Kicking the Odds: A Bayesian Framework for Football Match Outcome Prediction in Allsvenskan

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Abstract

This paper employs a bivariate Poisson and a Skellam's distribution-based models to predict goal difference distributions in Swedish league soccer games. This work contributes to the extensive literature on soccer match outcome prediction, adopting a Bayesian framework to model score differences, with a particular focus on the under-explored Allsvenskan. Finally, we propose a simple betting strategy using our results.

1. Introduction

On 2022-10-03, the Swedish betting site SvenskaSpel introduced a new betting game called "Fullträff." The rules are relatively straightforward; the goal is to correctly predict the number of goals in 13 soccer games from primarily English and Swedish leagues. Since its debut, no one has ever been able to predict all 13 games, and thus, there has been a massive jackpot of 55 million SEK amassed.

This scenario exemplifies the essence of sports betting, where participants make conditional wagers based on their predictions for future events in exchange for an upfront payment. In essence, betting can be seen as a game characterized by specific components. A bettor invests an amount of F and formulates a forecast regarding the outcome of a forthcoming, uncertain event—the number of goals in this context. Following the event's occurrence, the bettor receives an amount $S > 0$, where $S - F > 0$ if their forecast is correct with a probability of p. In contrast, they receive 0 if their prediction is incorrect with a probability of $1 - p$. In the case of a correct prediction, the bettor realizes a profit of $S - F > 0$; however, an incorrect forecast results in a loss of $-F < 0$. Therefore, we can define profits as:

$$\pi = \begin{cases} S - F > 0 & \text{with probability } p \\ -F < 0 & \text{with probability } (1-p) \end{cases} \tag{1}$$

Inspired by the "Fullträff" seemingly impossible task and the possibility of implementing the models in other betting strategies, we aim to use a bivariate Poisson model to predict the goal distribution and goal differences of soccer games from the Swedish league. We also aim to use a model based on Skellam's distribution to model goal differences for the same dataset.

The field of statistics has extensive literature dedicated to forecasting soccer match outcomes and identifying profitable betting opportunities. Early works that gained popularity employed Poisson models to predict soccer scores (Maher, 1982; Dixon & Coles, 1997). Authors have recently endeavored to address this prediction problem within a Bayesian framework (Baio & Blangiardo, 2010; Robberechts et al., 2021). This paper builds upon this existing literature, aiming to model and predict score differences before the commencement of matches within a Bayesian framework, focusing on an under-explored league, such as the Swedish league Allsvenskan. The paper leverages the fantastic visual and modeling tools developed by Egidi (2022).

2. Data

We have constructed a dataset by using information from two distinct sources. Firstly, we harnessed data made accessible through the football-data.co.uk website, which encompasses match results for nearly all European leagues up to the present day. Secondly, we incorporated data from https://www.kaggle.com/, which comprises ratings for every team featured in the EA Sports FIFA 22 Video Game.[1]

Our final dataset includes 240 observations for each match in the Allsvenskan 2022 season.[2] For each observation,

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[1]EA Sports FC 24 complete player dataset. (n.d.). Retrieved October 15, 2023, from https://www.kaggle.com/datasets/stefanoleone992/ea-sports-fc-24-complete-player-dataset

[2]We can derive the 240 matches using the fact that each team plays against each other twice a season, then $240 = 2\binom{16}{2}$.

we included the following set of variables: full-time goals scored by both the home and away teams and the date of each match. Furthermore, we established a preseason ranking for all teams. This ranking was obtained by computing a simple average using the defense, midfield, and attack ratings assigned to each team within the EA Sports FIFA 22 rating system. When fitting the models we exclude the last 32 games, i.e., the last two game weeks, from the sample so as to be able to perform out-of-sample predictions.

Table 1. Descriptive Statistics Allsvenskan 2022

	MIN	MEDIAN	MEAN	SD	MAX
HOME GOALS	0.00	1.00	1.55	1.25	5.00
AWAY GOALS	0.00	1.00	1.21	1.20	6.00
HOME - AWAY	-6.00	0.00	0.33	1.84	5.00

3. Models

3.1. Static Models

The models employed in this study are based on the work of Egidi (2022). Specifically, we utilized a bivariate Poisson model described as:

$$y_n^h, y_n^a | \lambda_{1n}, \lambda_{2n}, \lambda_{3n} \sim BivPoisson(\lambda_{1n}, \lambda_{2n}, \lambda_{3n}) \quad (2)$$

$$\begin{aligned} log(\lambda_{1n}) = \mu + home + att_{h_n} + def_{a_n} + \\ \frac{\gamma}{2}(rank_{h_n} - rank_{a_n}) \end{aligned} \quad (3)$$

$$\begin{aligned} log(\lambda_{2n}) = \mu + att_{a_n} + def_{h_n} - \\ \frac{\gamma}{2}(rank_{h_n} - rank_{a_n}) \end{aligned} \quad (4)$$

$$log(\lambda_{3n}) = \beta_0 + \gamma_1 \beta_{h_n} + \gamma_2 \beta_{a_n} + \gamma_3 \beta w_n \quad (5)$$

where (y_n^h, y_n^a) denotes the number of goals scored by the home and the away team in the n-th game, respectively. $\lambda_{1n}, \lambda_{2n}$ represent the home and away teams' scoring rates, respectively. In the equation for each λ_{in}, μ represent a constant intercept, $home$ is the benefit from playing at your stadium, att_{h_n} and def_{h_n} each represent the attack and defense ability of home team h playing in game n, and likewise att_{a_n}, def_{a_n} represent the same for the away team a in game n. The model incorporates the (re-scaled) EA Sports FIFA ranking as a predictor ($rank_{h_n} - rank_{a_n}$). The priors for the parameters of each team t in the model, are:

$$att_t \sim N(\mu_{att}, \sigma_{att}) \quad (6)$$

$$def_t \sim N(\mu_{def}, \sigma_{def}) \quad (7)$$

$$\sigma_{att}, \sigma_{def} \sim Cauchy^+(0, 5) \quad (8)$$

$$\gamma \sim N(0, 1) \quad (9)$$

Which are standard weakly informative priors commonly used in the literature for these types of models.

One of the benefits of using a bivariate Poisson model is that we include a third equation that enables covariance between the λ_{in}'s. In the double Poisson model, for example, you have to assume that the number of goals scored by each team is conditionally independent, which is not a reasonable assumption.

Intuitively, there is a big difference in outcomes in a team's scoring depending on how much the other team scores. So the equation for $log(\lambda_{3n})$ tries to capture this covariance, β_0 is the intercept, β_{h_n}, β_{a_n} are parameters for each home and away team in each game, w_n is a vector of covariates for the n-th match used to model the covariance term and $\boldsymbol{\beta}$ is its vector of regression coefficients. Finally, the γ_i's are dummy indicators, enabling us to single out the source of the covariance. If $\gamma_1 = \gamma_2 = \gamma_3 = 0$ then we consider constant covariance equal β_0; otherwise, if for example, we have $(\lambda_1, \lambda_2, \lambda_3) = (1, 0, 1)$ then we assume that the covariance depends on only team 1's scoring ability and further match covariates, but not on team 2's scoring ability, and so forth. If $\lambda_{3n} = 0$, then the model reduces to a double Poisson with no covariance between each team's scoring ability.

To be able to achieve identifiability of the model, we assume a constraint of the attacking and defensive parameters:

$$\sum_{t=1}^{T} att_t = 0, \sum_{t=1}^{T} def_t = 0 \quad (10)$$

I.e., that the sum of all attacking and defensive parameters must sum to zero.

Then, following the work of Karlis & Ntzoufras (2008), we used a Skellam's distribution, which is defined as the difference of two independent random variables where both are Poisson-distributed with expected value μ_1 and μ_2.[3] Then we can model the goal difference as:

$$y_n^h - y_n^a | \lambda_{1n}, \lambda_{2n} \sim PD(\lambda_{1n,}, \lambda_{2n}) \quad (11)$$

where the model parameters λ_{1n} and λ_{2n} adopt the same structure as in Equations 3 and 4 for the bivariate Poisson model.

3.2. Dynamic Models

A limitation of the models from Section 3.1 arises from the assumption of static team-specific parameters. Assuming

[3] Consult Appendix A for more information on Skellam Distribution.

that teams maintain a consistent level of performance over time, as determined by their attack (att) and defense (def) abilities may not be realistic. Teams often exhibit improvements or go through streaks throughout a season, which is why assuming weekly dynamic team abilities appears reasonable.

To incorporate weekly dynamics into the model, we can modify our original models by including auto-regressive team parameters priors for attack and defense abilities.

$$att_{t,\tau} \sim N(att_{t,\tau-1}, \sigma_{att}) \tag{12}$$
$$def_{t,\tau} \sim N(def_{t,\tau-1}, \sigma_{def}) \tag{13}$$

for the initial period $\tau = 1$ we have

$$att_{t,1} \sim N(\mu_{att}, \sigma_{att}) \tag{14}$$
$$def_{t,1} \sim N(\mu_{def}, \sigma_{def}) \tag{15}$$

Notice that the identifiability constraint must be imposed for each time τ.

We proceeded to estimate the dynamic cases for our bivariate Poisson and Skellam models.

3.3. Sensitivity Analysis

To conduct a sensitivity analysis, we opted to explore other prior specifications for both our static and dynamic models. In doing so, we modified the priors for the team-specific parameters, namely att and def, as well as assigned distinct priors to the group-level standard deviations. For each team t, we considered the following prior distributions:

$$att_t \sim t(4, \mu_{att}, \sigma_{att}) \tag{16}$$

$$def_t \sim t(4, \mu_{def}, \sigma_{def}) \tag{17}$$

$$\sigma_{att}, \sigma_{def} \sim Laplace^{+}(0, 1) \tag{18}$$

These adjustments allow us to assess the impact of prior choices on our model results, enhancing the robustness of our analysis.

4. Results

4.1. Model Comparisons

To draw inferences and make reliable predictions, we approximated the posterior distributions for the parameters of the models employing the Markov Chain Monte Carlo (MCMC) algorithm.

Table 2 shows that the best-performing model according to the $elpd_{loo-cv}$ values is the static Skellam model with the original priors, the static Skellam with alternate priors is marginally worse, and the dynamic Skellam regardless of priors is only slightly worse. All Skellam models outperform the Bivariate Poisson models in estimates of out-of-sample predictive performance. Additionally, all the Pareto $\hat{k}$-values are $\hat{k} < 0.7$.

Given the close model comparisons and similar Posterior Predictive Distributions of goal differences seen in Figure 4-11, we have mainly focused on presenting the results of the best-performing model, the static Skellam model, with the original priors. There is only a marginal difference between the models, regardless of priors. In Table 3 you can see the parameter estimates of the static Skellam model. Since there are hundreds of parameter estimates we only include a few to get a general understanding of how the model works, but they don't really make sense alone, only in the context of the model equation 11.

4.2. Model Checking

To assess the model fit, we computed some posterior predicting checks, where hypothetical replications of goal differences $(y^h - y^a)^{rep}$ are evaluated under the posterior predictive distribution

$$\begin{aligned} p\left((y_n^h - y_n^a)^{rep} | y_n^h - y_n^a\right) = \\ \int p\left((y_n^h - y_n^a)^{rep} | \boldsymbol{\theta}\right) \pi\left(\boldsymbol{\theta} | y_n^h - y_n^a\right) d\boldsymbol{\theta} \end{aligned} \tag{19}$$

and then check whether the replicated values $(y^h - y^a)^{rep}$ are close to the actual differences $(y^h - y^a)$.

Figure 1 depicts a visualization of match-ordered goal differences. The goal difference frequencies seem to be appropriately captured by the Static Skellam model's replications.

Figure 4 shows the overlap between the observed goal difference density and the replicated goal difference densities, confirming that the Static Skellam model reasonably captures the goal difference.

4.3. Predictive Accuracy

It is straightforward to generate observable out-of-sample differences $(\widetilde{y^h - y^a})$ conditioned on the posterior model's parameters estimates to predict test set matches.

$$\begin{aligned} p\left(\widetilde{y_n^h - y_n^a} | y_n^h - y_n^a\right) = \\ \int p\left(\widetilde{y_n^h - y_n^a} | \boldsymbol{\theta}\right) \pi\left(\boldsymbol{\theta} | y_n^h - y_n^a\right) d\boldsymbol{\theta} \end{aligned} \tag{20}$$

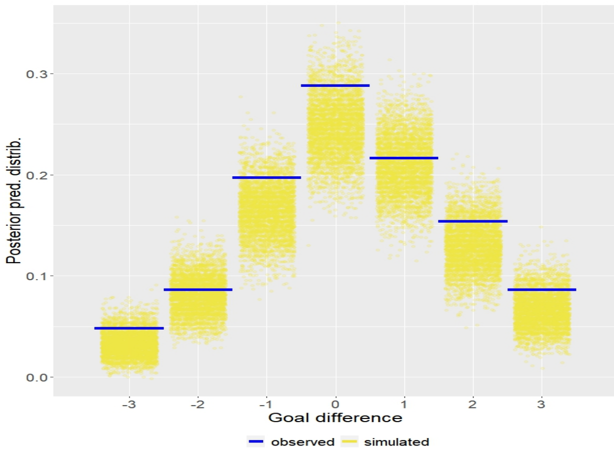

Figure 1. Posterior Predictive Distribution Static Skellam

Figure 2 exhibits the probabilities of the posterior results for all the matches used in the test set, corresponding to the last two weeks of the 2022 Season. The red square represents the observed result.

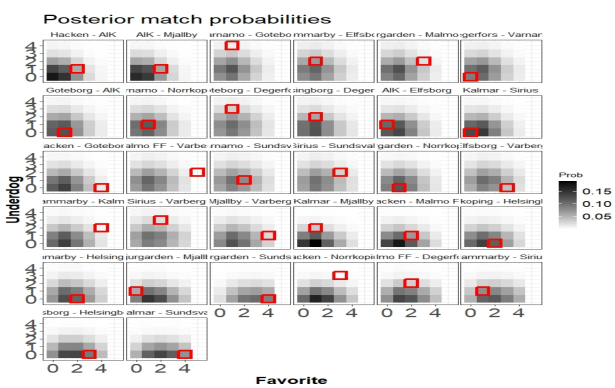

Figure 2. Posterior Results Probabilities Static Skellam

Using the out-of-sample posterior results probabilities, we computed the aggregated probabilities for home wins based on the MCMC-drawn samples (S) for a given match

$$p_{win} = Pr(y^h > y^a) = \frac{1}{S}\sum_{s=1}^{S} \left| \tilde{y}^{(s)_h} > \tilde{y}^{(s)_a} \right| \quad (21)$$

where $(\tilde{y}^{(s)_h}, \tilde{y}^{(s)_a})$ represents the s-th MCMC pair of the future home goals and away goals for a given match. We can also calculate the home draws, and losses in a similar way. Figure 3 shows the computed probabilities for a home win for the 32 test matches. The red cells denote more likely home wins. In the Kalmar v. Sundsvall game, for example, the probability for a Kalmar win was close to 0.8, and the observed result was a 4-0 win for Kalmar.

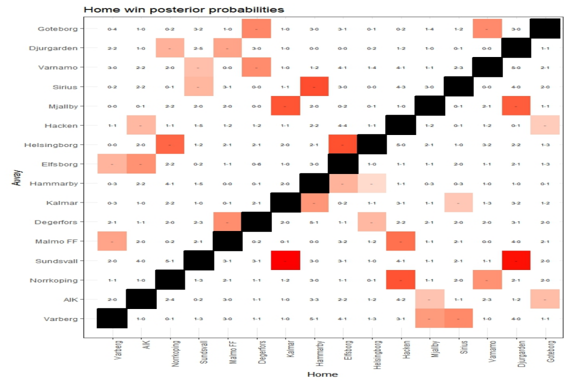

Figure 3. Round Robin Home Win Posterior Probabilities Static Skellam

Finally, we can reconstruct a final rank league table, predicting the position and the total amount of points for each team at the end of the season using the in-sample replications $(y^h - y^a)^{rep}$ to compute the credible intervals. Figure 12 displays yellow ribbons for the credible intervals and blue dots for the observed points.

5. Conclusion

According to the estimated $elpd_{loo-cv}$ values, there was a marginal difference between the four Skellam models in their predictive capacities, with the static Skellam performing best. The plots of the Posterior Predictive Distribution show that all eight estimated models capture and model the goal difference well. It is somewhat surprising that none of the dynamic models outperform their static counterparts. Intuitively these models should model the relative strength of teams week-to-week better than the static model, which assumes constant team strength and weakness.

We put our main focus on the static Skellam model, because of its accuracy as measured by the $elpd_{loo-cv}$ values. The static Skellam model produces good probability estimates for final results in the last two weeks of Allsvenskan in the 2022 season. These games weren't included in the training set, and the result of the model on these games can be seen in Table 4, as well as Figure 3 and Figure 12. The prediction of the final table is just a proxy for accurately predicting the outcomes in the final two game weeks. The most interesting result can be seen in Table 3, where each of the final 32 games can be seen with correct results as well as the predicted probabilities of the outcomes by the static Skellam model. To test how well this model could be implemented in the betting markets we simulated one of the simplest of betting strategies, betting one unit on the most probable outcome according to the model in each of the 32 games. Betting one unit means that whatever you are willing to risk in each game is your unit. The model accurately predicted 18 out of 32 games, which may not sound as much - only slightly more than half, but considering that there are three possible outcomes in each game this is very good. The pure profit of betting 100 SEK for each of the 32 final games on the most probable outcome according to the model would be 569 SEK. Return on Investment (ROI) is a simple measurement of how profitable a betting strategy is, it is calculated as

$$\begin{aligned} ROI &= \frac{Total\ Earnings - Total\ Wagered}{Total\ Wagered} \\ &= \frac{5.69}{32} = 0.178 = 17.8\% \end{aligned} \tag{22}$$

and translates to what interest you earn on the total amount you stake. Everything above zero means you're making a profit, and an ROI of 17.8% is great. And this is from the most simple betting strategy imaginable. Constructing a more advanced betting strategy based on Equation 1 could be even more profitable.

The model never places large probabilities on blow-out scores, as can be seen in 2. Most of the probability density is located near the origin, indicating lower scores. This isn't necessarily negative, since a lot of games are close in observed scores, as can be seen by the plotted observed difference in scores which is the dark-blue line in all of the figures for the Posterior Predictive Distributions. As a result, we can expect a betting strategy based on betting on exact results as predicted by the model would perform worse than one based on the most probable outcome. The model accurately predicts three of the last 32 games' exact scores, but each of the predictions has very low scores such as 1-1 and 1-0, which corresponds to low odds on the betting market. In comparison, the model was able to accurately predict many underdog wins if compared to bookies odds, thus not only accurately predicting the outcome often, but also being able to predict when less likely events happen which corresponds to higher odds from the bookies.

In conclusion, the static Skellam model provides surprisingly accurate predictions for the out-of-sample games in the 2022 season in Allsvenskan and is a promising model for analyzing further seasons. The results presented in the paper suggest the possibility that profitable betting strategies can be constructed based on the model. The model can be developed even further, with more advanced measures of team rankings or abilities. Further improvements should center around excluding other games than just the last two weeks of the season, for example, test excluding the first two weeks and see how to model performs on predicting these games. This only makes sense for the static models of course. Another improvement that could be made to the model is to estimate it on more data, i.e., more historical seasons. There is the possibility of overfitting on no longer relevant data, but this could be limited if the model were made hierarchical based on season, i.e., much like our dynamic models allowed team-specific parameters to change over weeks, you could allow the parameters in the new model to change over seasons. The results from such a model would be interesting to study.

Acknowledgements

We hereby grant our consent for utilizing this project report as reference material within the context of future editions of the course.

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A. Skellam Distribution

The Skellam Distribution is defined as the distribution of a random variable Z with a probability function

$$p(z|\lambda_1, \lambda_2) = e^{-(\lambda_1+\lambda_2)}(\frac{\lambda_1}{\lambda_2})^{k/2} I_k(2\sqrt{\lambda_1\lambda_2}) \tag{23}$$

Where $I_n(x)$ is the modified Bessel function of order n, defined as

$$I_n(x) = \left(\frac{x}{2}\right)^n \sum_{r=0}^{\infty} \frac{\left(\frac{x^2}{4}\right)^r}{r!\Gamma(n+r+1)} \tag{24}$$

B. Point-wise out-of-sample prediction accuracy

Table 2. Pointwise out-of-sample prediction accuracy

MODEL	PRIORS	ELPD$_{loo}$	p_{eff}	LOOIC
BIVPOISS DYN	6 - 9	-597.39 (11.75)	17.75 (1.39)	1,194.79 (23.51)
BIVPOISS STAT	6 - 9	-596.14 (11.29)	19.61 (1.35)	1,192.28 (22.59)
SKELLAM DYN	6 - 9	-399.5 (11.06)	25 (2.54)	799.01 (22.12)
SKELLAM STAT	6 - 9	-395.86 (11.01)	17.61 (1.83)	791.72 (22.03)
BIVPOISS DYN	16 - 18	-596.57 (11.58)	19.98 (1.53)	1,193.13 (23.17)
BIVPOISS STAT	16 - 18	-596.26 (11.36)	19.19 (1.33)	1,192.53 (22.73)
SKELLAM DYN	16 - 18	-399.67 (10.98)	26.18 (2.81)	799.33 (21.96)
SKELLAM STAT	16 - 18	-395.99 (11.10)	17.59 (1.83)	791.98 (22.196)

Note: We report the estimates for $elpd_{loo}$, p_eff, and LOOIC. Standard errors are reported in parentheses.

C. Appendix: Plots

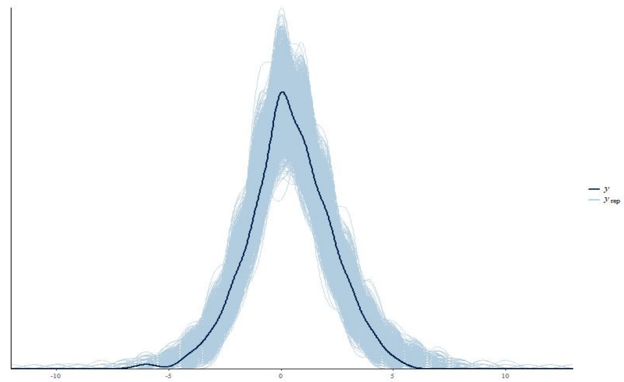

Figure 4. Posterior Predictive Distribution Static Skellam Original Priors

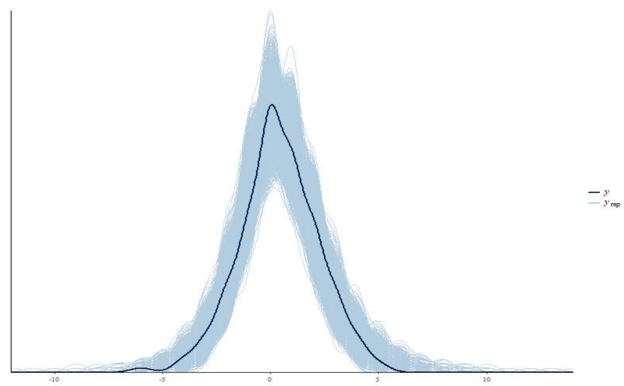

Figure 5. Posterior Predictive Distribution Static Skellam New Priors

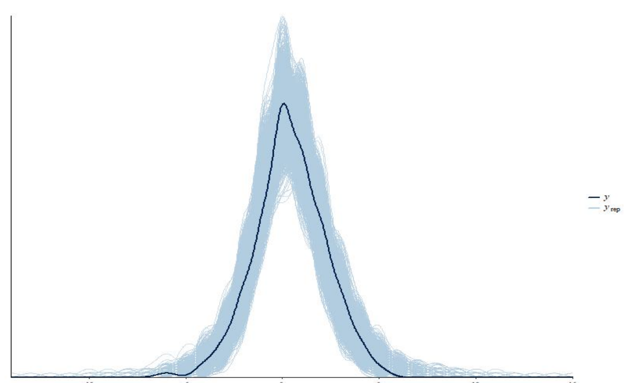

Figure 6. Posterior Predictive Distribution Dynamic Skellam New Priors

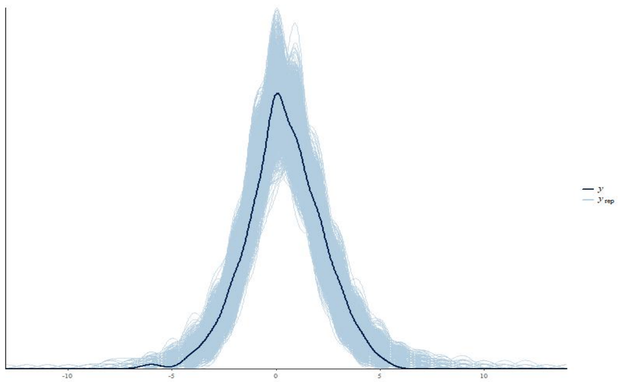

Figure 7. Posterior Predictive Distribution Dynamic Skellam Original Priors

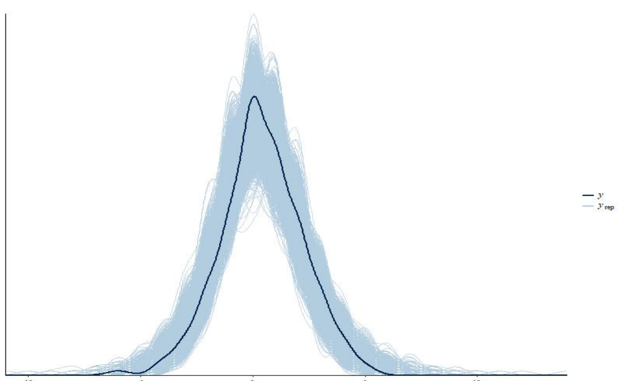

Figure 8. Posterior Predictive Distribution Dynamic Bivariate Poisson Original Priors

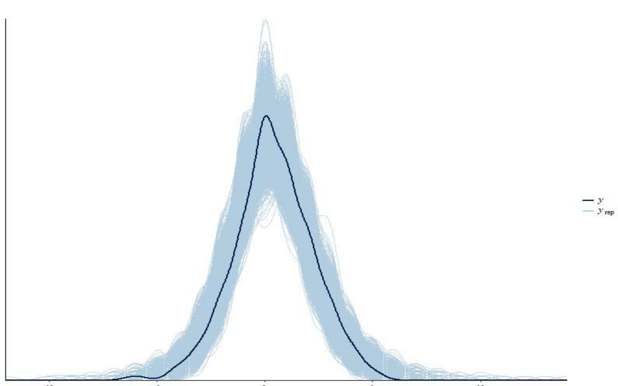

Figure 9. Posterior Predictive Distribution Static Bivariate Poisson Original Priors

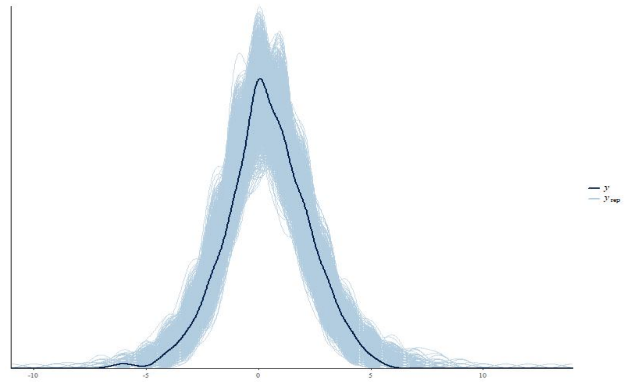

Figure 10. Posterior Predictive Distribution Static Bivariate Poisson New Priors

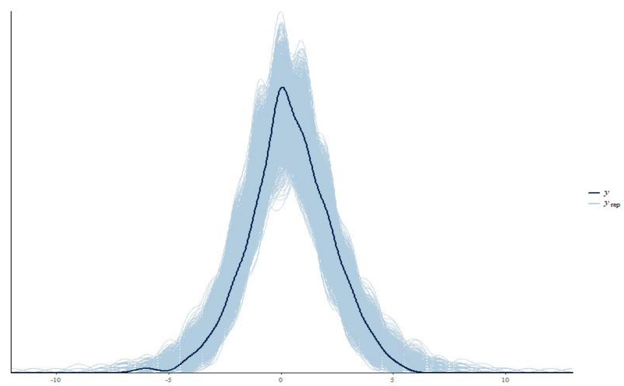

Figure 11. Posterior Predictive Distribution Dynamic Bivariate Poisson New Priors

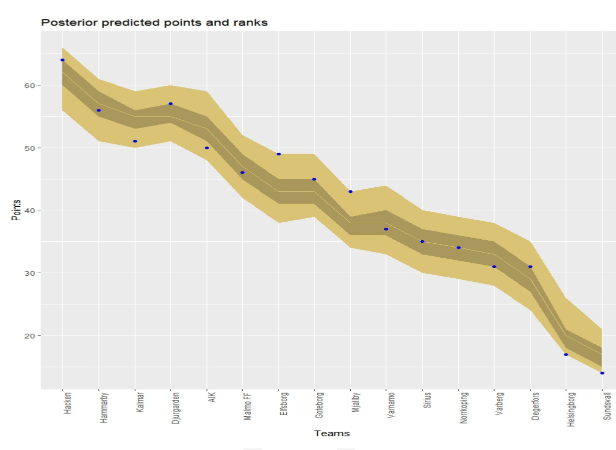

Figure 12. Reconstructed Table Ranks from Posterior Predicted Points Static Skellam

D. Parameter estimates in static Skellam model

Table 3. Parameter estimates in static Skellam model

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
home	0.30	0.00	0.07	0.16	0.26	0.31	0.35	0.44	4402	1
gamma	-0.01	0.01	1.00	-2.02	-0.69	-0.01	0.66	1.98	7064	1
att[1]	0.37	0.01	0.21	-0.01	0.22	0.37	0.51	0.78	959	1
def[1]	-0.22	0.01	0.27	-0.78	-0.38	-0.20	-0.04	0.26	1571	1
att[2]	0.16	0.00	0.19	-0.17	0.03	0.15	0.29	0.56	1515	1
def[2]	-0.49	0.01	0.31	-1.17	-0.69	-0.47	-0.27	0.04	1692	1
att[3]	0.11	0.00	0.18	-0.21	0.00	0.11	0.23	0.47	3288	1
def[3]	0.05	0.00	0.20	-0.36	-0.09	0.04	0.18	0.45	5738	1
sigma_att	0.29	0.00	0.13	0.08	0.20	0.28	0.37	0.57	664	1
sigma_def	0.38	0.00	0.13	0.16	0.30	0.37	0.46	0.67	1033	1

E. Static Skellam model out-of-sample predictions

Table 4. Static Skellam model out-of-sample predictions

Game	Result	Pr(Home Win)	Pr(Draw)	Pr(Away Win)	Odds for outcome	Profit
Varberg - Elfsborg	0-3	0,288	0,245	0,466	2,06	1,06
AIK - Hacken	1-2	0,322	0,325	0,353	2,78	1,78
Norrkoping - Helsingborg	2-0	0,548	0,257	0,194	1,76	0,76
Sundsvall - Varnamo	1-2	0,301	0,244	0,455	2,3	1,3
Malmo FF - Djurgarden	2-3	0,348	0,272	0,379	4,03	3,03
Degerfors - Goteborg	3-1	0,322	0,253	0,425	2,21	-1
Kalmar - Mjallby	1-2	0,526	0,294	0,18	5,78	-1
Hammarby - Sirius	1-1	0,684	0,192	0,124	7,18	-1
Elfsborg - Hammarby	2-1	0,358	0,261	0,381	3,55	-1
Helsingborg - Degerfors	1-2	0,425	0,276	0,299	2,39	-1
Hacken - Malmo FF	2-1	0,535	0,278	0,187	1,79	0,79
Mjallby - Varberg	4-1	0,532	0,246	0,221	2,34	1,34
Sirius - Kalmar	0-0	0,278	0,294	0,429	3,49	-1
Varnamo - Norrkoping	1-1	0,411	0,274	0,315	3,75	-1
Djurgarden - Sundsvall	4-0	0,813	0,125	0,063	1,13	0,13
Goteborg - AIK	1-0	0,396	0,285	0,319	2,97	1,97
Degerfors - Varnamo	0-0	0,382	0,271	0,347	4,09	-1
Goteborg - Hacken	0-4	0,281	0,281	0,438	1,88	0,88
Mjallby - AIK	1-2	0,325	0,316	0,358	2,22	1,22
Sundsvall - Sirius	2-3	0,3	0,247	0,454	1,93	0,93
Hammarby - Kalmar	4-2	0,49	0,272	0,237	1,68	0,68
Varberg - Malmo FF	2-5	0,302	0,253	0,445	2,74	1,74
Elfsborg - Helsingborg	3-0	0,656	0,212	0,132	1,36	0,36
Norrkoping - Djurgarden	0-1	0,28	0,265	0,455	2,12	1,12
AIK - Elfsborg	0-1	0,428	0,287	0,285	4,03	-1
Djurgarden - Mjallby	0-1	0,619	0,234	0,146	5,49	-1
Hacken - Norrkoping	3-3	0,616	0,245	0,14	4,7	-1
Helsingborg - Hammarby	0-2	0,187	0,235	0,578	1,49	0,49
Kalmar - Sundsvall	4-0	0,748	0,166	0,086	1,11	0,11
Malmo FF - Degerfors	2-2	0,627	0,224	0,148	4,52	-1
Sirius - Varberg	2-3	0,504	0,238	0,257	2,54	-1
Varnamo - Goteborg	1-4	0,368	0,267	0,366	2,28	-1
Sum						5,69

The results for the last 32 games of Allsvenskan in the 2022 season, the predicted probabilities for each outcome from the static Skellam model, the odds for the result in the game gotten from Pinnacle before match start and the profit from a simple betting strategy of betting one unit on the highest predicted probability of the model.