The Impact of Negative Relevance Judgements on nDCG

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Introduction

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- Commonly used at TREC, other venues
- Denote spam, inappropriate documents
- Same amount as "key documents"

TREC Web Track	Qrels Negative
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2012	5%
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Boundedness is necessary:

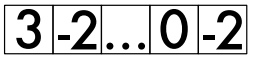
- Ensures nDCG's statistical properties
  nDCG is convergent, top-weighted, realizable, monotonous, localized, complete, scale invariant

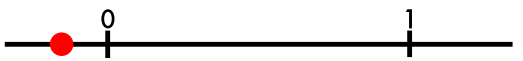
➜ How to handle negative gain values?

Strategies

(1) Original nDCG

- Use orig. nDCG formula on neg. gain values
- **Problem:** boundedness not guaranteed





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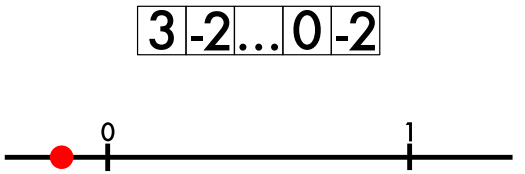
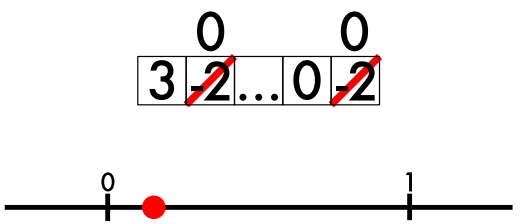


(2) Ignoring negative values

- Negative relevance values are treated as 0
- This is current practice of most eval tools
- **Problem:** loss of information



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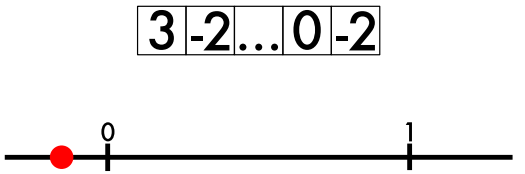

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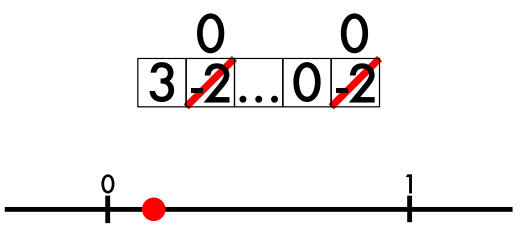
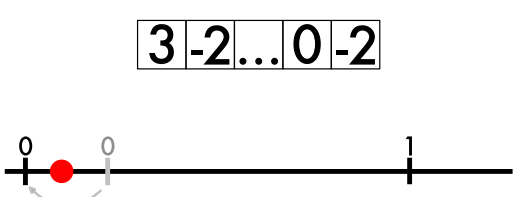


(3) Min-Max normalization

- Adopt full min-max-normalization by also including worst possible ranking
- **Problem:** unknown properties



Frequency and Impact

TREC Web Tracks 2010–2014

How often is boundedness violated?

- Between **70% and 100%** of topics violate the boundedness property (neg. scores possible) when using Original nDCG
- Between **8% and 68%** of topics may even score below -1

How do the two proposed solutions impact system rankings?

- Ignoring negative labels affects the rankings slightly ($\rho \approx 0.89$)
- Min-Max nearly reproduces rankings given by Original in full ($\rho \approx 0.98$)

Conclusions:

- Unboundedness is a widespread issue and needs to be addressed.
- The current best practice seems unsuitable, as it affects system rankings.

➜ Investigation of reliability, sensitivity, and stability of the three strategies.

Reliability

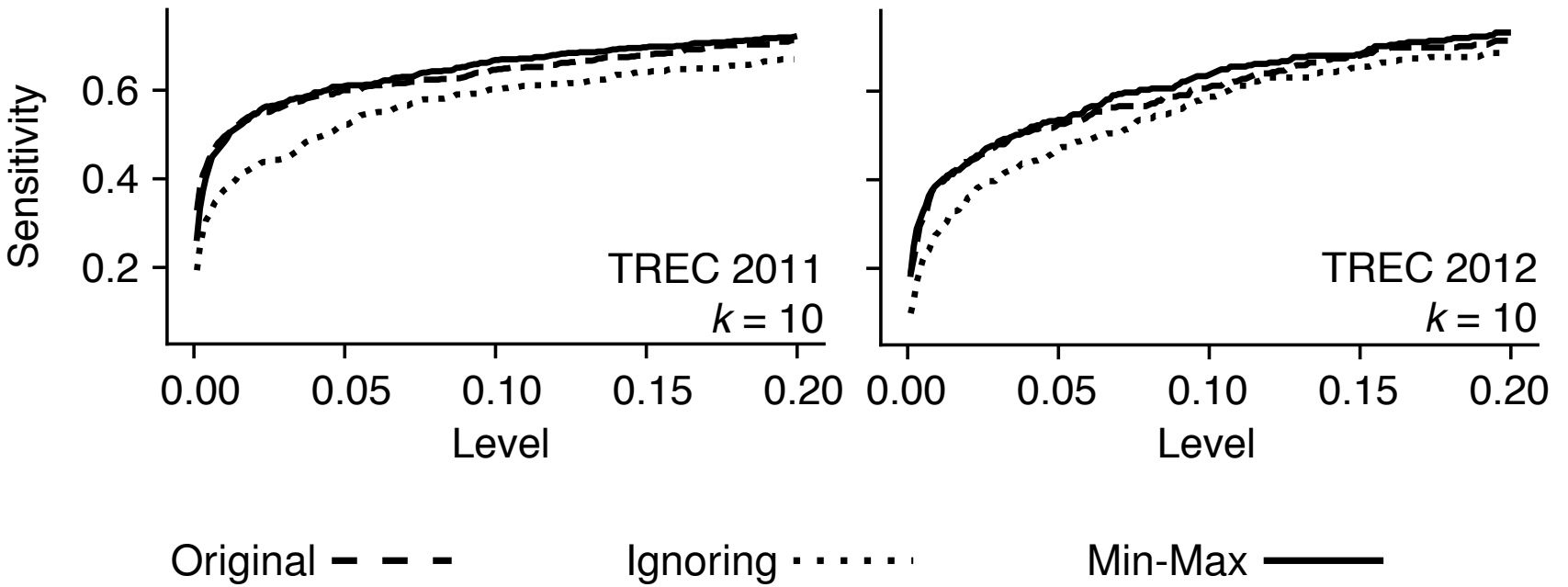
A measure's ability to reflect the actual performance differences of systems.

Strategy	TREC 2011	TREC 2012
Original	0.937	0.930
Ignoring	0.973	0.975
Min-Max	**0.993**	**0.995**

- Min-Max is most reliable, followed by ignoring negative labels, and Original
- Unboundedness increases the measurements' variance for Original

Sensitivity

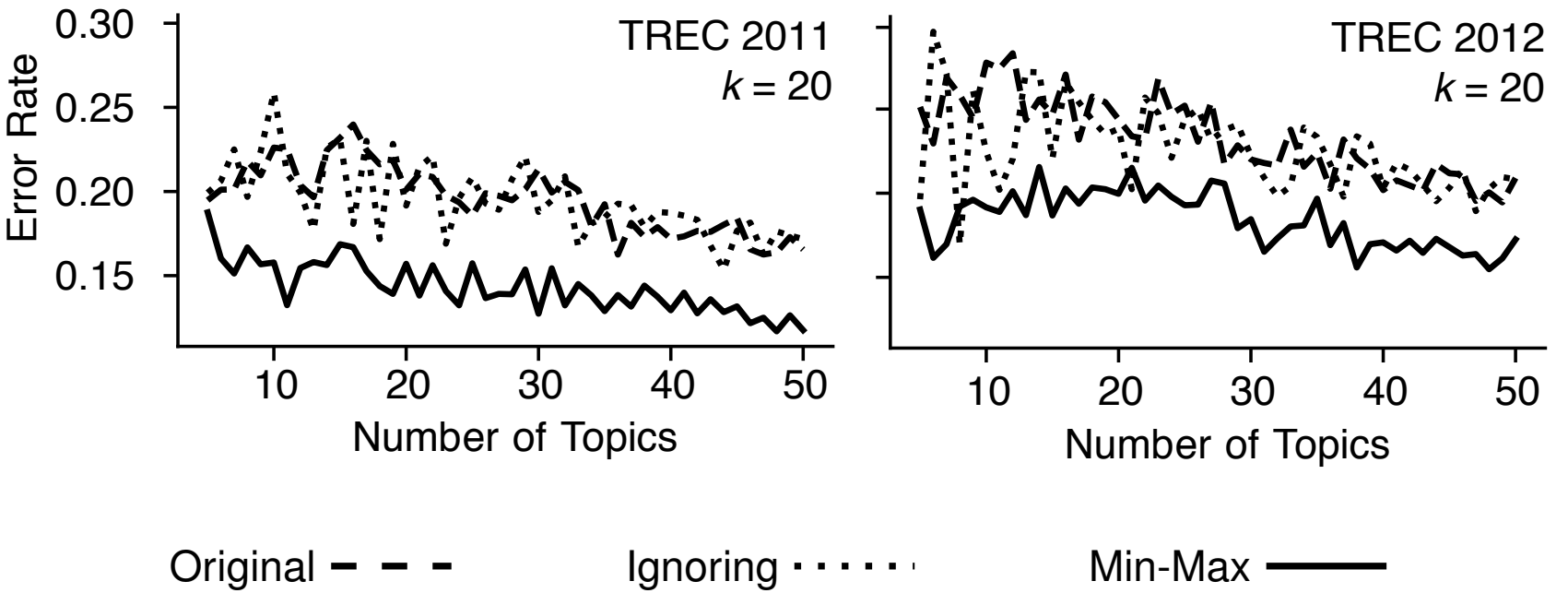
A measure's ability to successfully tell two systems apart at significance level.



- Min-Max performs best, followed by Original
- Ignoring negative values is disfavorable, as it negatively impacts sensitivity.

Stability

A measure's dependence on number of topics.



- Min-Max performs much better, likely due to reduced cross-topic variance.
- Even with more topics, other strategies can't match the improved error rate.

Conclusion

Identified Problem:

- Negative gain values can lead to boundedness violation for nDCG.
- Many evaluation experiments use negative relevance judgments.
- Current strategy is not equipped to adequately address these issues.

Proposed Solution:

- Adopting full min-max normalization.
- Restores boundedness while preserving system rankings.
- Yields additional benefits with increased stability, reliablity, and sensitivity.

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Thank you!