

Do Winners Do It Differently?: The In-Game Production of Winning and Losing Hockey Games

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Presentation Outline

Do high and low performing NHL teams play differently?

1. Motivation
2. Previous literature
3. Current research
4. In-game production of winning model
5. Data, empirical approach, and results
6. Sports analytics application
7. Concluding remarks

Motivation

In-game production of winning

- New model based on Bayesian updating.

Sports analytics application

- Model results are used to discern information relating to team-specific behaviours in terms of responding to goal scored and allowed incentives.

Previous Research

In-game production of winning

- Poisson and Brownian motion process (Washburn, 1991; Stern, 1994).
- Bivariate Poisson regression (Dimitris and Ntzoufras, 2003)
- Markov Model (Kaplan, Mongeon, and Ryan, 2013).

Applications

- Examine betting market efficiency (Choi and Hui, 2012; Croxson and Reade, 2014).
- In-game strategies (Morrison, 1976).
- Decision-making (Abrevaya and McCulloch, 2004; Mongeon and Mittelhammer, 2013).

Current Research

Bayesian updating model to calculate in-game win probabilities throughout the progression of games.

- Deterministic formula used to obtain conditional probabilities.
- Based on established probability axioms.
- Win probabilities are obtained through straight-forward statistical calculations.

Optimal team behaviour

- High-performing team's manage in-game goal scored and allowed incentives better than low-performing teams.
- Case study: New York Rangers, Montreal Canadians, Toronto Maple Leafs, and Buffalo Sabres.
- Examine from the home team perspective.

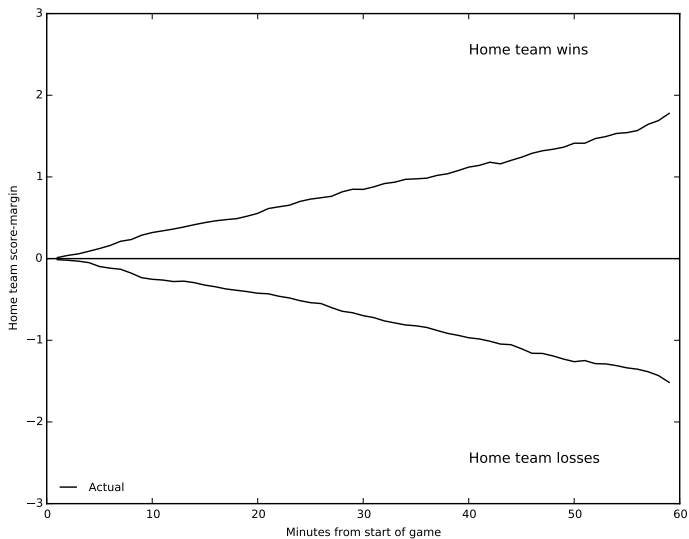
In-Game Production of Winning Model

$$p(H_g|S_{g,t}) = \frac{p(S_{g,t}|H_g)p(H_g)}{p(S_{g,t}|H_g)p(H_g)+p(S_{g,t}|\bar{H}_g)p(\bar{H}_g)}$$

$$\frac{p(H_g|S_{g,t})}{p(\bar{H}_g|S_{g,t})} = \frac{p(H_g)}{p(\bar{H}_g)} \times \frac{p(S_{g,t}|H_g)}{p(S_{g,t}|\bar{H}_g)}$$

posterior probability = prior odds \times likelihood ratio

Game progression average score-margins



Likelihood Ratio Estimation Procedure

Empirically describe the underlying game-state process separately across games won and lost as a generalized Poisson process

$$y_{g,t} = (y_{h,k,t}, y_{a,k,t} | H_k, \bar{H}_k) \sim \text{Poisson}(\lambda_{h,k,t}, \lambda_{a,k,t})$$

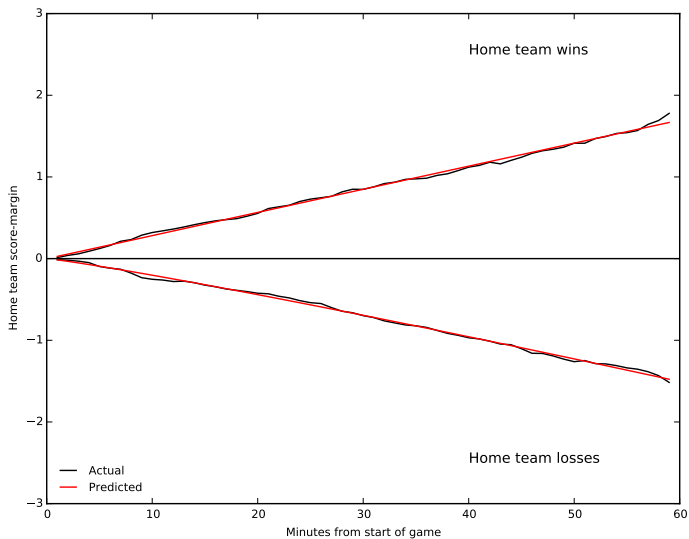
$$\log(\lambda_{h,k,t}) = \beta_0 + \beta_1 \text{minRem}_{k,t} + \epsilon_{h,k,t}$$

$$\log(\lambda_{v,k,t}) = \theta_0 + \theta_1 \text{minRem}_{k,t} + \epsilon_{a,k,t}$$

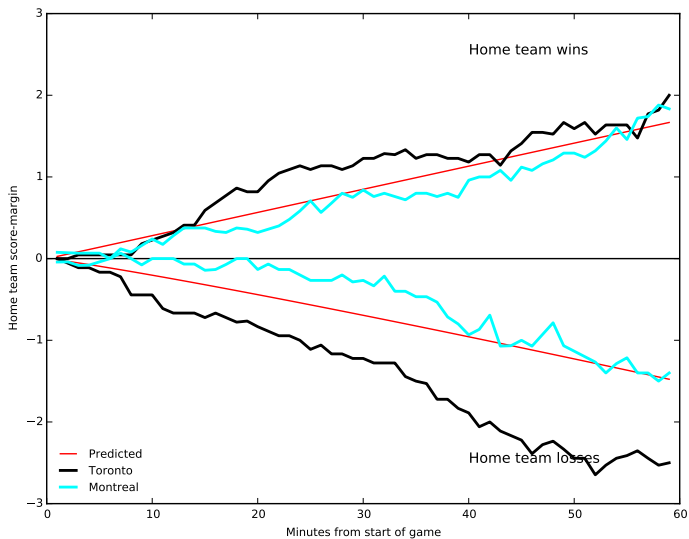
for historical games played during the 2013 season, where $k = 1, \dots, 1230$, and $t = 1, \dots, 60$.

$$E(SM_{k,t} | H_k, \bar{H}_k) = E(\lambda_{h,k,t}, \beta) - E(\lambda_{a,k,t}, \theta)$$

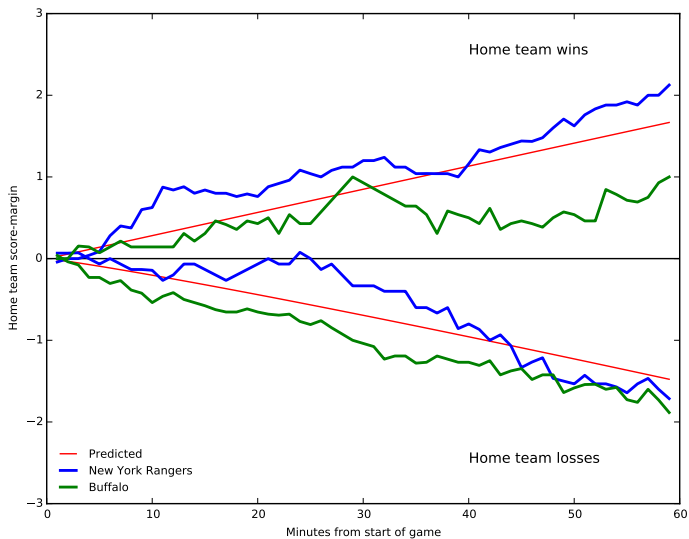
Game progression average score-margins



Game progression average score-margins



Game progression average score-margins



Game progression posterior probabilities

For 2014 games,

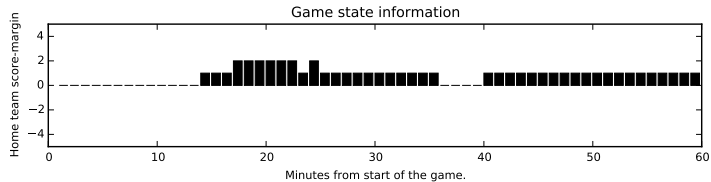
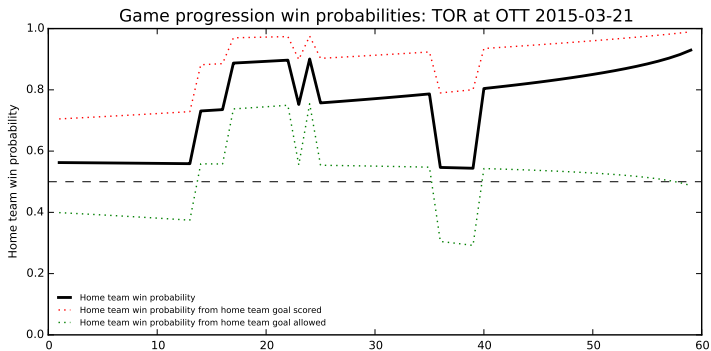
$$\frac{p(H_g|S_{g,t})}{p(H_g|S_{g,t})} = \frac{p(H_g)}{p(H_g)} \times \frac{p(S_{g,t}|H_g)}{p(S_{g,t}|H_g)}$$

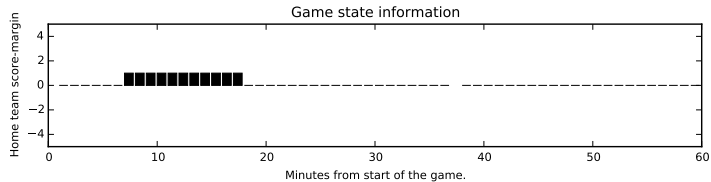
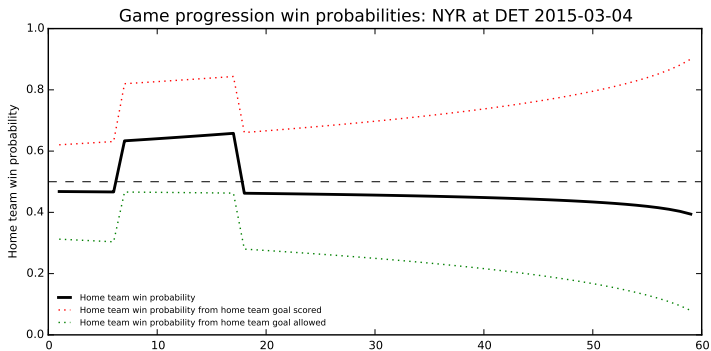
$$p(H_g) = \frac{YTDHomeWP_g}{YTDHomeWP_g + YTDawayWP_g}$$

$$p(\bar{H}_g) = 1 - p(H_g)$$

$$p(S_{g,t}|H_g) = \frac{e^{\lambda_{h,k,t}} \lambda_{h,k,t}^{y_{h,k,t}}}{y_{h,k,t}!} \frac{e^{\lambda_{a,k,t}} \lambda_{a,k,t}^{y_{a,k,t}}}{y_{a,k,t}!} | H_k$$

$$p(S_{g,t}|\bar{H}_g) = \frac{e^{\lambda_{h,k,t}} \lambda_{h,k,t}^{y_{h,k,t}}}{y_{h,k,t}!} \frac{e^{\lambda_{a,k,t}} \lambda_{a,k,t}^{y_{a,k,t}}}{y_{a,k,t}!} | \bar{H}_k$$





Average Team-Specific In-Game Win Probabilities

Team	Wins		
	All states	1 st Intermission	2 nd Intermission
Buffalo	0.48	0.42	0.50
Toronto	0.56	0.58	0.59
Montreal	0.67	0.66	0.68
New York	0.79	0.68	0.75
Team	Losses		
	All states	1 st Intermission	2 nd Intermission
Buffalo	0.24	0.29	0.20
Toronto	0.27	0.35	0.22
Montreal	0.54	0.65	0.50
New York	0.41	0.57	0.36

Sport Analytics Application

Optimal team behaviour

- A trade-off exists between playing offense and defense within teams.
- Asymmetric offensive and defensive incentives exist across competing teams.

Win probability state:	greater than 0.50	less than 0.50
Average benefit of a goal scored	0.13	0.20
Average cost of a goal allowed	0.19	0.14
Net benefit	-0.06	0.06

Sport Analytics Application

Optimal team behaviour

- Increase total production as the difference in the benefit of goal scored and cost of a goal allowed increases.
- $\frac{\partial(\text{production})}{\partial(\text{benefit}-\text{cost})} > 0$

Hypothesis

- High-performing teams respond to goal scored and allowed incentives better than low-performing teams.

Sport Analytics Application

Optimal team behaviour

$$prod_{g,t} = \alpha + X'_{g,t}B + \theta Z_{g,t} + \epsilon_{g,t}$$

- *prod*: goal score or goal allowed per 60 minutes.
- *X*: team indicator variable and the difference in the benefit of a goal score and the cost of a goal allowed interaction.
- *Z*: prior probability of a home team win.
- Unit of observation: game-minute increments.

The impact of net benefits/costs of goals on production.

Variable	Mean	Standard error
Buffalo	-2.51	(5.22)
Toronto	-2.49	(6.41)
Montreal	0.84	(5.63)
New York	2.00	(5.09)
Prior probability	-2.55	(2.44)
Constant	5.90	(1.26)

Concluding Remarks

- Bayes' Theorem to calculate in-game with probabilities throughout the progression of games.
- Application of the model results suggest that high-performing teams respond to goal incentives better than low-performing teams.
- Low-performing teams can potentially improve without roster adjustments.
- Future research relating stochastic frontier models to estimate team-specific in-game production of winning efficiencies.

Thank you.