Bayesian Skill Ranking

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1 Introduction

Template

2 Related Work

Let's talk about [1] and [2] and then just follow the citations that those guys make to introduce the general challenges and state-of-the art.

Basketball brings two key challenges to the field of Bayesian Skill estimation.

- Results are not binary Win/Lose outcomes.
- Results are influenced by the skill differential of more than two players.

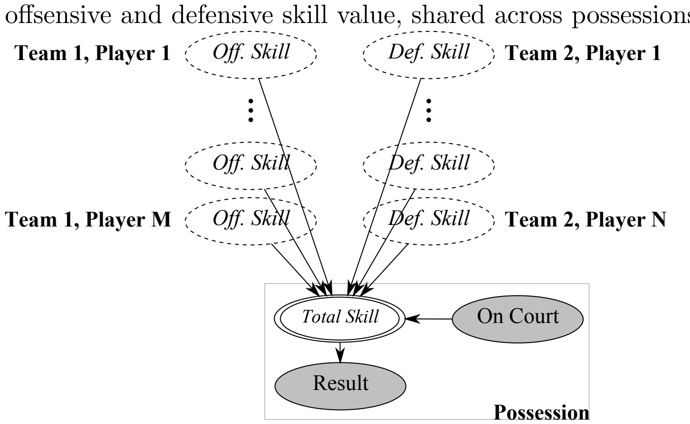
3 Method

3.1 Traditional Networks

We model the result of each possession as an independent and identically distributed random variable, *Result*. An NBA roster has 12 players, but only five of them are on the court for a given team during any single posession.

To reduce noise, we ignore "garbage time" posessions. To simplify the model we ignore possessions that end in a time-out.

We begin with a very basic model that follows traditional "skill ranking" in the sense that each player has an unobserved (or parameterized) skill that has some distribution, and using inference (or parameter estimation) we can determine the value of each player's skill. In this network, we decided each player would have a hidden offsensive and defensive skill value, shared across possessions:



These skills would contribute deterministically in some way to an "effective" total skill differential between the two teams, and then the *Result* variable would be one of four outcomes:

- $R = 0$ Offensive Team Scores nothing, change of possession (e.g. turnover, defensive rebound, etc.)
- $R = 1$ Offensive Team Scores 1 point
- $R = 2$ Offensive Team Scores 2 points
- $R = 3$ Offensive Team Scores 3 points

The *On Court* random variable "multiplexes" between those players that are on the court and those that are not.

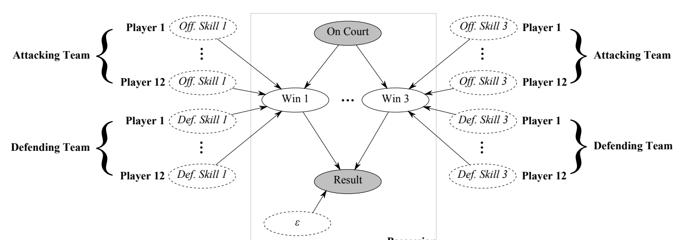
3.2 Issues

These traditional models [1] have difficulty capturing the proper causalities when Results can have multinomial-valued outcomes. For example, regardless of the parameterization of the *Results* CPD, both $\Pr\{R = 2\}$ and $\Pr\{R = 3\}$ would depend on the same skills of the same players. The relative distribution of outcomes $\Pr\{R = 2\}$ vs. $\Pr\{R = 3\}$ would be shared across all "units" (i.e. all combinations of *On Court* assignments).

In reality, a team that scores $R = 3$ half the time and $R = 1$ half the time is just as good as a team that scores $R = 2$ all the time. However, any traditional Win/Lose model will unfairly penalize the likelihood of one of these teams over the other and leads to under-fitting.

Secondly, there is a lot of value in being able to compare with the state-of-the-art in the Win/Lose based Bayesian Skill Ranking literature. Specifically, there is common debate over logistic vs. Gaussian skill/performance distributions and we wish to be sensitive to that conversation in this project. Having a multinomial outcome makes it difficult to directly compare logistic vs. Gaussian in the standard skill/performance framework because there is no consensus in the literature about how to extend these models just to support ties [3], let alone general multinomial outcomes.

3.3 Proposed Network



4 Implemention

Summary

5 Results

Data

6 Analysis

Details

7 Conclusions

Done

8 References

References

[1] R. Herbrich, T. Minka, and T. Graepel, “TrueSkillTM: A Bayesian skill rating system,” *Advances in Neural Information Processing Systems*, vol. 20, pp. 569–576, 2007.

[2] R. Coulom, “Whole-history rating: A bayesian rating system for players of time-varying strength,” *Computers and Games*, pp. 113–124, 2008.

[3] D. Hunter, “MM algorithms for generalized Bradley-Terry models,” *The Annals of Statistics*, vol. 32, no. 1, pp. 384–406, 2004.