Estimating Topic Difficulty Using Normalized Discounted Cumulated Gain

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How can we identify topics in offline IR evaluation for which systems (systematically) face retrieval problems?

Experimental Setting

Offline IR Evaluation

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- $p_{t,s}$ denotes effectiveness score of system s on topic t w.r.t. a measure on the relevance judgements

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Research Questions:

→ What is a suitable *aggregation* method for topic difficulty estimation?

→ How can it be applied in practice with minimal overhead?

Limitations of Existing Approaches

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(4) Discrete class labeling

- Problem: difficulty expressed as classes (“easy”, “hard”, ...)
- Solution: aggregation resulting in numerical scale

Ratio-based Topic Difficulty

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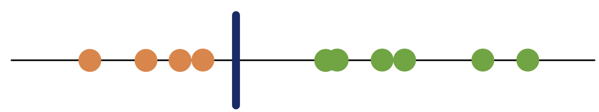
- ➜ Systems scoring higher than a baseline to overall number of systems



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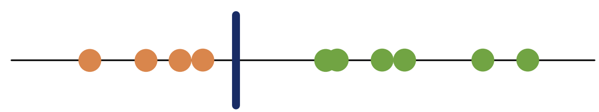

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Issues solved:

- ❑ *Topic set instability* – topics are now scored independently
- ❑ *Discrete class labeling* – ratio is numerical value between 0 and 1

Problem: What is a sensible baseline?

Ratio-based Topic Difficulty

Hypothetical Random Baseline Ranking

Requirements for a baseline:

- Domain-agnostic and comparable
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Proposed: hypothetical random ranking as as baseline

= A system drawing documents at random

- Restricted to random permutations of the pooling for practicability
- Its nDCG performance approaches the mean of the relevance label distribution

→ **Baseline**: mean relevance of judged documents to compare systems to

Ratio-based Topic Difficulty

Baseline Standardization

Procedure:

- Standardize the relevance label distribution (z-transformation)
- Baseline nDCG is 0 across all experiments
- Standardization affects nDCG scores linearly (proof in the paper)

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Benefits:

- Improves on the *local inconsistency* issue
- Intra-experiment results are unaffected
- Inter-experiment comparability is improved

→ transforms baseline into well-defined reference point

Ratio-based Topic Difficulty

Summary

Our novel measure can be simplified to the following three steps:

(1) Standardize the relevance label distribution of the topics' pooling

➜ improves *local inconsistency* issue

(2) Calculate nDCG scores

➜ solves *experimental inconsistency* issue

(3) Ratio of positive-scoring systems to total number of systems denotes difficulty

➜ solves *topic set instability* issue

➜ solves *discrete class labeling* issue

Conclusion

Our contribution:

- novel method of scoring difficulty of topics
- overcomes several existing limitations
- does not add any experimental requirements

Also included in the paper:

- reevaluation of TREC data to illustrate the practical advantages
- formal proof of the linear shift property of nDCG
- concept of random baseline ranking with potential applications beyond topic difficulty estimation

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Thank you!