

# Artificial Turf Advantage and Predictive Accuracy in Dutch Football

Gertjan Verhoeven

Data Scientist at Dutch Healthcare Authority

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# Presentation information

`https:  
//github.com/gsverhoeven/artificial_turf_predictive`

You'll find:

- ▶ These slides
- ▶ The paper as a reproducible Markdown document

## About this project

- ▶ Pet project not related to work (but positive externalities)
- ▶ My StanCon visit is paid for by my employer (the Dutch Healthcare Authority)
- ▶ Builds on work presented at first StanCon by Milad Kharratzadeh, as well as work by Ben Torvaney (<https://github.com/Torvaney/karlis-ntzoufras-reproduction>) and Rutger Lit

# About Dutch Football



**Figure 1** : European Championship 1988 Dutch Team

# The Artificial Turf Advantage



- ▶ Extra home advantage due to artificial turf
- ▶ Two requirements:
  - ▶ The match is played on Artificial Turf
  - ▶ The away team has natural grass in their Home Stadium
- ▶ 2017 paper by Economist Jan van Ours: +0.5 extra goals per match
- ▶ Compare with:
  - ▶ Regular home advantage: +0.4 extra goals
  - ▶ On average teams score 1-2 times per match

# Some facts on Dutch Eredivisie and Artificial Turf

- ▶ 18 clubs play in Dutch Eredivisie
- ▶ Eredivisie is highest professional league
- ▶ Per season, each team plays each other team twice
- ▶ Budget differs one order of magnitude between clubs
- ▶ Since 2014/2015 season, 6 out of 18 clubs have artificial turf in their home stadium
- ▶ Cost primary motivation for clubs to switch

# Must haves for a parametric football model

- ▶ include regular home advantage (+0.4 goals on average)
- ▶ address correlation between home and away goals
- ▶ allow changes in team ability over time
- ▶ partial pooling of variance of team ability time evolution

# Overview of the models

- ▶ Predict Goal difference of match  $Y_{ijt}$  between home team  $i$  and away team  $j$  at time  $t$
- ▶  $Y_{ijt}$  is a function of latent “scoring intensities”  
 $Y_{ijt} = Y(\lambda_{it}, \lambda_{jt})$
- ▶ Two variants:  
 $Y_{ijt} \sim t(\lambda_{it} - \lambda_{jt}, \sigma_Y, \nu)$   
 $Y_{ijt} \sim \text{Skellam}(\lambda_{it}, \lambda_{jt}) \Leftrightarrow Y_{ijt} \sim \text{Poisson}(\lambda_{it}) - \text{Poisson}(\lambda_{jt})$

```
real skellam_lpmf( ... ) real skellam_rng( ... )
```



# Model details

- ▶ Scoring intensities for Skellam model with Attack/defense abilities:

$$\lambda_{it} = \exp(\mu + \delta + \kappa d_{ijt} + \alpha_{it} - \beta_{jt})$$

$$\lambda_{jt} = \exp(\mu + \alpha_{jt} - \beta_{it})$$

- ▶ Team ability time evolution modeled by random walk

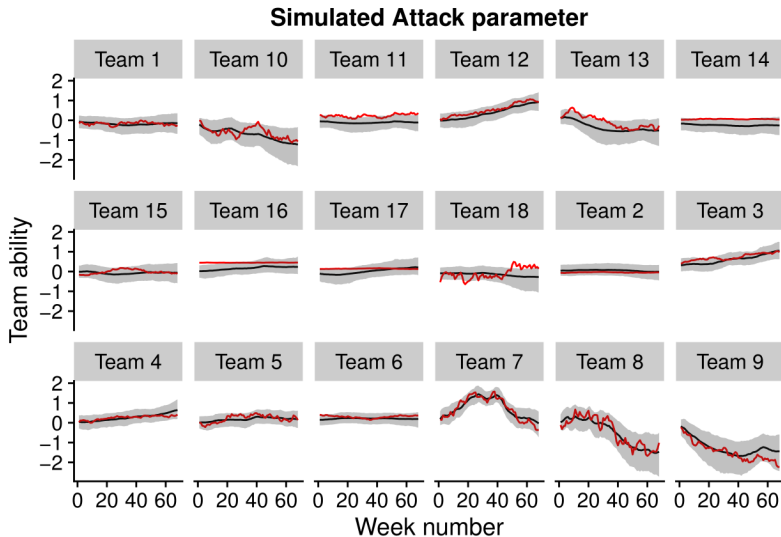
$$\alpha_{it} = \alpha_{i,t-1} + \eta_{it}$$

$$\eta_{it} \sim \text{Normal}(0, \sigma_{it})$$

- ▶ Priors weakly informative based on typical n\_goals scored

# The Core of Modern Statistical Workflow

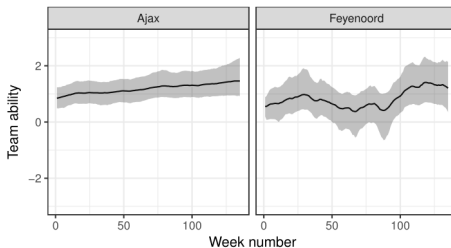
- Fit model to fake data simulated from generative model



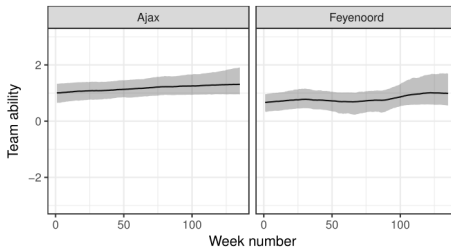
**Figure 2**

# Partial pooling versus no pooling

**A** T-distribution base model: no pooling



**B** T-distribution base model: partial pooling

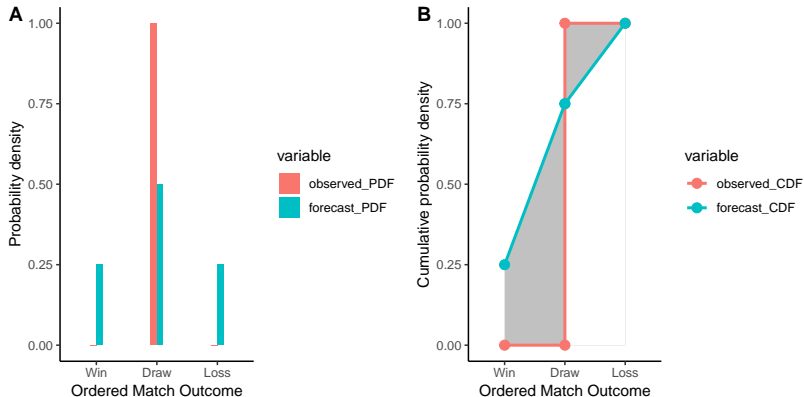


**Figure 3**

# Forecasting approach

- ▶ Out-of-sample forecasts using expanding window
- ▶ Use posterior predictive distribution  $p(y_{rep}|y)$  for next's week matches
- ▶ Gives for each match a probabilistic forecast  $p_{win}, p_{draw}, p_{loss}$
- ▶ Use Ranked Probability Score to quantify discrepancy

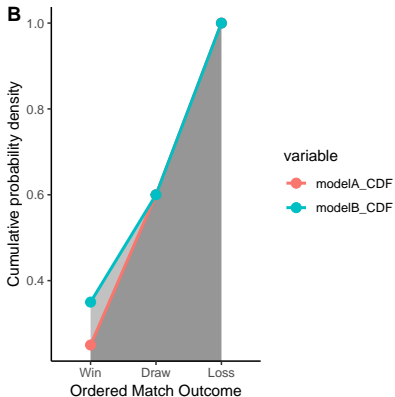
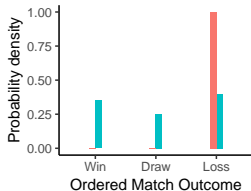
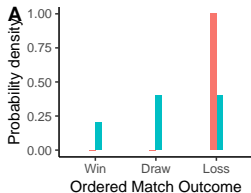
# Ranked Probability Score (RPS)



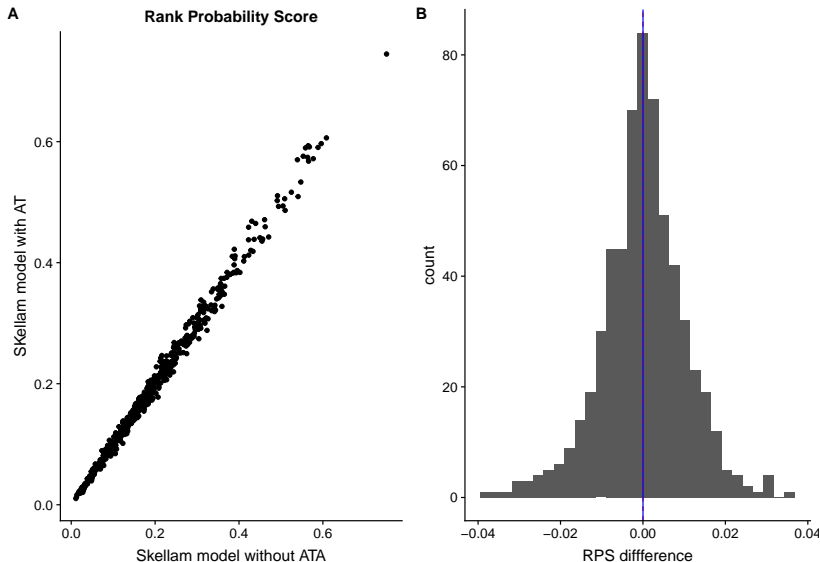
```
calculate_rps(rbind(c(0.25, 0.5, 0.25),  
                    c(1/3, 1/3, 1/3)),  
              rbind(c(0, 1, 0),  
                    c(0, 1, 0)))
```

```
## [1] 0.062500 0.111111
```

# Ranked Probability Score is distance sensitive



# RPS for Skellam model with and without artificial turf

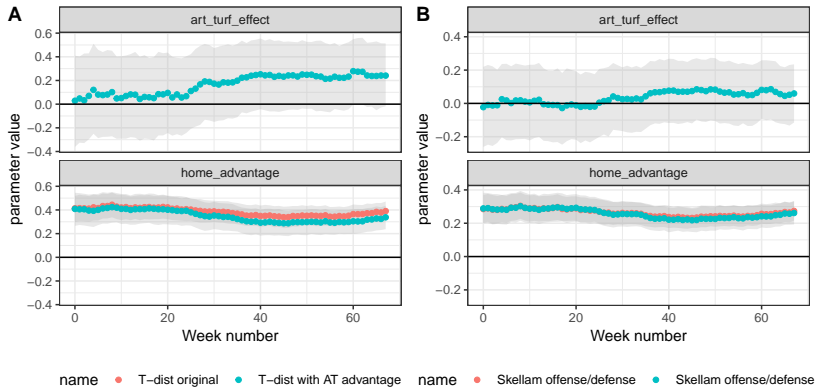


## Results

Model	distribution	aRPS	DM statistic
Bet365 odds	Benchmark	0.1893	NA
William_hill odds	Benchmark	0.1902	-1.5
Skellam, no zif, offense/defense	Skellam	0.1914	-1.3
Skellam offense/defense with AT	Skellam	0.1917	-1.4
Skellam offense/defense	Skellam	0.1917	-1.4
Skellam single ability	Skellam	0.1920	-1.7
T-dist original	T-dist	0.1921	-1.7
T-dist with AT advantage	T-dist	0.1923	-1.7
T-dist no pooling	T-dist	0.1957	-3.0
T-dist no HA	T-dist	0.1981	-2.9
Equal probability odds	Benchmark	0.2375	-8.4



# Artificial Turf Advantage Coefficient



# Summary

- ▶ Implemented dynamic Skellam model in Stan
- ▶ Models using data on goals scored do not beat bookies but come close
- ▶ Artificial Turf Advantage (ATA) does not improve forecasts
- ▶ Evidence for a large effect of ATA is not strong
- ▶ Is comparing predictive accuracy the best way to learn about the DGP?

**Thanks!**