Real-time forecasting in football matches (and in other sports)

Seminar at Newcastle University

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Outline

Acknowledgements

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Motivation

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  - Discrete events (cricket, baseball etc.)
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  - Dynamic / Continuous events (football, basketball etc.)
- Need for within-game forecasting in sports:
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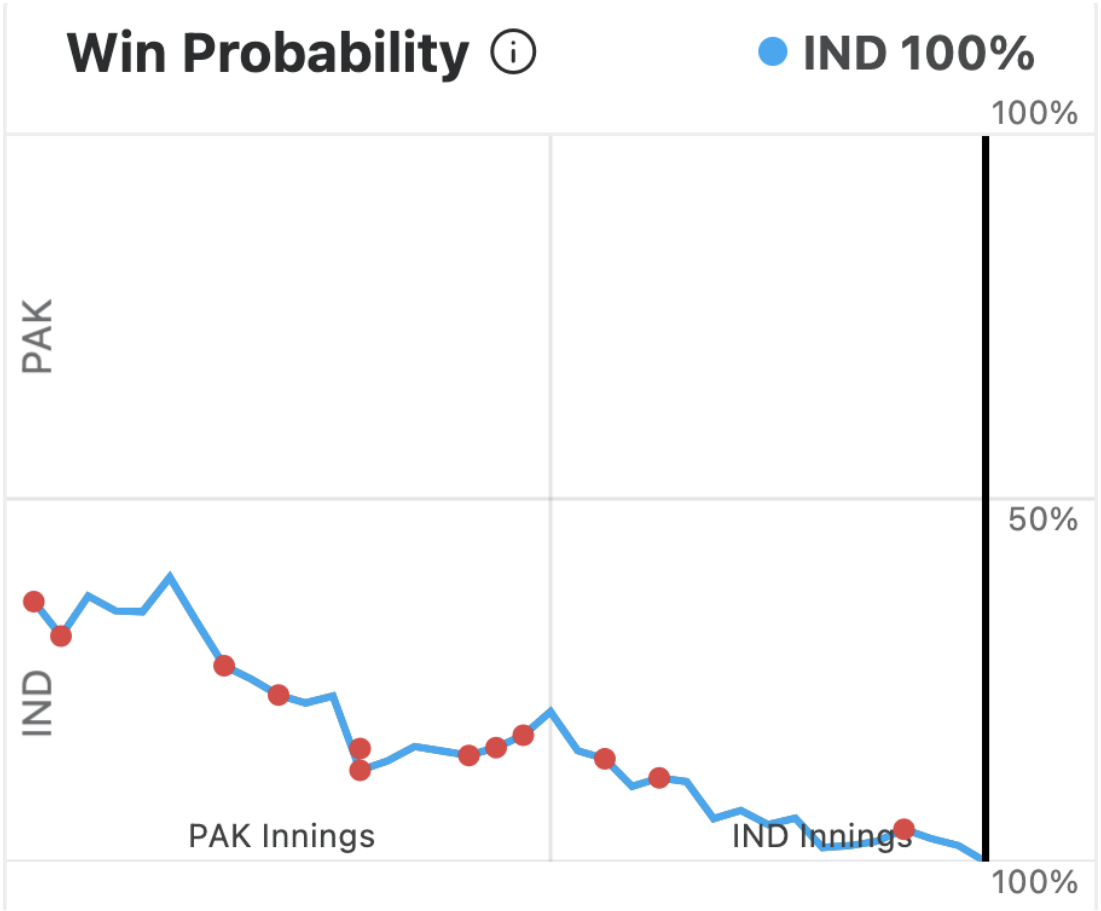
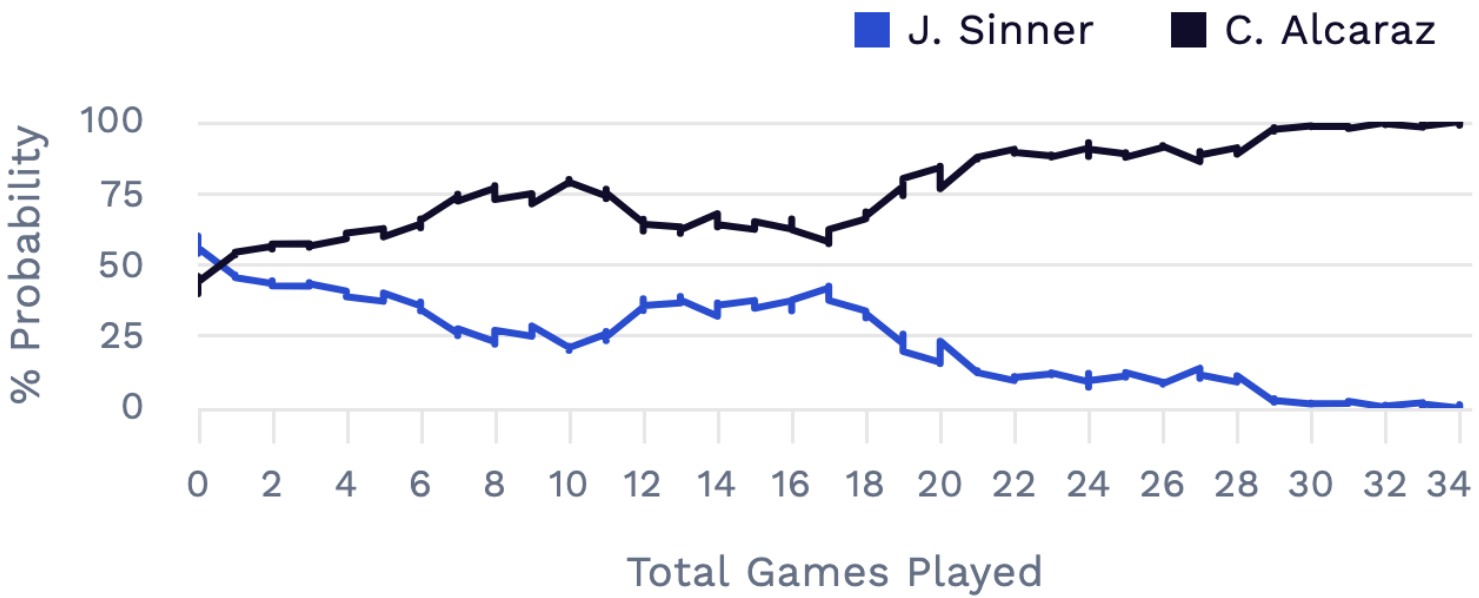
  - Performance improvement and strategy building
  - Broadcasting, content optimization
- Football is unique as a sport for within-game forecasting

Example of in-game forecasting in cricket



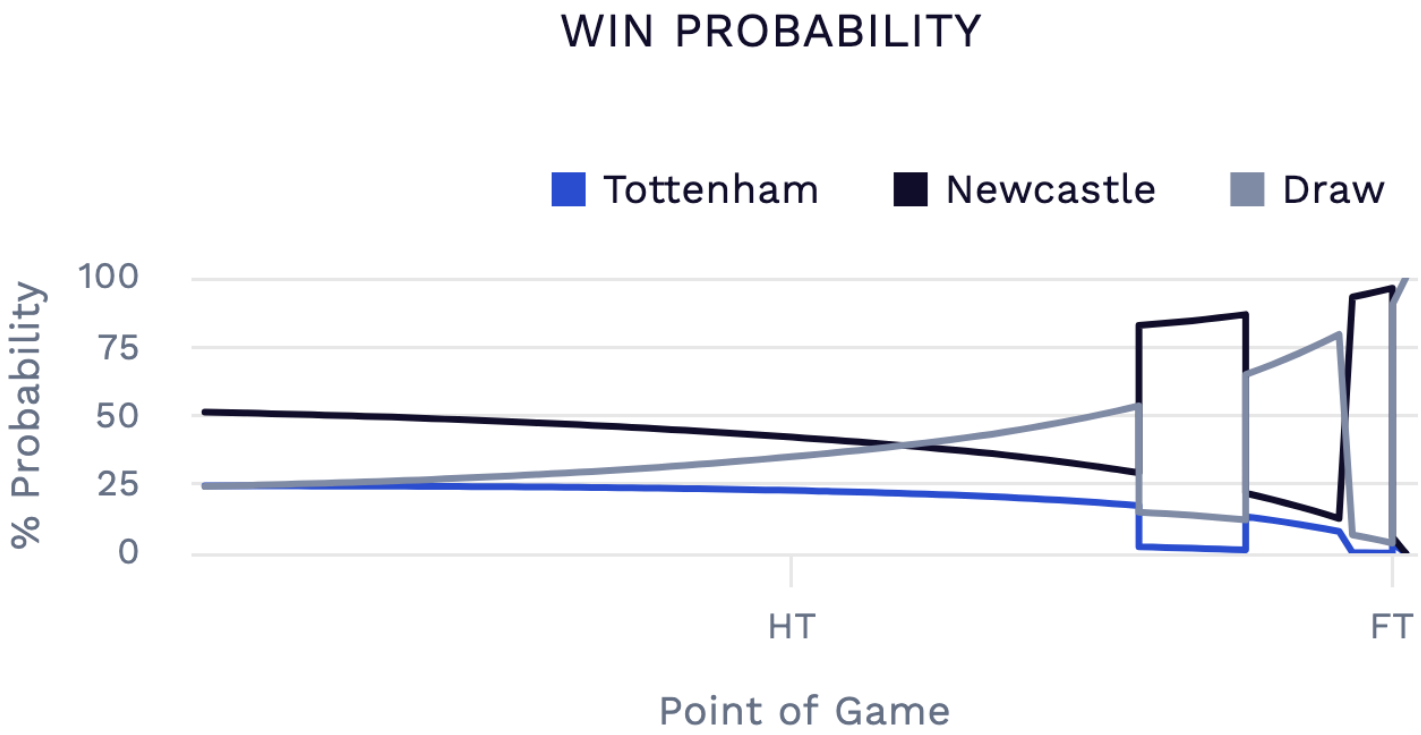
India vs Pakistan, Asia Cup 2025 (source: https://www.espncricinfo.com/)

Example of in-game forecasting in tennis



J Sinner vs C Alcaraz, US Open 2025 (source: https://www.dimers.com/)

Example of in-game forecasting in football



Tottenham vs Newcastle, EPL 2025 (source: https://www.dimers.com/)

Our contribution

- We develop a Bayesian latent variable model for analyzing and forecasting soccer match outcomes in real-time.
- Our method considers different types of events, not only goals.
- Time-varying effects of various events are estimated.
- The predictions are accompanied with a credible interval to reflect how confident one should be.
- Details can be seen in the paper by Divekar, Deb & Roy (2024).

Outline

Data

- The data is obtained for 3040 matches played over 8 seasons from 2008-2016 in the English Premier League.
- Along with goals, we consider shots-off and shots-on target, red and yellow cards, crosses, corners, fouls.
- Here's how the data may look:

	Event type k						
Game ID	1^{st} min (H)	1^{st} min (A)	2^{nd} min (H)	2^{nd} min (A)	...	90^{th} min (H)	90^{th} min (A)
1	0	1	2	0	...	2	1
2	2	0	0	0	...	1	0
			⋮				
3040	0	0	3	1	...	0	0

- A few time-independent covariates, such as team strengths before the match starts, are also used as features.

Proposed model (I)

- We model the outcome of a game from the perspective of the team playing at home.
- The dependent variable is an ordered multinomial random variable with three categories – loss, draw or win.
- The focus of the model is on forecasting the outcome in real-time, that is, after every minute of the match.

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- Let Y_i denote the outcome for the home team in the i^{th} match. Then define a latent variable Π_i and cut-offs δ_1, δ_2 such that,

$$Y_i = \begin{cases} -1, & \text{if } \Pi_i < \delta_1 \\ 0, & \text{if } \delta_1 \leqslant \Pi_i \leqslant \delta_2 \\ 1, & \text{if } \Pi_i > \delta_2. \end{cases} \tag{1}$$

Proposed model (II)

- For the i^{th} match till the t^{th} time point we write

$$\Pi_i^{(t)} = \mathbf{z}_i^\top \boldsymbol{\gamma} + \sum_{k \in [K]} \mathbf{x}_{ik}^{(t)^\top} \boldsymbol{\beta}_k^{(t)} + \epsilon_i^{(t)}, \tag{2}$$

  where, $\mathbf{x}_{ik}^{(t)}$ is the set of time-dependent features, $\boldsymbol{z}_i$ is the set of time-independent features, and $\boldsymbol{\epsilon}^{(t)} \sim \mathcal{N}(0, \sigma_y^2 \boldsymbol{I}_n)$.
- The vector $\boldsymbol{\gamma}$ captures the effects of time-independent features, and $\boldsymbol{\beta}_k^{(t)}$ captures the time-varying effects of different types of events.
- We use 90 different models, one after every time point $t \in [1, 90]$.

Bayesian estimation

- The model is implemented via a complete Bayesian framework, using the principles of Gibbs sampling, Geweke statistic etc.
- For the computation, we specify Gaussian priors for γ and β_k as

$$\begin{aligned} \gamma &\sim \mathcal{N}_p(\mathbf{0}, \boldsymbol{I}_p), \\ \beta_k^{(t)} &\sim \mathcal{N}_{2t}(\mathbf{0}, \boldsymbol{\Sigma}_k^{(t)}). \end{aligned} \tag{3}$$

- The structure of the covariance matrix $\boldsymbol{\Sigma}_k^{(t)}$ is defined through exponentially decaying function, i.e., correlation between the time-varying effects reduces at an exponential rate.
- We also use Gaussian priors for the cut-offs in the latent process:

$$\delta_j \sim \mathcal{N}(0, \tau^2),\ j \in \{1, 2\}. \tag{4}$$

Posterior computation (I)

- For estimation, we combine the covariates into a single matrix $\boldsymbol{M}$.
- Likewise, we denote the parameters by $\boldsymbol{\nu} = [\gamma \ \boldsymbol{\beta}_1 \ ... \ \boldsymbol{\beta}_K]$.
- Due to conjugacy in the priors we obtain Gaussian conditional posteriors for γ, β and Π:

$$\begin{aligned} \Pi_i \mid \boldsymbol{M}, \boldsymbol{\nu}, \boldsymbol{\delta} &\sim \mathcal{TN}(\boldsymbol{M}_i' \boldsymbol{\nu}, \sigma_y^2, \delta_{j-1}, \delta_j) \\ \boldsymbol{\nu} \mid \boldsymbol{M}, \Pi, \mathbf{y}, \boldsymbol{\delta} &\sim \mathcal{N}_{p+2Kt}\left(\boldsymbol{\mu}_\nu, \tilde{\boldsymbol{\Sigma}}\right) \end{aligned} \tag{5}$$

where $\tilde{\boldsymbol{\Sigma}} = (\sigma_y^{-2} \boldsymbol{M}' \boldsymbol{M} + \boldsymbol{\Sigma}_0^{-1})^{-1}$ and $\boldsymbol{\mu}_\nu = \sigma_y^{-2} \tilde{\boldsymbol{\Sigma}} (\boldsymbol{M}' \Pi)$.

Posterior computation (II)

- We establish a correspondence between the multinomial categories through a transformation of a Dirichlet(α_1,α_2,α_3) distribution to obtain,

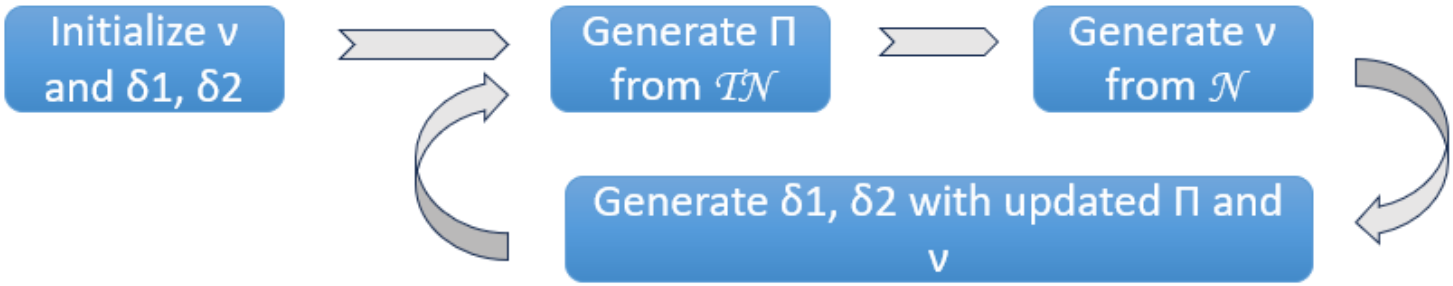
$$\begin{aligned}\Phi(\delta_1 \mid \delta_2, \boldsymbol{M}, \Pi, \mathbf{y}, \boldsymbol{\nu}) &\sim \Phi(\delta_2)\mathrm{Beta}(\alpha_1, \alpha_2),\\ \Phi(\delta_2 \mid \delta_1, \boldsymbol{M}, \Pi, \mathbf{y}, \boldsymbol{\nu}) &\sim [1-\Phi(\delta_1)]\mathrm{Beta}(\alpha_2, \alpha_3) + \Phi(\delta_1).\end{aligned} \tag{6}$$

where

$$\begin{aligned}\Phi(\max\{\Pi_i : Y_i = -1\}) \leqslant \Phi_{\delta_1} \leqslant \Phi(\min\{\Pi_i : Y_i = 0\}),\\ \Phi(\max\{\Pi_i : Y_i = 0\}) \leqslant \Phi_{\delta_2} \leqslant \Phi(\min\{\Pi_i : Y_i = 1\}).\end{aligned}$$

Posterior computation (III)

- Gibbs-sampling procedure is used to obtain the joint posterior distribution of the parameters from their conditional posteriors.



- To assess convergence, we use the Geweke statistic.
- We draw a sample for the posterior distribution after the chains converge, and utilize thinning in this step.

Predictive analysis

- We thus obtain $\hat{\Pi}_i^{(t)}$ and $\hat{Y}_i^{(t)}$ for every time point t.
- The probabilities of the different categories for the outcome variable, corresponding to the home team, can be calculated as

$$\begin{aligned} P\,(\text{Win}) &= 1 - \Phi_{\hat{\Pi}_i}(\hat{\delta}_2), \\ P\,(\text{Draw}) &= \Phi_{\hat{\Pi}_i}(\hat{\delta}_2) - \Phi_{\Pi_i}(\hat{\delta}_1), \\ P\,(\text{Loss}) &= \Phi_{\hat{\Pi}_i}(\hat{\delta}_1), \end{aligned} \tag{7}$$

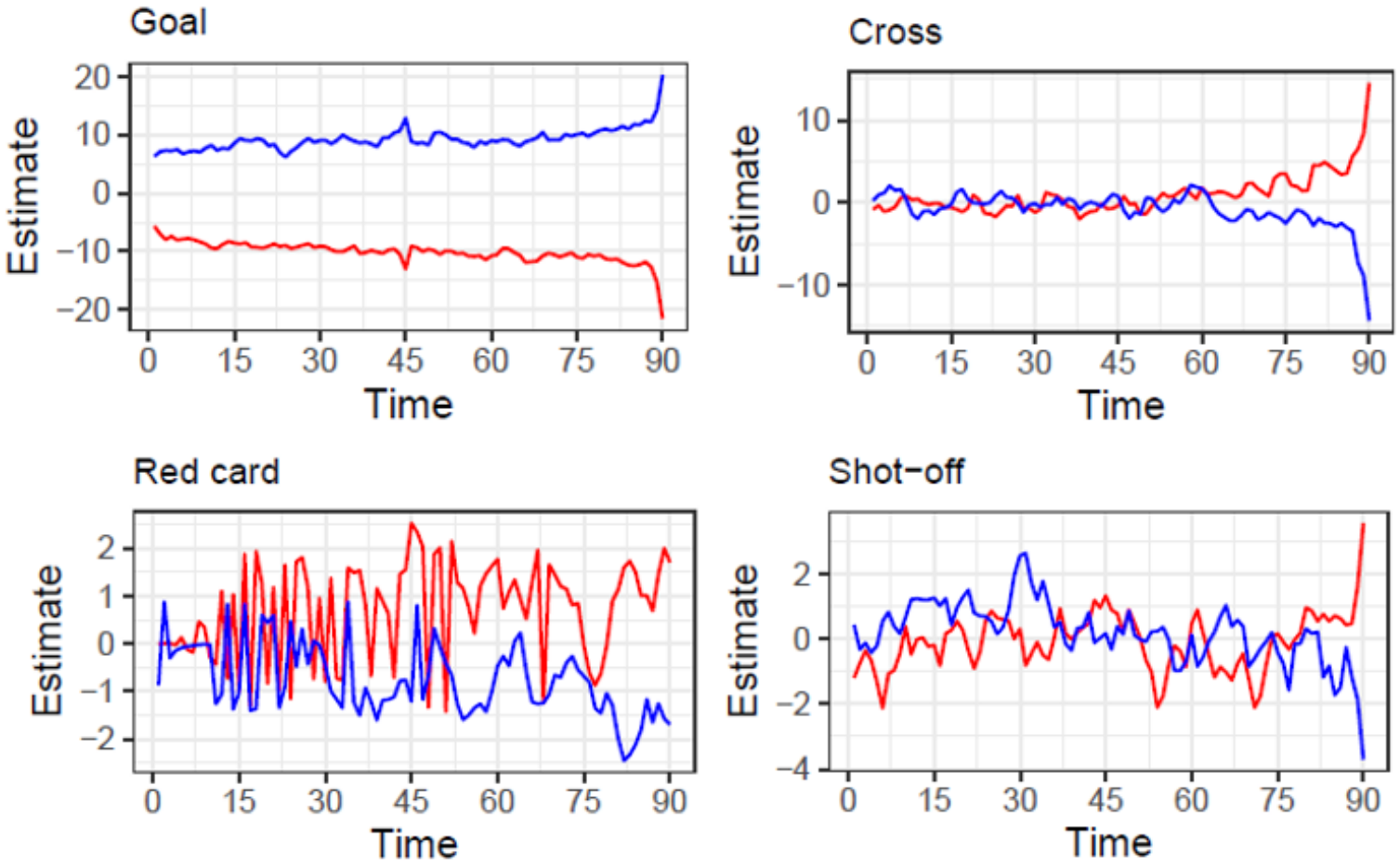
where $\Phi_{\hat{\Pi}_i}$ is the Gaussian cumulative distribution function of $\hat{\Pi}_i$.

Outline

Summary of the results

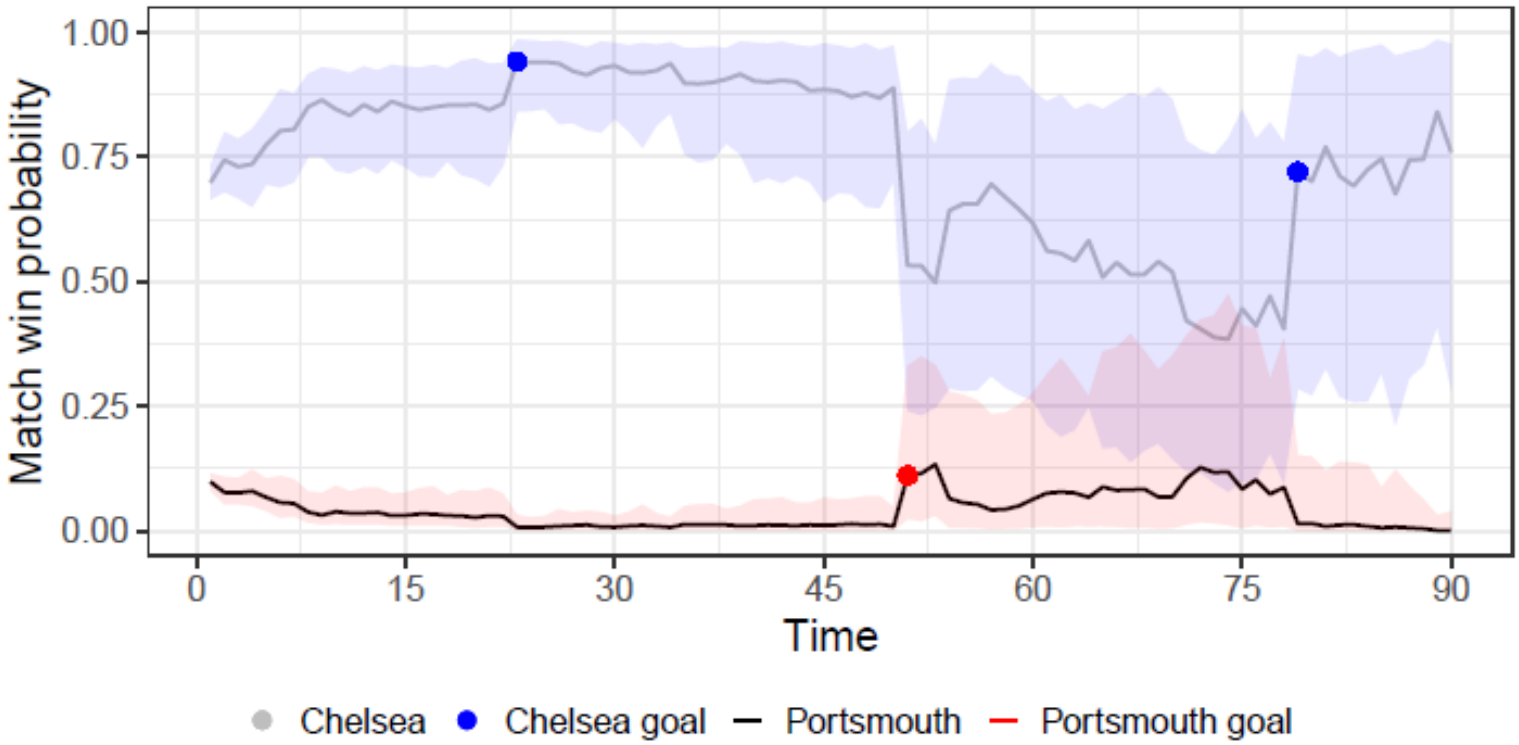
- All events have differential impact on the win probability depending on the time of occurrences.
- Goals and red cards have maximal impact; while crosses and shots have significant impact as well.
- The effect of home strength and away strength are relatively equal and of opposite signs.
- We employ a 90:10 (train:test) split for assessing predictive ability. Our method records great accuracy for the second half of the game.

Estimated time-varying effects



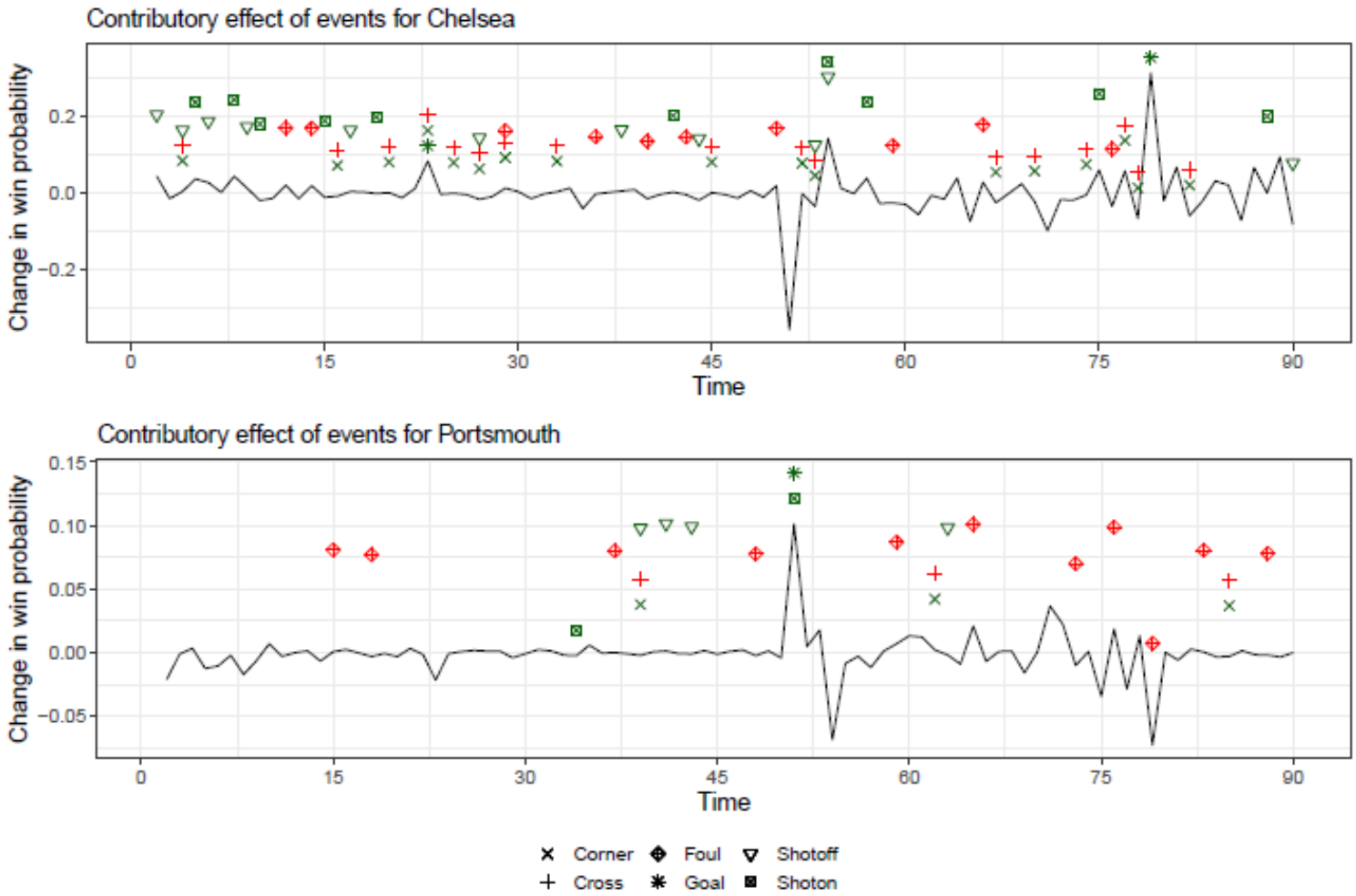
Effect of some events on the outcome of the match captured at every time-point for both teams. Such effects are estimated for all types of events.

An application of our method



Minute-by-minute forecast of the win probability, along with the credible interval, for the Chelsea vs Portsmouth match.

Further insights



The probabilistic effect of the time-varying events for the Chelsea vs Portsmouth match.

Model competitors

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- In context of football, machine learning algorithms have been used as predictive algorithms, which can be extended for our purpose. On those lines, we employ a linear SVM as a comparative model, which assumes linearly separable classes (L-SVM).
- For the next model, we incorporate non-linearity in the SVM in the form of a Gaussian radial basis function (R-SVM).

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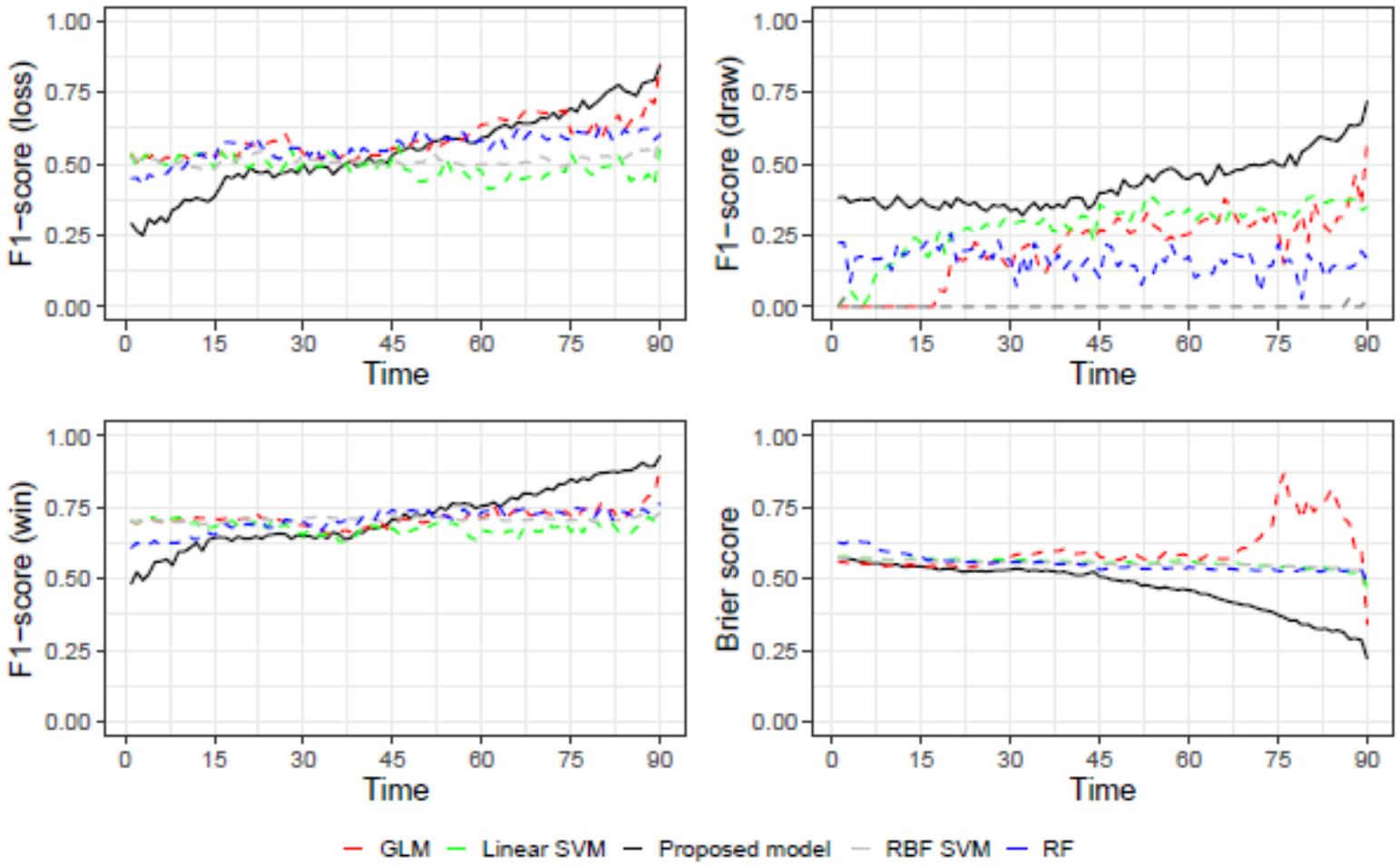
- For the next model, we incorporate non-linearity in the SVM in the form of a Gaussian radial basis function (R-SVM).
- As the fourth model in the comparative discussions, we modify the standard random forest (RF) algorithm.

Comparative performance



F1-score and Brier score (averaged over the test set) for different models, with respect to their within-game forecasting accuracy as a soccer match progresses

Robustness checks

- Teams are split into two groups – 'big six' and 'others'. Results remain similar for both groups.
- We predict the outcomes of the matches for a certain team, by training the model on the dataset excluding all matches of that team. Results display a consistent pattern.

Outline

Contribution

- We developed a Bayesian latent variable model for analyzing and forecasting soccer match outcomes in real-time.
- The article is the first in academic literature to furnish real-time predictions in football.
- The proposed model can assist with in-game adjustments and decision making for the managers.

Other applications

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- In-game forecasting can be successfully utilized in various interesting applications, such as substitution strategy, within-match betting markets, advertisement in broadcasting, etc.
- Our method is adaptable to other situations where the key variable is categorical in nature.
- We developed a modified algorithm for a multinomial time series for predicting winner of an election, when the counting is in progress (Deb, Roy, & Das, 2024).

Outline

Within-match forecasting in Cricket[1]

- A novel approach to within-game cricket forecasting is introduced by treating each match as a dynamic time series.
- We develop a new time series classification method, which leverages trend parallelism. Additionally, the aim is to study the changing influence of covariates within a match on the final outcome.

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Within-match forecasting in Cricket[1]

- A novel approach to within-game cricket forecasting is introduced by treating each match as a dynamic time series.
- We develop a new time series classification method, which leverages trend parallelism. Additionally, the aim is to study the changing influence of covariates within a match on the final outcome.
- For main analysis, we consider all completed T20 matches between 2005 to 2025 with detailed information.
- Covariates are categorized into two groups: pre-match covariates and within-match covariates.

[1] This is a work in progress.

Motivation behind the classification algorithm

- We define difference of (modelled and adjusted for other factors) scores as a time series of length $t \leqslant 120$.

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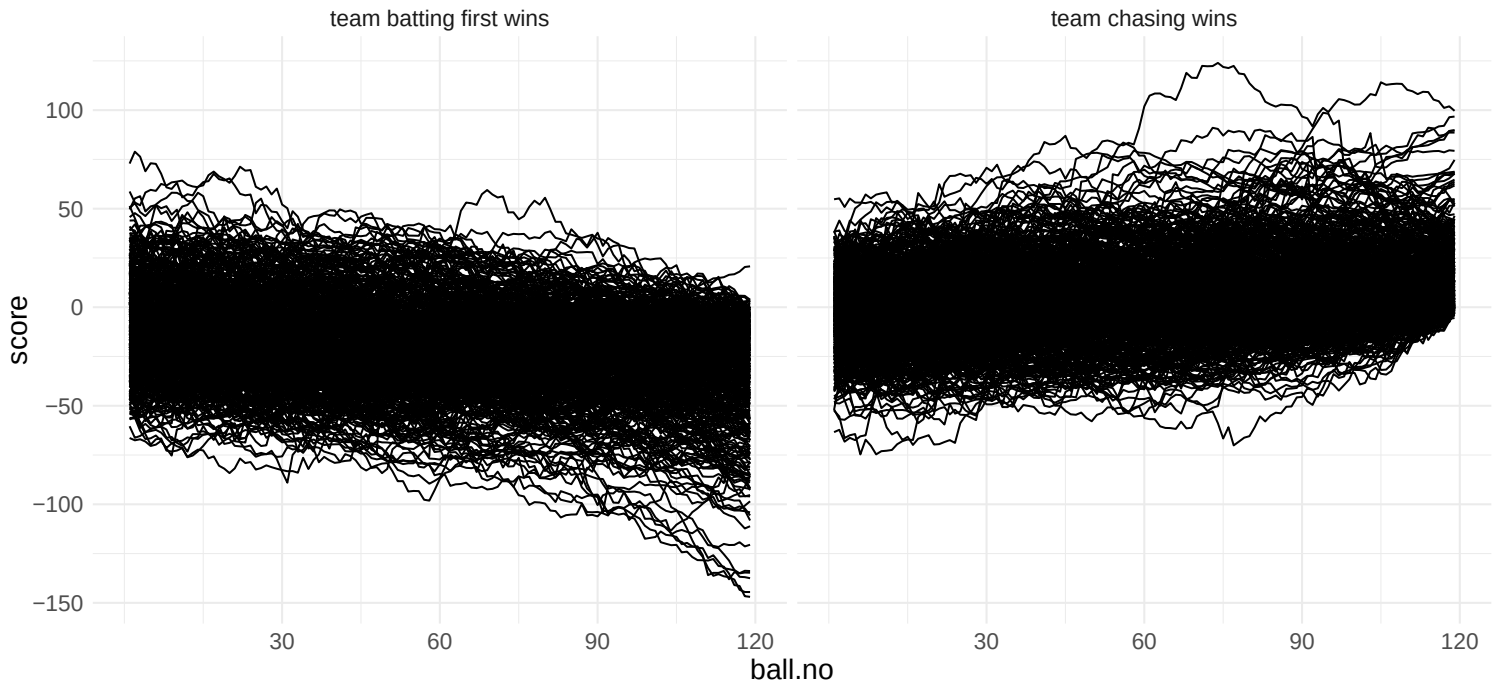
- This produces a distinct pattern for matches where the team batting first won, to the matches where the team batting second won.



Proposed classification algorithm

Input: $(x_{k,i})_{i=1}^{n}$: new time series to be classified
Output: Classification of $(x_{k,i})_{i=1}^{n}$
Start with $\mathcal{M}$ classes $C_1, C_2, \ldots, C_{\mathcal{M}}$;
for *each class* C_j **do**
    Estimate trend functions of time series within C_j using local linear estimation;
    Use the estimated trends to compute $\hat{\mu}_{C_j}(.)$ and $\hat{c}_k$, $k \in C_j$;
    Compute $RSS_{C_j} = \sum_{k \in C_j} \sum_{i=1}^{n} \{y_{k,i} - \hat{\mu}_{C_j}(i/n) - \hat{c}_k\}^2$;

for $l = 1$ *to* $\mathcal{M}$ **do**
    Assign $(x_{k,i})_{i=1}^{n}$ to C_l keeping rest of the classes unchanged;
    Recalculate RSS_{C_l};
    $RSS_l = \sum_{i=1}^{\mathcal{M}} RSS_{C_i}$;
    Reset C_l by removing $(x_{k,i})_{i=1}^{n}$ from it;

Classify $(x_{k,i})_{i=1}^{n}$ to C_t, where RSS_t is least;

Motivation is taken from Zhang (2013), Chazin et al. (2018).

Within-match forecasting in Tennis

- We work with point-by-point data from Wimbledon single's matches.
- Main objective is to understand whether first set offers key insights about how the match is going to end.
- LASSO-induced logistic regression model with random effects is developed to draw insights and to predict the outcomes.
- Details are in the paper by Gupta, Krishnamurthy & Deb (2024).

Model

Regressors

- Differences in the player's game statistics (except SEED and HAND).

$$g_{ij} = s_{ij} - r_{ij},\ 1 \leqslant i \leqslant n,\ 1 \leqslant j \leqslant p.$$

- Interaction terms (z_{ij}).

Proposed Model

- Variables selection is through LASSO, which avoids multicollinearity and overfitting issues.
- Random intercepts (corresponding to both players' seed categories) help to explain unexplained variance.
- Estimates are obtained from logistic regression setup, which helps with debiasing (Meinhausen, 2007).

Algorithm : LILRM_SEED_RI estimators

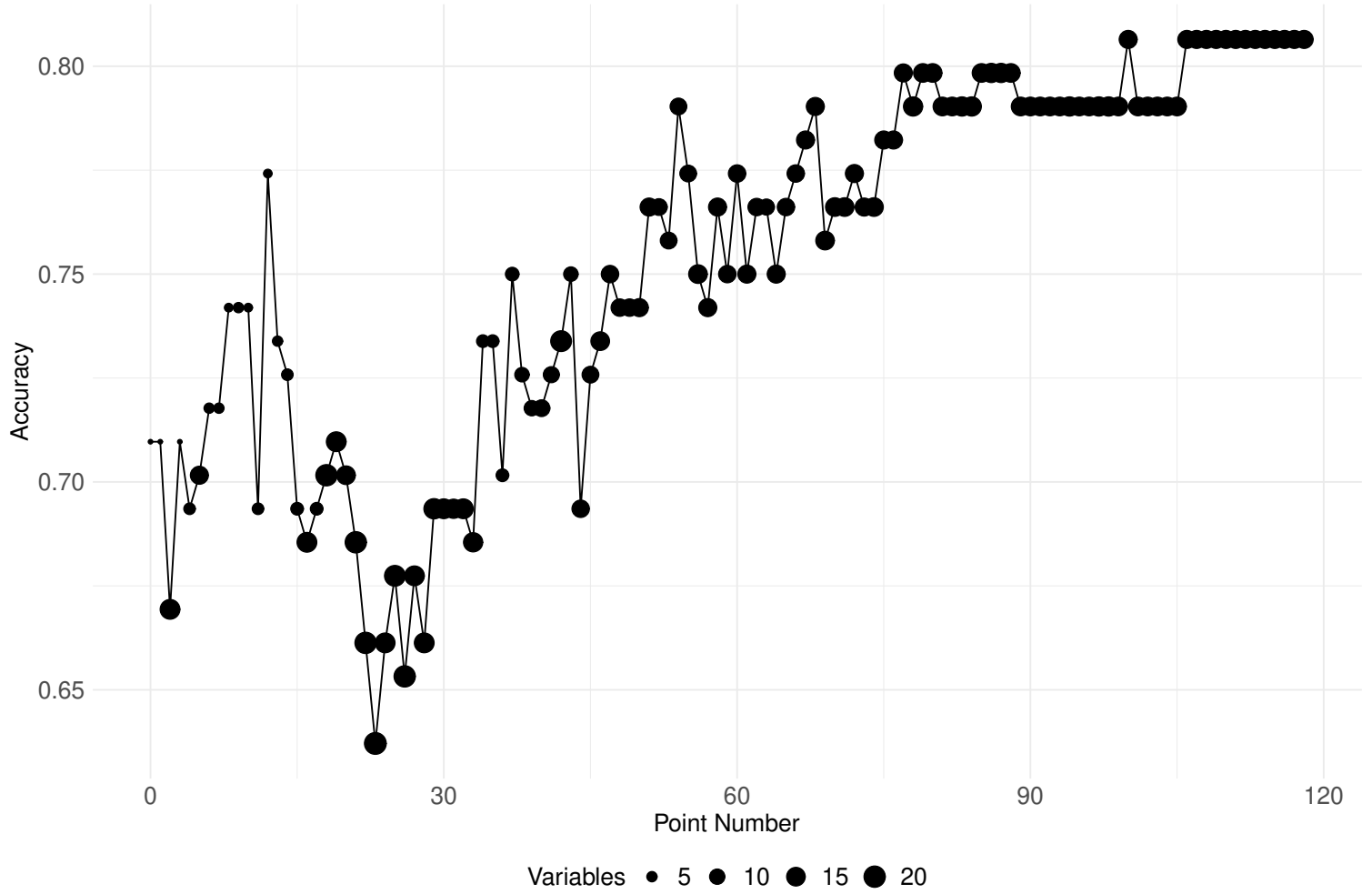
Input: Dataset $(Y, \mathcal{X})$, where Y is response, $\mathcal{X}$ is information on regressors.
Output: $\hat{S}$ = set of selected variables, $\hat{\Theta}$ = estimated coefficient vector.
Steps :

1. Create the design matrix X. Let m be the total number of variables.
2. Perform LASSO on (Y, X). Use $\hat{\phi}$ to denote the LASSO estimators.
3. Obtain index set of non-zero LASSO estimators: $\hat{S} = \{1 \leqslant k \leqslant m \mid \hat{\phi}_k \neq 0\}$.
4. Use seed wise random intercept models with the index set as covariates.
5. Consider the negative binomial log likelihood and use adaptive quadrature of gauss-hermite (AQGH) algorithm to find the estimates for all the variables in the index set $\hat{S}$. These estimates are called LILRM_SEED_RI estimators $(\hat{\Theta})$.

return $(\hat{S}, \hat{\Theta})$.

Average predictive performance after each point

Gender, age and rating difference variables are mandatory variables.



Outline

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Thank you!

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