

# A Comparative Study for Single Image Blind Deblurring

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# Bradley–Terry model

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- Given pairwise comparison votes, we want to fit a global score/ranking for each evaluated method.

- Input: a winning matrix  $C \in R^{N \times N}$  where

$$C_{ij} = \begin{cases} \text{\#times that } i \text{ beats } j, & \text{if } i \neq j \\ 0 & , \text{if } i = j \end{cases}$$

–  $N$  is the number of evaluated methods

- Output:  $N$  scores  $s_1, s_2, \dots, s_N$

# Bradley–Terry model

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- Assume the probability that users chooses  $i$  over  $j$  is:

$$P_{ij} = \frac{e^{s_i}}{e^{s_i} + e^{s_j}}$$

- We want to maximize the likelihood:

$$L(s) = \prod_{i=1}^N \prod_{j=1, j \neq i}^N (P_{ij})^{c_{ij}}$$

# Bradley–Terry model

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- Minimize the negative log likelihood:

$$\begin{aligned} E(s) &= - \sum_{i=1}^N \sum_{j=1, j \neq i}^N C_{ij} \log P_{ij} \\ &= \sum_{i=1}^N \sum_{j=1, j \neq i}^N C_{ij} \log(e^{s_i} + e^{s_j}) - \sum_{i=1}^N \sum_{j=1, j \neq i}^N C_{ij} \log(e^{s_i}) \\ &= E_1(s) - E_2(s) \end{aligned}$$

# Bradley–Terry model

$$E_1(s) = \sum_{i=1}^N \sum_{j=1, j \neq i}^N C_{ij} \log(e^{s_i} + e^{s_j})$$

$$\frac{\partial E_1(s)}{\partial s_k} = \boxed{\sum_{j=1, j \neq k}^N \frac{C_{kj} \cdot e^{s_k}}{e^{s_k} + e^{s_j}}} + \boxed{\sum_{i=1, i \neq k}^N \frac{C_{ik} \cdot e^{s_k}}{e^{s_i} + e^{s_k}}}$$

when  $i = k$

when  $i \neq k$

$$= \sum_{v=1, v \neq k}^N \frac{C_{kv} \cdot e^{s_k}}{e^{s_k} + e^{s_v}} + \sum_{v=1, v \neq k}^N \frac{C_{vk} \cdot e^{s_k}}{e^{s_v} + e^{s_k}} = \sum_{v=1, v \neq k}^N \frac{N_{kv} \cdot e^{s_k}}{e^{s_k} + e^{s_v}}$$

replace  $j$  with  $v$                       replace  $i$  with  $v$

$$\text{where } N_{kv} = C_{kv} + C_{vk}$$

# Bradley–Terry model

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$$\begin{aligned} E_2(s) &= \sum_{i=1}^N \sum_{j=1, j \neq i}^N C_{ij} \log(e^{s_i}) \\ &= \sum_{i=1}^N \sum_{j=1, j \neq i}^N C_{ij} s_i \end{aligned}$$

$$\frac{\partial E_2(s)}{\partial s_k} = \sum_{j=1, j \neq k}^N C_{kj}$$

# Bradley–Terry model

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- Minimize the negative log likelihood:

$$\begin{aligned}\frac{\partial E(s)}{\partial s_k} &= \frac{\partial E_1(s)}{\partial s_k} - \frac{\partial E_2(s)}{\partial s_k} \\ &= \sum_{v=1, v \neq k}^N \frac{N_{kv} \cdot e^{s_k}}{e^{s_k} + e^{s_v}} - \sum_{j=1, j \neq k}^N C_{kj}\end{aligned}$$

- Since  $C_{ii} = 0, N_{ii} = 0$ :

$$\frac{\partial E(s)}{\partial s_k} = \sum_{v=1}^N \frac{N_{kv} \cdot e^{s_k}}{e^{s_k} + e^{s_v}} - \sum_{j=1}^N C_{kj}$$

# Bradley–Terry model

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- Let  $\frac{\partial E(s)}{\partial s_k} = 0$ , we can derive the following EM-like iterative form:

$$e^{s_k^{t+1}} = \frac{\sum_{j=1}^N C_{kj}}{\sum_{v=1}^N \frac{N_{kv}}{e^{s_k^t} + e^{s_v^t}}}$$

$$s_k^{t+1} = \log \left( \frac{\sum_{j=1}^N C_{kj}}{\sum_{v=1}^N \frac{N_{kv}}{e^{s_k^t} + e^{s_v^t}}} \right)$$