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Bayesian hierarchical models for predicting individual performance in fantasy football (soccer)

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Fantasy football has become a cornerstone among football fans and statistical amateurs. Generally, fantasy games involve



- roster selection at the beginning of the season;
- match-by-match challenges against other participants, with the results determined by the collective performance of the players on the fantasy rosters;
- **a lot of free and available data**, which allows for statistical analysis.

So far, there is no statistical literature referring to fantasy football models: *we try to fill this gap*, by using **hierarchical Bayesian models** (Gelman and Hill, 2006) for predicting the players' performances.

For player i in match t the total *fantasy rating* y_{it} is given by

$$y_{it} = R_{it} + P_{it}, \quad (1)$$

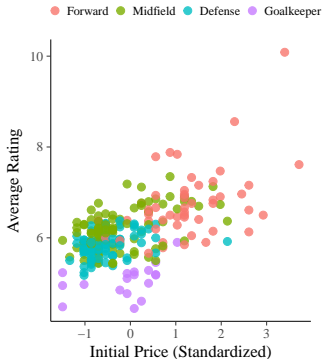
where **R** is the **raw subjective score** on a scale from one to ten assigned by some prominent newspaper, and **P** is the **point score**, that takes care of specific in-game events.

Event	Points
Goal	+3
Assist	+1
Penalty saved*	+3
Yellow card	-0.5
Red Card	-1
Goal conceded*	-1
Own Goal	-2
Missed penalty	-3

Table: Point scores. * = events only applicable to goalkeepers.

Overview of the game

We refer to the Italian fantasy football version *Fantacalcio*. At the beginning of the season, Fantacalcio managers are allocated a limited amount of virtual money with which to buy the players that will comprise their roster.

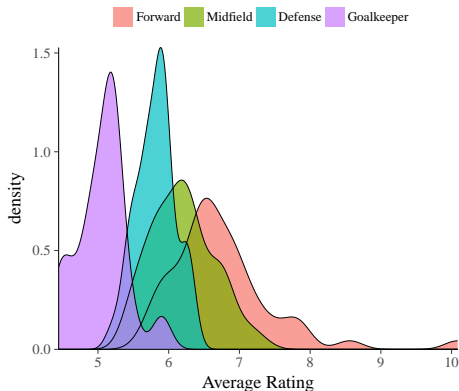


Main challenge There may be **missing values**: in fact, y_{it} will be missing if the player

- does not play in the match;
- does not participate in the match for long enough for being judged by the subjective raw score.

A natural question is: **how modeling the missingness?**

Data All data are from the 2015–2016 season of the Italian Serie A and were collected from the Italian publication [La Gazzetta dello Sport](#).¹



- $N = 237$ players, grouped into
- $J = 4$ positions (18 goalkeepers, 90 defenders, 78 midfielders, and 51 forwards), and $K = 5$ team clusters;
- $T = 38$ matches.

¹<http://www.gazzetta.it>.

Predictors and models notation

- h_{it} : home/away predictor. $h_{it} = 1$ if player i 's team plays match t at its home stadium and $h_{it} = 0$ if the match is played at the opponent's stadium;
- q_i : initial standardized price for player i ;
- α_i : individual intercepts corresponding to each player $i = 1, \dots, N$;
- $\gamma_{k[i]}$ and $\beta_{k[i],t}$: intercepts for the team-cluster of player i and the team-cluster of the team opposing player i in match t , respectively, with $k = 1, \dots, K$;
- $\rho_j[i]$: the position-specific intercept, with $j = 1, \dots, J$;
- $\delta_j[i]$: coefficient for the prices;
- $\lambda_{j[i]}\bar{y}_{i,t-1}$: autoregressive term;
- $\zeta_{j[i]}\bar{y}_{i,t-1}$: autoregressive term in the mixture model.

Mixture (MIX) model for the ratings

Assuming that it is very rare for a player to play in every match during a season, we can try to model the overall propensity for *missingness*. Let V_{it} denote a latent variable

$$V_{it} = \begin{cases} 1, & \text{if player } i \text{ participates in match } t, \\ 0, & \text{otherwise.} \end{cases}$$

If $\pi_{it} = Pr(V_{it} = 1)$, then we can specify a mixture of a Gaussian distribution and a point mass at 0 (Gottardo and Raftery, 2008)

$$p(y_{it} | \eta_{it}, \sigma_y) = \pi_{it} \text{Normal}(y_{it} | \eta_{it}, \sigma_y) + (1 - \pi_{it}) \delta_0, \quad (2)$$

where δ_0 is the Dirac mass at zero and η_{it} is the linear predictor:

$$\eta_{it} = \alpha_0 + \alpha_i + \beta_{k[i],t} + \gamma_{k[i]} + \rho_{j[i]} + \delta_{j[i]} q_i + \lambda_{j[i]} \bar{y}_{i,t-1} + \theta h_{it}, \quad (3)$$

and σ_y is the standard deviation of the error in predicting the outcome.

Mixture (MIX) model for the ratings

The probability π_{it} is modeled using a logit regression,

$$\pi_{it} = \text{logit}^{-1} (p_0 + \zeta_{j[i]} \bar{y}_{i,t-1}), \quad (4)$$

which takes into account $\bar{y}_{i,t-1}$, the average rating for player i up to match $t - 1$; p_0 is an intercept for the logit model. The individual-level, position-level, and team-cluster-level parameters are given hierarchical normal priors,

$$\alpha_i \sim \text{Normal}(0, \sigma_\alpha), \quad i = 1, \dots, N \quad (5)$$

$$\gamma_k \sim \text{Normal}(0, \sigma_\gamma), \quad k = 1, \dots, K \quad (6)$$

$$\beta_k \sim \text{Normal}(0, \sigma_\beta), \quad k = 1, \dots, K \quad (7)$$

$$\rho_j \sim \text{Normal}(0, \sigma_\rho), \quad j = 1, \dots, J \quad (8)$$

with weakly informative prior distributions for the remaining parameters and hyperparameters.

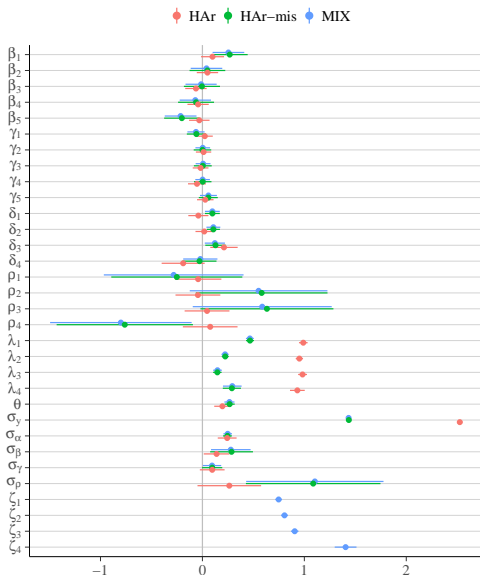
Our mixture specification allows for some natural other models extensions

- $\pi_{it} \sim \text{logit}^{-1} \rightarrow$ **MIX**
- $\pi_{it} = 1$, fixed
 - missing $y_{it} = 0 \rightarrow$ Hierarchical autoregressive model (**HAr**);
 - missing $y_{it} \sim f \rightarrow$ Hierarchical autoregressive model with missing model (**HAr-Mis**);

Remark We want to estimate our models and predict the fantasy rating on a test set. Some interesting issue arise: missingness, model calibration, posterior predictive checks, out-of-sample predictions...

Setup We use the first half of the season as training set and the second half as test set.

Posterior mean \pm sd



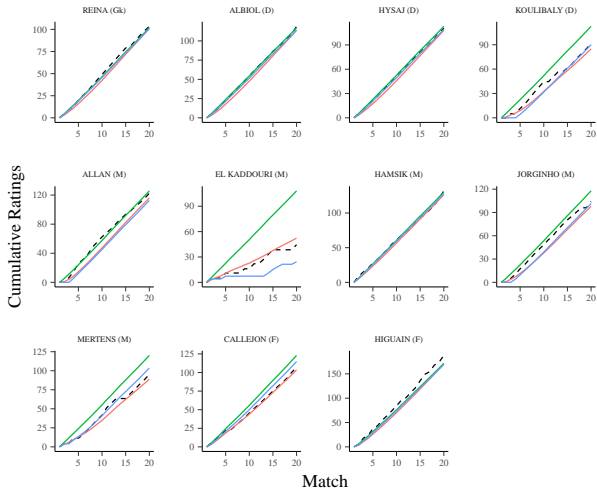
MIX and HAR-Mis, that take care of the missingness, produce similar result. (Models fitted via Markov chain Monte Carlo (3000 iter., burn-in=1000)) using RStan Stan Development Team (2016a) and monitored convergence as recommended in Stan Development Team (2016b)).

Posterior predictive checks

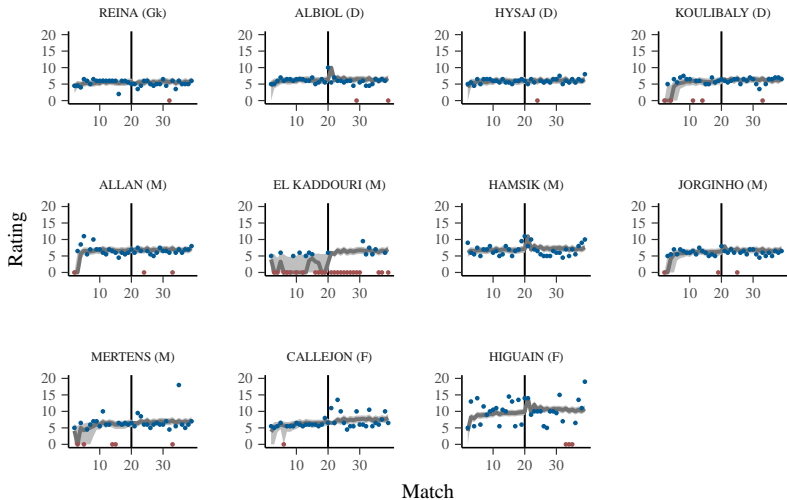
Observed vs predicted cumulative ratings

for selected team Napoli

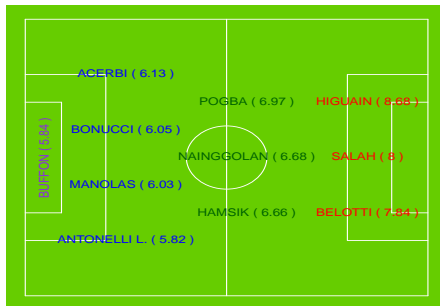
— HAR — HAR-mis — MIX — — Observed



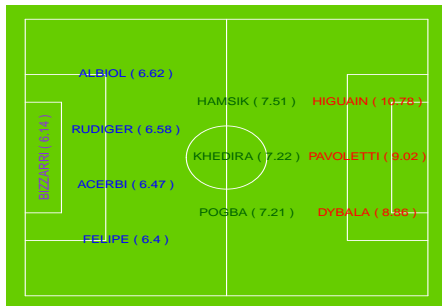
Calibration for the MIX model for selected team Napoli



Final aim **Select the best roster.** According to our posterior predictions for the second part of the season, we can create the best roster.



(a) Observed team



(b) MIX team

Let us note that the **MIX** is quite competitive; moreover Rudiger (defender, Roma) and Khedira (midfield, Juventus) performed pretty well in the 2016-2017 Serie A season.

- We proposed a class of hierarchical Bayesian models for predicting player ratings, in the presence of noisy fantasy football (soccer) data;
- these fantasy ratings may be seen as a crude proxy for players' performances;
- we took care of the missingness issue;
- after controlling for missingness, the out-of sample predictive fit is good (the selected team appears to be competitive). Still checking for calibration.
- **Further work**
 - Dynamic prediction (match after match), adding data for more seasons, adding predictors;
 - **app** for fantasy football managers (working on).

- Gelman, A. and J. Hill (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.
- Gottardo, R. and A. E. Raftery (2008). Markov chain monte carlo with mixtures of mutually singular distributions. *Journal of Computational and Graphical Statistics* 17(4), 949–975.
- Stan Development Team (2016a). RStan: the R interface to Stan, version 2.14.1.
- Stan Development Team (2016b). *Stan Modeling Language User's Guide and Reference Manual, Version 2.14.0*.
<http://mc-stan.org/>.