

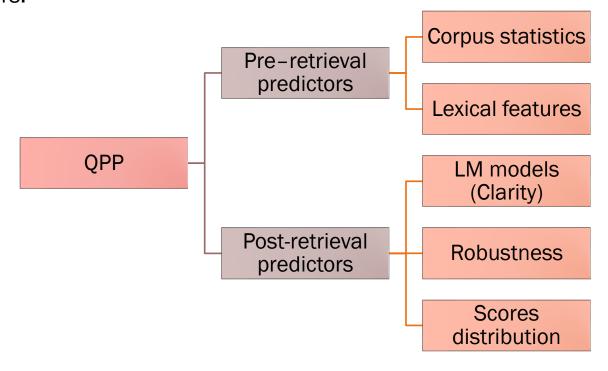
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Query Performance Prediction (QPP)

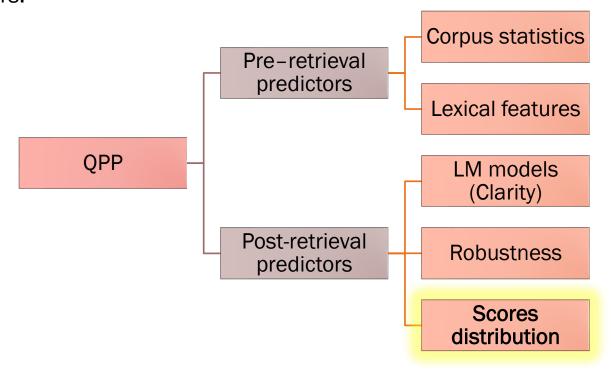
Estimating the effectiveness of a search result, without relying on human assessors.





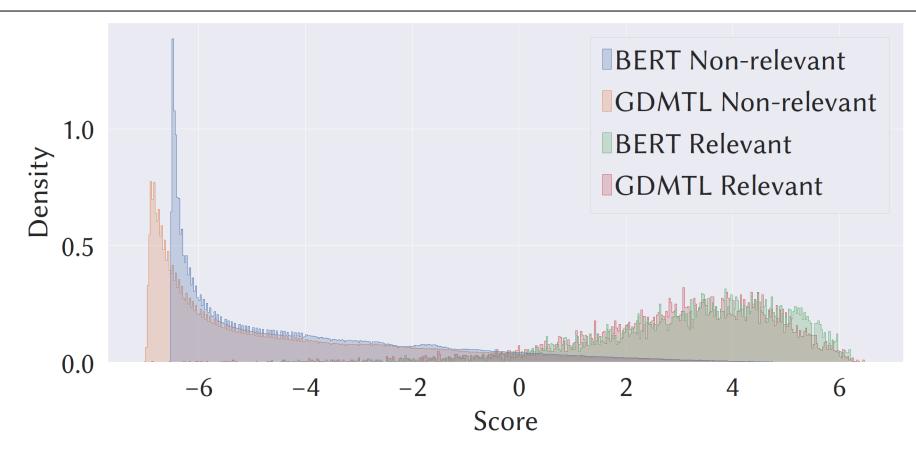
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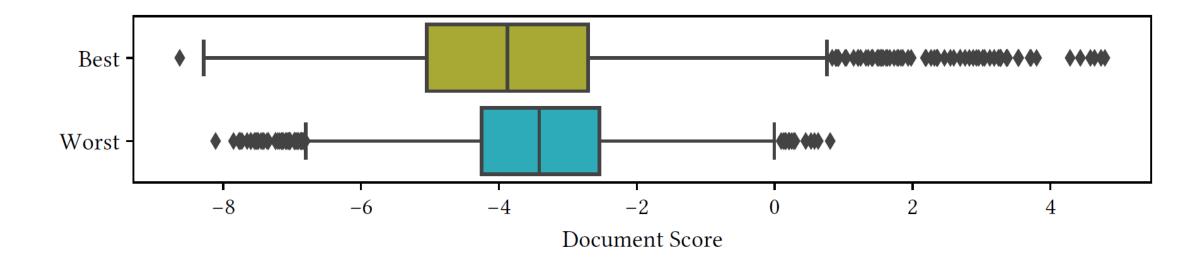


Neural IR Scores Distribution



Score distributions for MS MARCO collection.

Different Score Distributions



Score distributions on Robust04 collection for 5 extreme queries.

Scores Distribution QPP

Use retrieval score values (RSVs) generated by the retrieval system to estimate the success of the search.

- Simple to calculate
- Computationally efficient
- Do not require any additional information
- Explainable (to some extent)

Examples:

• NQC¹, WIG², SMV³, RSD⁴

¹A. Shtok, O. Kurland, D. Carmel, F. Raiber, G. Markovits, Predicting Query Performance by Query-Drift Estimation, ACM Trans. Inf. Sys. 30 (2012) 1–35. ²Y. Zhou, W. B. Croft, Query Performance Prediction in Web Search Environments, in: Proc. SIGIR, 2007, pp. 543–550.

³Tao, Y., Wu, S.: Query performance prediction by considering score magnitude and variance together. In: Proceedings of the CIKM, pp. 1891–1894 (2014)

⁴H. Roitman, S. Erera, B. Weiner, Robust Standard Deviation Estimation for Query Performance Prediction, in: Proc. ICTIR, 2017, pp. 245–248.

Standard Deviation (SD) as QPP

Most common scores based QPP methods rely on SD.

For example: NQC¹, σ_{100}^2 , $n(\sigma_{50\%})^3$, SMV⁴, RSD⁵

$$\sigma = \sqrt{\frac{\sum_{d \in D_q} (S(q,d) - \mu)^2}{|D_q|}}, \text{ where } \mu = \frac{\sum_{d \in D_q} S(q,d)}{|D_q|}.$$

Standard deviation

¹A. Shtok, O. Kurland, D. Carmel, Predicting Query Performance by Query-Drift Estimation in: Proc. ICTIR, 2009, 305–312.

²J. Pérez-Iglesias, L. Araujo, Ranking List Dispersion as a Query Performance Predictor, in: Proc. ICTIR, 2009, pp. 371–374.

³R. Cummins, J. Jose, C. O'Riordan, Improved Query Performance Prediction Using Standard Deviation, in: Proc. SIGIR, 2011, pp. 1089–1090.

⁴Tao, Y., Wu, S.: Query performance prediction by considering score magnitude and variance together. In: Proc. CIKM, 2014, pp. 1891–1894.

⁵H. Roitman, S. Erera, B. Weiner, Robust Standard Deviation Estimation for Query Performance Prediction, in: Proc. ICTIR, 2017, pp. 245–248.

Entropy as QPP

$$H(q) = -\sum_{d \in D_q} P(d|q) \log P(d|q)$$

Entropy

$$P(d|q) = \frac{exp(S(q,d))}{\sum_{d' \in D_q} exp(S(q,d'))}$$

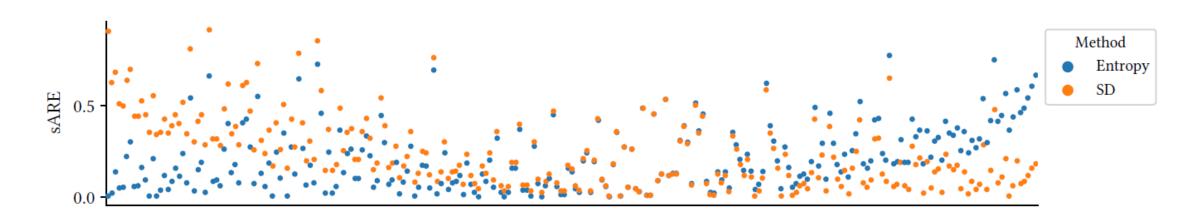
Softmax function

Entropy vs SD – Prediction Quality

		QL			NeuralRanker		
		sMARE	P-r	K- au	sMARE	P-r	$K ext{-} au$
Robust04	SD Entropy	0.224 0.221	0.481 0.385*	0.345 0.349	0.220 0.214 *	0.526 0.529	0.359 0.388 *

Entropy vs SD – Similarity

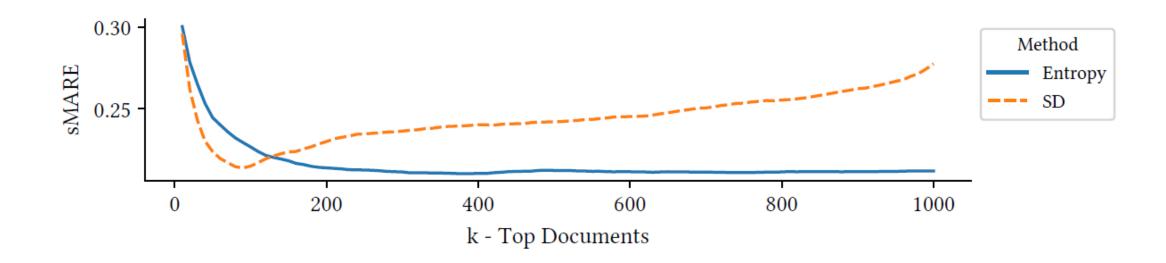
sARE (error) value per query



Queries ordered by difference in sARE (SD – Entropy)
The overall correlation is r=0.5

Entropy vs SD – Robustness

sMARE (mean error) for all queries

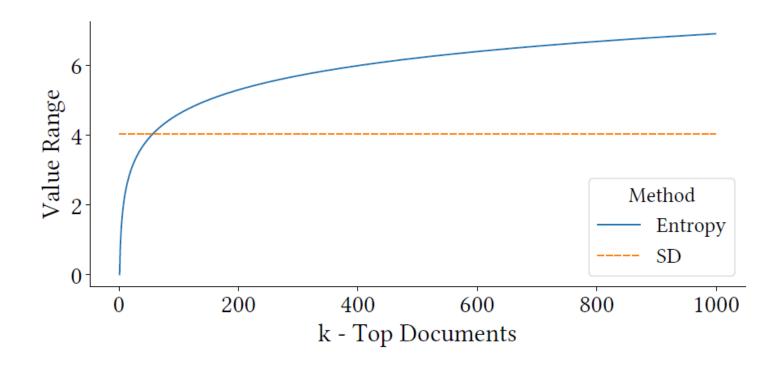




Why
Doesn't SD
Keeps
Improving?

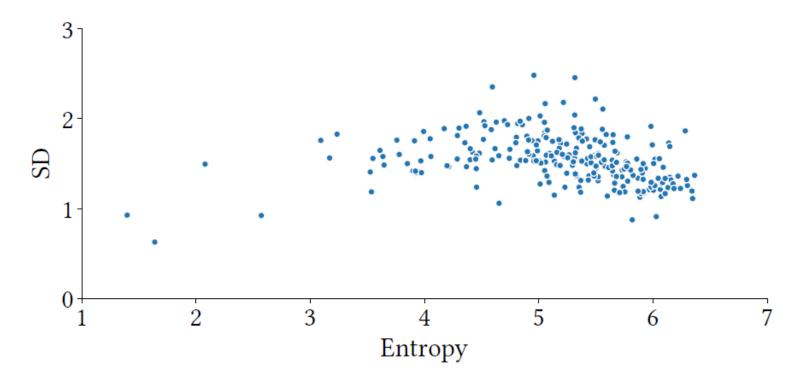
Entropy vs SD – Discussion

Maximal possible value



Entropy vs SD – Discussion cont.

Actual (empirical) values for 1000 documents over 250 queries



Conclusions

Introduced *Entropy* as a new QPP method, it is:

- competitive with SD,
- differs from SD;
- more robust than SD.



Future Directions

Test the proposed method

- on other collections and tasks;
- with other retrieval systems.

Test the proposed method within different QPP frameworks:

- with reference queries;
- with reference lists.

Test additional measures of dispersion, e.g.,

- Kurtosis;
- Mean absolute difference.



Questions