Toward A Fine-Grained Analysis of Distribution Shifts in MSMARCO

Simon Lupart  
Naver Labs Europe  
Meylan, France  
simon.lupart@naverlabs.com

Stéphane Clinchant  
Naver Labs Europe  
Meylan, France  
stephane.clinchant@naverlabs.com

ABSTRACT

Recent IR approaches based on Pretrained Language Models (PLM) have now largely outperformed their predecessors on a variety of IR tasks. However, what happens to learned word representations with distribution shifts remains unclear. Recently, the BEIR benchmark was introduced to assess the performance of neural rankers in zero-shot settings and revealed deficiencies for several models. In complement to BEIR, we propose to control explicitly distribution shifts. We selected different query subsets leading to different distribution shifts: short versus long queries, wh-words types of queries and 5 topic-based clusters. Then, we benchmarked state of the art neural rankers such as dense Bi-Encoder, SPLADE and ColBERT under these different training and test conditions. Our study demonstrates that it is possible to design distribution shift experiments within the MSMARCO collection, and that the query subsets we selected constitute an additional benchmark to better study factors of generalization for various models.

1 INTRODUCTION

If deep learning has revolutionized artificial intelligence, generalization to unseen cases, under distribution shifts, is still a major challenge and concern for systems deployed in the real world. For instance, the research on autonomous vehicles [4] has brought to light the lack of robustness to domain shifts and adversarial vulnerabilities of computer vision models.

In IR, the question of generalization was often eluded due to the robust and long-standing performance of term-based models. Thanks to the progress of Pretrained Language Models (PLM) based IR models, the generalization question comes back into play, as recently shown in the BEIR benchmark [23]. First, BERT-based rerankers were shown to be robust. Second, it revealed that dense Bi-Encoders first stage rankers such as [10], which were gaining a lot of attention, actually suffered severely from domain shifts as a standard BM25 outperformed them. Third, models that performed well on BEIR have a lexical prior in their matching process such as docT5 and ColBERT([12, 16]).

A very recent study entitled A Fine-Grained Analysis on Distribution Shift [24] benchmarked many computer vision models under various distribution shifts. Their research question was to assess the important shifts for which robustness is required and which models are indeed effective. Even if BEIR is a relevant benchmark and contains many subtasks, we would like to explicitly control the distribution shifts to understand which shifts are indeed critical for robustness. This paper is a first step in this direction.

We show that within MSMARCO, we can construct some distribution shift experiments that we believe will ease study of these phenomena. The main contributions of this paper are as follows:

- We design and release multiple distribution shifts based on query attributes from MSMARCO, to help analyse robustness.
- We compare first-stage rankers in those different controlled shifts (Bi-Encoder, ColBERT, SPLADE) and show that ColBERT is the most robust.
- We analyse how the drops of effectiveness are linked to the distance between train and test query distributions.

2 RELATED WORKS

The literature on domain adaptation or zero-shot transfer is abundant in Computer Vision (CV) [3, 4]. In the NLP community, there is also a vast range of methods summarized in this survey [18].

With regard to domain adaptation in IR, the literature remains limited to our knowledge [25]. In [15], it was shown that neural rankers were prone to catastrophic forgetting when trained in series of retrieval tasks. In [14], the problem of encoder adaptation is addressed and shows that query and document encoders have different impacts on the generalization properties. In a recent paper, [8] study the behaviour of first-stage rankers to term matching. Their study suggests some issues when generalizing lexical matching to out-of-domain collections.

More importantly, the BEIR benchmark [23] involves a test suite of 17 datasets for zero-shot retrieval. The selected datasets were chosen by three main factors: diversity in tasks, domains and difficulty. To measure similarity between domains, the authors measured a weighted jaccard similarity on unigram word overlap between the document collections, and argues that BEIR contains indeed a diverse set of tasks. However, due to the numerous number of tasks and collections, it is difficult to analyse specifically the losses with respect to individual changes/shifts. In addition, we could argue that some of their tasks are too far from the initial objective, for instance Arguana, where the goal is to retrieve the best counterargument for a given input argument.

1 The split of MSMARCO queries is available at https://github.com/naver/ms-marco-shift
Specifically on re-rankers, [17] conducted an evaluation of multiple second-stage rankers. In their study, they have shown that simple variations of the query (misspelling, paraphrasing, etc) decrease efficiency by 20%. In [9], the authors clustered the MSMARCO dataset, in 8 groups (based on cosine similarity), to then evaluate continual learning across those different clusters. Their study focuses on how models behave in such real world conditions, where they might be some trends either on queries or documents. However, as for [17], their study focuses on second stage rankers, after a top-1000 retrieve of BM25. Overall, there seems to be a lack of a systematic study of domain shift for first stage rankers, which is exactly the purpose of this paper.

3 METHODOLOGY

To investigate model behaviour to different types of shifts, we started from the MSMARCO dataset [2]. Our goal here was to cover both lexical, semantic and syntactic shifts within this single query set and collection to better identify model behaviours to shifts.

3.1 Type of Distribution Shifts

Query Topics. As a first shift, we separated queries in five main clusters based on their BERT embeddings [5]. Those clusters are noted $C_0$, $C_1$, $C_2$, $C_3$, $C_4$; for simplicity, we also define $C_i = \{C_j | j \in [0,4], j \neq i \}$. The creation-process can be described in three steps: a) create 100 clusters using a k-means algorithm on CLS tokens from all queries, b) select the five clusters that maximize the sum of pairwise distances (euclidean) between their resp. centroids, c) expand those clusters by joining nearest clusters, until we have groups of $\approx 30k$ queries (without any overlap). Their union contains 150k queries from the entire set of 400k queries. Example queries from the five groups are given in Table 1: they correspond to different topics, so the distribution shift here is more semantic. Starting from 100 clusters helps defining more specific topics. We compared using an average pooling instead of the CLS tokens and starting from more than 100 clusters, but neither the clustering score nor our data visualization (t-sne/PCA) showed any improvement. Finally, we split each cluster in a train/test split of size 26.000/6.200 to compare performance with or without such queries at training time.

Wh-words Queries. Besides query topics, we investigated queries styles and goals, through an analysis of question words [21, 26]. For this, we manually created three clusters (wha, how, who), for queries related to definition ("what", "definition"), context and period of time ("how/"how long") and more general questions linked to persons, locations or context ("who", "when", "where", "which"). Again each cluster has a train/test split of size 48.500/6.500.

Short vs Long Queries. Finally, it has been shown that query length was a critical factor, and especially that it was difficult to aggregate information from long queries [23]. To analyse this effect, we split the train set in groups of short versus long queries from the median length (6 for MSMARCO). Train/test split is 100.000/3.500.

Similarity. We report in Figure 1 Jaccard and Cosine similarities for the different shifts. Weighted Jaccard Similarity of cluster $C_i$, $J(S_i, T_i)$, is computed as defined in the F Appendix of the BEIR paper [23], where $S_i = Concat_{q_j \in C_i}(q_j)$ and $T_i = Concat_{q_j \in C_i}(q_j)$. We also define the cosine similarity for a cluster $C_i$ as:

$$\text{Cos}_i \sim \text{Sim}_{C_i} = \text{Mean}_{q_j \in C_i,q_k \in C_i} \text{Cos}_i \sim \text{Sim}(CLS_{q_j}, CLS_{q_k})$$

The same similarity is used for the wh-words (with three clusters) and Length clusters (two clusters).

3.2 Models Evaluated

Base Architectures. We compared three neural rankers: a classical dense Bi-Encoder [10, 20], ColBERT [12] and SPLADE-max [6], as those models had the best performance on the BEIR benchmark.

---

Table 1: Example queries from the 5 clusters. We identified the following topics: Names and Public figures, Dated events, Pricing and Units, Medical treatments and Biology/physics

| Cluster | Queries |
|---------|---------|
| $C_0$   | +what does the name brooke mean | +what does the name lauri mean | +what does the name tyler mean | Camel Two Humps called | How Did George Peppard Die | How Much is Bobby Brown Worth |
| $C_1$   | +when is mardi gras | +which president has living grandsons | 11/11/23 is what day of 2016 | 23 is what day of 2016 | 1776 continental currency dollar | 2015 ncca football rankings |
| $C_2$   | .which is an example of a commodity | 1 cm is how many millimeters | . what is the major difference between a treaty and an executive agreement? | 1 point perspective definition |
| $C_3$   | ECT is a treatment that is used for | The ABO blood types are examples of | The vitamin that prevents beriberi is | 1.5 grams of sodium per day | 20 mg of codeine equivalent to |
| $C_4$   | Ebolavirus is an enveloped virus, which means | % of earths crust is dysprosium | +what is forbs as a food for animals? | 1. how many autosomes are present in the body cell of a human being |

![Figure 1: Jaccard and Cosine similarities from one cluster to the others of the same shift.](image)
Table 2: Evaluation of SPLADE on Query Topics. Each cluster has a train/eval split to enable evaluation on seen/unseen clusters. Rows correspond to training, cols to evaluation.

| MRR@10 | C0 | C1 | C2 | C3 | C4 |
|--------|----|----|----|----|----|
| C0     | 0.345 | 0.386 | 0.303 | 0.255 | 0.242 |
| C1     | 0.360 | 0.339 | 0.314 | 0.270 | 0.258 |
| C2     | 0.369 | 0.381 | 0.302 | 0.268 | 0.256 |
| C3     | 0.371 | 0.395 | 0.317 | 0.246 | 0.246 |
| C4     | 0.372 | 0.384 | 0.315 | 0.256 | 0.247 |

Avg In: 0.368, 0.387, 0.312, 0.262, 0.250
Rel Loss Out: 6.3%, 12.2%, 3.2%, 6.4%, 1.4%

All three rely on a pretrained BERT-based models, which is then finetuned only on a particular query subset. Concerning training, we limited ourselves to their standard training procedure without further techniques such as distillation or hard negative mining, as those techniques are more general, not especially focused a priori to tackle distribution shifts, and may be applied to any baseline model. We leave that as future work.

4 EXPERIMENTS

Models were finetuned for 100k iterations using triplets from MS-MARCO. For Bi-Encoder and SPLADE we used a batch size of 128 (with 4 GPUs), while for ColBERT, a default batch size of 32 was used (with 2 GPUs). All models were trained with In-Batch negatives. Except for ColBERT, best checkpoints were selected using an approximate validation on a validation set composed of 1600 queries; the validation set was not subject to the shifts. For all other parameters, we adopted the default value reported in their original paper or corresponding github repository.

We use leave-one-out on all the shifts, so we train independently on C_i, for i ∈ [0, 4], and evaluate each time on test sets of all C_j. It therefore creates a zero-shot experiment on C_i, as its distribution was out-of-training. Similarly with wh-words, we trained on who, how and who and tested each time on resp. test sets.

4.1 Query Topics

LeaveOneOut SPLADE. To better explain our evaluation procedure, we begin with the SPLADE model in Table 2. It gives the results of the leave-one-out rotation when trained on 4 of the 5 clusters, and then evaluated on an evaluation set of each cluster. As some clusters may contain harder queries, what is interesting here is to compare the performance inside a column (i.e. on the same evaluation set but with different training sets). From the table, we can see, as expected, that in almost all cases, the lowest performance on a cluster is obtained when the given cluster is out of the training set (diagonal). We additionally report the Avg In as the avg MRR@10 when the distribution of the evaluated cluster was seen in training, and the Rel Loss Out as the relative loss between this avg. performance when seen, and the zero-shot ones, when the evaluated cluster was out of training distribution. Relative losses are in some cases minor, but in others more important (from the range [1.4%, 12.2%]), depending on the distances between clusters.

Table 3: Comparison of the avg. perf and relative losses (in MRR@10) from seen to unseen clusters. In Bold are the best of each cluster (in terms of perf and loss).

| Models     | C0   | C1   | C2   | C3   | C4   |
|------------|------|------|------|------|------|
| Siamese    | Avg In | 0.332 | 0.372 | 0.285 | 0.215 | 0.214 |
|            | Rel Loss | 8.3% | 18.0% | 9.0% | 11.5% | 8.6% |
| SPLADE     | Avg In | 0.368 | 0.387 | 0.312 | 0.262 | 0.250 |
|            | Rel Loss | 6.3% | 12.2% | 3.2% | 6.4% | 1.4% |
| ColBERT    | Avg In | 0.397 | 0.423 | 0.346 | 0.288 | 0.277 |
|            | Rel Loss | 2.7% | 8.5% | 3.4% | 3.7% | 2.2% |

Models Comparison. To compare the losses from the different models, we report in Table 3 the mean performances, and its losses from seen to unseen clusters. The absolute zero-shot performance (i.e. the off diagonal) is noted Out in the remaining of the paper. Overall, ColBERT achieves the best scores in all metrics.

Train/Test Similarity. To analyse the link between losses and similarities, we plot in Figure 2 the relative losses on each of the outside cluster, with respect to the weighted Jaccard (defined in 3.1). Except for Siamese which has larger losses, ColBERT and SPLADE have losses that are negligible for little shifts, but then increases as the words overlap decreases. This confirms the relationship between the two: the lower the train/test Jaccard similarity is, the larger is the relative drop in performance. It also confirms the observation made in [8] about generalization on unseen words. Note that for the topic shifts, cosine similarity is almost constant across topics, which enable us to compare the Jaccard. Only exception is for C0 (higher cosine similarity on Figure 1), which seems to be more beneficial for the two dense models (Siamese, ColBERT). This also shows that the proposed clustering exhibits different levels of difficulty, which makes it interesting to further study model generalization.
4.2 WH-Words Queries and Length
Concerning the wh-words and lengths splits, Table 4 displays the results of the leave-one-out rotation on wh-words with the 3 clusters, and the rotation for query lengths. First, on wh-words, results show that the losses are much more important, up to 31.7%. On this shift, SPLADE has lower relative losses than ColBERT (by 15.5%, 4.9% and 6.4%) - however, even with those losses, ColBERT keeps a better MRR@10 than SPLADE in zero-shot, as the Avg In for ColBERT was much higher than the one for SPLADE.

Table 4: Comparison of the avg. MRR@10 and relative losses in zero-shot for wh-words and query length.

| Models | wha | how | who | short | long |
|-------|-----|-----|-----|-------|------|
| Siamese | Avg In | 0.278 | 0.260 | 0.331 | 0.340 | 0.271 |
| | Out | 0.234 | 0.215 | 0.279 | 0.298 | 0.252 |
| | Rel Loss | 15.8% | 24.8% | 15.8% | 12.5% | 7.0% |

| SPLADE | Avg In | 0.303 | 0.289 | 0.377 | 0.349 | 0.303 |
| | Out | 0.286 | 0.212 | 0.325 | 0.335 | 0.271 |
| | Rel Loss | 5.5% | 26.8% | 13.7% | 3.9% | 10.4% |

| ColBERT | Avg In | 0.404 | 0.419 | 0.489 | 0.382 | 0.320 |
| | Out | 0.319 | 0.286 | 0.386 | 0.359 | 0.313 |
| | Rel Loss | 21.0% | 31.7% | 21.1% | 6.0% | 2.2% |

On length shifts, we notice that short queries are easier than longer ones, even for a model trained on long queries only. Also, ColBERT loss on long queries is moderate compared to the other models. On the other hand, SPLADE has the lowest relative decrease on short queries, which suggests that SPLADE is more robust to shorter queries. Looking at the BEIR numbers in [6], we can see indeed the same tendency regarding query length: on two IR tasks in the Bio-Medical Domain - NFCorpus and TREC-COVID - where queries avg length are resp. of 3.30 and 10.60, SPLADE has a little NDCG@10 margin over ColBERT on NFCorpus (0.305 < 0.313), and ColBERT is better on TREC-COVID (0.677 > 0.673).

4.3 Performances on entire MSMARCO
In this section, we investigate to which extend all previous models trained on subsets of MSMARCO behave on the MSMARCO dev (6980 queries) and TREC DL eval set. Each row of Table 5 is the average performances of the models trained on particular subsets of MSMARCO (for example Topics is the avg. across the models trained on $C_0, C_1, C_2, C_3$ and $C_4$). By comparing with the baseline trained on the original MSMARCO distribution (noted All), we see that the model ordering is the same, while the relative MRR drop compared to training on all the queries is about 10%. This is a smaller drop compared to the wh-queries experiment, indicating the difficulty of the proposed task.

4.4 Discussion
Overall, while on BEIR, SPLADE and ColBERT have similar performances, here ColBERT outperforms SPLADE by a large margin. A first explanation could be that the default hyperparameters for SPLADE and the Bi-Encoder may be suboptimal for the proposed distribution shifts, on the contrary to ColBERT. Another explanation could be the position bias in MSMARCO annotations [11] or some aggregation bias in BEIR, which could contrast with the BEIR dataset. Due to its larger learning capacity, ColBERT could better encompass this bias. We also believe that the addition of distillation may reduce the gap, as distillation has been shown to improve generalization. Finally, we note that the recent version of ColBERT-V2 [22] reports results on BEIR (and Lotte) by regrouping different subtasks where ColBERT outperformed SPLADE. The impact of MSMARCO annotations or the BEIR aggregation measures could be questioned and is worth investigating in future work.

Furthermore, we hypothesize that SPLADE and ColBERT may have two distinct behaviours; SPLADE needs a high word overlap (i.e. high Jaccard) due its reliance on the MLM head, while ColBERT a high coverage of the embedding space. In particular, for shifts with low cosine similarity and low Jaccard (as in the wh-words shift, or for $C_0$), ColBERT will outperform SPLADE. However, for stronger shifts with new out-of-domain words, having word overlap will in any cases help ColBERT, as this also cover more of the embedding space. This could be investigated further with few-shot experiments.

5 CONCLUSION
This paper deals with zero-shot evaluation of IR models and proposes to benchmark PLMs rankers against controlled distribution shifts. We release three query subsets based on different lexical, syntactic and query length characteristics. Then, we compared the performance of Bi-Encoder, SPLADE and ColBERT models and showed that ColBERT was the most robust. We illustrate the link between train and test similarity with relative drop in performance. Overall, we argue that the proposed benchmark would complement BEIR and would foster the development of few-shot methods and the study of distributional shifts.

There are important open questions for the IR community: the first one is how to measure model robustness and take into account
the train/test distances. Furthermore, the behaviour of rerankers and the effect of distillations remain to be investigated as it could possibly correct model bias and lead to better generalization. Last but not least, an important research direction would be to analyze models representations similarly to [7] and to investigate whether there is an analogous phenomenon to seq2seq models hallucinations for neural rankers [13, 19] when exposed to domain shifts.

REFERENCES

[1] Negar Arabzadeh, Alexandra Vtyurina, Xinxi Yan, and Charles L. A. Clarke. 2021. Shallow pooling for sparse labels. CoRR abs/2109.00062 (2021). arXiv:2109.00062 https://arxiv.org/abs/2109.00062

[2] Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, Mir Rosenberg, Xia Song, Alina Stoica, Saurabh Tiwary, and Tong Wang. 2018. MS MARCO: A Human Generated Machine Reading Comprehension Dataset. arXiv:1611.09268 [cs.CL]

[3] Gabriela Csurka. 2017. Domain Adaptation in Computer Vision Applications (1st ed.). Springer Publishing Company, Incorporated.

[4] Gabriela Csurka, Riccardo Volpi, and Boris Chidlovskii. 2021. Unsupervised Domain Adaptation for Semantic Image Segmentation: a Comprehensive Survey. arXiv:2112.03241 [cs.CV]

[5] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. CoRR abs/1810.04805 (2018). arXiv:1810.04805 http://arxiv.org/abs/1810.04805

[6] Thibault Formal, Carlos Lassance, Benjamin Piwowarski, and Stéphane Clanchant. 2021. SPLADE v2: Sparse Lexical and Expansion Model for Information Retrieval. arXiv:2109.10086 [cs.IR]

[7] Thibault Formal, Benjamin Piwowarski, and Stéphane Clanchant. 2020. A White Box Analysis of ColBERT. CoRR abs/2012.09650 (2020). arXiv:2012.09650 https://arxiv.org/abs/2012.09650

[8] Thibault Formal, Benjamin Piwowarski, and Stéphane Clanchant. 2021. Match Your Words! A Study of Lexical Matching in Neural Information Retrieval. arXiv:2112.05662 [cs.IR]

[9] Thomas Gerald and Laure Soulier. 2022. Continual Learning of Long Topic Sequences in Neural Information Retrieval. arXiv:2201.03536 [cs.IR]

[10] Sebastian Hofstätter, Sheng-Chieh Lin, Jheng-Hong Yang, Jimmy Lin, and Allan Hanbury. 2021. Efficiently Teaching an Effective Dense Retriever with Balanced Topic Aware Sampling. In Proc. of SIGIR

[11] Sebastian Hofstätter, Aldo Lipani, Sophia Althammer, Markus Zlabinger, and Allan Hanbury. 2021. Mitigating the Position Bias of Transformer Models in Passage Re-Ranking. arXiv preprint arXiv:2101.06980 (2021).

[12] Omar Khattab and Matei Zaharia. 2020. CoiBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval (Virtual Event, China) (SIGIR ’20). Association for Computing Machinery, New York, NY, USA, 39–48. https://doi.org/10.1145/3397271.3401075

[13] Katherine Lee, Orhan Firat, Ashish Agarwal, Clara Fanjingj, and David Susillo. 2019. Hallucinations in Neural Machine Translation. https://openreview.net/forum?id=SkgJ-309FQ

[14] Minghan Li and Jimmy Lin. 2021. Encoder Adaptation of Dense Passage Retrieval for Open-Domain Question Answering. CoRR abs/2110.01599 (2021). arXiv:2110.01599 https://arxiv.org/abs/2110.01599

[15] Jesin Lovón-Melgarejo, Laure Soulier, Karen Pinel-Sauvagnat, and Lynda Tamine. 2021. Studying Catastrophic Forgetting in Neural Ranking Models. In 43rd European Conference on Information Retrieval - ECIR 2021. Lucca (on line), Italy. https://hal.archives-ouvertes.fr/hal-03156630

[16] Rodrigo Nogueira and Jimmy Lin. 2019. From doc2query to docTTTTTquery. arXiv:2110.11305 [cs.IR]

[17] Gustavo Penha, Arthur Câmara, and Claudia Hauff. 2022. Evaluating the Robustness of Retrieval Pipelines with Query Variation Generators. arXiv:2111.13057 [cs.IR]

[18] Alan Ramponi and Barbara Plank. 2020. Neural Unsupervised Domain Adaptation in NLP—A Survey. In Proceedings of the 26th International Conference on Computational Linguistics. International Committee on Computational Linguistics, Barcelona, Spain (Online), 6838–6855. https://doi.org/10.18653/v1/2020.coling-main.603

[19] Vikas Raunak, Arul Menezes, and Marcin Junczys-Dowmunt. 2021. The Curious Case of Hallucinations in Neural Machine Translation. arXiv:2104.06683 [cs.CL]

[20] Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing, Association for Computational Linguistics. http://arxiv.org/abs/1908.10084

[21] Ruiyang Ren, Yingqi Qu, Jing Liu, Wayne Xin Zhao, Qiwei Yu, Yuchen Ding, Hua Wu, HaiFeng Wang, and Ji-Rong Wen. 2022. A Thorough Examination on Zero-shot Dense Retrieval. https://doi.org/10.48550/ARXIV.2204.12755

[22] Keshav Santhanam, Omar Khattab, Jon Saad-Falcon, Christopher Potts, and Matei Zaharia. 2021. CoiBERTv2: Effective and Efficient Retrieval via Lightweight Late Interaction. arXiv:2112.01488 [cs.IR]

[23] Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. 2020. BEIR: A Heterogenous Benchmark for Zero-shot Evaluation of Information Retrieval Models. CoRR abs/2104.08663 (2021). arXiv:2104.08663 https://arxiv.org/abs/2104.08663

[24] Olivia Wiles, Sven Gowal, Florian Stimberg, Sylvestre-Alvise Rebuffi, Ira Ktena, Krishnamurthy Dvijotham, and A. Taylan Cemgil. 2021. A Fine-Grained Analysis on Distribution Shift. CoRR abs/2110.11328 (2021). arXiv:2110.11328 https://arxiv.org/abs/2110.11328

[25] Chen Wu, Ruqing Zhang, Jiafeng Guo, Yixing Fan, and Xueqi Cheng. 2021. Are Neural Ranking Models Robust? arXiv:2110.01599 https://arxiv.org/abs/2110.01599

[26] Ingrid Zukerman and Eric Horvitz. 2001. Using Machine Learning Techniques to Invert WH-Questions. In Proceedings of the 39th Annual Meeting on Association for Computational Linguistics (Toulouse, France). ACL ’01. Association for Computational Linguistics, USA, 547–554. https://doi.org/10.3115/1073012.1073082