Groupwise Query Performance Prediction with BERT

Xiaoyang Chen\textsuperscript{1,2}, Ben He\textsuperscript{1,2}, and Le Sun\textsuperscript{2}

\textsuperscript{1} University of Chinese Academy of Sciences, Beijing, China
\textsuperscript{2} Institute of Software, Chinese Academy of Sciences, Beijing, China

\texttt{chenxiaoyang19@mails.ucas.ac.cn}
\texttt{benhe@ucas.ac.cn, sunle@iscas.ac.cn}

Abstract. While large-scale pre-trained language models like BERT have advanced the state-of-the-art in IR, its application in query performance prediction (QPP) is so far based on pointwise modeling of individual queries. Meanwhile, recent studies suggest that the cross-attention modeling of a group of documents can effectively boost performances for both learning-to-rank algorithms and BERT-based re-ranking. To this end, a BERT-based groupwise QPP model is proposed, in which the ranking contexts of a list of queries are jointly modeled to predict the relative performance of individual queries. Extensive experiments on three standard TREC collections showcase effectiveness of our approach. Our code is available at \url{https://github.com/VerdureChen/Group-QPP}.

1 Introduction

Query performance prediction (QPP) aims to automatically estimate the search results quality of a given query. While the pre-retrieval predictors enjoy the low computational overhead \cite{15,23,24,29}, the post-retrieval methods are in general more effective by considering sophisticated query and document features \cite{3,7,15,17,20,34,41,44,47,48,51,54,55}. Recently, the large-scale pre-trained transformer based language models, e.g. BERT \cite{19}, has shown to advance the ranking performance, which provides a new direction for task of QPP.

Indeed, recent results demonstrate that BERT effectively improves the performance of post-retrieval QPP \cite{4,22}. For instance, training with a large number of sparse-labeled queries and their highest-ranked documents, BERT-QPP \cite{4} examines the effectiveness of BERT on the MS MARCO \cite{30} and TREC DL \cite{13,14} datasets, by pointwise modeling of query-document pairs. Beyond learning from single query-document pairs, the groupwise methods have achieved superior performance on both learning-to-rank \cite{12,33,32} and BERT re-ranking \cite{8} benchmarks. To this end, we propose an end-to-end BERT-based QPP model, which employs a groupwise predictor to jointly learn from multiple queries and documents, by incorporating both cross-query and cross-document information. Experiments conducted on three standard TREC collections show that our model improves significantly over state-of-the-art baselines.
2 Related Work

Query performance prediction (QPP). Early research in QPP utilizes linguistic information \cite{29}, statistical features \cite{15,23,24} in pre-retrieval methods, or analyses clarity \cite{15,16}, robustness \cite{7,20,54,55}, retrieval scores \cite{34,41,44,47,55} for post-retrieval prediction, which further evolves into several effective frameworks \cite{17,20,28,38,40,45,46}. The QPP techniques have also been explored and analyzed in \cite{3,5,6,10,18,21,22,25,35,36,39,42,43,52,53,27}. With the recent development deep learning techniques, NeuralQPP \cite{61} achieves promising results by training a three-components deep network under weak supervision of existing methods. Recently, while NQA-QPP \cite{22} uses BERT to generate contextualized embedding for QPP in non-factoid question answering, BERT-QPP \cite{4} directly applies BERT with pointwise learning in the prediction task, outperforming previous methods on the MS MARCO dev set \cite{30} and TREC Deep Learning track query sets \cite{13,14}.

Groupwise Ranking. Beyond pointwise loss, pairwise and listwise losses are proposed to learn the relative relationships among documents \cite{9}. Recently, Ai et al. \cite{1} propose to represent documents into embedding with an RNN and refine the rank lists with local ranking context. Thereafter, a groupwise scoring function is proposed by Ai et al. \cite{2} to model documents jointly. In the learning-to-rank context, both Pasumarthi et al. \cite{33} and Pang et al. \cite{32} use self-attention mechanism with groupwise design to improve retrieval effectiveness. Furthermore, Co-BERT \cite{8} incorporates cross-document ranking context into BERT-based re-ranking models, demonstrating the effectiveness of using groupwise methods in boosting the ranking performance of BERT. In brief, while previous works are carried out on single query-document pairs with BERT, the groupwise methods have shown useful in multiple studies. To this end, this work proposes a groupwise post-retrieval QPP model based on pre-trained language models which simultaneously takes multiple queries and documents into account.

3 Method

Figure 1 shows our model architecture. Give an underlying retrieval method $M$ and a corpus $C$, in response to a query $q$, a document set $D$ is composed by the top $k$ documents retrieved from $C$ with $M$. As aforementioned, existing BERT-based QPP methods only use the text from individual query-document pairs; however, considering information from different queries and documents is necessary for QPP tasks, which aim to obtain relative performance among queries. Inspired by Co-BERT \cite{8}, to boost the performance of BERT-based QPP methods, a groupwise predictor is integrated to learn from multiple queries and documents simultaneously on the basis of a BERT encoder.

Encoding query-document pairs. Following Arabzadeh et al. \cite{4}, we first encode each query-document pair with BERT. As documents are frequently long enough to exceed BERT’s 512 token limit, similar to Co-BERT \cite{8}, we split long texts into equal-sized passages. We use a BERT checkpoint fine-tuned on MS
MARCO \cite{marco} to predict the relevance between each query and its corresponding passages. Each document used in the next steps is represented by its top-1 ranked passage. Consistent with common practices for text categorization using BERT, the token sequences $[CLS]Query[SEP]Document[SEP]$ are put into BERT to get encoded. We use the $[CLS]$ representation in the following groupwise step to further integrate the cross-query as well as cross-document information.

**Groupwise predictor.** To incorporate cross-document and cross-query context, we regard each batch as a single group of query-document pairs. Suppose the batch size is $n$ ($n \leq k$), the $[CLS]$ vectors in a batch are reshaped into a sequence of length $n$, and we denote the sequence as $z_1, z_2, z_3, \cdots, z_n$. For $i \in [1, \cdots, n]$, each $z_i$ is a $d$-dimensional vector, for example, $d = 768$ for BERT-Base. Similar to Chen et al. \cite{chen2020}, we use a four-layers transformer as the groupwise predictor, which enables the cross attention among the $[CLS]$ vectors in each batch, and then produces $n$ predicted performances of each query-document pair. During inference, suppose top $t$ documents of $q$ are used, we will get $t$ predicted scores for $q$. We use three aggregation methods to get the final QPP score of $q$: max-pooling, average-pooling, and the direct use of the predicted performance of the first-ranked retrieved document for query $q$. In our experiments, the aggregation method with the best performance on the training set is chosen.

By assigning different positional ids to $z_i$, our model can be designed to incorporate with different types of ranking context. Thus, several **variants of our models** are investigated. **(Random order)** denotes that all query-document pairs are shuffled before being fed into the model in both training and inference. **(Query order)** denotes for BERT groupwise model considering only the cross-query context. For a batch of $n$ samples, the $i$th ranked documents from $n$ queries are grouped together in the batch, and position ids are assigned by the initial query order derived by $n(\sigma_{X\%})$. We leave other choices of the initial QPP for future study. **(Doc order)** denotes for BERT groupwise model considering only the cross-document context. A batch consists of $n$ documents returned for a query, and the position ids are assigned by the initial document
ranking. (Query+Doc) denotes for BERT groupwise model considering both cross-document and cross-query context. Batches containing one of the above two contexts appear randomly during training. (R+Q+D) denotes for BERT groupwise model with all three types of orders mentioned above. According to the maximum batch size allowed by the hardware, we use the batch size of 128/64/16 for Small, Base and Large BERT models, respectively. Note that the training data is still shuffled among batches to avoid overfitting.

4 Experiment Setup

Dataset and Metrics. We use three popular datasets, namely, Robust04 [49], GOV2 [11], and ClueWeb09-B [12], with 249, 150 and 200 keyword queries, respectively. Following [3], we use the Pearson’s $ρ$ and Kendall’s $τ$ correlations to measure the QPP performance, which is computed using the predicted ordering of the queries with the actual ordering of average precision for the top 1000 documents (AP@1000) per query retrieved by the Query Likelihood (QL) model implemented in Anserini [50]. Following [51], we use 2-fold cross-validation and randomly generate 30 splits for each dataset. Each split has two folds, the first fold is used for model training and hyper-parameter tuning. The ultimate performance is the average prediction quality on the second test folds over the 30 splits. Statistical significance for paired two-tailed t-test is reported.

Baselines. Akin to [3], we compare our model with several popular baselines including Clarity [15], Query Feedback (QF) [55], Weighted Information Gain (WIG) [55], Normalized Query Commitment (NQC) [44], Score Magnitude and Variance (SMV) [47], Utility Estimation Framework (UEF) [45], $σ_k$ [51], $n(σ_X%)$ [17], Robust Standard Deviation (RSD) [41], WAND [42], and NeuralQPP [51]. We also compare to BERT-Small/Base/Large [37] baselines, which are configured the same as our model except that they do not have a groupwise predictor. Note that the BERT baselines share the same structures with BERT-QPP except we use more documents for each query in training due to the small number of queries. Following [3], our proposed predictor is linearly combined with $n(σ_X%)$. The BERT baselines perform the same linear interpolation.

Data preparation and Model training. Akin to [8], for the BERT-based models, documents are sliced using sliding windows of 150 words with an overlap of 75 words. The max sequence length of the concatenated query-document pair is 256. We use MSE loss for individual documents and explore two kinds of training labels: P@k and AP@1000. According to our pilot study on the BERT-Base baseline, we use P@k as the supervision signals on Robust04 and GOV2, and use AP@1000 on ClueWeb09-B. All BERT models are trained for 5 epochs. Due to the memory limit, BERT-based models are trained with top-100 documents and tested on the last checkpoint with the top-25 documents for each query retrieved by QL. We use Adam optimizer [26] with the learning rate schedule from [31]. We select the initial learning rate from $\{1e-4, 1e-5, 1e-6\}$, and set the warming up steps to 10% of the total steps.
5 Results

Table 1. Evaluation results. Statistical significance at 0.05 relative to BERT baselines of the same model size (e.g. (R+Q+D)-Large vs. BERT-Large) is marked with *.

| Method               | Robust04  | GOV2  | ClueWeb09-B |
|----------------------|-----------|-------|-------------|
|                      | P-ρ  | K-τ  | P-ρ  | K-τ  | P-ρ  | K-τ  |
| Clarity              | 0.528 | 0.385| 0.428| 0.291| 0.300| 0.213|
| QF                   | 0.390 | 0.324| 0.447| 0.314| 0.163| 0.072|
| WIG                  | 0.546 | 0.379| 0.502| 0.346| 0.316| 0.210|
| NQC                  | 0.516 | 0.388| 0.381| 0.323| 0.127| 0.138|
| SMV                  | 0.534 | 0.378| 0.352| 0.303| 0.236| 0.183|
| UEF                  | 0.502 | 0.402| 0.470| 0.329| 0.301| 0.211|
| σ_k                  | 0.522 | 0.389| 0.381| 0.323| 0.234| 0.177|
| n(σ_X%)              | 0.589 | 0.386| 0.556| 0.386| 0.334| 0.247|
| RSD                  | 0.455 | 0.352| 0.444| 0.276| 0.193| 0.096|
| WAND[n(σ_X%)]        | 0.566 | 0.386| 0.580| 0.411| 0.236| 0.142|
| NeuralQPP            | 0.611 | 0.408| 0.540| 0.357| 0.367| 0.229|
| BERT-Small           | 0.591 | 0.391| 0.615| 0.436| 0.394| 0.278|
| BERT-Base            | 0.585 | 0.423| 0.637| 0.454| 0.447| 0.321|
| BERT-Large           | 0.579 | 0.422| 0.645| 0.461| 0.342| 0.251|
| (Random order)-base  | 0.608*| 0.449*| 0.665*| 0.479*| 0.481*| 0.353*|
| (Query order)-base   | 0.615*| 0.456*| 0.676*| 0.486*| 0.455*| 0.327*|
| (Doc order)-base     | 0.563 | 0.383| 0.660*| 0.476*| 0.365| 0.262*
| (Query+Doc)-base     | 0.598 | 0.452*| 0.682*| 0.496*| 0.438| 0.317|
| (R+Q+D)-small        | 0.590 | 0.419*| 0.680*| 0.500*| 0.437*| 0.305*|
| (R+Q+D)-base         | 0.608*| 0.460*| 0.676*| 0.489*| 0.449| 0.324|
| (R+Q+D)-large        | 0.612*| 0.470*| 0.688*| 0.508*| 0.545*| 0.399*|

Overall effectiveness. According to Table 1, the proposed model outperforms all the baselines on all three collections. Compared with the previous state-of-the-art results without using BERT, except for the ρ on Robust04, our groupwise model trained on BERT-Base with the random input order has an improvement on all metrics by at least 10%. In general, our (R+Q+D) outperforms the BERT baselines with all three different model sizes. Additionally, varying the type of ranking contexts incorporated with the groupwise models leads to different observations on the three datasets. The query-level ranking context marginally improves the effectiveness on Robust04 and GOV2, while it decreases the result on ClueWeb09-B. Using document-level ranking context alone greatly harms the model performance on Robust04 and ClueWeb09-B. This may be due to the fact that the model has only learned the sequence information inside each query, but not the relative relations between the queries. Relative to the random case, using both contexts slightly elevates the performance on GOV2, while it has little effect on Robust04 and decreases the results on ClueWeb09-B. As the simultaneous use of all three types of context appears to be the best variant, we only report results of (R+Q+D)-Base in the following analysis.
Impact of factors. We examine the impact of training batch size and the number of top-k documents per query for inference on the model performance. We first evaluate with different training batch sizes in \{1, 8, 16, 32, 64\}. The greater the batch size is, the more query-document pairs are jointly modeled. A special case is to set batch size to 1, which is equivalent to the pointwise learning without any context from other queries or documents. The results in Figure 2 show that the cross-attention among queries is effective and improves upon the pointwise method by a large margin. The groupwise method works best with a group size of 8, which means the model may learn better with a relatively smaller group of queries. We also explore the impact of different numbers of documents per query used during inference, namely \{10, 25, 50, 100, 200\}. Results in Figure 2 indicate that inference with less than 100 documents per query on all three collections yields the best results. The reason might be that there are more positive samples in the top-ranked documents which contribute more to the target metric, i.e. AP@1000, while considering more negative examples not only have little impact on the target metric, but also are more likely to introduce noise.

Limitations. We count the number of floating-point operations for all BERT-based models. It turns out our model can predict the retrieval performance with less than 1% additional computational cost compared to its BERT counterpart. However, for document retrieval with BERT MaxP, the passage selection brings an approx. 1 min extra computational overhead, which is more expensive than the non-BERT baselines.

6 Conclusion

In this paper, we propose a BERT-based groupwise query performance prediction method, which simultaneously incorporates the cross-query and cross-document information within an end-to-end learning framework. Evaluation on three standard TREC test collections indicates the groupwise model significantly outperforms the BERT baselines nearly in all cases. In further research, we plan to work on the efficiency, as well as adoption of our approach to more advanced experimentation framework [21].
References

1. Ai, Q., Bi, K., Guo, J., Croft, W.B.: Learning a deep listwise context model for ranking refinement. In: SIGIR. pp. 135–144. ACM (2018)
2. Ai, Q., Wang, X., Bruch, S., Golbandi, N., Bendersky, M., Najork, M.: Learning groupwise multivariate scoring functions using deep neural networks. In: ICTIR. pp. 85–92. ACM (2019)
3. Arabzadeh, N., Bigdeli, A., Zihayat, M., Bagheri, E.: Query performance prediction through retrieval coherency. In: Hiemstra, D., Moens, M., Mothe, J., Perego, R., Potthast, M., Sebastiani, F. (eds.) Advances in Information Retrieval - 43rd European Conference on IR Research, ECIR 2021, Virtual Event, March 28 - April 1, 2021. Proceedings, Part II. Lecture Notes in Computer Science, vol. 12657, pp. 193–200. Springer (2021). https://doi.org/10.1007/978-3-030-72240-1_15
4. Arabzadeh, N., Khodabakhsh, M., Bagheri, E.: BERT-QPP: contextualized pre-trained transformers for query performance prediction. In: Demartini, G., Zuccon, G., Culpepper, J.S., Huang, Z., Tong, H. (eds.) CIKM ’21: The 30th ACM International Conference on Information and Knowledge Management, Virtual Event, Queensland, Australia, November 1 - 5, 2021. pp. 2857–2861. ACM (2021). https://doi.org/10.1145/3459637.3482063
5. Arabzadeh, N., Zarrinkalam, F., Jovanovic, J., Al-Obeidat, F.N., Bagheri, E.: Neural embedding-based specificity metrics for pre-retrieval query performance prediction. Inf. Process. Manag. 57(4), 102248 (2020). https://doi.org/10.1016/j.ipm.2020.102248
6. Arabzadeh, N., Zarrinkalam, F., Jovanovic, J., Bagheri, E.: Neural embedding-based metrics for pre-retrieval query performance prediction. In: Jose, J.M., Yilmaz, E., Magalhães, J., Castells, P., Ferro, N., Silva, M.J., Martins, F. (eds.) Advances in Information Retrieval - 42nd European Conference on IR Research, ECIR 2020, Lisbon, Portugal, April 14-17, 2020. Proceedings, Part II. Lecture Notes in Computer Science, vol. 12036, pp. 78–85. Springer (2020). https://doi.org/10.1007/978-3-030-45442-5_10
7. Aslam, J.A., Pavlu, V.: Query hardness estimation using jensen-shannon divergence among multiple scoring functions. In: Amati, G., Carpineto, C., Romano, G. (eds.) Advances in Information Retrieval, 29th European Conference on IR Research, ECIR 2007, Rome, Italy, April 2-5, 2007. Proceedings. Lecture Notes in Computer Science, vol. 4425, pp. 198–209. Springer (2007). https://doi.org/10.1007/978-3-540-71496-5_20
8. Chen, X., Hui, K., He, B., Han, X., Sun, L., Ye, Z.: Co-bert: A context-aware BERT retrieval model incorporating local and query-specific context. CoRR abs/2104.08523 (2021). https://arxiv.org/abs/2104.08523
9. Chen, Z., Eickhoff, C.: Poolrank: Max/min pooling-based ranking loss for listwise learning & ranking balance. CoRR abs/2108.03586 (2021). https://arxiv.org/abs/2108.03586
10. Chifu, A., Laporte, L., Mothe, J., Ullah, M.Z.: Query performance prediction focused on summarized letor features. In: Collins-Thompson, K., Mei, Q., Davison, B.D., Liu, Y., Yilmaz, E. (eds.) The 41st International
11. Clarke, C.L.A., Craswell, N., Soboroff, I.: Overview of the TREC 2004 terabyte track. In: Proceedings of the Thirteenth Text REtrieval Conference. NIST Special Publication, vol. 500-261, pp. 1–9. National Institute of Standards and Technology (2004)

12. Clarke, C.L.A., Craswell, N., Soboroff, I.: Overview of the TREC 2009 web track. In: Voorhees, E.M., Buckland, L.P. (eds.) Proceedings of The Eighteenth Text REtrieval Conference, TREC 2009, Gaithersburg, Maryland, USA, November 17-20, 2009. NIST Special Publication, vol. 500-278. National Institute of Standards and Technology (NIST) (2009), http://trec.nist.gov/pubs/trec18/papers/WEB09.OVERVIEW.pdf

13. Craswell, N., Mitra, B., Yilmaz, E., Campos, D.: Overview of the TREC 2020 deep learning track. CoRR abs/2102.07662 (2021), https://arxiv.org/abs/2102.07662

14. Craswell, N., Mitra, B., Yilmaz, E., Campos, D., Voorhees, E.M.: Overview of the TREC 2019 deep learning track. CoRR abs/2003.07820 (2020), https://arxiv.org/abs/2003.07820

15. Cronen-Townsend, S., Zhou, Y., Croft, W.B.: Predicting query performance. In: Järvelin, K., Beaulieu, M., Baeza-Yates, R.A., Myaeng, S. (eds.) SIGIR 2002: Proceedings of the 25th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, August 11-15, 2002, Tampere, Finland. pp. 299-306. ACM (2002). https://doi.org/10.1145/564376.564429

16. Cronen-Townsend, S., Zhou, Y., Croft, W.B.: Precision prediction based on ranked list coherence. Inf. Retr. 9(6), 723–755 (2006), https://doi.org/10.1007/s10791-006-9006-4

17. Cummins, R., Jose, J.M., O’Riordan, C.: Improved query performance prediction using standard deviation. In: Ma, W., Nie, J., Baeza-Yates, R., Chua, T., Croft, W.B. (eds.) Proceeding of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2011, Beijing, China, July 25-29, 2011. pp. 1089–1090. ACM (2011). https://doi.org/10.1145/2009916.2010063

18. Déjean, S., Ionescu, R.T., Mothe, J., Ullah, M.Z.: Forward and backward feature selection for query performance prediction. In: Hung, C., Cerný, T., Shin, D., Bechini, A. (eds.) SAC ’20: The 35th ACM/SIGAPP Symposium on Applied Computing, online event, [Brno, Czech Republic], March 30 - April 3, 2020. pp. 600–607. ACM (2020). https://doi.org/10.1145/3341105.3373904

19. Devlin, J., Chang, M., Lee, K., Toutanova, K.: BERT: pre-training of deep bidirectional transformers for language understanding. In: Burstein, J., Duran, C., Solorio, T. (eds.) Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers). pp. 4171–4186. Association for Computational Linguistics (2019). https://doi.org/10.18653/v1/n19-1423

20. Diaz, F.: Performance prediction using spatial autocorrelation. In: Kranjč, W., de Vries, A.P., Clarke, C.L.A., Fuhr, N., Kando, N. (eds.) SIGIR 2007: Pro
Groupwise Query Performance Prediction with BERT

21. Faggioli, G., Zendel, O., Culpepper, J.S., Ferro, N., Scholer, F.: An enhanced evaluation framework for query performance prediction. In: Hiemstra, D., Moens, M., Mothe, J., Perego, R., Potthast, M., Sebastiani, F. (eds.) Advances in Information Retrieval - 43rd European Conference on IR Research, ECIR 2021, Virtual Event, March 28 - April 1, 2021, Proceedings, Part I. Lecture Notes in Computer Science, vol. 12656, pp. 115–129. Springer (2021). https://doi.org/10.1007/978-3-030-72113-8_8

22. Hashemi, H., Zamani, H., Croft, W.B.: Performance prediction for non-factoid question answering. In: Fang, Y., Zhang, Y., Allan, J., Balog, K., Carterette, B., Guo, J. (eds.) Proceedings of the 2019 ACM SIGIR International Conference on Theory of Information Retrieval, ICTIR 2019, Santa Clara, CA, USA, October 2-5, 2019. pp. 55–58. ACM (2019). https://doi.org/10.1145/3341981.3344249

23. He, B., Ounis, I.: Query performance prediction. Inf. Syst. 31(7), 585–594 (2006). https://doi.org/10.1016/j.is.2005.11.003

24. He, J., Larson, M.A., de Rijke, M.: Using coherence-based measures to predict query difficulty. In: Macdonald, C., Ounis, I., Plachouras, V., Ruthven, I., White, R.W. (eds.) Advances in Information Retrieval, 30th European Conference on IR Research, ECIR 2008, Glasgow, UK, March 30-April 3, 2008. Proceedings. Lecture Notes in Computer Science, vol. 4956, pp. 689–694. Springer (2008). https://doi.org/10.1007/978-3-540-78646-7_80

25. Khodabakhsh, M., Bagheri, E.: Semantics-enabled query performance prediction for ad hoc table retrieval. Inf. Process. Manag. 58(1), 102399 (2021). https://doi.org/10.1016/j.ipm.2020.102399

26. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. In: 3rd International Conference on Learning Representations. pp. 1–15 (2015)

27. Krikon, E., Carmel, D., Kurland, O.: Predicting the performance of passage retrieval for question answering. In: Chen, X., Lebanon, G., Wang, H., Zaki, M.J. (eds.) 21st ACM International Conference on Information and Knowledge Management, CIKM'12, Maui, HI, USA, October 29 - November 02, 2012. pp. 2451–2454. ACM (2012). https://doi.org/10.1145/2396761.2398664

28. Kurland, O., Shtok, A., Carmel, D., Hummel, S.: A unified framework for post-retrieval query-performance prediction. In: Amati, G., Crestani, F. (eds.) Advances in Information Retrieval Theory - Third International Conference, ICTIR 2011, Bertinoro, Italy, September 12-14, 2011. Proceedings. Lecture Notes in Computer Science, vol. 6931, pp. 15–26. Springer (2011). https://doi.org/10.1007/978-3-642-23318-0_4

29. Mothe, J., Tanguy, L.: Linguistic features to predict query difficulty. In: SIGIR 2005 (2005)

30. Nguyen, T., Rosenberg, M., Song, X., Gao, J., Tiwary, S., Majumder, R., Deng, L.: MS MARCO: A human generated machine reading comprehension dataset. CoRR abs/1611.09268 (2016). http://arxiv.org/abs/1611.09268

31. Nogueira, R., Cho, K.: Passage re-ranking with BERT. CoRR abs/1901.04085 (2019)
32. Pang, L., Xu, J., Ai, Q., Lan, Y., Cheng, X., Wen, J.: Setrank: Learning a permutation-invariant ranking model for information retrieval. In: SIGIR. pp. 499–508. ACM (2020)

33. Pasumarthi, R.K., Wang, X., Bendersky, M., Najork, M.: Self-attentive document interaction networks for permutation equivariant ranking. CoRR abs/1910.09676 (2019)

34. Pérez-Iglesias, J., Araujo, L.: Standard deviation as a query hardness estimator. In: Chávez, E., Lonardi, S. (eds.) String Processing and Information Retrieval - 17th International Symposium, SPIRE 2010, Los Cabos, Mexico, October 11-13, 2010. Proceedings. Lecture Notes in Computer Science, vol. 6393, pp. 207–212. Springer (2010). [https://doi.org/10.1007/978-3-642-16321-0_21]

35. Raiber, F., Kurland, O.: Query-performance prediction: setting the expectations straight. In: Geva, S., Trotman, A., Bruza, P., Clarke, C.L.A., Järvelin, K. (eds.) The 37th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’14, Gold Coast , QLD, Australia - July 06 - 11, 2014. pp. 13–22. ACM (2014). [https://doi.org/10.1145/2600428.2609581]

36. Raviv, H., Kurland, O., Carmel, D.: Query performance prediction for entity retrieval. In: Geva, S., Trotman, A., Bruza, P., Clarke, C.L.A., Järvelin, K. (eds.) The 37th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’14, Gold Coast , QLD, Australia - July 06 - 11, 2014. pp. 1099–1102. ACM (2014). [https://doi.org/10.1145/2600428.2609519]

37. google research: GitHub - google-research/bert: TensorFlow code and pre-trained models for BERT. [https://github.com/google-research/bert]

38. Roitman, H.: An enhanced approach to query performance prediction using reference lists. In: Kando, N., Sakai, T., Joho, H., Li, H., de Vries, A.P., White, R.W. (eds.) Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, Shinjuku, Tokyo, Japan, August 7-11, 2017. pp. 869–872. ACM (2017). [https://doi.org/10.1145/3077136.3080665]

39. Roitman, H.: ICTIR tutorial: Modern query performance prediction: Theory and practice. In: Balog, K., Setty, V., Lioma, C., Liu, Y., Zhang, M., Berberich, K. (eds.) ICTIR ’20: The 2020 ACM SIGIR International Conference on the Theory of Information Retrieval, Virtual Event, Norway, September 14-17, 2020. pp. 195–196. ACM (2020). [https://dl.acm.org/doi/10.1145/3409256.3409813]

40. Roitman, H., Erera, S., Shalom, O.S., Weiner, B.: Enhanced mean retrieval score estimation for query performance prediction. In: Kamps, J., Kanoulas, E., de Rijke, M., Fang, H., Yilmaz, E. (eds.) Proceedings of the ACM SIGIR International Conference on Theory of Information Retrieval, ICTIR 2017, Amsterdam, The Netherlands, October 1-4, 2017. pp. 35–42. ACM (2017). [https://doi.org/10.1145/3121050.3121051]

41. Roitman, H., Erera, S., Weiner, B.: Robust standard deviation estimation for query performance prediction. In: Kamps, J., Kanoulas, E., de Rijke, M., Fang, H., Yilmaz, E. (eds.) Proceedings of the ACM SIGIR International Conference on Theory of Information Retrieval, ICTIR 2017, Amsterdam, The Netherlands, October 1-4, 2017. pp. 245–248. ACM (2017). [https://doi.org/10.1145/3121050.3121087]
42. Roitman, H., Kurland, O.: Query performance prediction for pseudo-feedback-based retrieval. In: Piwowarski, B., Chevalier, M., Gaussier, É., Maarek, Y., Nie, J., Scholer, F. (eds.) Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2019, Paris, France, July 21-25, 2019. pp. 1261–1264. ACM (2019). https://doi.org/10.1145/3331184.3331369

43. Roitman, H., Mass, Y., Feigenblat, G., Shraga, R.: Query performance prediction for multifield document retrieval. In: Balog, K., Setty, V., Lioma, C., Liu, Y., Zhang, M., Berberich, K. (eds.) ICTIR ’20: The 2020 ACM SIGIR International Conference on the Theory of Information Retrieval, Virtual Event, Norway, September 14-17, 2020. pp. 49–52. ACM (2020). https://dl.acm.org/doi/10.1145/3409256.3409821

44. Shtok, A., Kurland, O., Carmel, D.: Predicting query performance by query-drift estimation. In: Azzopardi, L., Kazai, G., Robertson, S.E., Rüger, S.M., Shokouhi, M., Song, D., Yılmaz, E. (eds.) Advances in Information Retrieval Theory, Second International Conference on the Theory of Information Retrieval, ICTIR 2009, Cambridge, UK, September 10-12, 2009. Proceedings, Lecture Notes in Computer Science, vol. 5766, pp. 305–312. Springer (2009). https://doi.org/10.1007/978-3-642-04417-5_30

45. Shtok, A., Kurland, O., Carmel, D.: Using statistical decision theory and relevance models for query-performance prediction. In: Crestani, F., Marchand-Maillet, S., Chen, H., Efthimiadis, E.N., Savoy, J. (eds.) Proceeding of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2010, Geneva, Switzerland, July 19-23, 2010. pp. 259–266. ACM (2010). https://doi.org/10.1145/1835449.1835494

46. Shtok, A., Kurland, O., Carmel, D.: Query performance prediction using reference lists. ACM Trans. Inf. Syst. 34(4), 19:1–19:34 (2016). https://doi.org/10.1145/2926790

47. Tao, Y., Wu, S.: Query performance prediction by considering score magnitude and variance together. In: Li, J., Wang, X.S., Garofalakis, M.N., Soboroff, I., Suel, T., Wang, M. (eds.) Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management, CIKM 2014, Shanghai, China, November 3-7, 2014. pp. 1891–1894. ACM (2014). https://doi.org/10.1145/2661829.2661906

48. Vinay, V., Cox, I.J., Milic-Frayling, N., Wood, K.R.: On ranking the effectiveness of searches. In: Efthimiadis, E.N., Dumais, S.T., Hawking, D., Järvelin, K. (eds.) SIGIR 2006: Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, Seattle, Washington, USA, August 6-11, 2006. pp. 398–404. ACM (2006). https://doi.org/10.1145/1148170.1148239

49. Voorhees, E.M.: Overview of the TREC 2004 robust track. In: Proceedings of the Thirteenth Text REtrieval Conference. NIST Special Publication, vol. 500-261, pp. 1–10. National Institute of Standards and Technology (2004)

50. Yang, P., Fang, H., Lin, J.: Anserini: Enabling the use of lucene for information retrieval research. In: Kando, N., Sakai, T., Joho, H., Li, H., de Vries, A.P., White, R.W. (eds.) Proceedings of the 40th International ACM SIGIR Conference on Re-
51. Zamani, H., Croft, W.B., Culpepper, J.S.: Neural query performance prediction using weak supervision from multiple signals. In: Collins-Thompson, K., Mei, Q., Davison, B.D., Liu, Y., Yilmaz, E. (eds.) The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, SIGIR 2018, Ann Arbor, MI, USA, July 08-12, 2018. pp. 105–114. ACM (2018). https://doi.org/10.1145/3209978.3210041, https://doi.org/10.1145/3209978.3210041

52. Zendel, O., Culpepper, J.S., Scholer, F.: Is query performance prediction with multiple query variations harder than topic performance prediction? In: Diaz, F., Shah, C., Suel, T., Castells, P., Jones, R., Sakai, T. (eds.) SIGIR ’21: The 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, Virtual Event, Canada, July 11-15, 2021. pp. 1713–1717. ACM (2021). https://doi.org/10.1145/3404835.3463039

53. Zendel, O., Shtok, A., Raiber, F., Kurland, O., Culpepper, J.S.: Information needs, queries, and query performance prediction. In: Piwowarski, B., Chevalier, M., Gaussier, É., Maarek, Y., Nie, J., Scholer, F. (eds.) Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2019, Paris, France, July 21-25, 2019. pp. 395–404. ACM (2019). https://doi.org/10.1145/3331184.3331253

54. Zhou, Y., Croft, W.B.: Ranking robustness: a novel framework to predict query performance. In: Yu, P.S., Tsotras, V.J., Fox, E.A., Liu, B. (eds.) Proceedings of the 2006 ACM CIKM International Conference on Information and Knowledge Management, Arlington, Virginia, USA, November 6-11, 2006. pp. 567–574. ACM (2006). https://doi.org/10.1145/1183614.1183696

55. Zhou, Y., Croft, W.B.: Query performance prediction in web search environments. In: Kraaij, W., de Vries, A.P., Clarke, C.L.A., Fuhr, N., Kando, N. (eds.) SIGIR 2007: Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, Amsterdam, The Netherlands, July 23-27, 2007. pp. 543–550. ACM (2007). https://doi.org/10.1145/1277741.1277835