Your 2 is My 1, Your 3 is My 9: Handling Arbitrary Miscalibrations in Ratings

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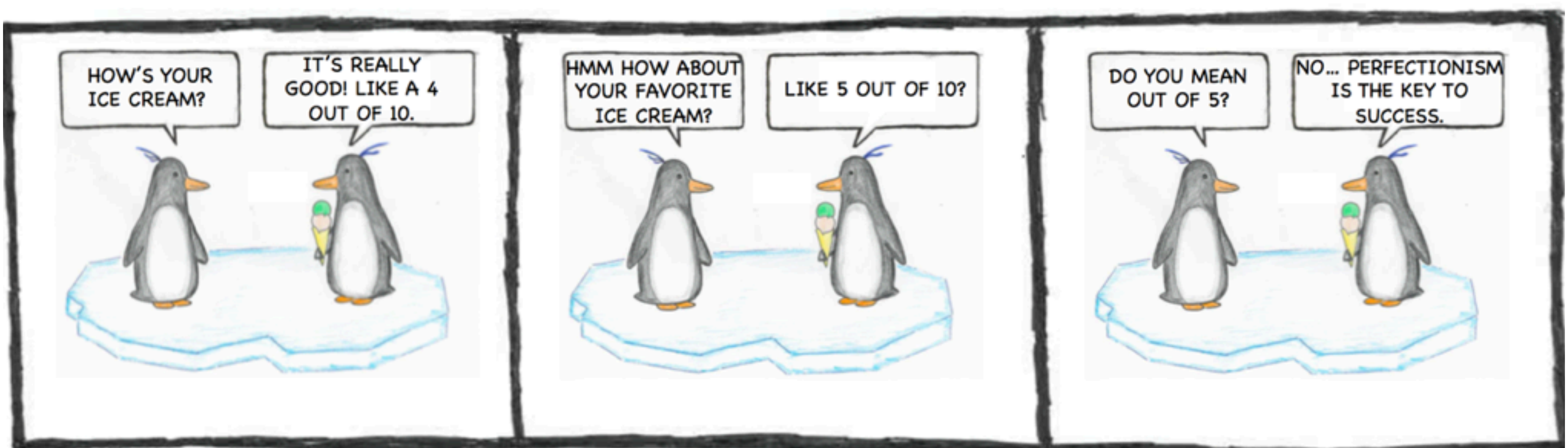
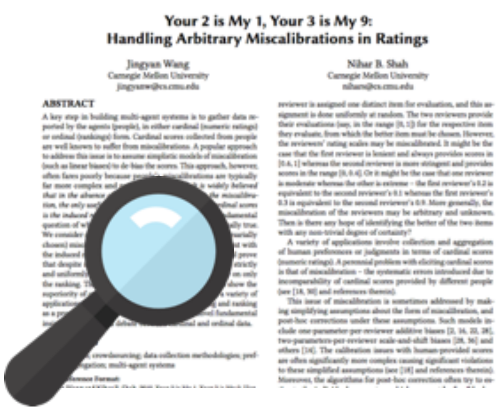


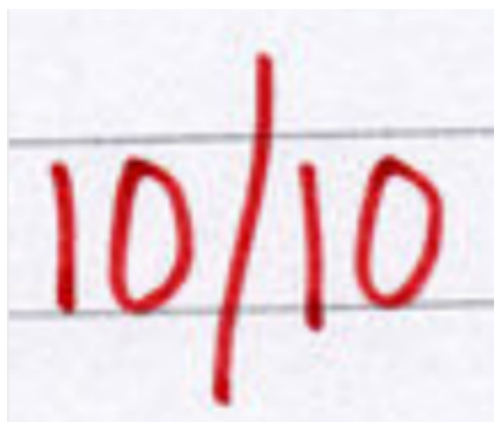
Miscalibration

People have <u>different scales</u>

when giving <u>numerical scores</u>.



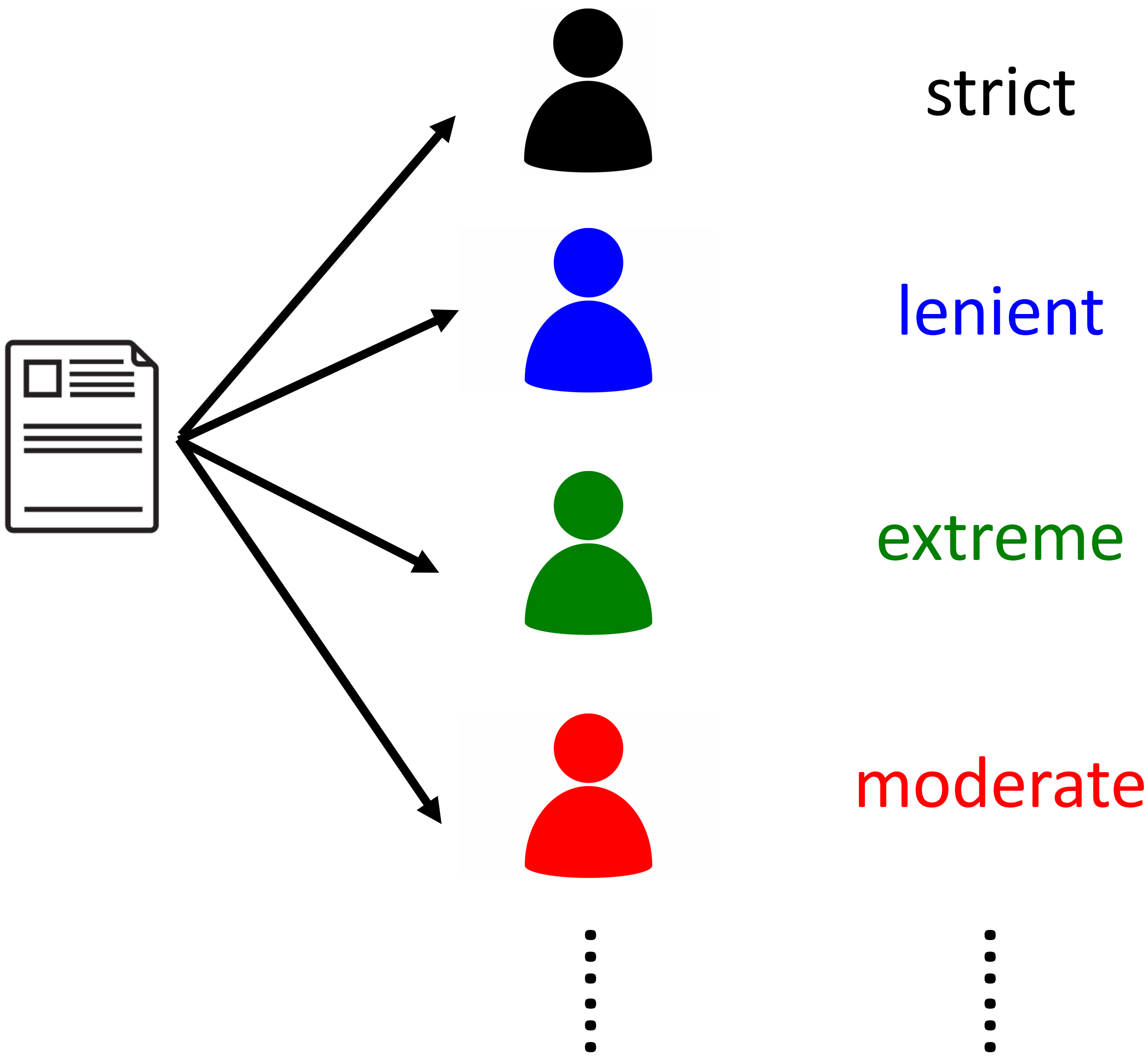
reviewing papers



grading essays

rating products

People are miscalibrated



Miscalibration

- **Ammar et al. 2012**
  “The rating scale as well as the individual ratings are often arbitrary and may not be consistent from one user to another.”

- **Mitliagkas et al. 2011**
  “A raw rating of 7 out of 10 in the absence of any other information is potentially useless.”

What should we do with these scores?

Two approaches in the literature

1. Assume simplified models for calibration

[Paul 1981, Flach et al. 2010, Roos et al. 2011, Baba and Kashima 2013, Ge et al. 2013, MacKay et al. 2017]

   - People are complex [e.g. Griffin and Brenner 2008]
   - Did not work well in practice:
     "We experimented with reviewer normalization and generally found it significantly harmful."
     — John Langford (ICML 2012 program co-chair)

2. Use rankings

[Rokeach 1968, Freund et al. 2003, Harzing et al. 2009, Mitliagkas et al. 2011, Ammar et al. 2012, Negahban et al. 2012]

   - Use rankings induced from the scores or directly collect rankings
   - Commonly believed to be the only useful information, if no assumptions on calibration

Folklore belief

Freund et al. 2003
"[Using rankings instead of ratings] becomes very important when we combine the rankings of many viewers who often use completely different ranges of scores to express identical preferences."

Is it possible to do better than rankings with essentially no assumptions on the calibration?

Simplified setting

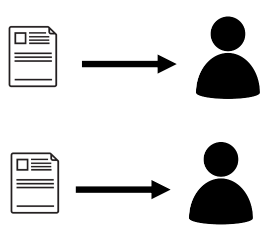
$x_A \in [0, 1]$

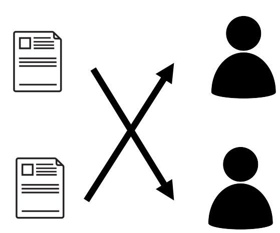
$x_B \in [0, 1]$

1 Calibration function $f_1: [0, 1] \to [0, 1]$
Gives score $f_1 (x_i)$ for $i \in \{A, B\}$

2 Calibration function $f_2: [0, 1] \to [0, 1]$
Gives score $f_2 (x_i)$ for $i \in \{A, B\}$

- f_1, f_2 are **strictly monotonic**
- **Adversary** chooses x_A, x_B and strictly monotonic f_1, f_2
- Papers assigned to reviewers at random

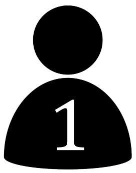




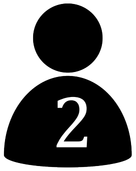
Simplified setting

$x_A \in [0,1]$

$x_B \in [0,1]$



Calibration function $f_1: [0,1] \rightarrow [0,1]$
Gives score $f_1\ (x_i)$ for $i \in \{A, B\}$



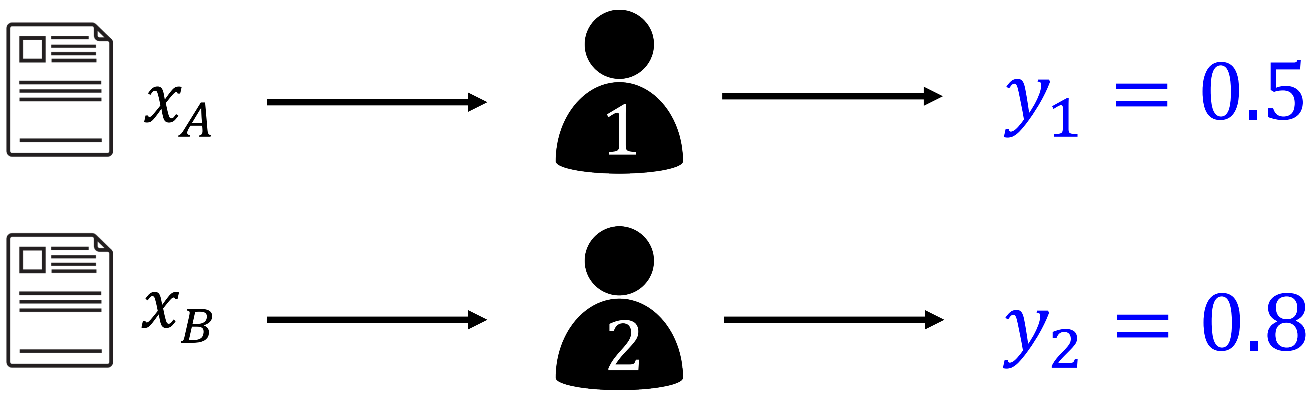
Calibration function $f_2: [0,1] \rightarrow [0,1]$
Gives score $f_2\ (x_i)$ for $i \in \{A, B\}$

- Goal: infer $x_A > x_B$ or $x_A < x_B$?
- Eliciting ranking vacuous: random guessing baseline
- y_i denotes score given by reviewer $i \in \{1, 2\}$

Given $\{y_1, y_2, \text{assignment}\}$, is it possible to infer $x_A > x_B$ or $x_A < x_B$ better than random guessing?

Impossibility?

Intuition: The reported scores can be either due to x, or due to f.



Case I:

$$f_1(x) = x \qquad x_A = 0.5$$
$$f_2(x) = x \qquad x_B = 0.8$$

$$\Rightarrow x_A < x_B$$

Case II:

$$f_1(x) = x/2 \qquad x_A = 1$$
$$f_2(x) = x \qquad x_B = 0.8$$

$$\Rightarrow x_A > x_B$$

Impossibility…
for deterministic algorithms

Theorem: No **deterministic** algorithm can always be strictly better than random guessing.

- Stein's paradox
  [Stein 1956]
- Empirical Bayes
  [Robbins 1956]
- Two envelope problem
  [Cover 1987]

Proposed algorithm

Algorithm: The paper with the higher score is better, with probability $\frac{1+|y_1-y_2|}{2}$.

Theorem: This algorithm uniformly and strictly outperforms random guessing.

Scores > rankings!

Intuition

Algorithm: The paper with the higher score is better, with probability $\frac{1+|y_1-y_2|}{2}$.

$x_A = 0$	
$x_B = 1$	

Intuition

Algorithm: The paper with the higher score is better, with probability $\frac{1+|y_1 - y_2|}{2}$.

	$\boldsymbol{f_1}$
$\boldsymbol{x_A = 0}$	0.1
$\boldsymbol{x_B = 1}$	0.3

Intuition

Algorithm: The paper with the higher score is better, with probability $\frac{1+|y_1-y_2|}{2}$.

	$\boldsymbol{f_1}$	$\boldsymbol{f_2}$
$\boldsymbol{x_A = 0}$	0.1	0.5
$\boldsymbol{x_B = 1}$	0.3	0.9

Intuition

Algorithm: The paper with the higher score is better, with probability $\frac{1+|y_1-y_2|}{2}$.

	$\boldsymbol{f_1}$	$\boldsymbol{f_2}$
$\boldsymbol{x_A = 0}$	0.1	0.5
$\boldsymbol{x_B = 1}$	0.3	0.9

- Under blue assignment, output paper B with probability
$$\frac{1+|0.1-0.9|}{2} = 0.9$$
- Under red assignment, output paper A with probability
$$\frac{1+|0.3-0.5|}{2} = 0.6$$
- On average, correct with probability
$$\frac{0.9+(1-0.6)}{2} = 0.65 > 0.5$$

Extensions

- A/B testing and ranking
- Noisy setting

Take-aways

- **Scores > rankings**

  in presence of arbitrary miscalibration

- **Randomized decisions**

  good for both inference and fairness

[Saxena et al. 2018]


Thanks! Questions?