Battling Demons in Peer Review

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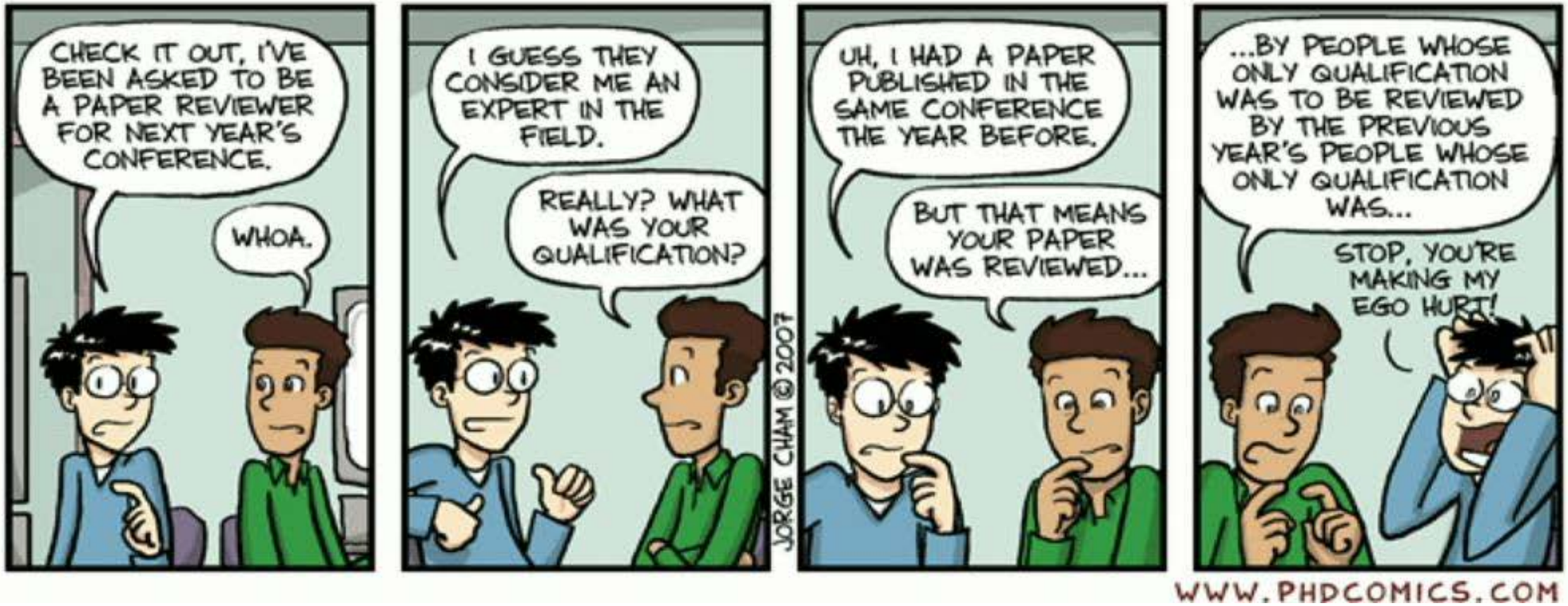


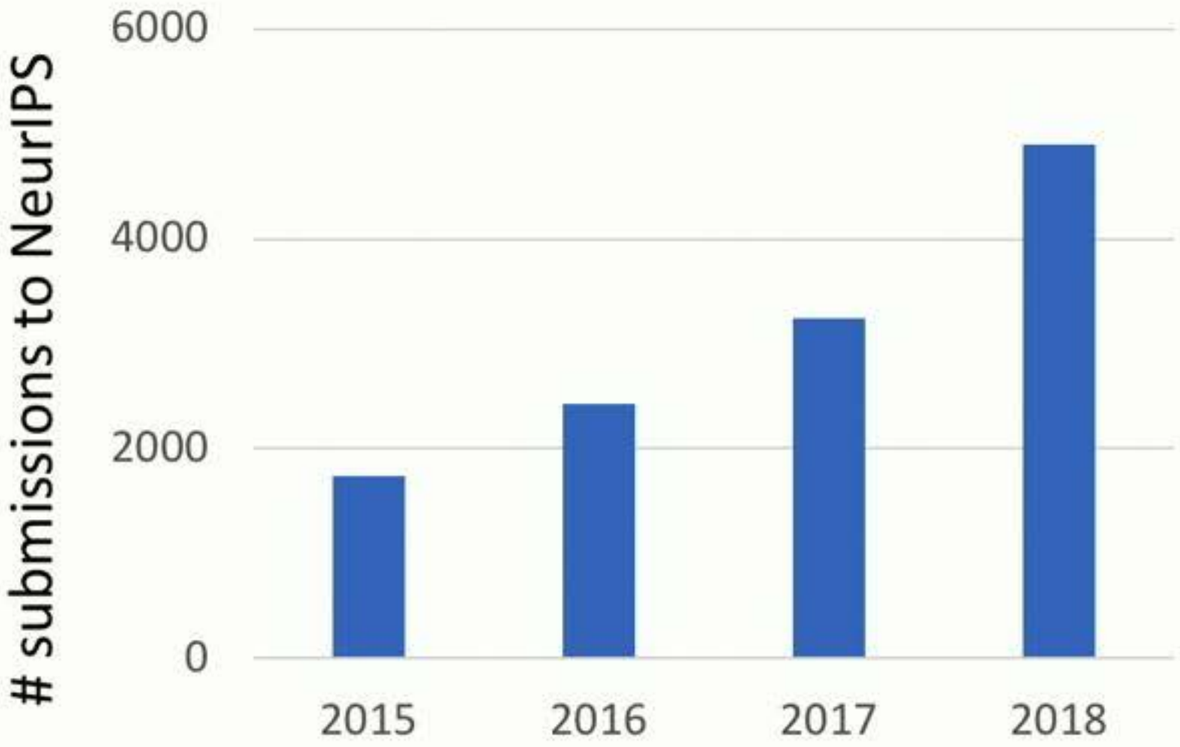
Challenge across many research fields

- **Drummond Rennie (Nature, 2016):**

  "Peer review ... is a human system. Everybody involved brings ***prejudices****,* ***misunderstandings*** *and gaps in knowledge, so no one should be surprised that peer review is often* ***biased*** *and* ***inefficient****. It is occasionally* ***corrupt****, sometimes a charade, an open temptation to plagiarists. Even with the best of intentions, how and whether peer review identifies high-quality science is unknown. It is, in short,* ***unscientific****."*

- **Overwhelming desire for improvement**
  [surveys by Smith 2006, Ware 2008, Mulligan et al. 2013]

Tremendous growth



Several thousands of submissions, 40% increase per year

Tackle systematic problems in peer review

using principled and practical approaches

Subjectivity

Miscalibration

Biases

Strategic behavior

Noise

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Miscalibration

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Strategic behavior

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UNFAIR

Subjectivity

Miscalibration

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Noise

Detail

Some detail

Brief overview

Many other applications

Hiring

Admissions

A/B testing

yelp
tripadvisor

Online ratings

Crowdsourcing

Peer grading

...

Subjectivity

with

Ritesh Noothigattu

Ariel Procaccia

Differing opinions about relative importance of criteria

[Kerr et al. 1977, Mahoney 1977, Bakanic et al. 1987, Hojat et al. 2003, Church 2005, Lamont 2009]

Novelty is not useful unless improvement by at least 10%

Novelty is extremely important

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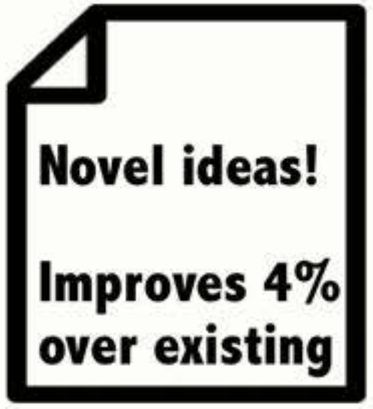

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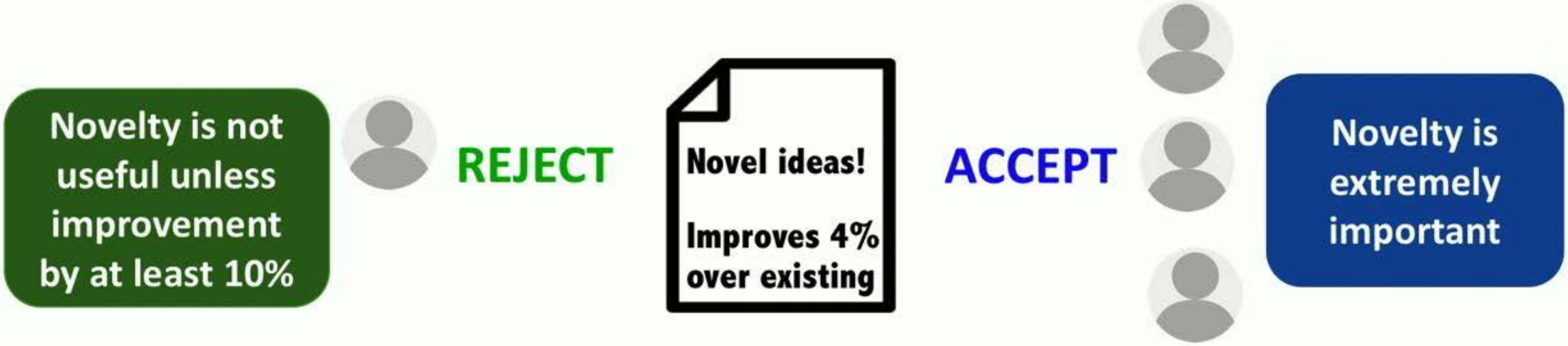

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REJECT

Novel ideas!

Improves 4% over existing

ACCEPT

Novelty is extremely important

How to ensure that every paper is judged by the same yardstick?

Problem setting

- Reviewers asked to judge papers on **k criteria**
  - E.g. (IJCAI 17): Originality, Relevance, Significance, Writing, Technical
- And an **overall score**
- Reviewer i gives to paper j:
  - Criteria scores $x_{ij} \in [0,1]^k$
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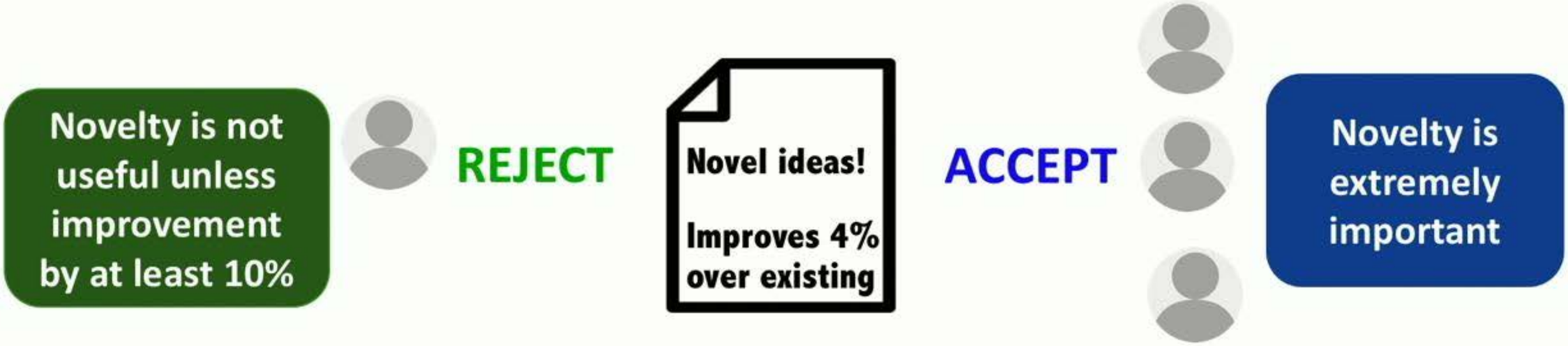

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For this talk: Suppose all papers reviewed by all reviewers

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Reviewers

Criteria scores

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Overall scores

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$\mathcal{F} = set\ of\ all\ monotonic\ functions$

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L_p norm *

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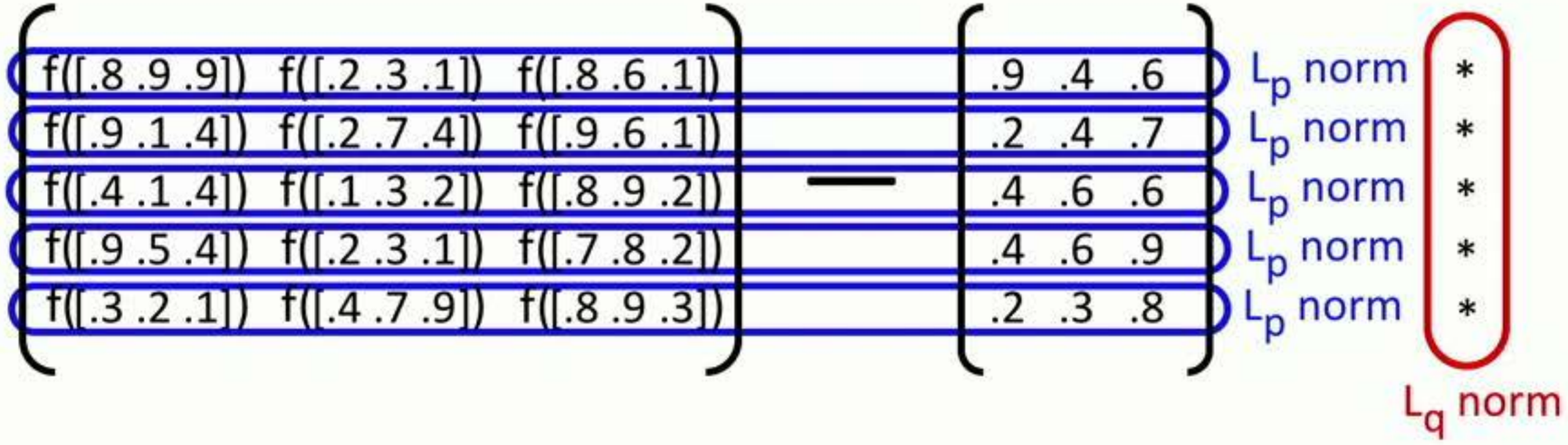

- Used in many applications

  [e.g., Ding et al. 2006, He and Cichocki 2008, Nie et al. 2010, Kong et al. 2011, Rahimpour et al. 2017...]

- Different L(p,q) losses used in different applications

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Which L(p,q) loss function to use?

Axiomatic approach

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- Identify scenarios that is easy to reason about
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Paper 1: $x_{11} = x_{21} = x_{31} = \cdots := x_1$
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Three natural axioms

Axiom 1: Consensus

For some $x \in [0,1]^k$ and $y \in [0,1]$, if all reviewers map x to y then $\hat{f}(x) = y$.

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Axiom 3: Strategyproofness

No reviewer can bring the learnt overall scores closer to her/his own opinion by strategic manipulation. For any reviewer i, let $(y_{i1}, \dots, y_{im})$ be overall scores she/he gives if honest. Let $\hat{f}$ denote learnt mapping in that case. Let $(y'_1, \dots, y'_m)$ be any other overall scores and $\hat{g}$ be the associated learnt mapping. Then we need:

$$\left\| \left(\hat{f}(x_1), \dots, \hat{f}(x_m) \right) - (y_{i1}, \dots, y_{im}) \right\| \leq \left\| \left(\hat{g}(x_1), \dots, \hat{g}(x_m) \right) - (y_{i1}, \dots, y_{im}) \right\|$$

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L(1,1) is the only L(p,q) loss that satisfies the three axioms.

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Paradoxical!

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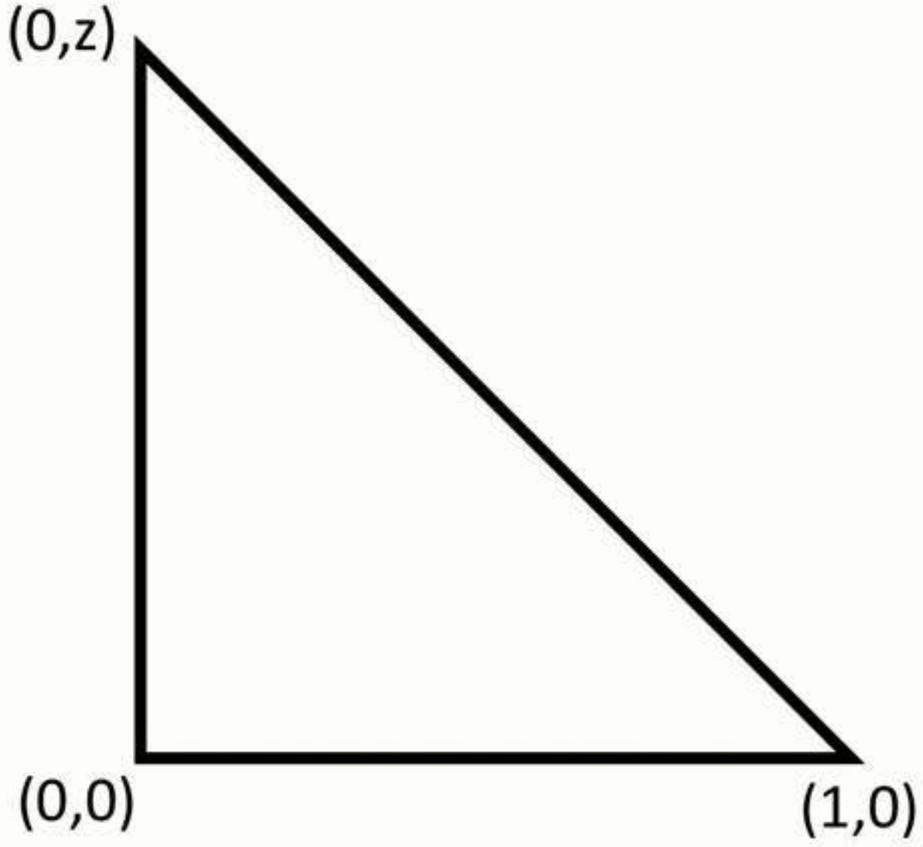
$\left(\hat{f}(x_1), \hat{f}(x_2)\right)$ is exactly the Fermat point of:



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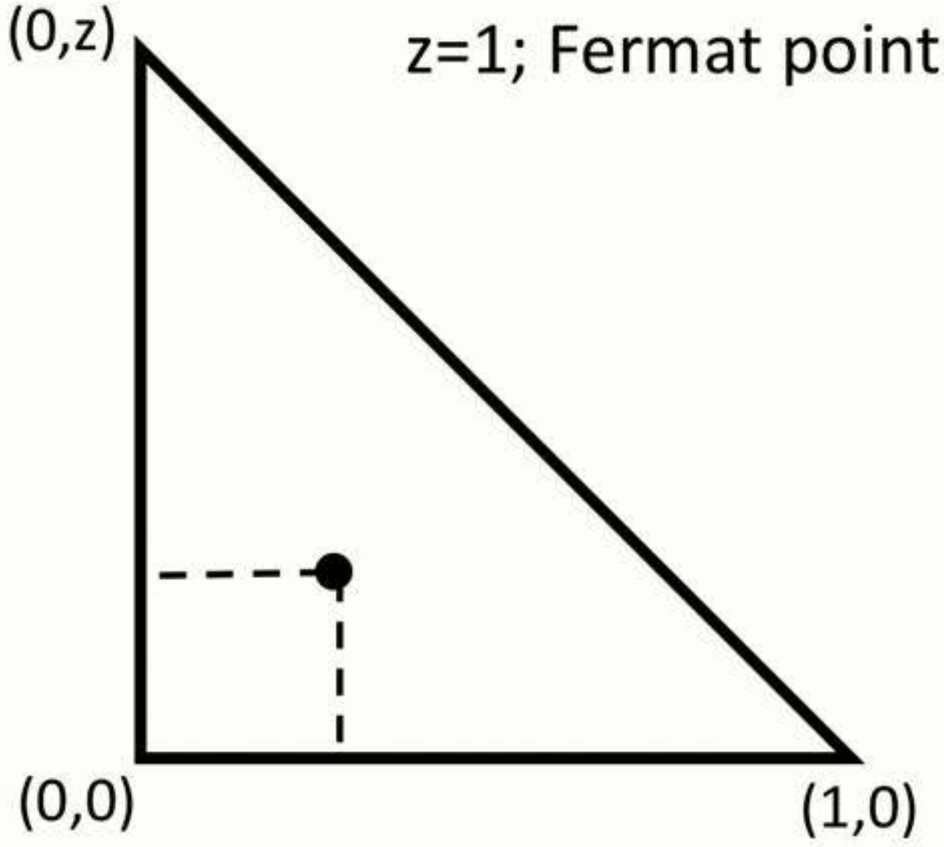

Dominance violated under L(2,1) loss

- 2 papers, 3 reviewers, k=2 criteria
- Criteria scores x_1 = [¼, ¾], x_2 = [¾, ¼]

- Overall scores:

	Paper 1	Paper 2
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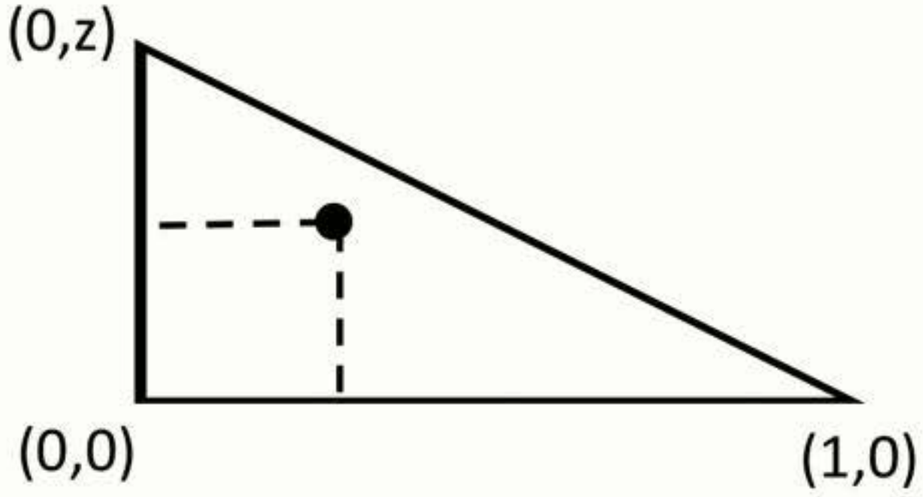

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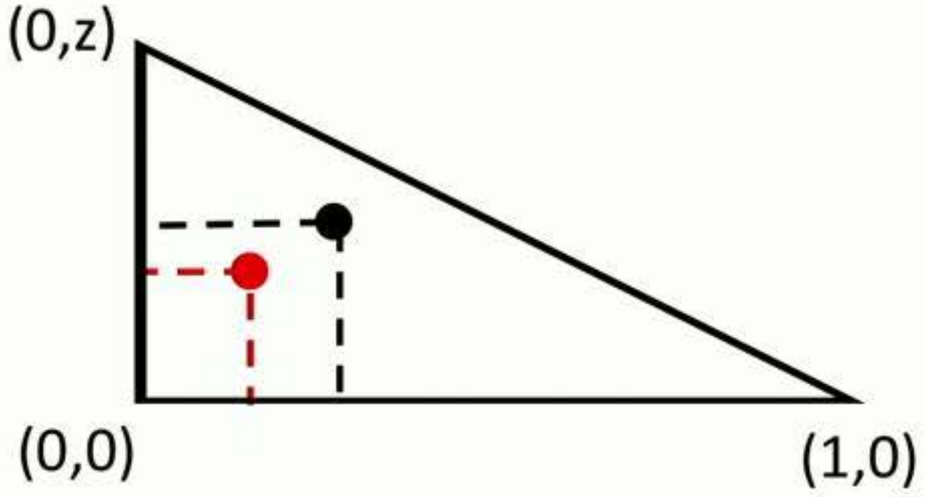

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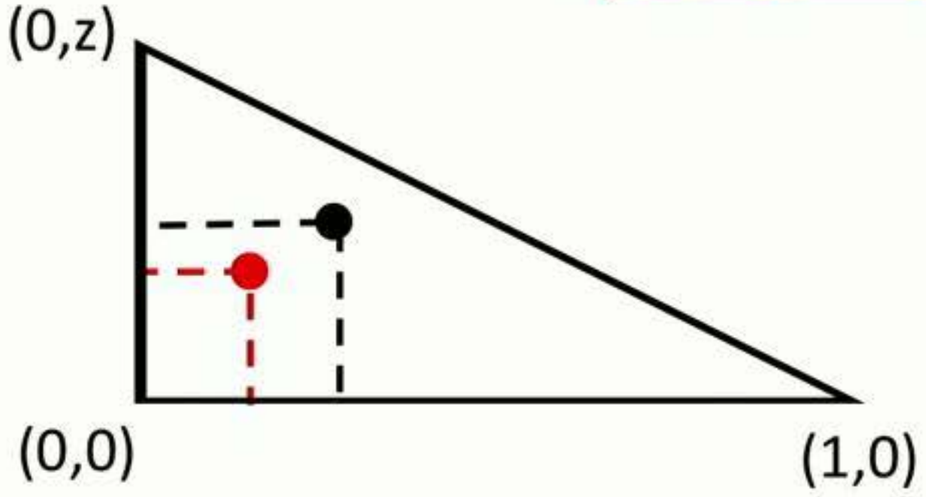

IJCAI 2017

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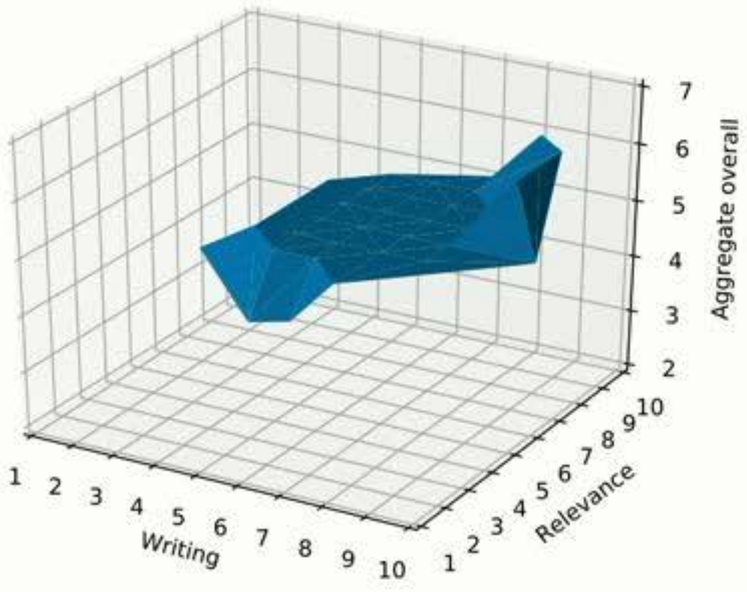

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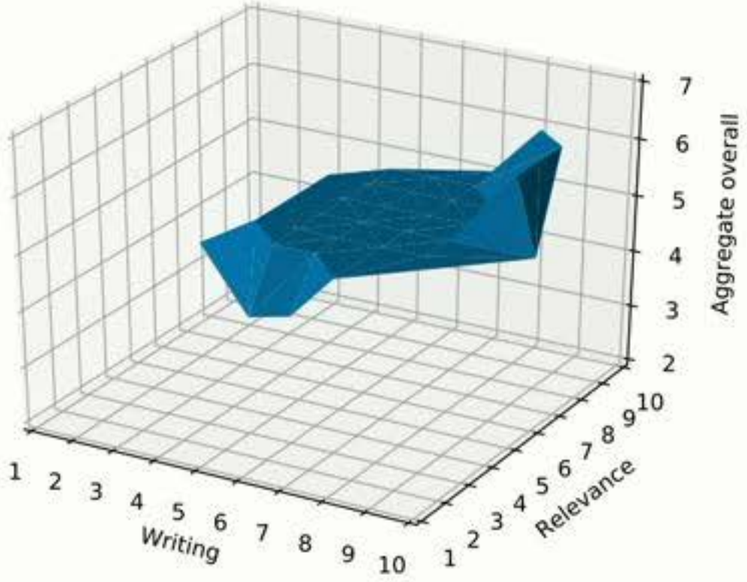

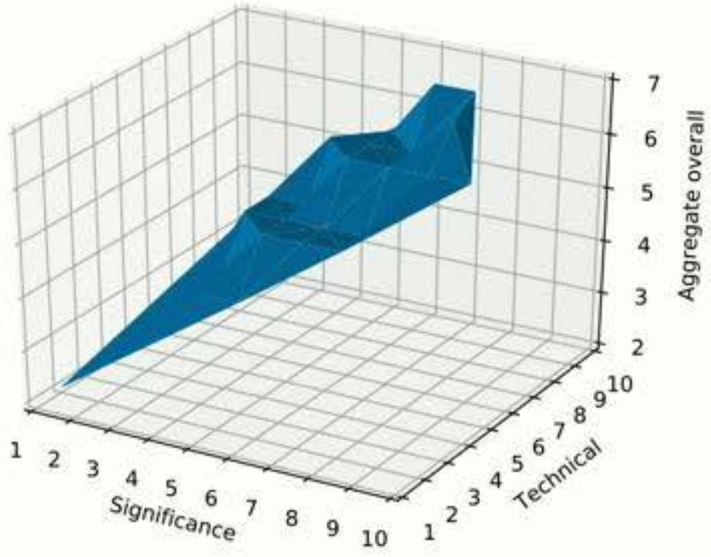

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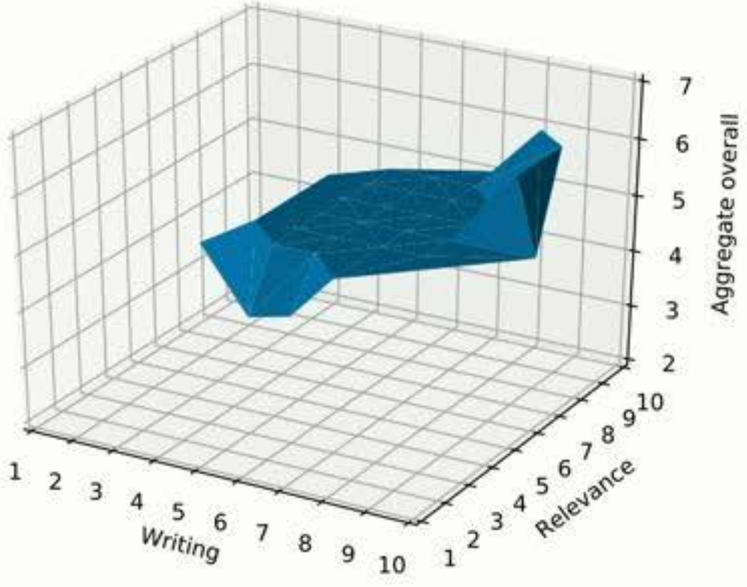
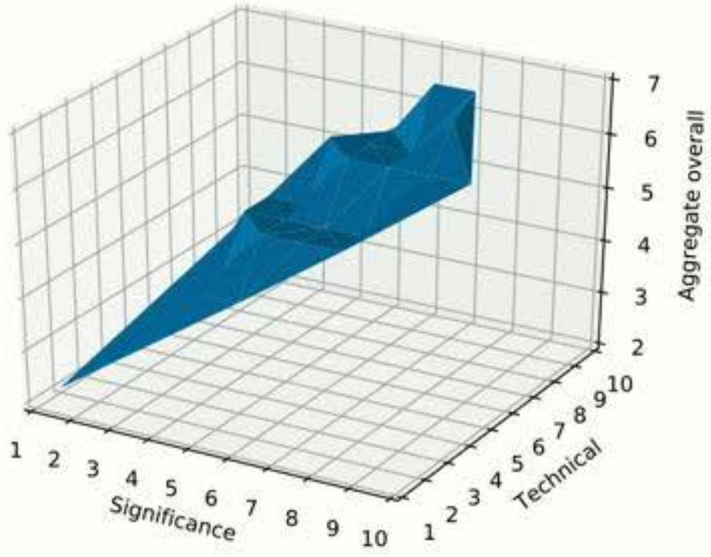
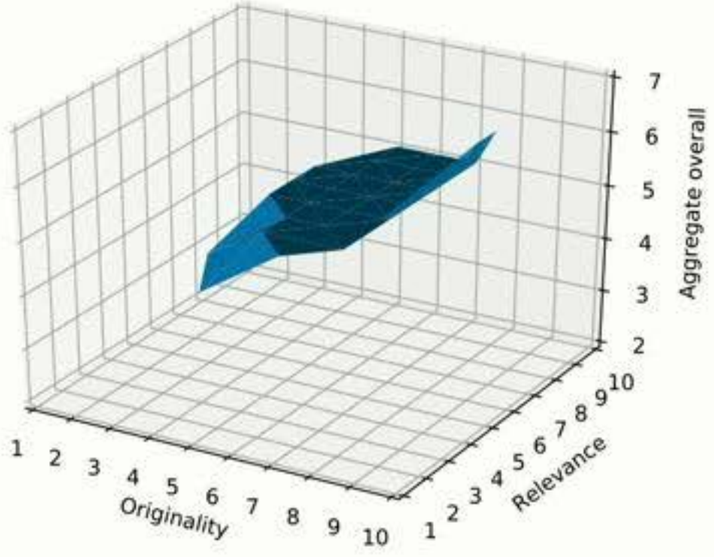
IJCAI 2017







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- Originality: moderate influence.

Miscalibration

with

Jingyan Wang

Best Student Paper Award at AAMAS 2019
Best Paper Nominee

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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."

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]

- Did not work well – NIPS 2016 program chairs.
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? **Is it possible to do better than rankings with essentially no assumptions on the calibration?**

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Theorem

No deterministic estimator has a success probability better than random guessing.

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Is it possible to do better than random guessing?

Inspirations and connections

- Stein's phenomenon
- Empirical Bayes
- Cover's envelope problem

Estimator

With probability $\frac{1 + |y_1 - y_2|}{2}$ pick paper which received higher score

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The estimator strictly outperforms random guessing.

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Theorem

The estimator strictly outperforms random guessing.

- **Ratings > rankings even if calibration is arbitrary/adversarial**
- **Building block for more general applications**

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Biases

with

Ivan Stelmakh

Aarti Singh

Single blind versus double blind

- Gender/race/fame/… biases? Lot of debate!
- “Where is the evidence (of bias in my research community)?”

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How to rigorously test for biases in peer review (while ensuring "good" review process)?

A remarkable experiment!

WSDM 2017 (Tomkins, Zhang, Heavlin)

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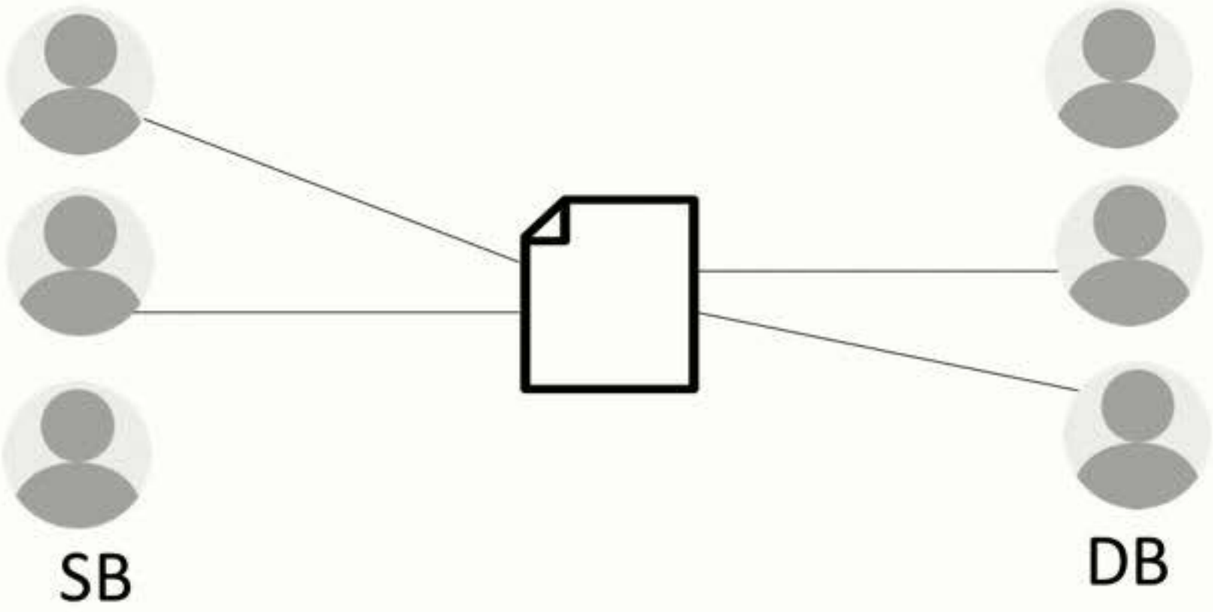

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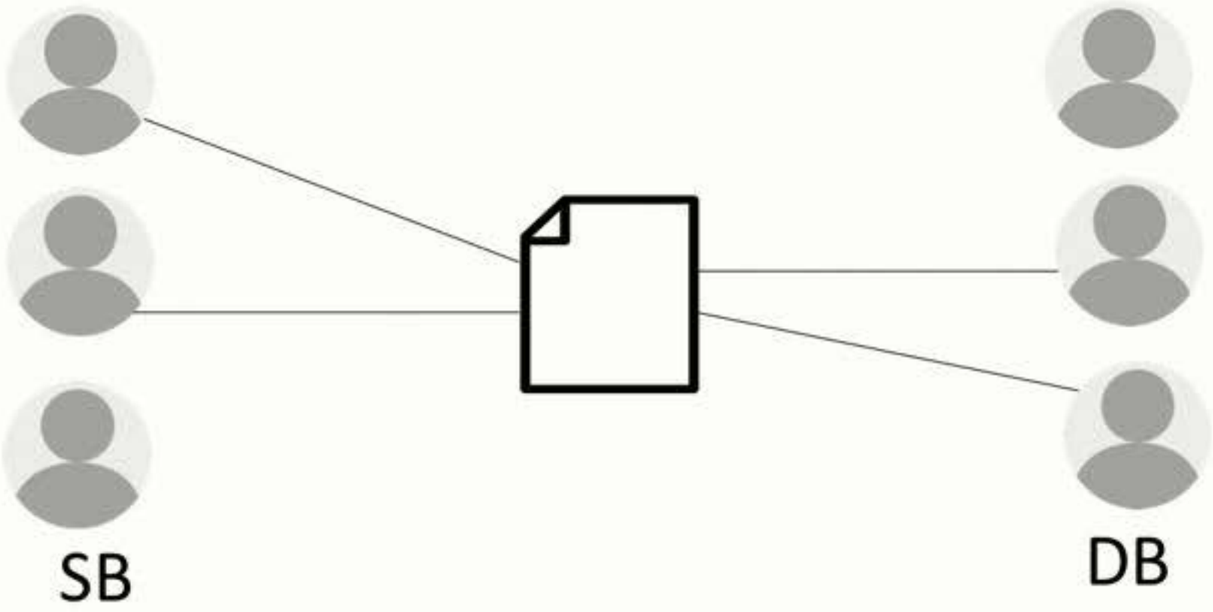
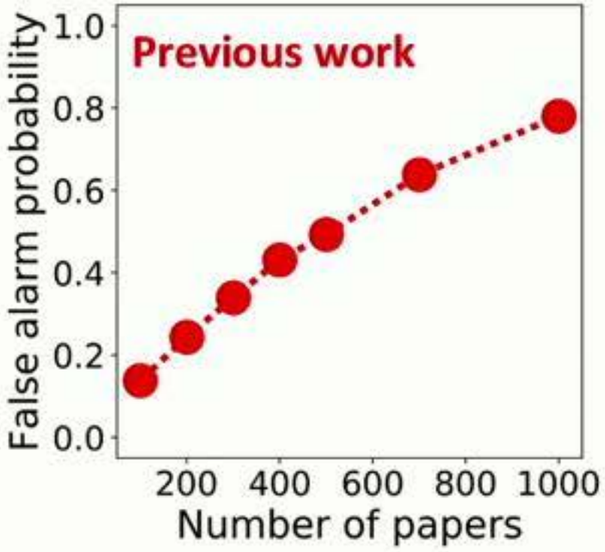


Our negative results: We identify a number of issues in the experimental setup and testing procedure which can lead to spurious (false) positives

Testing for biases

False alarm probability specified to be ≤ 0.05



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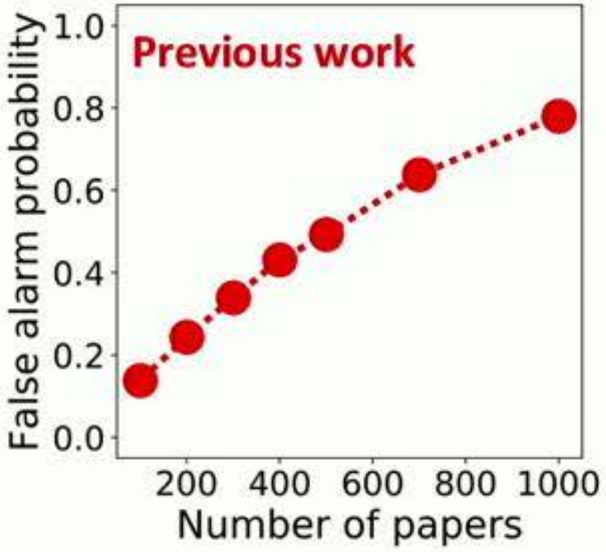

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  - Strong, rigorous guarantees

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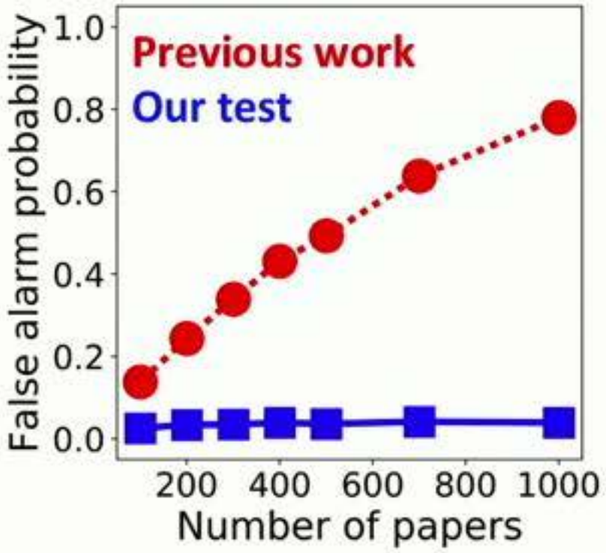

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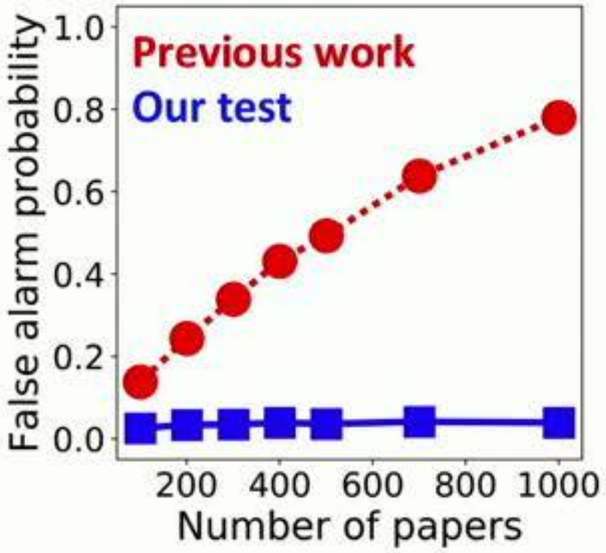
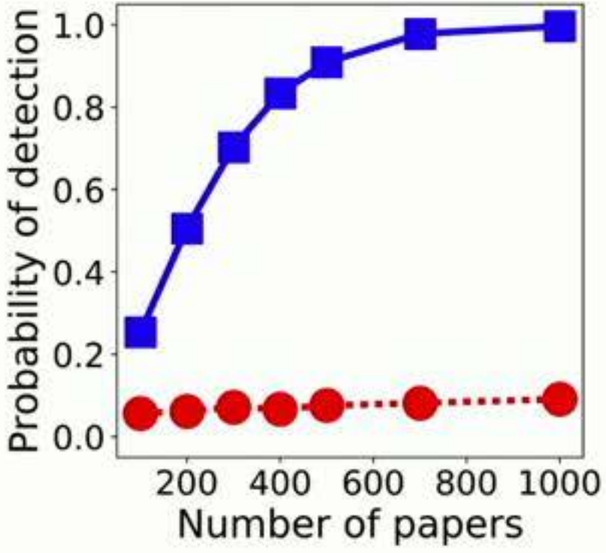


Under natural conditions



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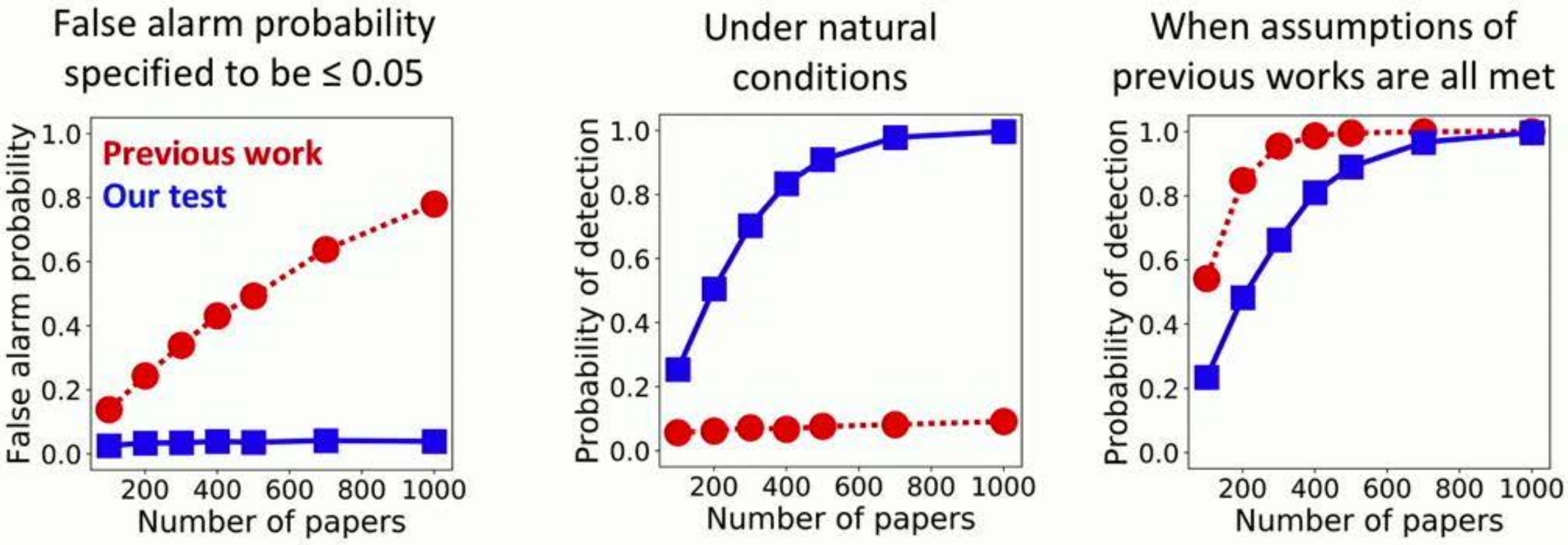

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Strategic behavior

with

Han Zhao

Yichong Xu

Xiaofei Shi

Motivation

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"competition incentivizes reviewers to behave strategically, which reduces the fairness of evaluations and the consensus among referees"

Also [Anderson et al. 2007, Langdford 2008 (blog), Akst 2010, Thurner and Hanel 2011...]

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How to make peer review strategyproof?

Strategyproofness

- ✓ Framework for strategyproof peer review
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ICLR 2016 empirical evaluation

✓ **Conditions for strategyproofness are indeed satisfied!**

Noise

with

Ivan Stelmakh

Aarti Singh

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- Poor reviews due to inappropriate choice of reviewers

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How to assign reviewers to papers ensuring fairness and accuracy?

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ICLR 2016

Fairness (assignment quality for worst-off paper)	↑ 25%
Average quality (TPMS objective quality)	↓ 2%

Conclusions

- **Urgent need to revamp and automate peer review**

  Observations & open problems: ***"Design and Analysis of the NIPS 2016 Review Process,"*** Shah, Tabibian, Muandet, Guyon, von Luxborg

- **Principled and practical approaches**
  - Impact!

- **Papers available on arXiv and my website**

  Short survey: **tinyurl.com/PeerReviewCMU**

tinyurl.com/PeerReviewCMU

Thank you!