strength (in points)	Expert indication regarding the current strength of the team in seasonal points.	[0,114]
II.	Confidence	Expert indication regarding its confidence about his input (I).	[Very High, High, Medium, Low, Very Low]
III.	Current Points	Assumption: Variance as demonstrated in figure 1, given variable "Number of matches played".	-
IV.	Points during season 2005/06	Assumption**:** variance=(Variance+3ˆ6)	-
V.	Points during season 2006/07	Assumption**:** variance=(Variance+3ˆ5)	-
VI.	Points during season 2007/08	Assumption**:** variance=(Variance+3ˆ4)	-
VII.	Points during season 2008/09	Assumption**:** variance=(Variance+3ˆ3)	-
VIII.	Points during season 2009/10	Assumption**:** variance=(Variance+3ˆ2)	-
IX.	Predicted mean (in points)	The predicted team strength after considering all of the seven parameters Assumption: mean=57, variance=300	-

Table A.2. Team Form (as presented in Figure 3)

ID	Variable (node)	Description	Subjective Scenarios
I.	Primary key-player availability	Expert indication regarding his confidence about the availability of the primary key-player.	[Very High, High, Medium, Low, Very Low]
II.	Secondary key-player availability	Expert indication regarding his confidence about the availability of the secondary key-player.	[Very High, High, Medium, Low, Very Low]
III.	Tertiary key-player availability	Expert indication regarding his confidence about the availability of the tertiary key-player.	[Very High, High, Medium, Low, Very Low]
IV.	Remaining first team players availability	Expert indication regarding his confidence about the availability of the remaining first-team players.	[Very High, High, Medium, Low, Very Low]
V.	First team players returning	Expert indication regarding the potential return of other first team players who missed the last few matches.	[Very High, High, Medium, Low, Very Low]

Table A.3. Team Psychology (as presented in Figure 4)

ID	Variable (node)	Description	Subjective Scenarios
I.	Team spirit and motivation	Expert indication regarding the team's level of motivation and team spirit	[Very High, High, Normal, Low, Very Low]
II.	Confidence	Expert indication regarding its confidence about his input in (I).	[Very High, High, Medium, Low, Very Low]
III.	Managerial impact	Expert indication regarding the impact of the current managerial situation.	[Very High, High, Normal, Low, Very Low]
IV.	Head-to-Head bias	Expert indication regarding potential biases in a head-to-head encounter between the two teams.	[High advantage for home team, Advantage for home team, No bias, Advantage for away team, High advantage for away team]

Table A.4. Team Fatigue (as presented in Figure 5)

ID	Variable (node)	Description	Subjective Scenarios
I.	Toughness of previous match	Expert indication regarding the toughness of previous match.	[Lowest, Very Low, Low, Medium, High, Very High, Highest]
II.	First team players rested during last match	Expert indication regarding the first team players rested during last match.	[1-2, 3, 4, 5, 6+]
III.	National team participation	Expert indication regarding the level of international participation by the first team players.	[None, Few, Half team, Many, All]

APPENDIX B: An actual example of component's 1 process (as presented in Fig. 2)

Figure B.1 presents a real component 1 example between Manchester City (home team) and Manchester United, as prepared for the 11th of October 2010. The steps for calculating component's 1 forecast are enumerated below:

1) **Previous information**: the points accumulated per previous season are passed as five distinct ordered inputs. Starting from the oldest season, the inputs are [43, 42, 55, 50, 67] for Man City, and [83, 89, 87, 90, 85] for Man United. Note that Man City generates a significantly higher variance than that of Man United, with the more recent seasons having greater impact as described and illustrated in section 3.1.

2) **Current information:** the points accumulated for the current season, as well as the total number of matches played are passed as a single parameter with the appropriate variance as described and illustrated in section 3.1. For Man City the inputs are [20, 11] and for Man United the inputs are [23, 11], for points accumulated and number of matches played respectively.

3) **Subjective information** (optional): the optional subjective indication about the current team's strength in total points, as well as the confidence with reference to that indication are passed as a single parameter. For Man City, we suggested that the team was playing as a 72-point team (a 5-point increase from last season) with "High" confidence (out of "Very High")[§§§§]. On the other hand, we have introduced a 5-point decrease for Man United with "High" confidence[*****]. Accordingly, the inputs were [72, 'High'] and [80, 'High'] for Man City and Man United respectively.

4) The model summarises the seven parameters in node "Mean". The impact each parameter has is dependent on its certainty (variance). For Man City the summarised belief in total points (node "Mean") is 68.95 whereas for Man United is 80.78. Note that the variance introduced for Man City is a higher than that of Man United; 26.83 and 21.92 respectively.

5) Each team's "Mean" is converted in the predetermined 14-scale ranking. The model suggests that Man City will most likely perform similar to teams ranked 3 to 4 (out of 14), whereas for Man United it mostly suggests ranks 1 and 2.

6) The model generates the objective forecast in node "Match Prediction", by considering each teams estimated ranking, before proceeding to potential forecast revisions suggested by the expert constructed component models 2, 3 and 4.

[§§§§]A 5-point increase was suggested due to high profile players joining the team during the summer transfer window.

[*****]A 5-point decrease was suggested due to the significant decrease in stamina observed by the older core-team players (e.g. Scholes, Giggs, Ferdinand, Vidic) without taking care of appropriate replacements.

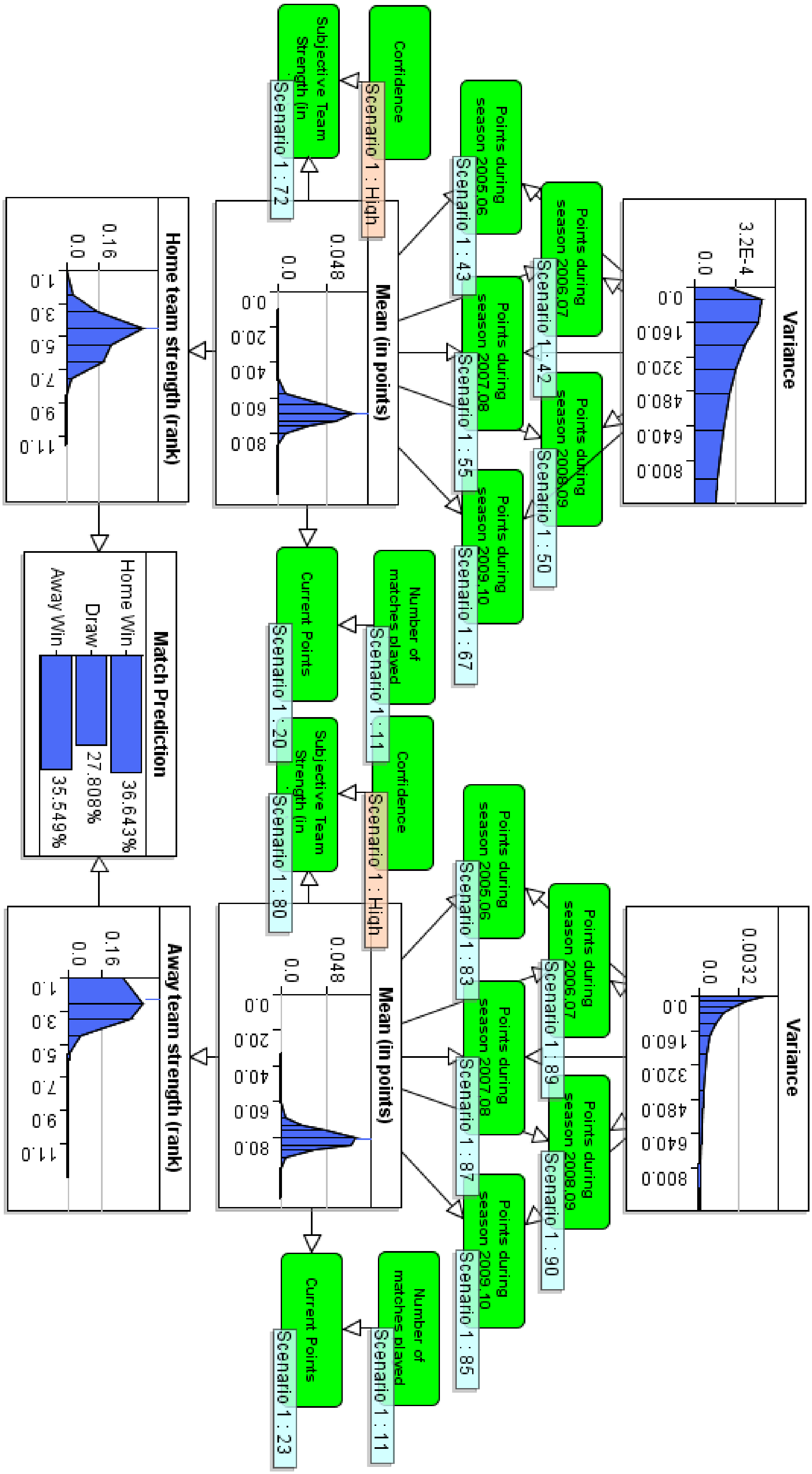

Figure B1. An actual example of the Bayesian network (from Figure 2) at component 1. The parameters represent the actual observations provided from the Man City vs. Man United match, 10th of November, 2010.

APPENDIX C: Match RPS per dataset

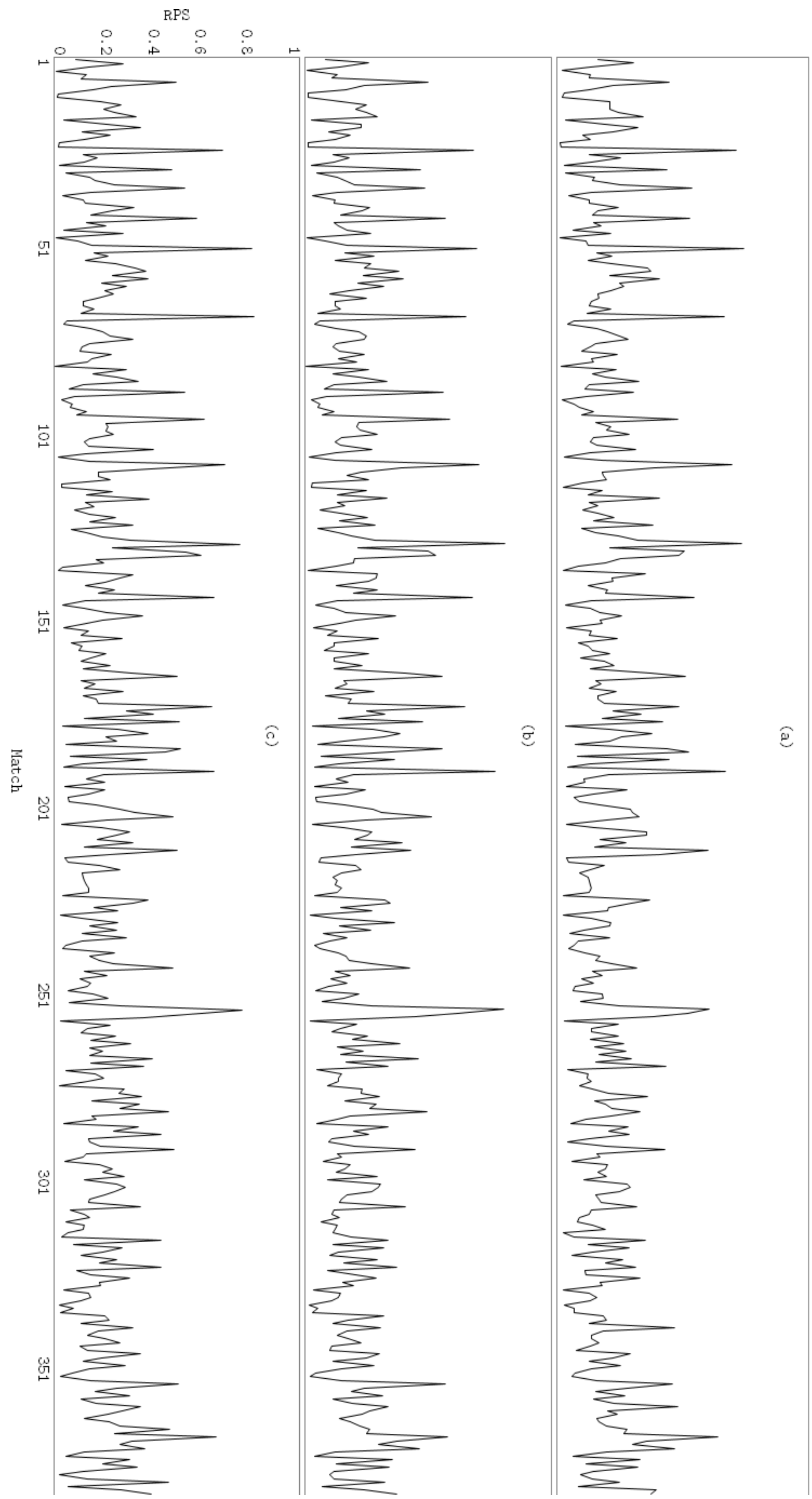

Figure C.1. RPS per match for datasets f_O (a), f_S (b), and f_B (c) respectively.

APPENDIX D: Evidence of significant improvements in f_O by subjective information

In this section we provide evidence of football matches in which subjective information revised f_O the most. Table D1 presents 17 with the highest absolute RPS discrepancies between f_O and f_S forecasts, assuming a minimum discrepancy level of 0.1. The instances are ranked by highest discrepancy and the 'Decision' column indicates whether the subjective information improved f_O.

Overall, the results appear to be particularly encouraging. Only in 6 out of the 17 cases our subjective information leads to a higher forecast error. The results are even more encouraging when we only concentrate on the first 10 highest discrepancy instances, in which subjective revisions improve 8 out of the 10 instances. Further, in those 17 instances we have observed 15 distinct teams, and no evidence exist that strong subjective indications follow a particular type of a team. A rather surprising and interesting observation is that the observed outcome is a draw in only in 1 out of the 17 instances presented here.

Table D1. RPS discrepancies ≥ 0.1 between objective (f_O) and revised (f_S); ranked by highest discrepancy

RPS		Home	Away		Objective (f_O)			Revised (f_S)			
Discrep.	Date	Team	Team	R	p(H)	p(D)	p(A)	p(H)	p(D)	p(A)	Decision
.2078	14/05/2011	Sunderland	Wolves	A	.4942	.3403	.1656	.2627	.4124	.3250	✓
.1765	06/03/2011	Liverpool	Man Utd	H	.2392	.2219	.5389	.3423	.3691	.2887	✓
.1614	03/10/2010	Liverpool	Blackpool	A	.8303	.1412	.0285	.6516	.2895	.0589	✓
.1582	09/04/2011	Man Utd	Fulham	H	.7570	.1881	.0549	.4016	.4552	.1432	✗
.1421	22/05/2011	Stoke	Wigan	A	.5140	.3023	.1837	.3535	.3684	.2781	✓
.1406	02/10/2010	Sunderland	Man Utd	D	.1223	.1940	.6837	.2029	.3973	.3998	✓
.1322	18/09/2010	Tottenham	Wolves	H	.7422	.1751	.0827	.4396	.4063	.1541	✗
.1307	06/11/2010	Bolton	Tottenham	H	.2519	.2523	.4958	.3384	.3358	.3259	✓
.1270	22/08/2010	Newcastle	Aston Villa	H	.2693	.3161	.4146	.3828	.3514	.2658	✓
.1228	25/01/2011	Wigan	Aston Villa	A	.3436	.3431	.3133	.2058	.3433	.4508	✓
.1219	29/12/2010	Liverpool	Wolves	A	.7162	.1717	.1121	.8058	.1406	.0536	✗
.1156	23/04/2011	Sunderland	Wigan	H	.4138	.3310	.2552	.2848	.3568	.3584	✗
.1150	01/02/2011	Sunderland	Chelsea	A	.2661	.3861	.3478	.1556	.3363	.5082	✓
.1104	27/12/2010	Arsenal	Chelsea	H	.4034	.3383	.2583	.2828	.3578	.3594	✗
.1102	28/12/2010	Sunderland	Blackpool	A	.5200	.2791	.2009	.3929	.3380	.2692	✓
.1063	25/09/2010	Arsenal	West Br.	A	.8196	.1499	.0305	.7063	.2424	.0512	✓
.1023	22/01/2011	Wolves	Liverpool	A	.3070	.3465	.3466	.4038	.3465	.2497	✗

APPENDIX E: Betting simulation given objective forecasts

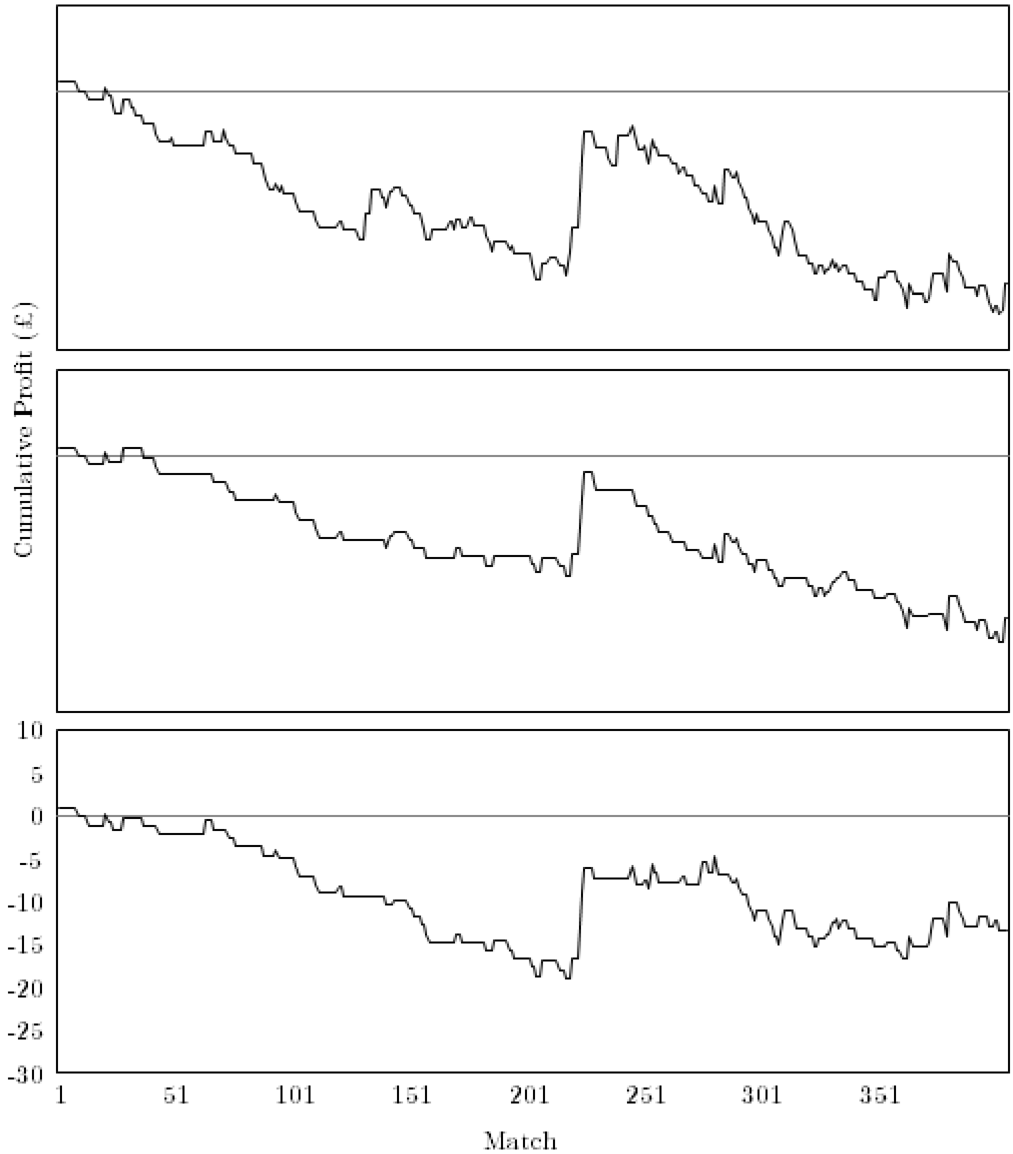

Figure E1. Cumulative profit/loss observed given f_O when simulating the standard betting strategy at discrepancy levels of ≥ 5% against a) f_{maxB}, b) f_{meanB} and c) f_{WH}.

APPENDIX F: Betting simulation at different levels of discrepancy given f_S

Table D.1. Betting simulation stats given f_S against) f_{maxB}, b) f_{meanB} and c) f_{WH} at discrepancy levels from 1% to 20%

	Maximum odds			Mean odds			William Hill odds		
Discrepancy	No. of bets	Returns (£)	Profit/Loss (£)	No. of bets	Returns (£)	Profit/ Loss (£)	No. of bets	Returns (£)	Profit/Loss (£)
1%	358	356.24	-0.49%	280	266.25	-4.91%	284	276.04	-2.80%
2%	325	320.21	-1.47%	240	225.93	-5.86%	234	235.98	0.85%
3%	275	277.85	1.04%	189	187.07	-1.02%	192	191.12	-0.46%
4%	225	236.87	5.28%	136	144.85	6.51%	147	159.44	8.46%
5%	169	183.19	8.40%	109	112.13	2.87%	123	134.66	9.48%
6%	131	148.4	13.28%	85	84.96	-0.05%	95	102.31	7.69%
7%	107	119.92	12.07%	68	64.86	-4.62%	67	68.91	2.85%
8%	84	92.43	10.04%	53	54.79	3.38%	45	49.53	10.07%
9%	71	82.36	16.00%	36	39.19	8.86%	34	32.71	-3.79%
10%	52	62.61	20.40%	26	16.97	-34.73%	24	23.55	-1.88%
11%	41	55.61	35.63%	15	7.82	-47.87%	19	21.82	14.84%
12%	25	18.05	-27.80%	12	7.82	-34.83%	13	7.82	-39.85%
13%	15	10.39	-30.73%	10	7.82	-21.80%	10	7.82	-21.80%
14%	12	8.3	-30.83%	8	7.82	-2.25%	10	7.82	-21.80%
15%	10	8.3	-17.00%	7	7.82	11.71%	7	7.82	11.71%
16%	7	8.3	18.57%	5	6.2	24.00%	6	6.2	3.33%
17%	6	8.3	38.33%	2	0	-100%	3	2.4	-20.00%
18%	5	5.9	18.00%	2	0	-100%	2	0	-100%
19%	2	0	-100%	1	0	-100%	1	0	-100%
20%	2	0	-100%	1	0	-100%	1	0	-100%

APPENDIX G: Forecasts generated by pi-football

Table F.1. Objective (f_O) and subjective (f_S) forecasts generated by pi-football, for all of the 380 EPL matches during season 2010/11

Date	Home Team	Away Team	Result	Objective (f_O) p(H)	p(D)	p(A)	Subjective (f_S) p(H)	p(D)	p(A)
14/08/2010	Aston Villa	West Ham	H	60.92	23.971	15.109	61.735	23.67	14.596
14/08/2010	Blackburn	Everton	H	34.382	29.314	36.304	36.338	29.781	33.881
14/08/2010	Bolton	Fulham	D	46.863	29.199	23.938	46.863	29.199	23.938
14/08/2010	Chelsea	West Brom	H	87.055	12.706	0.24	89.581	10.227	0.192
14/08/2010	Sunderland	Birmingham	D	44.366	29.623	26.011	44.197	29.679	26.124
14/08/2010	Tottenham	Man City	D	35.178	33.654	31.168	32.82	33.756	33.424
14/08/2010	Wigan	Blackpool	A	53.939	30.156	15.905	53.939	30.156	15.905
14/08/2010	Wolves	Stoke	H	38.763	31.563	29.674	37.778	31.746	30.477
15/08/2010	Liverpool	Arsenal	D	51.705	27.305	20.99	54.007	26.773	19.22
16/08/2010	Man United	Newcastle	H	81.665	16.058	2.277	83.853	14.18	1.966
21/08/2010	Arsenal	Blackpool	H	85.569	12.668	1.763	85.695	12.56	1.746
21/08/2010	Birmingham	Blackburn	H	44.269	29.088	26.643	49.695	28.632	21.673
21/08/2010	Everton	Wolves	D	73.202	17.433	9.365	69.731	20.077	10.192
21/08/2010	Stoke	Tottenham	A	27.657	29.283	43.059	28.289	29.58	42.13
21/08/2010	West Brom	Sunderland	H	36.848	33.163	29.989	36.325	33.216	30.459
21/08/2010	West Ham	Bolton	A	39.606	32.217	28.177	35.012	33.074	31.913
21/08/2010	Wigan	Chelsea	A	9.945	16.713	73.342	6.465	14.345	79.19
22/08/2010	Fulham	Man United	D	13.416	22.345	64.239	12.059	21.442	66.499
22/08/2010	Newcastle	Aston Villa	H	26.934	31.612	41.455	38.277	35.144	26.58
23/08/2010	Man City	Liverpool	H	55.566	26.104	18.33	59.331	24.983	15.686
28/08/2010	Blackburn	Arsenal	A	29.444	31.547	39.009	24.496	31.194	44.31
28/08/2010	Blackpool	Fulham	D	28.052	31.672	40.276	28.272	31.732	39.996
28/08/2010	Chelsea	Stoke	H	80.673	16.736	2.591	84.022	13.905	2.073
28/08/2010	Man United	West Ham	H	82.525	15.553	1.922	84.627	13.711	1.662
28/08/2010	Tottenham	Wigan	A	73.716	17.443	8.841	73.327	17.74	8.934
28/08/2010	Wolves	Newcastle	D	40.609	32.837	26.554	37.192	33.491	29.318
29/08/2010	Aston Villa	Everton	H	45.276	31.446	23.277	44.676	31.63	23.695
29/08/2010	Bolton	Birmingham	D	39.858	31.208	28.934	36.146	32.013	31.84
29/08/2010	Liverpool	West Brom	H	80.318	15.187	4.495	77.822	17.212	4.967
29/08/2010	Sunderland	Man City	H	21.155	20.44	58.405	21.584	21.237	57.179
11/09/2010	Arsenal	Bolton	H	70.745	19.864	9.391	70.751	19.861	9.388
11/09/2010	Everton	Man United	D	27.891	25.825	46.284	31.386	28.593	40.021
11/09/2010	Fulham	Wolves	H	46.98	29.379	23.641	48.281	29.125	22.594
11/09/2010	Man City	Blackburn	D	69.118	20.636	10.246	62.251	25.453	12.296
11/09/2010	Newcastle	Blackpool	A	55.782	31.301	12.918	51.035	33.384	15.581
11/09/2010	West Brom	Tottenham	D	22.674	28.013	49.314	25.911	30.475	43.614
11/09/2010	West Ham	Chelsea	A	7.98	16.013	76.007	7.879	15.911	76.21
11/09/2010	Wigan	Sunderland	D	40.77	32.102	27.128	41.178	32.039	26.784
12/09/2010	Birmingham	Liverpool	D	30.374	29.364	40.262	35.557	31.287	33.155
13/09/2010	Stoke	Aston Villa	H	29.946	29.846	40.208	35.597	31.808	32.595
18/09/2010	Aston Villa	Bolton	D	67.813	20.418	11.768	66.943	21.027	12.03
18/09/2010	Blackburn	Fulham	D	49.733	28.365	21.902	48.58	28.861	22.559
18/09/2010	Everton	Newcastle	A	64.358	22.042	13.6	63.488	22.615	13.898
18/09/2010	Stoke	West Ham	D	45.372	31.286	23.342	39.697	33.048	27.255
18/09/2010	Sunderland	Arsenal	D	17.051	20.505	62.444	21.997	30.62	47.383
18/09/2010	Tottenham	Wolves	H	74.223	17.506	8.271	43.964	40.629	15.407
18/09/2010	West Brom	Birmingham	H	33.397	32.167	34.436	34.729	32.261	33.01
19/09/2010	Chelsea	Blackpool	H	88.112	11.363	0.525	88.753	10.751	0.496
19/09/2010	Man United	Liverpool	H	58.15	28.169	13.681	61.165	26.618	12.217
19/09/2010	Wigan	Man City	A	23.721	26.167	50.113	25.023	27.358	47.619
25/09/2010	Arsenal	West Brom	A	81.961	14.987	3.053	70.632	24.244	5.124

25/09/2010	Birmingham	Wigan	D	54.241	27.582	18.178	53.257	28.065	18.678
25/09/2010	Blackpool	Blackburn	A	28.071	31.656	40.272	33.513	33.138	33.349
25/09/2010	Fulham	Everton	D	33.45	29.153	37.397	36.143	29.914	33.943
25/09/2010	Liverpool	Sunderland	D	69.694	19.891	10.415	72.217	18.689	9.094
25/09/2010	Man City	Chelsea	H	31.548	24.982	43.471	38.166	29.88	31.955
25/09/2010	West Ham	Tottenham	H	25.853	29.778	44.369	25.086	29.662	45.252
26/09/2010	Bolton	Man United	D	12.292	20.227	67.482	11.997	20.036	67.967
26/09/2010	Newcastle	Stoke	A	45.146	30.079	24.775	46.394	29.859	23.746
26/09/2010	Wolves	Aston Villa	A	26.205	29.783	44.012	28.369	30.817	40.814
02/10/2010	Birmingham	Everton	A	38.327	28.256	33.417	40.387	28.632	30.98
02/10/2010	Stoke	Blackburn	H	41.814	30.393	27.793	45.514	30.076	24.41
02/10/2010	Sunderland	Man United	D	12.232	19.402	68.366	20.289	39.734	39.977
02/10/2010	Tottenham	Aston Villa	H	45.611	31.226	23.163	35.735	34.341	29.924
02/10/2010	West Brom	Bolton	D	38.636	32.525	28.839	42.537	32.083	25.38
02/10/2010	West Ham	Fulham	D	38.871	31.665	29.464	41.24	31.5	27.26
02/10/2010	Wigan	Wolves	H	47.082	31.398	21.52	50.128	30.439	19.432
03/10/2010	Chelsea	Arsenal	H	55.499	31.552	12.949	68.15	24.093	7.757
03/10/2010	Liverpool	Blackpool	A	83.028	14.121	2.851	65.158	28.952	5.89
03/10/2010	Man City	Newcastle	H	69.015	20.215	10.77	67.616	21.204	11.18
16/10/2010	Arsenal	Birmingham	H	73.152	18.677	8.171	73.421	18.526	8.053
16/10/2010	Aston Villa	Chelsea	D	27.41	25.289	47.302	31.543	28.886	39.571
16/10/2010	Bolton	Stoke	H	43.004	31.18	25.816	40.326	31.916	27.758
16/10/2010	Fulham	Tottenham	A	30.507	29.647	39.847	32.301	30.264	37.435
16/10/2010	Man United	West Brom	D	80.131	17.444	2.425	69.147	26.037	4.816
16/10/2010	Newcastle	Wigan	D	50.237	29.989	19.774	44.426	32.331	23.243
16/10/2010	Wolves	West Ham	D	34.805	33.216	31.978	33.163	33.291	33.546
17/10/2010	Blackpool	Man City	A	19.058	22.282	58.66	21.625	26.473	51.902
17/10/2010	Everton	Liverpool	H	37.244	35.333	27.422	36.72	35.36	27.92
18/10/2010	Blackburn	Sunderland	D	50.774	28.047	21.179	45.887	30.234	23.878
23/10/2010	Birmingham	Blackpool	H	51.229	30.312	18.459	40.33	34.762	24.908
23/10/2010	Chelsea	Wolves	H	91.6115	8.12	0.268	92.6	7.167	0.233
23/10/2010	Sunderland	Aston Villa	H	33.092	29.171	37.737	36.562	30.19	33.248
23/10/2010	Tottenham	Everton	D	53.169	28.302	18.529	39.808	34.551	25.641
23/10/2010	West Brom	Fulham	H	35.666	32.905	31.429	40.066	32.708	27.226
23/10/2010	West Ham	Newcastle	A	40.079	32.607	27.313	38.989	32.811	28.2
23/10/2010	Wigan	Bolton	D	39.8	32.941	27.259	39.961	32.913	27.126
24/10/2010	Liverpool	Blackburn	H	67.392	21.046	11.561	62.613	24.333	13.054
24/10/2010	Man City	Arsenal	A	57.072	28.88	14.048	60.097	27.326	12.577
24/10/2010	Stoke	Man United	A	15.56	22.269	62.171	15.878	22.839	61.283
30/10/2010	Arsenal	West Ham	H	75.413	18.952	5.635	78.621	16.698	4.681
30/10/2010	Blackburn	Chelsea	A	12.937	22.801	63.262	11.713	21.386	66.9
30/10/2010	Everton	Stoke	H	65.761	21.532	12.708	69.335	20.067	10.598
30/10/2010	Fulham	Wigan	H	52.376	29.856	17.768	54.391	29.04	16.568
30/10/2010	Man United	Tottenham	H	59.871	26.767	13.362	64.858	24.269	10.872
30/10/2010	Wolves	Man City	H	12.056	21.037	66.908	12.811	22.684	64.505
31/10/2010	Aston Villa	Birmingham	D	63.479	22.659	13.861	65.037	22.055	12.908
31/10/2010	Bolton	Liverpool	A	29.074	30.394	40.532	28.123	30.351	41.526
31/10/2010	Newcastle	Sunderland	H	41.415	30.91	27.675	39.765	31.328	28.907
01/11/2010	Blackpool	West Brom	H	37.027	33.292	29.681	31.828	33.817	34.355
06/11/2010	Birmingham	West Ham	D	50.221	30.446	19.334	51.217	30.082	18.701
06/11/2010	Blackburn	Wigan	H	53.216	29.369	17.414	53.328	29.324	17.348
06/11/2010	Blackpool	Everton	D	23.549	29.372	47.079	22.156	29.028	48.817
06/11/2010	Bolton	Tottenham	H	25.189	25.228	49.583	33.837	33.576	32.587
06/11/2010	Fulham	Aston Villa	D	33.447	28.567	37.986	34.73	28.99	36.28
06/11/2010	Man United	Wolves	H	80.859	17.451	1.689	81.129	17.208	1.663
06/11/2010	Sunderland	Stoke	H	50.329	28.961	20.71	54.193	27.86	17.947
07/11/2010	Arsenal	Newcastle	A	73.855	18.326	7.819	74.692	17.846	7.462
07/11/2010	Liverpool	Chelsea	H	26.171	24.62	49.209	26.384	24.832	48.784
07/11/2010	West Brom	Man City	A	26.702	27.227	46.071	30.34	29.745	39.915
09/11/2010	Stoke	Birmingham	H	44.783	31.251	23.966	46.241	30.911	22.848
09/11/2010	Tottenham	Sunderland	D	66.721	21.393	11.885	71.013	19.486	9.501

10/11/2010	Aston Villa	Blackpool	H	76.043	16.08	7.877	77.209	15.485	7.306
10/11/2010	Chelsea	Fulham	H	76.844	19.222	3.934	77.467	18.727	3.807
10/11/2010	Everton	Bolton	D	68.112	20.433	11.455	69.986	19.609	10.405
10/11/2010	Man City	Man United	D	36.643	27.808	35.549	39.878	28.709	31.413
10/11/2010	Newcastle	Blackburn	A	45.099	30.455	24.445	38.999	32.436	28.565
10/11/2010	West Ham	West Brom	D	44.405	32.322	23.273	45.802	31.931	22.267
10/11/2010	Wigan	Liverpool	D	21.08	26.045	52.875	20.938	26.012	53.05
10/11/2010	Wolves	Arsenal	A	16.317	20.375	63.308	12.448	19.413	68.139
13/11/2010	Aston Villa	Man United	D	25.753	27.238	47.01	24.822	27.184	47.993
13/11/2010	Man City	Birmingham	D	70.046	19.767	10.187	70.325	19.631	10.043
13/11/2010	Newcastle	Fulham	D	48.821	29.418	21.761	47.323	30.013	22.663
13/11/2010	Stoke	Liverpool	H	30.598	29.287	40.115	33.666	30.421	35.913
13/11/2010	Tottenham	Blackburn	H	64.657	22.104	13.238	69.881	20.009	10.11
13/11/2010	West Ham	Blackpool	D	47.004	32.211	20.785	48.04	31.844	20.116
13/11/2010	Wigan	West Brom	H	42.439	32.585	24.976	43.507	32.335	24.157
13/11/2010	Wolves	Bolton	A	36.735	32.97	30.295	33.865	33.264	32.871
14/11/2010	Chelsea	Sunderland	A	76.971	19.073	3.956	82.265	14.877	2.858
14/11/2010	Everton	Arsenal	A	27.991	34.823	37.186	25.933	34.32	39.746
20/11/2010	Arsenal	Tottenham	A	58.795	26.428	14.777	55.153	28.433	16.414
20/11/2010	Birmingham	Chelsea	H	13.331	19.902	66.767	15.643	25.346	59.011
20/11/2010	Blackpool	Wolves	H	45.645	32.793	21.562	41.673	33.911	24.416
20/11/2010	Bolton	Newcastle	H	42.115	32.293	25.592	42.821	32.146	25.032
20/11/2010	Liverpool	West Ham	H	74.864	16.165	8.971	51.942	34.137	13.92
20/11/2010	Man United	Wigan	H	80.968	18.2	0.832	84.236	15.081	0.683
20/11/2010	West Brom	Stoke	A	37.69	33.012	29.298	34.663	33.388	31.95
21/11/2010	Blackburn	Aston Villa	H	35.91	28.198	35.892	33.907	28.628	37.465
21/11/2010	Fulham	Man City	A	28.746	28.707	42.547	33.106	30.809	36.085
22/11/2010	Sunderland	Everton	D	37.409	28.494	34.097	37.946	28.6	33.454
27/11/2010	Aston Villa	Arsenal	A	27.253	37.103	35.644	32.379	36.901	30.72
27/11/2010	Bolton	Blackpool	D	57.516	25.639	16.845	60.982	24.45	14.568
27/11/2010	Everton	West Brom	A	71.562	17.413	11.025	73.89	16.559	9.551
27/11/2010	Fulham	Birmingham	D	43.901	31.578	24.522	46.18	31.068	22.752
27/11/2010	Man United	Blackburn	H	75.003	19.036	5.961	71.486	21.66	6.854
27/11/2010	Stoke	Man City	D	31.785	30.822	37.393	32.847	31.048	36.105
27/11/2010	West Ham	Wigan	H	40.019	33.681	26.3	46.357	32.292	21.351
27/11/2010	Wolves	Sunderland	H	26.742	30.355	42.904	26.192	30.28	43.527
28/11/2010	Newcastle	Chelsea	D	15.617	23.408	60.975	14.954	23.078	61.968
28/11/2010	Tottenham	Liverpool	H	52.733	28.524	18.743	51.181	29.237	19.583
04/12/2010	Arsenal	Fulham	H	73.506	19.093	7.401	75.389	17.94	6.671
04/12/2010	Birmingham	Tottenham	D	27.92	27.289	44.792	29.476	28.286	42.238
04/12/2010	Blackburn	Wolves	H	55.76	29.196	15.044	59.178	27.539	13.283
04/12/2010	Chelsea	Everton	D	74.367	19.131	6.502	76.757	17.553	5.69
04/12/2010	Man City	Bolton	H	64.607	22.599	12.794	54.067	29.452	16.481
04/12/2010	Wigan	Stoke	D	31.571	33.214	35.216	26.096	32.929	40.975
05/12/2010	Sunderland	West Ham	H	58.154	26.8	15.045	62.631	24.837	12.532
05/12/2010	West Brom	Newcastle	H	40.515	32.678	26.807	35.333	33.68	30.987
06/12/2010	Liverpool	Aston Villa	H	50.164	28.5	21.336	54.956	27.296	17.748
11/12/2010	Aston Villa	West Brom	H	57.042	25.604	17.354	55.306	26.561	18.133
11/12/2010	Everton	Wigan	D	66.037	20.248	13.715	67.117	19.9	12.984
11/12/2010	Fulham	Sunderland	D	32.792	31.816	35.392	31.52	31.854	36.627
11/12/2010	Newcastle	Liverpool	H	31.394	28.552	40.054	23.19	29.295	47.516
11/12/2010	Stoke	Blackpool	A	55.878	27.479	16.643	60.595	25.619	13.786
11/12/2010	West Ham	Man City	A	18.952	23.895	57.153	22.625	29.006	48.369
12/12/2010	Bolton	Blackburn	H	47.264	29.15	23.585	46.863	29.304	23.833
12/12/2010	Tottenham	Chelsea	D	39.029	30.132	30.838	38.913	30.159	30.928
12/12/2010	Wolves	Birmingham	H	32.795	34.254	32.952	32.649	34.247	33.103
13/12/2010	Man United	Arsenal	H	53.829	31.548	14.623	61.041	27.679	11.28
18/12/2010	Blackburn	West Ham	D	57.05	28.713	14.237	59.66	27.397	12.943
18/12/2010	Sunderland	Bolton	H	45.302	29.622	25.076	46.014	29.512	24.474
20/12/2010	Man City	Everton	A	69.252	20.695	10.053	69.672	20.479	9.849
26/12/2010	Aston Villa	Tottenham	A	34.247	34.31	31.443	29.639	34.302	36.059

26/12/2010	Blackburn	Stoke	A	47.056	29.366	23.578	38.03	32.759	29.211
26/12/2010	Bolton	West Brom	H	54.46	26.715	18.825	52.41	27.76	19.831
26/12/2010	Fulham	West Ham	A	53.582	31.989	14.429	50.62	33.183	16.197
26/12/2010	Man United	Sunderland	H	74.785	20.193	5.022	76.584	18.842	4.575
26/12/2010	Newcastle	Man City	A	32.917	30.948	36.136	34.527	31.218	34.255
26/12/2010	Wolves	Wigan	A	43.216	32.645	24.138	43.624	32.539	23.837
27/12/2010	Arsenal	Chelsea	H	40.34	33.832	25.828	28.281	35.777	35.941
28/12/2010	Birmingham	Man United	D	11.757	17.747	70.496	15.875	29.988	54.137
28/12/2010	Man City	Aston Villa	H	71.089	19.66	9.251	69.691	20.672	9.638
28/12/2010	Stoke	Fulham	A	57.835	25.435	16.729	61.486	24.186	14.329
28/12/2010	Sunderland	Blackpool	A	52.003	27.906	20.092	39.288	33.797	26.915
28/12/2010	Tottenham	Newcastle	H	66.218	21.486	12.296	66.543	21.347	12.109
28/12/2010	West Brom	Blackburn	A	43.631	31.394	24.975	42.293	31.769	25.938
28/12/2010	West Ham	Everton	D	30.271	32.04	37.689	20.918	31.493	47.589
29/12/2010	Chelsea	Bolton	H	73.346	16.831	9.823	74.191	16.479	9.33
29/12/2010	Liverpool	Wolves	A	71.617	17.172	11.211	80.584	14.059	5.357
29/12/2010	Wigan	Arsenal	D	21.663	18.646	59.691	21.876	19.116	59.008
01/01/2011	Birmingham	Arsenal	A	23.507	21.556	54.937	23.05	21.594	55.356
01/01/2011	Liverpool	Bolton	H	42.373	29.558	28.068	45.995	29.376	24.629
01/01/2011	Man City	Blackpool	H	72.492	18.562	8.946	73.892	17.837	8.271
01/01/2011	Stoke	Everton	H	42.739	28.654	28.607	37.715	30.31	31.975
01/01/2011	Sunderland	Blackburn	H	51.026	28.134	20.841	47.422	29.751	22.828
01/01/2011	Tottenham	Fulham	H	68.926	19.506	11.569	72.556	18.028	9.415
01/01/2011	West Brom	Man United	A	13.399	18.245	68.356	11.517	17.564	70.919
01/01/2011	West Ham	Wolves	H	45.545	32.521	21.933	46.881	32.086	21.033
02/01/2011	Chelsea	Aston Villa	D	72.334	16.753	10.913	73.451	16.364	10.185
02/01/2011	Wigan	Newcastle	A	38.091	33.745	28.163	36.049	33.978	29.973
04/01/2011	Blackpool	Birmingham	A	53.159	29.447	17.394	56.098	28.244	15.658
04/01/2011	Fulham	West Brom	H	40.193	32.785	27.022	36.468	33.472	30.06
04/01/2011	Man United	Stoke	H	75.552	20.948	3.5	75.665	20.854	3.481
05/01/2011	Arsenal	Man City	D	61.217	27.972	10.81	53.938	31.925	14.136
05/01/2011	Aston Villa	Sunderland	A	41.094	25.892	33.014	36.634	27.542	35.824
05/01/2011	Blackburn	Liverpool	H	37.661	27.284	35.055	37.974	27.373	34.654
05/01/2011	Bolton	Wigan	D	57	26.6	16.4	62.34	24.552	13.108
05/01/2011	Everton	Tottenham	H	30.833	29.23	39.937	24.313	29.569	46.117
05/01/2011	Newcastle	West Ham	H	53.442	30.48	16.079	43.114	34.917	21.969
05/01/2011	Wolves	Chelsea	H	19.848	19.807	60.345	22.852	25.955	51.193
12/01/2011	Blackpool	Liverpool	H	40.262	29.308	30.43	42.61	29.398	27.992
15/01/2011	Chelsea	Blackburn	H	72.914	18.056	9.03	65.418	23.695	10.886
15/01/2011	Man City	Wolves	H	68.776	20.83	10.394	67.938	21.414	10.648
15/01/2011	Stoke	Bolton	H	45.804	27.396	26.8	42.485	28.73	28.786
15/01/2011	West Brom	Blackpool	H	34.185	34.096	31.719	38.721	33.779	27.499
15/01/2011	West Ham	Arsenal	A	22.375	19.991	57.634	24.533	24.055	51.412
15/01/2011	Wigan	Fulham	D	40.591	32.608	26.801	38.662	32.987	28.351
16/01/2011	Birmingham	Aston Villa	D	42.202	31.839	25.959	45.445	31.240	23.315
16/01/2011	Liverpool	Everton	D	41.988	28.313	29.7	35.717	30.355	33.928
16/01/2011	Sunderland	Newcastle	D	46.873	29.43	23.697	50.266	28.769	20.965
16/01/2011	Tottenham	Man United	D	30.77	26.137	43.093	34.041	28.259	37.7
22/01/2011	Arsenal	Wigan	H	74.599	20.494	4.907	72.697	21.873	5.43
22/01/2011	Aston Villa	Man City	H	24.124	32.367	43.51	28.806	33.979	37.215
22/01/2011	Blackpool	Sunderland	A	41.193	27.308	31.499	43.491	27.661	28.848
22/01/2011	Everton	West Ham	D	54.409	29.936	15.655	50.266	31.799	17.934
22/01/2011	Fulham	Stoke	H	34.81	34.431	30.759	33.648	34.443	31.909
22/01/2011	Man United	Birmingham	H	78.318	17.89	3.792	79.806	16.717	3.477
22/01/2011	Newcastle	Tottenham	D	31.446	33.081	35.473	25.406	32.767	41.827
22/01/2011	Wolves	Liverpool	A	30.7	34.646	34.655	40.382	34.648	24.97
23/01/2011	Blackburn	West Brom	H	49.841	29.948	20.212	50.764	29.647	19.588
24/01/2011	Bolton	Chelsea	A	32.036	31.673	36.291	33.322	31.86	34.818
25/01/2011	Blackpool	Man United	A	18.4	25.274	56.325	12.691	23.141	64.168
25/01/2011	Wigan	Aston Villa	A	34.358	34.314	31.328	20.584	34.332	45.084
26/01/2011	Liverpool	Fulham	H	55.98	26.043	17.977	58.728	25.192	16.08

01/02/2011	Arsenal	Everton	H	72.076	16.004	11.921	74.661	15.344	9.995
01/02/2011	Man United	Aston Villa	H	73.407	24.454	2.139	65.315	29.851	4.835
01/02/2011	Sunderland	Chelsea	A	26.606	38.612	34.782	15.555	33.625	50.82
01/02/2011	West Brom	Wigan	D	51.24	31.979	16.781	55.501	29.954	14.545
02/02/2011	Birmingham	Man City	D	29.2	17.236	53.564	29.846	18.6	51.554
02/02/2011	Blackburn	Tottenham	A	32.177	29.575	38.249	34.513	30.26	35.227
02/02/2011	Blackpool	West Ham	A	52.143	31.581	16.276	45.866	34.056	20.078
02/02/2011	Bolton	Wolves	H	53.172	31.714	15.114	53.099	31.743	15.158
02/02/2011	Fulham	Newcastle	H	40.249	32.199	27.551	44.674	31.561	23.766
02/02/2011	Liverpool	Stoke	H	57.149	27.589	15.262	57.149	27.589	15.262
05/02/2011	Aston Villa	Fulham	D	49.779	28.029	22.192	55.27	26.886	17.844
05/02/2011	Everton	Blackpool	H	51.737	29.678	18.585	58.762	27.052	14.186
05/02/2011	Man City	West Brom	H	69.204	18.789	12.007	73.014	17.414	9.572
05/02/2011	Newcastle	Arsenal	D	17.627	28.922	53.45	10.549	24.387	65.064
05/02/2011	Stoke	Sunderland	H	41.595	27.126	31.28	49.052	28.268	22.68
05/02/2011	Tottenham	Bolton	H	67.068	21.107	11.825	64.681	22.742	12.577
05/02/2011	Wigan	Blackburn	H	33.625	34.605	31.770	33.619	34.605	31.776
05/02/2011	Wolves	Man United	H	6.657	11.875	81.468	5.019	10.591	84.39
06/02/2011	Chelsea	Liverpool	A	65.828	21.391	12.781	67.747	20.619	11.634
06/02/2011	West Ham	Birmingham	A	41.836	32.669	25.495	49.665	30.95	19.385
12/02/2011	Arsenal	Wolves	H	77.072	20.783	2.146	79.874	18.27	1.856
12/02/2011	Birmingham	Stoke	H	38.85	31.723	29.427	41.33	31.544	27.126
12/02/2011	Blackburn	Newcastle	D	46.677	29.524	23.799	49.469	28.983	21.548
12/02/2011	Blackpool	Aston Villa	D	36.412	33.668	29.92	32.311	33.977	33.711
12/02/2011	Liverpool	Wigan	D	69.965	18.236	11.799	70.294	18.12	11.586
12/02/2011	Man United	Man City	H	49.572	28.652	21.776	43.473	31.226	25.301
12/02/2011	Sunderland	Tottenham	A	35.277	35.553	29.17	42.5	34.256	23.244
12/02/2011	West Brom	West Ham	D	50.78	30.879	18.341	46.452	32.575	20.973
13/02/2011	Bolton	Everton	H	43.758	28.87	27.372	38.39	30.697	30.914
14/02/2011	Fulham	Chelsea	D	30.282	25.162	44.556	30.714	25.495	43.791
15/02/2011	Birmingham	Newcastle	A	47.039	28.957	24.005	52.483	28.026	19.491
20/02/2011	West Brom	Wolves	D	51.521	31.145	17.334	55.625	29.325	15.05
22/02/2011	Blackpool	Tottenham	H	29.66	21.862	48.478	31.218	23.759	45.023
23/02/2011	Arsenal	Stoke	H	71.478	16.77	11.752	71.545	16.75	11.705
26/02/2011	Aston Villa	Blackburn	H	47.73	28.369	23.901	50.369	27.953	21.678
26/02/2011	Everton	Sunderland	H	43.643	27.209	29.148	52.011	27.805	20.183
26/02/2011	Newcastle	Bolton	D	43.32	28.284	28.396	43.557	28.285	28.158
26/02/2011	Wigan	Man United	A	8.484	10.992	80.524	11.487	29.988	58.525
26/02/2011	Wolves	Blackpool	H	32.388	33.781	33.831	37.894	33.789	28.317
27/02/2011	Man City	Fulham	D	71.786	17.945	10.269	66.644	21.802	11.555
27/02/2011	West Ham	Liverpool	H	25.49	34.775	39.735	30.4	35.476	34.124
28/02/2011	Stoke	West Brom	D	52.449	30.305	17.246	54.686	29.341	15.973
01/03/2011	Chelsea	Man United	H	30.182	24.464	45.354	34.258	27.944	37.798
05/03/2011	Arsenal	Sunderland	D	72.646	17.327	10.027	71.858	17.926	10.215
05/03/2011	Birmingham	West Brom	A	49.843	32.894	17.263	53.066	31.362	15.572
05/03/2011	Bolton	Aston Villa	H	49.719	27.957	22.324	44.921	30.057	25.022
05/03/2011	Fulham	Blackburn	H	46.044	30.892	23.064	52.487	29.259	18.253
05/03/2011	Man City	Wigan	H	73.713	17.754	8.533	70.779	19.981	9.240
05/03/2011	Newcastle	Everton	A	42.579	28.484	28.937	41.87	28.718	29.412
05/03/2011	West Ham	Stoke	H	36.8	34.365	28.835	42.217	33.493	24.29
06/03/2011	Liverpool	Man United	H	23.922	22.193	53.885	34.225	36.905	28.871
06/03/2011	Wolves	Tottenham	D	26.329	27.83	45.841	38.689	35.829	25.482
07/03/2011	Blackpool	Chelsea	A	28.94	16.817	54.243	18.598	21.149	60.252
09/03/2011	Everton	Birmingham	D	59.269	26.032	14.699	61.619	25.009	13.372
19/03/2011	Aston Villa	Wolves	A	50.185	34.83	14.985	46.394	35.99	17.616
19/03/2011	Blackburn	Blackpool	D	46.776	32.499	20.725	46.312	32.641	21.047
19/03/2011	Everton	Fulham	H	55.225	26.746	18.03	49.491	29.702	20.806
19/03/2011	Man United	Bolton	H	71.833	19.096	9.071	63.677	25.084	11.239
19/03/2011	Stoke	Newcastle	H	44.58	31.023	24.398	44.691	30.999	24.31
19/03/2011	Tottenham	West Ham	D	68.556	22.246	9.198	55.029	31.384	13.587
19/03/2011	West Brom	Arsenal	D	16.039	23.079	60.882	21.931	32.729	45.34

19/03/2011	Wigan	Birmingham	H	32.405	34.045	33.550	31.461	33.998	34.541
20/03/2011	Chelsea	Man City	H	55.423	23.06	21.517	61.049	22.684	16.268
20/03/2011	Sunderland	Liverpool	A	35.764	25.958	38.278	39.712	27.832	32.456
02/04/2011	Arsenal	Blackburn	D	76.124	18.665	5.211	76.96	18.062	4.978
02/04/2011	Birmingham	Bolton	H	36.492	33.089	30.419	34.051	33.317	32.633
02/04/2011	Everton	Aston Villa	D	62.753	24.685	12.562	56.433	28.519	15.048
02/04/2011	Newcastle	Wolves	H	49.803	31.135	19.062	49.146	31.381	19.473
02/04/2011	Stoke	Chelsea	D	24.88	28.882	46.238	24.359	28.799	46.842
02/04/2011	West Brom	Liverpool	H	28.019	28.746	43.235	23.484	28.628	47.887
02/04/2011	West Ham	Man United	A	12.878	20.974	66.148	16.46	28.689	54.851
02/04/2011	Wigan	Tottenham	D	25.065	32.276	42.659	31.056	34.203	34.741
03/04/2011	Fulham	Blackpool	H	49.702	30.63	19.668	50.969	30.176	18.854
03/04/2011	Man City	Sunderland	H	71.016	18.966	10.018	65.363	23.109	11.528
09/04/2011	Blackburn	Birmingham	D	43.66	32.916	23.424	46.161	32.195	21.644
09/04/2011	Bolton	West Ham	H	54.175	28.45	17.375	53.679	28.686	17.635
09/04/2011	Chelsea	Wigan	H	68.19	20.89	10.919	54.579	30.332	15.089
09/04/2011	Man United	Fulham	H	75.702	18.805	5.493	40.164	45.515	14.321
09/04/2011	Sunderland	West Brom	A	49.538	29.404	21.057	38.386	33.937	27.677
09/04/2011	Tottenham	Stoke	H	62.639	23.388	13.974	55.538	27.837	16.625
09/04/2011	Wolves	Everton	A	33.054	33.781	33.165	37.103	33.708	29.189
10/04/2011	Aston Villa	Newcastle	H	42.746	30.928	26.327	51.79	29.582	18.628
10/04/2011	Blackpool	Arsenal	A	22.7	18.673	58.627	20.834	19.004	60.162
11/04/2011	Liverpool	Man City	H	36.062	32.644	31.294	31.949	33.034	35.017
16/04/2011	Birmingham	Sunderland	H	44.066	31.724	24.21	47.947	30.805	21.248
16/04/2011	Blackpool	Wigan	A	48.956	30.306	20.738	42.418	32.797	24.785
16/04/2011	Everton	Blackburn	H	59.818	26.582	13.6	59.495	26.762	13.743
16/04/2011	West Brom	Chelsea	A	21.829	28.118	50.053	26.505	31.766	41.73
16/04/2011	West Ham	Aston Villa	A	35.743	33.979	30.279	33.749	34.077	32.174
17/04/2011	Arsenal	Liverpool	D	58.532	26.317	15.151	51.919	29.957	18.125
19/04/2011	Newcastle	Man United	D	19.212	22.361	58.427	17.748	22.121	60.131
20/04/2011	Chelsea	Birmingham	H	73.125	17.868	9.007	75.176	16.851	7.973
20/04/2011	Tottenham	Arsenal	D	42.478	26.437	31.085	46.457	27.136	26.407
23/04/2011	Aston Villa	Stoke	D	50.696	28.548	20.755	46.9	30.207	22.893
23/04/2011	Blackpool	Newcastle	D	35.304	34.396	30.299	32.119	34.478	33.403
23/04/2011	Chelsea	West Ham	H	79.896	18.9	1.204	82.427	16.531	1.043
23/04/2011	Liverpool	Birmingham	H	62.558	24.6	12.841	69.079	21.484	9.438
23/04/2011	Man United	Everton	H	77.905	19.07	3.025	75.304	21.035	3.661
23/04/2011	Sunderland	Wigan	H	41.382	33.1	25.518	28.478	35.683	35.839
23/04/2011	Tottenham	West Brom	D	66.201	23.219	10.58	57.886	28.618	13.496
23/04/2011	Wolves	Fulham	D	34.833	34.624	30.543	38.528	34.189	27.284
24/04/2011	Bolton	Arsenal	H	28.135	35.891	35.975	29.789	35.894	34.316
25/04/2011	Blackburn	Man City	A	24.238	30.423	45.339	23.37	30.201	46.428
26/04/2011	Stoke	Wolves	H	49.752	35.425	14.823	51.017	34.689	14.294
27/04/2011	Fulham	Bolton	H	42.252	29.976	27.772	46.154	29.689	24.157
30/04/2011	Blackburn	Bolton	H	34.182	33.893	31.925	38.446	33.645	27.909
30/04/2011	Blackpool	Stoke	D	32.167	35.24	32.593	35.74	34.971	29.289
30/04/2011	Chelsea	Tottenham	H	50.391	34.776	14.832	56.827	31.086	12.088
30/04/2011	Sunderland	Fulham	A	41.272	31.5	27.228	36.332	32.67	30.998
30/04/2011	West Brom	Aston Villa	H	43.354	31.236	25.41	36.114	33.26	30.626
30/04/2011	Wigan	Everton	D	30.793	32.043	37.163	33.225	32.432	34.343
01/05/2011	Arsenal	Man United	H	32.917	30.689	36.394	34.096	30.908	34.996
01/05/2011	Birmingham	Wolves	D	51.307	33.699	14.994	52.118	33.249	14.633
01/05/2011	Liverpool	Newcastle	H	63.797	23.926	12.277	72.138	19.865	7.997
01/05/2011	Man City	West Ham	H	78.248	14.216	7.537	80.421	13.194	6.384
07/05/2011	Aston Villa	Wigan	D	51.851	32.412	15.737	52.549	32.053	15.398
07/05/2011	Bolton	Sunderland	A	56.538	26.858	16.604	62.294	24.66	13.046
07/05/2011	Everton	Man City	H	36.103	31.682	32.216	37.753	31.709	30.538
07/05/2011	Newcastle	Birmingham	H	46.531	31.521	21.949	43.413	32.526	24.06
07/05/2011	Tottenham	Blackpool	D	78.337	15.82	5.843	79.366	15.171	5.463
07/05/2011	West Ham	Blackburn	D	30.531	34.041	35.428	28.511	33.809	37.681
08/05/2011	Man United	Chelsea	H	44.417	38.544	17.04	41.451	38.936	19.613

08/05/2011	Stoke	Arsenal	H	28.281	27.756	43.963	29.45	28.439	42.112
08/05/2011	Wolves	West Brom	H	32.945	34.709	32.346	34.259	34.619	31.122
09/05/2011	Fulham	Liverpool	A	31.142	27.555	41.303	32.065	28.016	39.92
10/05/2011	Man City	Tottenham	H	54.601	26.086	19.313	51.66	27.622	20.718
14/05/2011	Blackburn	Man United	D	12.343	21.662	65.995	14.736	26.561	58.703
14/05/2011	Blackpool	Bolton	H	33.551	35.215	31.234	38.924	34.608	26.468
14/05/2011	Sunderland	Wolves	A	49.415	34.028	16.557	26.268	41.236	32.496
14/05/2011	West Brom	Everton	H	40.482	22.429	37.089	39.992	22.647	37.361
15/05/2011	Arsenal	Aston Villa	A	72.539	16.634	10.827	63.25	23.793	12.957
15/05/2011	Birmingham	Fulham	A	36.748	33.603	29.649	42.402	32.938	24.660
15/05/2011	Chelsea	Newcastle	D	72.353	18.017	9.629	76.582	16.049	7.37
15/05/2011	Liverpool	Tottenham	A	41.873	33.444	24.682	50.715	31.128	18.157
15/05/2011	Wigan	West Ham	H	53.285	29.28	17.435	53.375	29.243	17.382
17/05/2011	Man City	Stoke	H	70.539	20.083	9.377	73.339	18.591	8.07
22/05/2011	Aston Villa	Liverpool	H	32.978	26.024	40.998	28.332	27.003	44.665
22/05/2011	Bolton	Man City	A	27.614	28.864	43.522	18.352	28.445	53.203
22/05/2011	Everton	Chelsea	H	25.528	39.243	35.228	25.343	39.144	35.513
22/05/2011	Fulham	Arsenal	D	32.334	31.683	35.983	37.735	32.416	29.849
22/05/2011	Man United	Blackpool	H	78.663	18.806	2.531	56.194	35.903	7.903
22/05/2011	Newcastle	West Brom	D	45.389	29.826	24.784	39.59	31.815	28.595
22/05/2011	Stoke	Wigan	A	51.396	30.232	18.371	35.349	36.840	27.811
22/05/2011	Tottenham	Birmingham	H	69.06	19.372	11.568	65.563	21.888	12.549
22/05/2011	West Ham	Sunderland	A	32.595	33.337	34.068	29.53	33.267	37.203
22/05/2011	Wolves	Blackburn	A	43.866	33.421	22.713	41.8	33.913	24.287

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