Bayesian Analysis of Soccer Referees' Skin Tone Bias

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Abstract

This analysis is built as a hierarchical Bayesian model that links the number of cards received by a particular player to that player's style of playing, his interaction with referee and skin tone effect. In turn, the referee behavior is explained by his personal rigorousness and by bias coming from explicit and implicit white preference scores coming from referee's country of origin. The result suggests that there is high probability that darker skin tone has a positive effect on the number of received red cards at 94.5% probability. The estimated influences of implicit and explicit race preferences in referee's countries on particular referee's decisions are also not significant at 95% level (92.3% and 77.1% respectively).

One Sentence Summary

This study found that although it may be likely that the dark-skinned players receive more red cards than other players, the prejudices in referees' country of origin play no significant role.

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Results

The motivation for using Bayesian hierarchical model was to utilize the hierarchical structure of the data. Players have individual styles of play, but all of them play in Western-European leagues and may be subjected to prejudices related to their skin tone. Referees coming from the same country will share cultural background. Nevertheless all of them must obey the rules of play. Apart from that, each referee has individual judgment on how to react to player's actions in the field.

None of extra possible covariates (age, position, weight, height,...) was used as it could be only used to explain the particular player's parameters, not the overall skin tone effect.

Initial Approach

The initial model was built separately for the question of skin tone effect on number of received cards and separately for the issue of implicit/explicit preferences effect on referee's behavior. In the initial analysis the skin color was treated as a 5-level factor. The dataset was limited to cases where both raters agreed and information about implicit/explicit preferences was present.

Final Approach

After learning about approaches and justification of analytical choices of other teams I have modified the model to treat skin tone as a continuous variable. I was also able to extend the model to estimate parameters for all considered questions at once.

The dataset was limited to cases where information about implicit/explicit preferences was present (I presumed it was missing at random). For cases where raters disagreed, the average of their answers was used. The scale for skin tone rating was scaled to range [-1,1] (lighest to darkest tone). The IAT/Exp scores were centered with the mean across all referee's countries.

The final model can be described as follows: y_{ij} is the number of red cards received by player i from referee j, games_{ij} is the number of games in which player i played under referee j and SkinTone_i is the skin tone of i-th player. Then:

$$y_{ij} \sim \text{Binom}(p_{ij}, games_{ij})$$

$$p_{ij} = \frac{\exp(p'_{ij})}{1 + \exp(p'ij)}$$

$$p'_{ij} = \mu + \mu_i + \mu_j + \mu_{Skin} \cdot SkinTone_i$$
The parameters for individual player i are estimated from following relations:
$$\mu \sim \text{Normal}(0, \tau)$$

$$\mu_i \sim \text{Normal}(\mu_{Players}, \tau_{Players})$$

$$\mu_{Players} \sim \text{Normal}(0, \tau_{AllPlayers})$$
The parameters for i-th referee are estimated from following relations:

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\mu_{j} \sim \text{Normal}(\mu'_{j}, \tau_{j})
\mu'_{j} = \mu_{Referees} + \mu_{IAT} \cdot IAT_{Country(j)} + \mu_{Exp} \cdot EXP_{Country(j)}
\mu_{Referees} \sim \text{Normal}(0, \tau_{Referees})
\mu_{IAT} \sim \text{Normal}(0, \tau_{IAT})
\mu_{EXP} \sim \text{Normal}(0, \tau_{EXP})
IAT_{k} \sim \text{Normal}(meanIAT_{k}, \tau_{IAT,k}) \quad k = 1, \dots, \#countries
EXP_{k} \sim \text{Normal}(meanEXP_{k}, \tau_{EXP,k}) \quad k = 1, \dots, \#countries
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The implicit and explicit scores for each country are drawn from normal distributions according to precision calculated from sample size and standard error provided in the dataset. All other precision parameters T have vague priors, giving large standard deviation.

The data for this model was preprocessed in R, while the model itself was programmed using JAGS.

The estimation of parameters values was obtained from run of MCMC algorithm with 5000 iterations, with 2000 iteration of burn-in.

Conclusion

Although it is clear that none of these results is significant at 95% level, the high probability of positive effect of player's skin tone on number of received red cards makes the question open for further research. For example it would be interesting to check if dark-skinned players who came to European leagues from Africa receive more red cards than those who were trained in Europe.

Tables

	mean odds	CI (95%)	Probability of >1
μ_{Skin}	1.101	[0.983 1.265]	0.945
μ_{IAT}	3.777	[0.805 110.086]	0.923
μ_{Exp}	1.078	[0.776 1.512]	0.771

Table 1 Estimated parameter values

Data and Output

https://osf.io/kighq/

References and Notes

Please feel free to correct and edit my non-native English into polite and unbiased expressions.

- [1] R Core Team (2014). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.
- [2] Martyn Plummer (2014). rjags: Bayesian graphical models using MCMC. R package version 3-13. http://CRAN.R-project.org/package=rjags
- [3] John K. Kruschke (2010). Doing Bayesian Data Analysis: A Tutorial with R and BUGS, Academic Press, ISBN 0123814855