

Assessing Ranking Fidelity of Competition Structures via Weighted Mutual Information

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Introduction

- ▶ There exists numerous competition formats across all professional sports
- ▶ Which competition structure is best?
- ▶ The “best” competition structure depends on how well it reflects the competitors’ true strengths
- ▶ We will propose a metric that quantifies how effectively different tournament structures convey information about competitors’ true strengths

Game Simulation

- ▶ Given the assigned “known strength”, θ , we simulate a game using the Bradley-Terry Model

$$\Pr(i > j) = \frac{e^{\theta_i}}{e^{\theta_i} + e^{\theta_j}} = \frac{1}{1 + e^{\theta_j - \theta_i}}$$

Tournament Simulations

- ▶ Each competition structure is simulated given the number of teams, n , and θ
- ▶ Below is an example of the output from one simulation of a single elimination tournament structure

##	r	theta	r_hat	game_wins	game_losses
## 1	1	1.221	6	0	1
## 2	2	0.765	1	3	0
## 3	3	0.431	4	1	1
## 4	4	0.140	2	2	1
## 5	5	-0.140	7	0	1
## 6	6	-0.431	5	0	1
## 7	7	-0.765	8	0	1
## 8	8	-1.221	3	1	1

Mutual Information

- ▶ If one views the true ranking of the teams in a tournament as a message to be sent to a receiver and the outcome of the tournament as a message that is received, we can measure the “goodness” of a tournament in terms of its ability to accurately transmit the true ranking.
- ▶ The notation for mutual information is:

$$I(X; Y) = \sum_{y \in Y} \sum_{x \in X} p(x, y) \log \frac{p(x, y)}{p(x)p(y)}$$

- ▶ In our case, it can be simplified to:

$$I(r, \hat{r}) = n! \sum_{\hat{r}} p(r, \hat{r}) \log \frac{p(r, \hat{r})}{(\frac{1}{n!})^2} = n! \log ((n!)^2)$$

Weighted Mutual Information

- ▶ A limitation of mutual information is that it does not distinguish between the direction of information
- ▶ In other words, a ranking of (1, 2, 3, 4) is equivalent to (4, 3, 2, 1)
- ▶ Because of this, we proposed a weighting function $w(r, \hat{r})$
- ▶ So, the new formula is:

$$wl_m(r, \hat{r}) = \sum_r \sum_{\hat{r}} w(r, \hat{r}) * p(r, \hat{r}) \log \frac{p(r, \hat{r})}{p(r)p(\hat{r})}$$

Weighting Function

- ▶ In our original paper submission, we used squared error loss as the weighting function:

$$w(r, \hat{r}) = \begin{cases} \frac{1}{\hat{r}^2 r}, & r \neq \hat{r} \\ 1, & r = \hat{r} \end{cases}$$

- ▶ However, after comments and reviews from people at CSAS and CMSAC, we have decided to use a weighted Kendall's Tau

Weighted Kendall

$$\tau_w = \frac{\sum_{i \neq j} W_{ij} \times \text{sgn}(i - j) \times \text{sgn}(R_i - R_j)}{\sum_{i,j} W_{ij} - \sum_i W_{ii}}$$

- ▶ W is a $n \times n$ lower-triangular matrix, where

$$W_{ij} = w_{\min(i,j)}, \text{ for } i, j = m, 2m, \dots, n \times m$$

- ▶ m : vector of length n representing the “salient weights”, or the importance of correctly getting each ranking
- ▶ If $\tau_w = 1$, then the ranking is identical to the true ranking; if $\tau_w = 0$, then the order of teams is perfectly inversely proportional to the true rankings

Weighted Kendall Example

- If $\hat{r} = (2, 1, 3, 4)$ and $m = (3, 1, 1, 0)$, then:

$$W = \begin{pmatrix} 3 & 3 & 3 & 3 \\ 3 & 1 & 1 & 1 \\ 3 & 1 & 1 & 1 \\ 3 & 1 & 1 & 0 \end{pmatrix}$$

$$\sum_{i,j} W_{ij} = 29; \sum_i W_{ii} = 5; \sum_{i \neq j} W_{ij} \times \text{sgn}(i-j) \times \text{sgn}(R_i - R_j) = 18$$

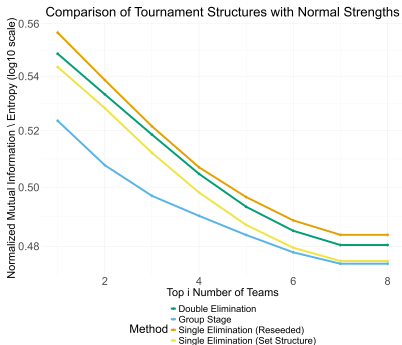
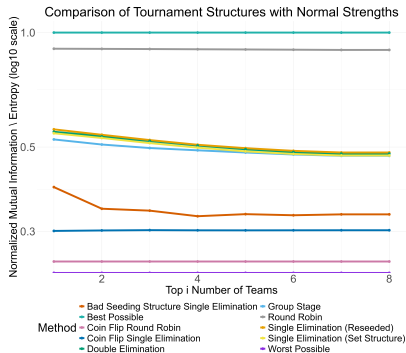
- So, τ_w for this example would be $\frac{18}{29-5} = 0.75$

Normalizing Mutual Information

- ▶ Mutual Information can be normalized by dividing by the joint entropy
- ▶ Entropy: $-p(x) \log p(x)$
- ▶ Assuming r and \hat{r} are independent, joint entropy can be written as $H(r, \hat{r}) = H(r) + H(\hat{r})$
- ▶ $H(r)$ and $H(\hat{r})$ are theoretically equivalent, leaving $H(r, \hat{r}) = -2 \sum_r p(r) \log(p(r)) = -2(n!) \times (1/n!) \times \log_2(1/n!) = \log_2((n!)^2)$
- ▶ So, the final formula for the metric is:

$$\frac{wl_m(r, \hat{r})}{H(r) + H(\hat{r})} = \frac{\sum_r \sum_{\hat{r}} w(r, \hat{r}) * p(r, \hat{r}) \log \frac{p(r, \hat{r})}{p(r)p(\hat{r})}}{\log_2((n!)^2)}$$

Results



Limitations

- ▶ The “known” strengths are assumptions that can be estimated but never truly known
- ▶ Ties are not addressed in any of the games
- ▶ Ties in the \hat{r} are randomly assigned

Future Work

- ▶ Evaluate structures using various distributions and “known” weights
- ▶ Estimate the θ s in a real-world example and compare recent changes to the old format

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