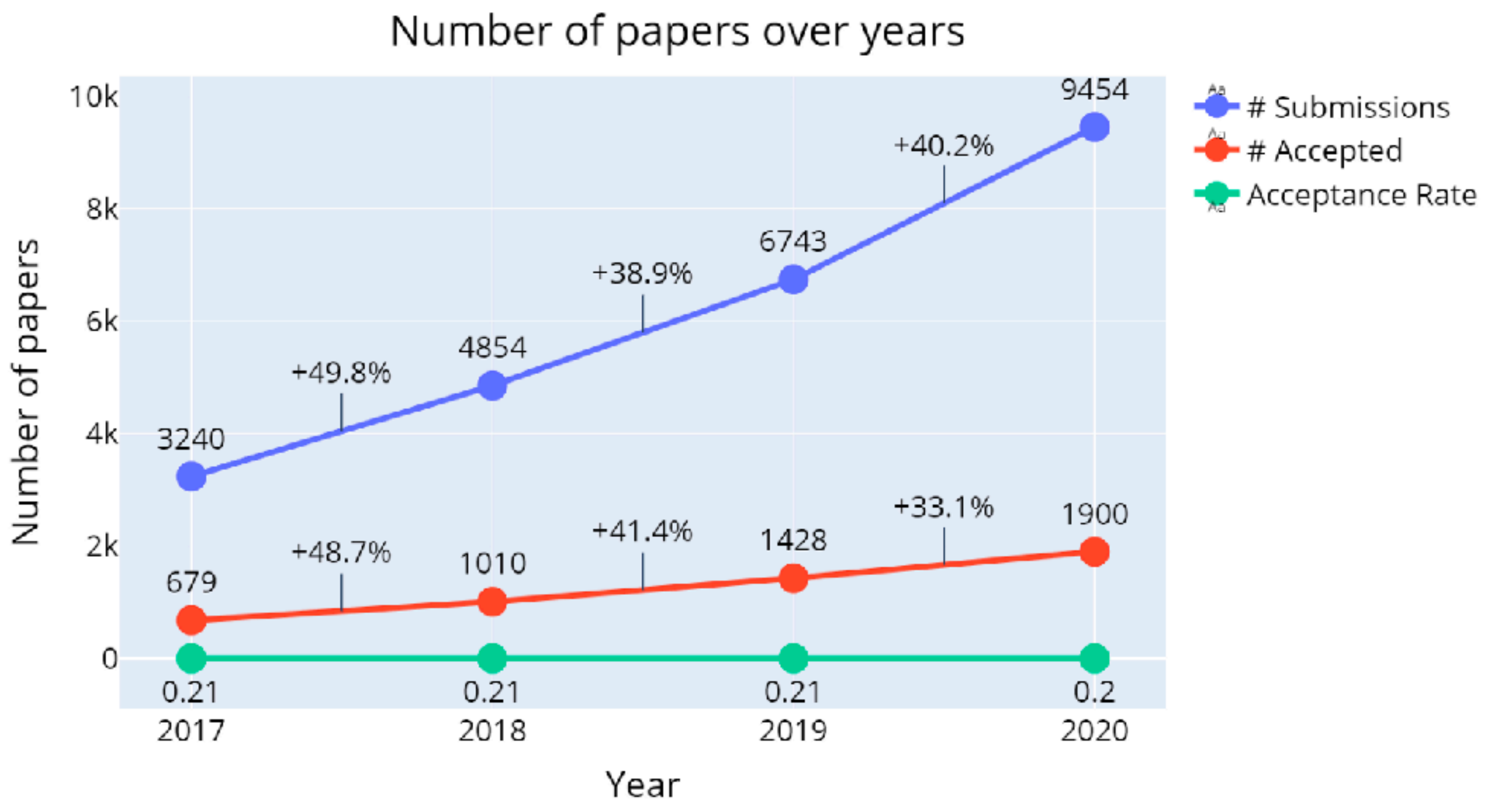
An Author-Assisted Approach to Improving Peer Review for Large CS Conferences, with Experiments at ICML 2023

Weijie Su

Wharton & CS, UPenn

What’s happening at ML/AI conferences?



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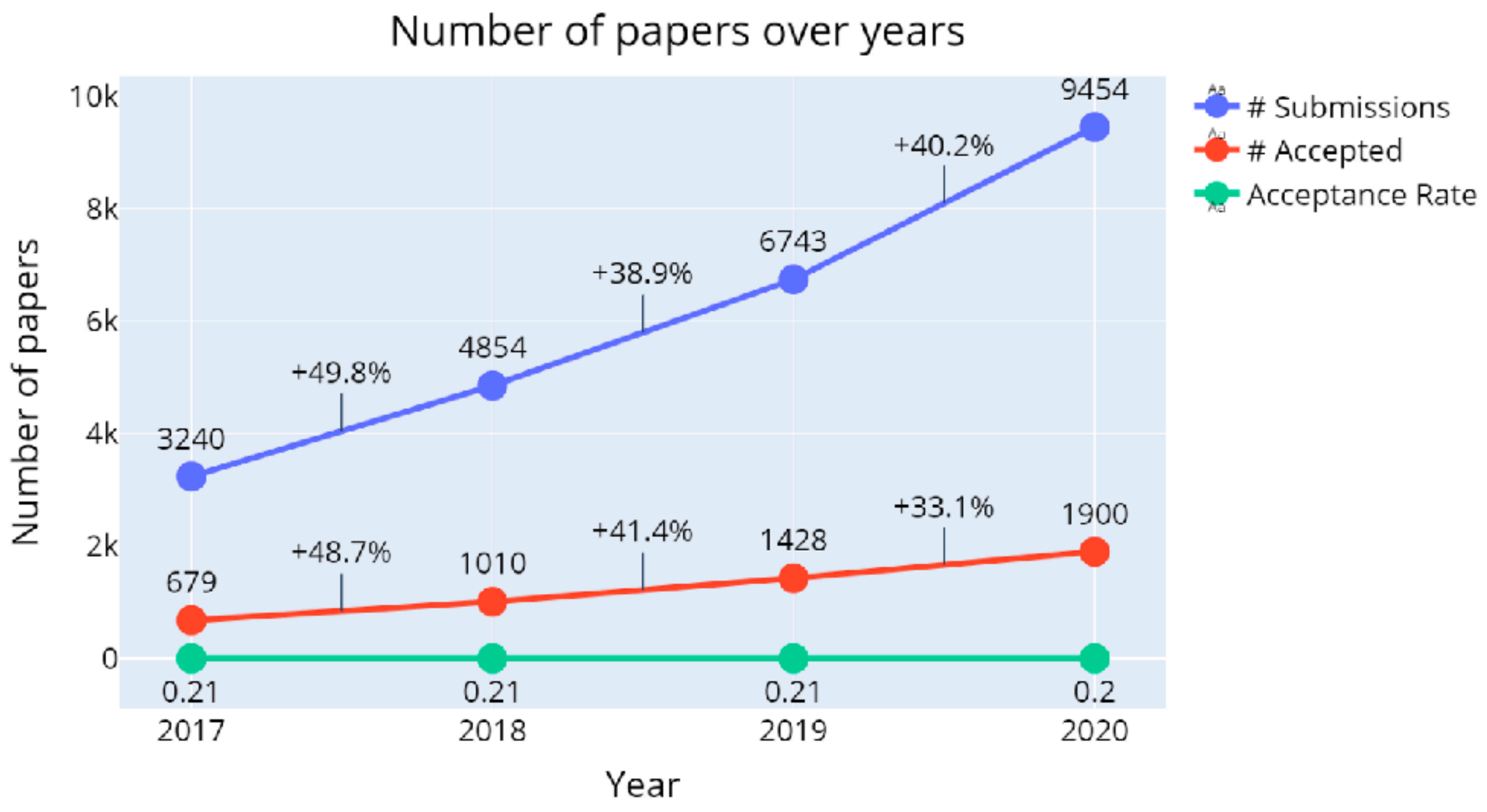

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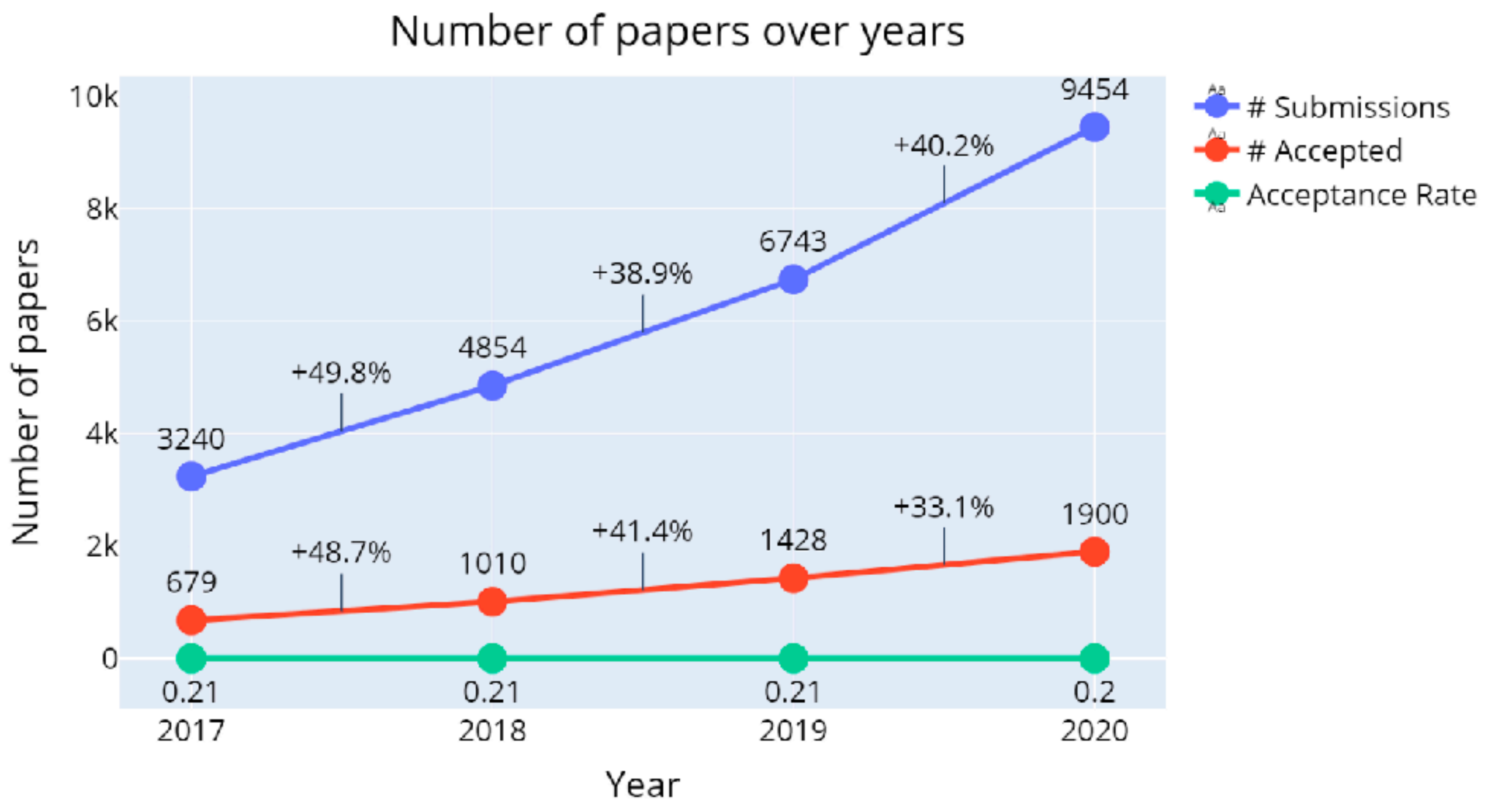


- A few weeks to review 6 or more papers
- 70% of reviewers in NeurIPS 2016 are PhD students (Shah 2022)

Trouble at ML/AI conferences

Inconsistency in Conference Peer Review: Revisiting the 2014 NeurIPS Experiment

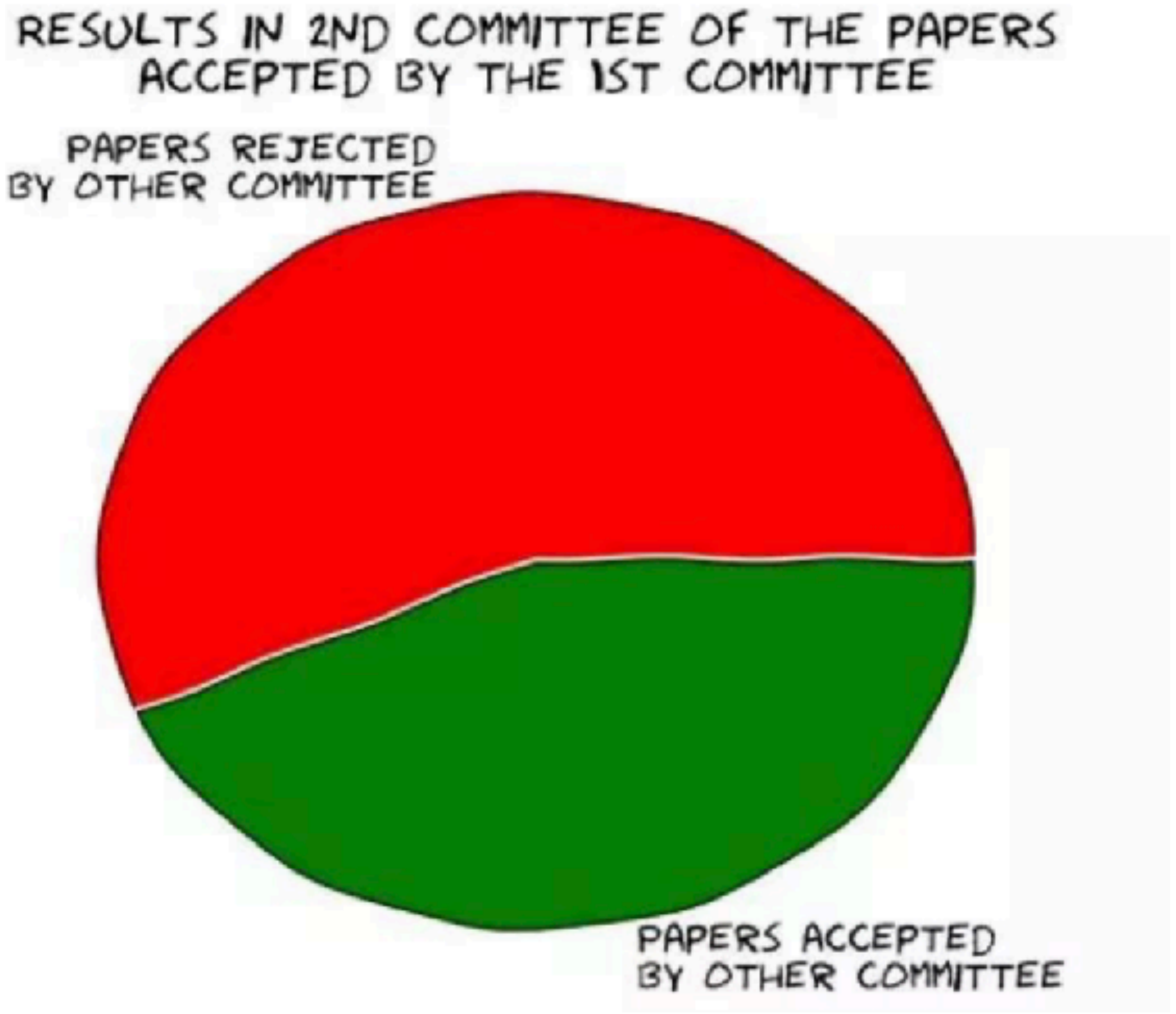
Corinna Cortes* and Neil D. Lawrence†

*Google Research, New York
†Computer Lab, University of Cambridge

September 22, 2021

Abstract

In this paper we revisit the 2014 NeurIPS experiment that examined inconsistency in conference peer review. We determine that 50% of the variation in reviewer quality scores was subjective in origin. Further, with seven years passing since the experiment we find that for *accepted* papers, there is no correlation between quality scores and impact of the paper as measured as a function of citation count. We trace the fate of rejected papers, recovering where these papers were eventually published. For these papers we find a correlation between quality scores and impact. We conclude that the reviewing process



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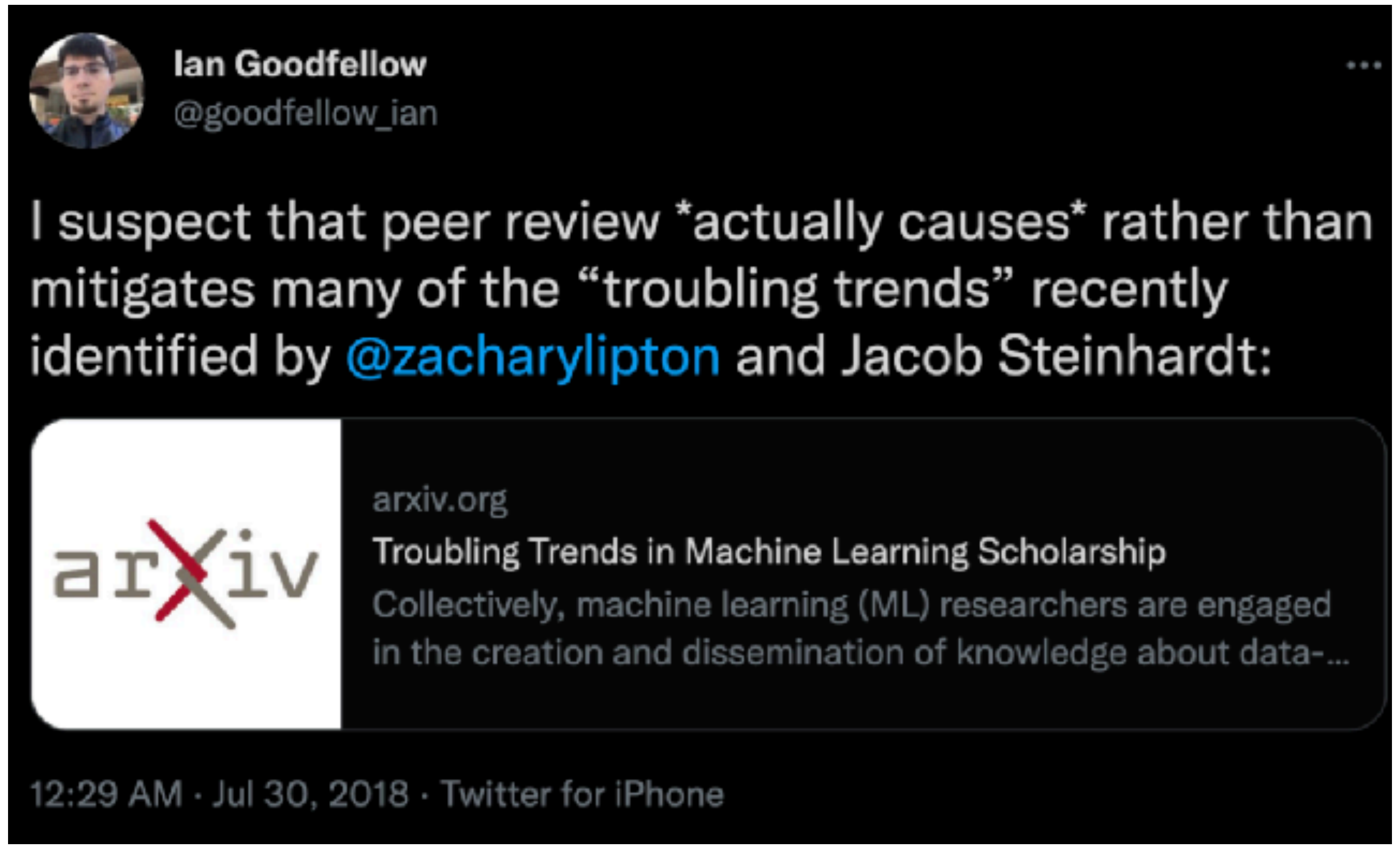

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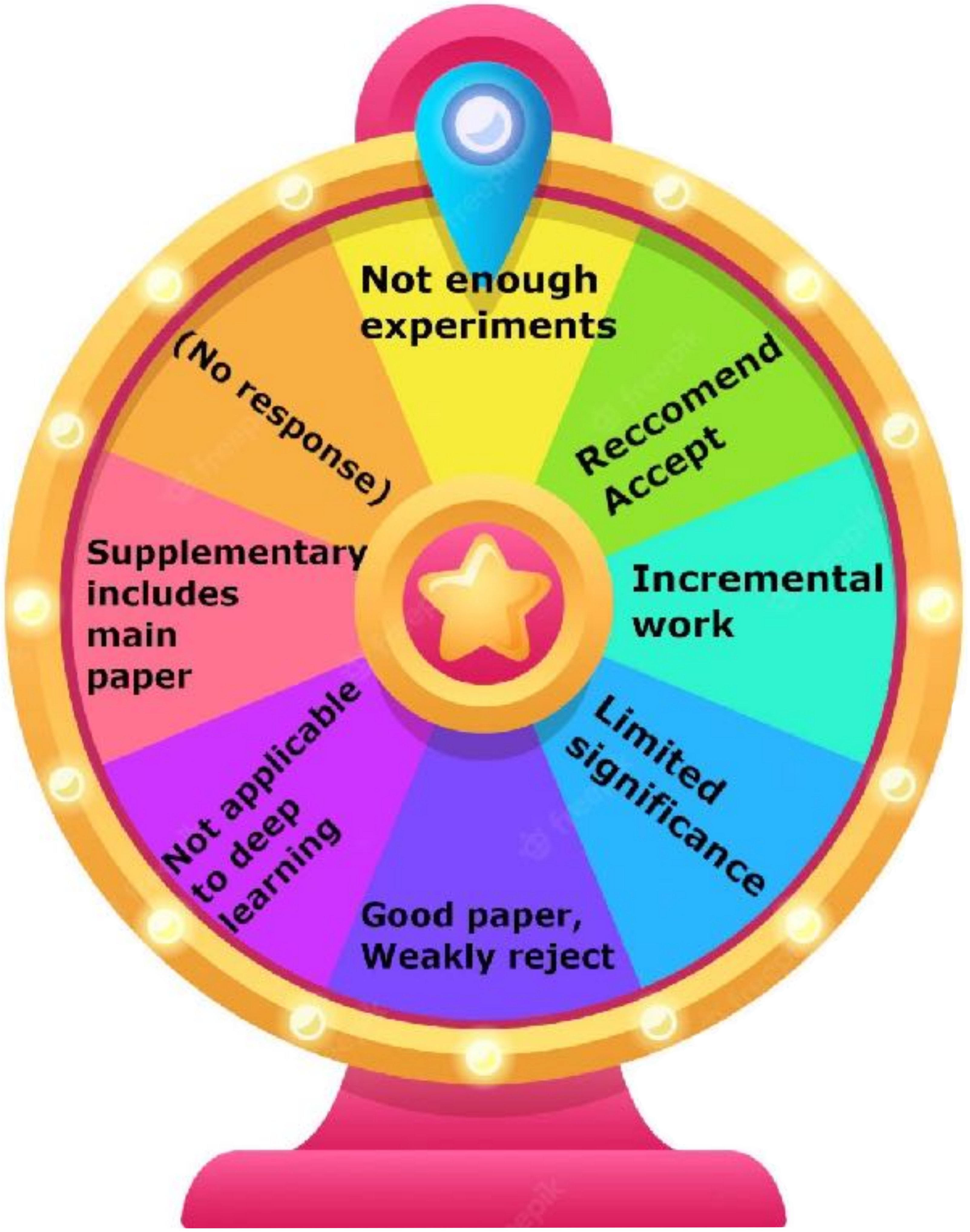


Trouble at ML/AI conferences


Ian Goodfellow
@goodfellow_ian

I suspect that peer review *actually causes* rather than mitigates many of the “troubling trends” recently identified by @zacharylipton and Jacob Steinhardt:

arxiv.org
Troubling Trends in Machin
Collectively, machine learn
in the creation and dissemi

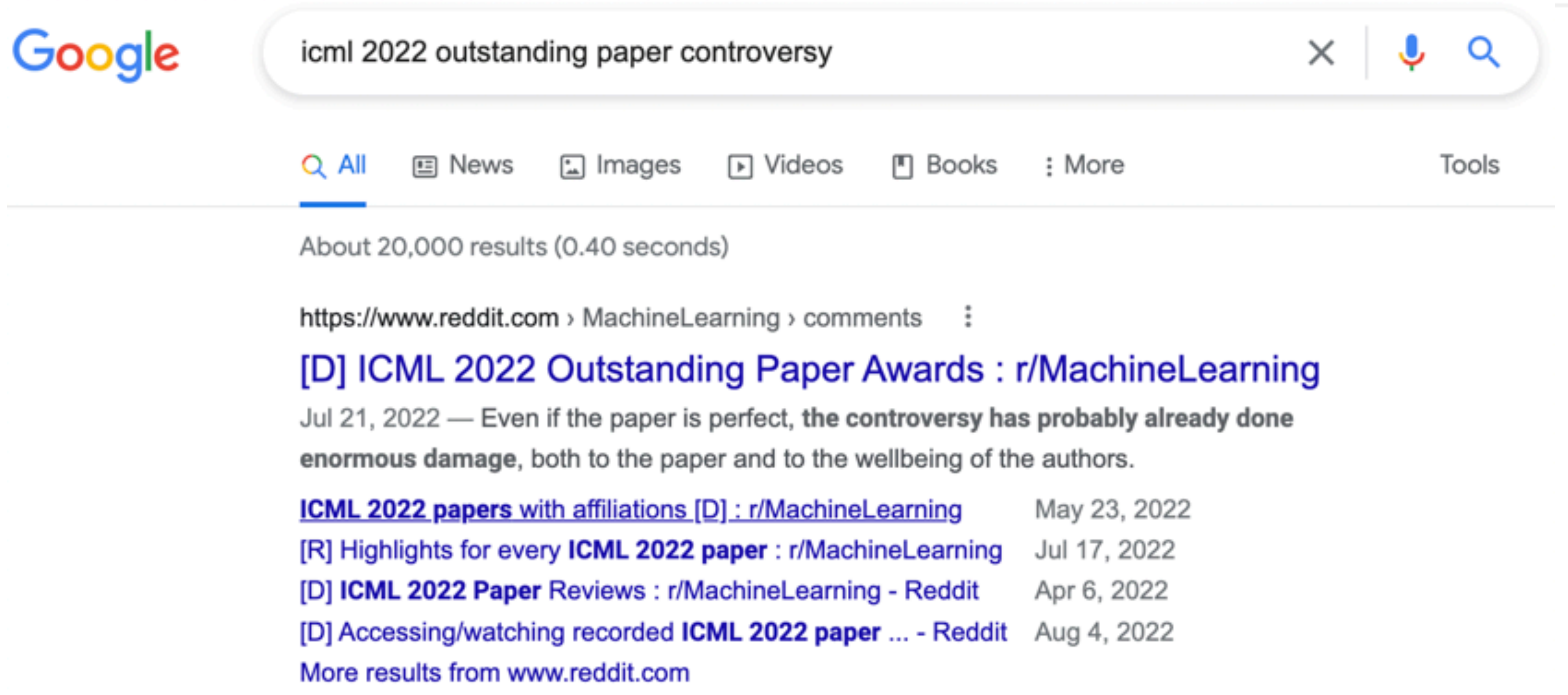
12:29 AM · Jul 30, 2018 · Twitter for iPhone


Yann LeCun
@ylecun

Verdict from @icmlconf:
3 out of 3 ..... rejected.

If I go by tweet statistics, ICML has rejeted every single paper this year 🤣

4:54 PM · May 15, 2022 · Twitter Web App


Google
icml 2022 outstanding paper controversy

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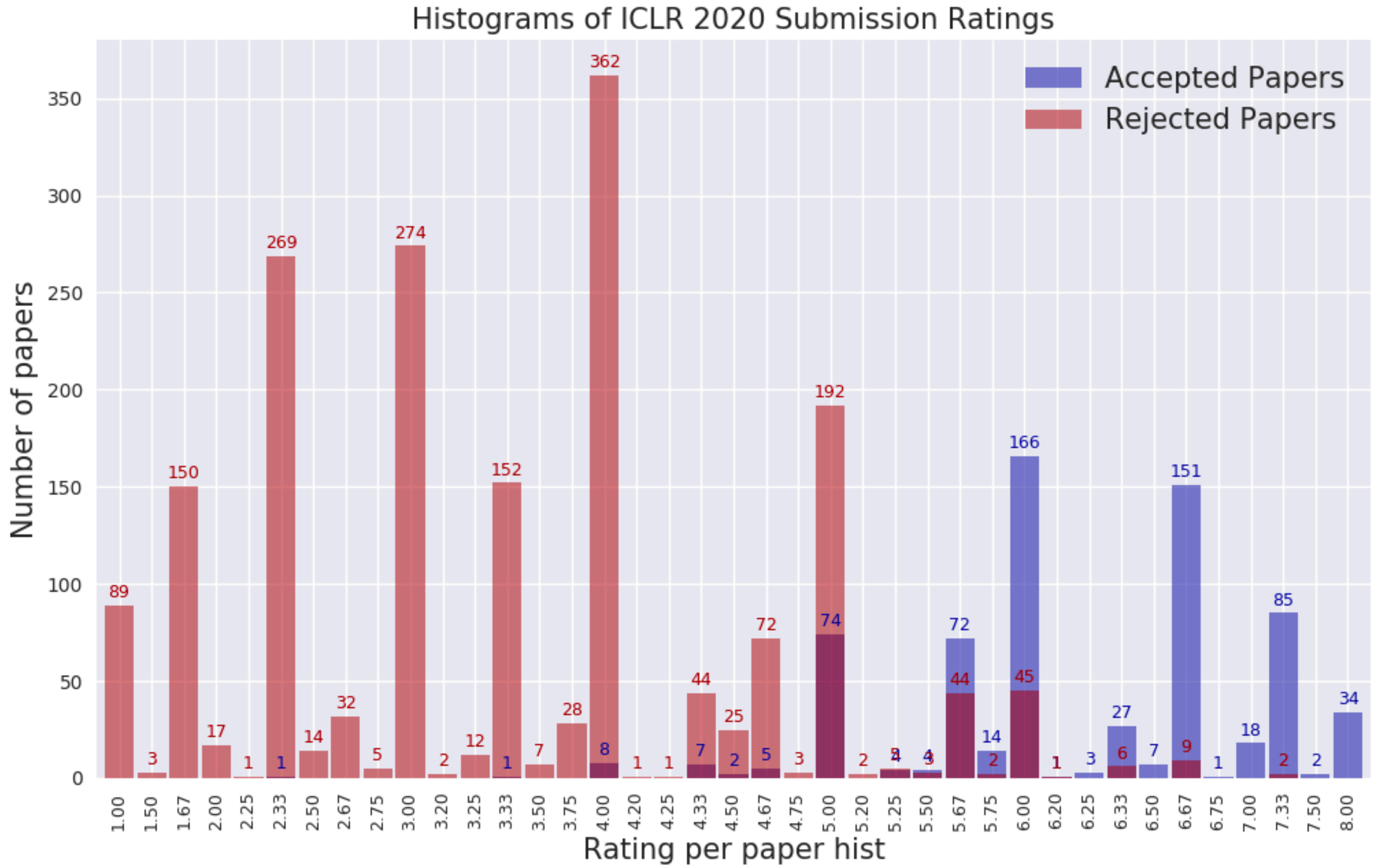
About 20,000 results (0.40 seconds)

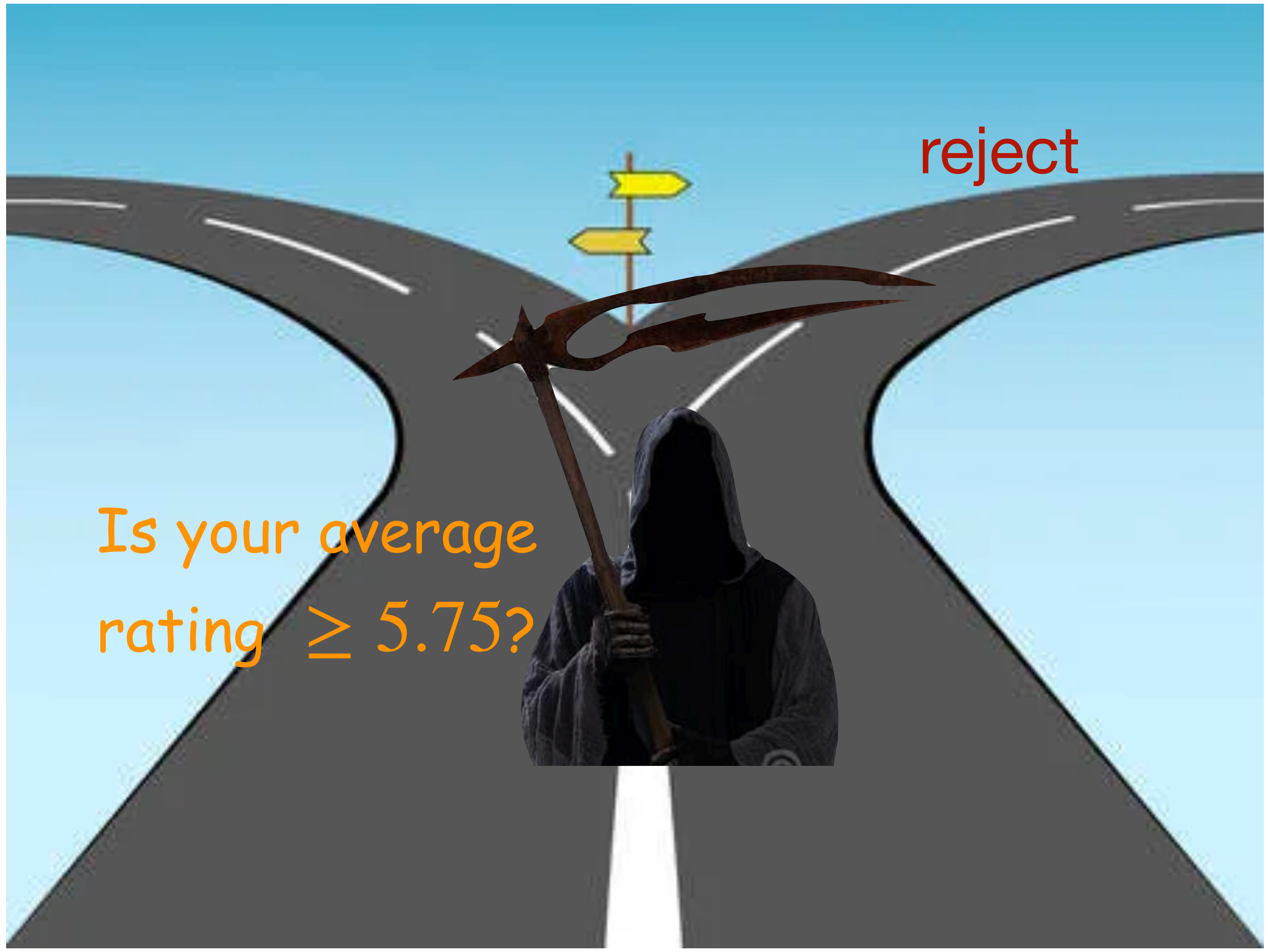
https://www.reddit.com › MachineLearning › comments
[D] ICML 2022 Outstanding Paper Awards : r/MachineLearning
Jul 21, 2022 — Even if the paper is perfect, **the controversy has probably already done enormous damage**, both to the paper and to the wellbeing of the authors.

ICML 2022 papers with affiliations [D] : r/MachineLearning — May 23, 2022
[R] Highlights for every ICML 2022 paper : r/MachineLearning — Jul 17, 2022
[D] ICML 2022 Paper Reviews : r/MachineLearning - Reddit — Apr 6, 2022
[D] Accessing/watching recorded ICML 2022 paper ... - Reddit — Aug 4, 2022
More results from www.reddit.com

Peer review via ratings



Credit: S.-H. Sun



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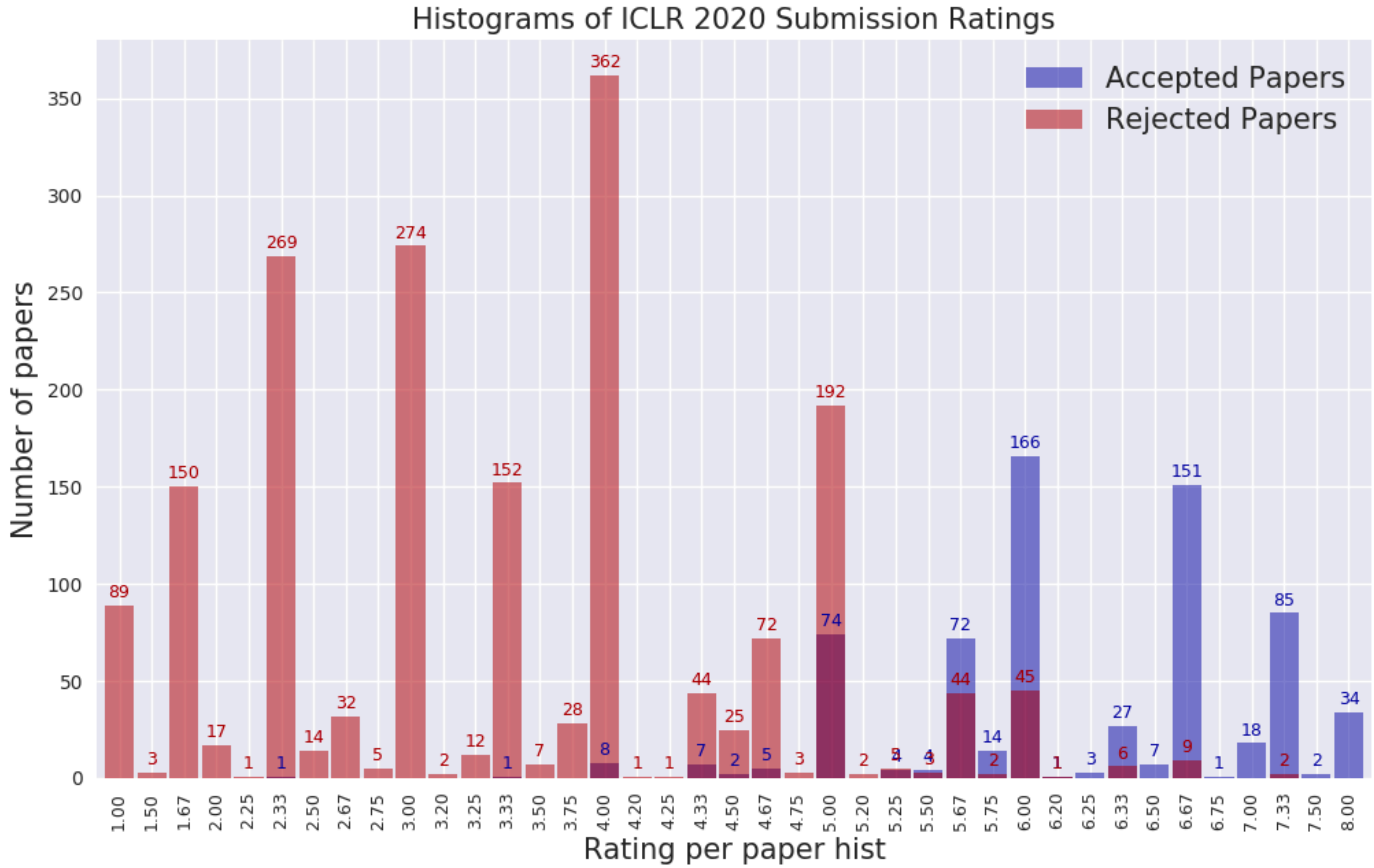

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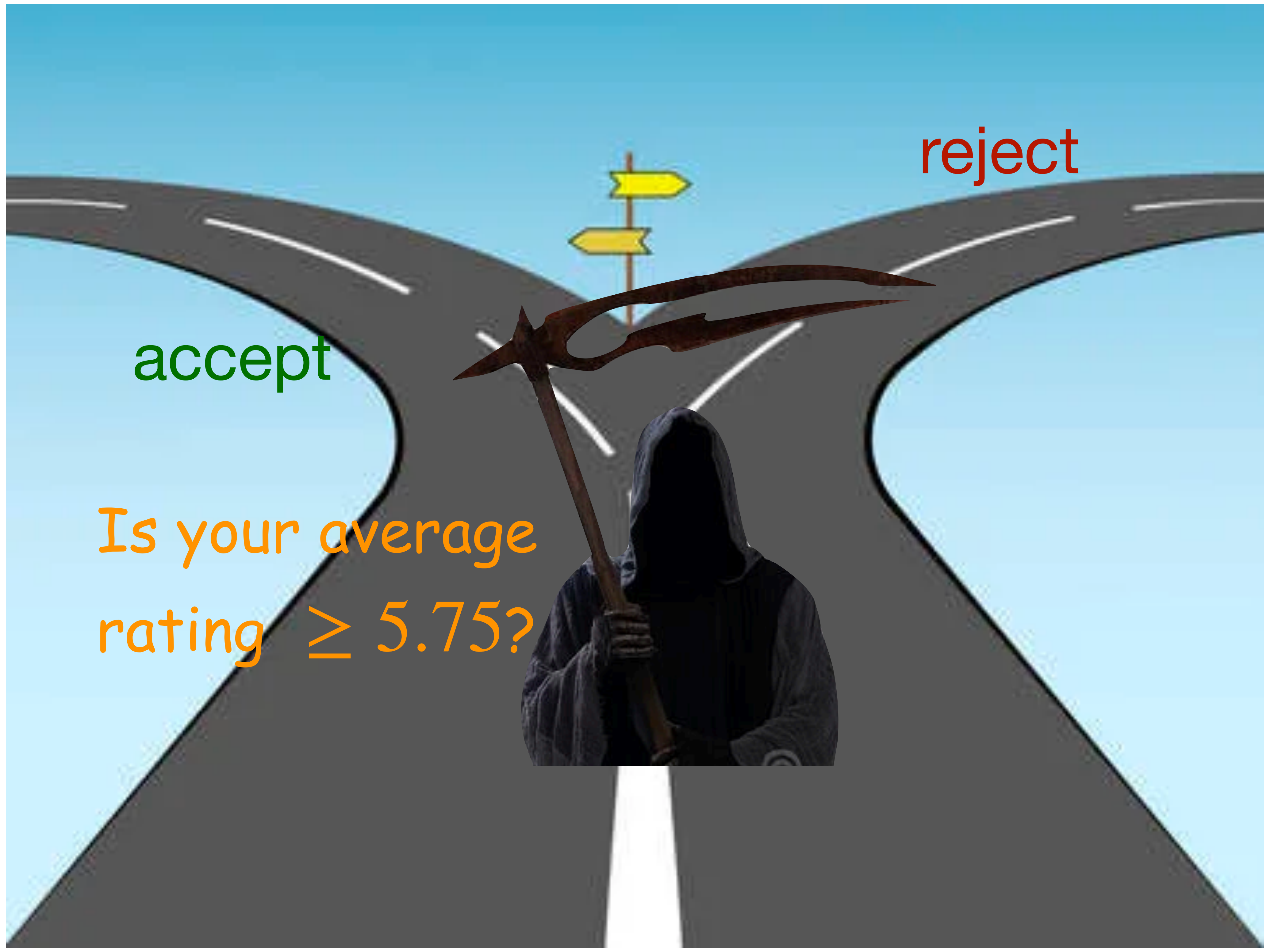

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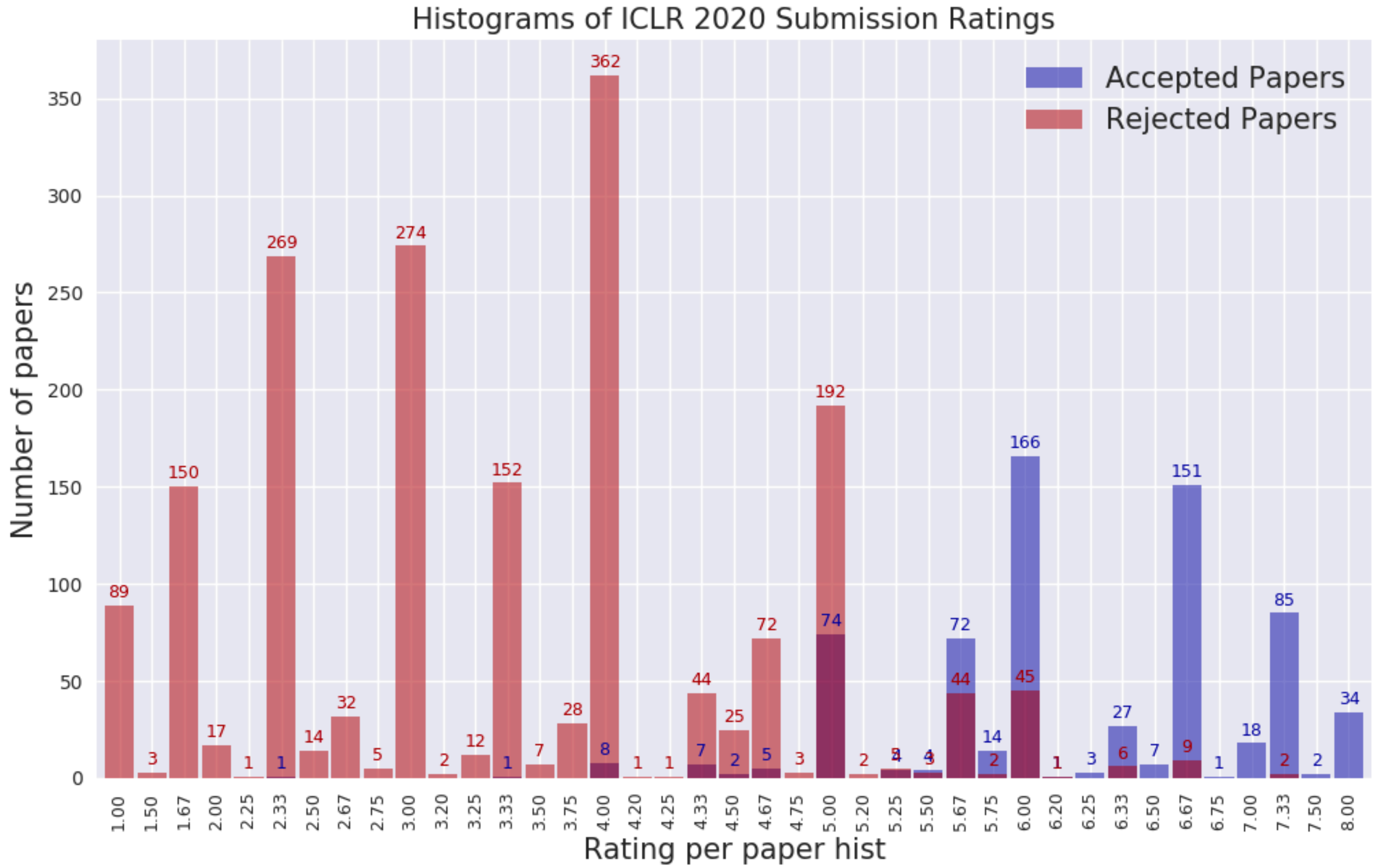

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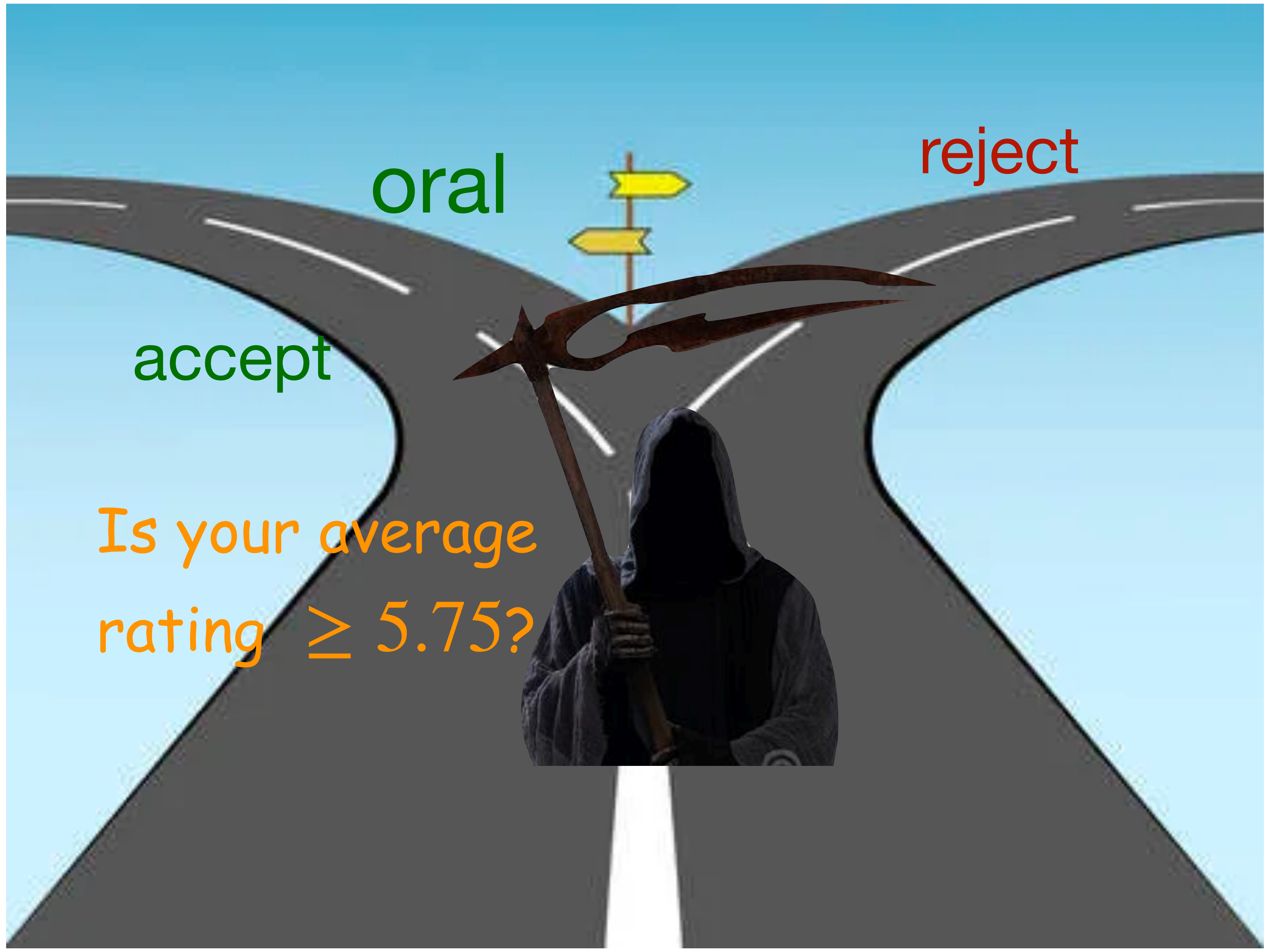

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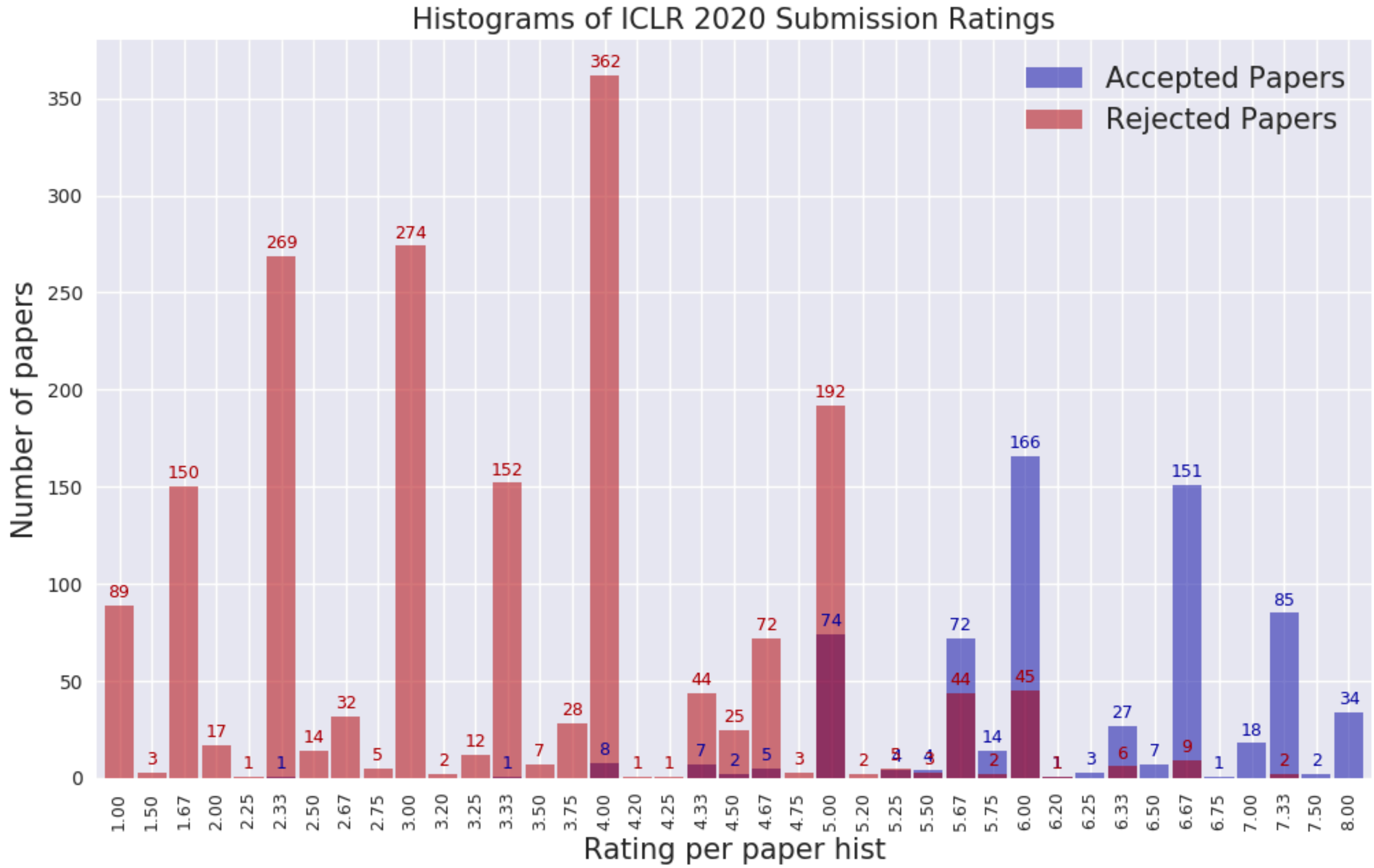

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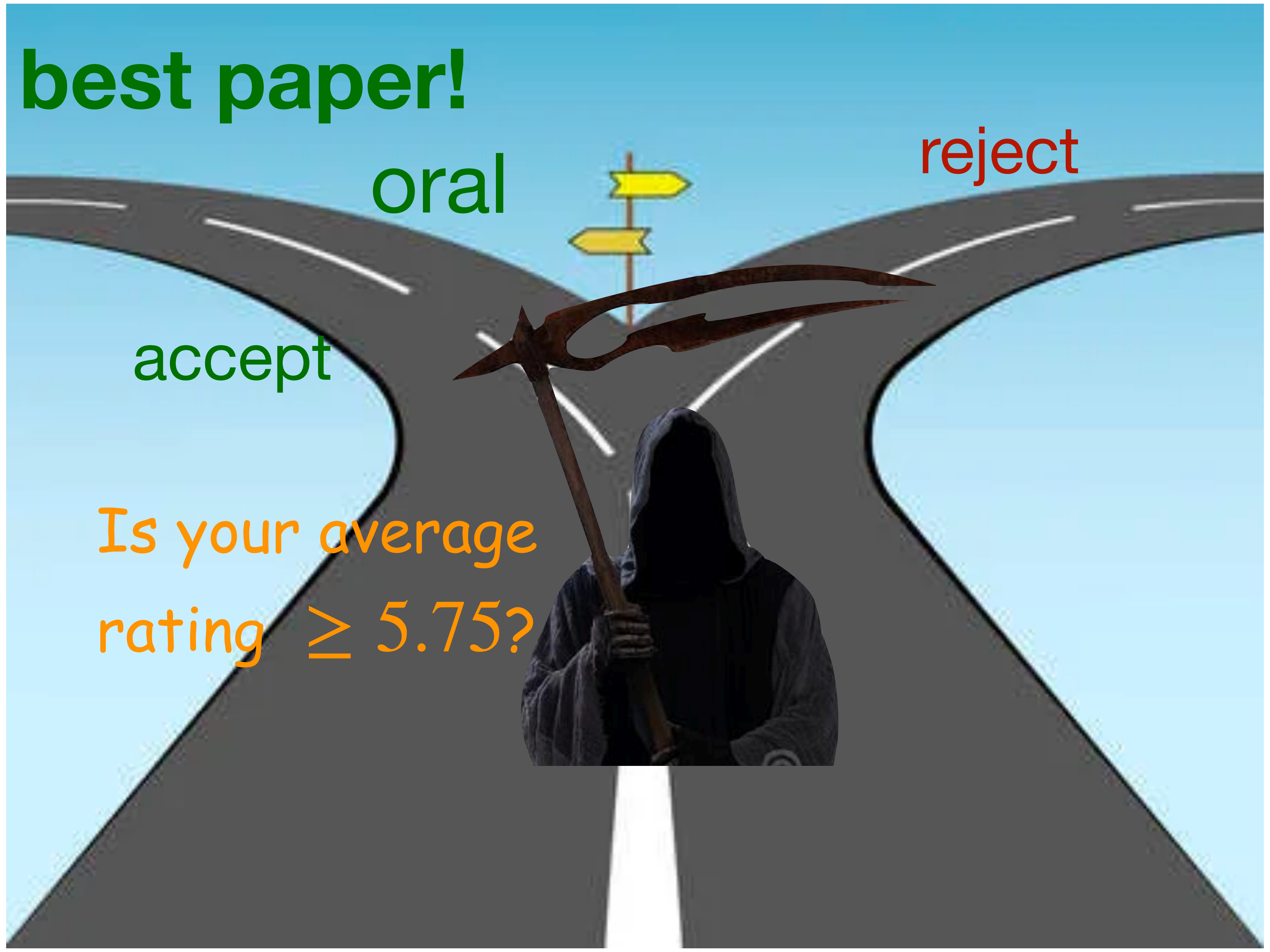
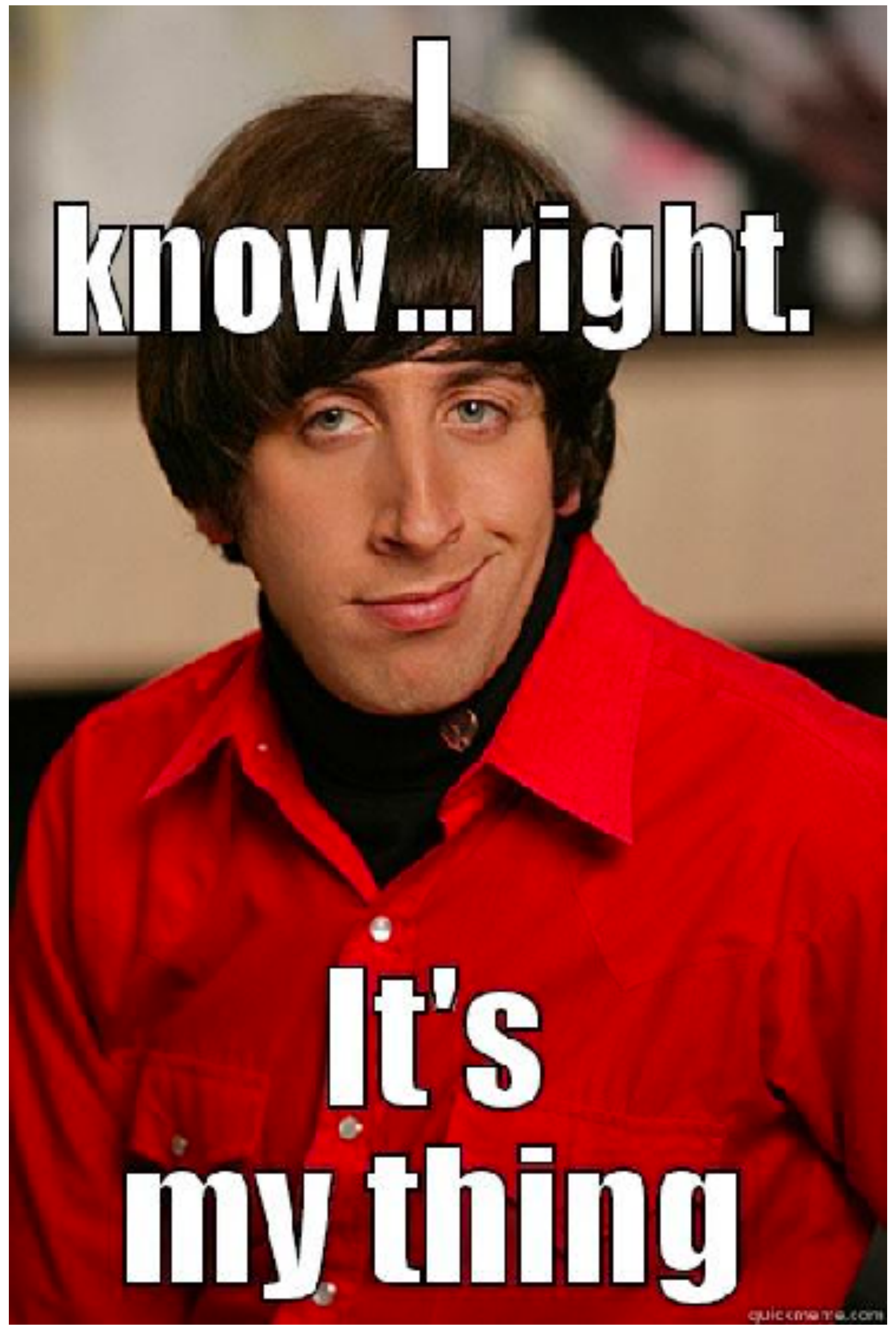


You (are supposed to) know your stuff well

Knowing yourself is the beginning of all wisdom



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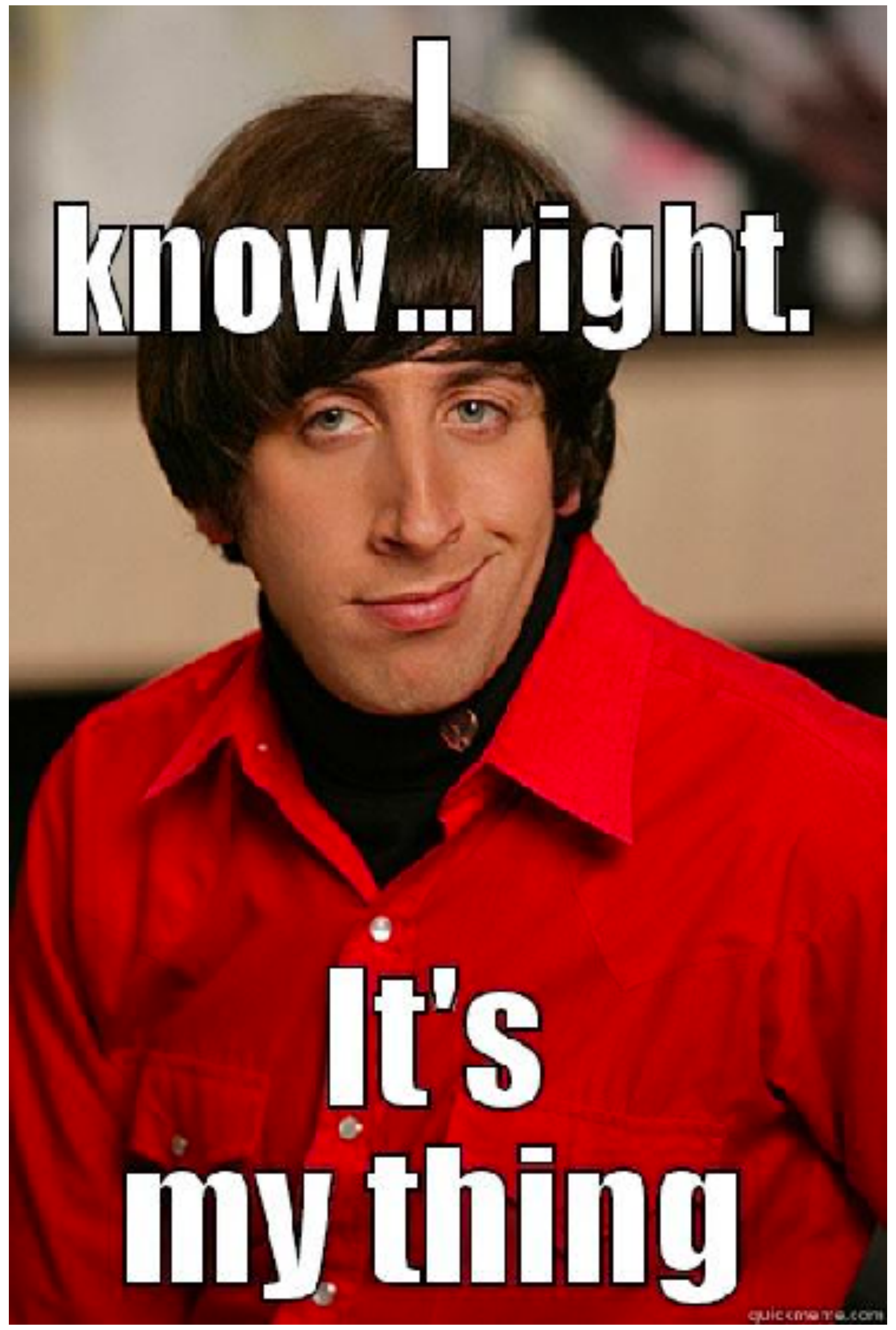

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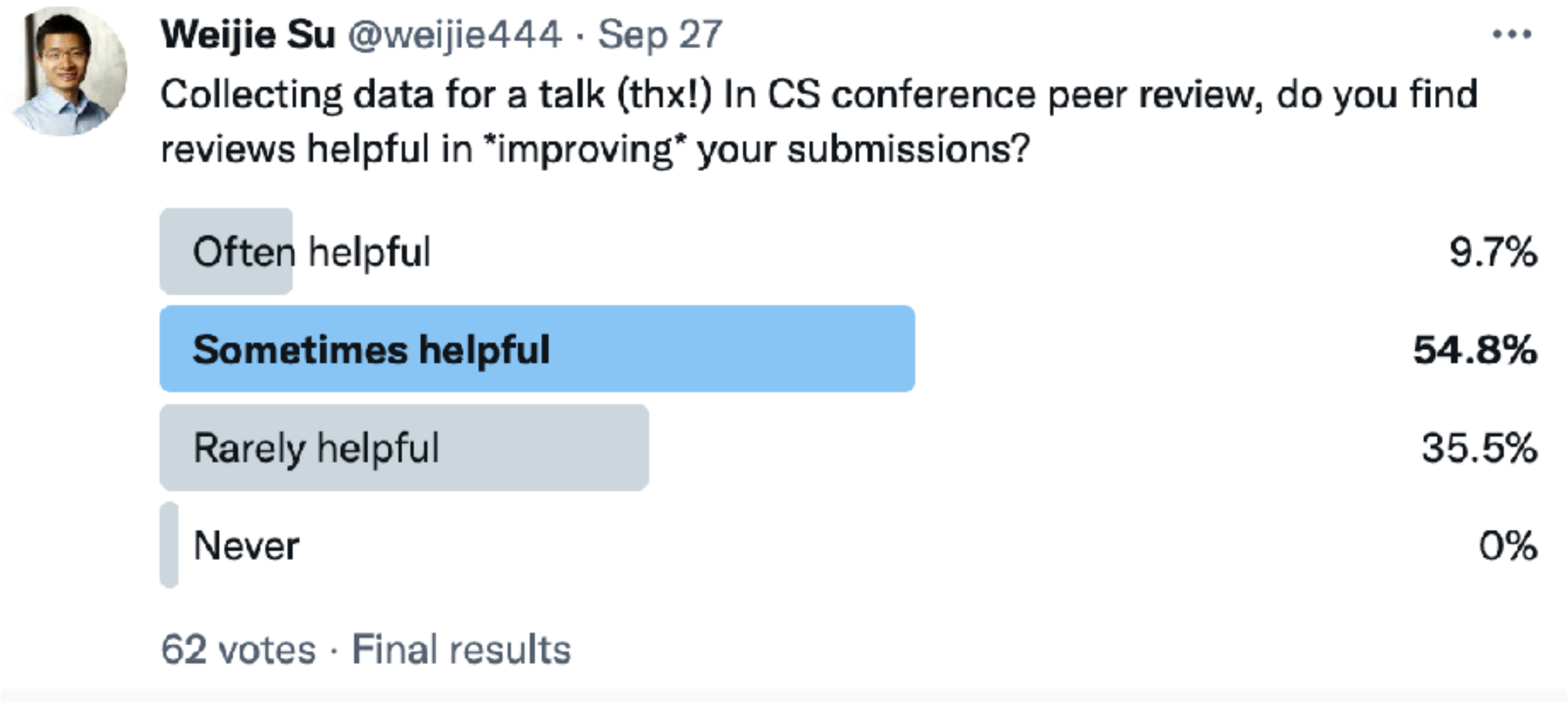


What does the community think?

Weijie Su @weijie444 · Sep 27

Collecting data for a talk (thx!) In CS conference peer review, do you find reviews helpful in *improving* your submissions?

Often helpful	9.7%
Sometimes helpful	**54.8%**
Rarely helpful	35.5%
Never	0%

62 votes · Final results

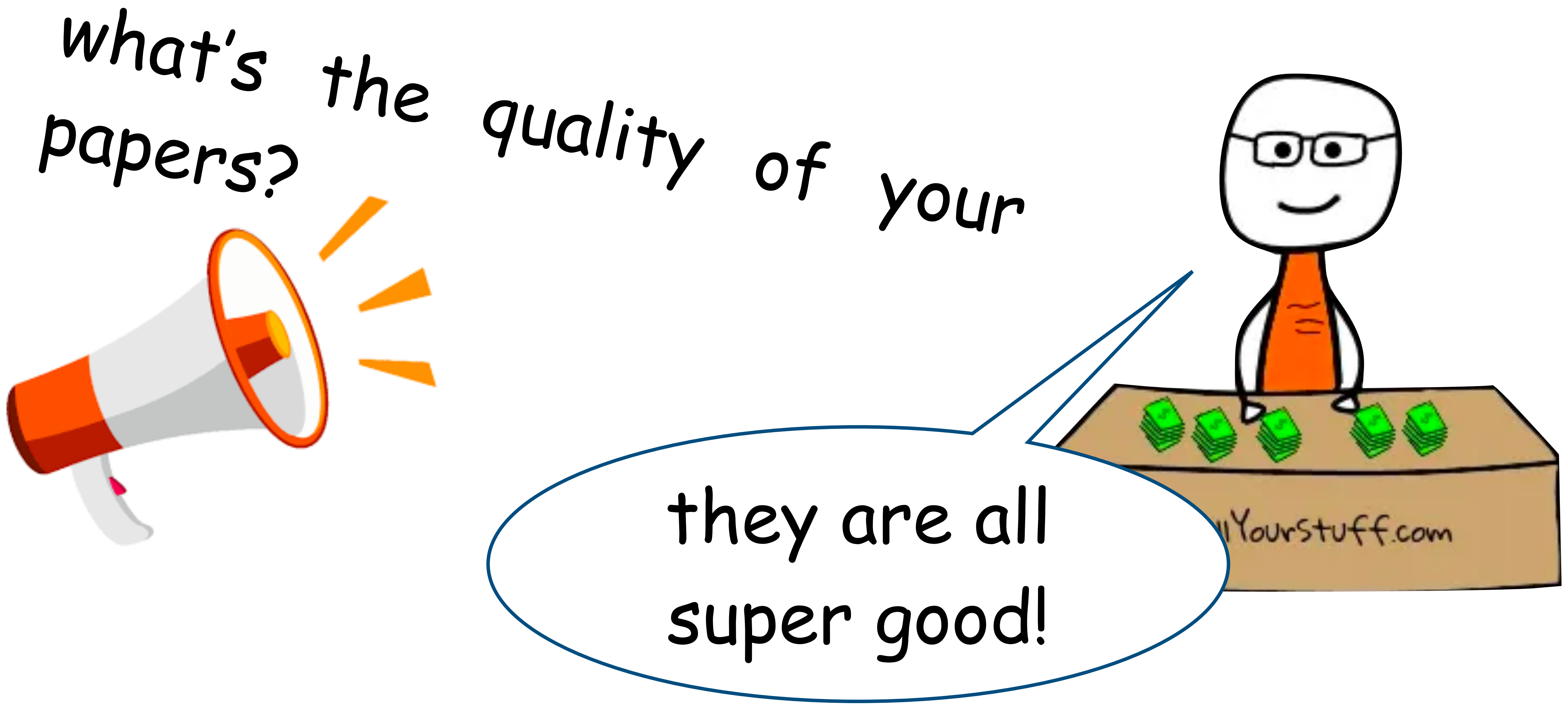
Weijie Su @weijie444 · Sep 27

Collecting more data for a talk (thx!!!) In CS conference peer review, did you see reviewers who knew about your submissions even better than you do (in an overall sense)?

Often	3.4%
Sometimes	11.6%
Rarely	**55.1%**
Never	29.9%

147 votes · Final results

Self evaluation? A bit ironic



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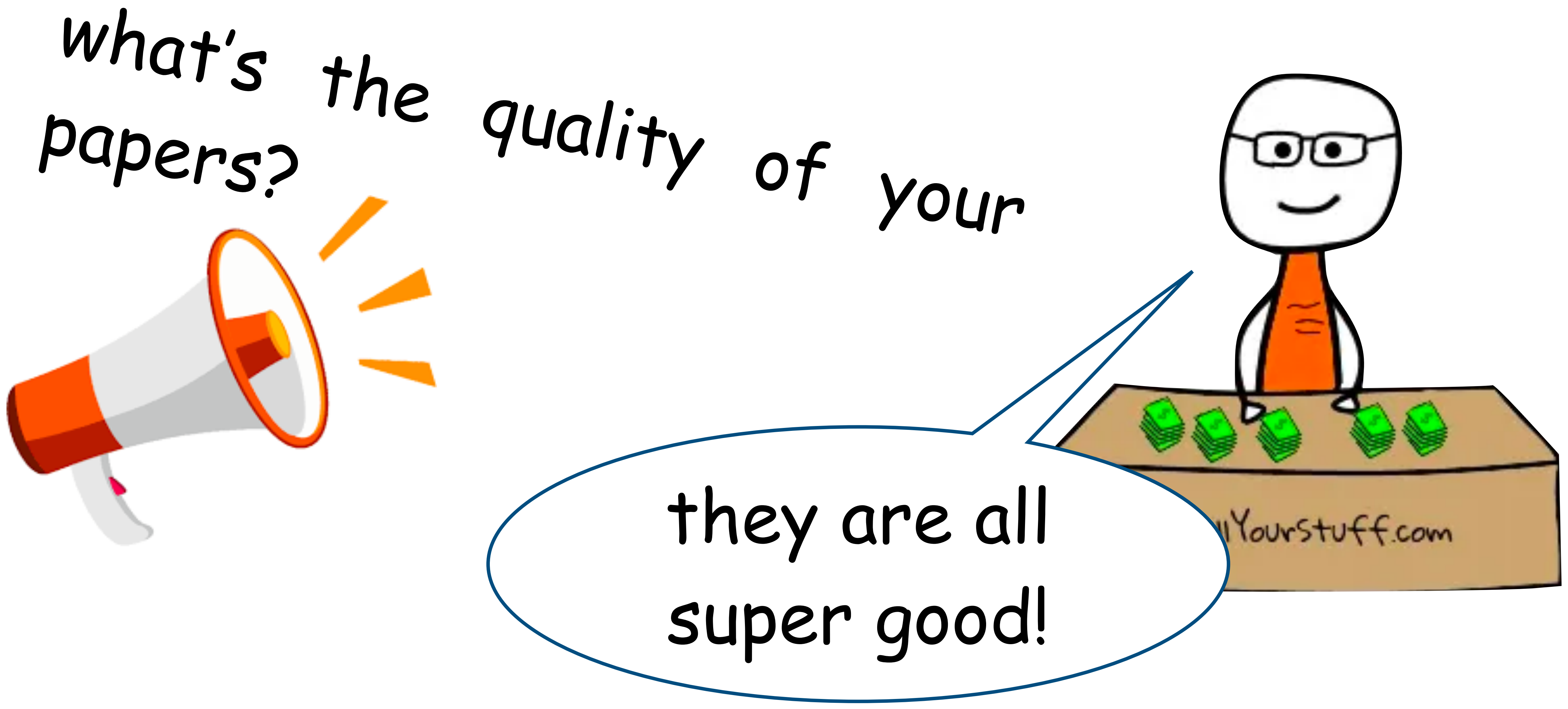

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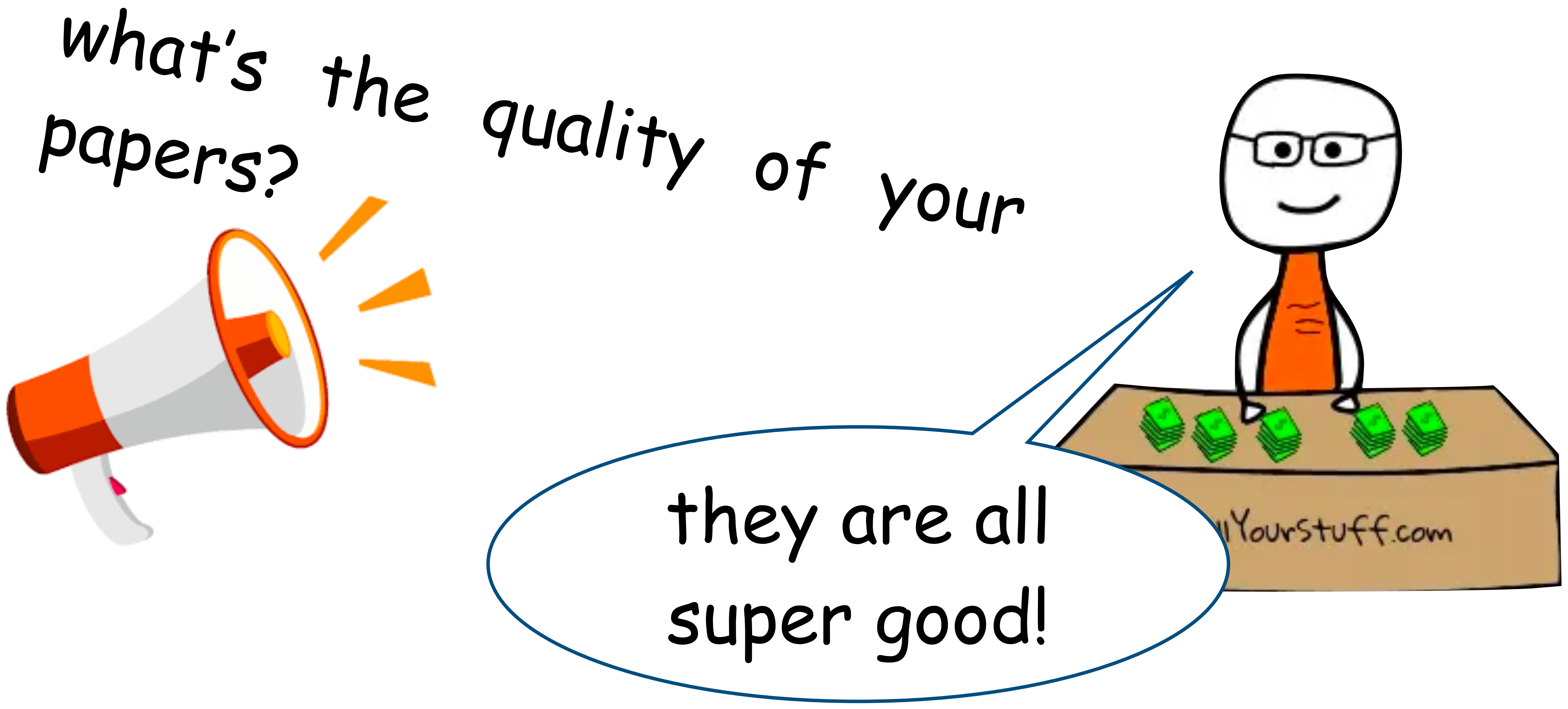

- Unfortunately, for most questions, the owner won't be truthful
- Lesson learned from the 737 Max crashes (FAA and Boeing)
- Related to property elicitation

A game between the *owner* and the *appraiser*

An owner and an appraiser

Alice owns many items

Bob estimates the underlying quality

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exogenous

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exogenous

An owner and an appraiser

Bob does NOT know $\boldsymbol{R}$

Alice owns many items

Alice does NOT observe $\boldsymbol{y}$

Bob estimates the underlying quality

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3. What is Alice's goal? What does she want?

Problem setup

Model: $y_i = R_i + z_i$

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1. $\mathcal{S} = \{S_1, S_2, \ldots, S_m\}$ is a (knowledge) partition of $\mathbb{R}^n$. Bob asks which knowledge element S from $\mathcal{S}$ contains $\boldsymbol{R} = (R_1, R_2, \ldots, R_n)$

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2. Given Alice's answer S, Bob solves $\hat{\boldsymbol{R}}$ from:

$$\begin{aligned} \min_{\boldsymbol{r}} \quad & \|\boldsymbol{y} - \boldsymbol{r}\|^2 \\ \text{s.t.} \quad & \boldsymbol{r} \in S \end{aligned}$$

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shape-restricted regression; or simply projection

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3. Alice strives to maximize her expected utility $\mathbb{E}\left[U(\hat{R}_1) + \cdots + U(\hat{R}_n)\right]$ by reporting any knowledge element, *truthfully* or *not*

Examples of knowledge partitions

Knowledge partition $\mathcal{S}$ is fixed at the beginning

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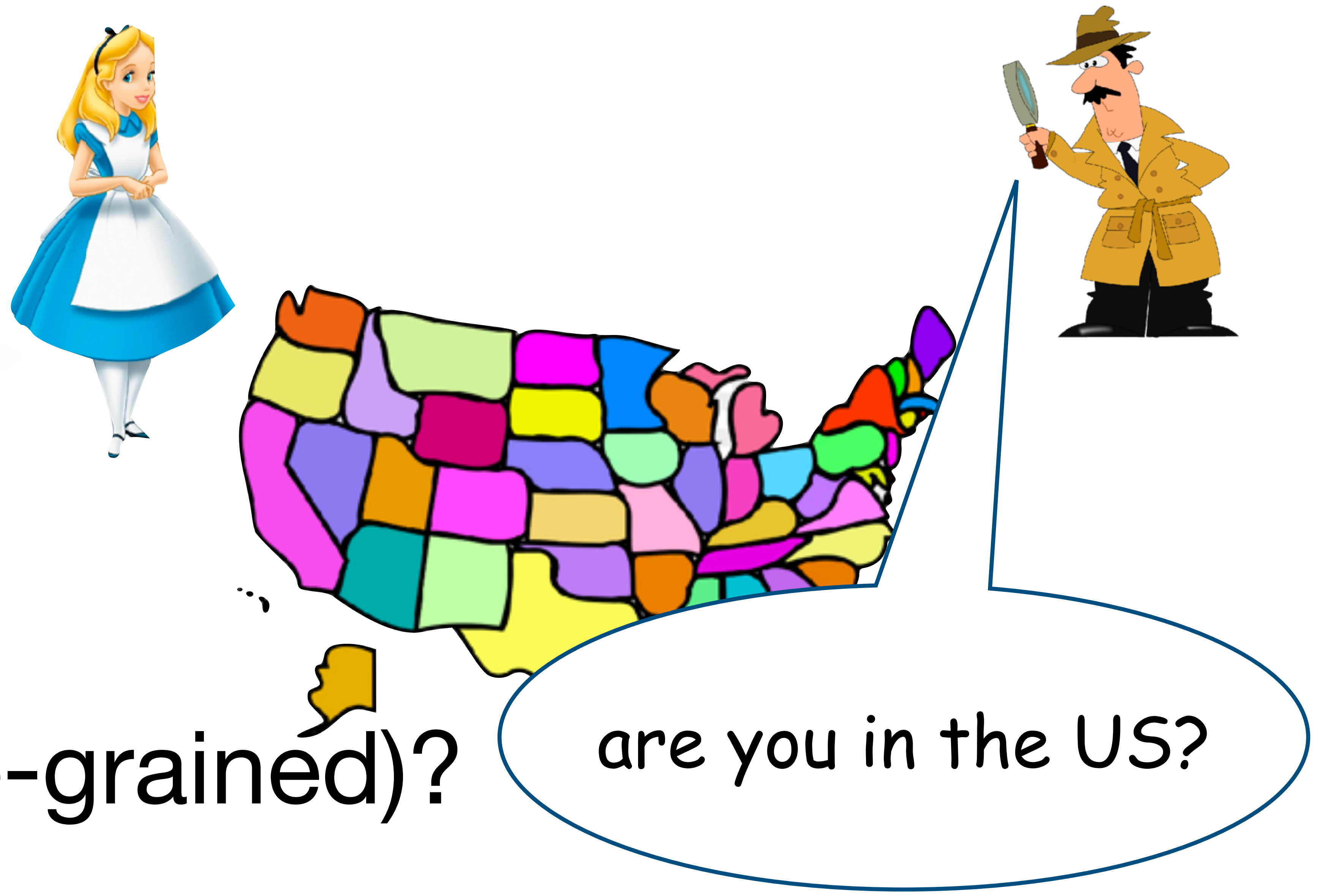

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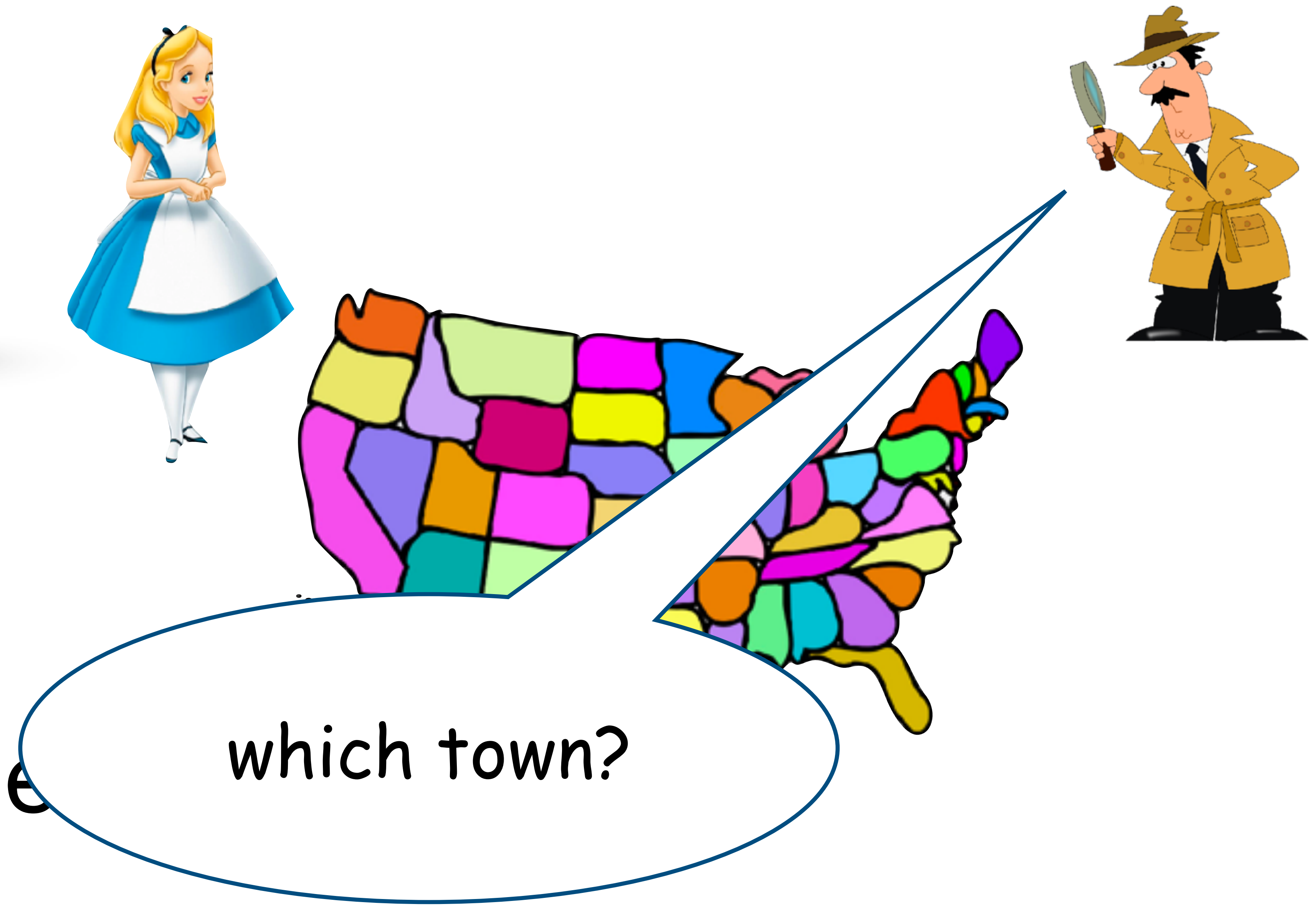

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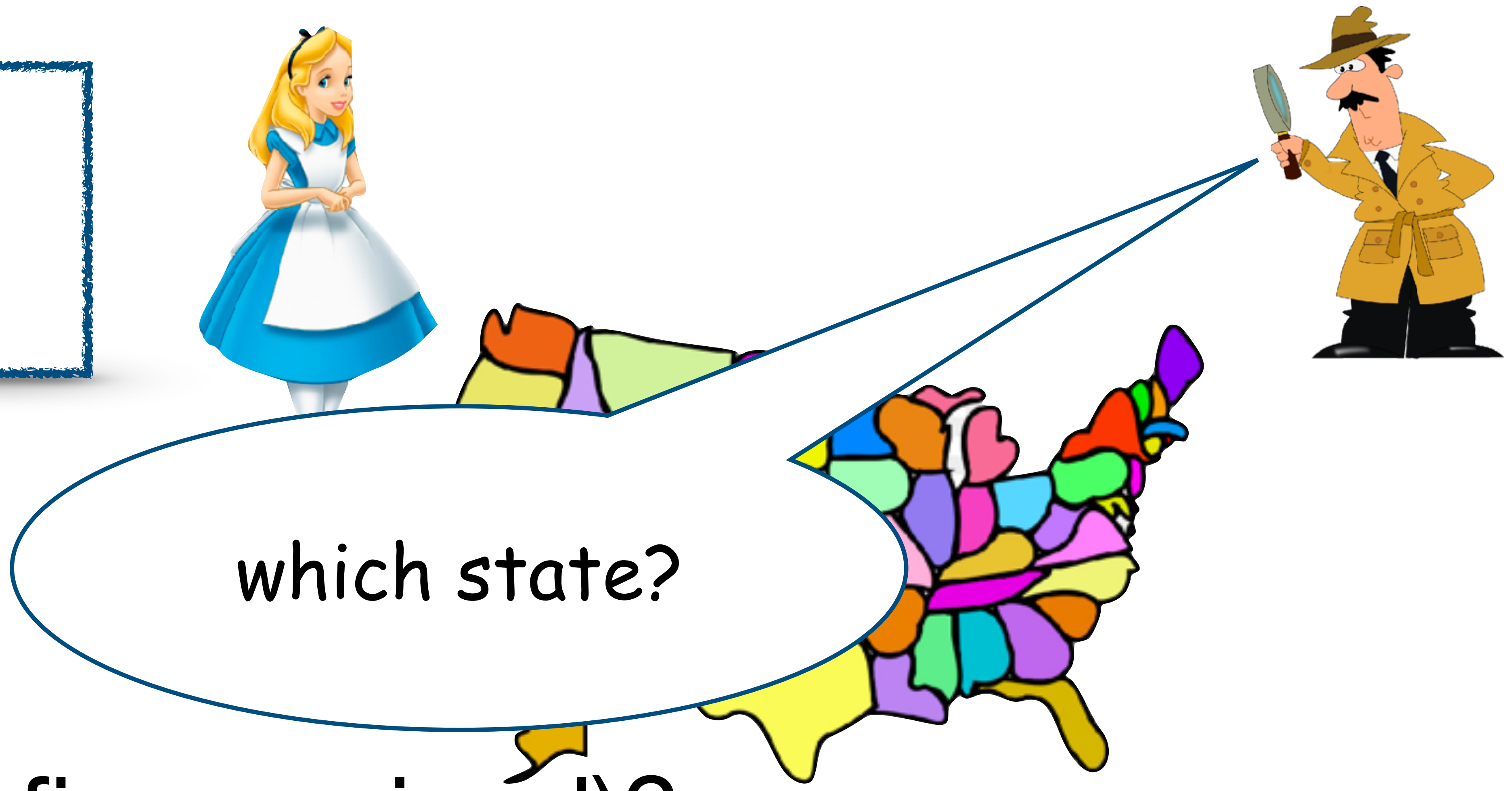

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Truthfulness improves estimation

Suppose S is convex and contains $\boldsymbol{R}$. Bob improves estimation:

$$\mathbb{E}\|\hat{\boldsymbol{R}}_S - \boldsymbol{R}\|^2 \leq \mathbb{E}\|\boldsymbol{y} - \boldsymbol{R}\|^2$$

- $\mathbb{E}\|\boldsymbol{y} - \boldsymbol{R}\|^2$ corresponds to the trivial knowledge partition $\{\mathbb{R}^n\}$
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Let z_i's be i.i.d. normally distributed. Let cone S_2 be a subset of cone S_1. If $\boldsymbol{R} \in S_2$,

$$\limsup_{\sigma \to 0} \frac{\mathbb{E}\|\hat{\boldsymbol{R}}_{S_2} - \boldsymbol{R}\|^2}{\mathbb{E}\|\hat{\boldsymbol{R}}_{S_1} - \boldsymbol{R}\|^2} \leq 1, \quad \limsup_{\sigma \to \infty} \frac{\mathbb{E}\|\hat{\boldsymbol{R}}_{S_2} - \boldsymbol{R}\|^2}{\mathbb{E}\|\hat{\boldsymbol{R}}_{S_1} - \boldsymbol{R}\|^2} \leq 1$$

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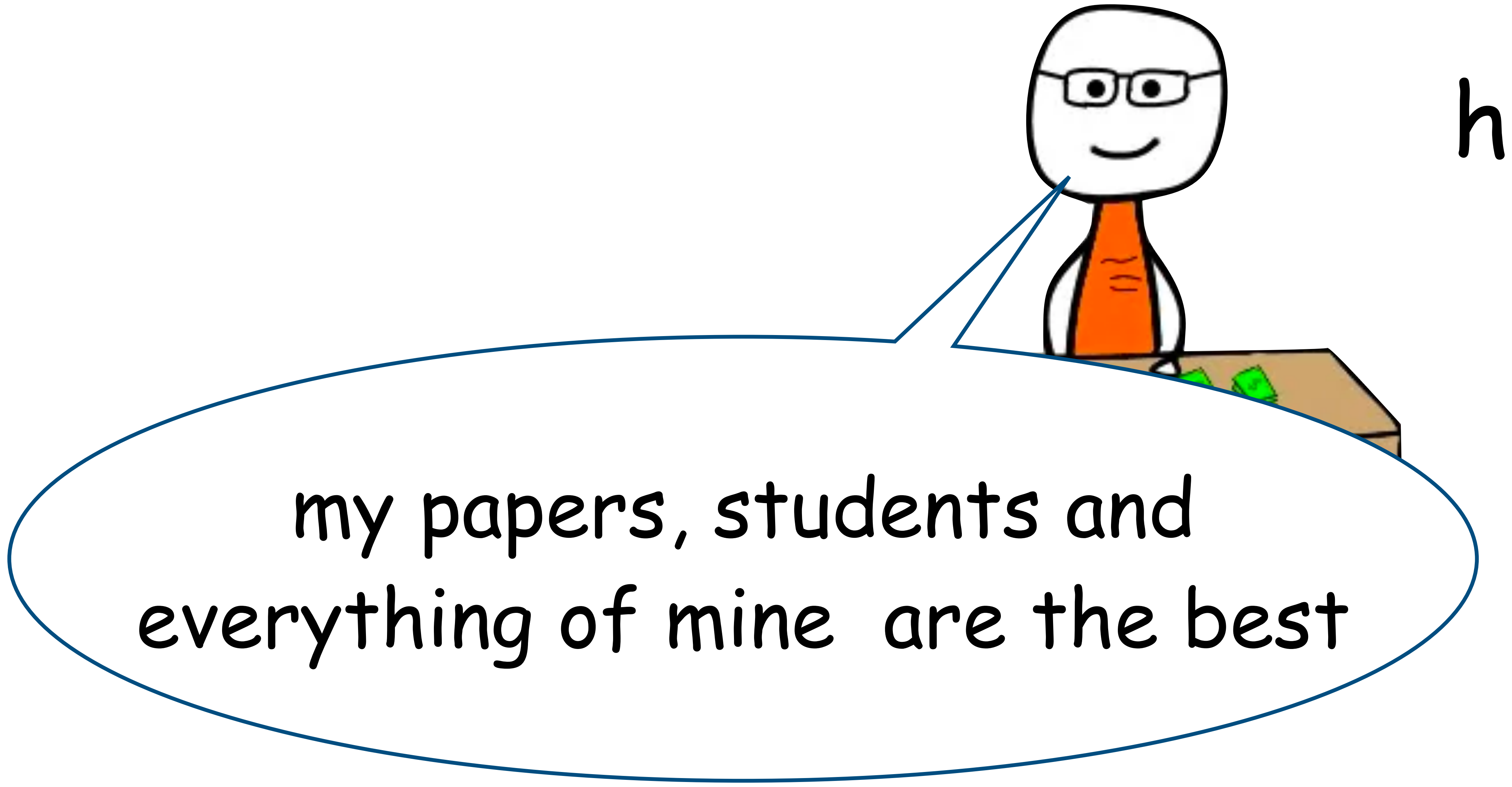

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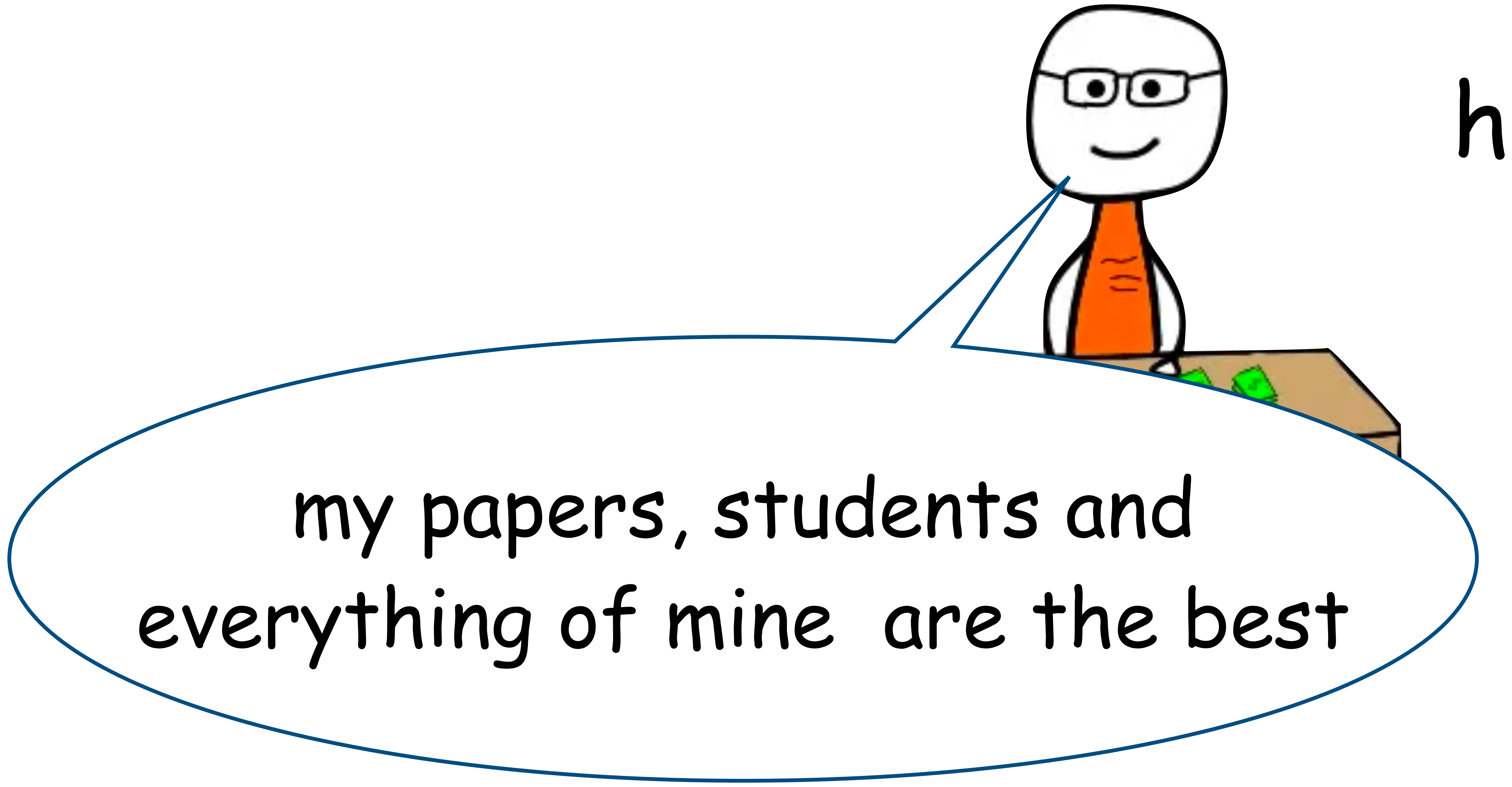

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can be relaxed to exchangeability

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Assumptions

STAY TUNED

more discussions later

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3. Alice's utility function U is a (nondecreasing) convex function

can be non-decomposable (Schur convex) and heterogeneous

On the convexity assumption

why $U(\text{so so}) + U(\text{outstanding}) \geq 2U(\text{good})$?
At least for some applications

Alice is rational and wants to maximize

$$\mathbb{E}\left[U(\hat{R}_1) + \cdots + U(\hat{R}_n)\right]$$

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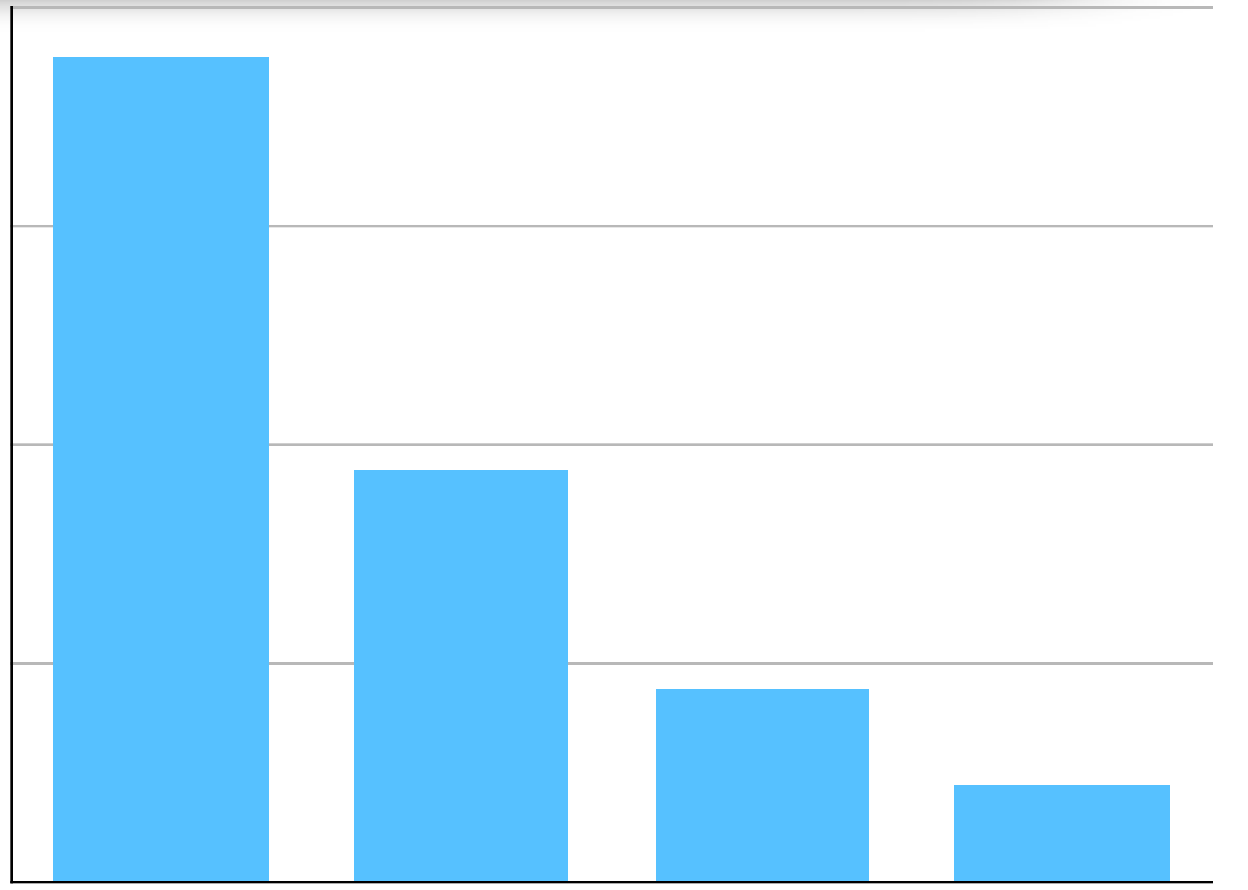
1. Best paper award $\ggg$ oral presentation $\gg$ spotlight > poster



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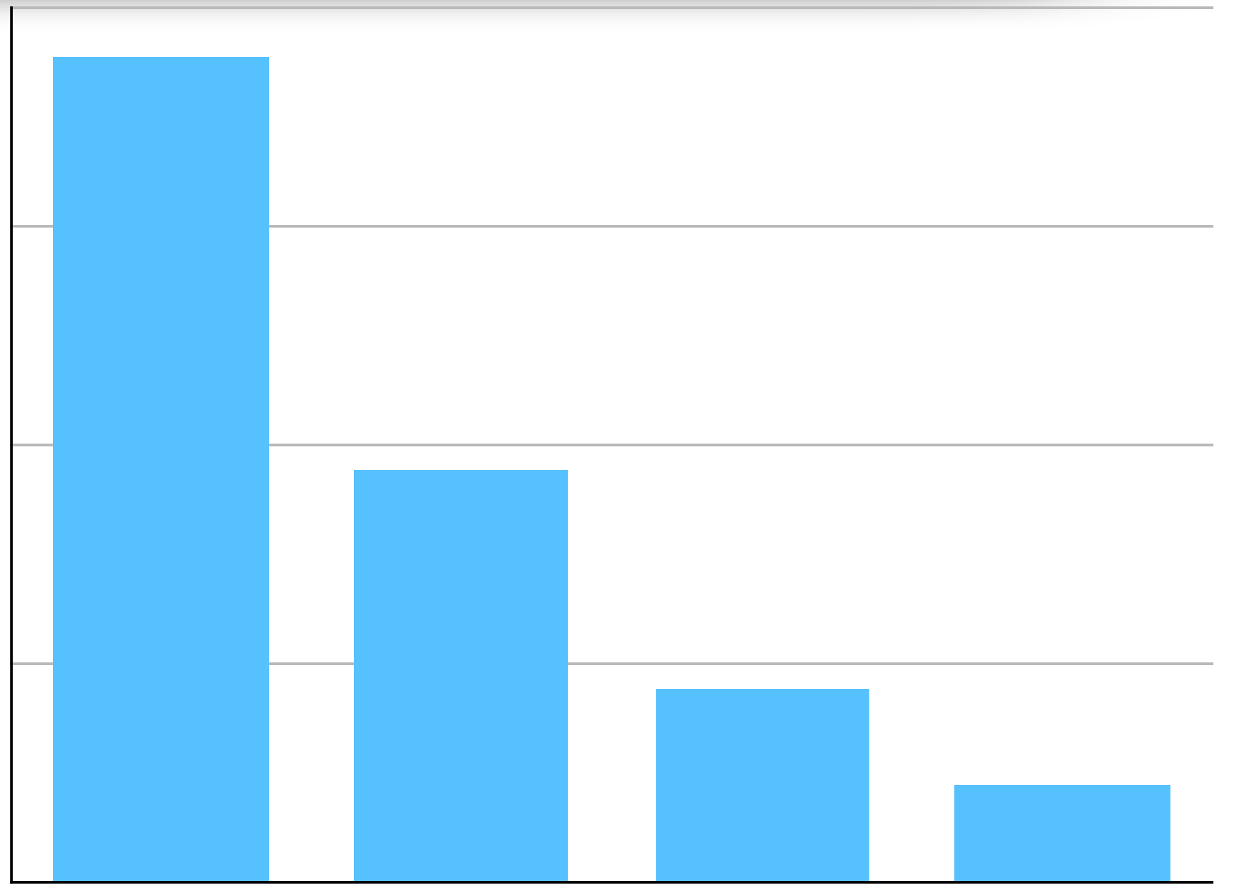
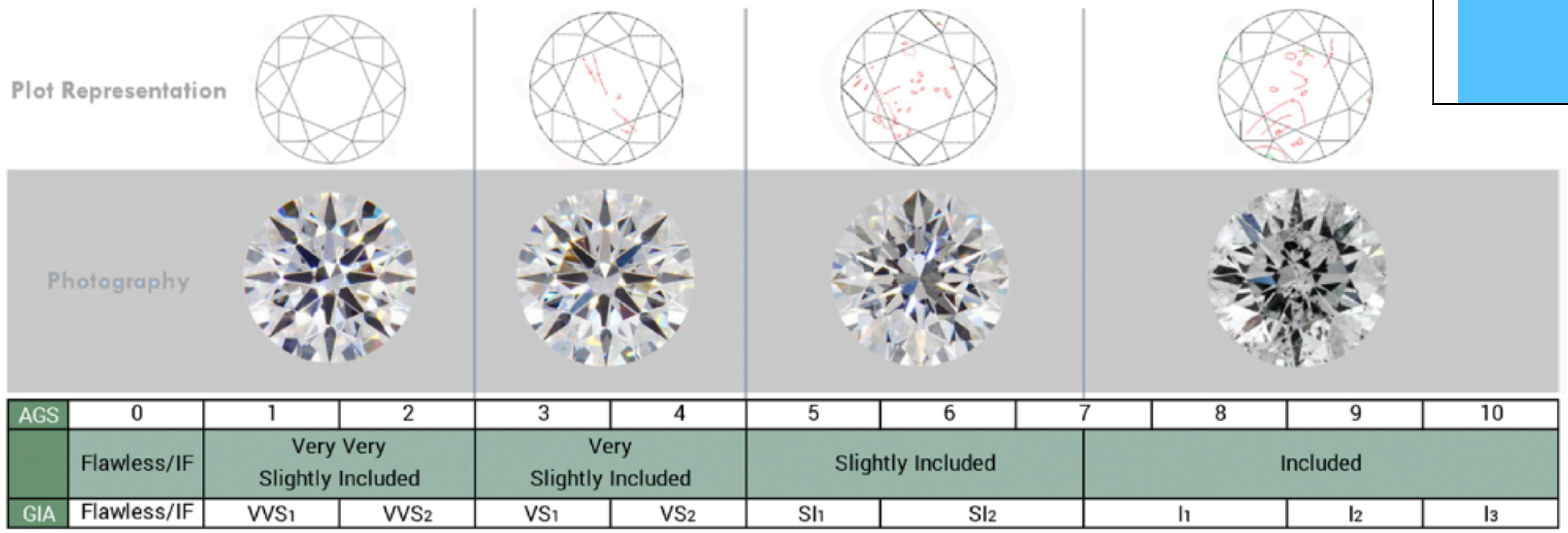


1. Best paper award $\ggg$ oral presentation $\gg$ spotlight $>$ poster
2. Diamond value varies drastically with grades

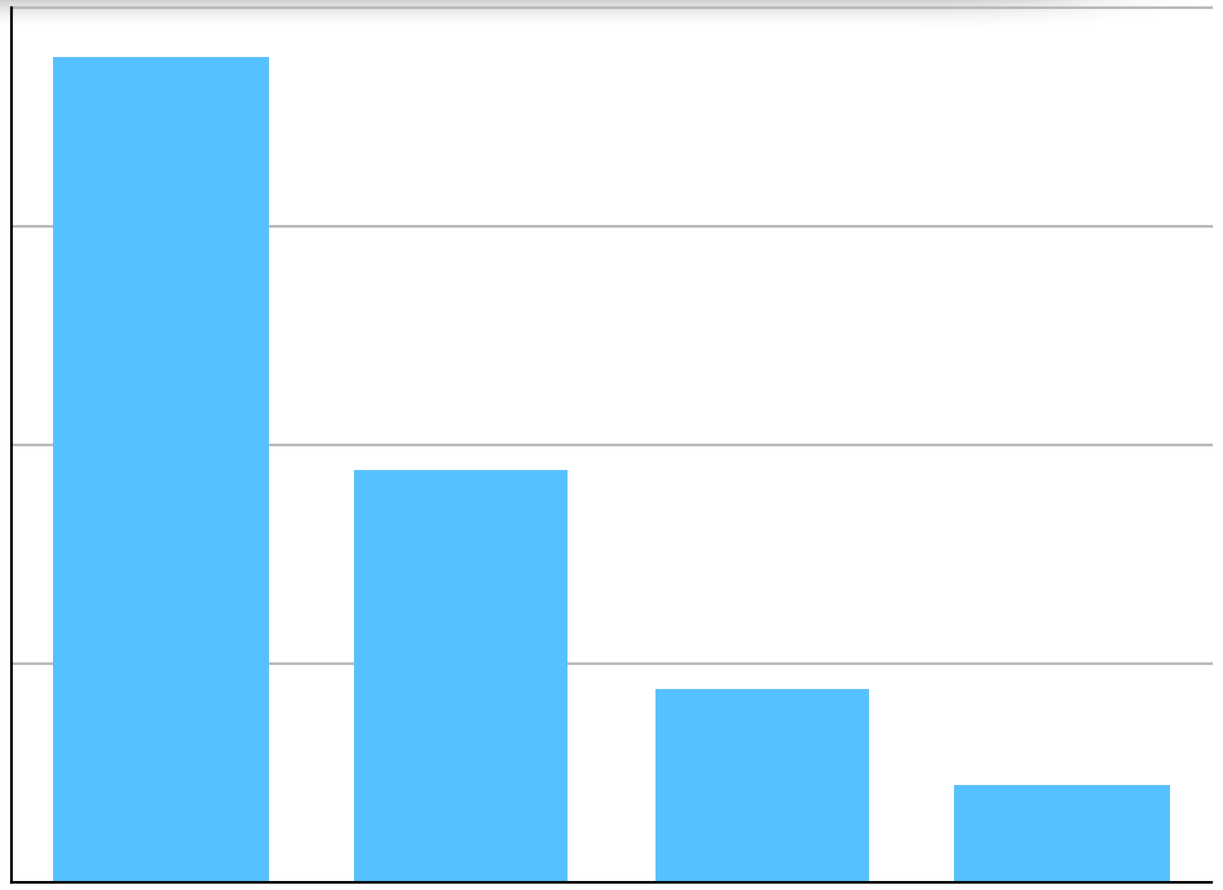


On the convexity assumption

why $U(\text{so so}) + U(\text{outstanding}) \geq 2U(\text{good})$?
At least for some applications

Alice is rational and wants to maximize

$$\mathbb{E}\left[U(\hat{R}_1) + \cdots + U(\hat{R}_n)\right]$$



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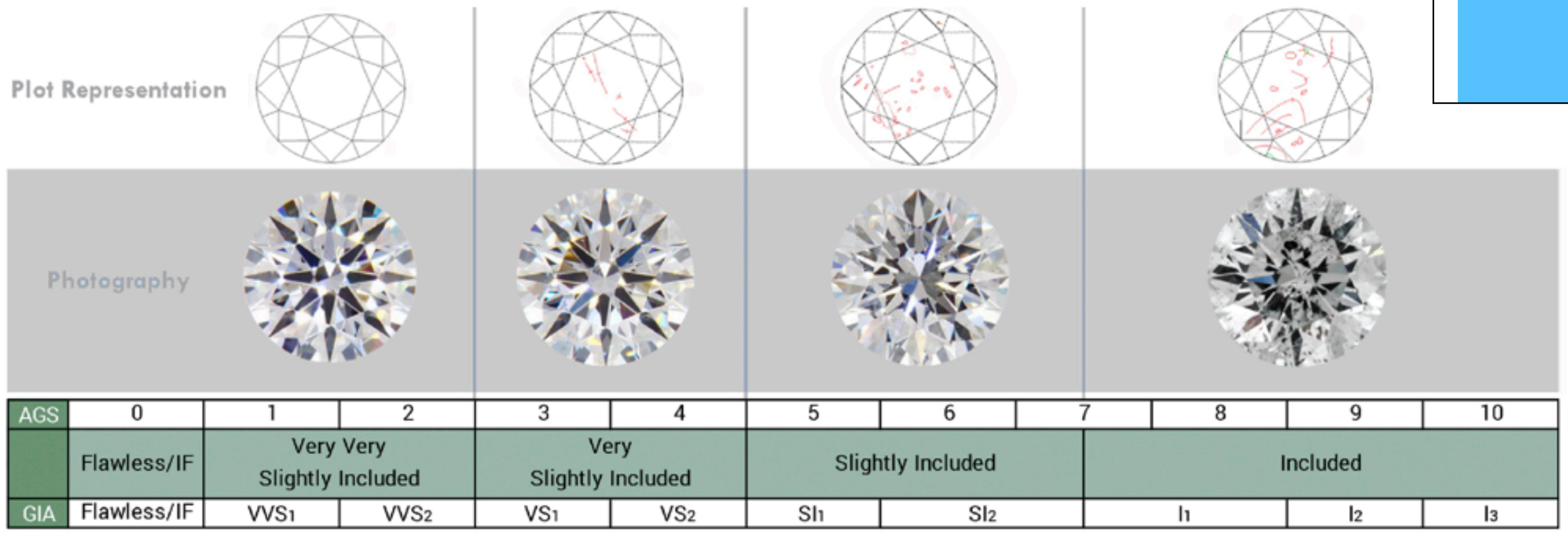
depends on categorization



Truthfulness implies *pairwise comparisons*

Theorem (S. 2022)

If Alice is always truthful, then the knowledge partition $\mathcal{S}$ must be cut by ***pairwise-comparison*** *hyperplanes $x_i - x_j = 0$ for some pairs $i < j$*

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'Is your 3rd paper better than your 5th paper?'

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- Suffice to know $g(R_i)$ for (unknown) monotone g (calibration not needed!)

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- Which entry of $\boldsymbol{R}$ is the largest? **maybe** (Yes, as we'll see soon)

Why pairwise comparisons? Some intuition

When $n = 2$, $\mathcal{S}$ must be either $\{\{x_1 \geq x_2\}, \{x_1 < x_2\}\}$ or $\{\mathbb{R}^2\}$

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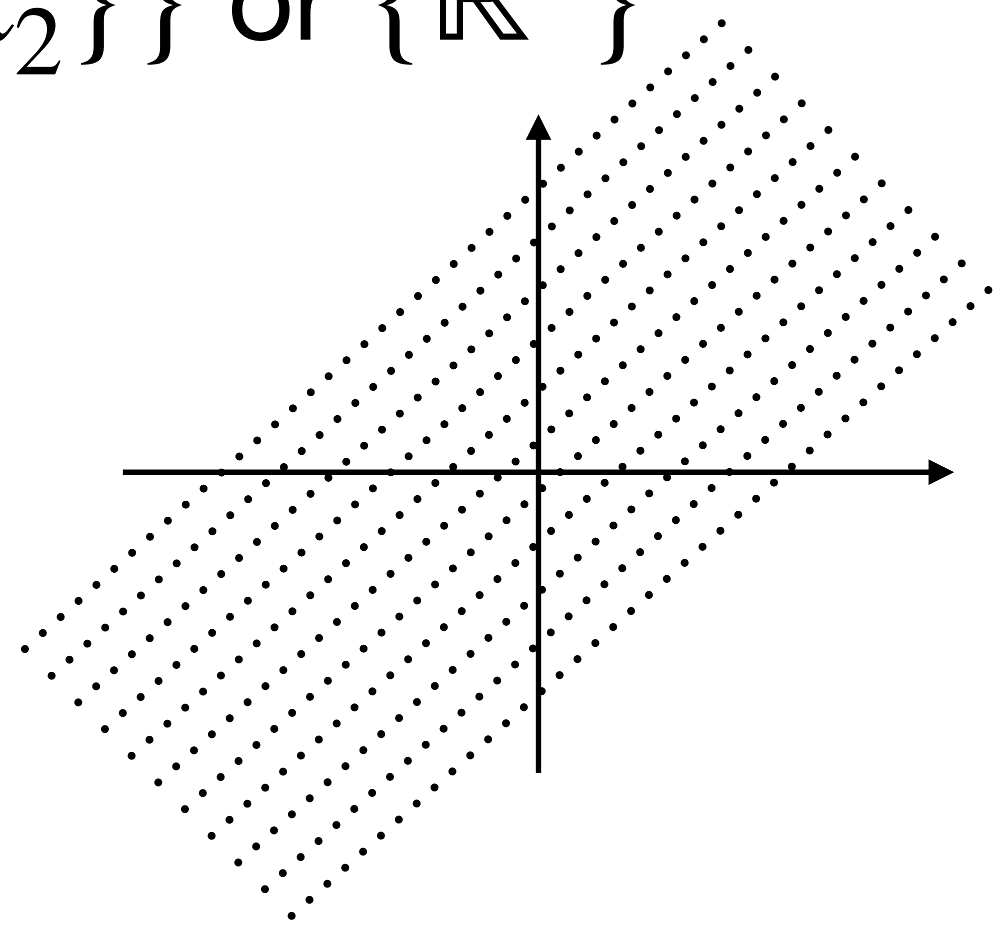
instead of asking whether $R_1 \geq R_2$, can Bob ask what's the value of $R_1 - R_2$?



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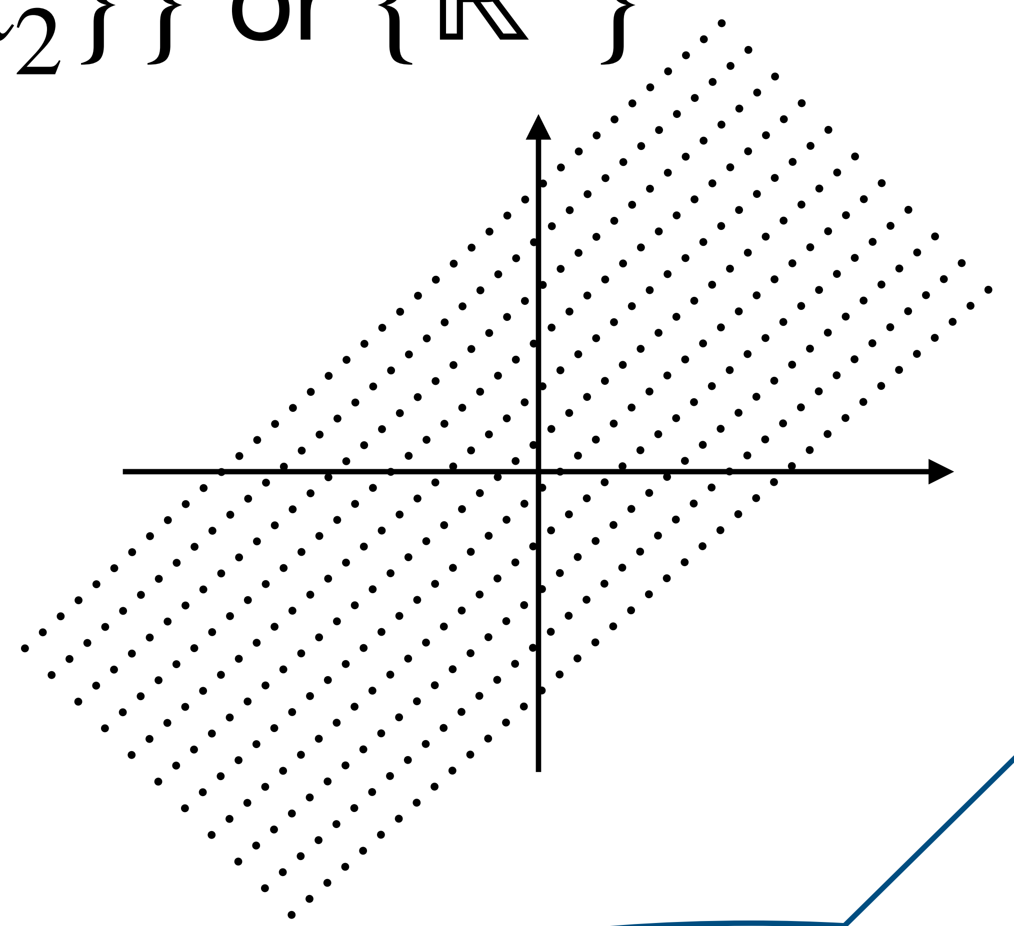

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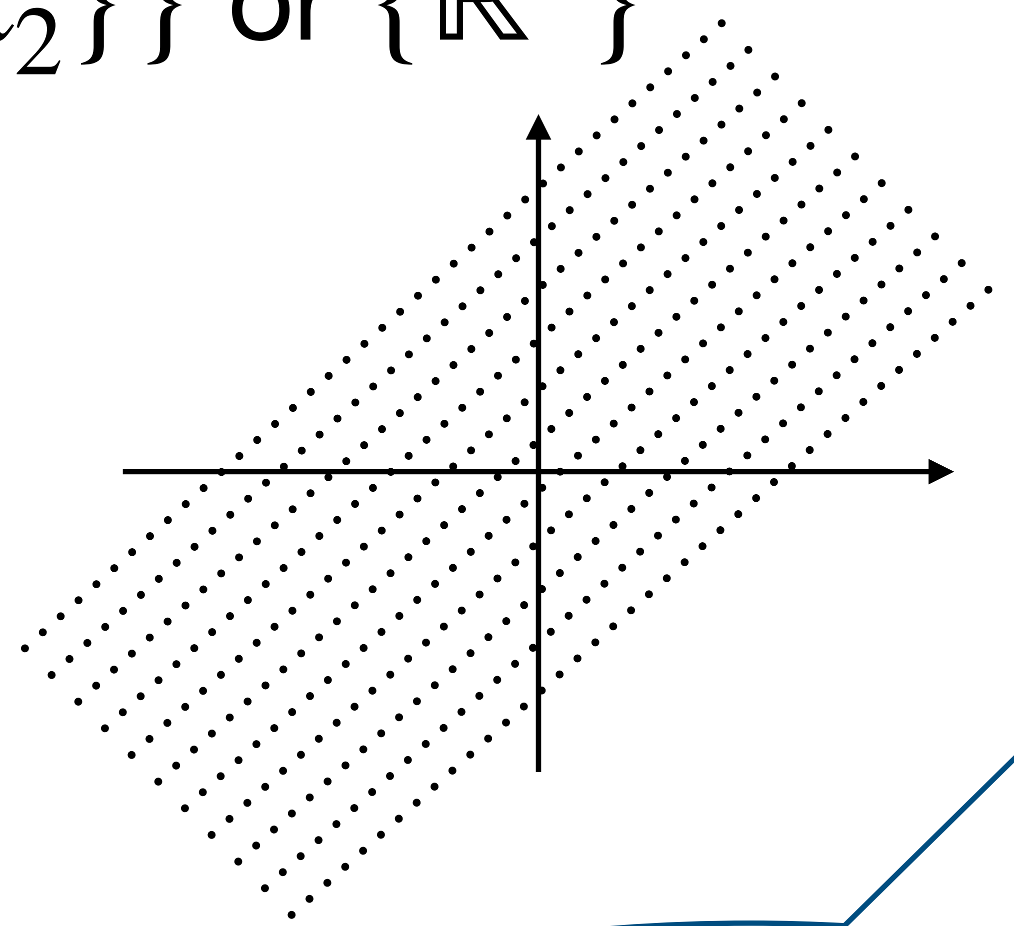

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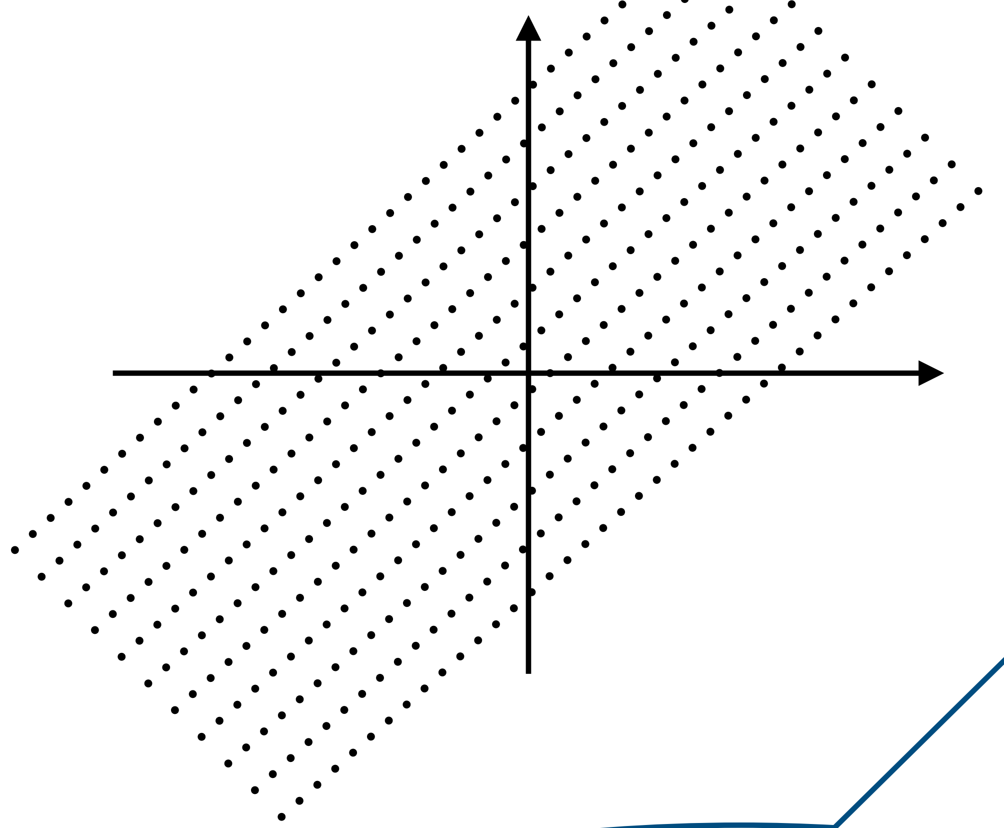

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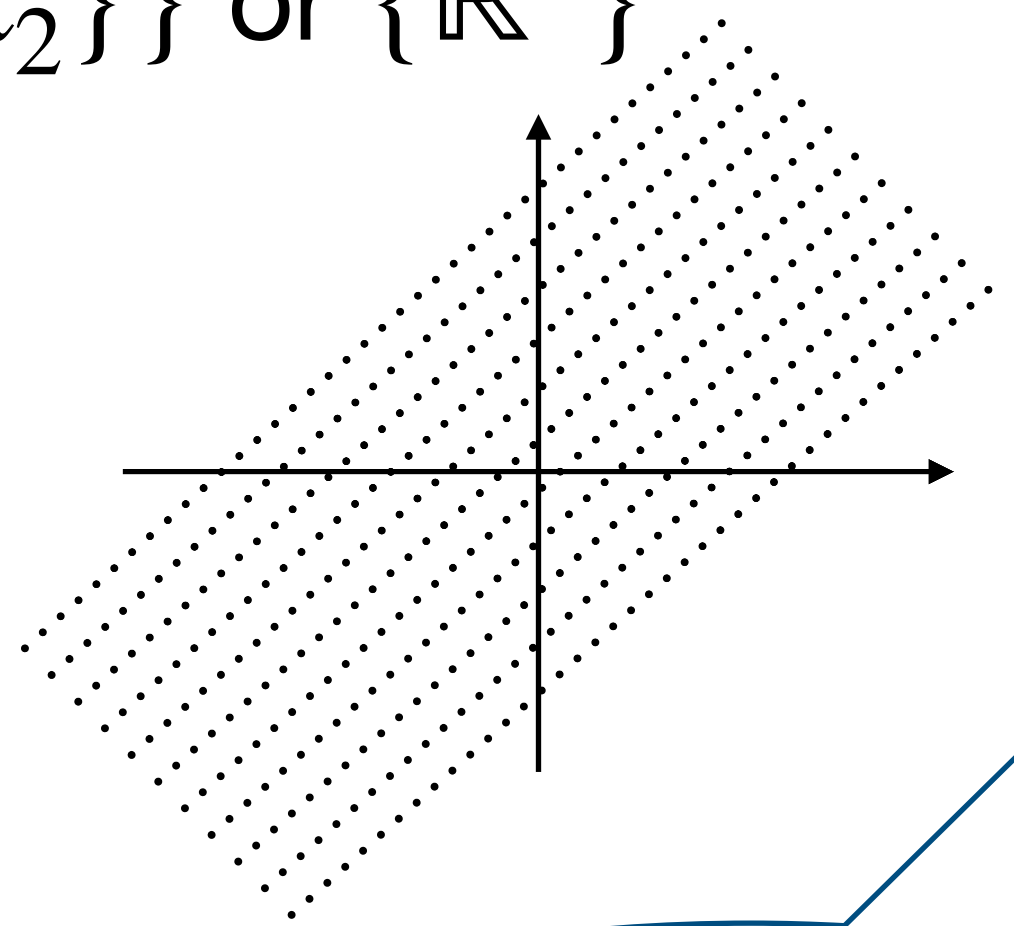

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- For a *generic* convex function, e.g., $U(x) = \max(0, x)$, this gives $U(\hat{R}_1) + U(\hat{R}_2) = \infty$

what's the most fine-grained truthful knowledge partition?

Candidate: all $n!$ rankings

The most fine-grained knowledge partition is the collection of isotonic cones $\{\boldsymbol{x} : x_{\pi(1)} \geq x_{\pi(2)} \geq \cdots \geq x_{\pi(n)}\}$ *for all permutations* π *of* $1,\ldots,n$

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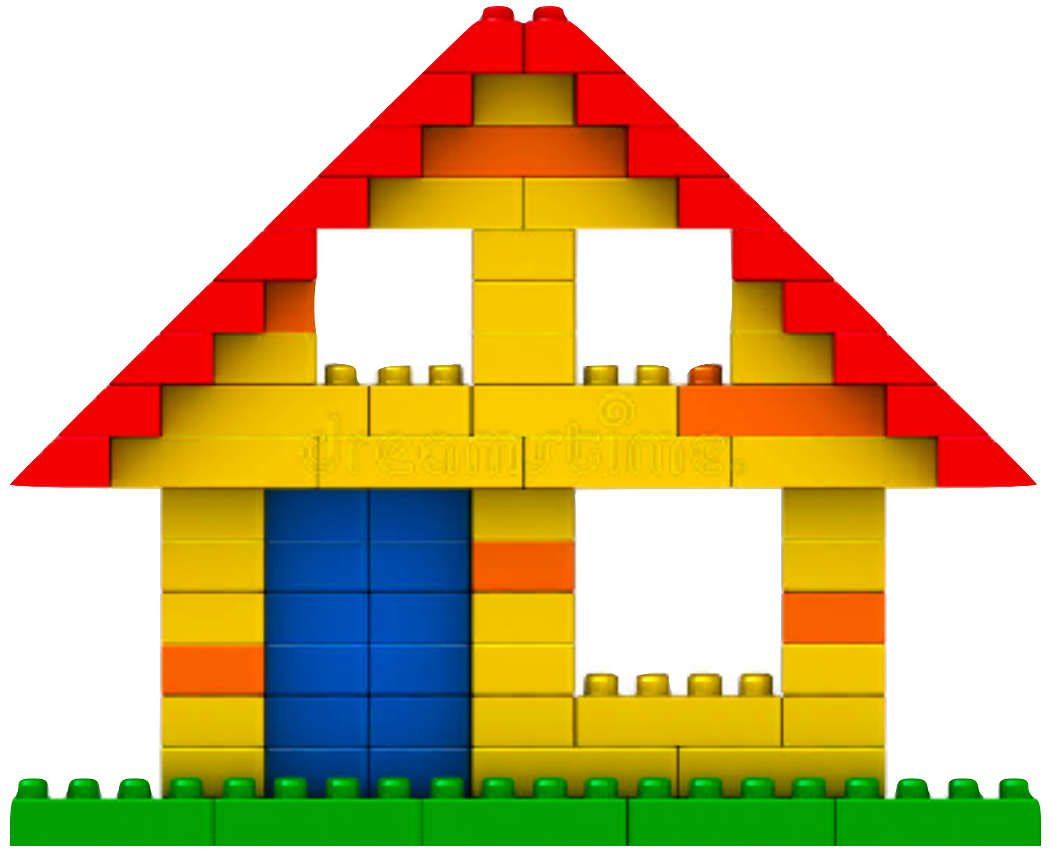

- Alice is asked to provide a ranking of her items
- If a knowledge partition $\mathcal{S}$ is truthful, then it is *coarser* than rankings, *with* cardinality no more than $n!$
- $\mathcal{S}$ can be generated by rankings

Our dream would come true if…

- Alice is truthful, so the ground truth $\boldsymbol{R}$ is really in S
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$$\min_{\boldsymbol{r}} \quad \|\boldsymbol{y} - \boldsymbol{r}\|^2$$
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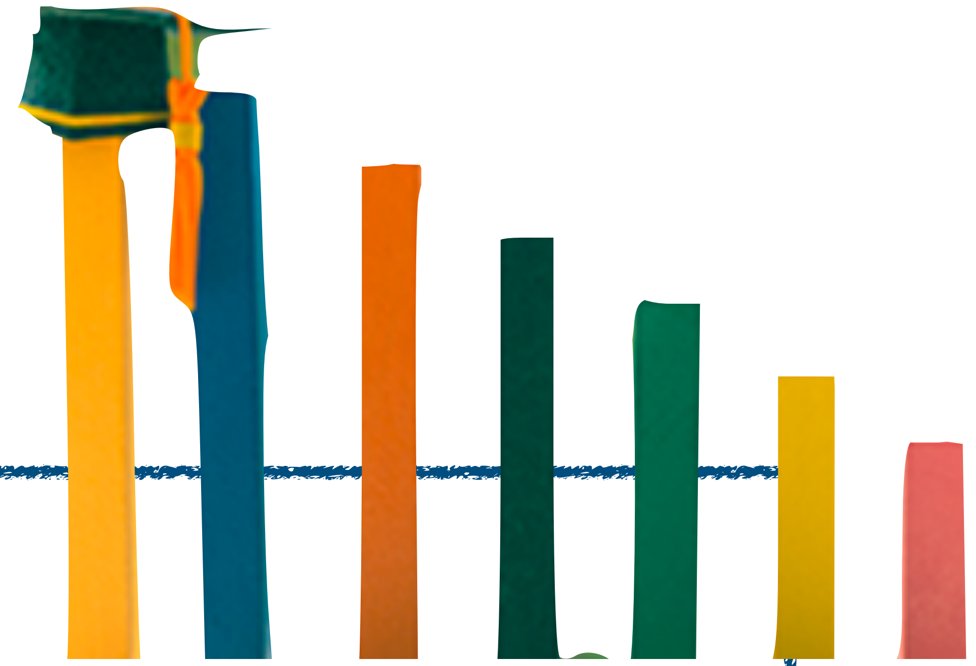

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this is just isotonic regression!

An example

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A friend of mine submitted 6 papers to NeurIPS 2021

Ranking	Score	Decision	Isotonic score
1	5.5	Reject	6.25
2	7	**Accept**	6.25
3	5	Reject	5.92
4	6.75	**Accept**	5.92
5	6	**Accept**	5.92
6	4.67	Reject	4.67

Alice (and Bob) in the Wonderland!

Theorem (S. 2021)

The Isotonic Mechanism is truthful: Alice's optimal strategy is to report the ground-truth ranking $\pi^\star$*satisfying* $R_{\pi^\star(1)} \geq R_{\pi^\star(2)} \geq \cdots \geq R_{\pi^\star(n)}$

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- Combining the previous theorem, this gives…

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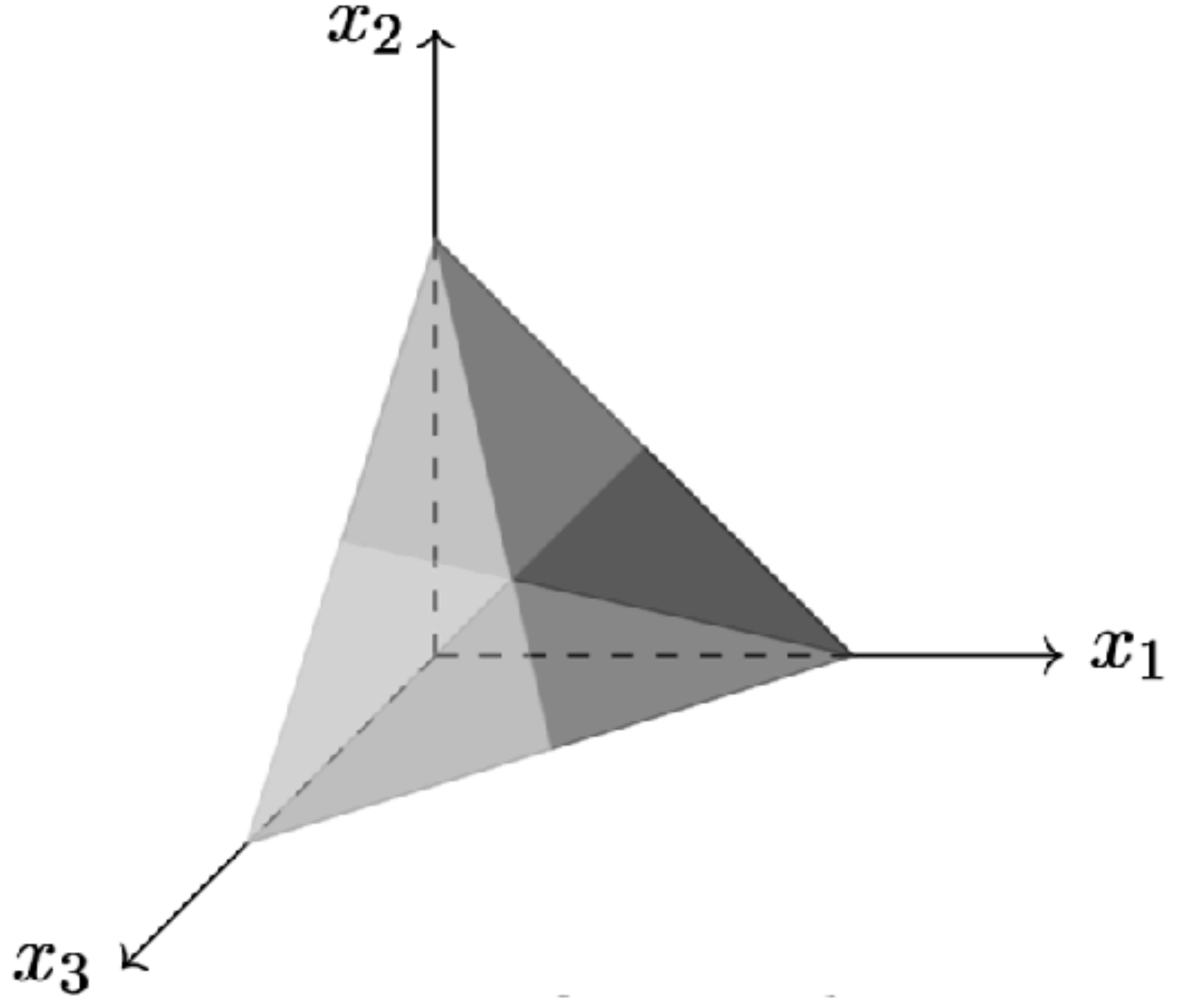

Proof ideas

WLOG, assume $R_1 \geq \cdots \geq R_n$, so $\pi^\star(i) = i$

truthful

$$\begin{aligned} \min_{\boldsymbol{r}} \quad & \|\boldsymbol{y} - \boldsymbol{r}\|^2 \\ \text{s.t.} \quad & r_1 \geq \cdots \geq r_n \end{aligned}$$

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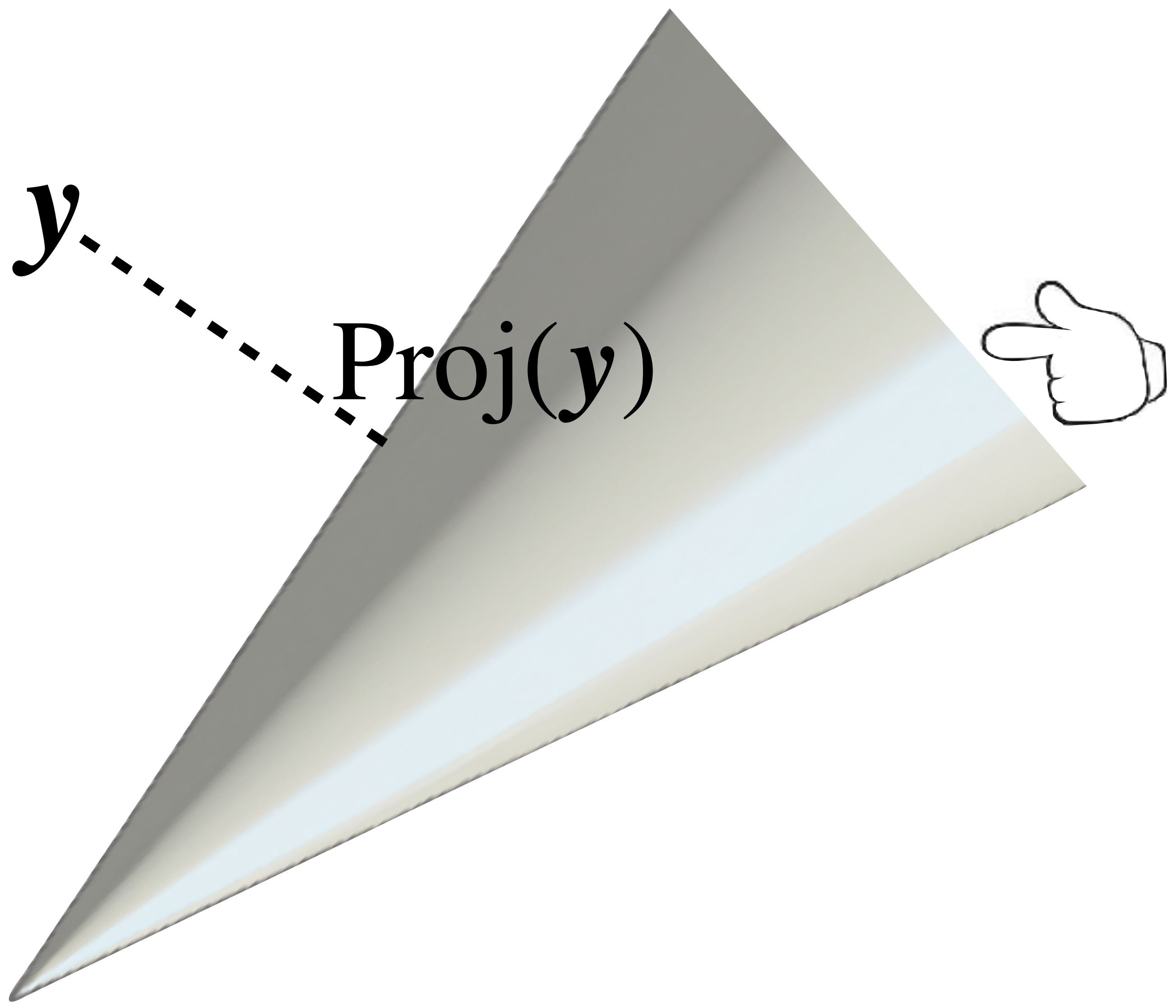

isotonic cone: $\{\boldsymbol{r} : r_1 \geq \cdots \geq r_n\}$

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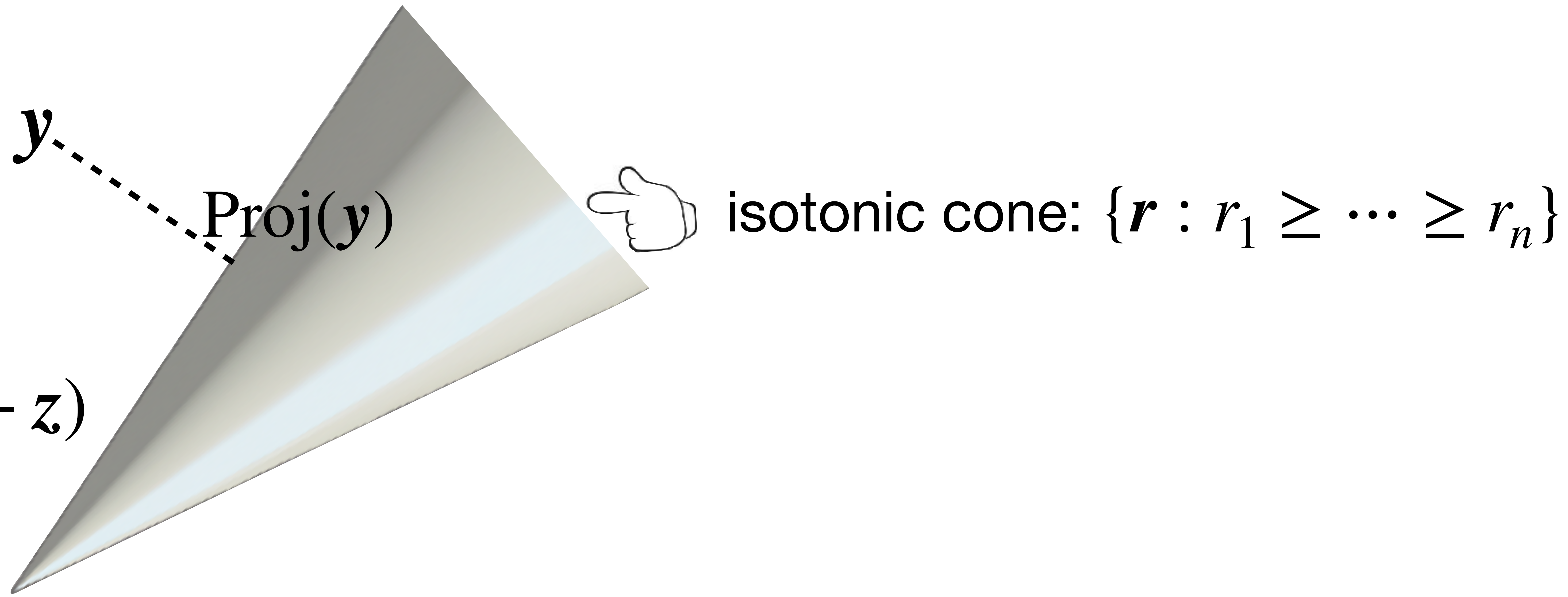

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vs

let π be a different ranking

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⇕ order the coordinates

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⇔ coupling

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Let $\boldsymbol{a} = \boldsymbol{R} + \boldsymbol{z}$ and $\boldsymbol{b} = \pi \circ \boldsymbol{R} + \boldsymbol{z}$. Then $\sum_{i=1}^{k} a_i \geq \sum_{i=1}^{k} b_i$ for all i with equality when $i = n$

Different from majorization: $\sum_{i=1}^{k} u_{(i)} \geq \sum_{i=1}^{k} v_{(i)}$, where order statistics $u_{(1)} \geq \cdots \geq u_{(n)}$

Proof ideas

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Lemma (S. 2021)

$\mathrm{Proj}(\boldsymbol{a})$ *majorizes* $\mathrm{Proj}(\boldsymbol{b})$

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Hardy–Littlewood–Pólya inequality

If $\boldsymbol{u}$ majorizes $\boldsymbol{v}$, then $U(\boldsymbol{u}) \geq U(\boldsymbol{v})$ for any convex U

Intuition as to why true ranking maximizes utility?

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PAVA algorithm for isotonic regression (Kruskal 1964)

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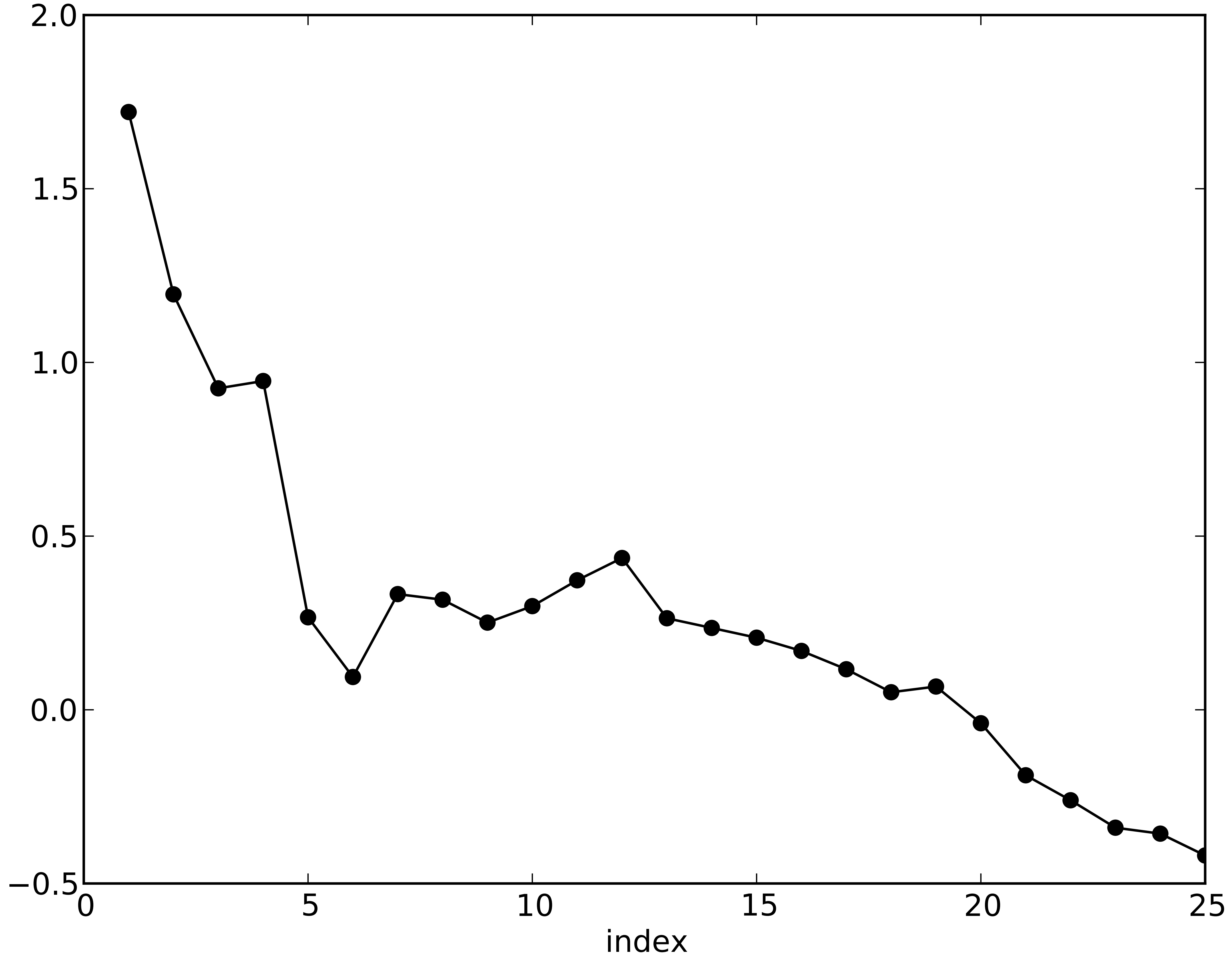

mean-preserving $\sum_{i=1}^{n} \hat{R}_i = \sum_{i=1}^{n} y_i$

averaging reduces convex sum!

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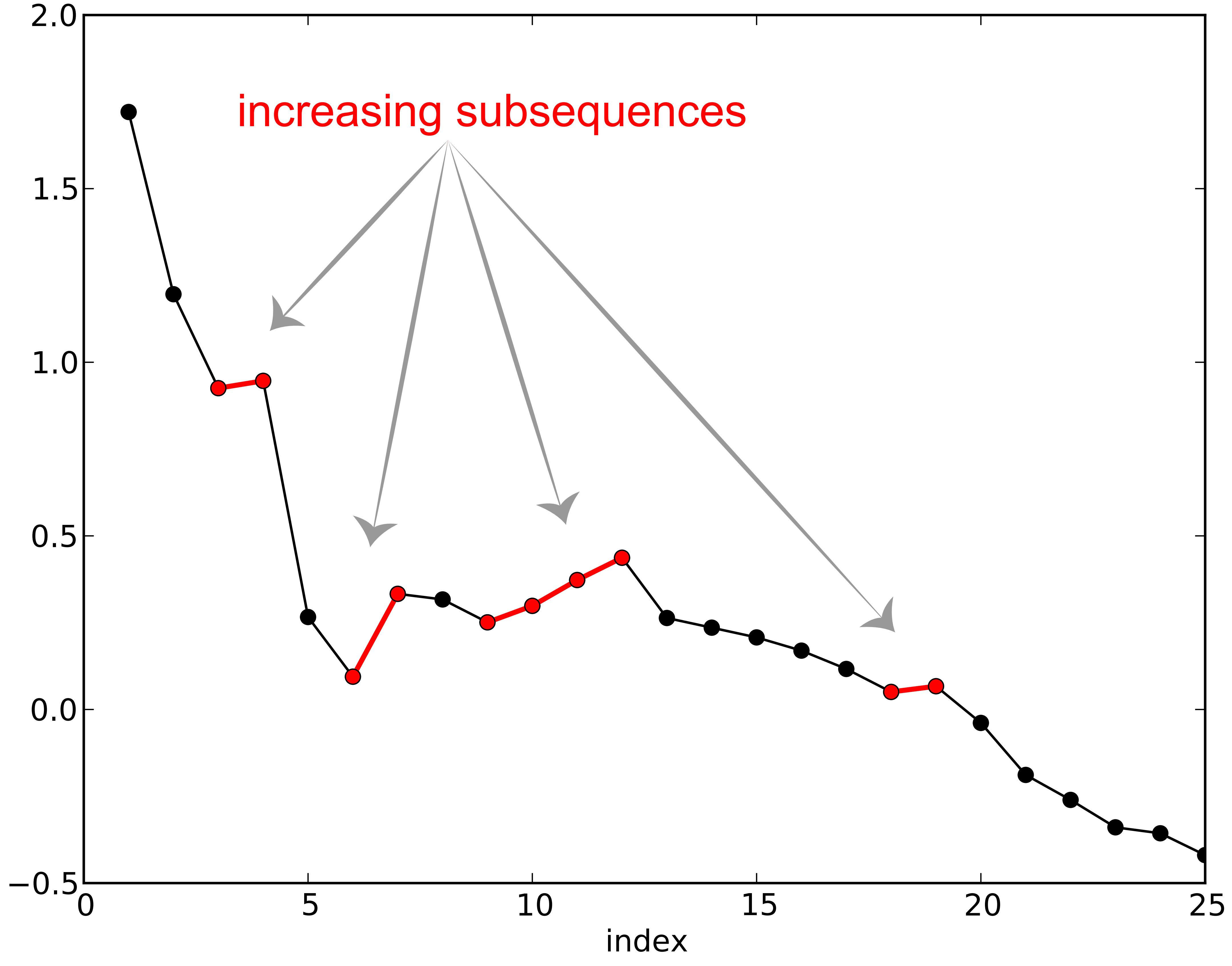

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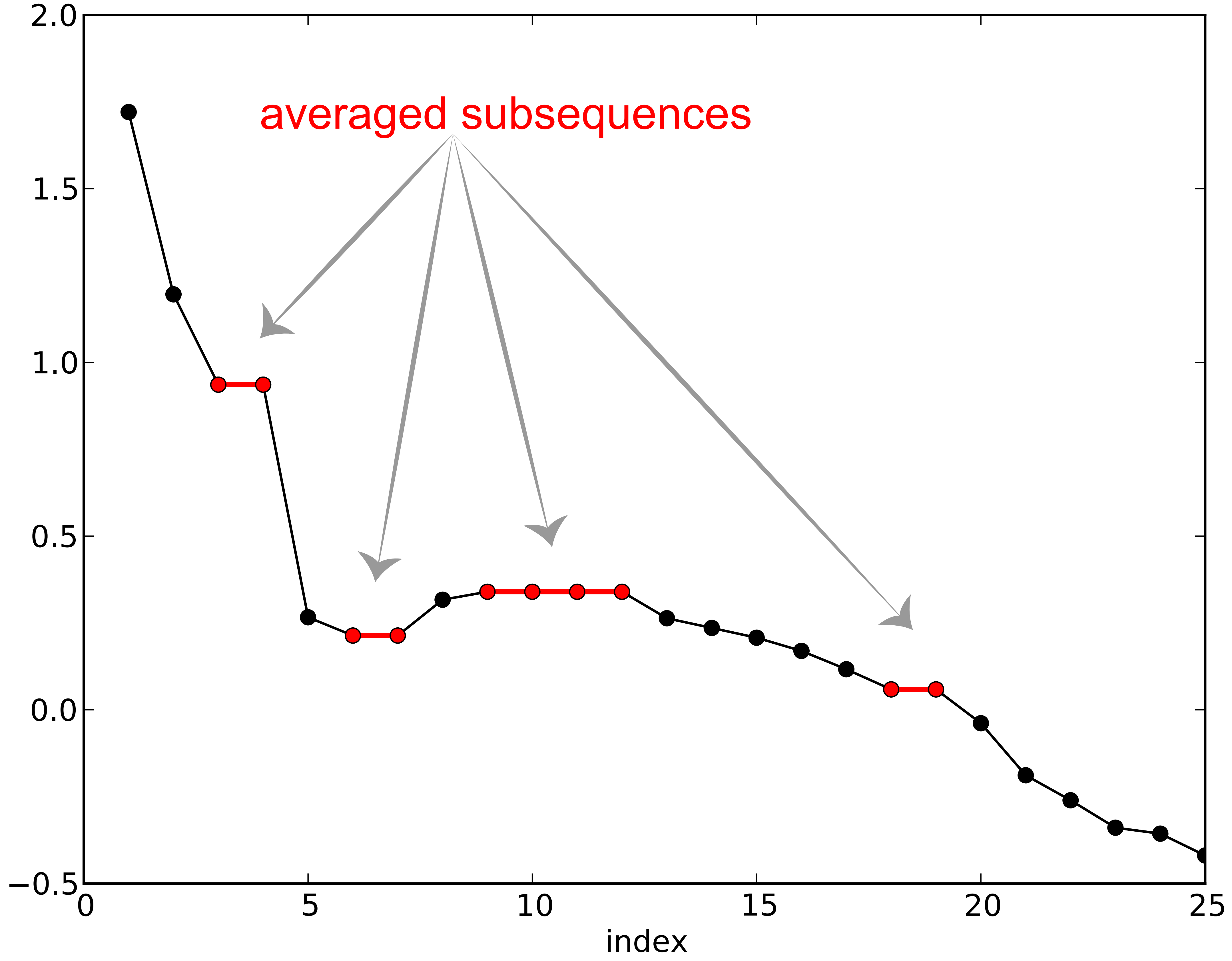
Intuition as to why true ranking maximizes utility?

PAVA algorithm for isotonic regression (Kruskal 1964)



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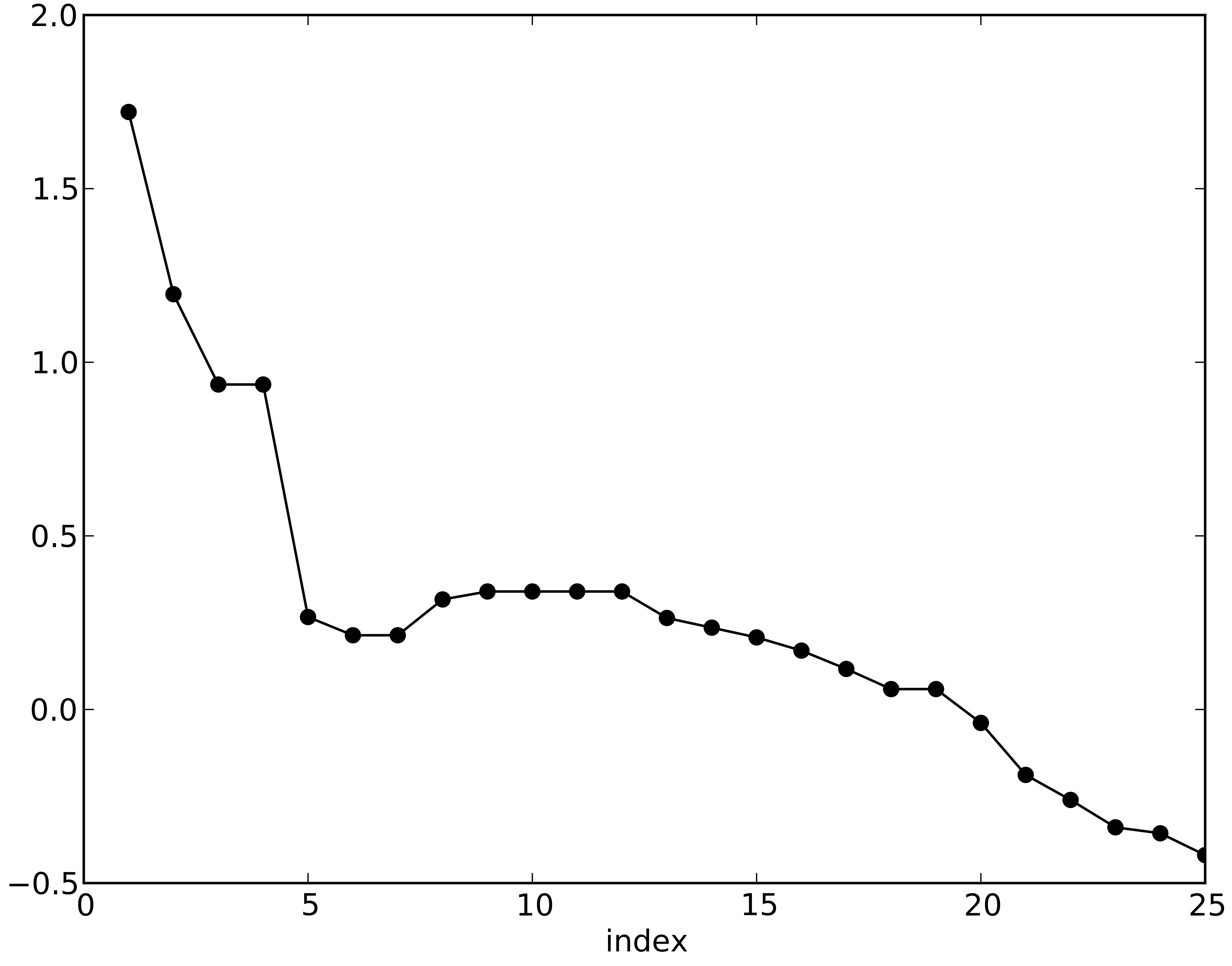

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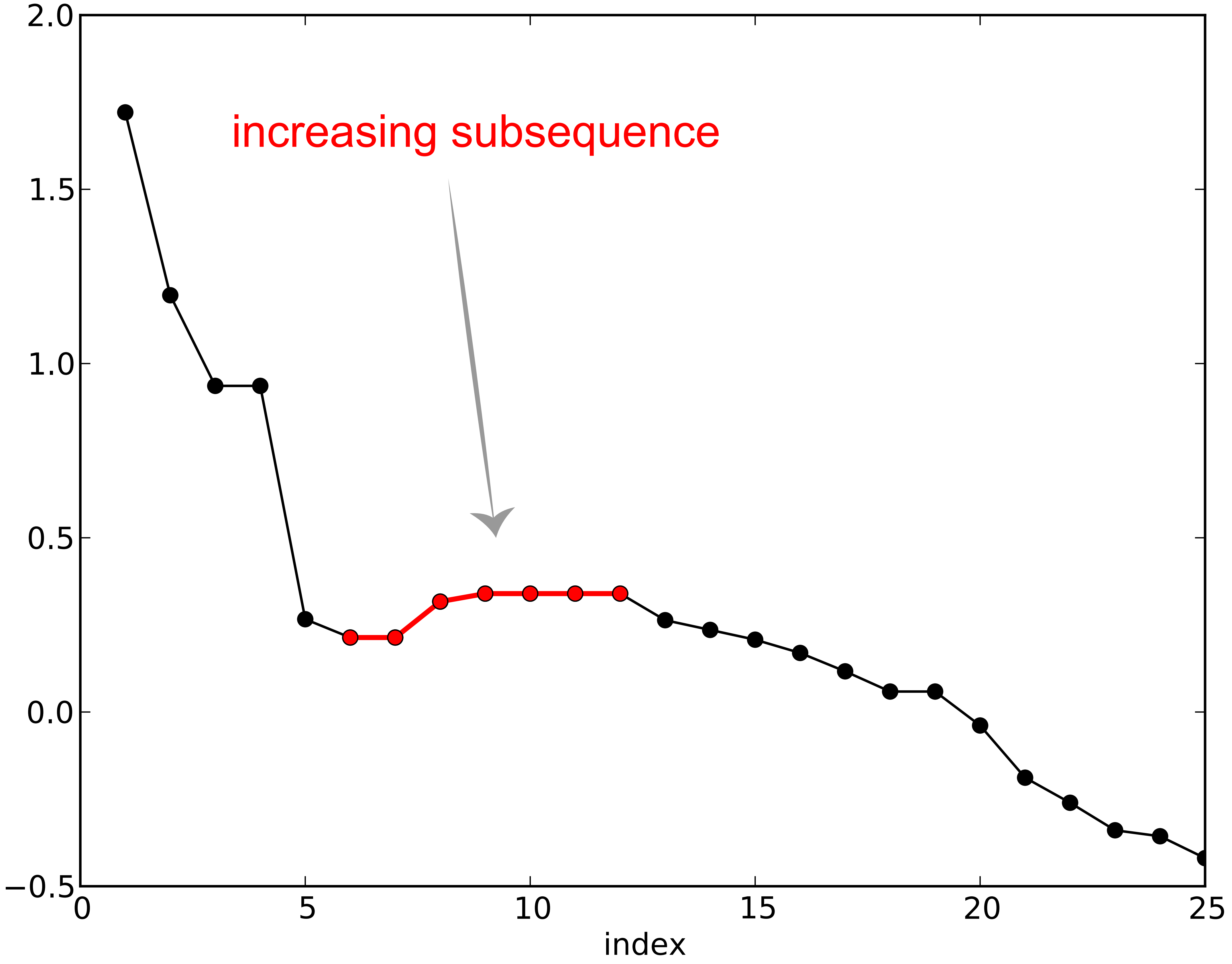

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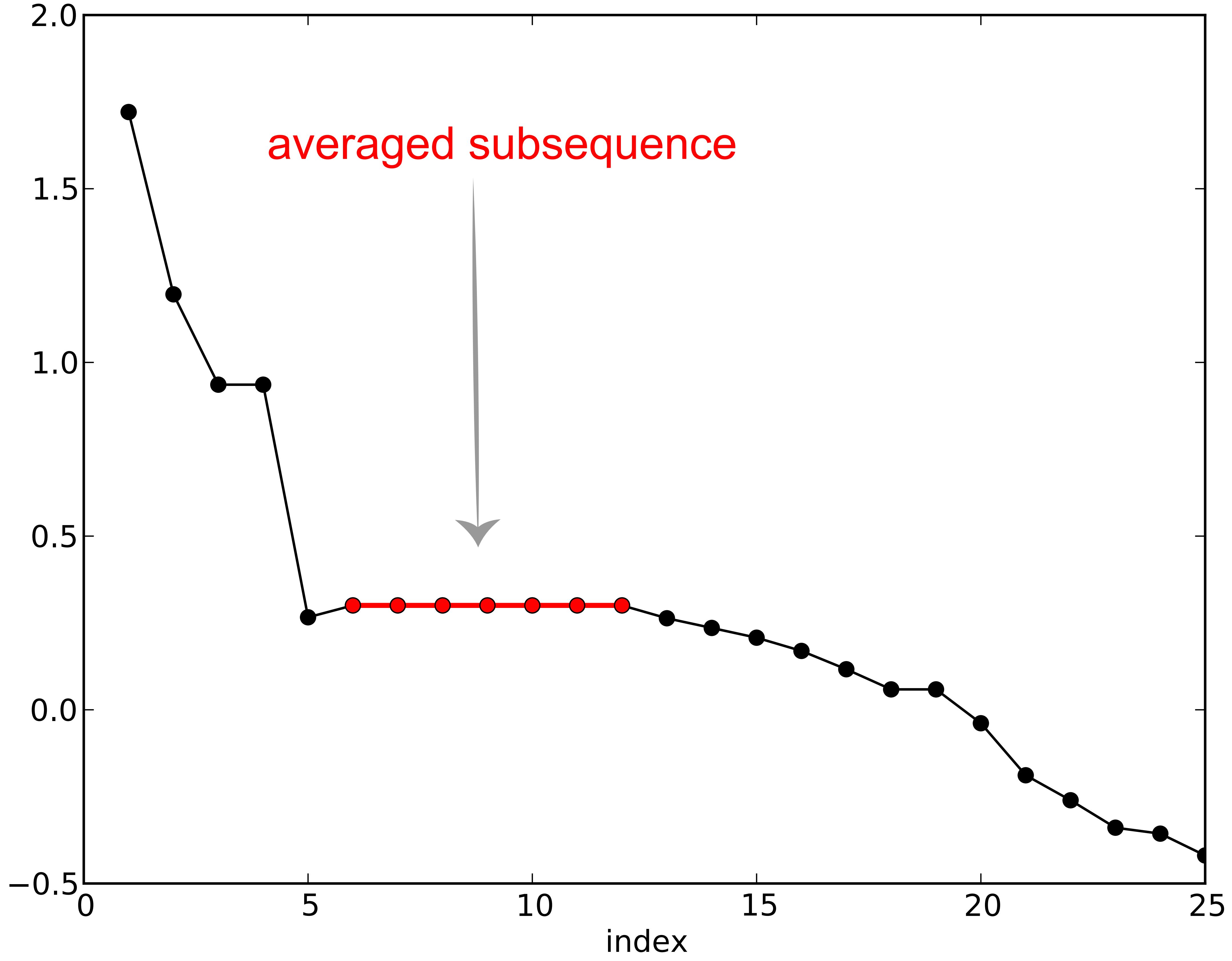

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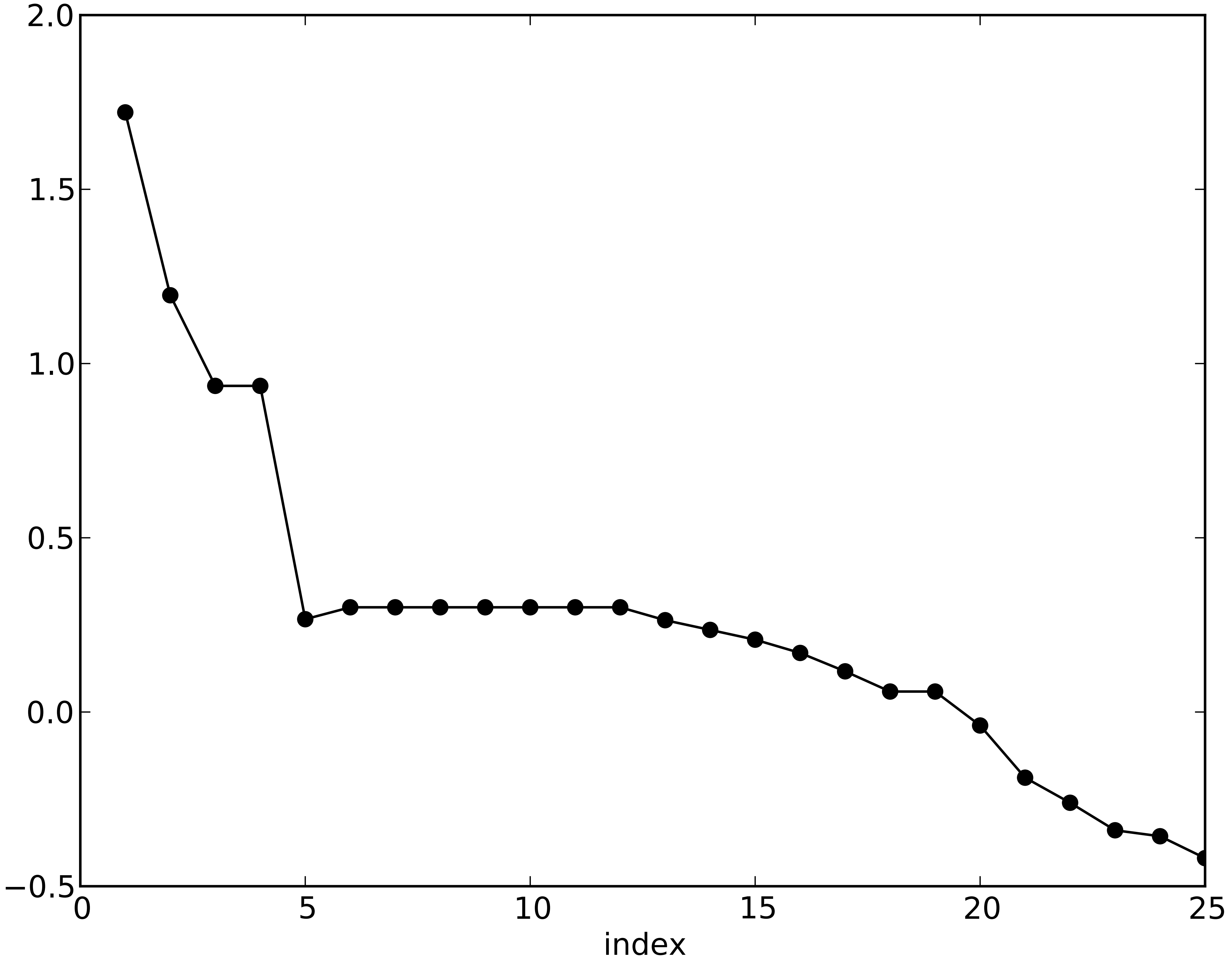

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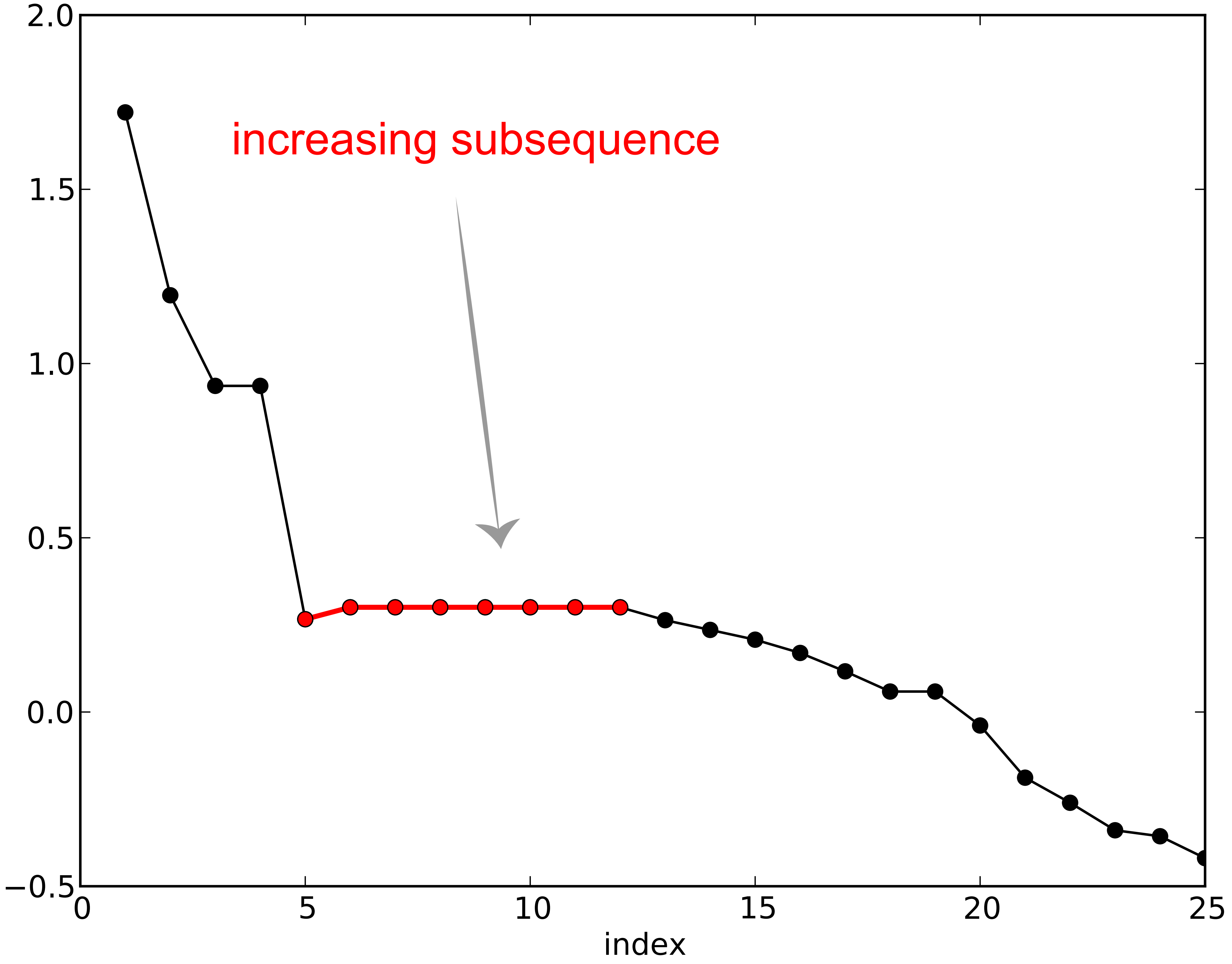

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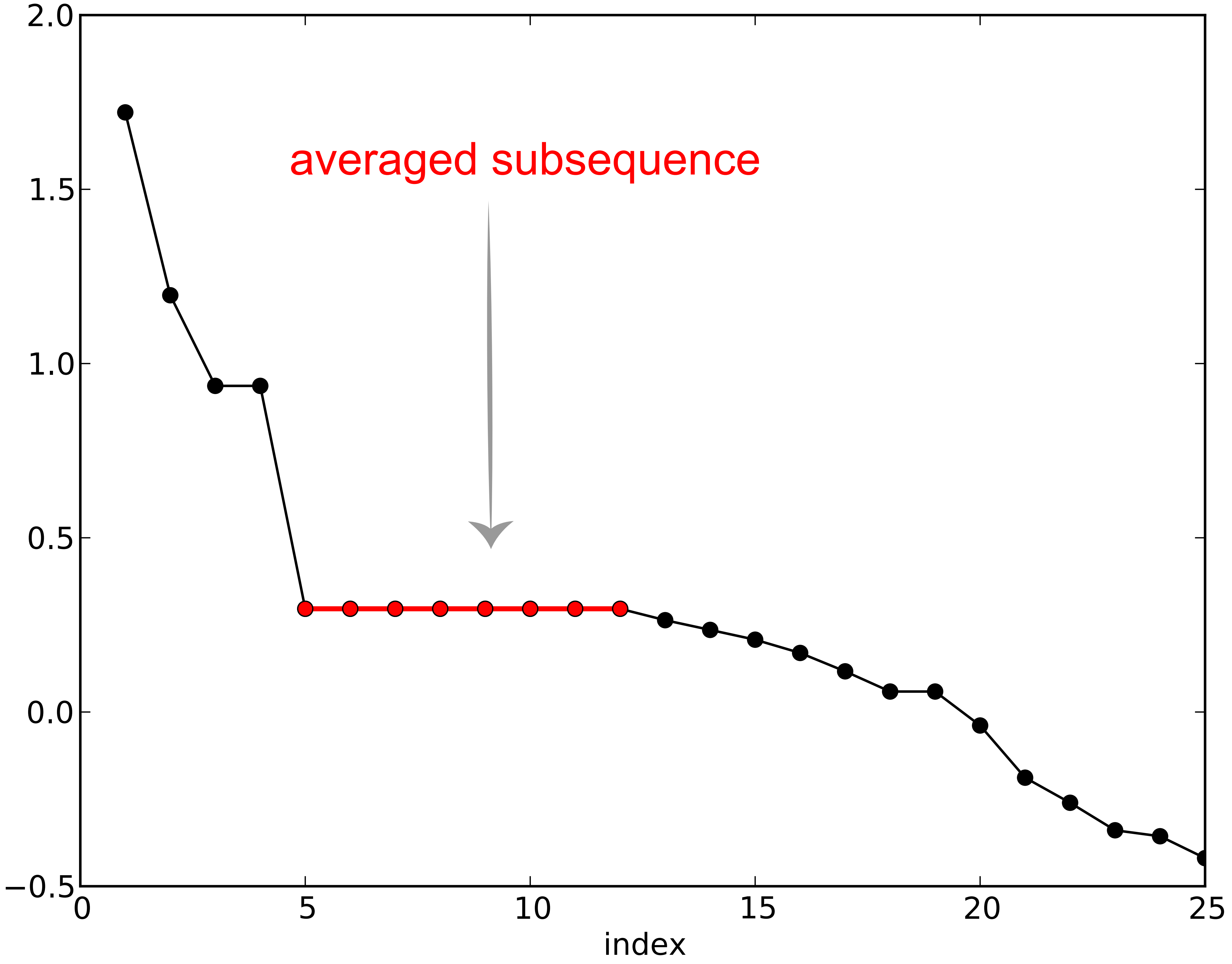

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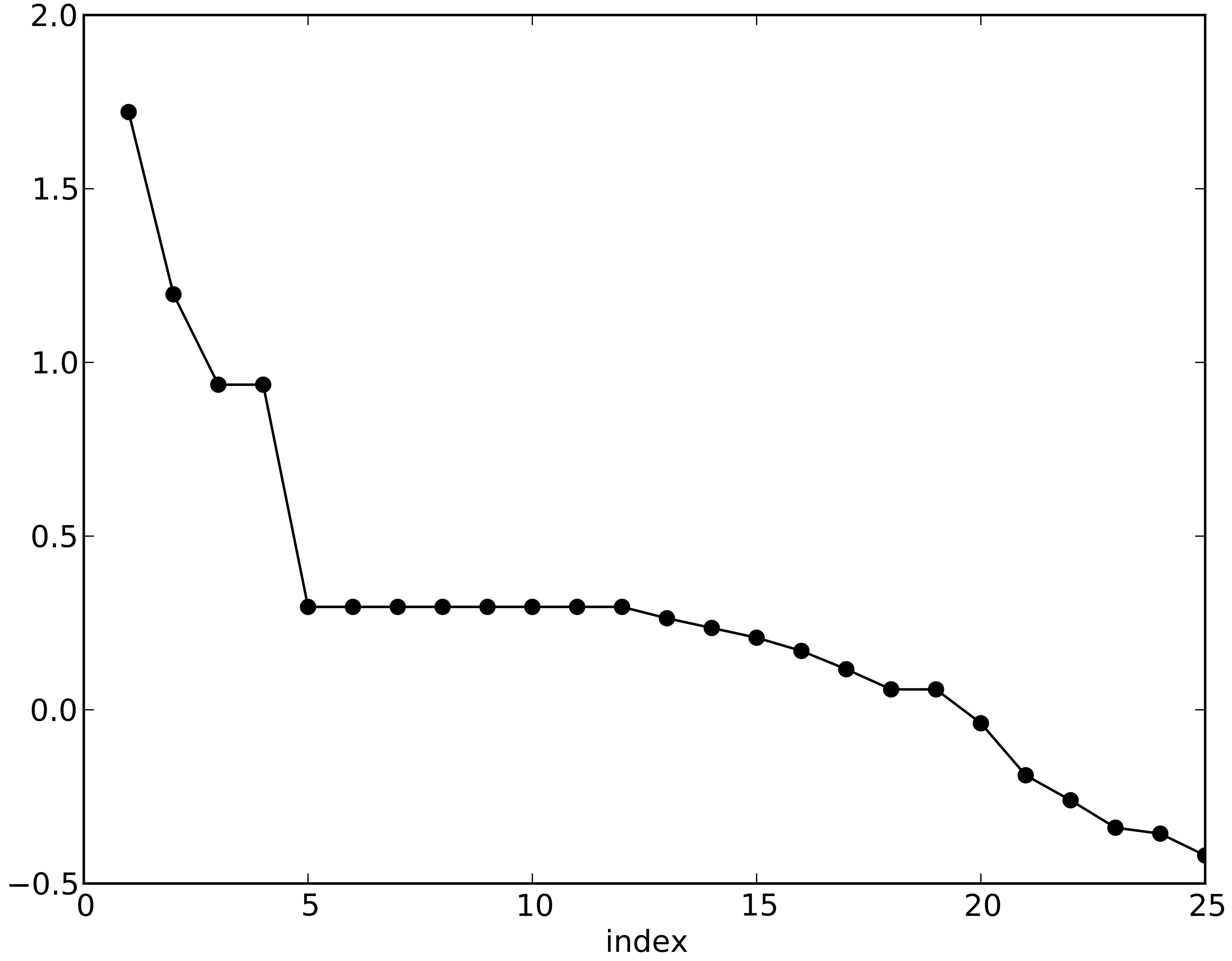

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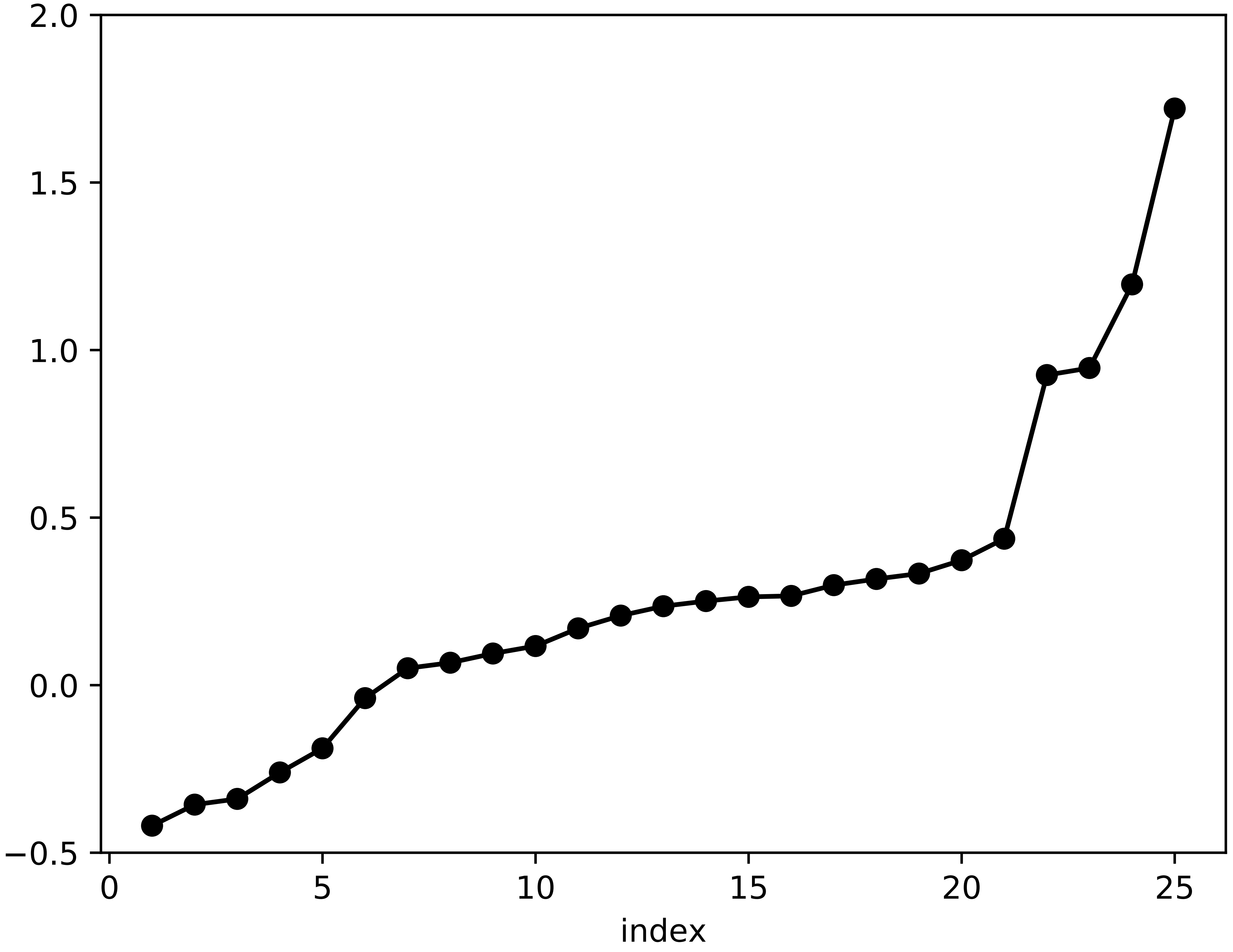

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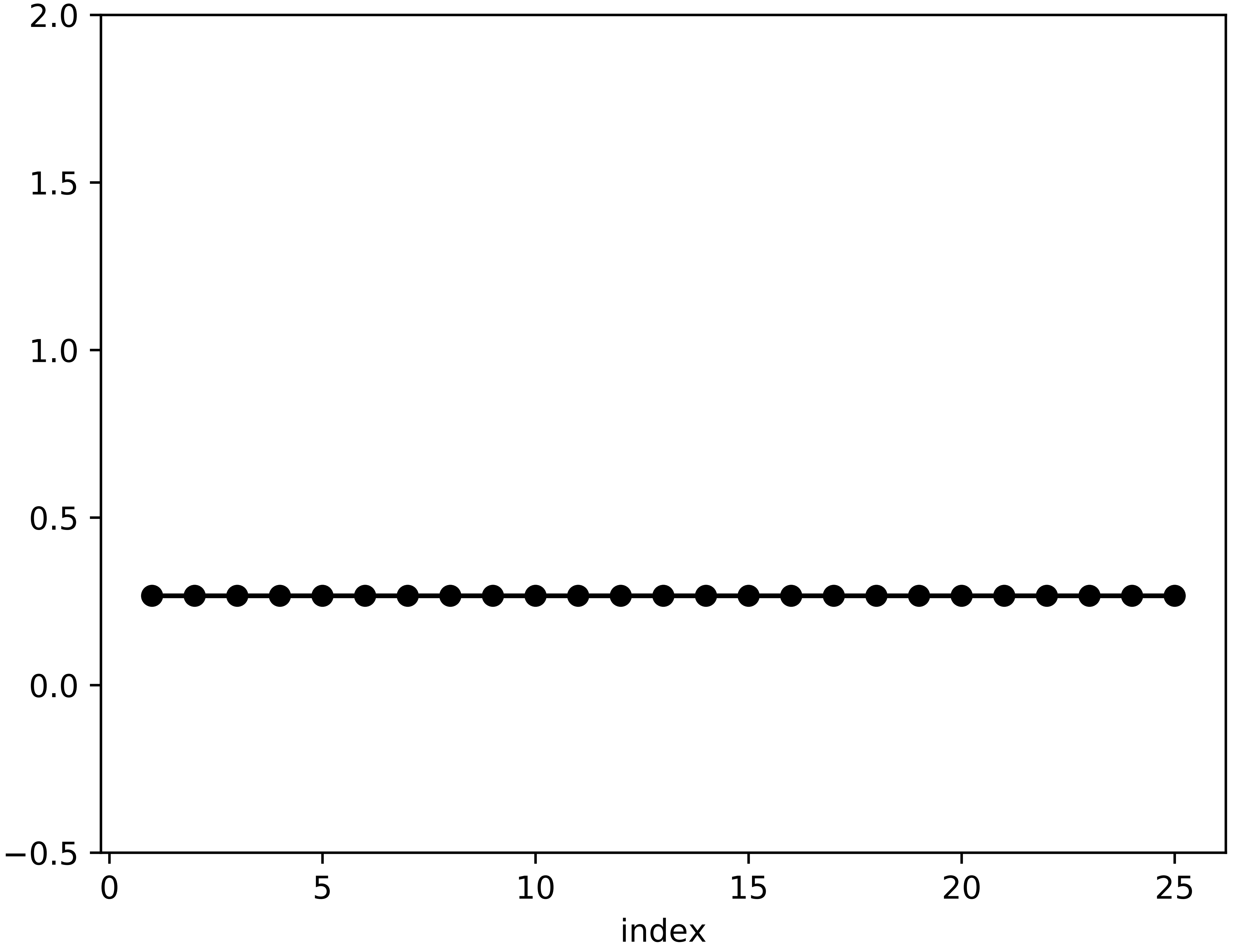

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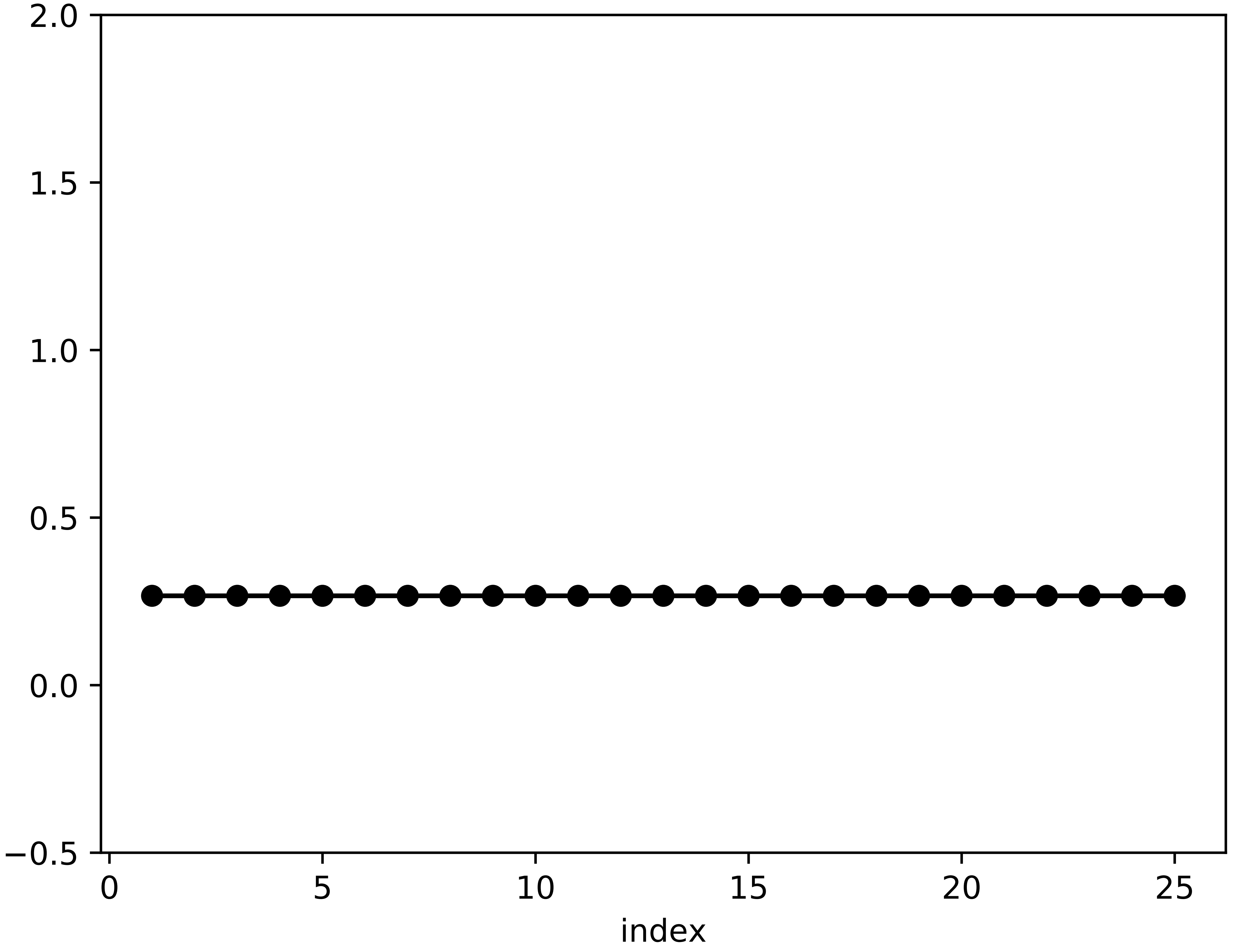

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If $R_1 \gg R_2$ (an outstanding paper and a junk paper)

If Alice is honest: oral presentation + rejection

If Alice lies: two accepted posters

When is the gain significant?

Total variation $\mathrm{TV}(\boldsymbol{R}) := \max_i R_i - \min_i R_i$

Proposition (Zhang 2002)

Letting noise sd σ and V be fixed, we have

$$0.4096 + o_n(1) \leq \frac{\sup_{\boldsymbol{R}:\mathrm{TV}(\boldsymbol{R})\leq V} \mathbb{E}\|\hat{\boldsymbol{R}}(\pi^\star) - \boldsymbol{R}\|^2}{n^{\frac{1}{3}}\sigma^{\frac{4}{3}}V^{\frac{2}{3}}} \leq 7.5625 + o_n(1)$$

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- The raw observation $\boldsymbol{y}$ has risk $n\sigma^2$
- Gain is more significant when n is large and σ is large too

How large is n in peer review?

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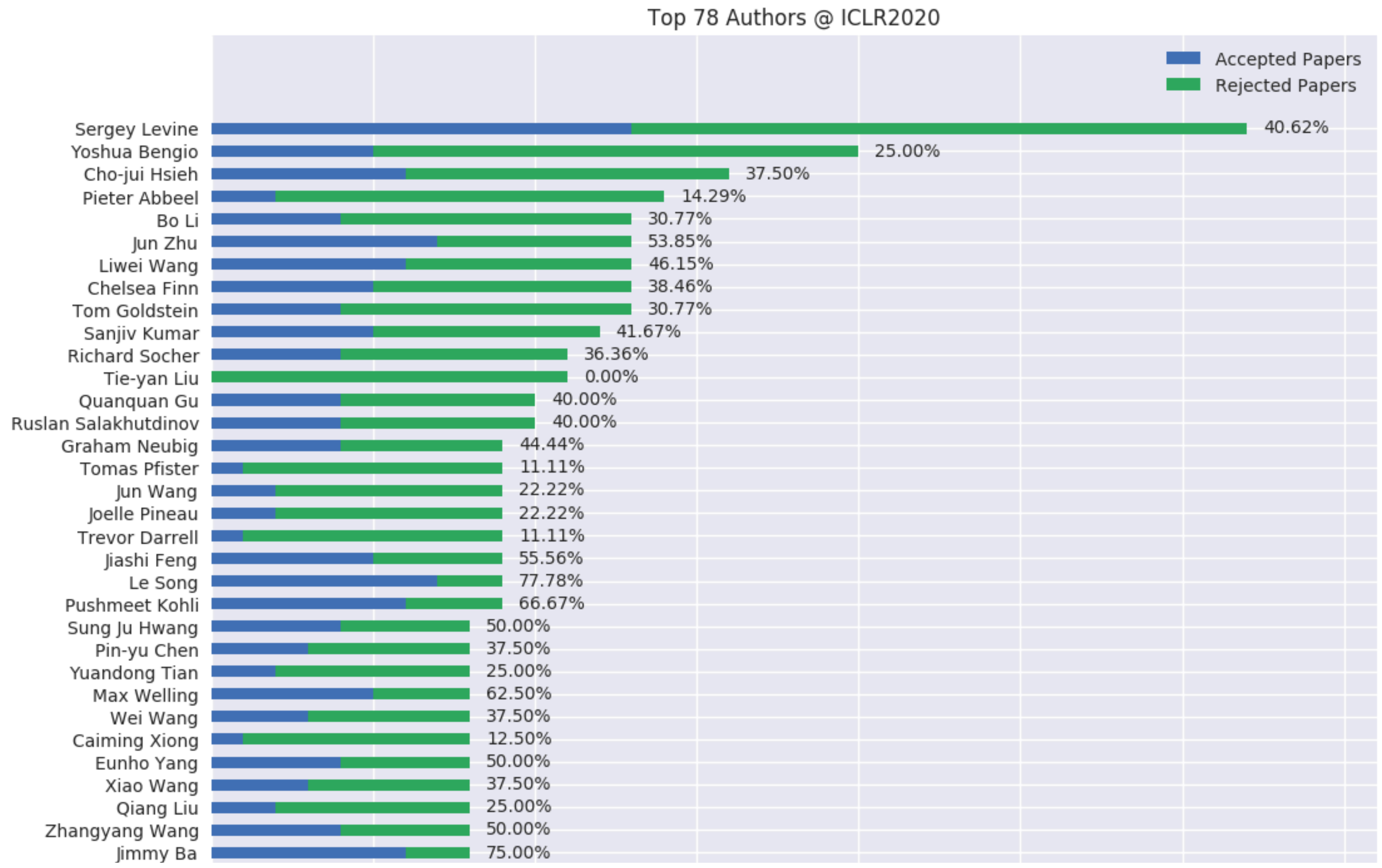

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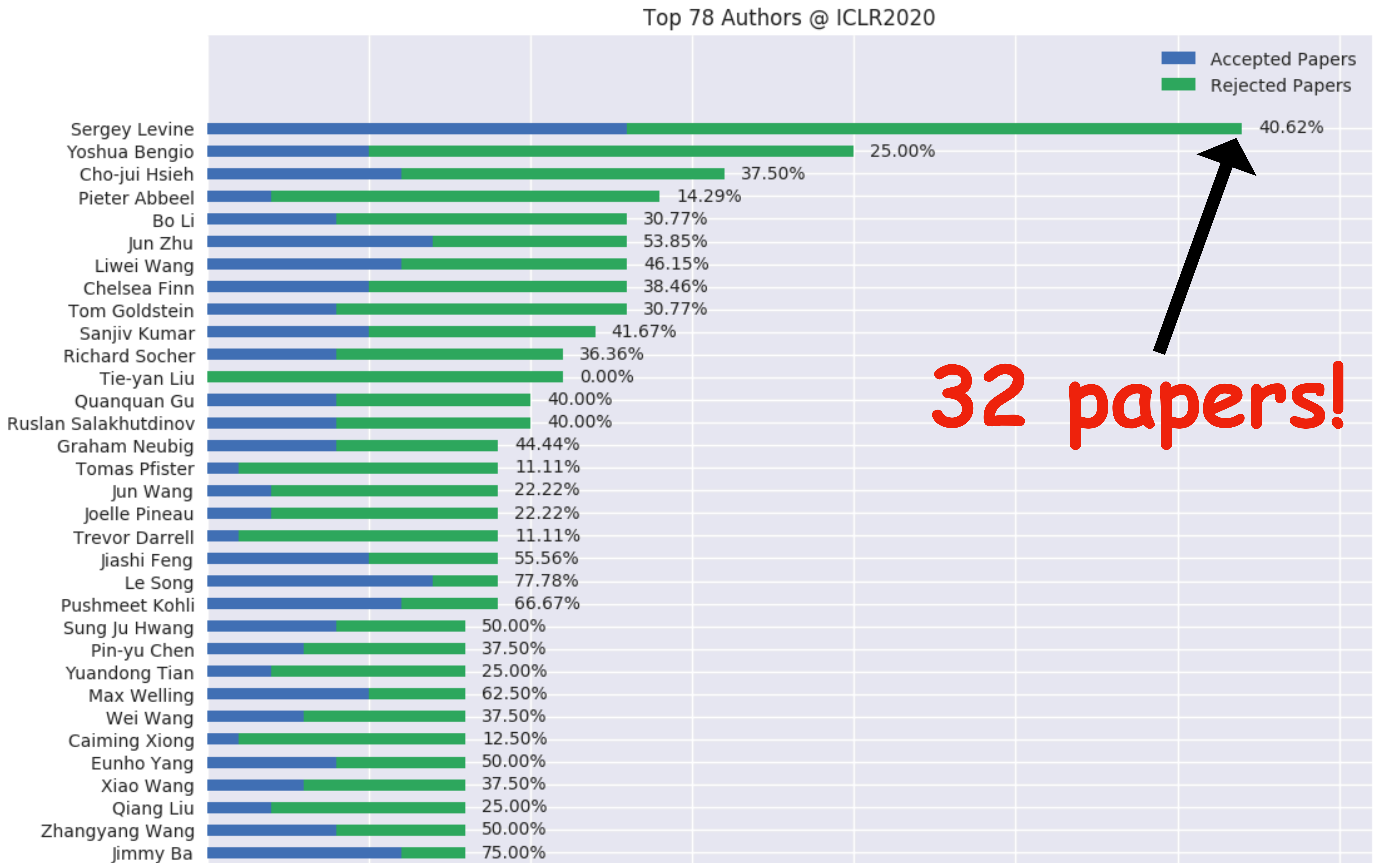

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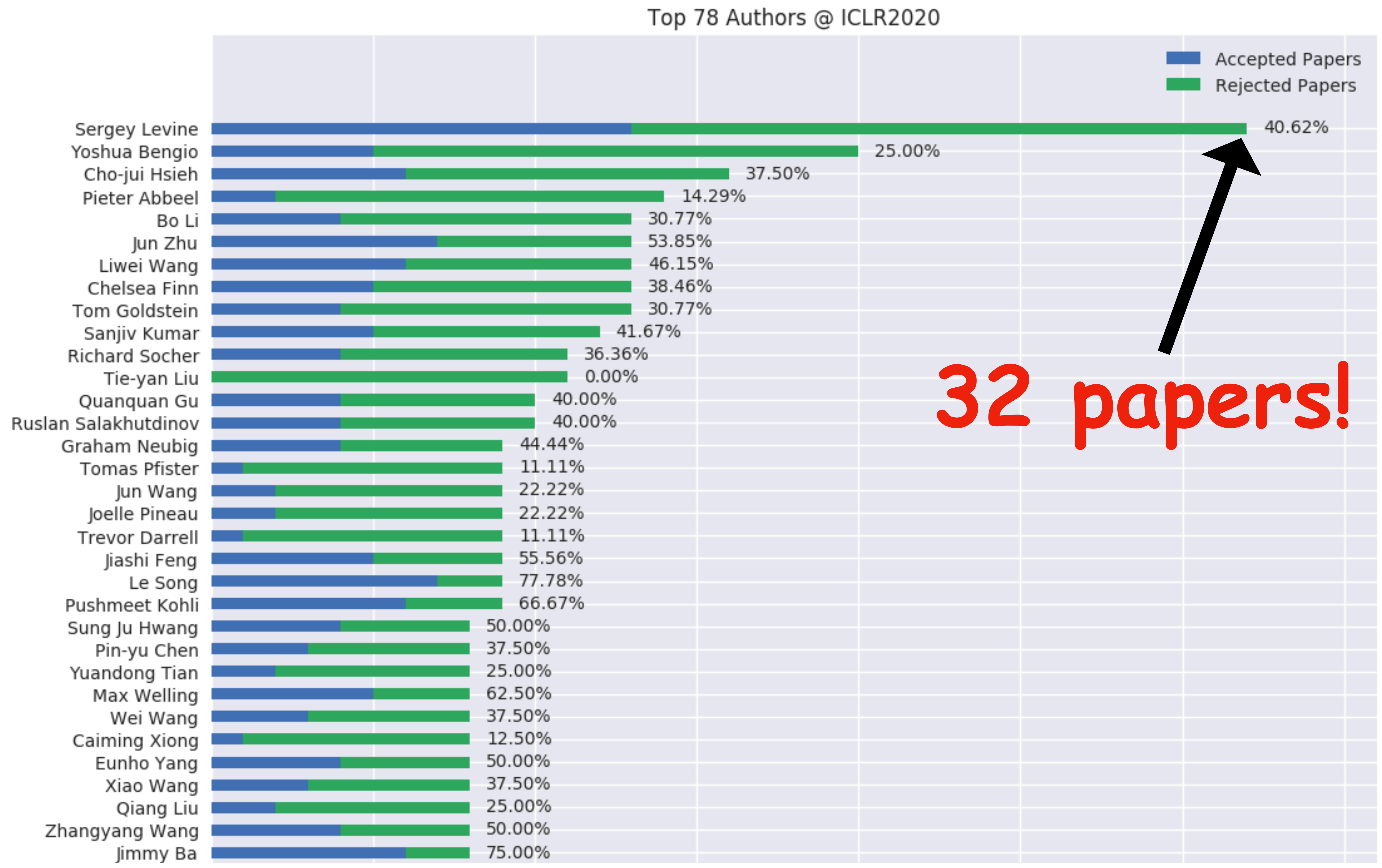

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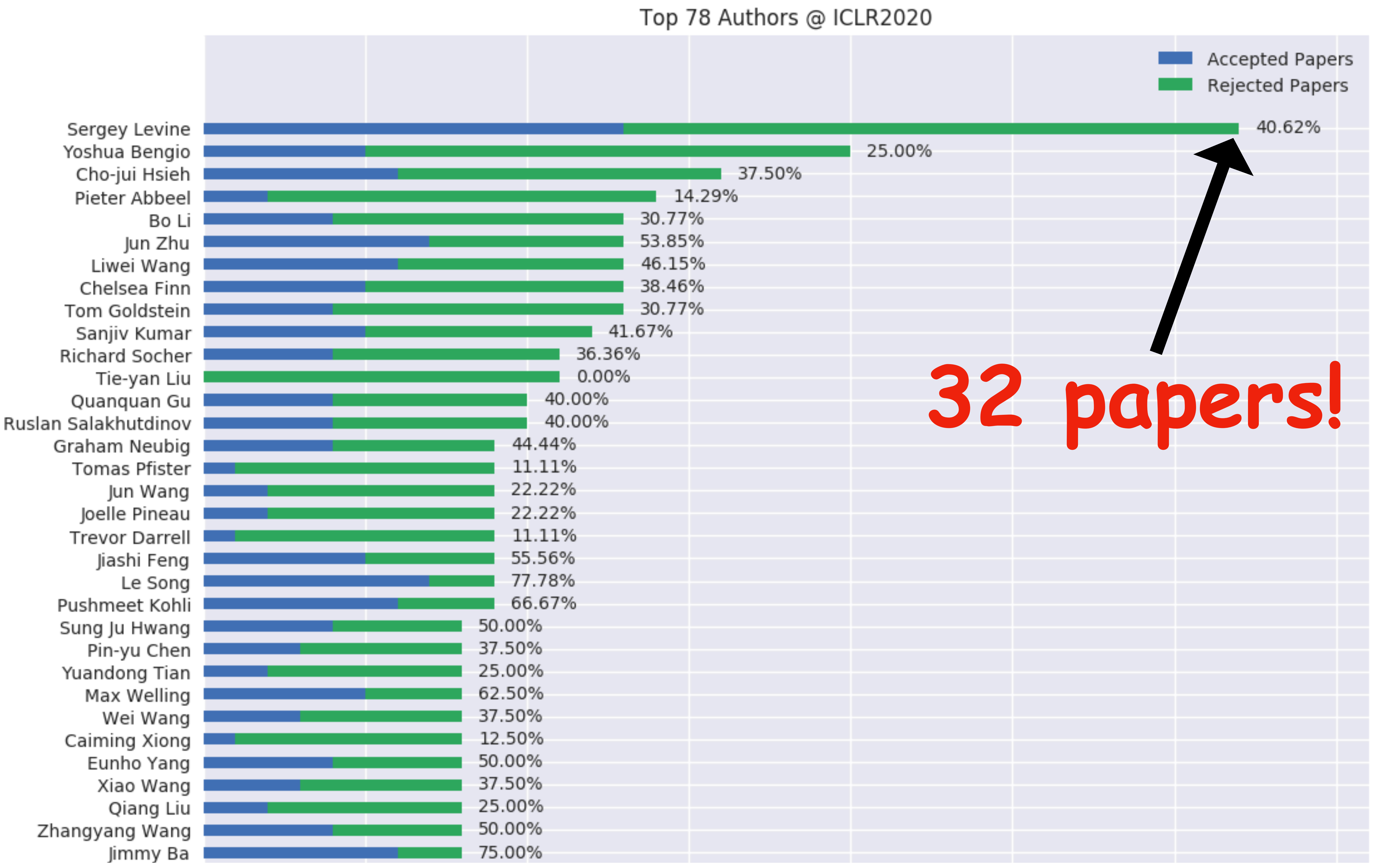

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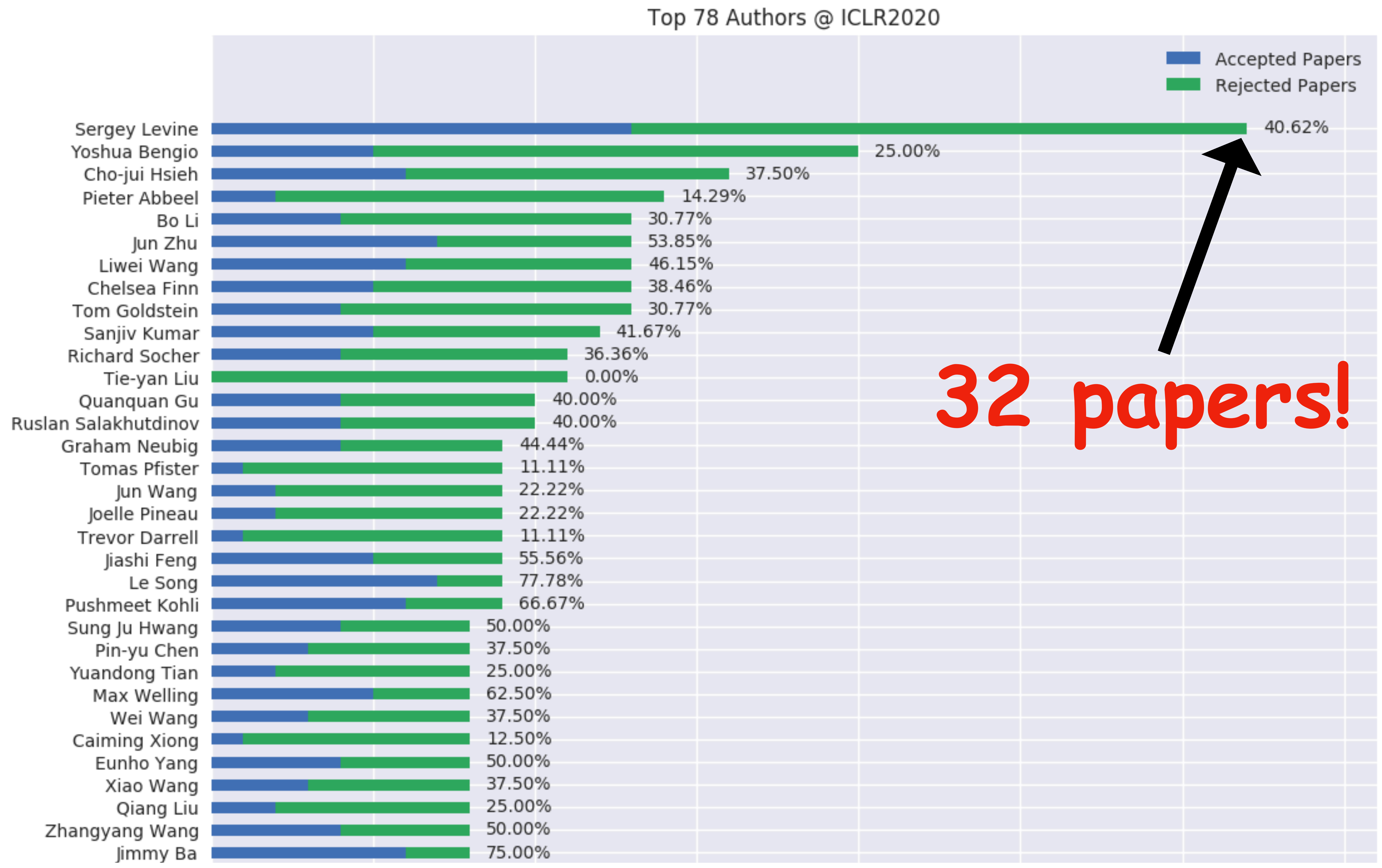

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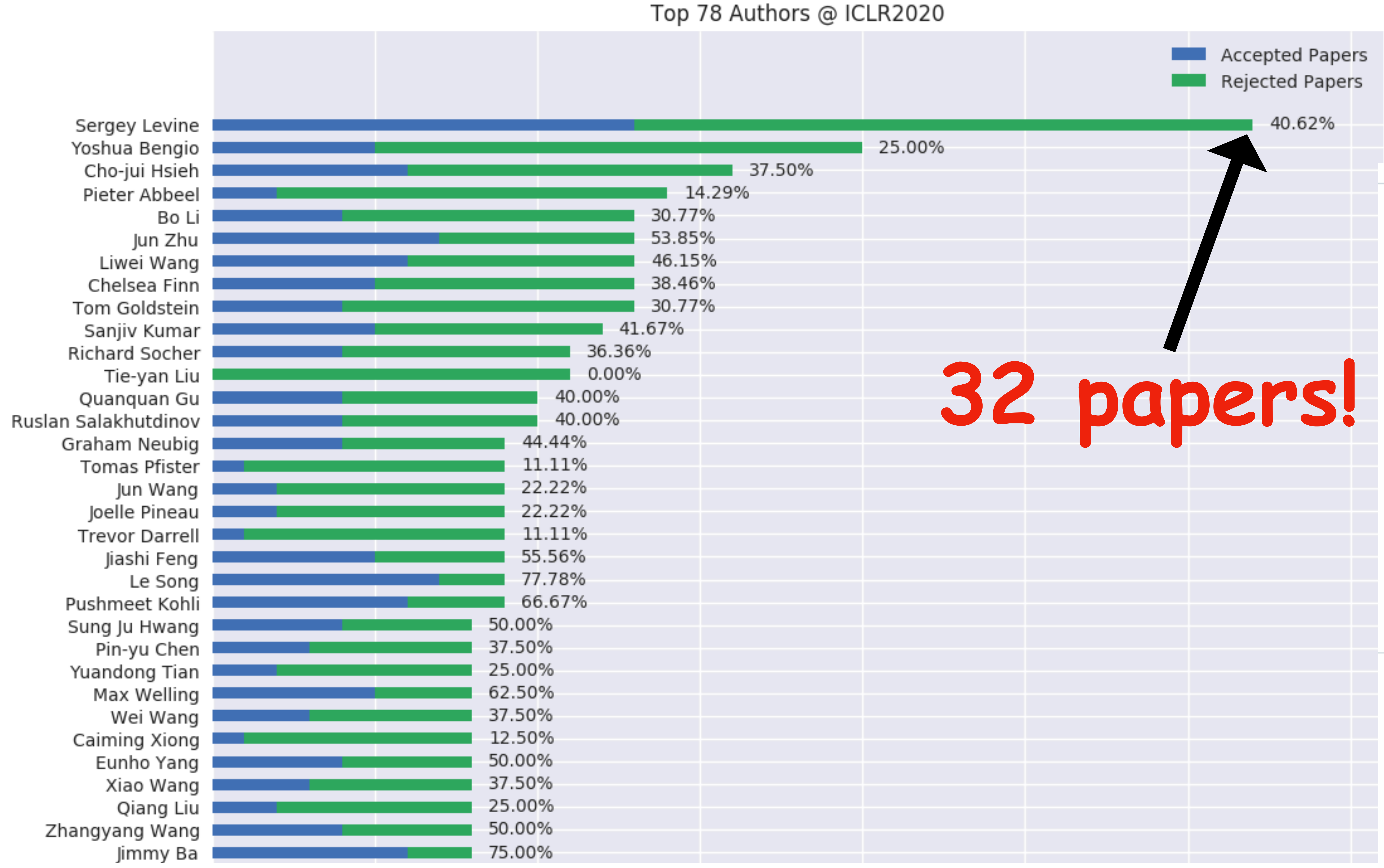

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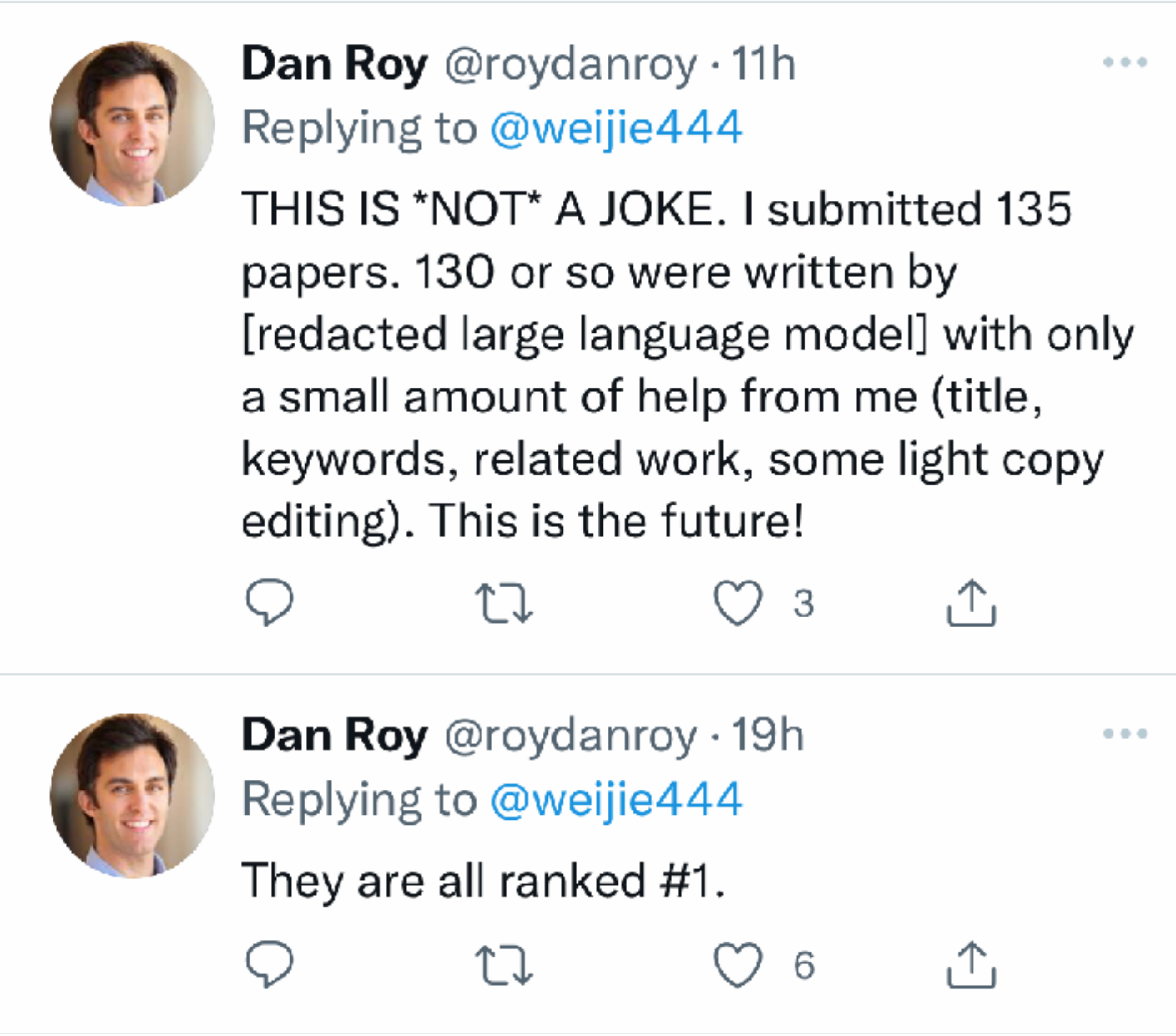

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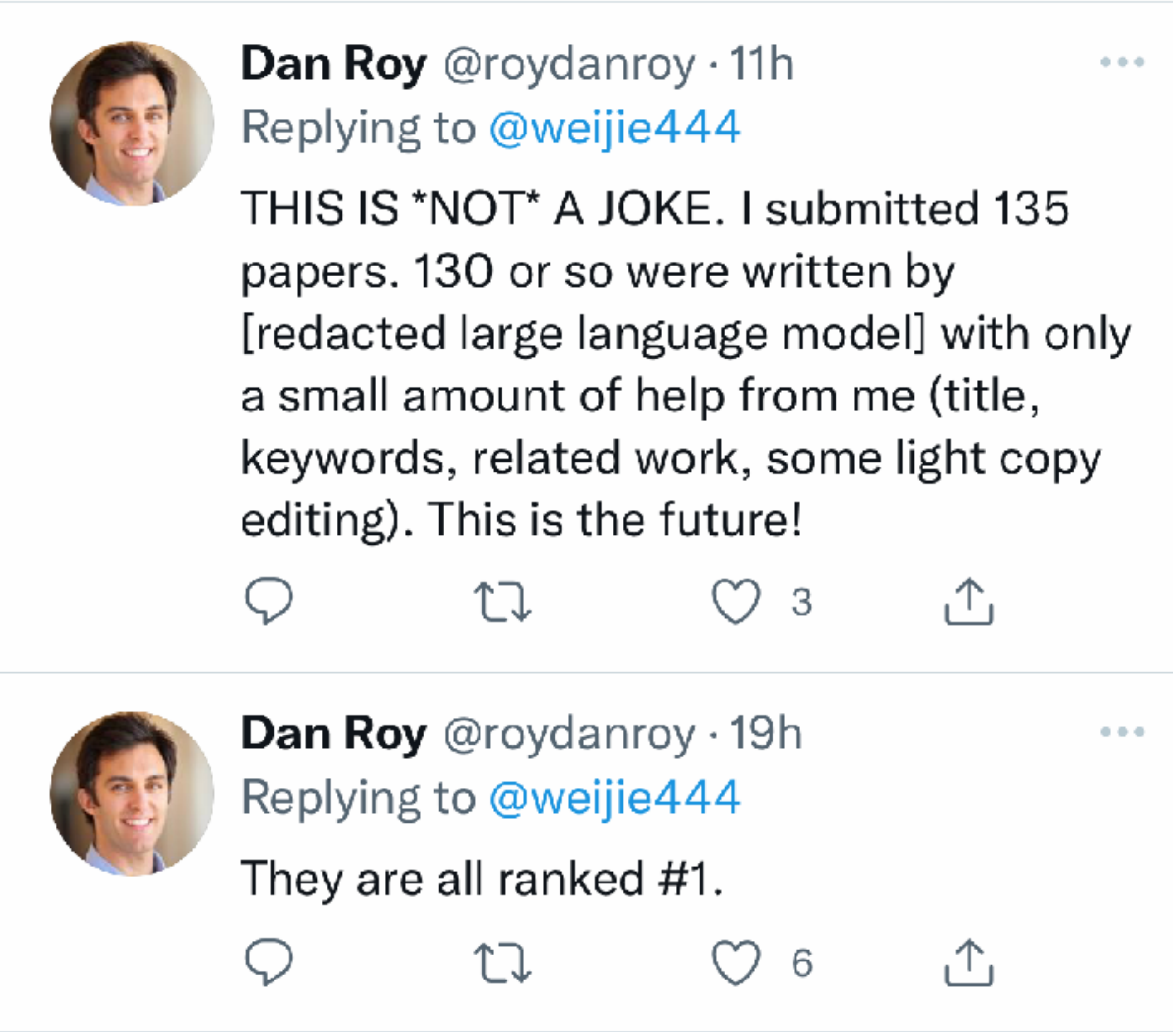

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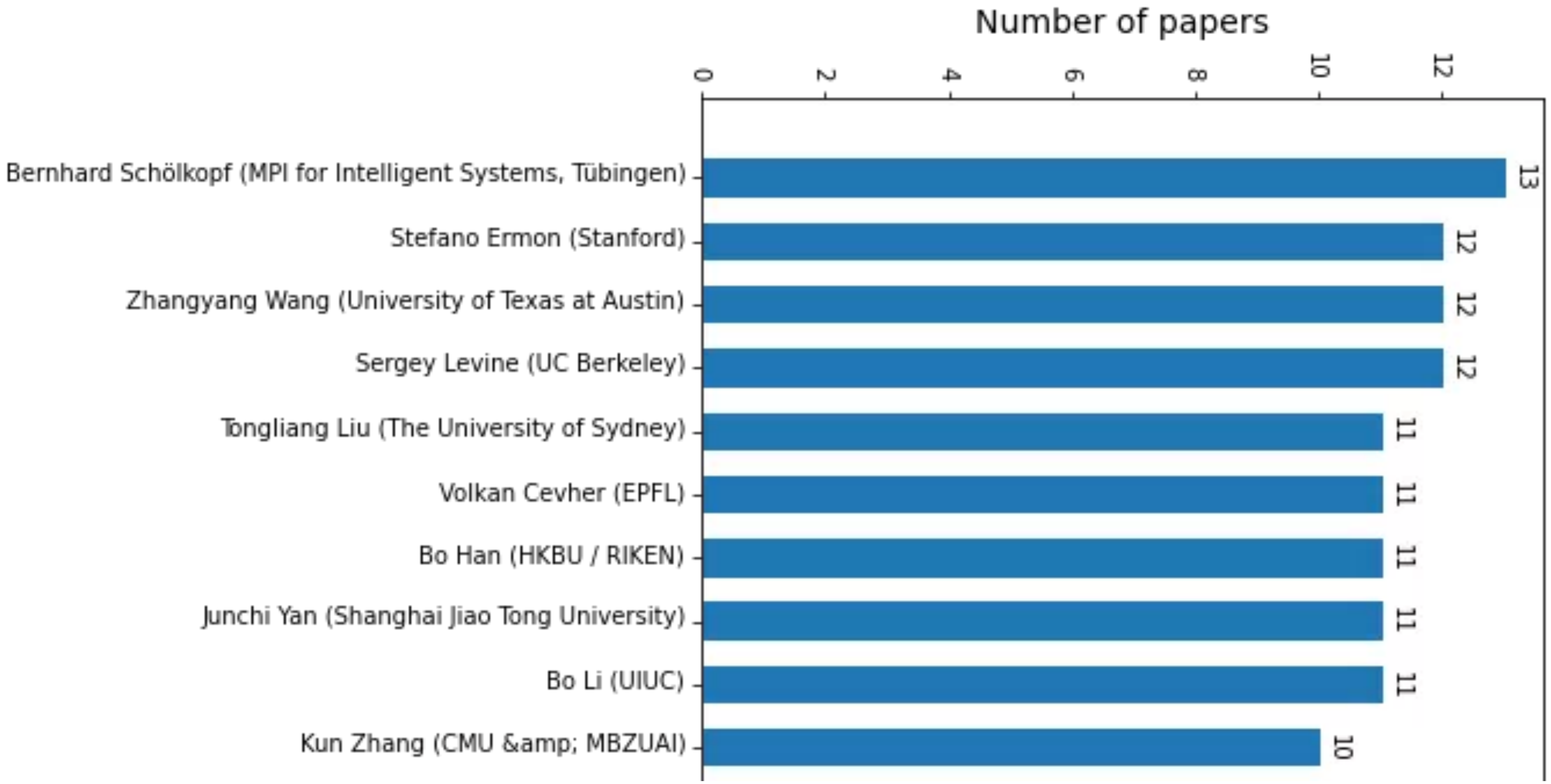

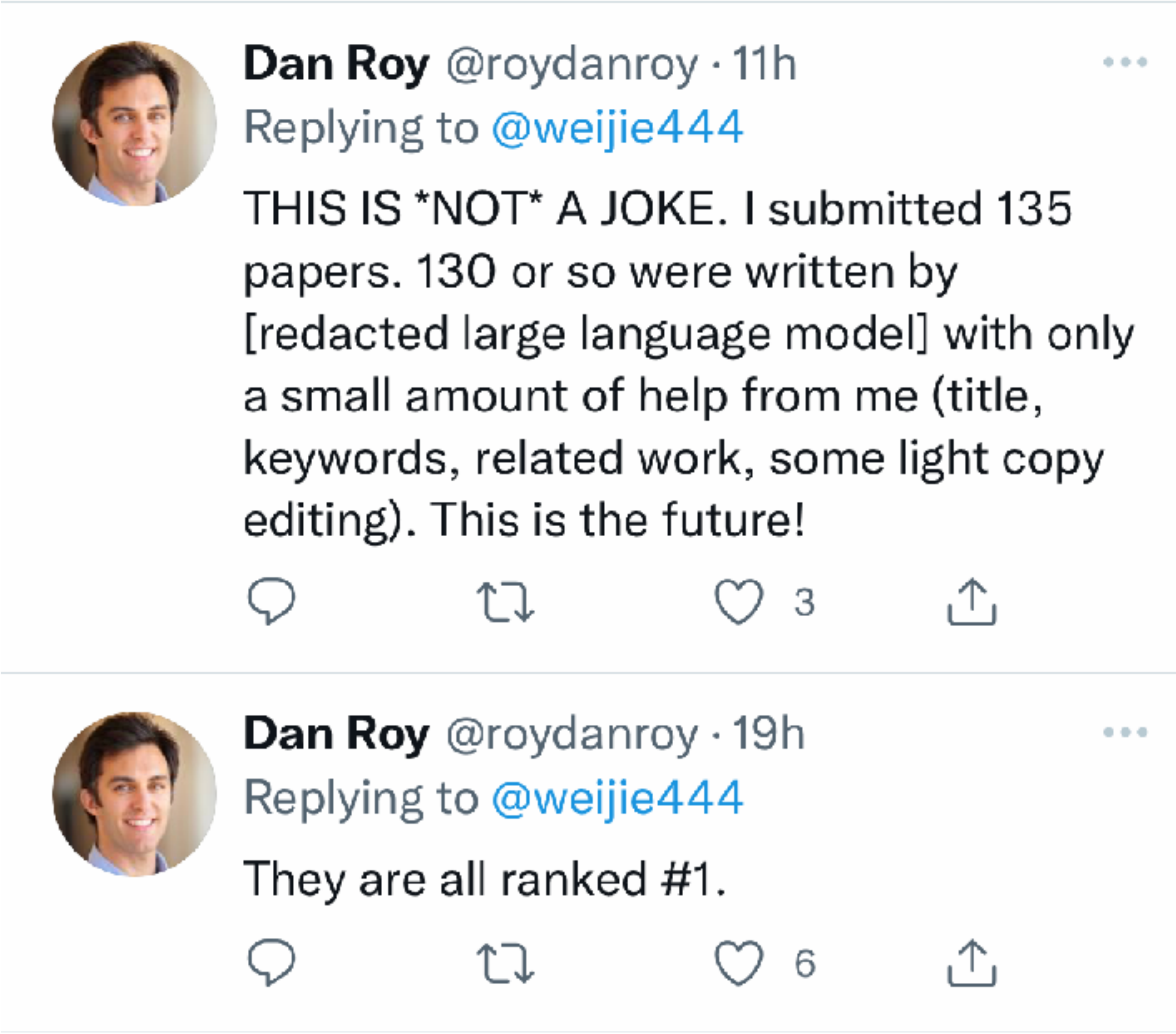

Extensions (can we do something when…)

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Ratings are generated from other statistics models

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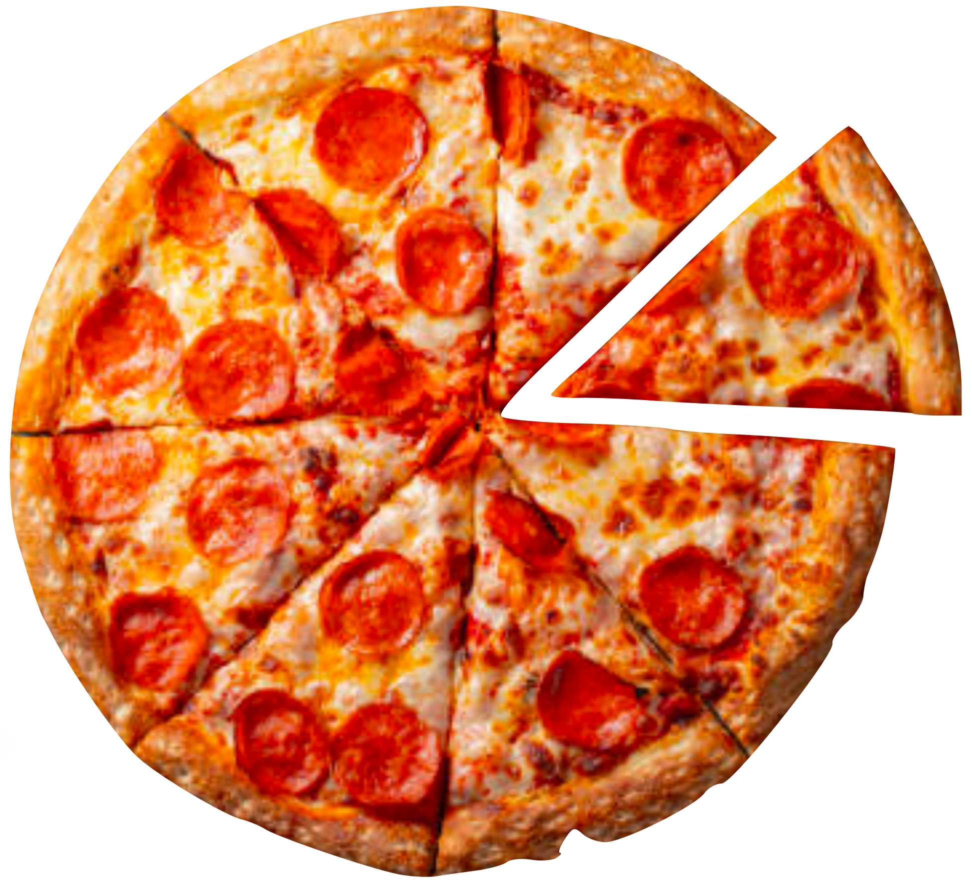
Examples of non-truthful knowledge partitions

Non-existence when the dimension $n = 1$

Other than the trivial knowledge partition, there does not exist a truthful knowledge partition when $n = 1$

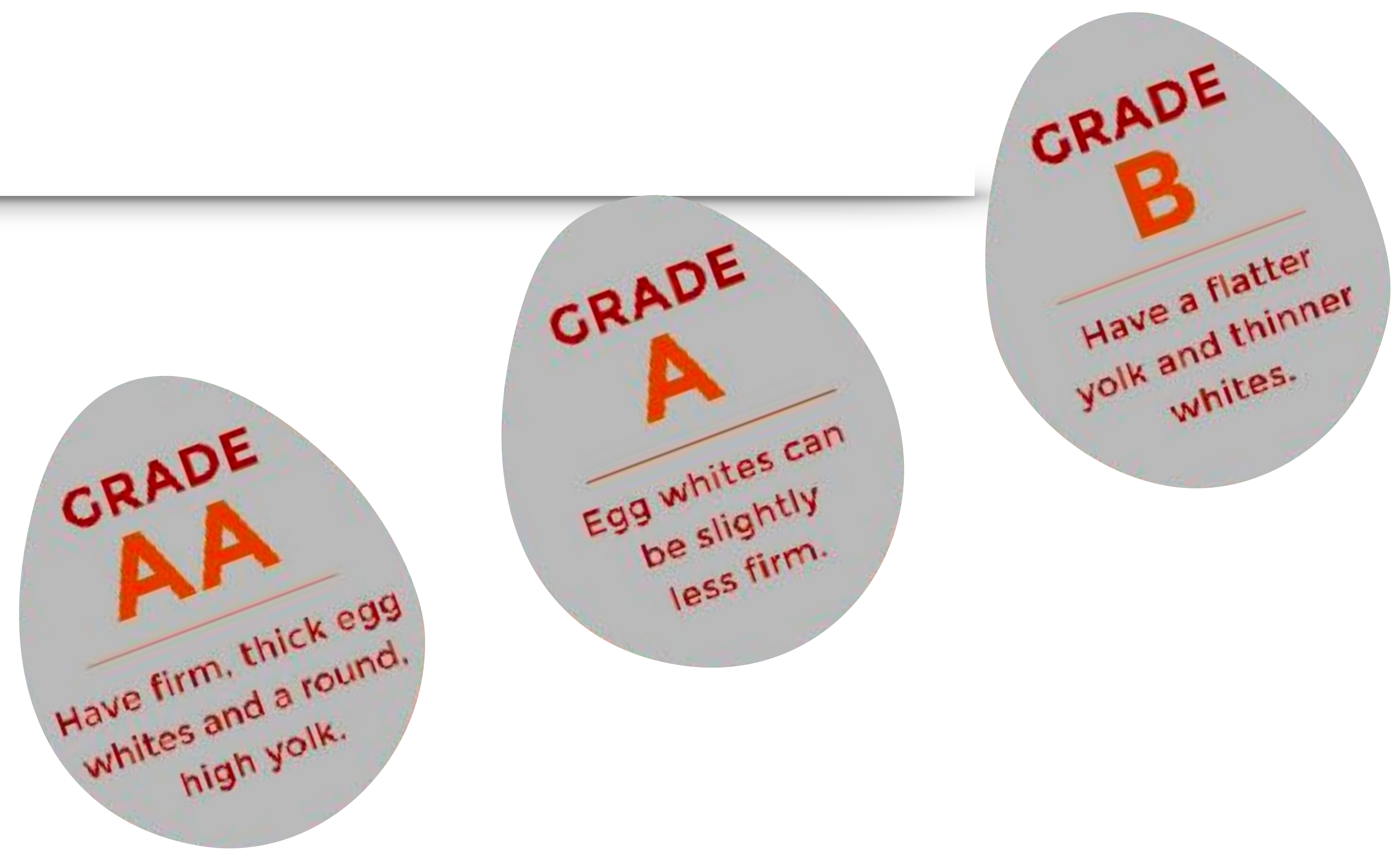
A counterexample when $n \geq 3$

let $\mathcal{S} = \{S_1, S_2\}$, where $S_1 = \{\boldsymbol{x} : x_1 \geq x_2 \geq \cdots \geq x_n\}$ and $S_2 = \mathbb{R}^n \backslash S_1$, and $\boldsymbol{R} = (n\epsilon, (n-1)\epsilon, \ldots, 2\epsilon, \epsilon) \in S_1$



Alice with incomplete knowledge

Alice has n_q items in grade q. Items of different grades have very different values, but Alice cannot determine for those of the same grade



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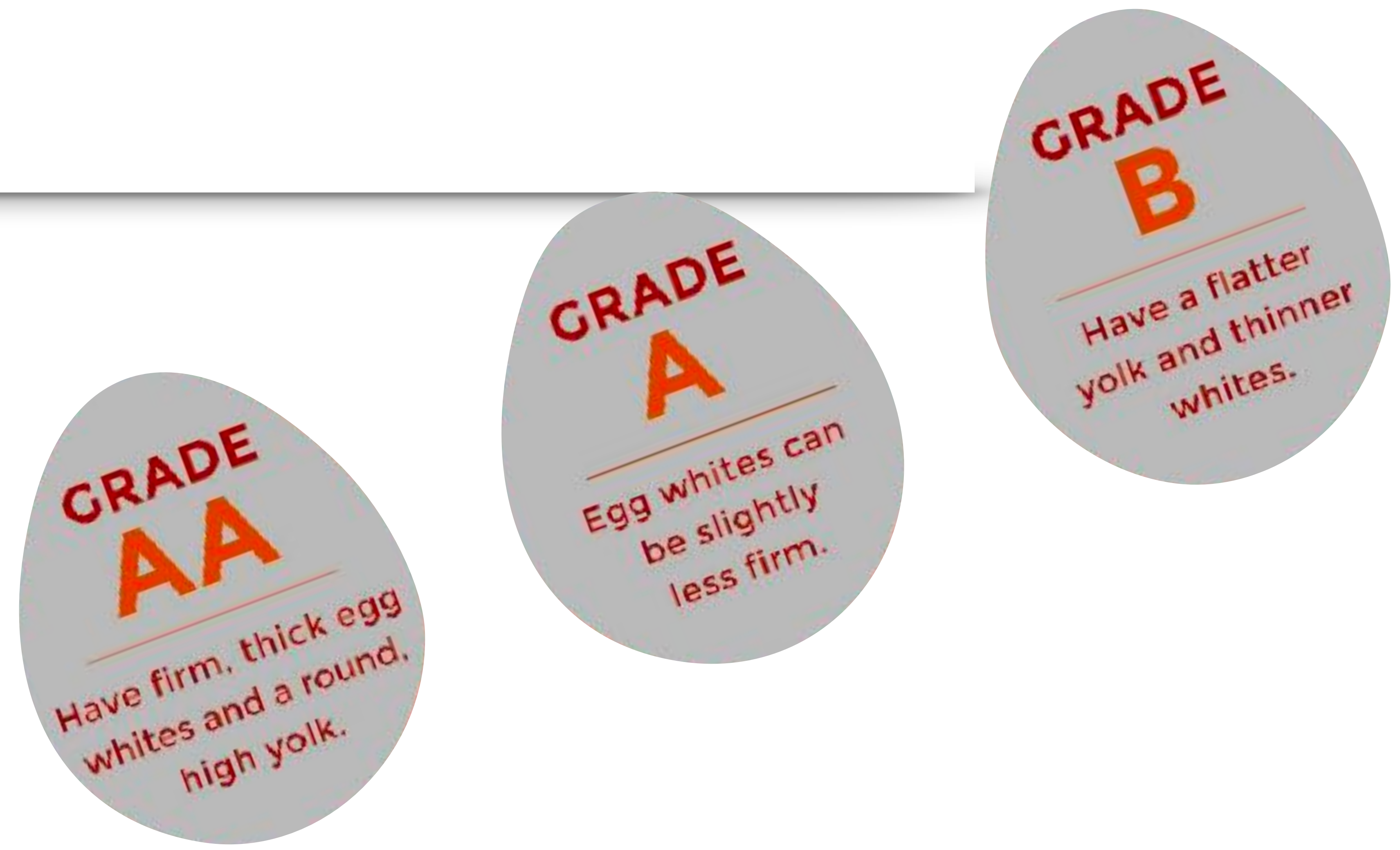

Coarse ranking

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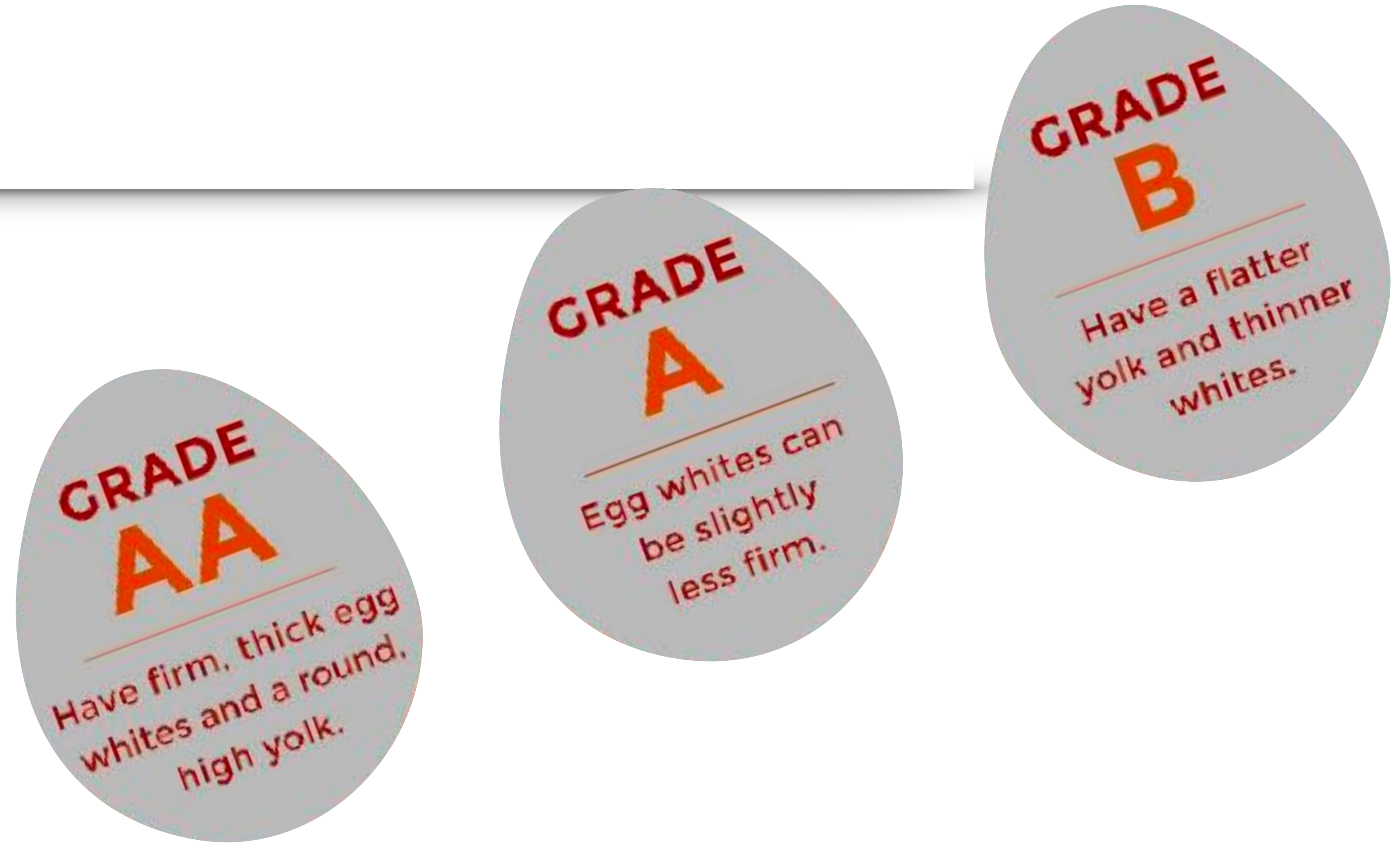

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1. Set $n_1, n_2, \ldots, n_p$ that sum to n

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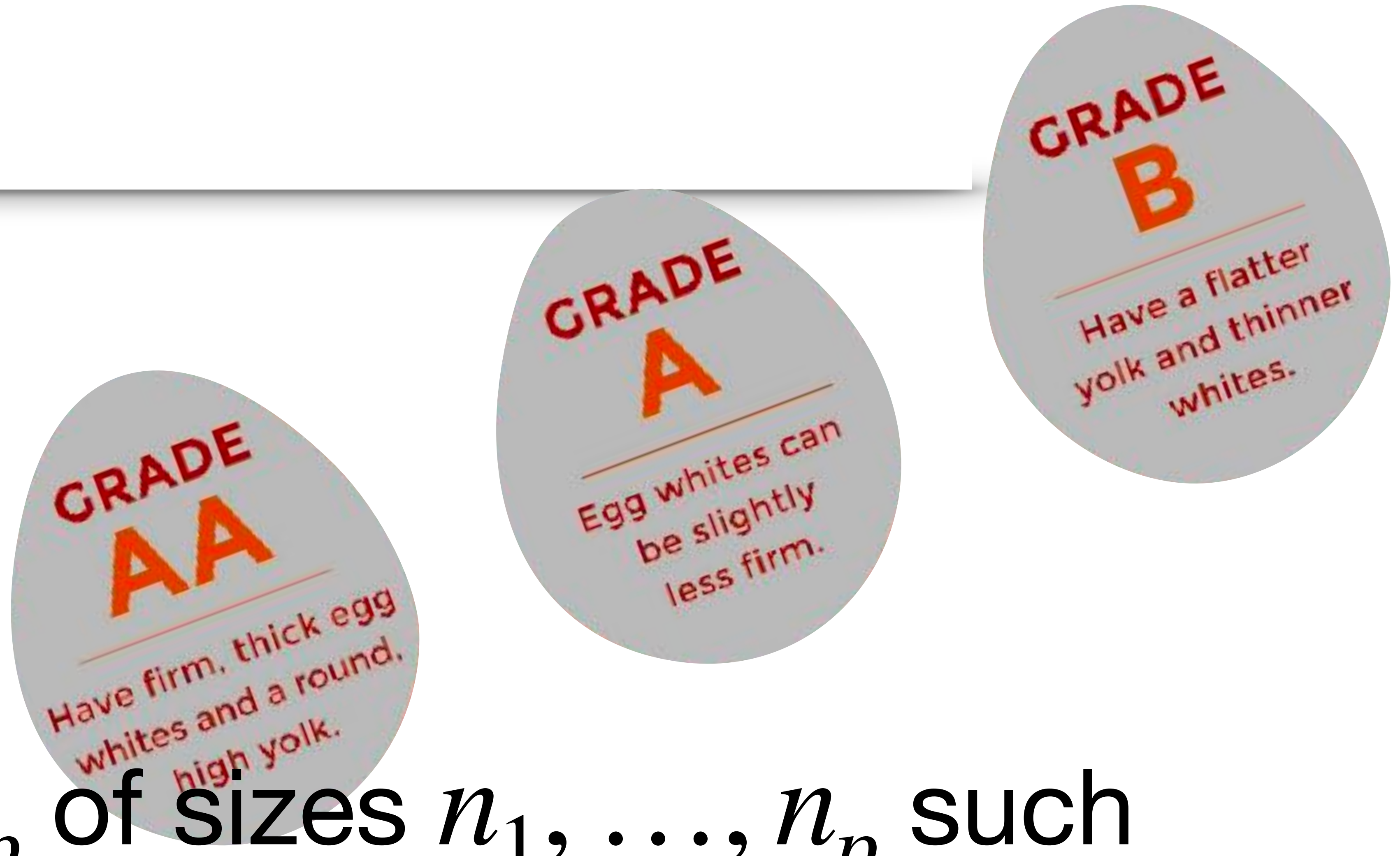

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1. Set $n_1, n_2, \ldots, n_p$ that sum to n
2. Split $\{1,2,\ldots,n\}$ into ordered subsets $I_1, \ldots, I_p$ of sizes $n_1, \ldots, n_p$ such that

$$\boldsymbol{R}_{I_1} \geq \boldsymbol{R}_{I_2} \geq \cdots \geq \boldsymbol{R}_{I_p}$$

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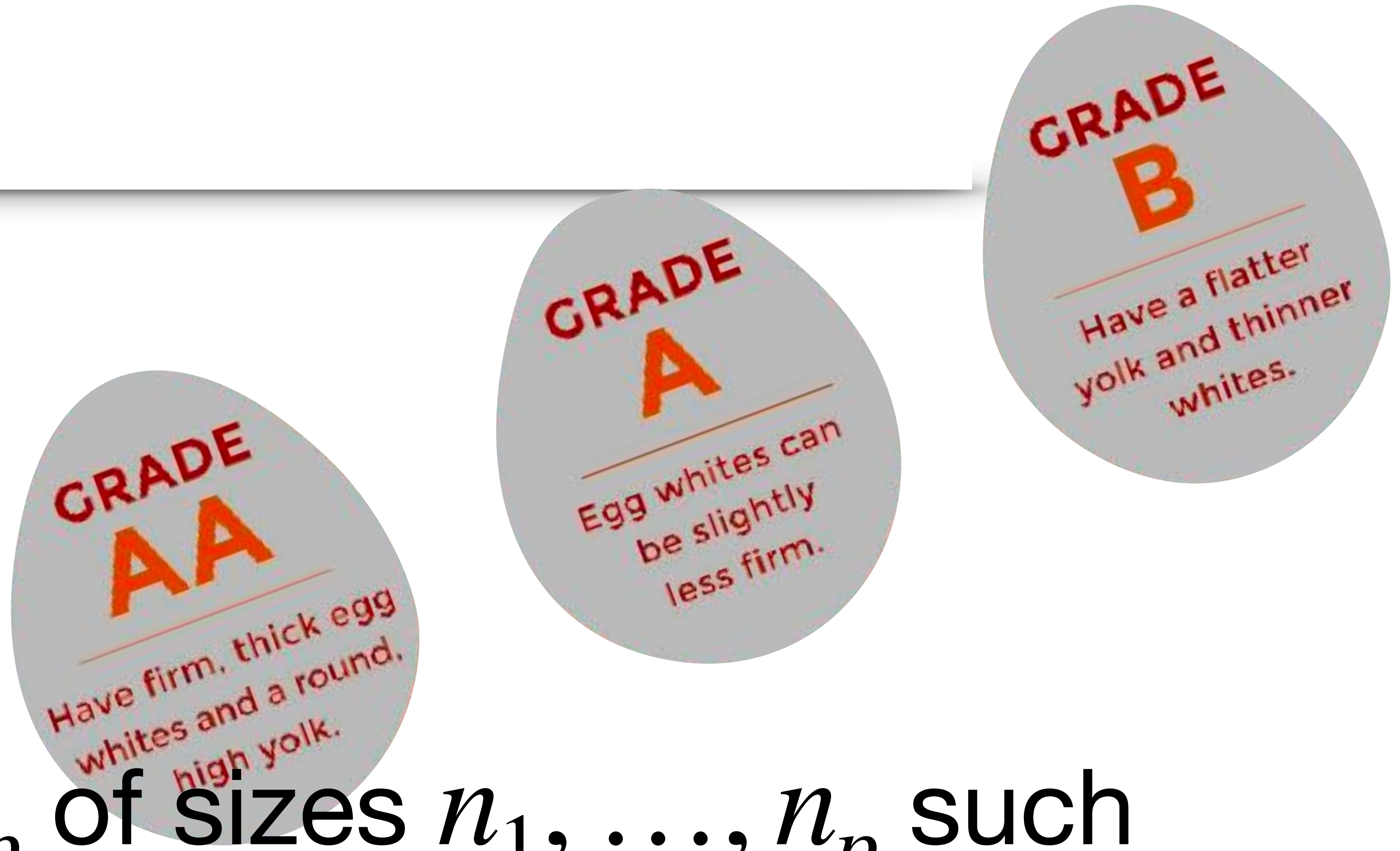

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3. But not required to make any within-subset comparisons

Alice with incomplete knowledge

Alice has n_q items in grade q. Items of different grades have very different values, but Alice cannot determine for those of the same grade

Examples

- $n_1 = \cdots = n_{p-1} = 1$ and $n_p = n - p + 1$: Alice ranks only the top $p - 1$ items

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Examples

- $n_1 = \cdots = n_{p-1} = 1$ and $n_p = n - p + 1$: Alice ranks only the top $p - 1$ items
- $n_1 = \cdots = n_{10} = n/10$: which items are the top 10%, which are the next top 10%, ...?

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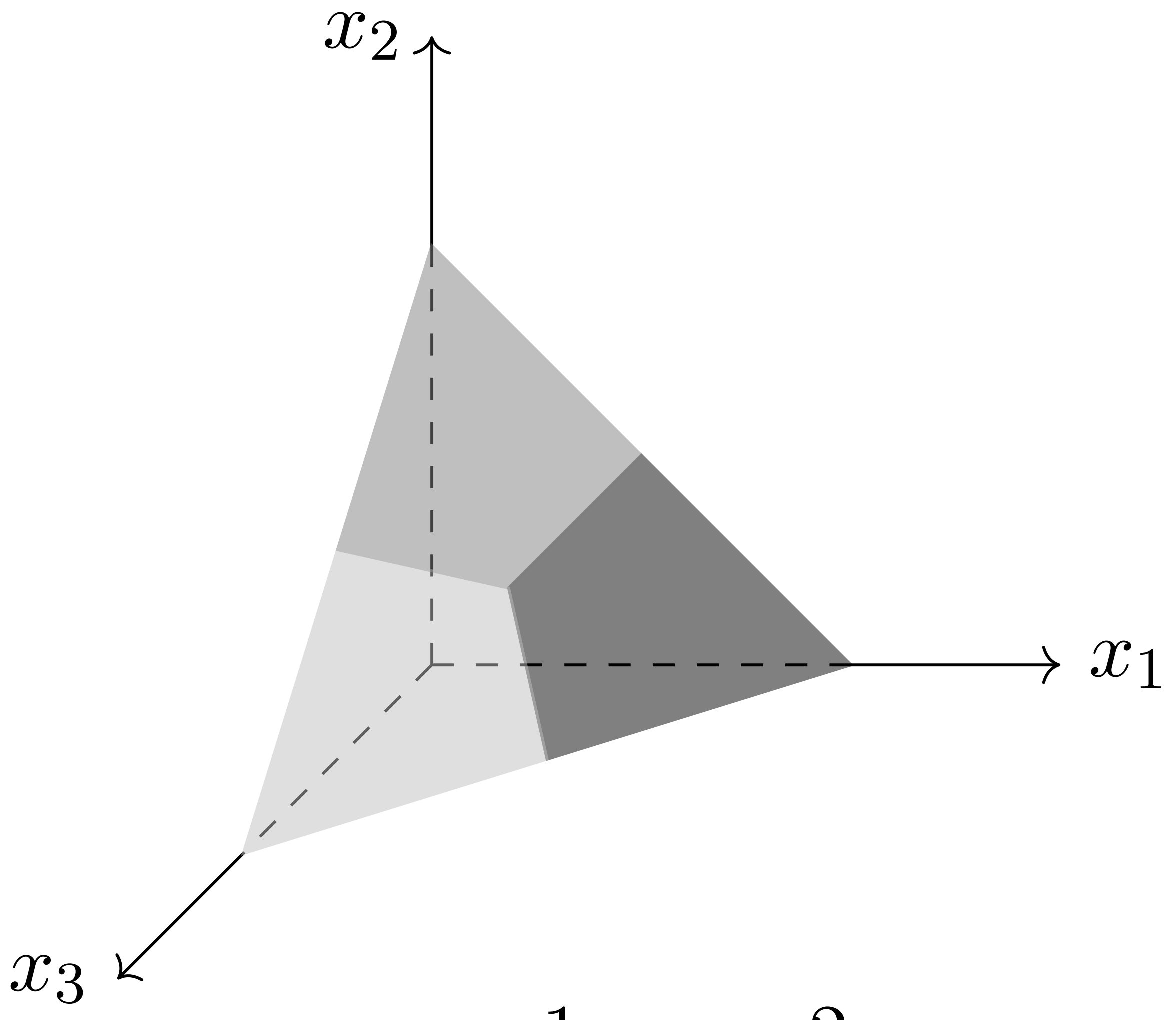
- $n_1 = \cdots = n_{10} = n/10$: which items are the top 10%, which are the next top 10%, …?
- $n_1 = n_2 = n/2$: which half are better than the other?

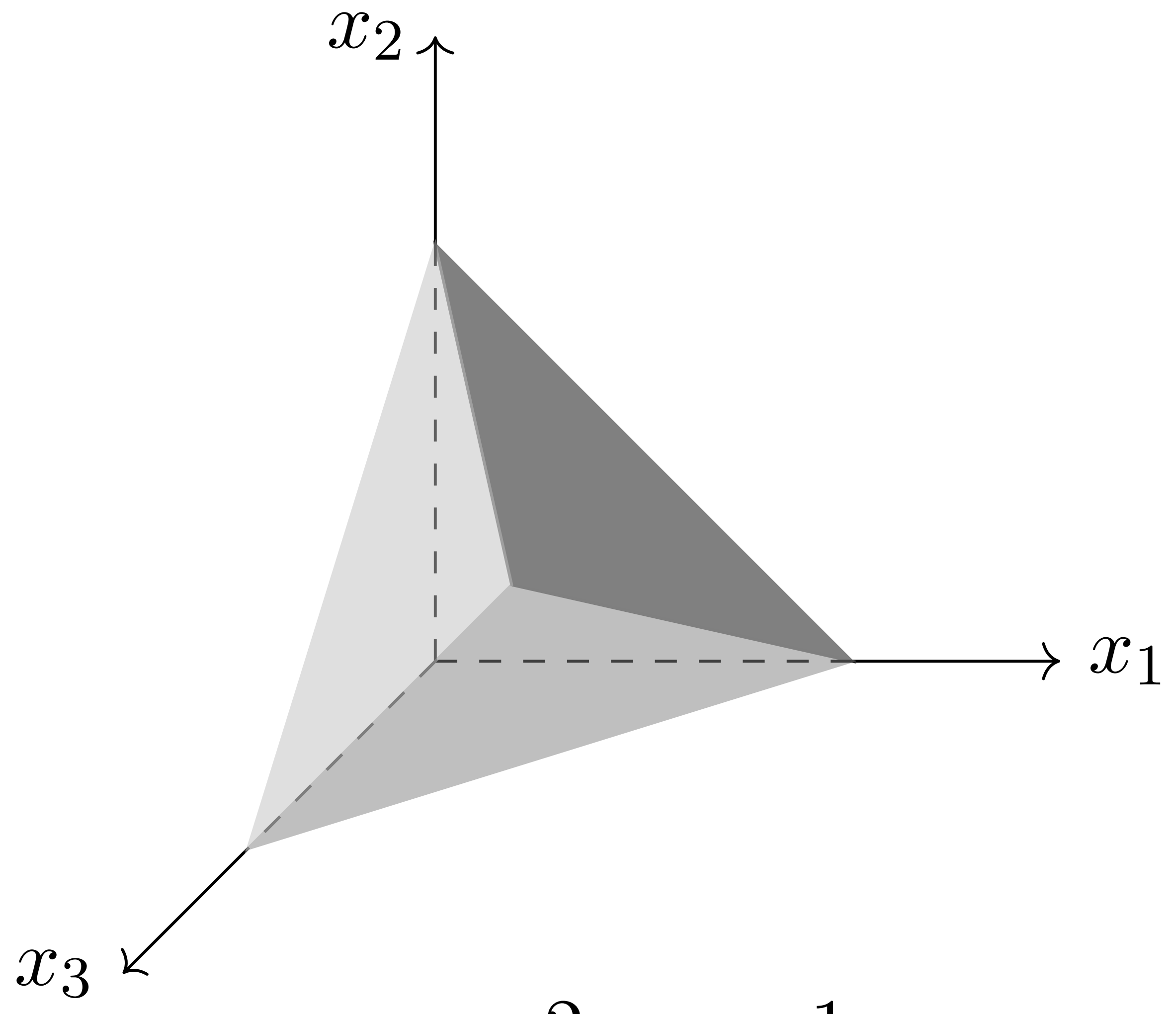
Alice remains truthful

Coarse ranking

Report ordered subsets $I_1, \ldots, I_p$ of sizes $n_1, \ldots, n_p$ such that $\boldsymbol{R}_{I_1} \geq \boldsymbol{R}_{I_2} \geq \cdots \geq \boldsymbol{R}_{I_p}$



$n_1 = 1, n_2 = 2$



$n_1 = 2, n_2 = 1$

Alice remains truthful

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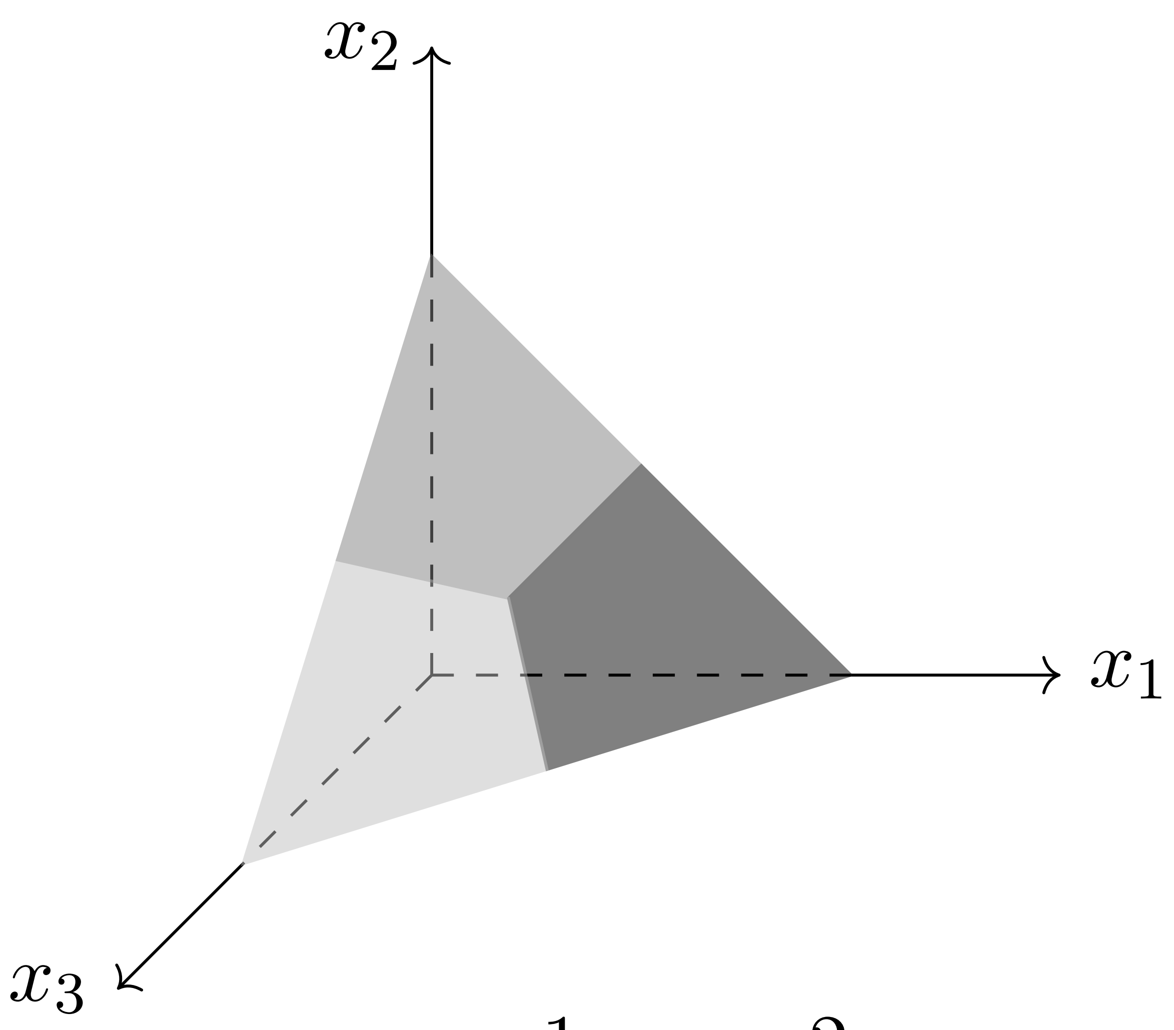

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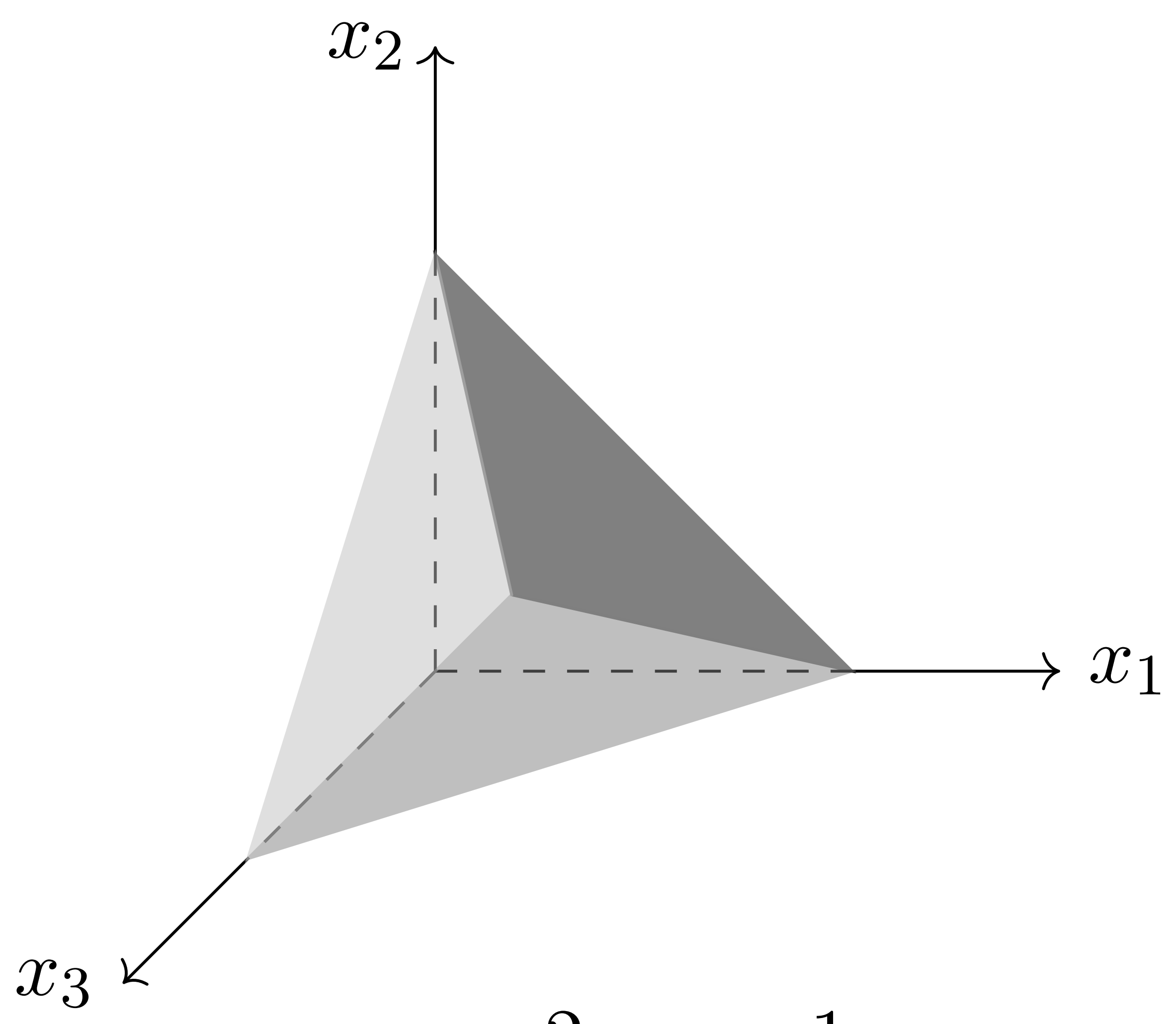

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best among your 3 papers?

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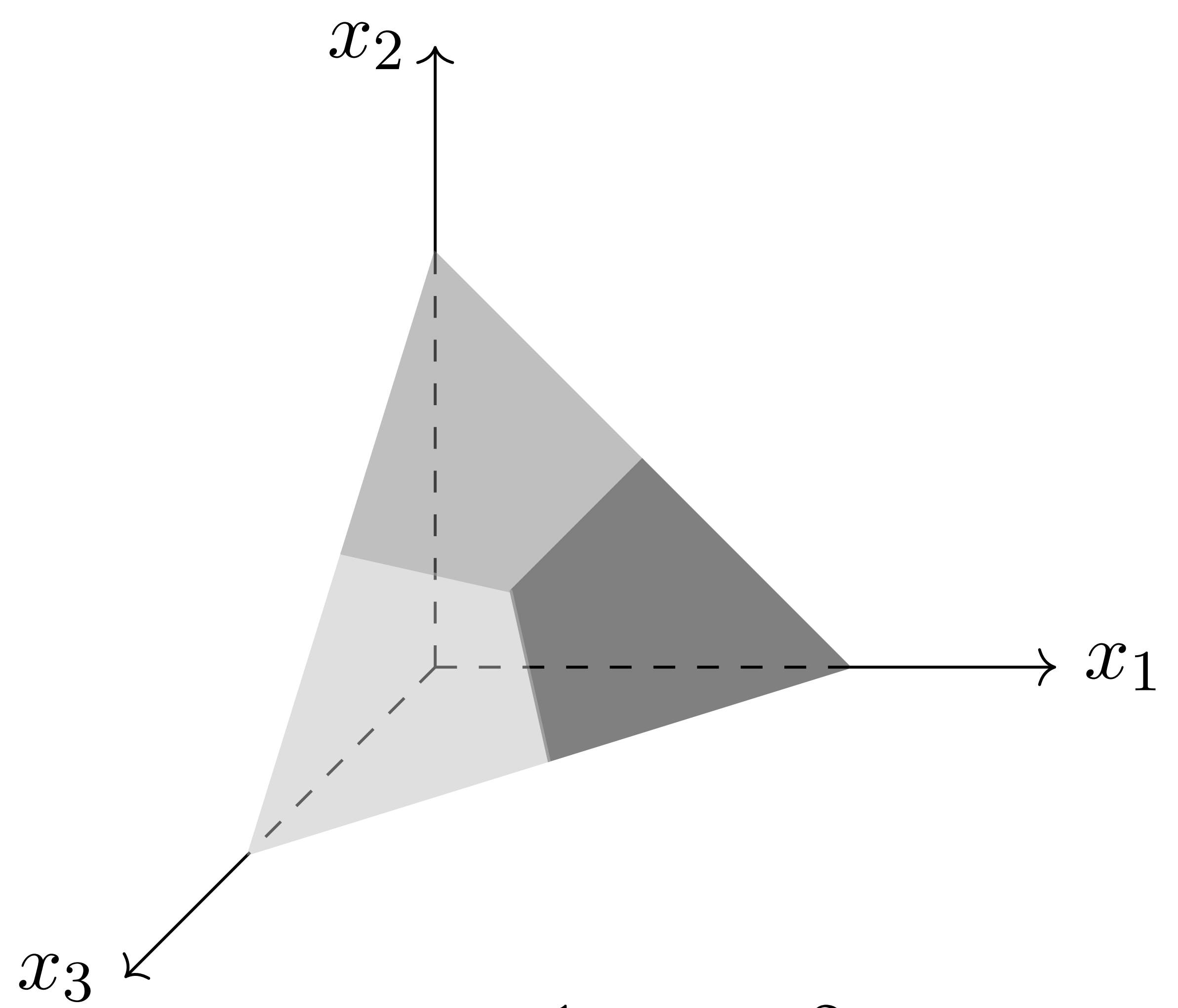

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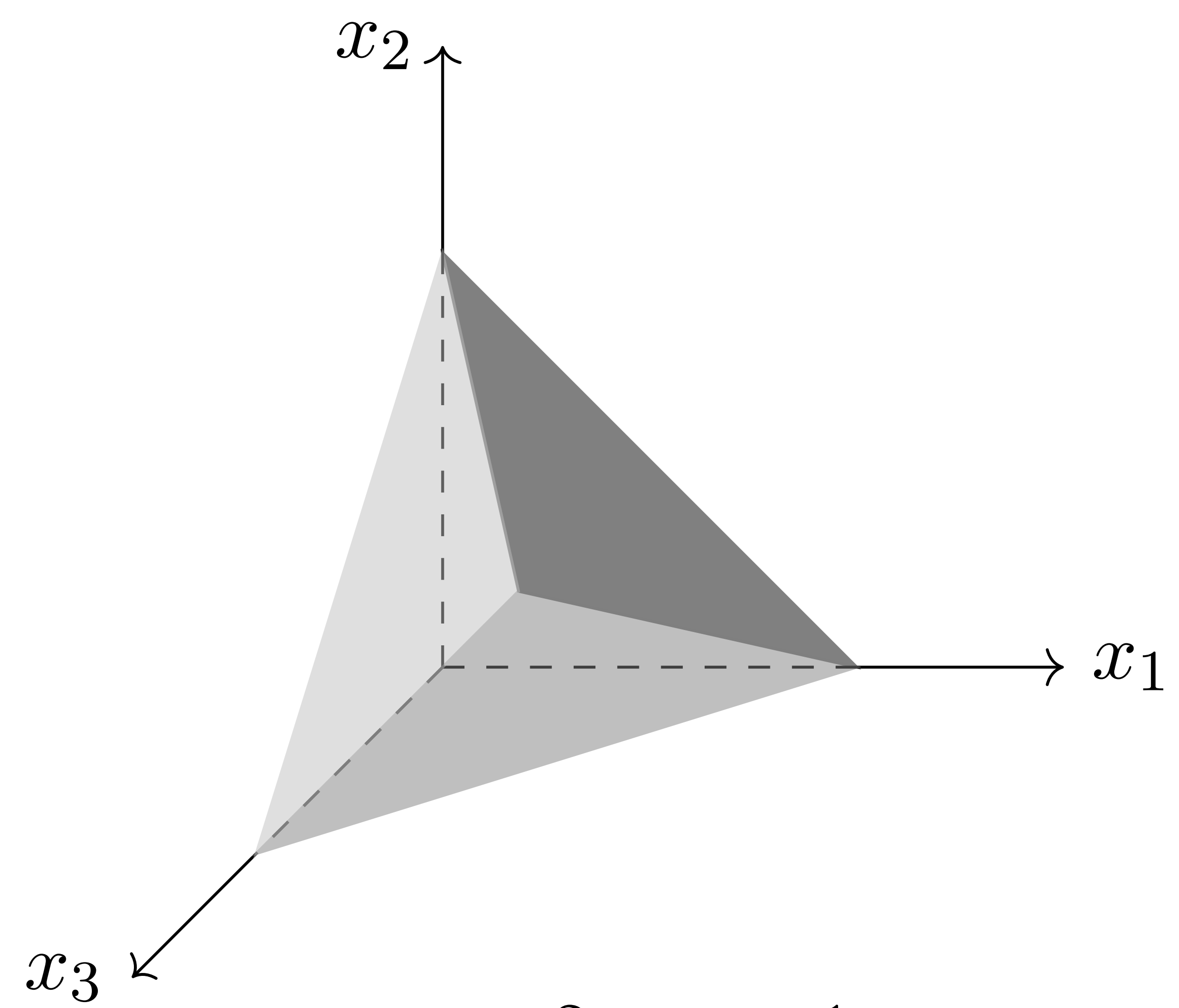

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worst among your 3 papers?

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Report ordered subsets $I_1, \ldots, I_p$ of sizes $n_1, \ldots, n_p$ such that

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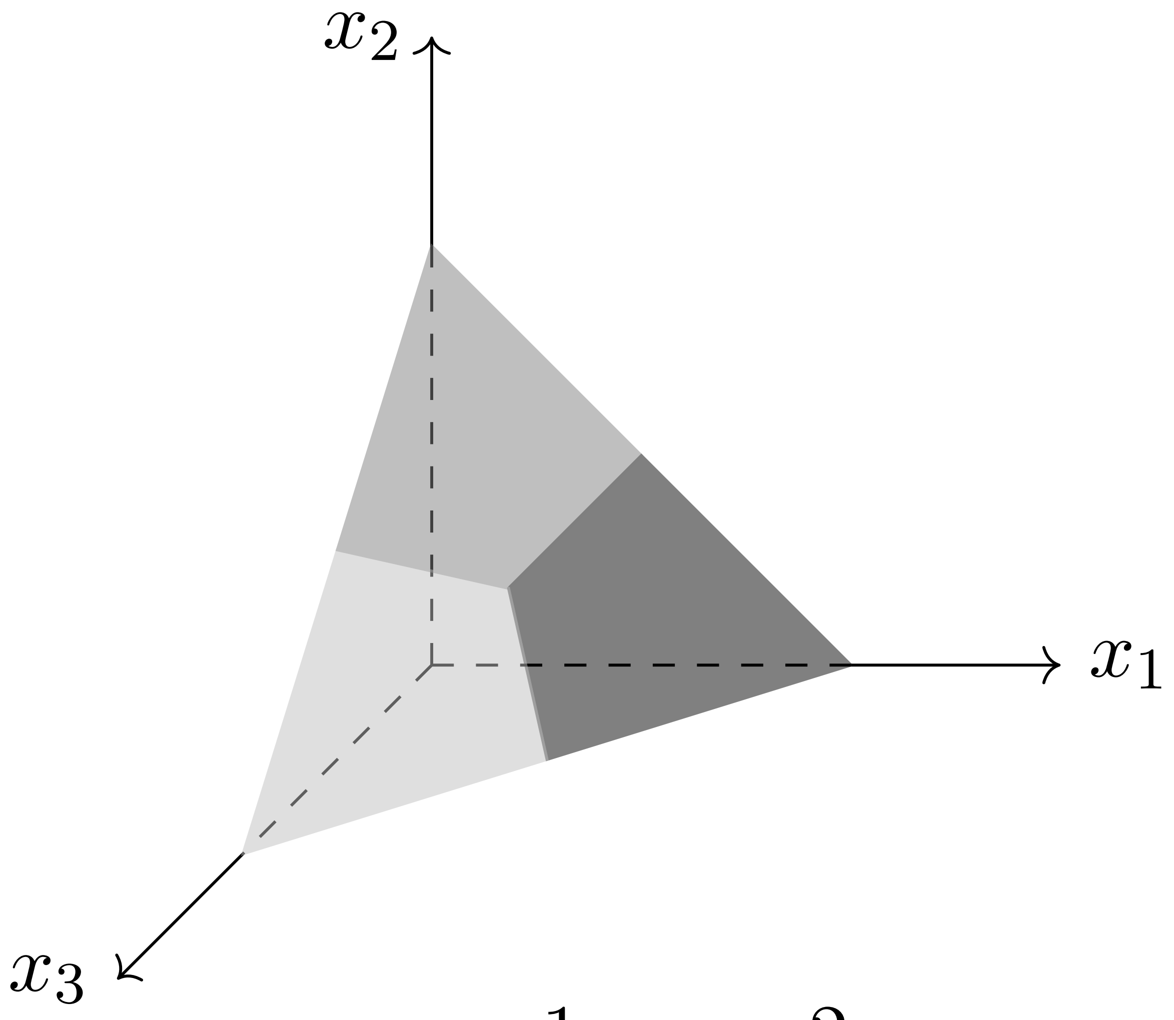

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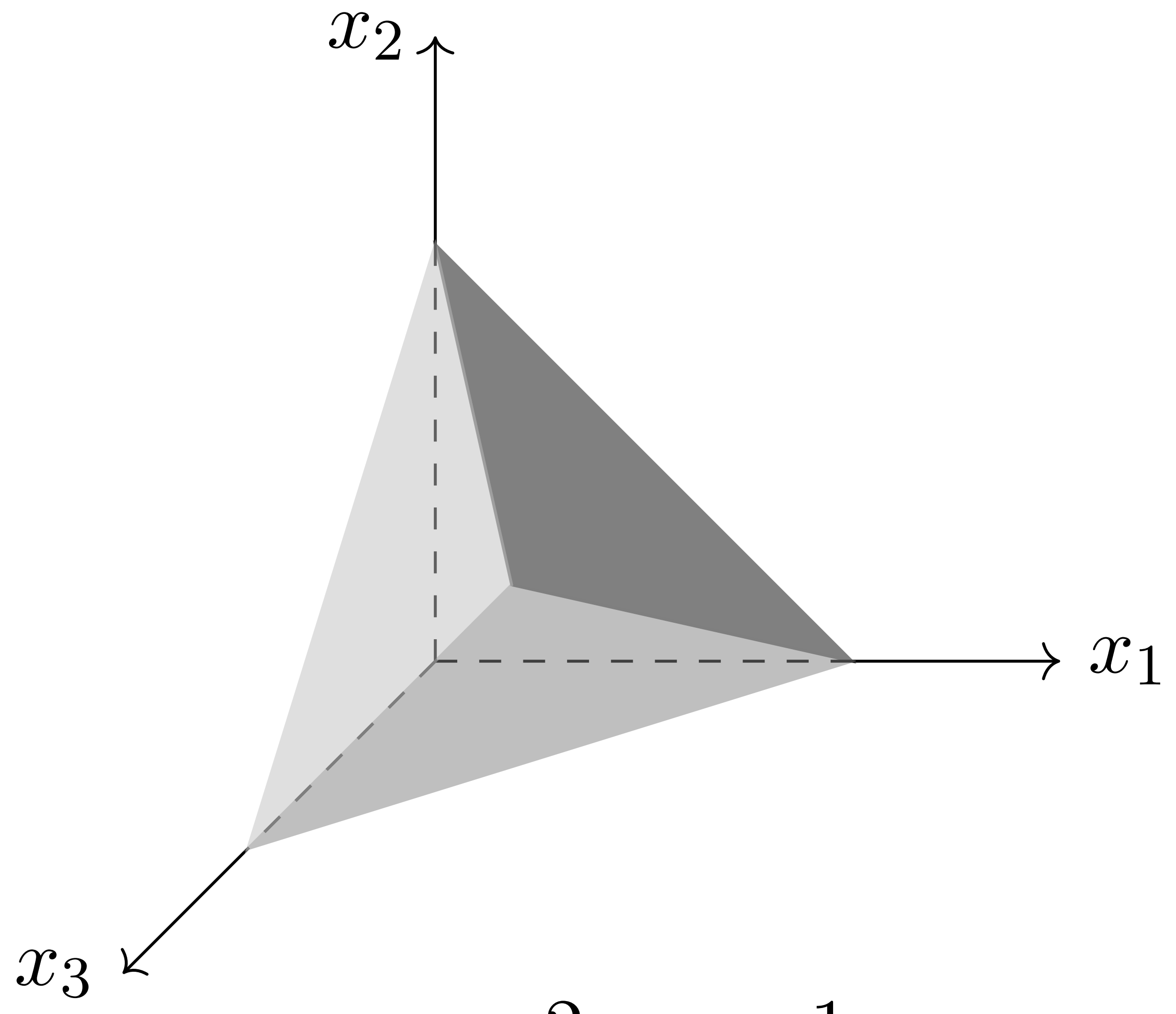

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Theorem (S. 2021)

Alice maximizes her utility if she truthfully reports the coarse ranking

Alice remains truthful

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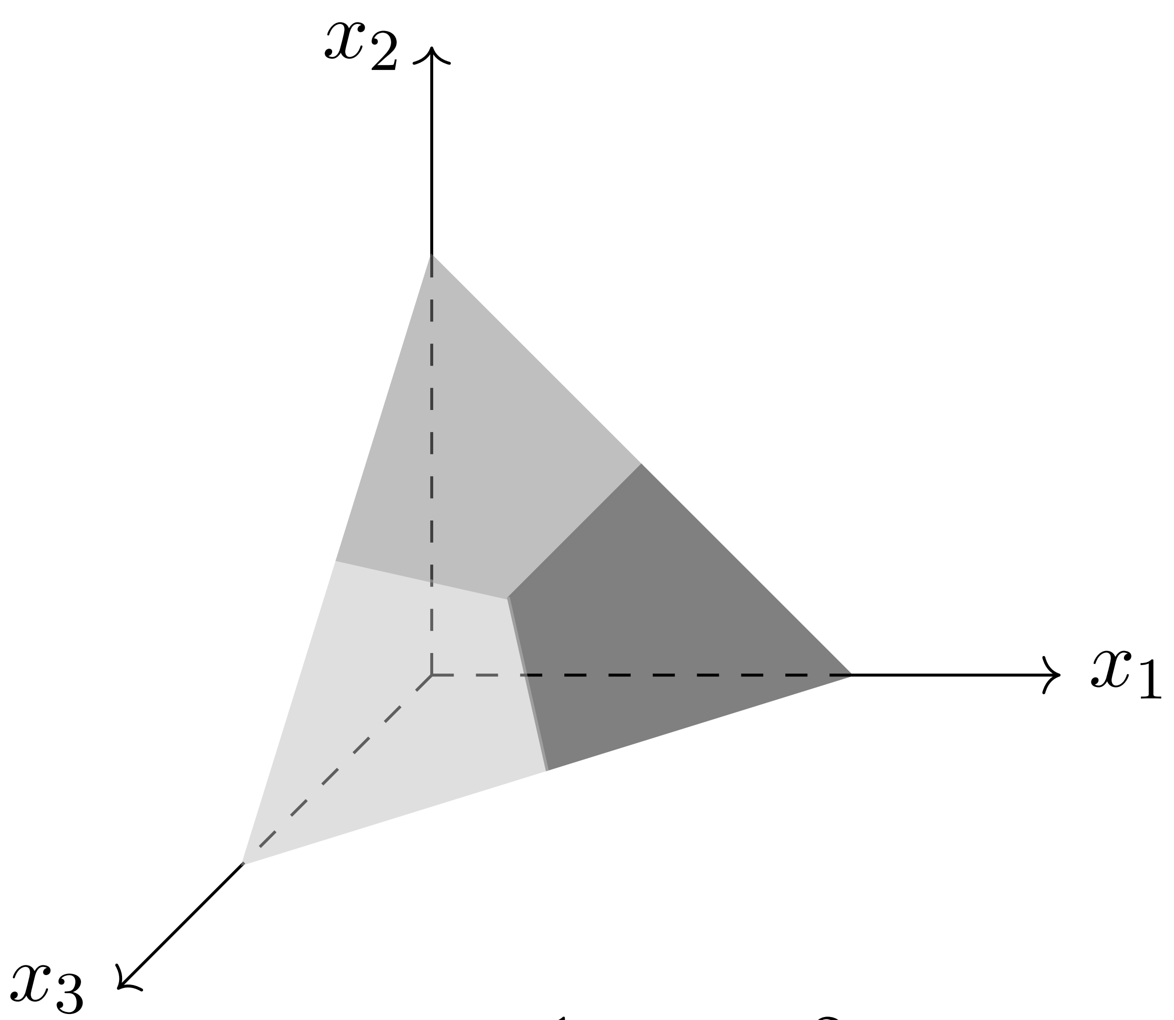

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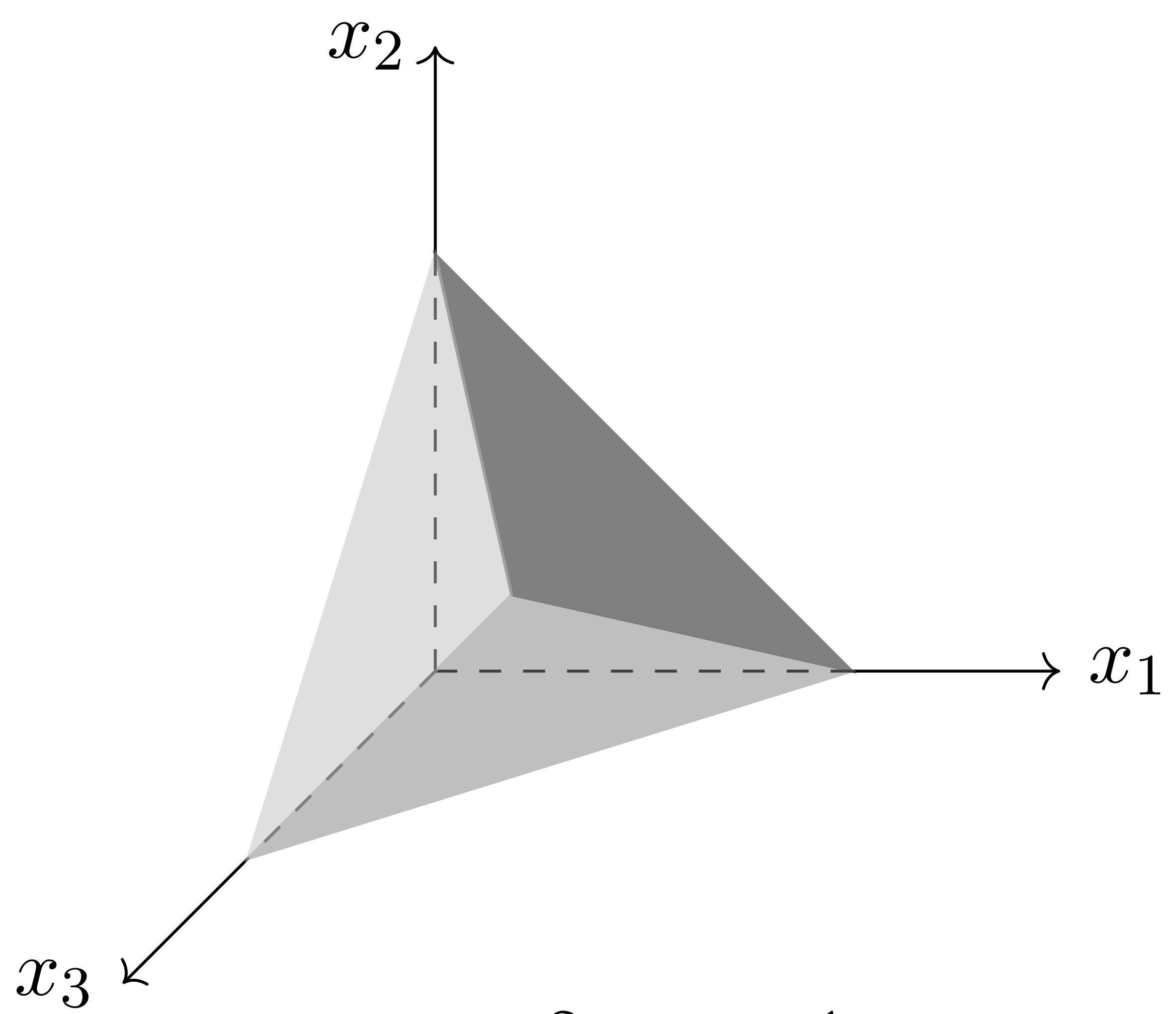

$n_1 = 2, n_2 = 1$

worst among your 3 papers?

Theorem (S. 2021)

Alice maximizes her utility if she truthfully reports the coarse ranking

- "Which is your best paper" is truthful: $n_1 = 1,\ n_2 = n - 1$

Alice remains truthful

Coarse ranking

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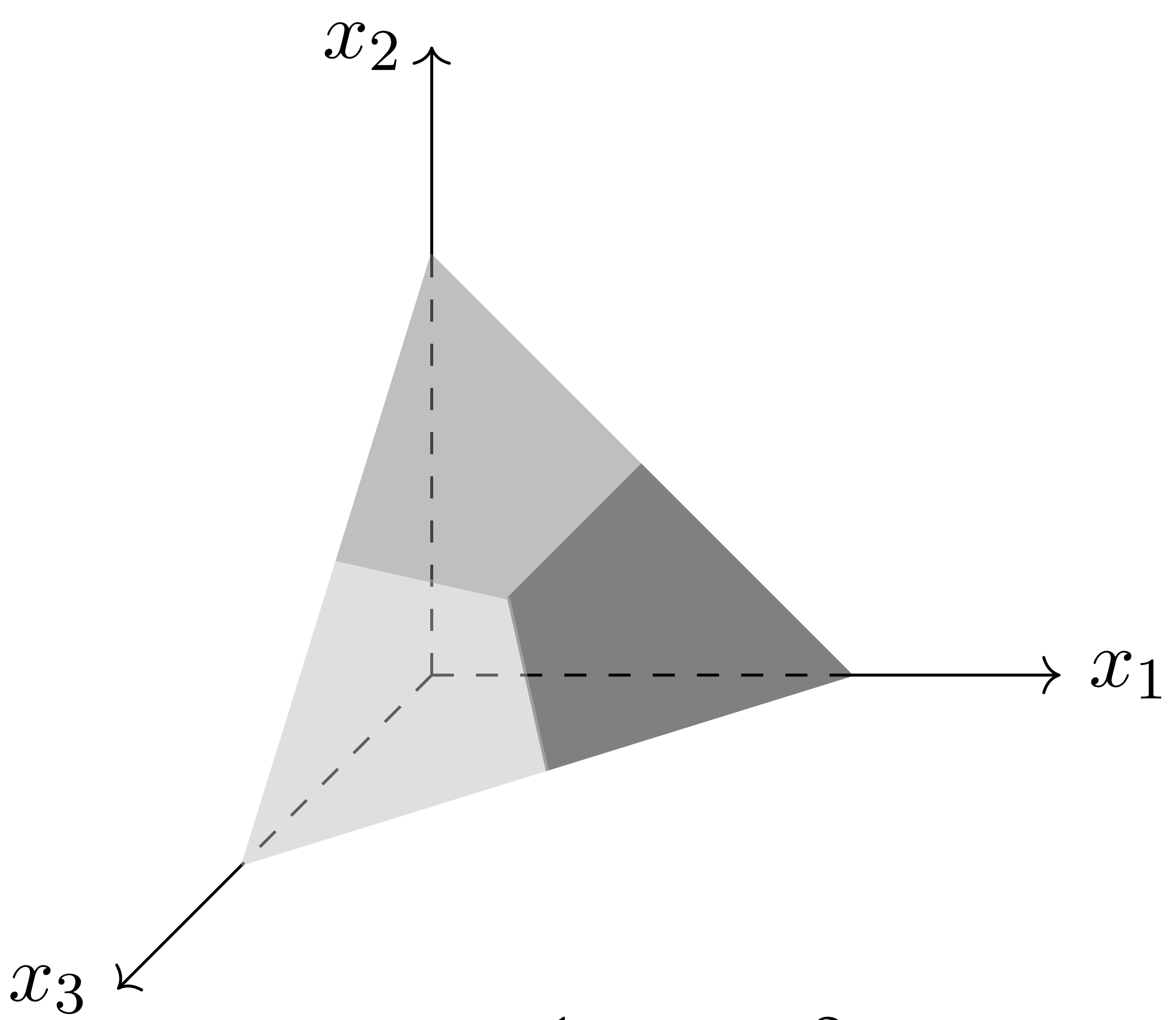

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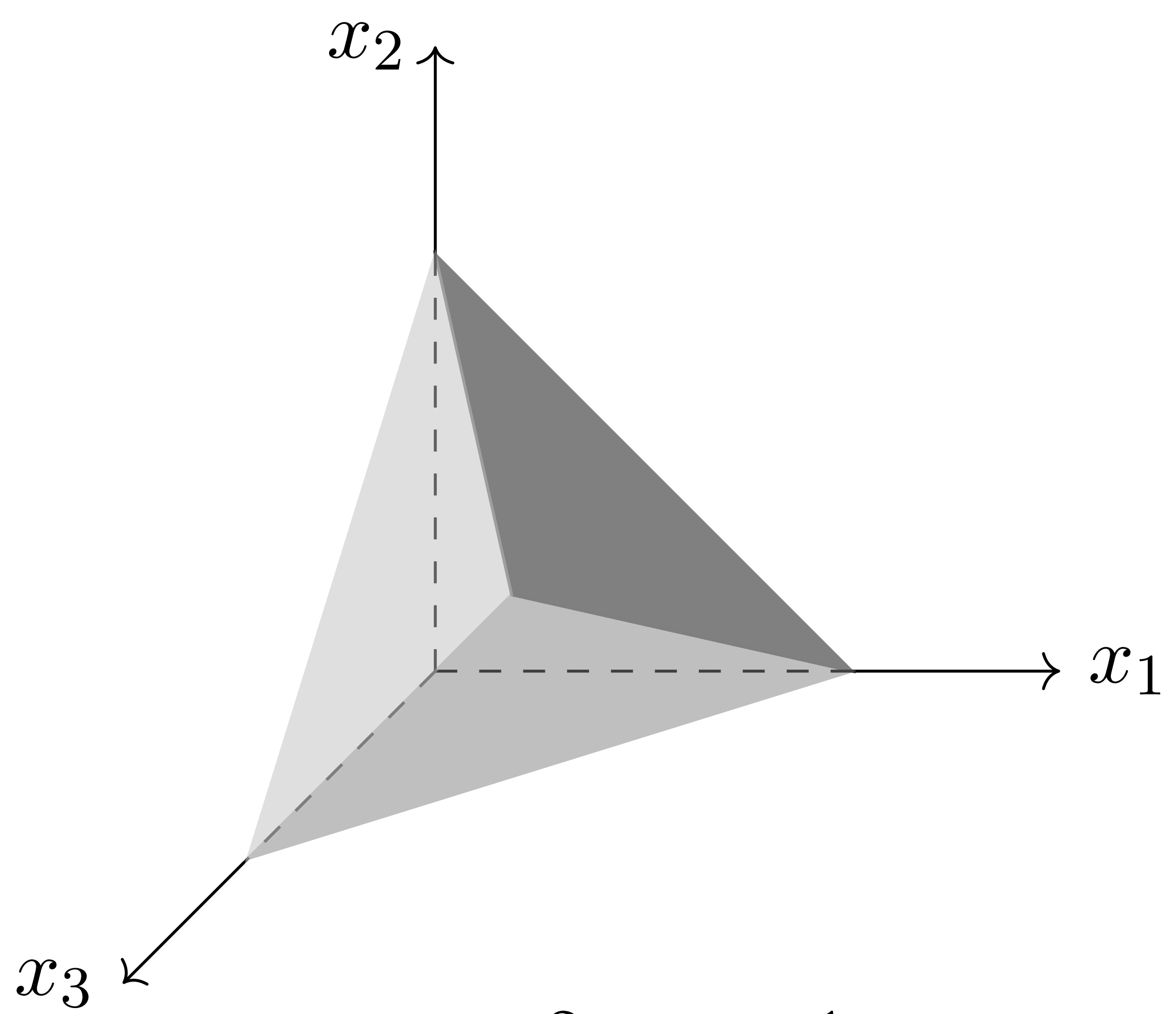

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- "Which is your best paper" is truthful: $n_1 = 1,\ n_2 = n - 1$
- Convex, so *better* estimation

Isotonic Mechanism with exponential family

Joint work with Jianqing Fan and Yuling Yan

Let $y_i \sim f_{\theta_i^\star}$, where $f_\theta(y) = \mathrm{e}^{\theta y - b(\theta)} h(y)$

- Variance of ratings depends on the mean

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Alice is asked to provide a ranking π:

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$$\text{s.t.} \quad \theta_{\pi(1)} \geq \cdots \geq \theta_{\pi(n)}$$

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$$\Longleftrightarrow$$

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{n} (y_i - \mu_i)^2 \quad \text{s.t.} \quad \mu_{\pi(1)} \geq \cdots \geq \mu_{\pi(n)}$$

- $\mu = \mathbb{E}_\theta Y = b'(\theta)$ (Barlow and Brunk 1972)

Truthfulness and optimality

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Theorem (Yan, S., and Fan 2023)

✤ *The Isotonic Mechanism for exponential family observations is truthful*

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✤ ***The Isotonic Mechanism for exponential family observations is truthful***

✤ ***If a knowledge partition is truthful and cut by hyperplanes, it must be cut by pairwise comparisons***

- Ranking remains optimal in this sense
- Implementation doesn't require knowing $b(\theta)$ and $h(y)$!

If you're gonna get a best paper award…

If you’re gonna get a best paper award…

- Great if your *best* paper receives the award

If you’re gonna get a best paper award…

- Great if your *best* paper receives the award otherwise…

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Vitaly Feldman
@vitalyFM

🤔 Sorry to rain on this parade but from a quick look at this paper I see that the analysis of privacy guarantees makes no sense: the authors apparently do not realize that their (unsubstantiated) assumption implies stronger privacy guarantees then what they prove from it.

> @lingjuan_lyu · Jul 19
>
> #icml2022 #sony #PPML So happy to share that our Sony AI PPML team's paper "Privacy for Free: How does Dataset Condensation Help Privacy?" won an Outstanding Paper Award from ICML'22. Congrats to my team and collaborator!
>
> Check out our work here: arxiv.org/abs/2206.00240
>
> Oral
>
> **Privacy for Free: How does Dataset Condensation Help Privacy?**
>
> Room 318 - 320
>
> Outstanding Paper

[Submitted on 29 Sep 2022]

No Free Lunch in "Privacy for Free: How does Dataset Condensation Help Privacy"

Nicholas Carlini, Vitaly Feldman, Milad Nasr

New methods designed to preserve data privacy require careful scrutiny. Failure to preserve privacy is hard to detect, and yet can lead to catastrophic results when a system implementing a ``privacy-preserving'' method is attacked. A recent work selected for an Outstanding Paper Award at ICML 2022 (Dong et al., 2022) claims that dataset condensation (DC) significantly improves data privacy when training machine learning models. This claim is supported by theoretical analysis of a specific dataset condensation technique and an empirical evaluation of resistance to some existing membership inference attacks.
In this note we examine the claims in the work of Dong et al. (2022) and describe major flaws in the empirical evaluation of the method and its theoretical analysis. These flaws imply that their work does not provide statistically significant evidence that DC improves the privacy of training ML models over a naive baseline. Moreover, previously published results show that DP-SGD, the standard approach to privacy preserving ML, simultaneously gives better accuracy and achieves a (provably) lower membership attack success rate.

True-grade-dependent utility

Heterogeneity in utility $U(\hat{\boldsymbol{R}}) := \sum_{i=1}^{n} U(\hat{R}_i; R_i)$

1. $U(x; R)$ is convex in its first argument
2. $\dfrac{\mathrm{d}U(x;R)}{\mathrm{d}x} \geq \dfrac{\mathrm{d}U(x;R')}{\mathrm{d}x}$ whenever $R > R'$

- Examples: $U(x; R) = g_1(R)h_1(x) + g_2(R)h_2(x) + \cdots + g_L(R)h_L(x)$ with nondecreasing $g_1, \ldots, g_L \geq 0$ and nondecreasing convex $h_1, \ldots, h_L$

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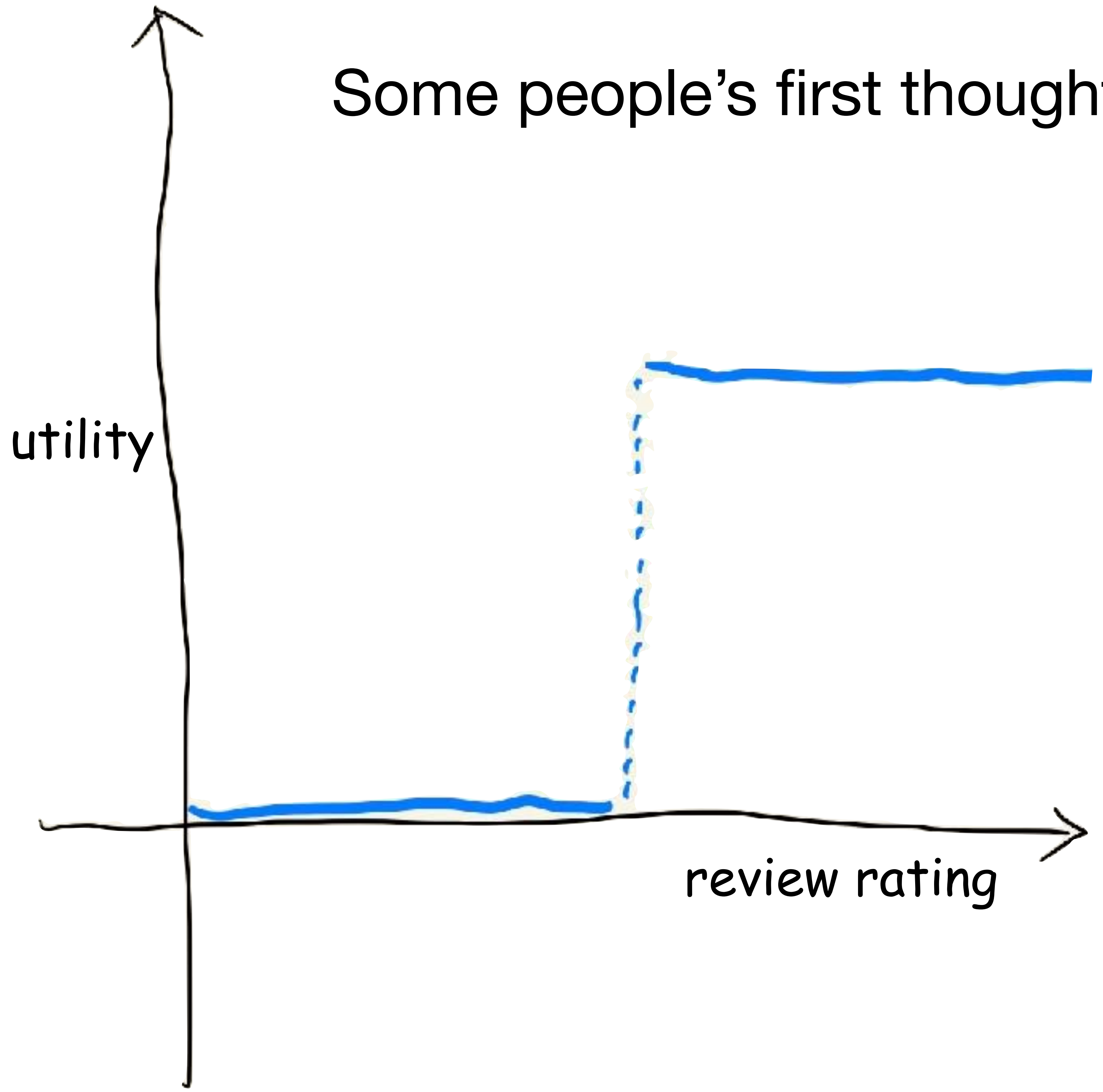
Theorem (S. 2022)

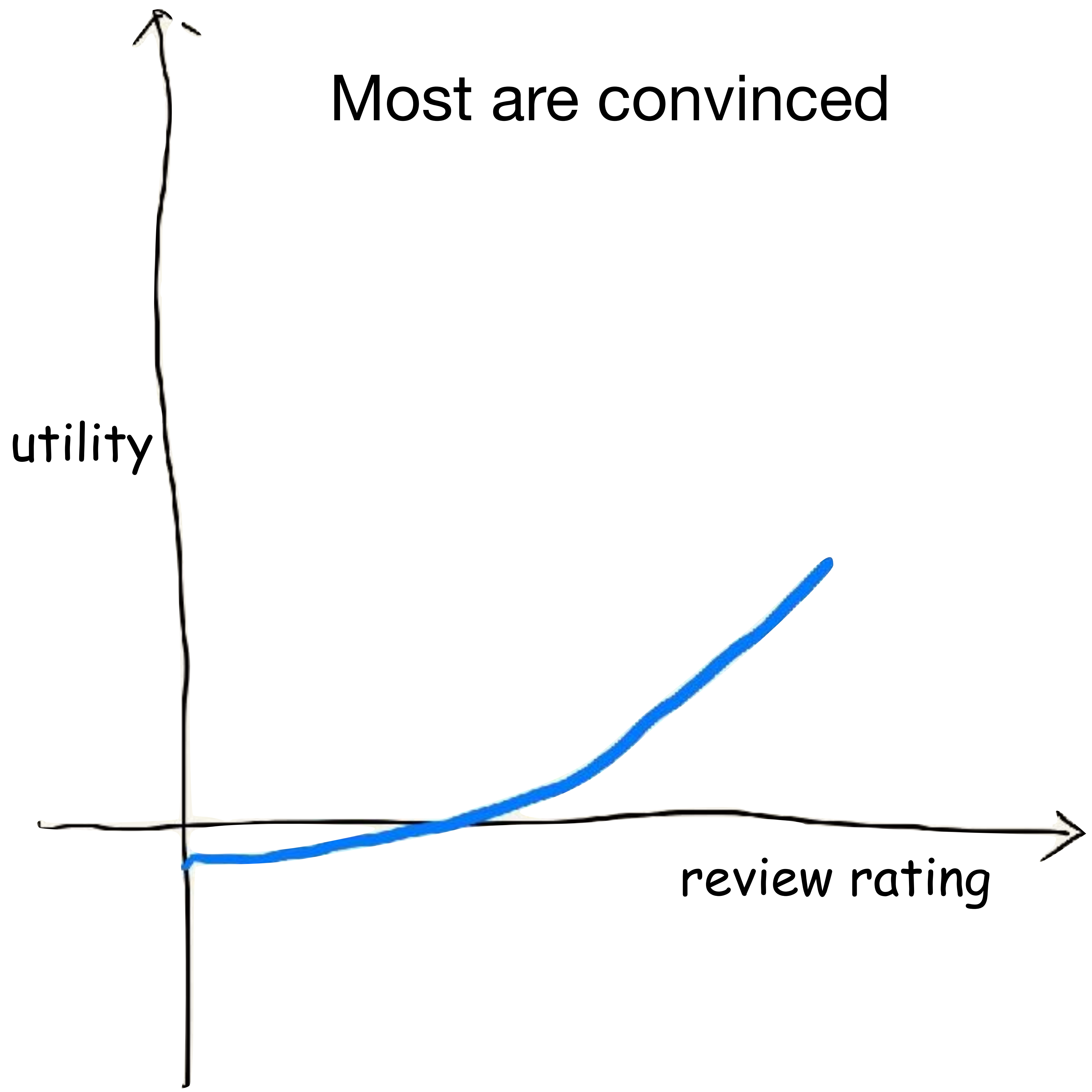
The Isotonic Mechanism remains truthful

Let's engineer utility

Some people's first thought



Let’s engineer utility



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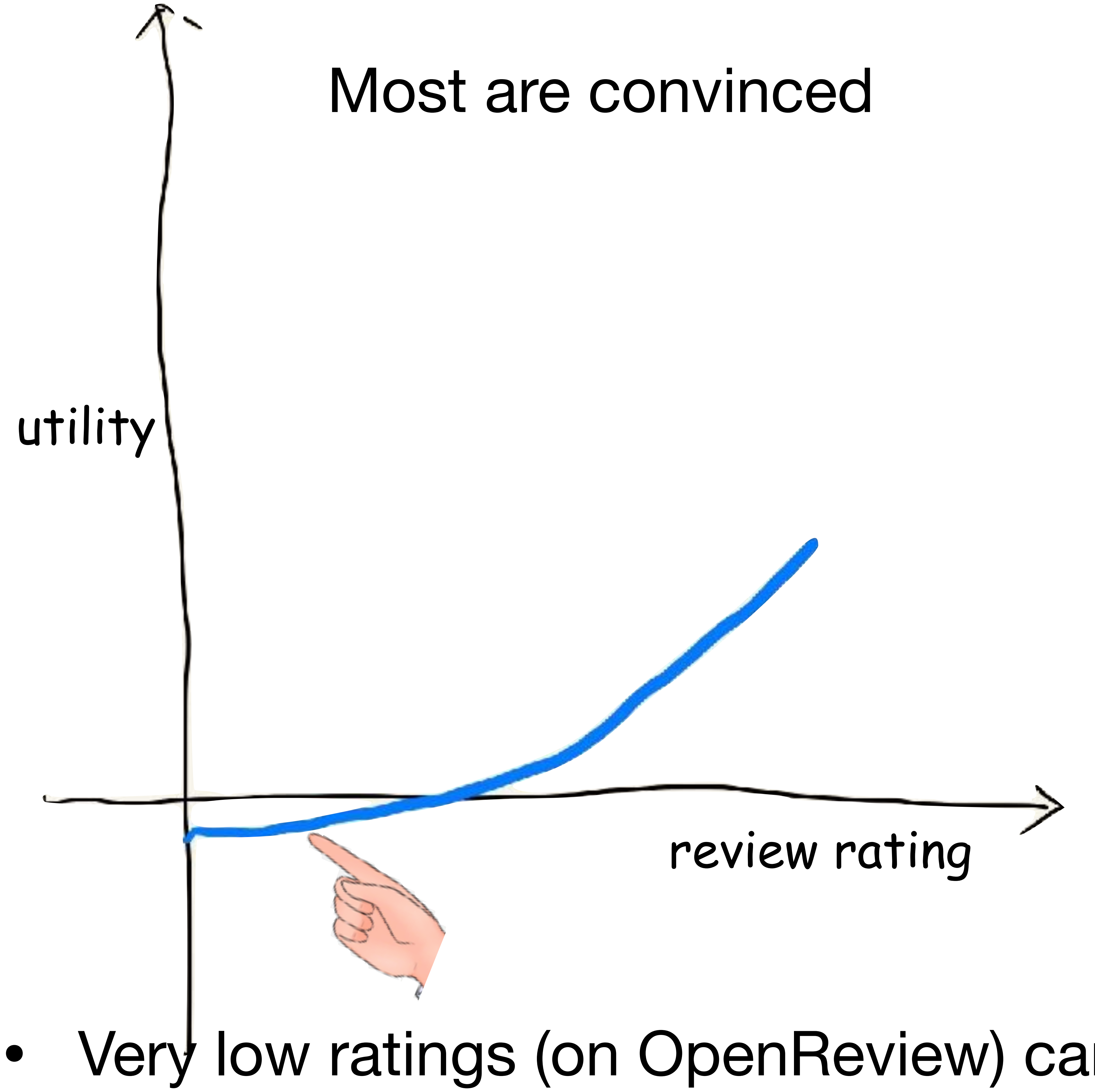

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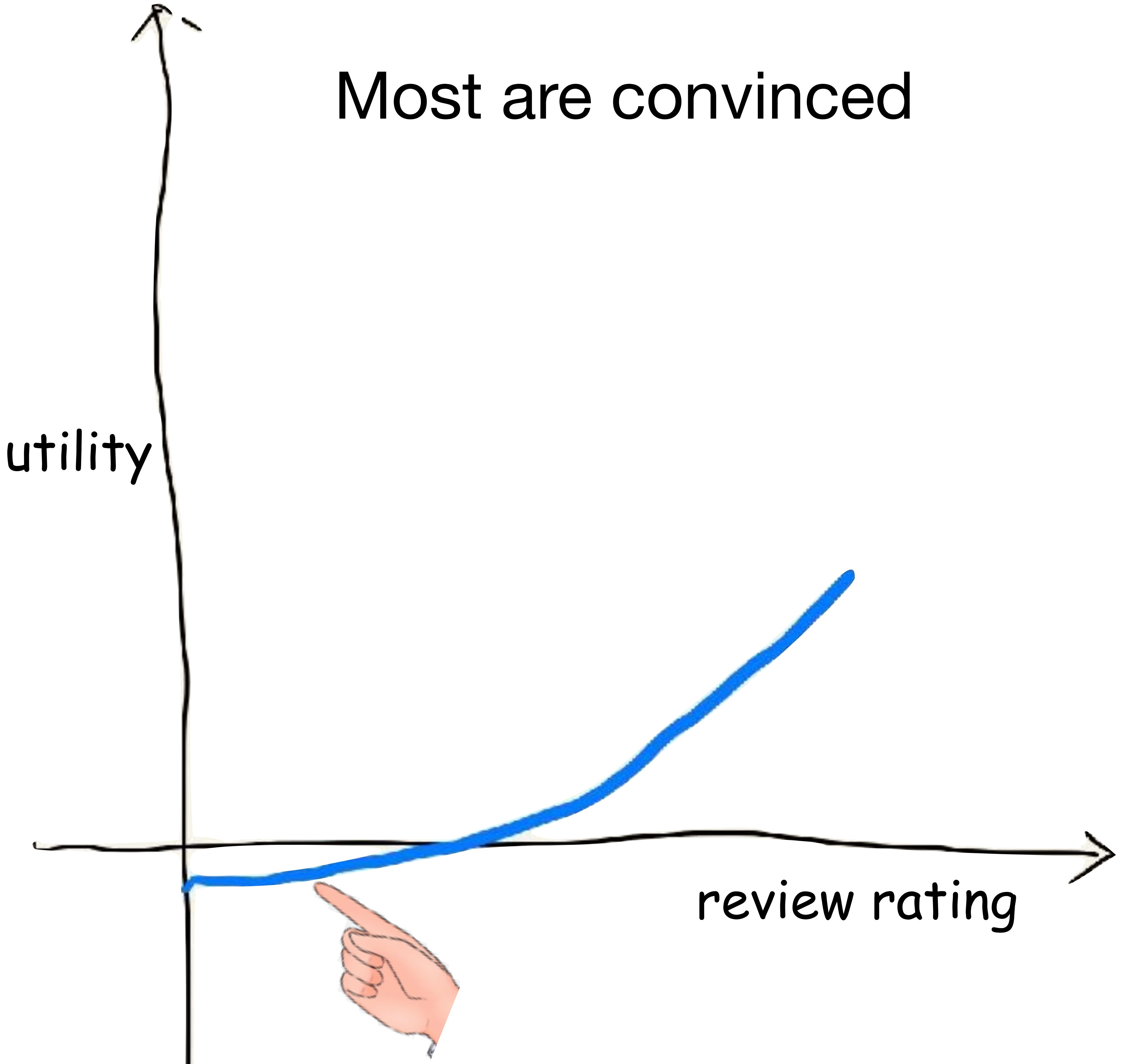

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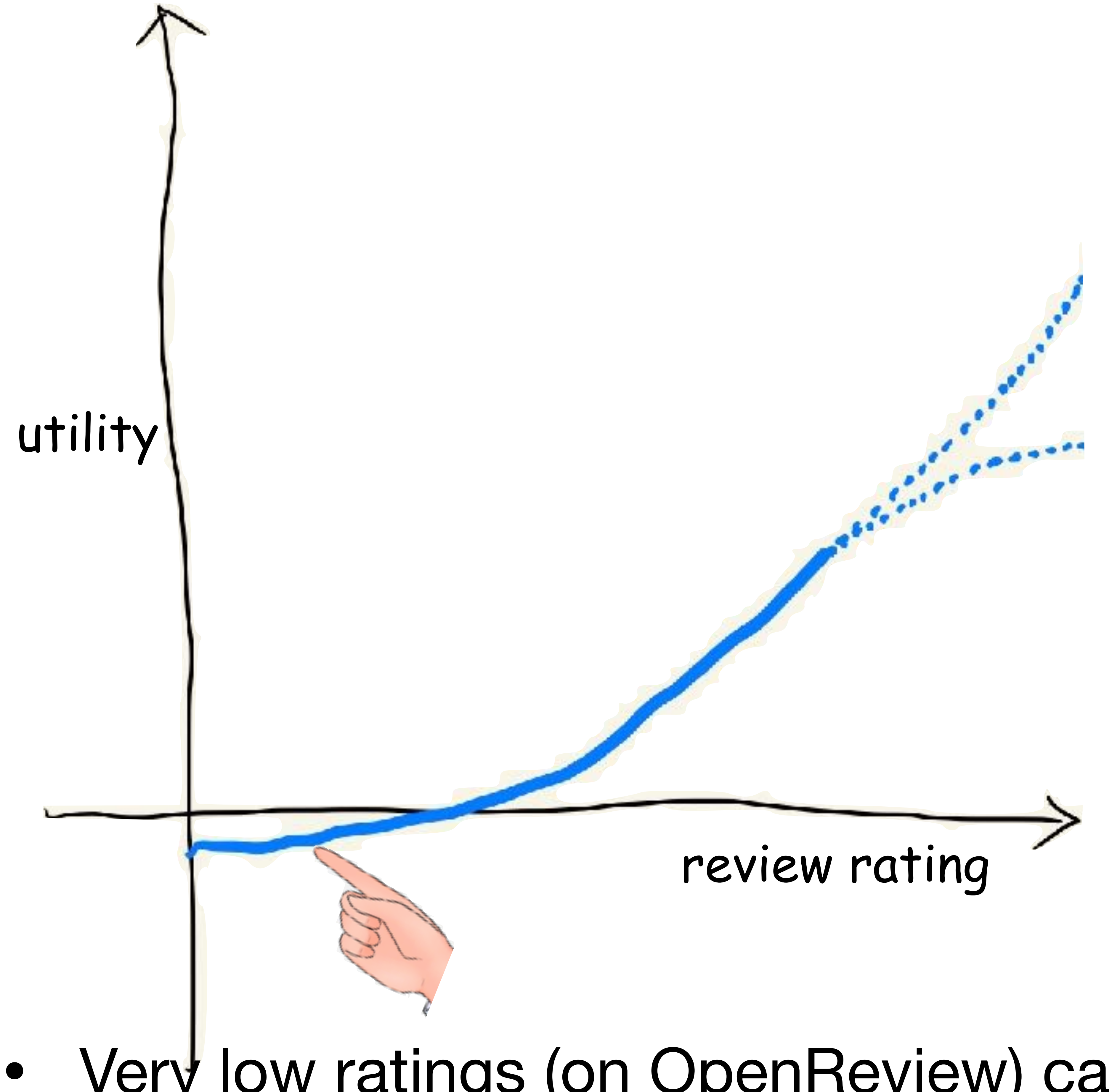
- Submitting many junk papers isn't a good idea

Let’s engineer utility



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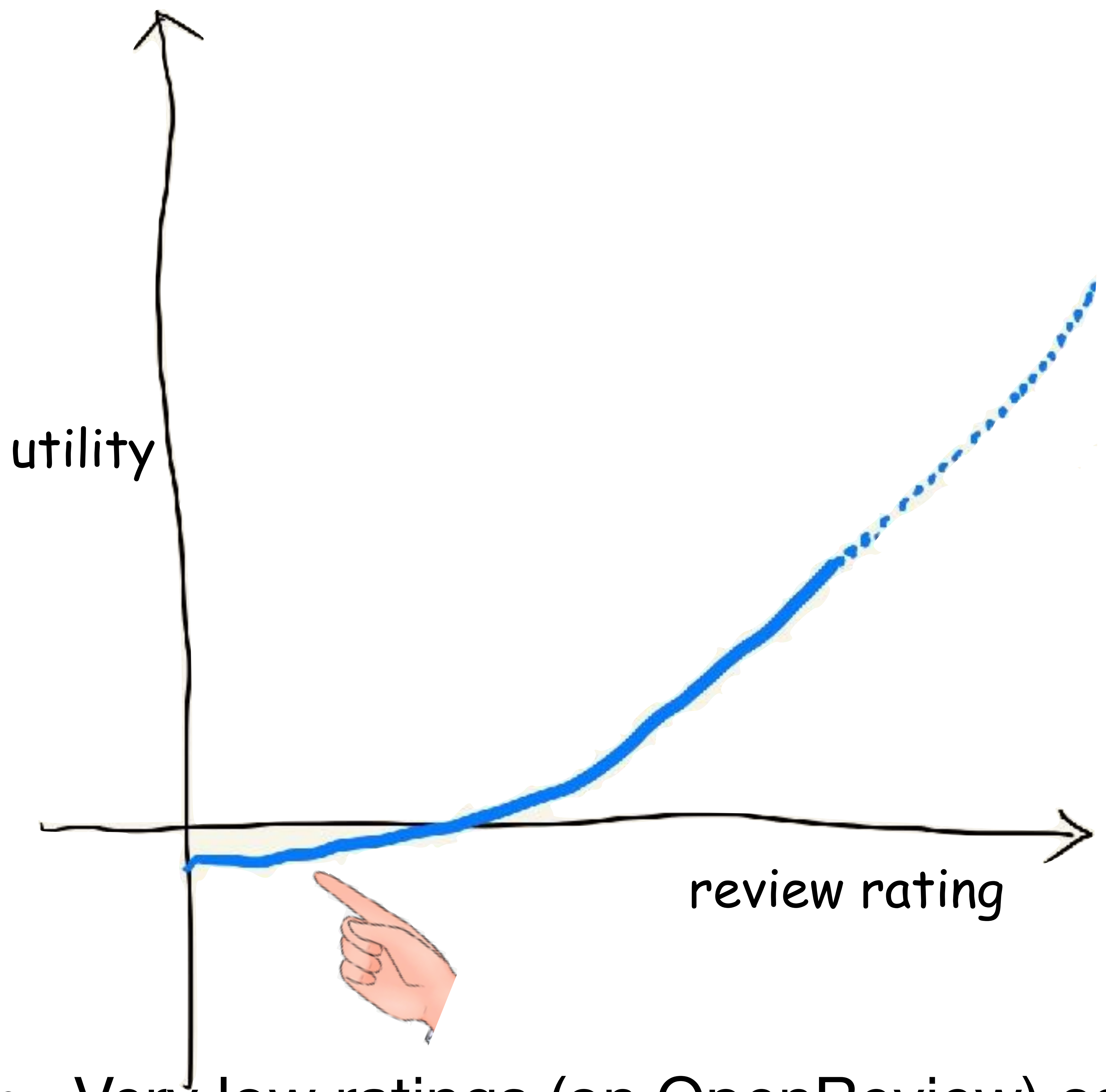

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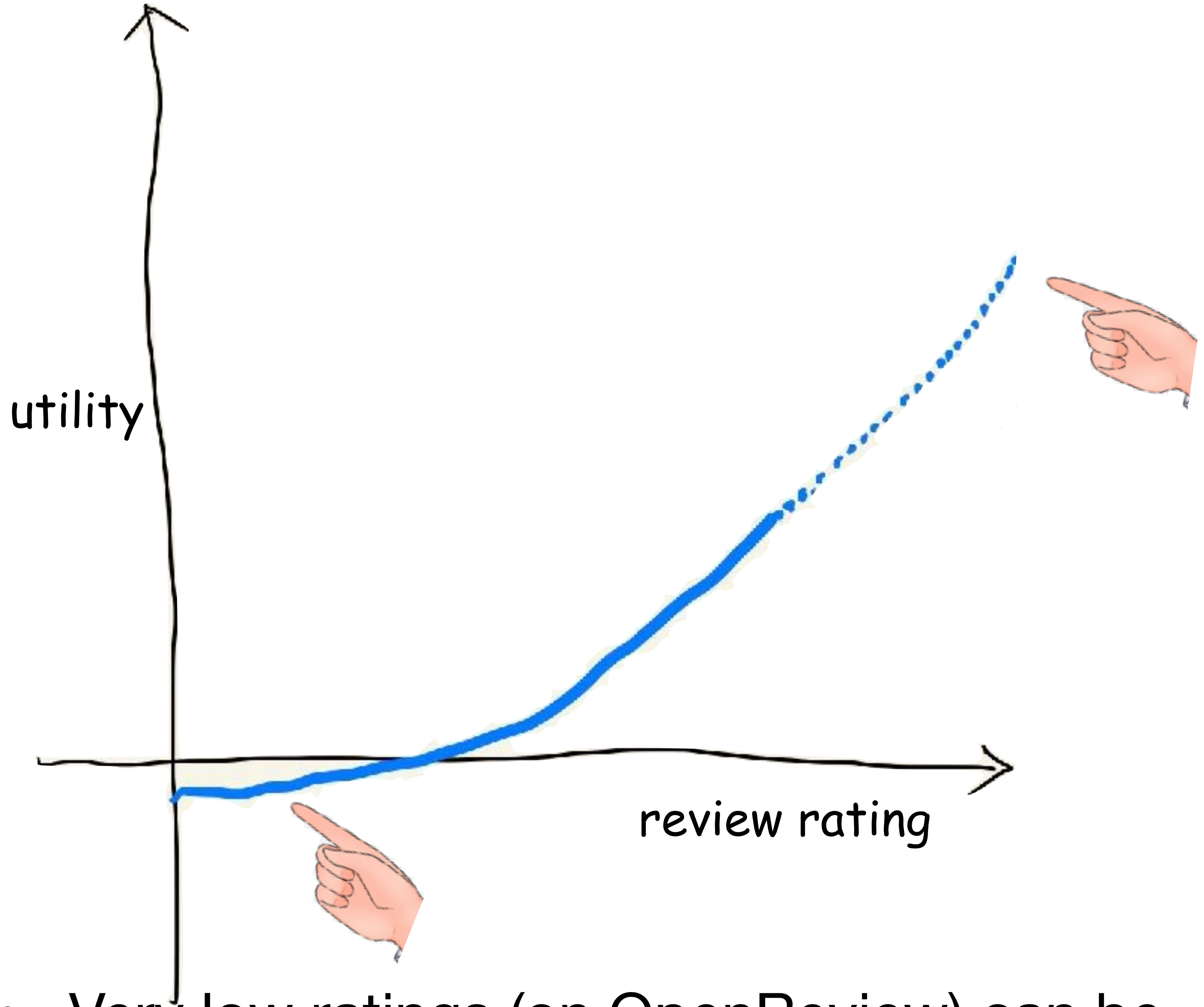

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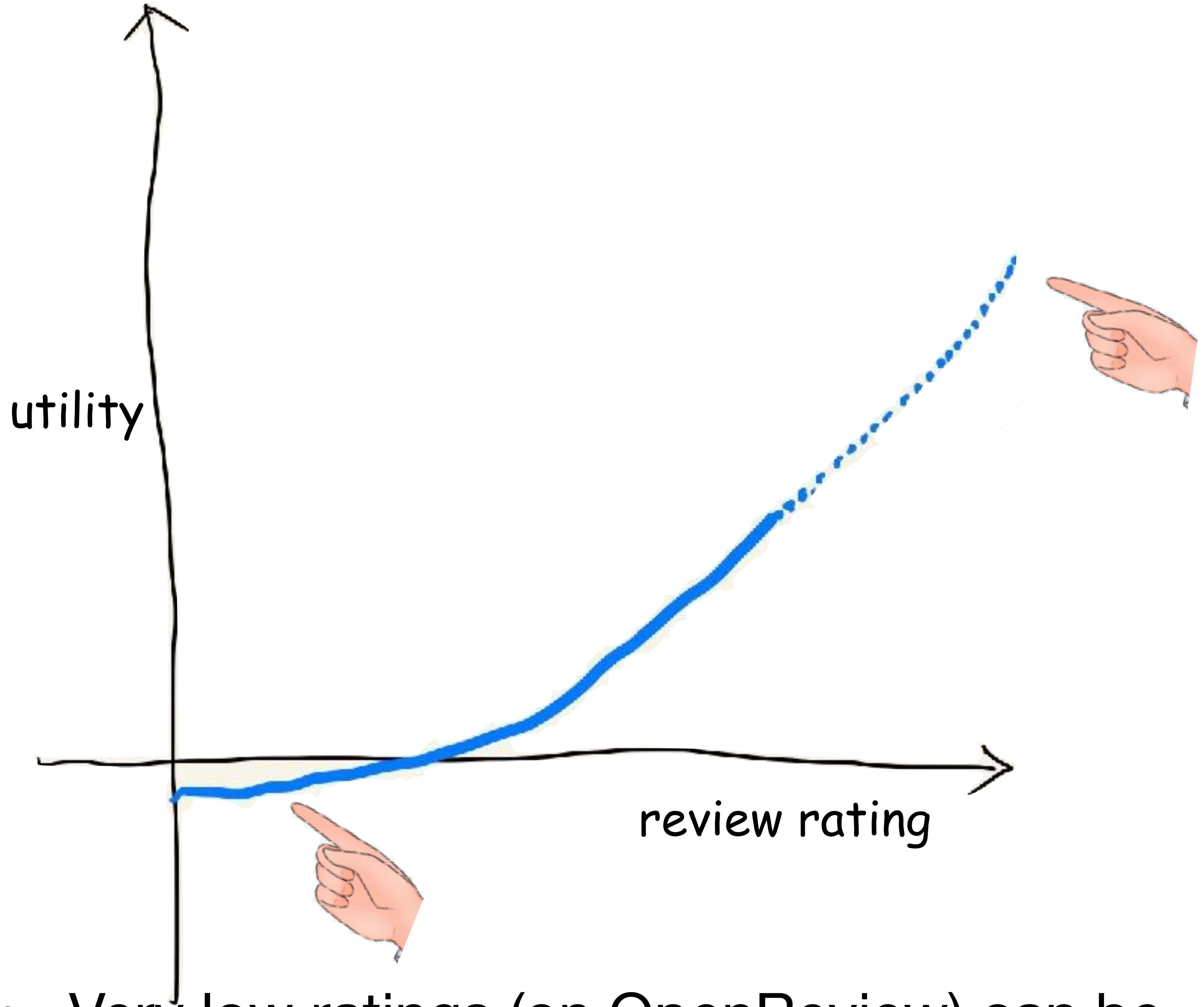

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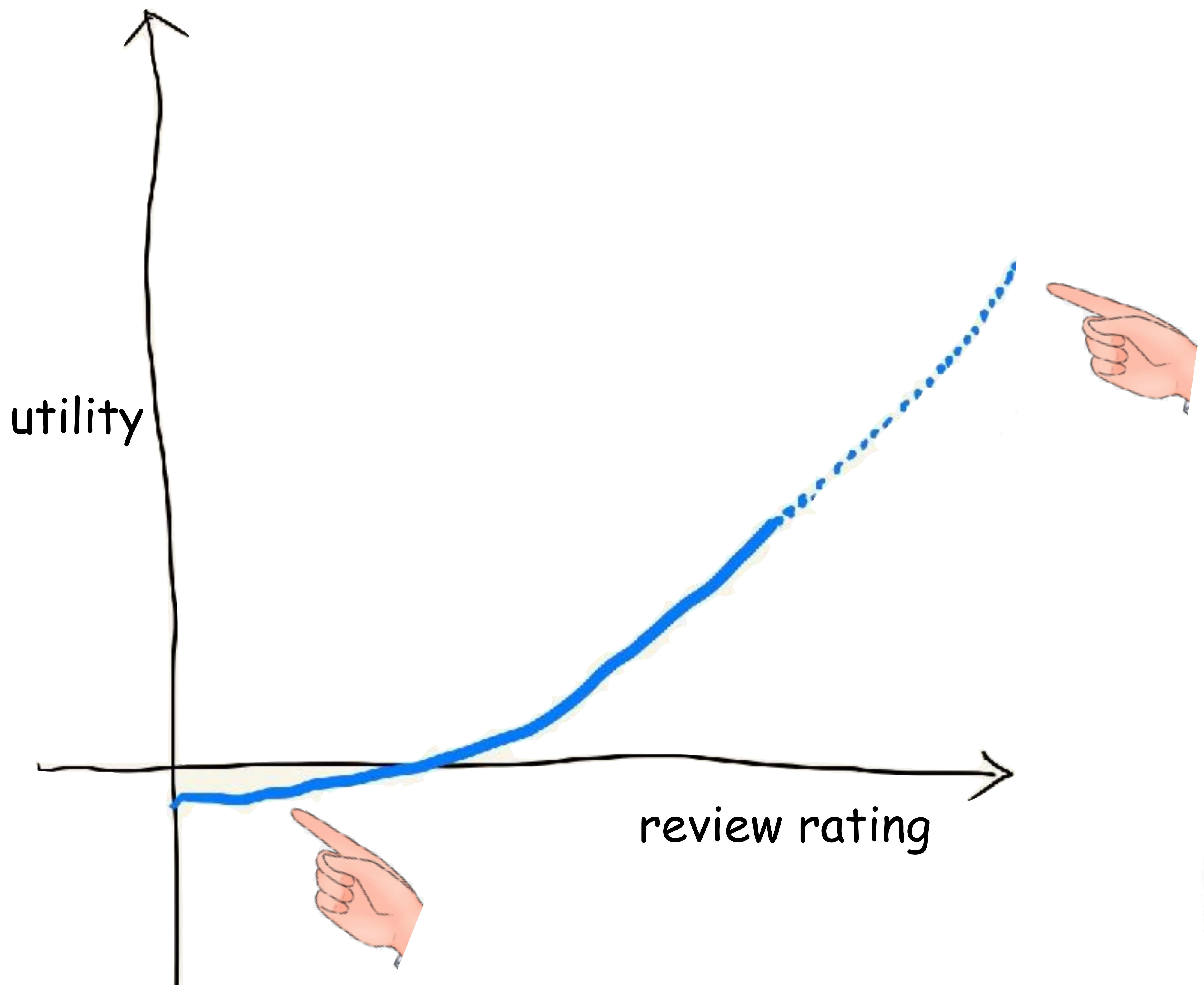

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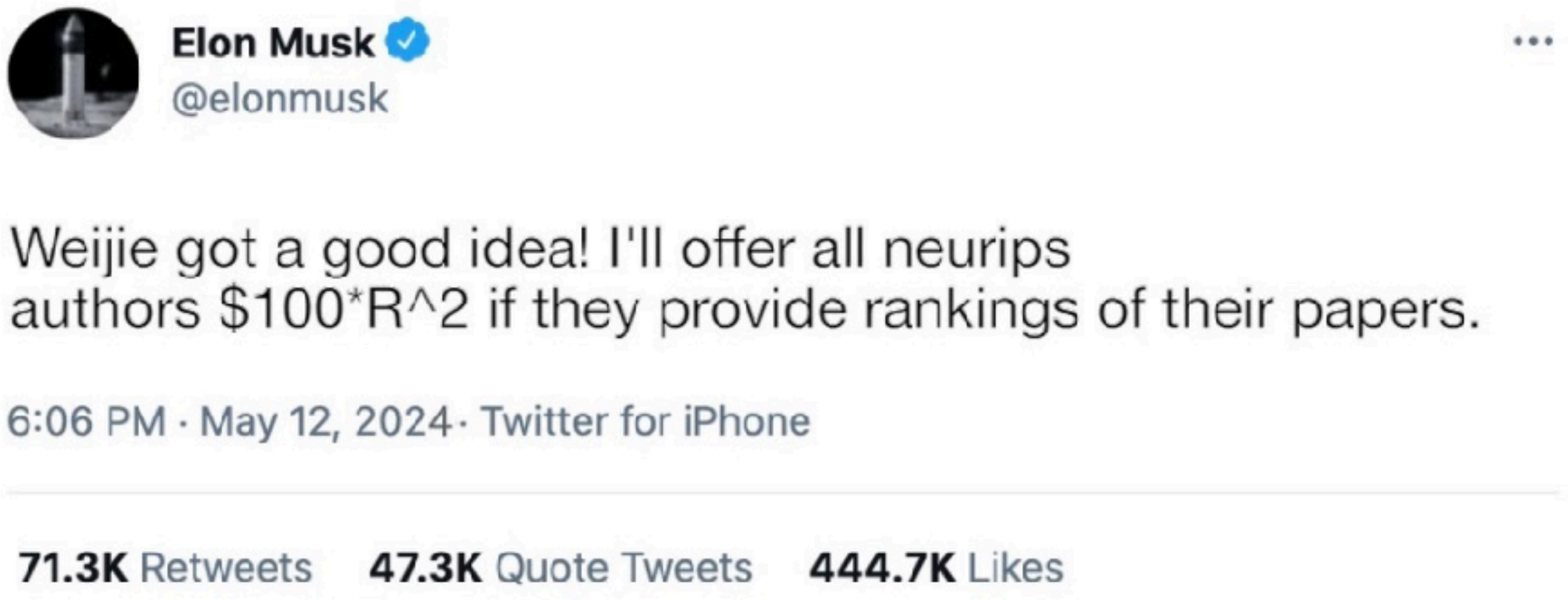

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the ICML 2023 experiment

Ranking data of ICML

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- The Isotonic Mechanism was experimented this January at ICML 2023, which received 6538 papers

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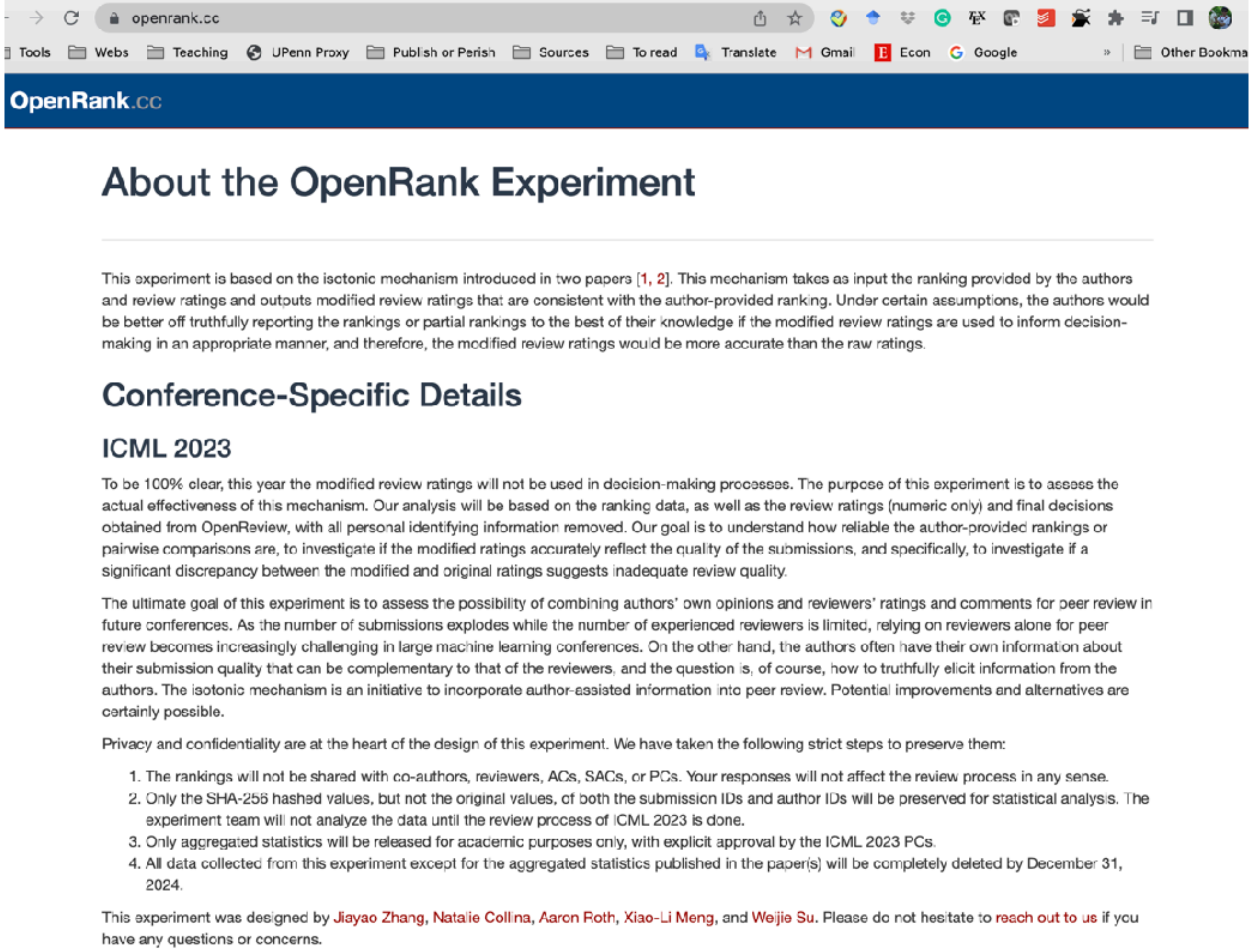

openrank.cc

Tools Webs Teaching UPenn Proxy Publish or Perish Sources To read Translate Gmail Econ Google Other Bookma

OpenRank.cc

About the OpenRank Experiment

This experiment is based on the isotonic mechanism introduced in two papers [1, 2]. This mechanism takes as input the ranking provided by the authors and review ratings and outputs modified review ratings that are consistent with the author-provided ranking. Under certain assumptions, the authors would be better off truthfully reporting the rankings or partial rankings to the best of their knowledge if the modified review ratings are used to inform decision-making in an appropriate manner, and therefore, the modified review ratings would be more accurate than the raw ratings.

Conference-Specific Details

ICML 2023

To be 100% clear, this year the modified review ratings will not be used in decision-making processes. The purpose of this experiment is to assess the actual effectiveness of this mechanism. Our analysis will be based on the ranking data, as well as the review ratings (numeric only) and final decisions obtained from OpenReview, with all personal identifying information removed. Our goal is to understand how reliable the author-provided rankings or pairwise comparisons are, to investigate if the modified ratings accurately reflect the quality of the submissions, and specifically, to investigate if a significant discrepancy between the modified and original ratings suggests inadequate review quality.

The ultimate goal of this experiment is to assess the possibility of combining authors' own opinions and reviewers' ratings and comments for peer review in future conferences. As the number of submissions explodes while the number of experienced reviewers is limited, relying on reviewers alone for peer review becomes increasingly challenging in large machine learning conferences. On the other hand, the authors often have their own information about their submission quality that can be complementary to that of the reviewers, and the question is, of course, how to truthfully elicit information from the authors. The isotonic mechanism is an initiative to incorporate author-assisted information into peer review. Potential improvements and alternatives are certainly possible.

Privacy and confidentiality are at the heart of the design of this experiment. We have taken the following strict steps to preserve them:

1. The rankings will not be shared with co-authors, reviewers, ACs, SACs, or PCs. Your responses will not affect the review process in any sense.
2. Only the SHA-256 hashed values, but not the original values, of both the submission IDs and author IDs will be preserved for statistical analysis. The experiment team will not analyze the data until the review process of ICML 2023 is done.
3. Only aggregated statistics will be released for academic purposes only, with explicit approval by the ICML 2023 PCs.
4. All data collected from this experiment except for the aggregated statistics published in the paper(s) will be completely deleted by December 31, 2024.

This experiment was designed by Jiayao Zhang, Natalie Collina, Aaron Roth, Xiao-Li Meng, and Weijie Su. Please do not hesitate to reach out to us if you have any questions or concerns.

Ranking data of ICML

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O OpenReview
To: Su, Weijie
Thu 1/26/2023 4:33 PM

Dear Weijie:

We are asking all researchers who submitted papers to ICML 2023 to participate in a very short survey until February 10 AOE. The goal of this survey is to assess the relationship between three things: an author's perceptions of the relative quality of their papers, the reviews of their papers, and the research impact of these papers. The collected data will be analyzed to inform the improvement of peer review in large machine learning conferences.

This survey is conducted through a collaboration between OpenReview and OpenRank, an open survey platform. Please visit the following link to respond to the survey:

https://openrank.cc/rank/c643b6af-c408-4960-8d4e-5d257d01073c

We recognize the sensitivity of this information and will keep your responses fully confidential from your co-authors, reviewers, ACs, and SACs. The rankings are purely meant to evaluate a mechanism for improving peer review [1, 2] and we emphasize that they will *not* affect decision-making at all. See About the Experiment and Privacy Policy pages from the link sent above for the steps taken to ensure full confidentiality.

This experiment has been approved by the UPenn IRB and was designed in collaboration with Jiayao Zhang, Natalie Collina, Aaron Roth, Xiao-Li Meng, and Weijie Su.

ICML 2023 Program Chairs
Emma Brunskill, Kyunghyun Cho, and Barbara Engelhardt

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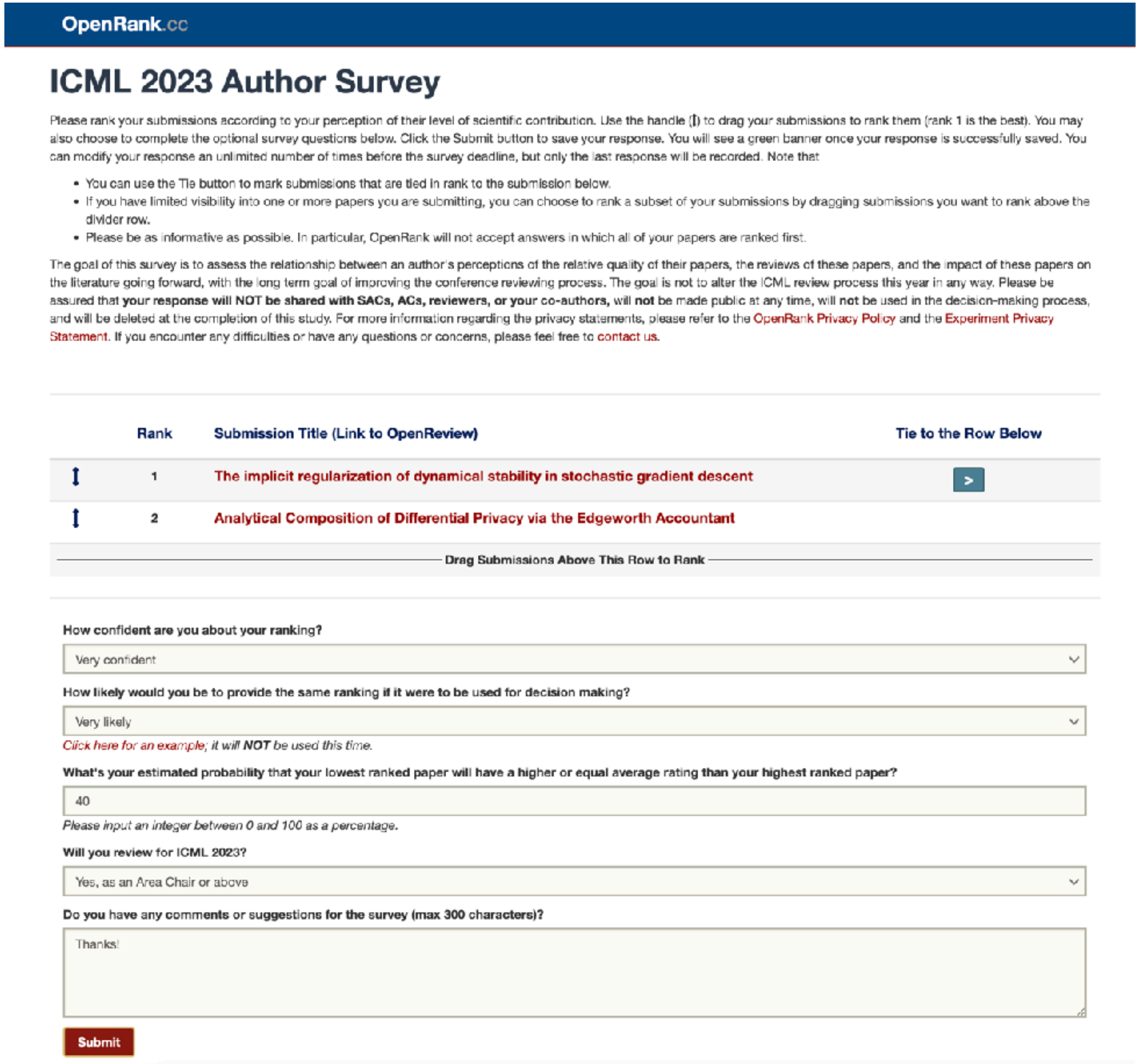

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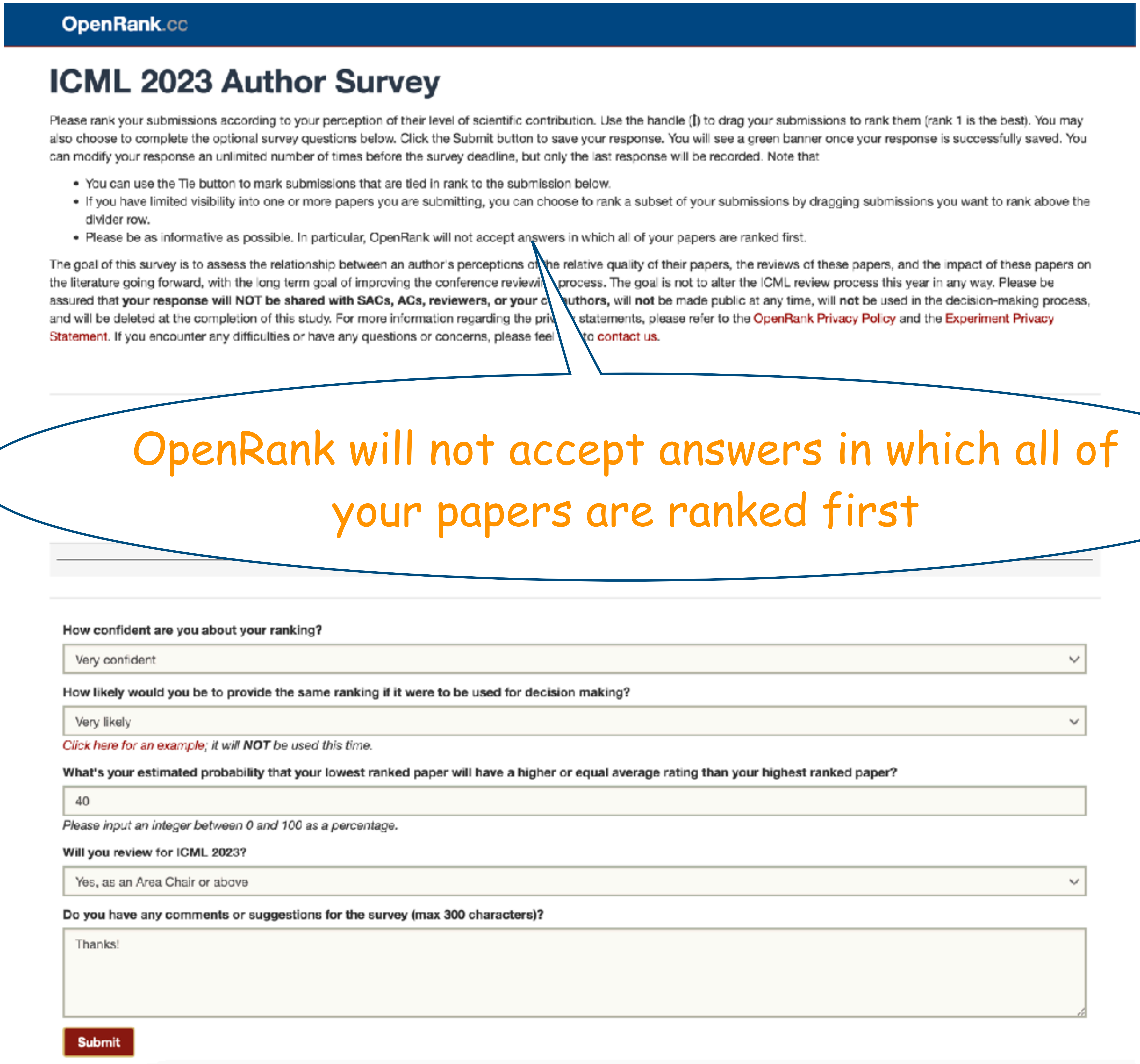

OpenRank.cc

ICML 2023 Author Survey

Please rank your submissions according to your perception of their level of scientific contribution. Use the handle (⁞) to drag your submissions to rank them (rank 1 is the best). You may also choose to complete the optional survey questions below. Click the Submit button to save your response. You will see a green banner once your response is successfully saved. You can modify your response an unlimited number of times before the survey deadline, but only the last response will be recorded. Note that

- You can use the Tie button to mark submissions that are tied in rank to the submission below.
- If you have limited visibility into one or more papers you are submitting, you can choose to rank a subset of your submissions by dragging submissions you want to rank above the divider row.
- Please be as informative as possible. In particular, OpenRank will not accept answers in which all of your papers are ranked first.

The goal of this survey is to assess the relationship between an author's perceptions of the relative quality of their papers, the reviews of these papers, and the impact of these papers on the literature going forward, with the long term goal of improving the conference reviewing process. The goal is not to alter the ICML review process this year in any way. Please be assured that **your response will NOT be shared with SACs, ACs, reviewers, or your co-authors,** will **not** be made public at any time, will **not** be used in the decision-making process, and will be deleted at the completion of this study. For more information regarding the privacy statements, please refer to the OpenRank Privacy Policy and the Experiment Privacy Statement. If you encounter any difficulties or have any questions or concerns, please feel free to contact us.

How confident are you about your ranking?

Very confident

How likely would you be to provide the same ranking if it were to be used for decision making?

Very likely

*Click here for an example; it will **NOT** be used this time.*

What's your estimated probability that your lowest ranked paper will have a higher or equal average rating than your highest ranked paper?

40

Please input an integer between 0 and 100 as a percentage.

Will you review for ICML 2023?

Yes, as an Area Chair or above

Do you have any comments or suggestions for the survey (max 300 characters)?

Thanks!

Submit

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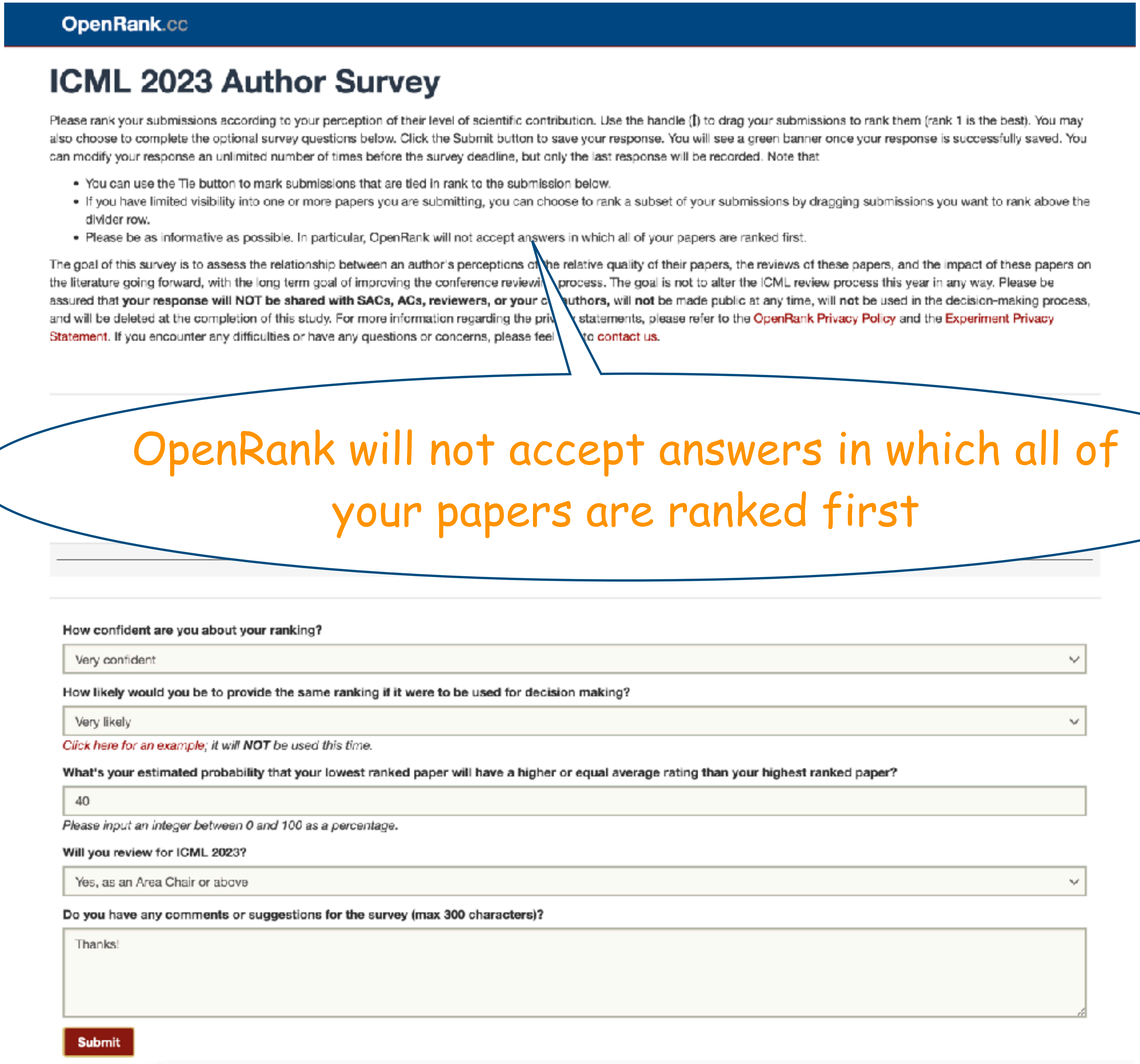
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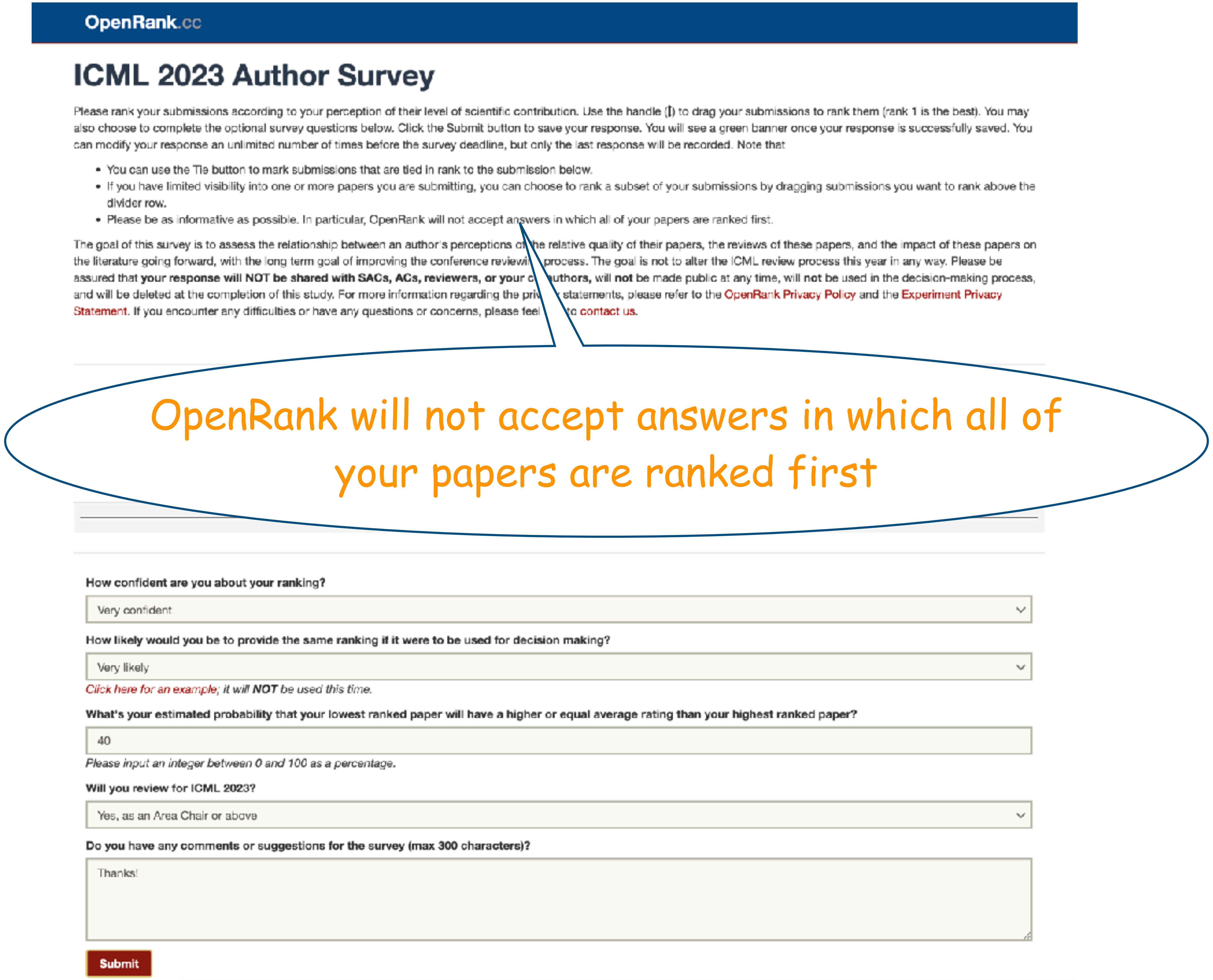
- Have been analyzing since April 22, when decisions were made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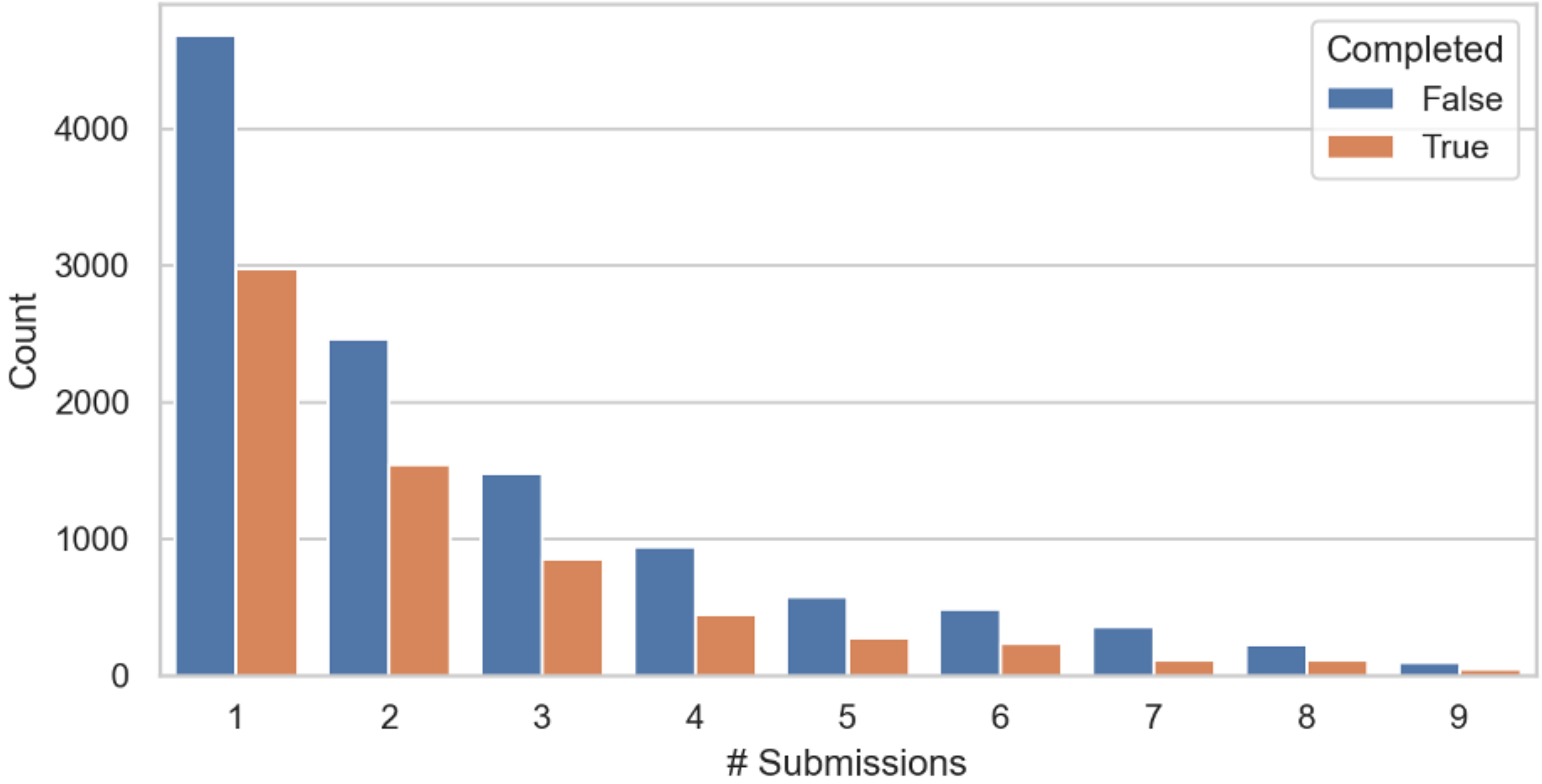
How many completed?



Discrepancy between reviews and author options

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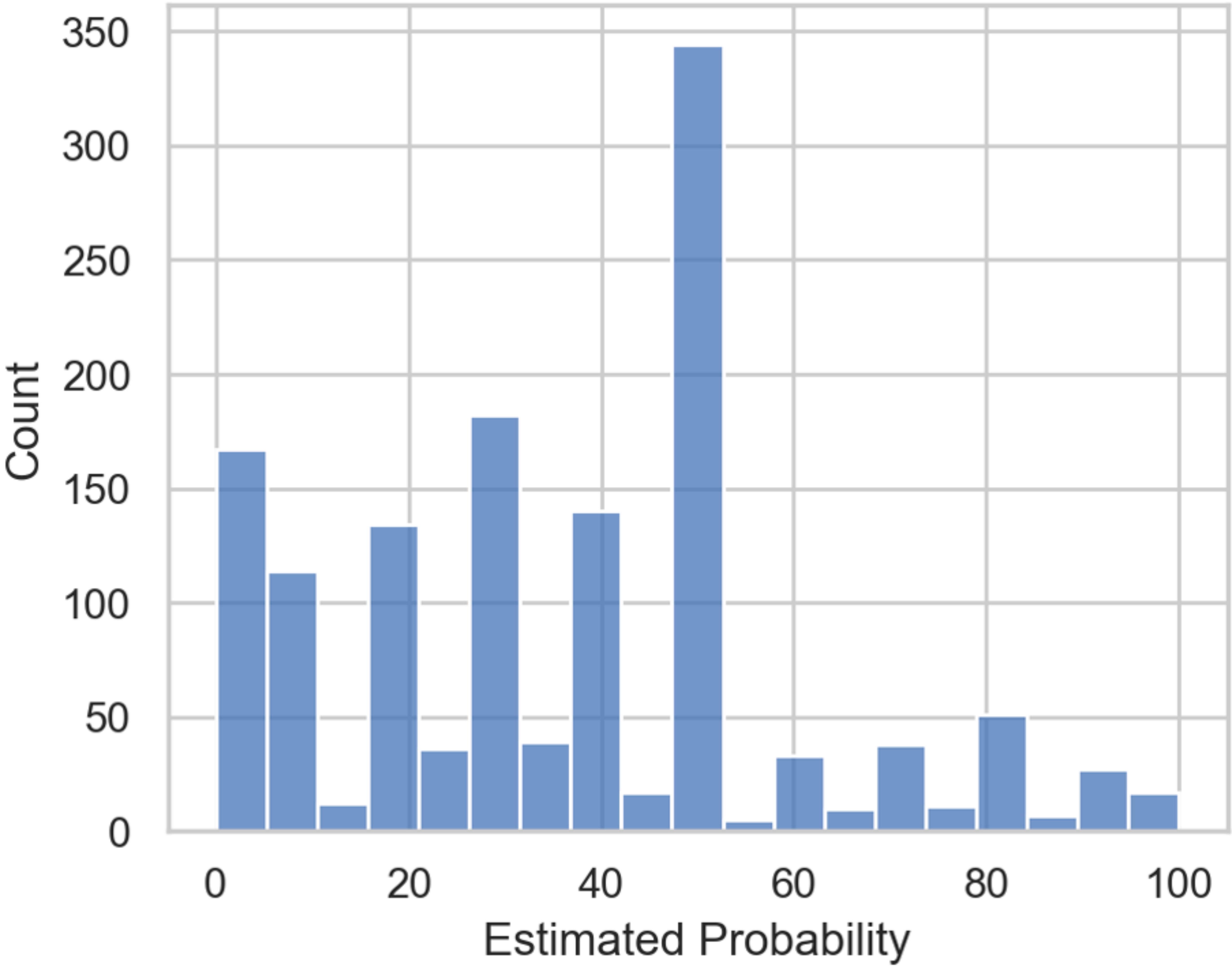
Estimated probability that lowest ranked paper will be rated higher than highest ranked paper

Discrepancy between reviews and author options

Estimated probability that lowest ranked paper will be rated higher than highest ranked paper



The bitter side of social media

The bitter side of social media

icml.cc

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OpenReview and Rankings:

This year we will use OpenReview and we will require that authors of multiple submissions, upon submission confirmation, submit a rank ordering of their papers from their own perspective. For this year we will only use such information in extreme situations to help inform acceptance decisions, and potentially for awards.

The bitter side of social media

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OpenReview and Rankings:

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如何看待ICML2023将尝试作者审阅自己的论文?

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Gautam Kamath
@thegautamkamath

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some rambling thoughts

Many examples of “you know the best”

#	player	Age	Nat.	Contract	Market value
17	Kevin De Bruyne Attacking Midfield	30		Jun 30, 2025	€90.00m
47	Phil Foden Central Midfield	22		Jun 30, 2024	€90.00m
7	Raheem Sterling Left Winger	27		Jun 30, 2023	€85.00m
10	Jack Grealish Left Winger	26		Jun 30, 2027	€80.00m
20	Bernardo Silva Attacking Midfield	27		Jun 30, 2025	€75.00m
3	Rúben Dias Centre-Back	25		Jun 30, 2027	€75.00m
16	Rodri Defensive Midfield	25		Jun 30, 2024	€70.00m
27	João Cancelo Right-Back	28		Jun 30, 2027	€60.00m
31	Ederson Goalkeeper	28		Jun 30, 2026	€50.00m
9	Gabriel Jesus Centre-Forward	25		Jun 30, 2023	€50.00m

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Player valuation: coach knows his/her players well

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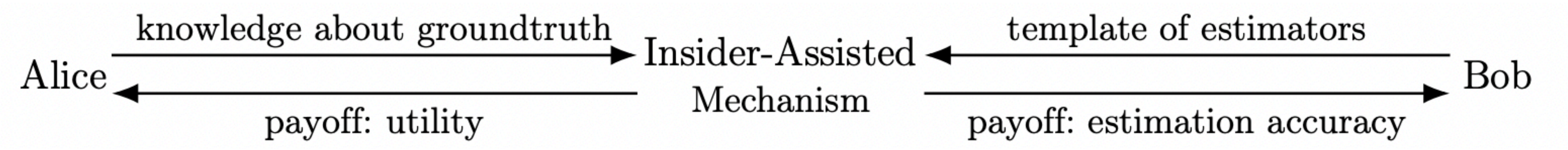
Second-hand market: leasing company knows its cars well

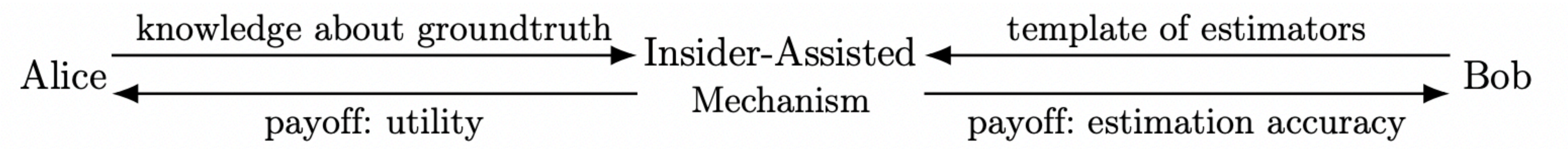
Teacher and students; parent company and subsidiary companies; make medical appointments

An owner-assisted estimation framework





An owner-assisted estimation framework



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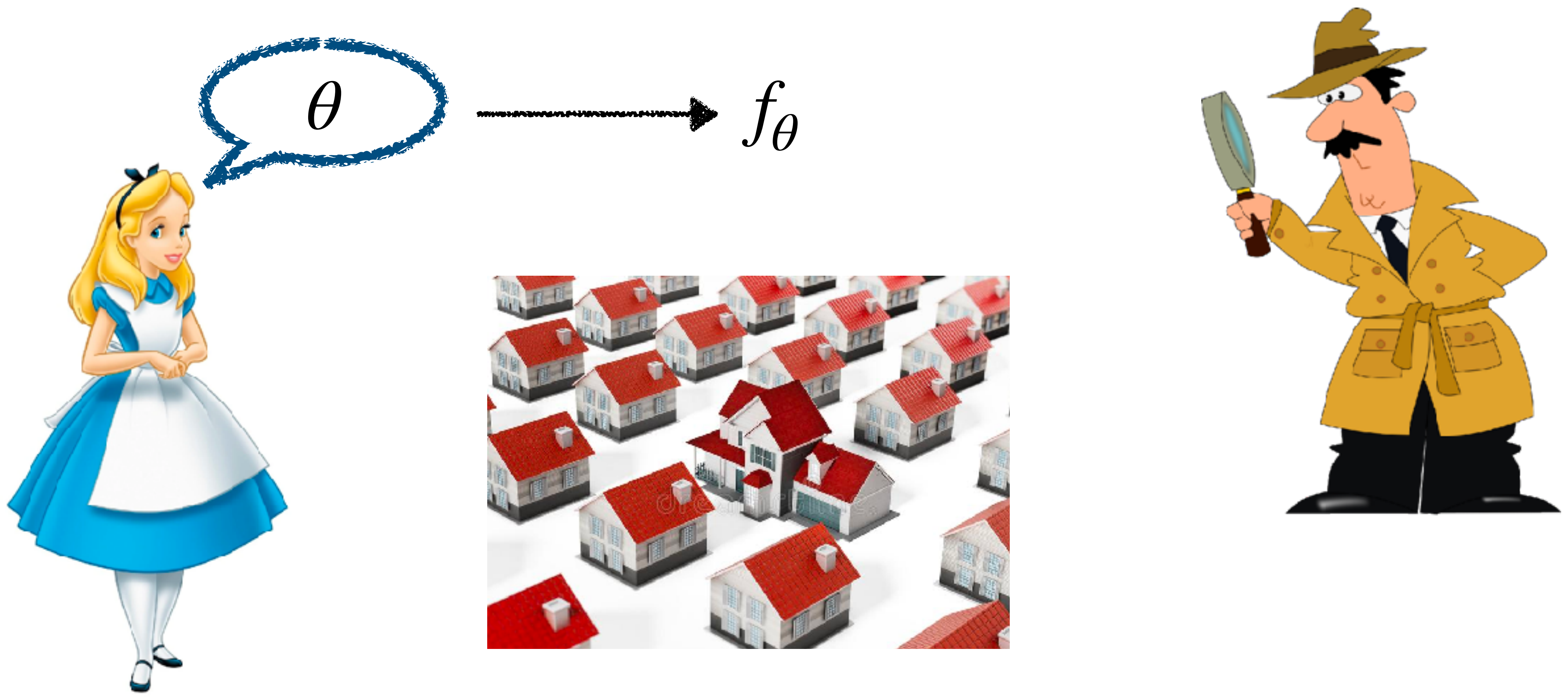

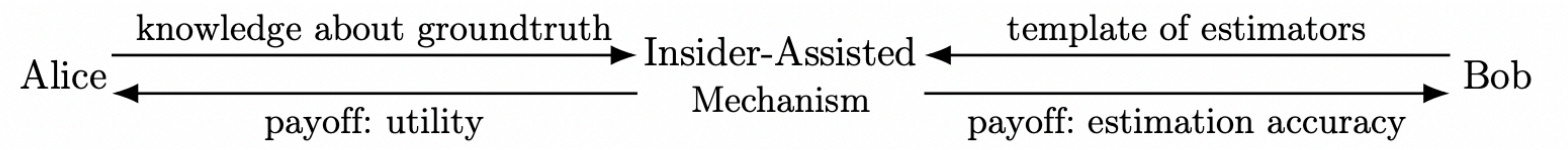

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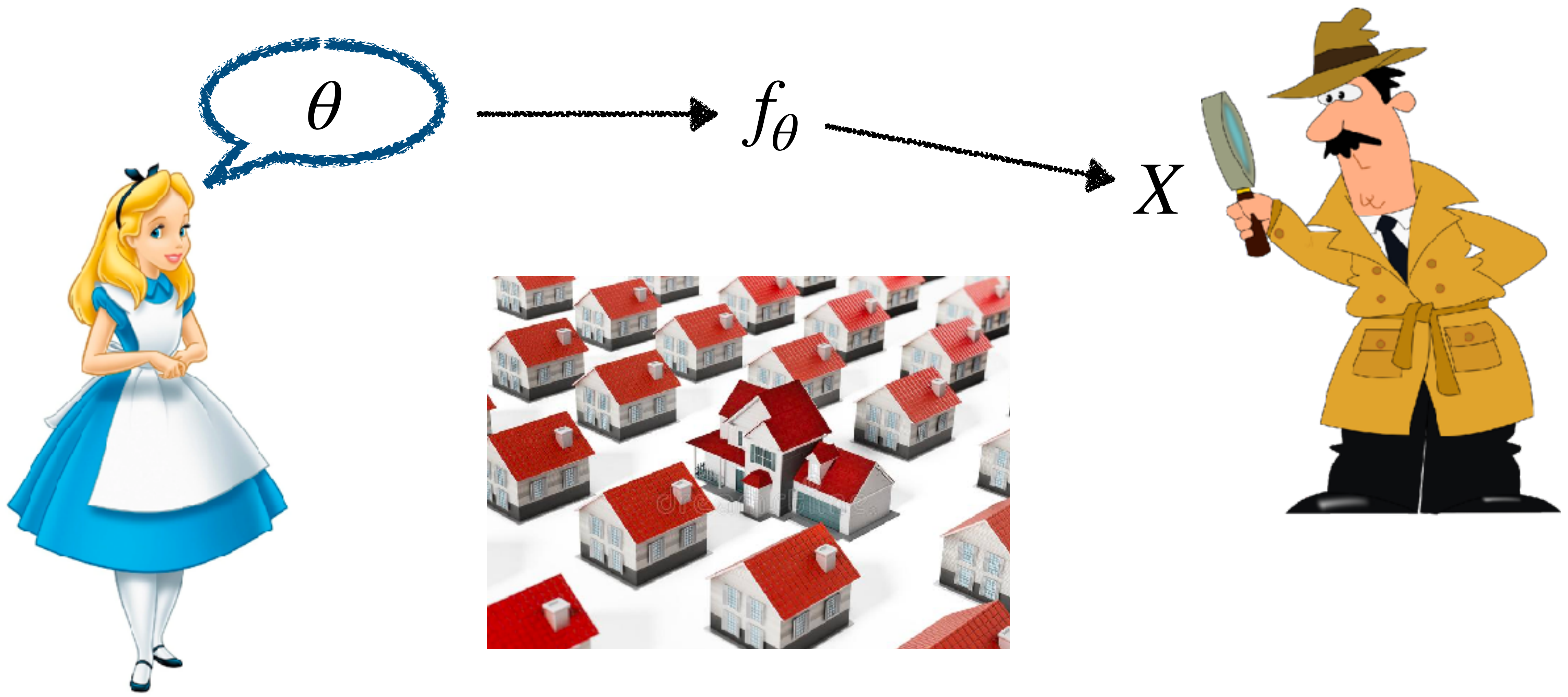

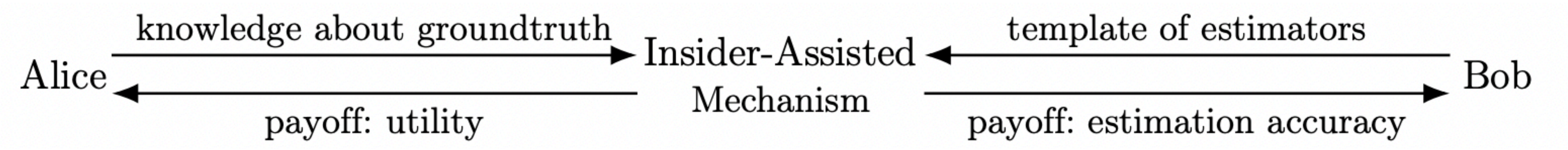

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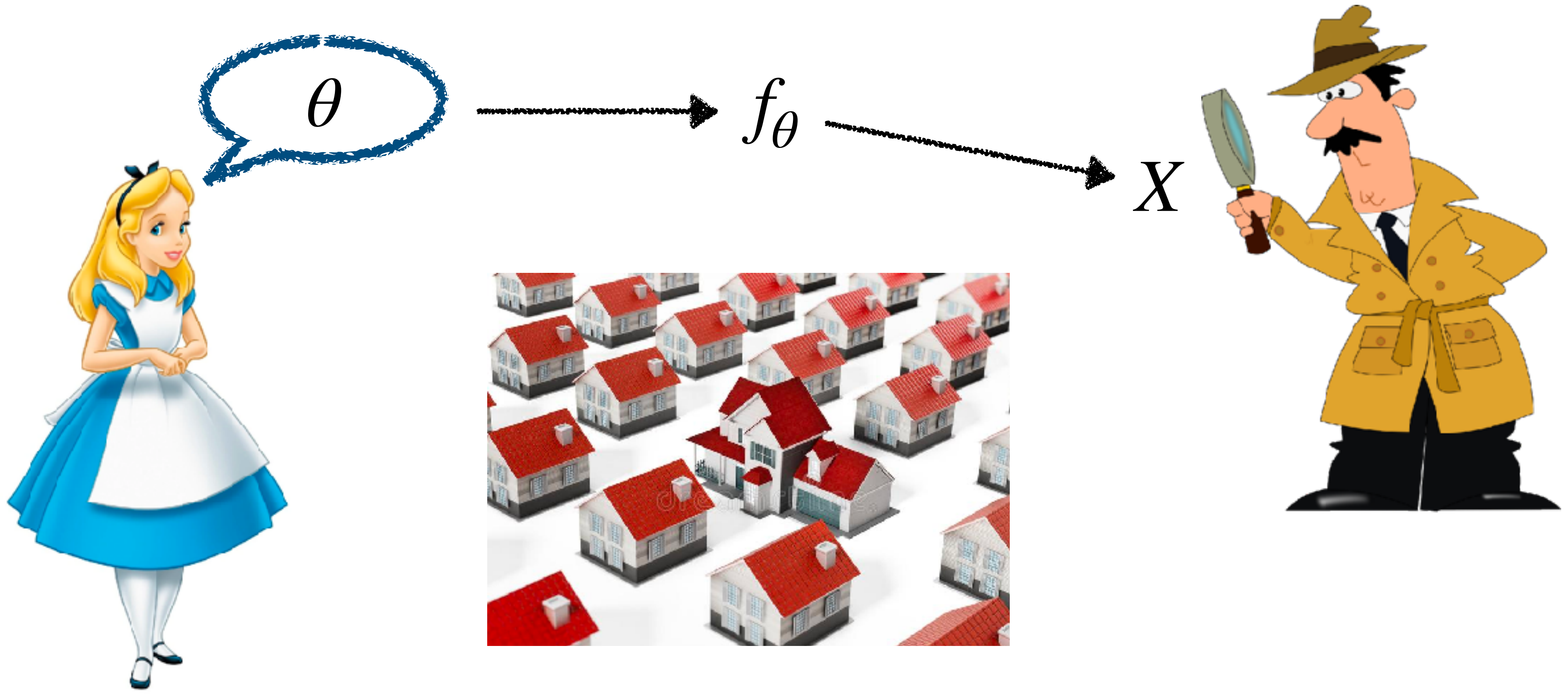
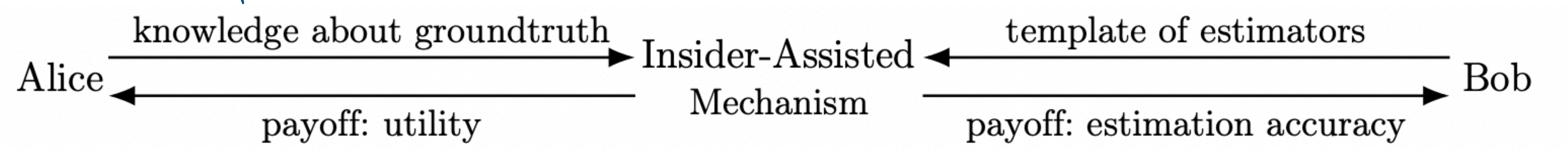


how to model "knowing about the ground truth"?



Another example of *ranking* + *alignment*

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Isotonic Mechanism is author alignment using ranking

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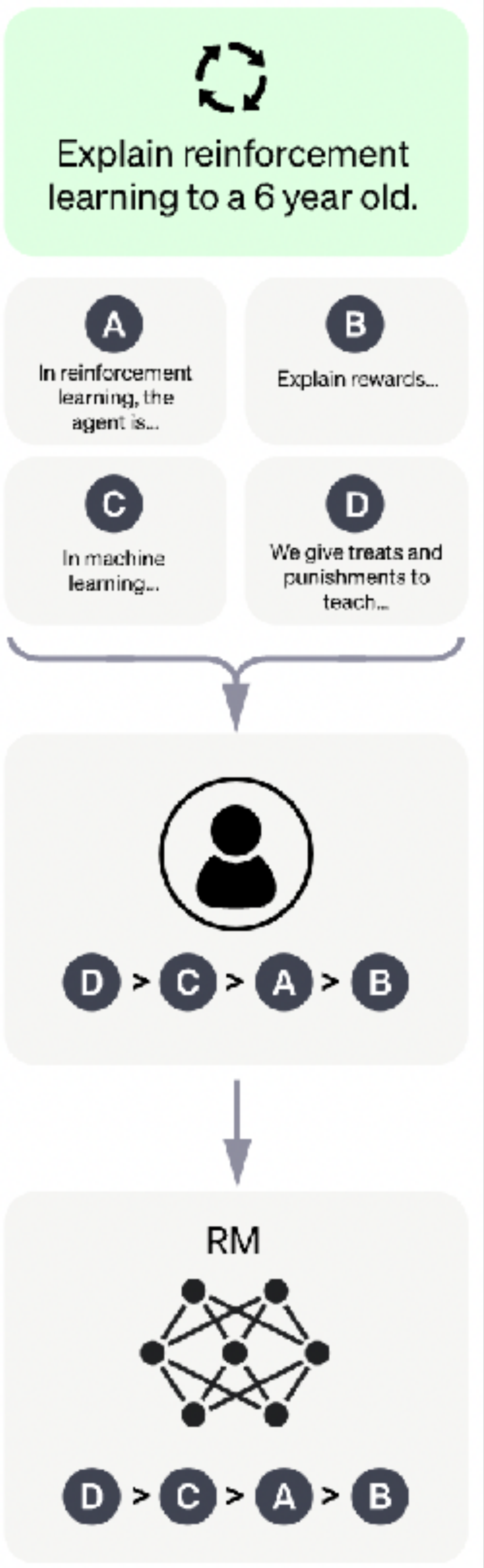
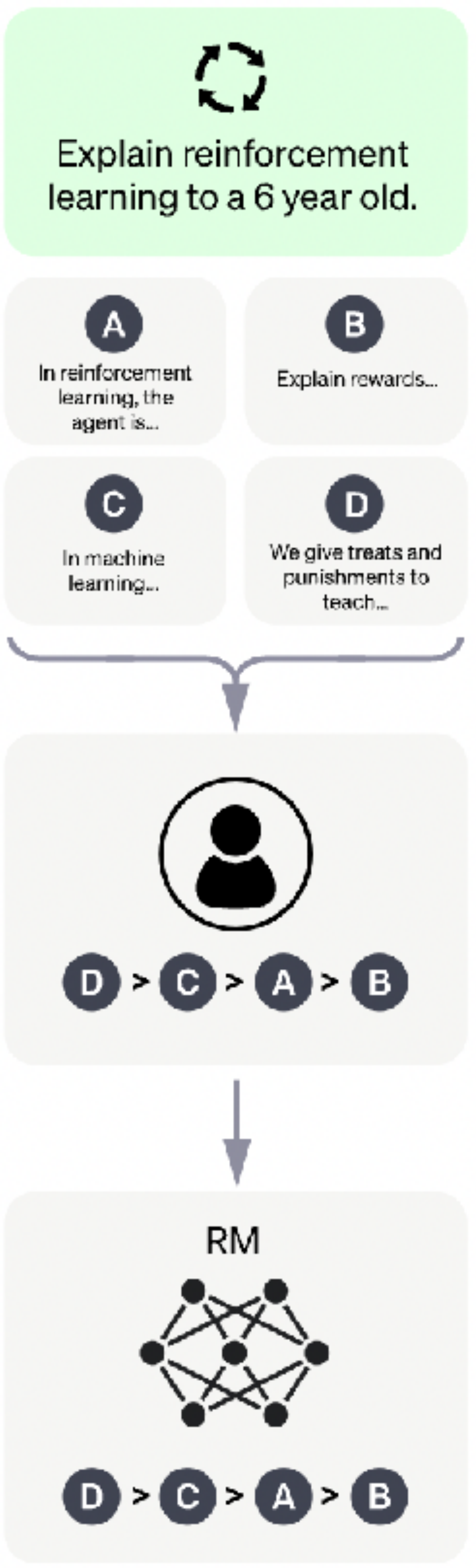


Source: OpenAI

Another example of *ranking + alignment*

Isotonic Mechanism is author alignment using ranking

- ChatGPT generates several outputs with the same question/prompt



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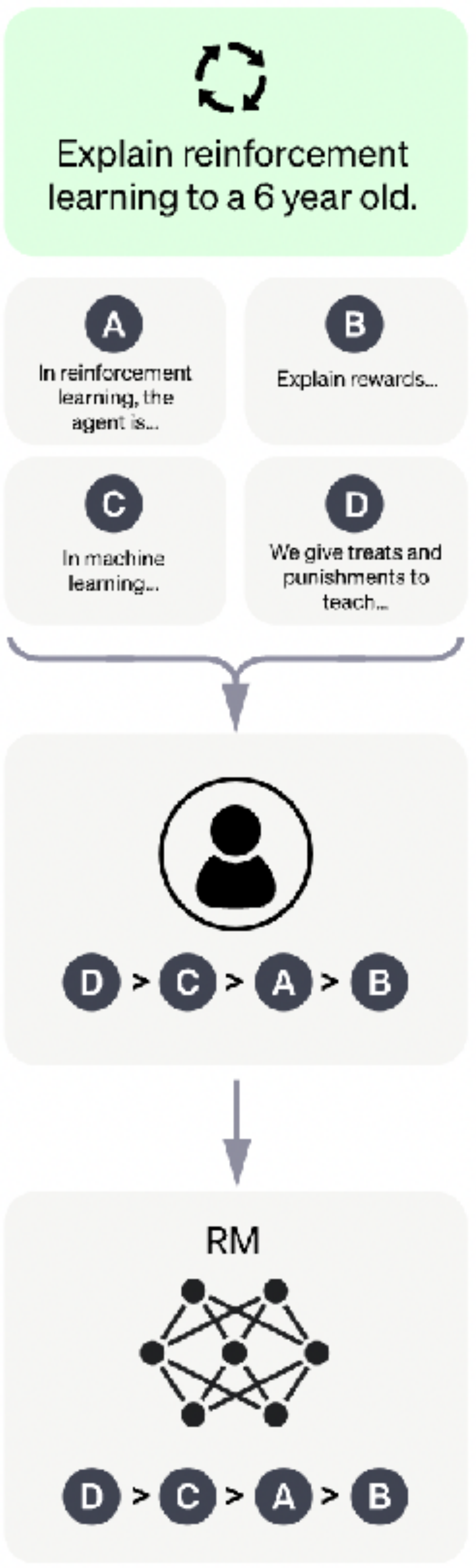

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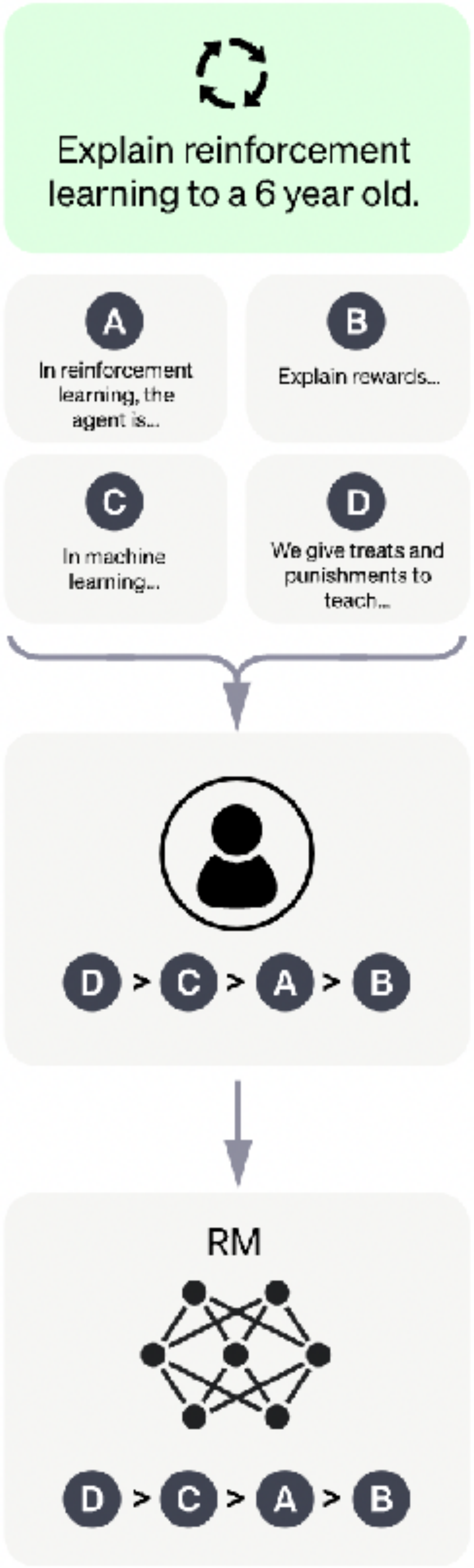
Another example of *ranking + alignment*

Isotonic Mechanism is author alignment using ranking

- ChatGPT generates several outputs with the same question/prompt
- Labelers rank the outputs based on human preferences

- Authors know about their submissions better than reviewers
- Humans know about ethics better than machines



Source: OpenAI

Future work

- Extension to multi-owner settings
- Relax convexity assumption
- Other use cases? Recommender systems where an influencer submits multiple videos to TikTok

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- *The Isotonic Mechanism for exponential family estimation*. Yuling Yan, Weijie Su, and Jianqing Fan. arXiv:2304.11160
- *An Isotonic Mechanism for overlapping ownership*. Jibang Wu, Haifeng Xu, Yifan Guo, and Weijie Su. arXiv:2306.11154

Multiple owners

Joint work with Jibang Wu and Haifeng Xu

- n items shared by m owners with the same ground-truth ranking
- Multiple Isotonic Mechanism: final estimator is

$$\frac{1}{m}\sum_{j=1}^{m}\hat{\boldsymbol{R}}^j$$

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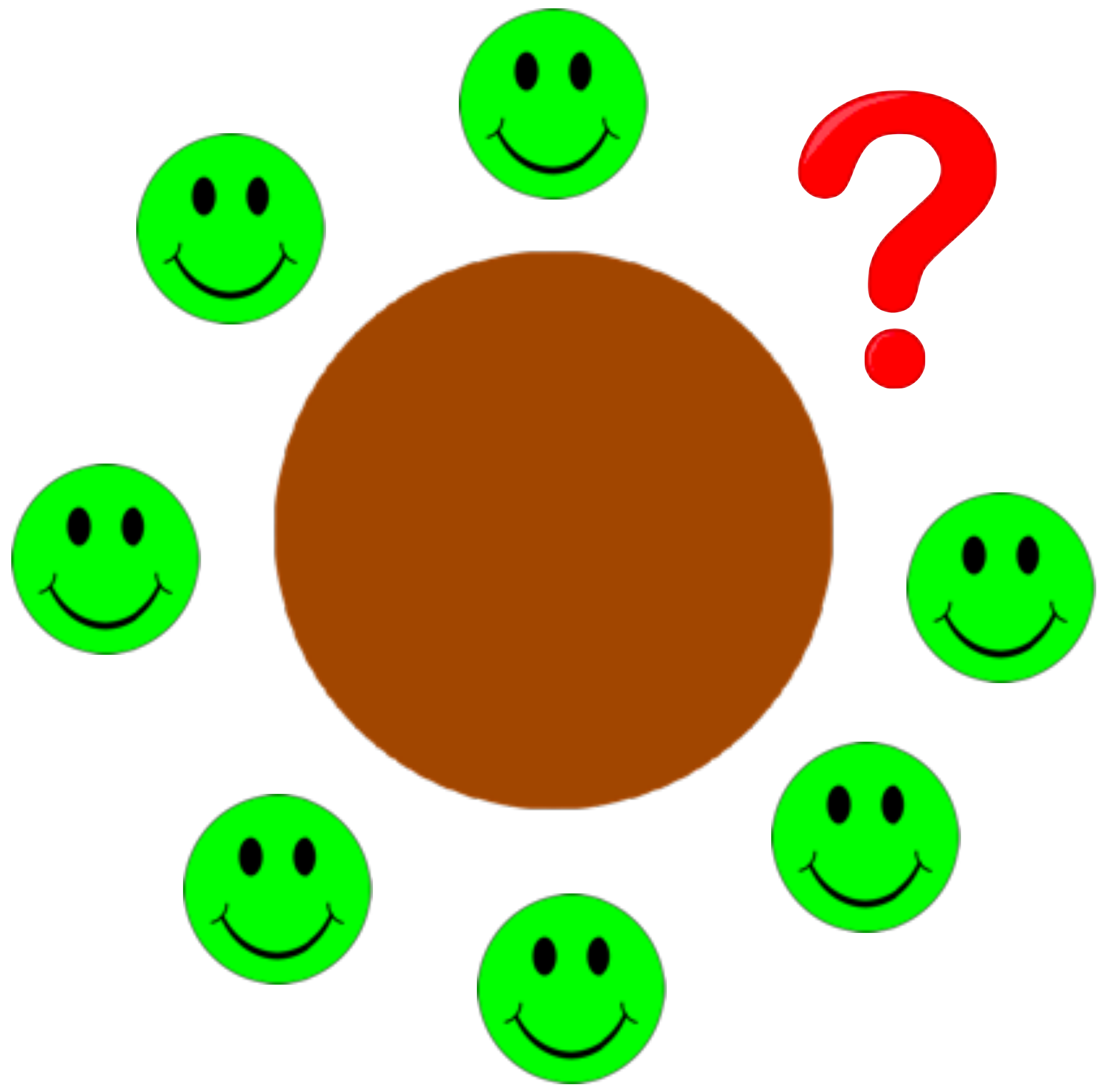

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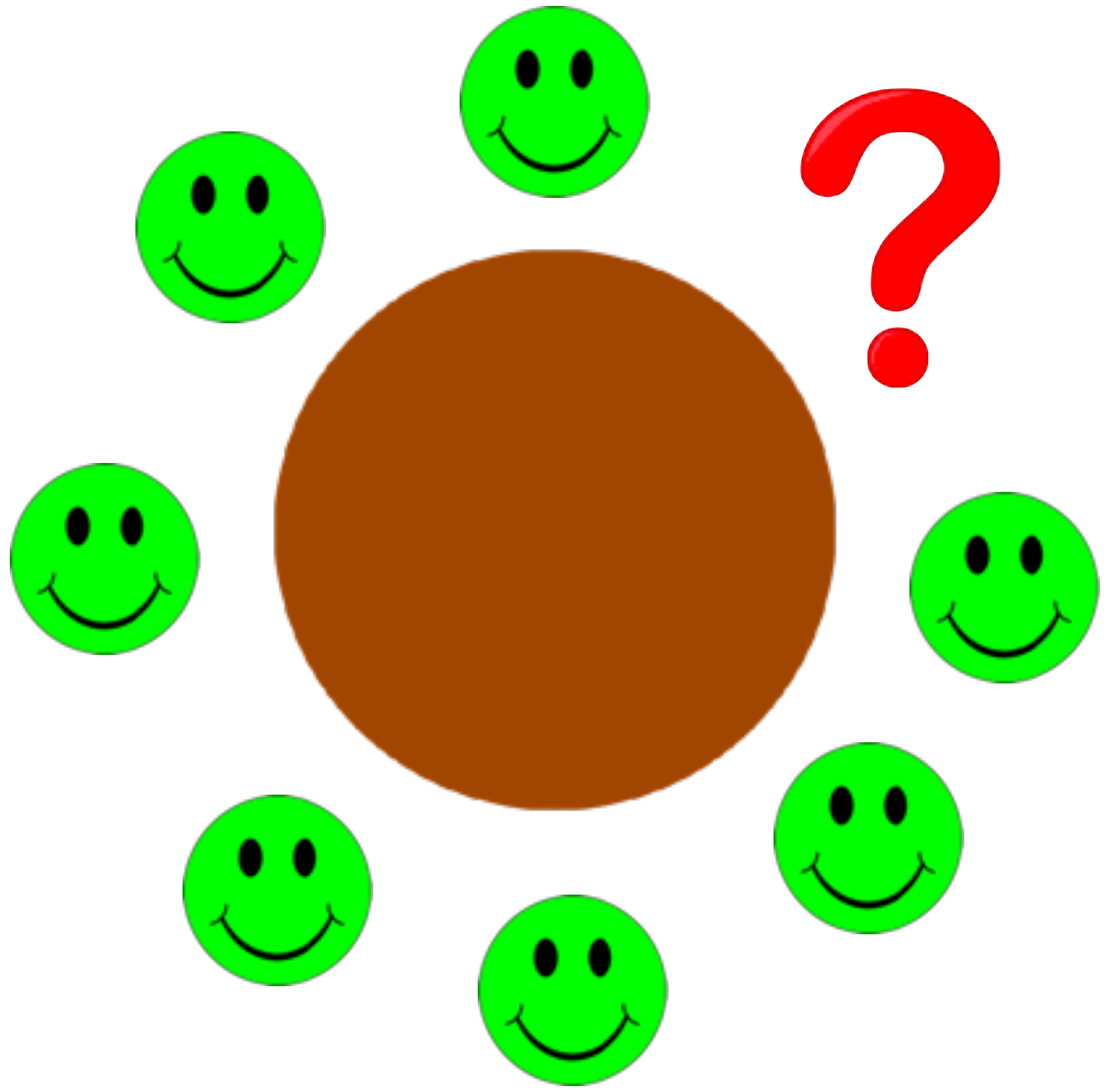
Theorem (S., Wu, and Xu 2023)

All owners reporting the truth is a Nash equilibrium in the multiple-owner Isotonic Mechanism



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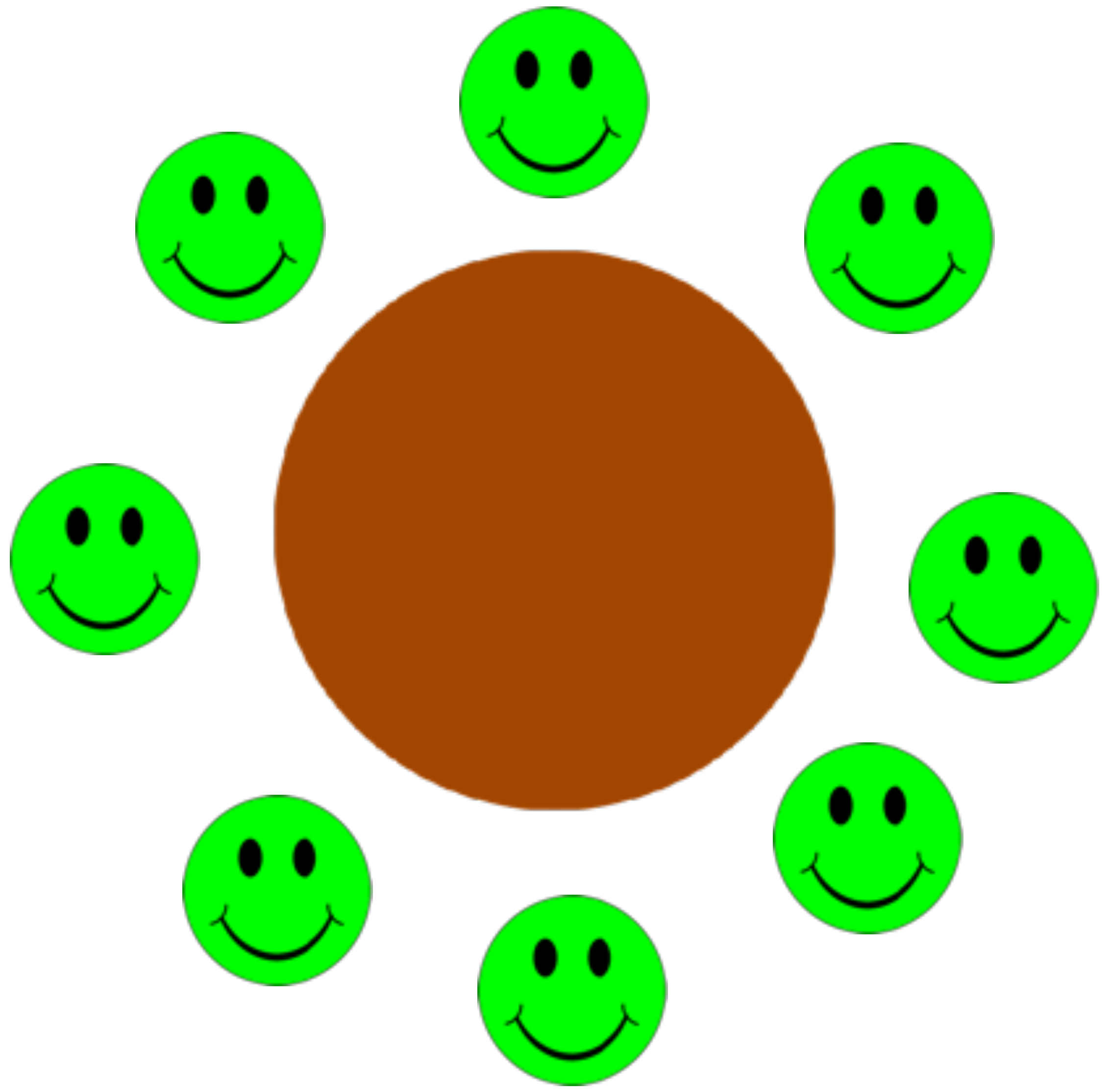

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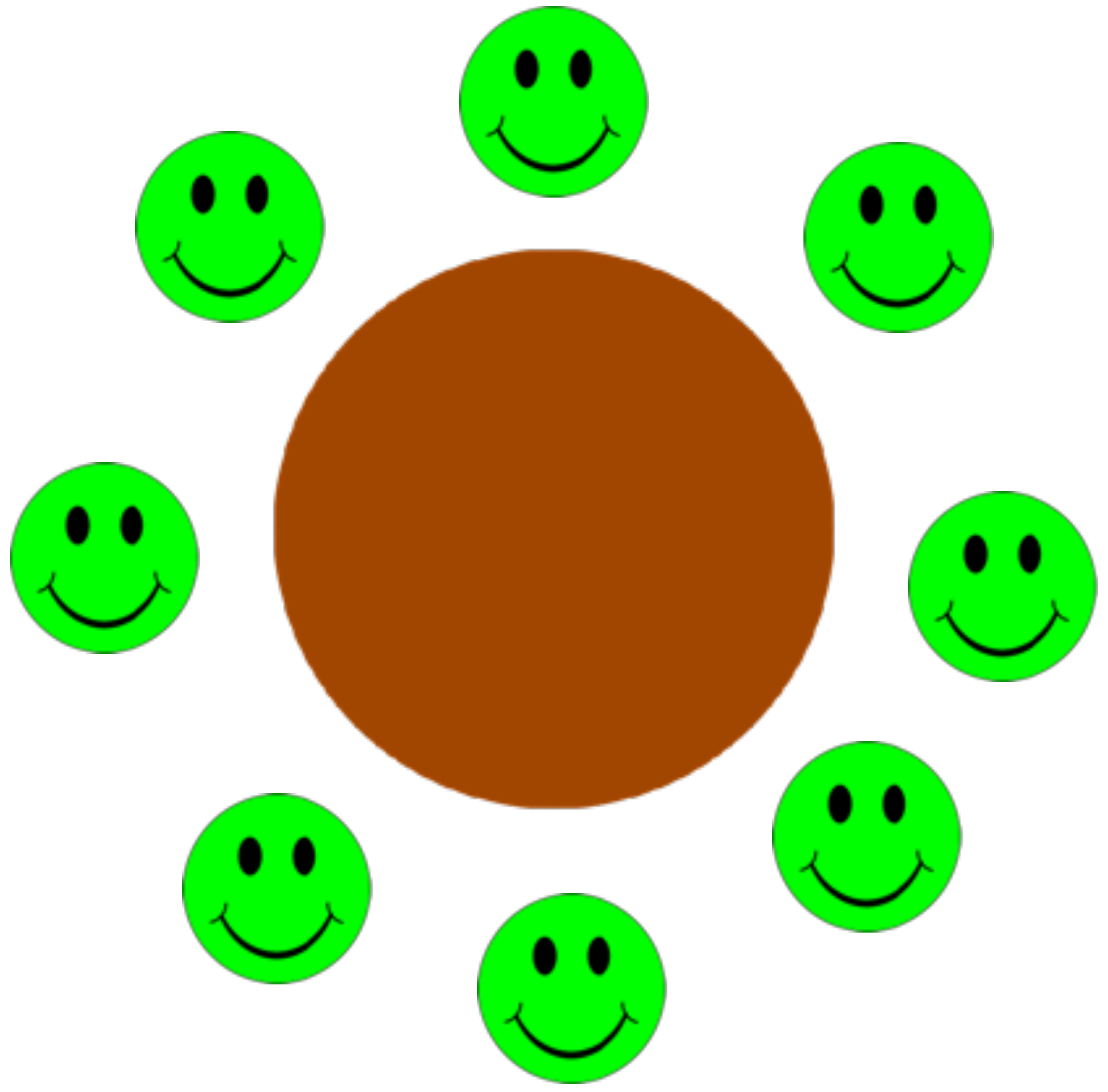

- Future work: model probabilistic rankings

Other reasons for using the Isotonic Mechanism

Other reasons for using the Isotonic Mechanism

- Quota of accepted papers: it’s really about comparisons
- Conference papers are easier to compare than journal papers
- Even if the utility is non-convex, it might still be truthful in some cases (e.g., concerning only the highest rating for best paper awards)
- Most people are not adversarial
- Can use it ‘softly’: only SACs or above know the adjusted ratings
- Might discourage guest authorship
- Current system not working well (e.g., controversies on the ICML 2022 outstanding paper awards)