Bayesian Ranking of Quiz Bowl Teams

Final Presentation for 553.432

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Research Question

Research Question

Problem:

- · Run large tournaments for Quiz Bowl Club on Campus
- · Have to seed teams before tournament
- · Using intuition currently which is slow and sees little of the data

Question:

- Who is the current best high school/middle school team?
- What game statistics are the best to determine outcomes?

Literature Review

Literature Review

Ranking for Teams

- · Extremely well developed field
- Based around a couple established methods
 - · ELO and GLICKO
 - · Bradley-Terry
 - · Plackett-Luce
 - · Davidson Model
 - · Thurstone-Mosteller
 - Trueskill and Trueskill 2



Literature Review contd.

Ranking for Quiz Bowl Teams

- GrogerRanks
 - · Homespun overfit model
 - · Created without much statistical methods
- HSQBRank
 - · Defunct
 - · Used one indicator of strength

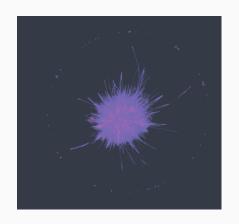
Data

Data Collection and Cleaning

- Scraped 10,000 tournaments over 20 years from the largest host of quiz bowl tournaments
- · Over 16,000 teams
- Collected 398,827 matches that included a winner and loser
- · Not all matches had scores or statistics

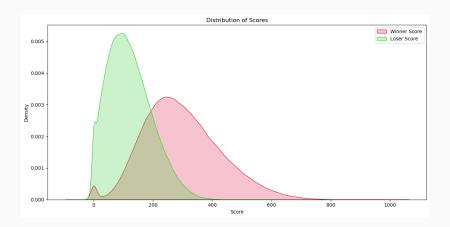


Competitive Network Visualization

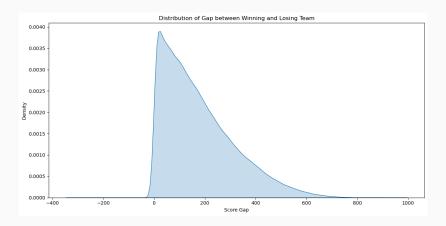




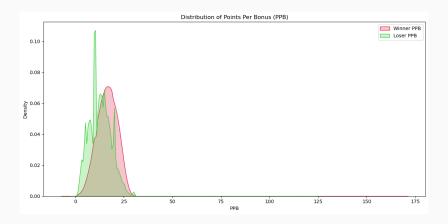
Score Statistics



Score Statistics contd.



Other Statistics



Methods

Bradley-Terry

Likelihood:

$$\mathbb{P}[i \text{ beats } j] = \frac{\exp \lambda_i}{\exp \lambda_i + \exp \lambda_j}$$
$$y_{i,j} \sim \text{Bernoulli}(\mathbb{P}[i \text{ beats } j])$$

Prior:

$$\lambda_i \sim \mathcal{N}(0, \sigma_{\lambda}^2)$$

$$\sigma_{\lambda}^2 = 1$$

Generalized Bradley-Terry

Likelihood:

$$\mathbb{P}[i \text{ beats } j] = \frac{\exp \lambda_i}{\exp \lambda_i + \exp \lambda_j}$$
$$\lambda_i = \sum_{i=1}^p \beta_i X_i$$
$$y_{i,j} \sim \text{Bernoulli}(\mathbb{P}[i \text{ beats } j])$$

Prior:

$$eta_i \sim \mathcal{N}(0, \sigma_{\beta}^2)$$
 $\sigma_{\beta}^2 = 1$

Spike and Slab Generalized Bradley-Terry

Likelihood:

$$\mathbb{P}[i \text{ beats } j] = \frac{\exp \lambda_i}{\exp \lambda_i + \exp \lambda_j}$$

$$\lambda_i = \sum_{i=1}^{p} \beta_i X_i$$

$$\beta_i = Z_i b_i$$

$$y_{i,j} \sim \text{Bernoulli}(\mathbb{P}[i \text{ beats } j])$$

Prior:

$$b_i \sim \mathcal{N}(0, \sigma_b^2)$$

 $z_i \sim \mathsf{Bernoulli}(p_z)$
 $\sigma_b^2 = 1$
 $p_z = 0.5$

Sampling Methods

- Uses special sampling algorithm called No-U-Turn Sampler (NUTS)
- Chooses samples based on shape of posterior using using partial derivatives
- · Spike and Slab uses NUTS + Gibbs

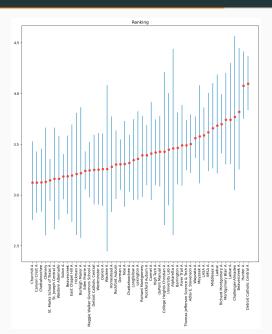


Preliminary Findings

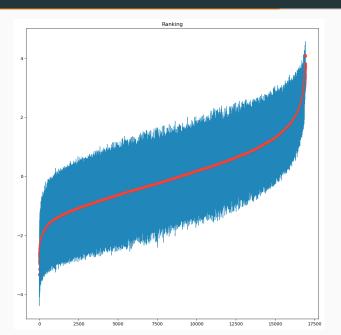
Bayesian Bradley Terry

- · Extremely successful
- · Outputted average scores with 95% CIs
- · Agrees with widely held knowledge

Top 50 Rankings



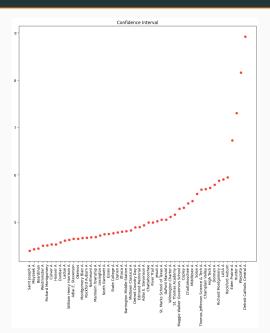
Total Rankings



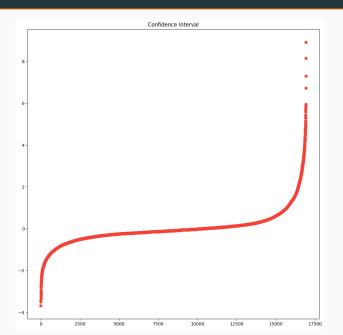
MLE Bradley Terry

- · No 95% CIs
 - · Could use Fisher Information
 - Extremely taxing to compute
- · Possible overfit
- · Does not agree as well with widely held knowledge

Top 50 Rankings



Total Rankings



Generalized Bradley Terry

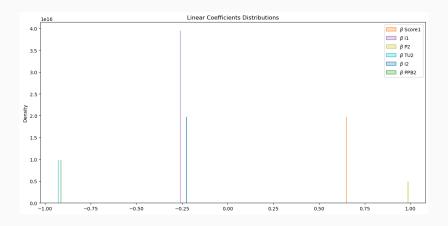
Bayesian methods failed

- · Coefficients changed with every run
- · Nonsense Coefficients
- Extremely overfit
- · Same behavior with Spike and Slab

MLE methods failed

Too much RAM/VRAM was needed to run it

Generalized Bradley Terry



Generalized Bradley Terry

