An introduction to football modelling at Smartodds
Oxford SIAM Conference 2011

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Smartodds Ltd

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Introduction

- Introduction to Smartodds
- Practical example: building a football model




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- Actively recruiting!

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- Here we model the divisions Premier League, Championship, League 1 and League 2
- There are 92 teams in total to model
- We want to predict the probability of team A winning against team B where team A and team B could be from any of the 4 leagues

Literature review

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  - Means based on each teams' past performance
- Dixon and Coles (1997) took this idea further by accounting for fluctuations in performance of individual teams and estimation between leagues
- Dixon and Robinson (1998) modelled the scores during a game as a two-dimensional birth process




Model formulation

- Assume that home and away goals follow a Poisson distribution

$$Pr(\text{x goals}) = \frac{\lambda^x e^{-\lambda}}{x!}$$

$$Pr(\text{y goals}) = \frac{\mu^y e^{-\mu}}{y!}$$

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$$Pr(\text{y goals}) = \frac{\mu^y e^{-\mu}}{y!}$$

- To estimate the probabilities of x and y goals we need λ and μ




Model 1: Mean goals

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- However we may believe that there is some advantage associated with playing at home

Model 2: Home Advantage

- Include a term to take account of home advantage

$$\lambda = \gamma \times \tau$$

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- γ is the common mean and τ represents the home advantage

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$$\gamma = 1.10$$

- This implies mean goals scored by the home team are $2.56 - 1.10 = 1.46$
- Using the above we can estimate τ as

$$\tau = 1.46/1.10 = 1.33$$




Model 3: Team Strengths

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- Better teams score more goals. Give each team an attack parameter denoted α
- Better teams concede fewer goals. Give each team a defence parameter denoted β




Model 3: Team Strengths (Cont)

- Write λ and μ in terms of the attack and defence parameters of the home and away teams, which we denote by i and j, giving

$$\lambda = \gamma \times \tau \times \alpha_i \times \beta_j$$

$$\mu = \gamma \times \alpha_j \times \beta_i$$




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- The model is overparameterised, so we apply the constraints

$$\frac{1}{n}\sum_{i=1}^{n} \alpha_i = 1, \ \frac{1}{n}\sum_{i=1}^{n} \beta_i = 1.$$

Model 3: Pseudolikelihood

- The pseudolikelihood for this model is:

$$L(\gamma, \tau, \alpha_i, \beta_i; i = 1, \ldots, n) =$$

$$\prod_k \{\exp(-\lambda_k)\lambda_k^{x_k} \exp(-\mu_k)\mu_k^{y_k}\}^{\phi(t-t_k)}$$




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- Other downweighting functions could be used




Estimation techniques

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- In this example we have 186 parameters to estimate
- Various optimisation techniques could be used to obtain parameter estimates (numerical maximisation of the likelihood function, MCMC)
- High dimensional problems may also require more sophisticated computing solutions (MPI)




Parameter estimates

- These are Smartodds' current estimates of the attack and defence parameters of the top 6 teams in the Premier League

Team	Attack Parameter	Defence Parameter
Chelsea	3.15	0.34
Man Utd	3.08	0.35
Arsenal	2.84	0.37
Man City	2.44	0.42
Tottenham	2.22	0.44
Liverpool	2.12	0.39




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- We can use λ and μ to obtain the probability of Man Utd winning the match

Predicting outcomes (Cont)

- The probability of a specific score is given as follows

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$$Pr(x,y) = \frac{\lambda^x e^{-\lambda}}{x!} \frac{\mu^y e^{-\mu}}{y!}$$

- So the probability of the score, Man Utd 2 Man City 1, is

$$Pr(2,1) = \frac{1.89^2 e^{-1.89}}{2!} \frac{0.94^1 e^{-0.94}}{1!} = 0.099$$

Predicting outcomes (Cont)

- Obtain the probability matrix of all possible scores

	0	1	2	3	4	...
0	0.059	0.112	0.105	0.066	0.031	...
1	0.055	0.105	0.099	0.062	0.029	...
2	0.026	0.049	0.047	0.029	0.014	...
3	0.008	0.015	0.015	0.009	0.004	...
4	0.002	0.004	0.003	0.002	0.001	...
⋮	⋮	⋮	⋮	⋮	⋮	⋱




Predicting outcomes (Cont)

- Sum over all events where home goals are greater than away goals

	0	1	2	3	4	...
0	0.059	0.112	0.105	0.066	0.031	...
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⋮	⋮	⋮	⋮	⋮	⋮	⋱

Predicting outcomes (Cont)

- Giving the probability that Man Utd win at home to Man City as 59.6%

	0	1	2	3	4	...
0	0.059	0.112	0.105	0.066	0.031	...
1	0.055	0.105	0.099	0.062	0.029	...
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- These models take into account no external information about match circumstances
  - Injuries
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  - Newly signed players
- So betting off a mathematical model would be dangerous!




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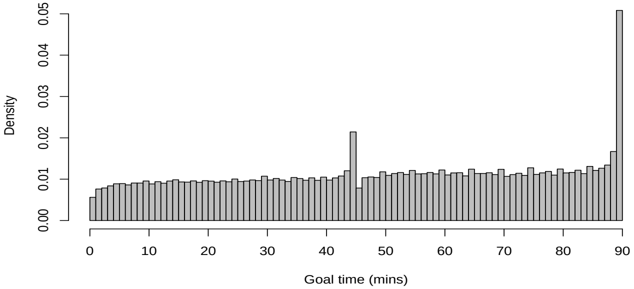
  - Goals don't have a Poisson distribution
  - Goals scored by the home and away teams aren't independent
- Dixon and Coles corrected for this by modifying the predicted distribution to increase probability of draws and 0-1 and 1-0 scores
- However this isn't entirely satisfactory — would be better to model what is happening directly




Goal time distribution



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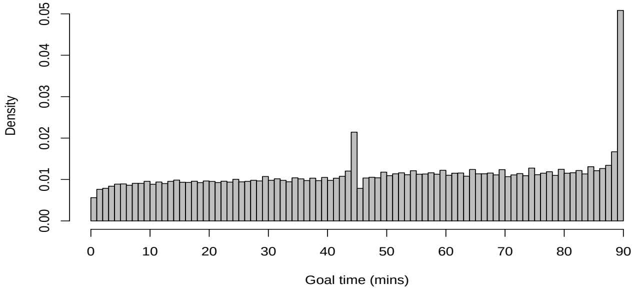

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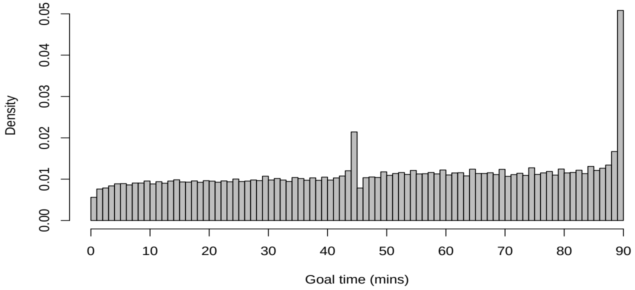

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- Notice the spikes every 5 minutes in the second half - due to rounding?

Dixon and Robinsons' model

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- For match k between teams i and j

$$\lambda_k(t) = \lambda_k = \gamma \times \tau \times \alpha_i \times \beta_j$$

$$\mu_k(t) = \mu_k = \gamma \times \alpha_j \times \beta_i$$

Dixon and Robinsons' model (continued)

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3. Increasing goal-scoring intensity through the game (due to tiredness of players)

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Estimates of $\lambda(x, y)$ and $\mu(x, y)$

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  $\hat{\mu}(1,0) = 1.35$
- $\hat{\lambda}(0,1) = 1.10$
  $\hat{\mu}(0,1) = 1.07$




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- The adjusted scoring rates are

$$\lambda_k(t) = \begin{cases} \rho_1 \lambda_{xy} \lambda_k & t \in (44, 45]\text{mins}, \\ \rho_2 \lambda_{xy} \lambda_k & t \in (89, 90]\text{mins}, \\ \lambda_{xy} \lambda_k & \text{otherwise} \end{cases}$$




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- and similarly for $\mu_k(t)$




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- Replace $\lambda_k(t)$ and $\mu_k(t)$ with

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- ξ_1 and ξ_2 could be constrained to be positive to ensure that the hazard functions above are constrained to always be positive, but in practice this is not neccessary
- Scoring rates are estimated to be about 75% higher at the end of the game then at the start of the game.




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- Also explains the home/away dependencies and non-Poisson pdfs observed in the data

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  - Normal distribution for American Football
  - Negative binomial for baseball




References

- M.J. Maher, 1982, Modelling association football scores, *Statist. Neerland.*, 36, 109-1188

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- M. Dixon and M. Robinson, 1998. A birth process model for association football matches. *JRSS D*, 47(3), 523-538




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- Then email us at careers@smartodds.co.uk




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