

# Player Rating Estimation via Bayesian Inference

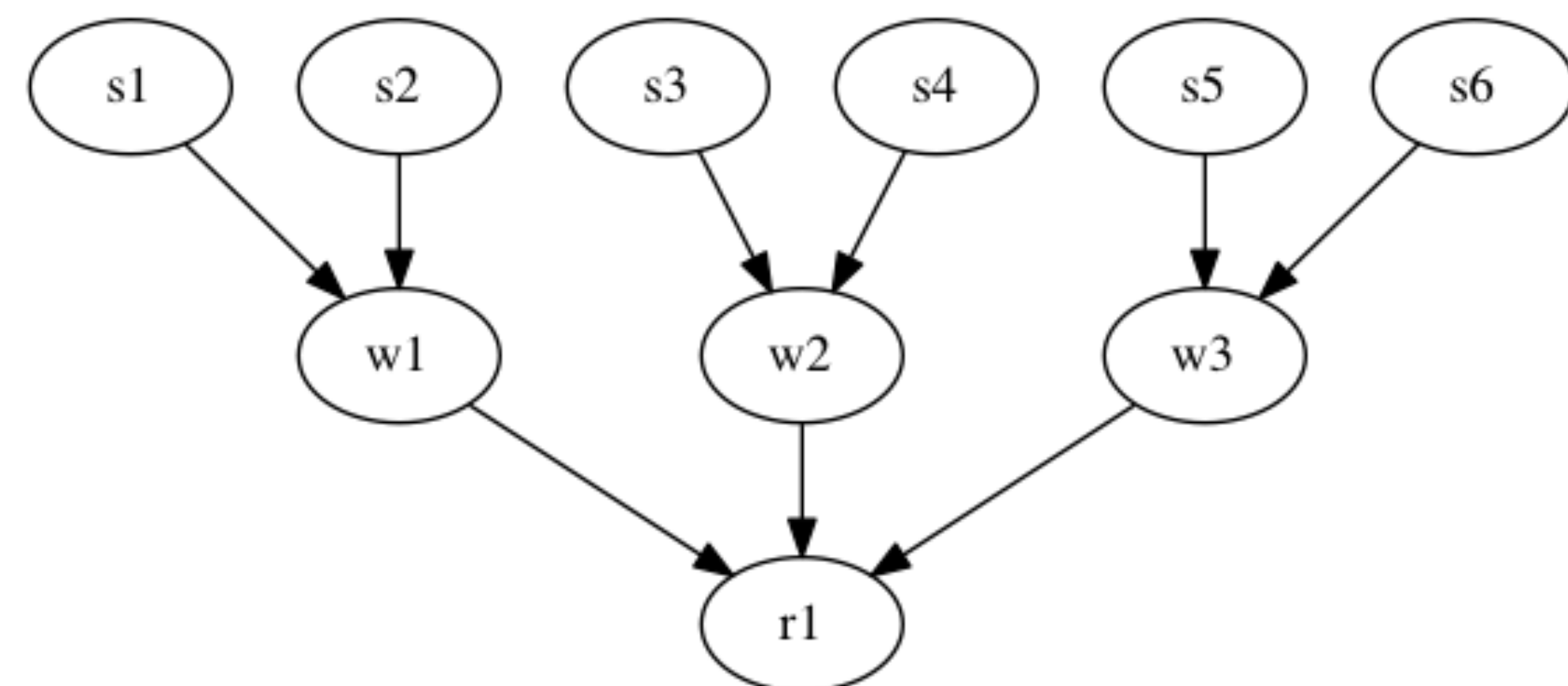
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## Motivation

- Player rating systems are essential to games in situated in all different contexts (video games, sports etc).
- If we can devise a model which captures real-life dynamics of match-making and fit players of the game in that model, then we can:
  - 1. Estimate outcomes of future matches
  - 2. Arrange matches that are more likely to be exciting
  - 3. Rank players of the game

## Method I: MCMC

- Assume a model where a skill value is associated with each player and skill values regulate the probabilities for different outcomes of matches.
- Assume players form teams (which might contain a single member as well) that eventually compete in matches.

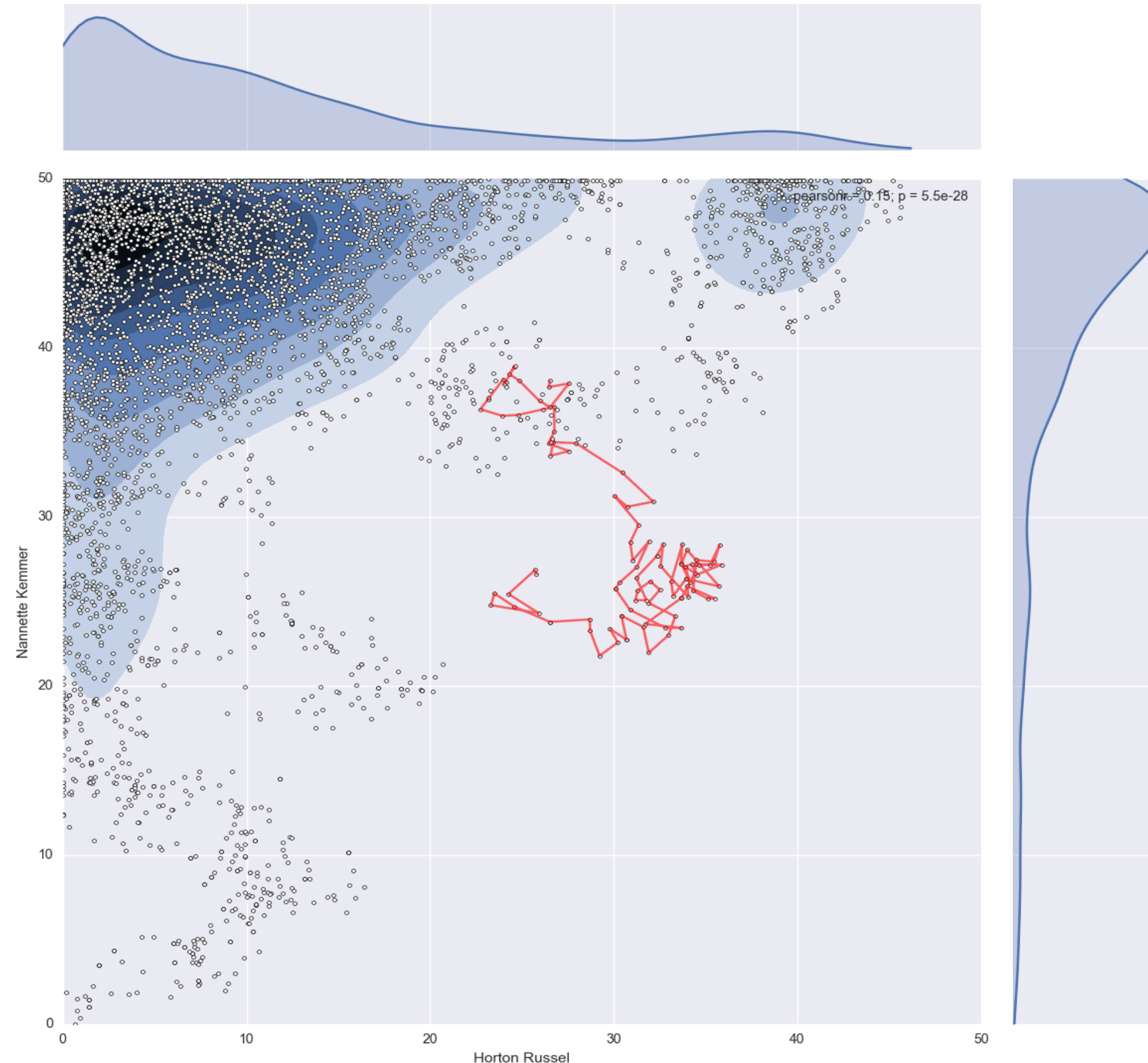


$$p(r|w_1, w_2) = \begin{cases} \exp(|w_1 - w_2|, c_1, c_2) & \text{if } r = 0 \\ (1 - \exp(|w_1 - w_2|, c_1, c_2)) * \sigma(w_1 - w_2, c_3) & \text{if } r = 1 \\ (1 - \exp(|w_1 - w_2|, c_1, c_2)) * \sigma(w_2 - w_1, c_3) & \text{if } r = -1 \end{cases}$$

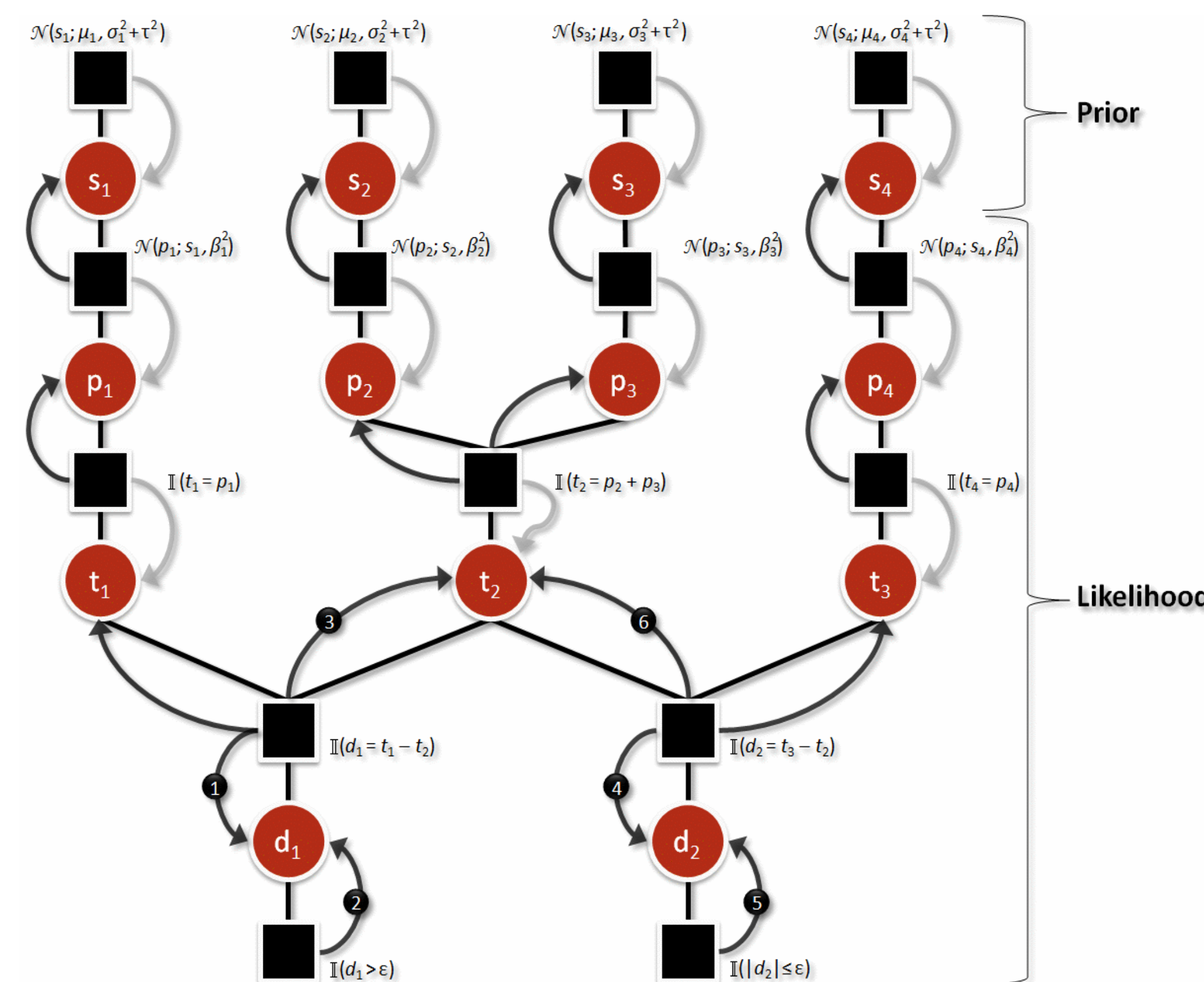
$$p(s|r = \text{Data}) = \frac{p(r = \text{Data}|s)}{\int p(r = \text{Data}|s) ds}$$

$$p(s|r = \text{Data}) \propto p(r = \text{Data}|s)$$

- Approach I:** Sample from the posterior distribution with *Metropolis-Hasting algorithm*
- Approach II:** Since we can calculate the conditional and can sample from it, we can sample from the target posterior distribution using *Gibbs sampler*
- Compute mean of samples to be the point estimate of actual skill of the player.



## Method II: Expectation Propagation



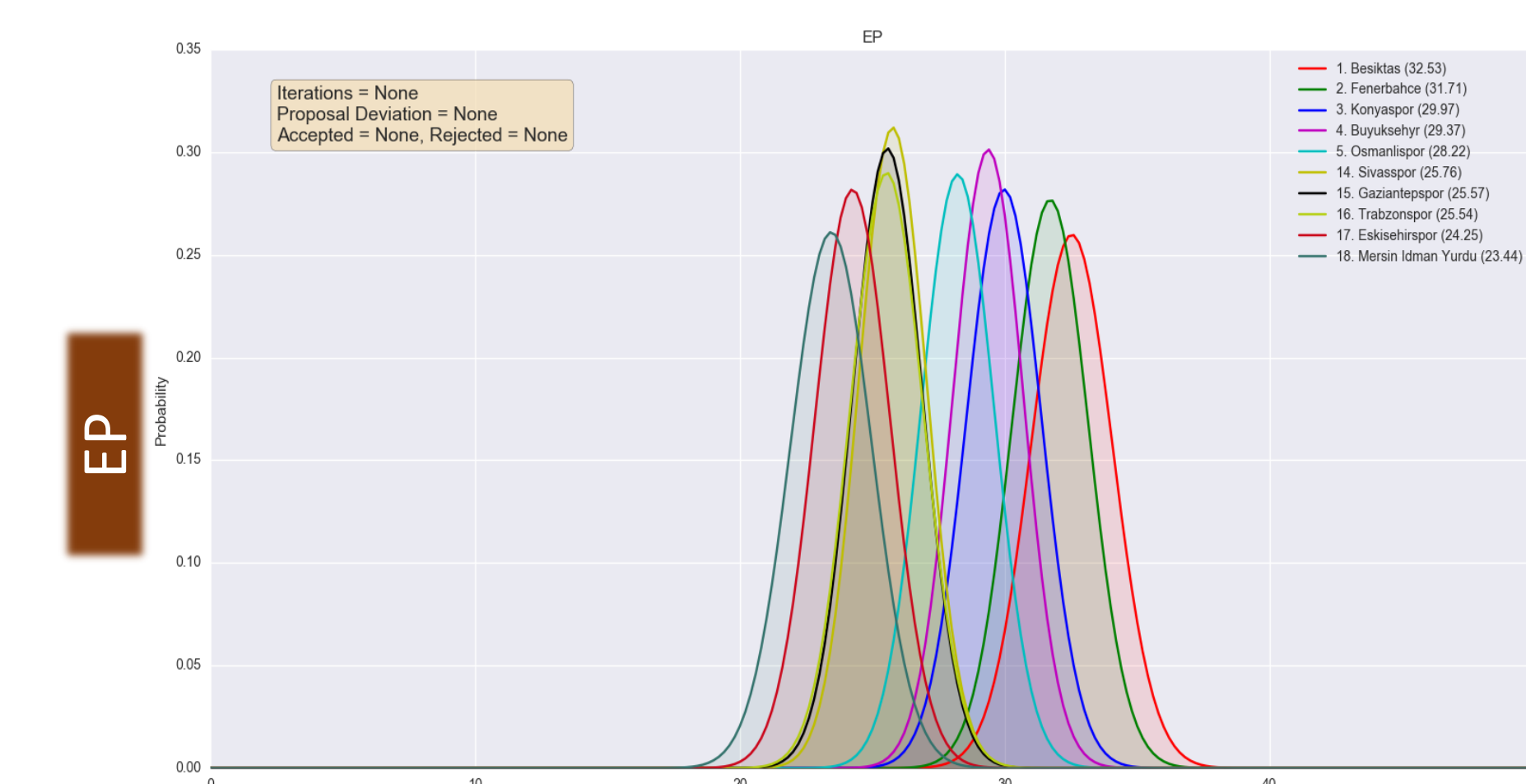
- Assume a similar and slightly more complex model where:
- Players produce a performance each match based on their skill
- We use a Gaussian distribution to represent a skill whose variance stands for the uncertainty.
- Approach III:** Use an online Bayesian inference algorithm *Expectation Propagation* to update prior distributions of skills.
- Model is defined such that upsetting results cause a greater decay in uncertainty and a greater shift in mean

## Data

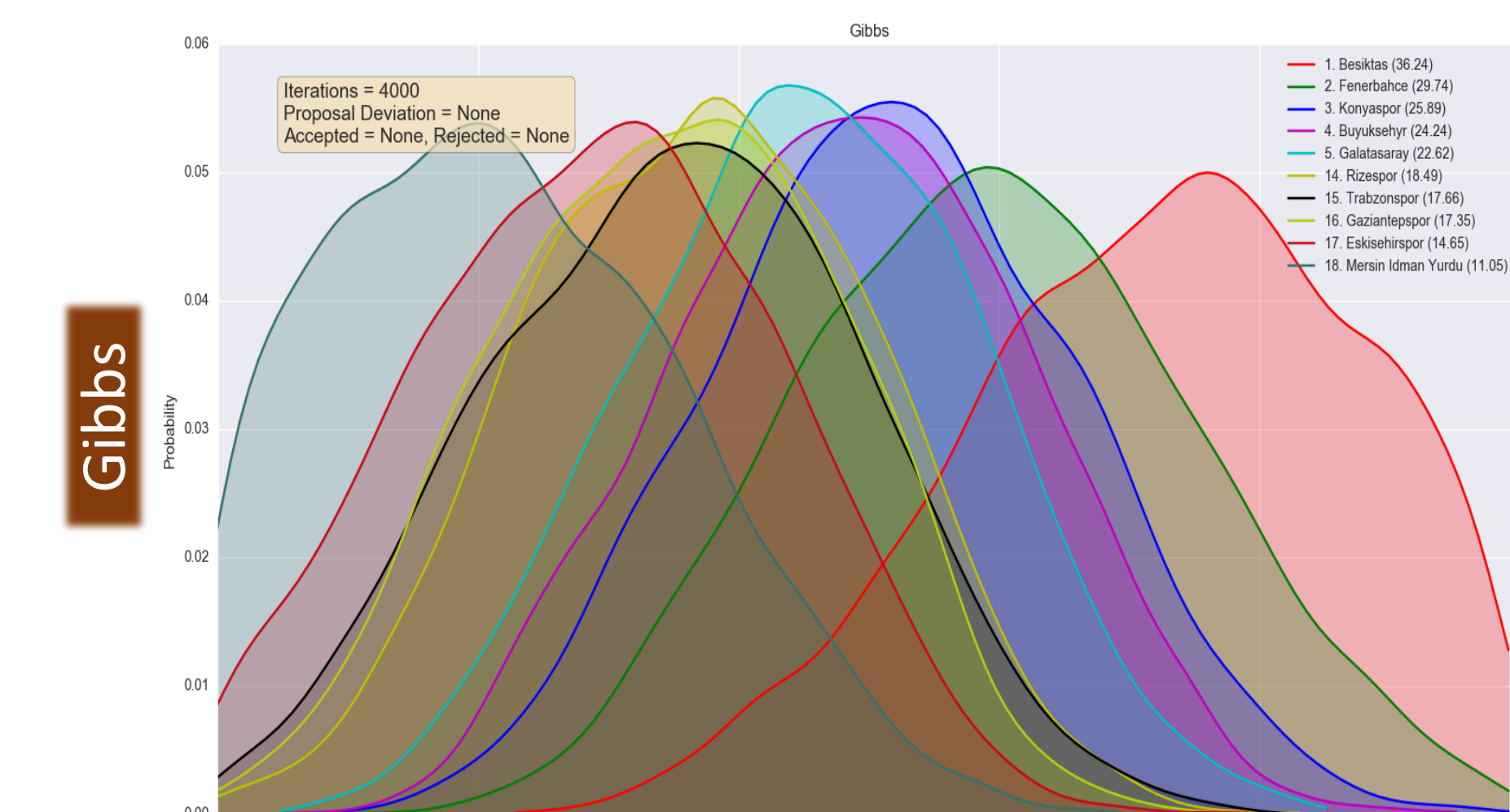
- Synthetic Data:** We generated synthetic data with various configurations assuming the model described for MCMC methods to solve.
- Real-World Data:** We collected match results of
  - Tennis Grand Slams in 2013
  - German, Spanish, Turkish, English primary national football leagues of 2015-2016 season
  - NBA 2015-2016 season
- Preprocessed data has the following form:

Team 1	Team 2	Result
Munich	Dortmund	1
Karlsruhe	Köln	0
Stuttgart	Hamburg	-1
...	...	...

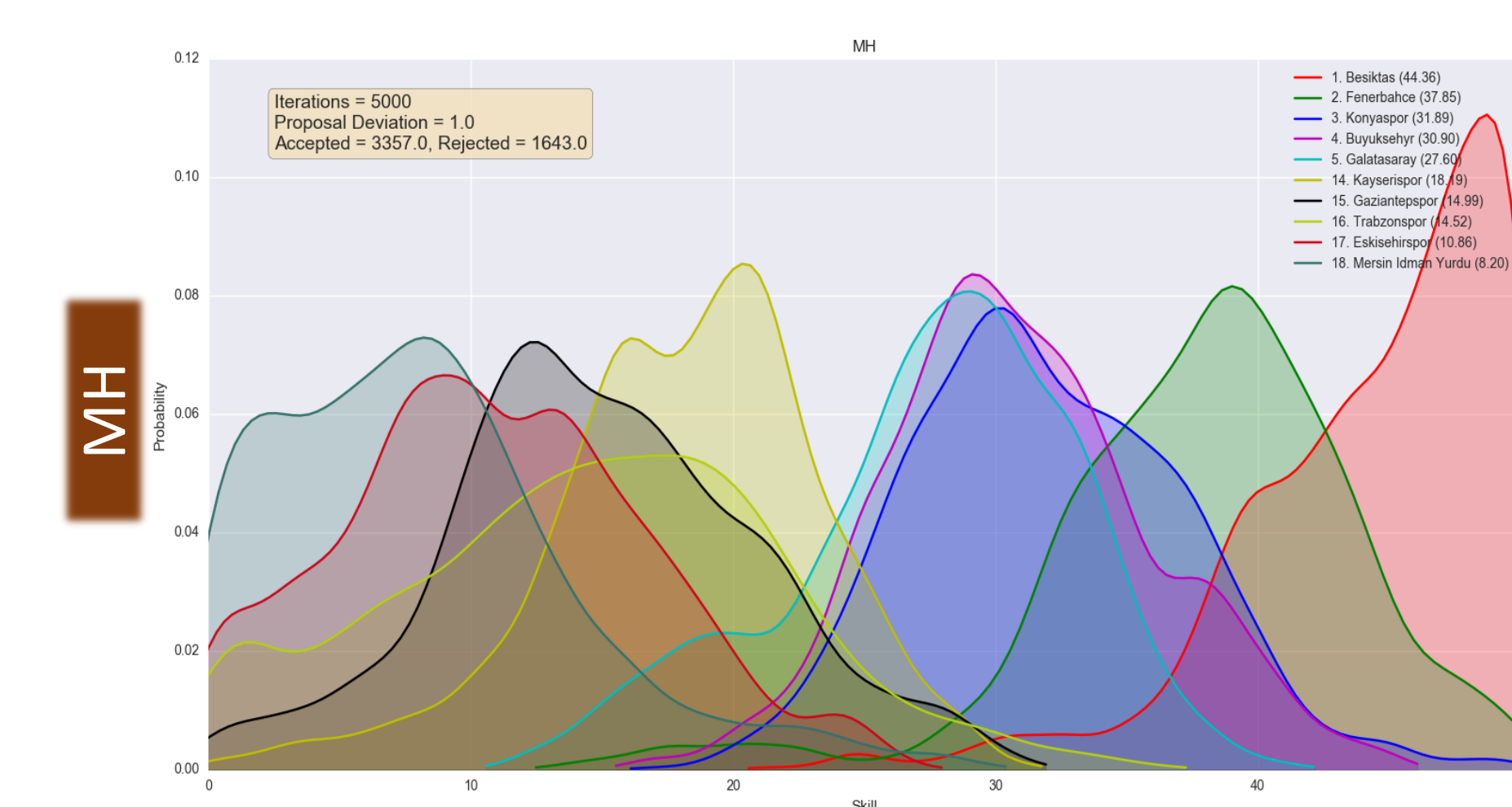
## Results



#	P1	Skill
1	Besiktas	32.53
2	Fenerbahce	31.71
3	Konyaspor	29.97
4	Buyuksehr	29.37
5	Osmanlispor	28.22
14	Sivasspor	25.76
15	Gaziantepspor	25.57
16	Trabzonspor	25.54
17	Eskisehirspor	24.25
18	Mersin Idman Yurdu	23.44



#	P1	Skill
1	Besiktas	36.24
2	Fenerbahce	29.74
3	Konyaspor	25.89
4	Buyuksehr	24.24
5	Galatasaray	22.62
14	Rizespor	18.49
15	Trabzonspor	17.66
16	Gaziantepspor	17.35
17	Eskisehirspor	14.65
18	Mersin Idman Yurdu	11.05



#	P1	Skill
1	Besiktas	44.36
2	Fenerbahce	37.85
3	Konyaspor	31.89
4	Buyuksehr	30.90
5	Galatasaray	27.60
14	Kayserispor	18.19
15	Gaziantepspor	14.99
16	Trabzonspor	14.52
17	Eskisehirspor	10.86
18	Mersin Idman Yurdu	8.20