Saving Dense Retriever from Shortcut Dependency in Conversational Search

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Abstract

Conversational search (CS) needs a holistic understanding of conversational inputs to retrieve relevant passages. In this paper, we demonstrate the existence of a *retrieval shortcut* in CS, which causes models to retrieve passages solely relying on partial history while disregarding the latest question. With in-depth analysis, we first show that naively trained dense retrievers heavily exploit the shortcut and hence perform poorly when asked to answer history-independent questions. To build more robust models against shortcut dependency, we explore various hard negative mining strategies. Experimental results show that training with the model-based hard negatives (Xiong et al., 2020) effectively mitigates the dependency on the shortcut, significantly improving dense retrievers on recent CS benchmarks. In particular, our retriever outperforms the previous state-of-the-art model by 11.0 in Recall@10 on QReCC (Anantha et al., 2021).[1]

Figure 1: An example of a retrieval shortcut in conversational search. While we expect the retriever to predict relevant passages by using all conversational inputs up to q_3 (Blue solid line), a dense retriever often ignores current turn question q_3 and only exploits previous history, a_2 (Red dashed line). We show the shortcut dependency is harmful to robust retrieval.

1 Introduction

Conversational search (CS) is a task of retrieving relevant passages from a large amount of web text given the current question and its conversational history, which consists of previously asked questions and their answers (Dalton et al., 2019). Unlike open-domain question answering (ODQA) taking a single question (Voorhees and Tice, 2000; Chen et al., 2017), CS assumes a sequence of questions interactively taken from information seekers. Hence, the questions need to be understood with the conversational history to find relevant evidence at each turn.

To build a retriever that properly makes use of the conversational history, we first analyze a simple dense retriever baseline trained on one of the CS datasets, QReCC (Anantha et al., 2021). Our analysis shows us the existence of a retrieval shortcut in recent CS datasets, indicating dense retrievers heavily rely on the shortcut and retrieve irrelevant passages. Specifically, these shortcuts represent the spurious correlation between the conversational history and the relevant passages, pushing the dense retrievers to ignore current questions. For example, as illustrated in Figure 1, a dense retriever retrieves wrong passages only paying attention to '*Russia*' and '*World Cup*' mentioned in the previous history (a_1, a_2) while ignoring the crucial cue '*win the World Cup*' in the current question q_3.

Motivated by our observation, we further test how much the shortcut contributes to the performance of current retrievers. First, we build a simple BM25 baseline, which only takes the previous conversational history as input, but still performs

◇ Work done while interning at NAVER AI Lab

[1]The code is available at github.com/naver-ai/cs-shortcut.

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surprisingly well on QReCC. Similarly, a dense retriever trained by feeding the conversational history without the current question keeps 70-80% of the original performance. It implies a significant effect of the shortcut dependency on dense retrievers. From our analysis, we find the shortcut is more likely to be learned when the topic of conversation is constant. In other words, performance of the models drops especially when they are asked to answer history-independent questions.

To alleviate the overreliance on the shortcut, we explore using hard negative mining strategies, which have been recently proposed in ODQA and CS (Karpukhin et al., 2020; Xiong et al., 2020; Yu et al., 2020; Lin et al., 2021b). Experimental results show the model-based hard negatives make remarkable improvements in various CS benchmarks and are especially helpful to history-independent questions, mitigating the dependency on the shortcut effectively. Our retrievers outperform baselines by 11.0 in Recall@10 on QReCC.

Our contributions are summarized in three folds:

- We reveal the presence of a *retrieval shortcut* in the conversational search, and dense retriever dependent on the shortcut is poor at generalizing toward a real scenario.
- We show training the dense retriever with hard negatives effectively mitigates the heavy shortcut dependency by in-depth analysis.
- We achieve a new state-of-the-art of recent CS benchmarks, QReCC and OR-QuAC.

2 Background and Related Work

Let $X_t = \{q_1, a_1, ..., a_{t-1}, q_t\}$ is a conversation up to turn t where the q_t and a_t are the question and answer at turn t. We assume pre-chunked passages collection $\mathcal{C} = \{p_1, p_2, ..., p_{|\mathcal{C}|}\}$ for the retrieval. Then, the formal objective of conversational search is learning function $f : (X_t, \mathcal{C}) \rightarrow P_t$, where the $P_t = \{p_1, p_2, ..., p_k\} \subset \mathcal{C}$ and $k \ll |\mathcal{C}|$.

On the other hand, conversational query rewriting (CQR) is a generative task that rewrites the conversational input X_t into a standalone question $q_t^{'}$ (Yu et al., 2020; Voskarides et al., 2020; Lin et al., 2021c; Kumar and Callan, 2020; Anantha et al., 2021; Wu et al., 2021). Then, existing retrieval systems such as BM25 take the standalone question $q_t^{'}$ to find P_t at inference time, i.e. $f(q_t^{'}, \mathcal{C}) \rightarrow P_t$. As a result, the CQR approaches do not require to re-train additional retriever in a conversational manner. However, the approach is limited in triggering information loss and long latency while rewriting the conversation into the standalone question.

To overcome the limitations, Yu et al. (2021); Lin et al. (2021b) attempt to train dense retrievers to directly represent the multi-round questions into a single dense vector. They usually focused on few-shot adaptation or weak supervision utilizing other accessible resources including the standalone questions for hard negative mining.

3 Retrieval Shortcut

First, we demonstrate the presence of the shortcut in CS datasets. Formally, we define the shortcut as where gold passage p_t^+ can be predicted in top-k predictions even without the current question q_t. Then, we show how heavily dense retriever relies on the shortcut and how its overall performance is overestimated.

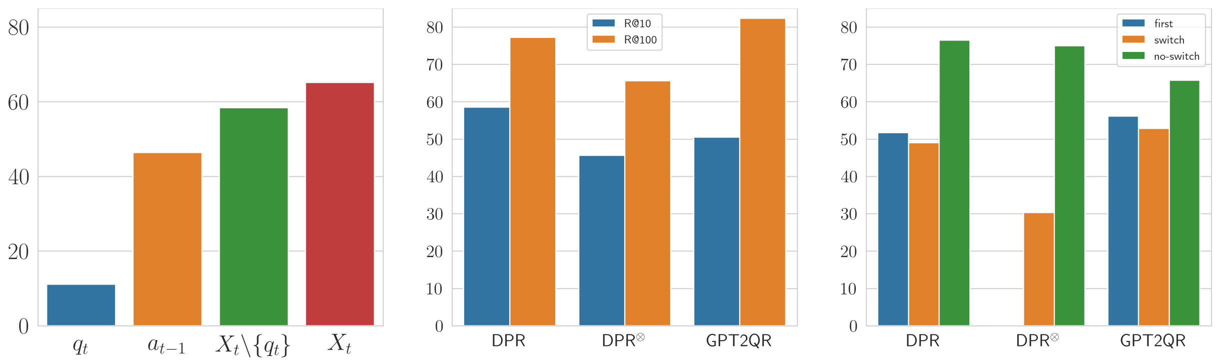
3.1 Lexical Analysis

We investigate whether there are spurious *lexical cues* to predict relevant gold passages in CS. Specifically, we input $X_t \backslash \{q_t\} = \{q_1, a_1, ..., a_{t-1}\}$ to the BM25 to measure the shortcut. Figure 2 (a) shows the result. Surprisingly, we observe the BM25 taking $X_t \backslash \{q_t\}$ achieves 58.4 for R@10 on QReCC (Anantha et al., 2021) even without the current question q_t. It retains about 90% of its original performance from BM25 (X_t as an input), indicating $X_t \backslash \{q_t\}$ contains enough lexical cues to predict p_t^+. However, a model taking only current question q_t does not predict the gold passage well since it does not contain enough lexical cues. Instead, the previous answer a_{t-1} is more responsible for the performance, achieving 46.4 of R@10.

3.2 Lower and Upper bounds Analysis

To examine how dense retriever trained on the dataset behave, we contrast a dense retriever with its lower and upper bound models in terms of dependency on the retrieval shortcut. For this, we train two Dense Passage Retriever (DPR) models with in-batch negatives (Karpukhin et al., 2020) by feeding X_t and $X_t \backslash \{q_t\}$ as input query to each model.[2] We denote the latter one as DPR$^{\otimes}$, and it represents the lower bound model that does not consider the current question q_t at all. Surprisingly, we find the DPR$^{\otimes}$ performs 78% of R@10 and 85%

[2]Please see § 4.1 for the training details.



(a) R@10 by input rep. to BM25 (b) Comparison with lower and upper bounds (c) R@10 by models and question types

Figure 2: Analysis on QReCC (Anantha et al., 2021) for identifying the shortcut. We denote X_t as a conversational input including the current question q_t while $X_t \backslash \{q_t\}$ does not contain the q_t. (a) Lexical assessment using BM25 to quantify the shortcut in the dataset. BM25 shows small performance drop in R@10 even without considering the current question. (i.e. $X_t \backslash \{q_t\}$ as an input.) (b) Comparison of original DPR (Karpukhin et al., 2020) with its lower bound in terms of shortcut dependency, DPR$^{\otimes}$ taking only $X_t \backslash \{q_t\}$ and upper bound, GPT2QR generating and using standalone question $q_t^{'}$ to retrieve. DPR$^{\otimes}$ shows comparable performance without using the current question. (c) Breakdown results of each model by three question types in R@10. Most of the performance gain comes from *no-switch* questions on both original and shortcut-dependent DPRs.

of R@100 compared to DPR as shown in Figure 2 (b). Thus, we presume the original DPR model is also likely to depend on the shortcut. Next, we introduce the upper bound model, GPT2QR (Anantha et al., 2021). It is less likely to be exposed to the shortcut since it first generates standalone question $q_t^{'}$, and then its BM25 retriever only takes the decontextualized $q_t^{'}$ as input. We also find that the DPR$^{\otimes}$ is comparable with GPT2QR in R@10 despite the heavy shortcut dependency. It reminds us the overall score is not enough to identify robust retrieval methods.

3.3 Breakdown by Question types

To probe when and how models take the shortcut, we break down the evaluation results by question types as in Wu et al. (2021). Specifically, we define three question types, *first*, *no-switch*, and *switch*. The *first* question is literally first question of conversation without any history. The *no-switch* and *switch* questions can be distinguished by whether p_{t-1}^{+} contains similar or same topics as p_t^{+}, where the p_t^{+} is a gold passage at turn t and $t > 1$.[3]

Figure 2 (c) shows the breakdown result of R@10. The DPR$^{\otimes}$ achieves competitive performance with the DPR in *no-switch* questions, which can benefit from previous conversational history. However, the performances in other two types, *first* and *switch*, drop significantly. Similarly, when we compare DPR with the GPT2QR, we find the performance at *no-switch* turn largely contributes to the gain while degraded in *first* and *switch* types. As a result, its overreliance on the shortcut prevents the model from generalizing toward real scenarios where a large proportion of topic-switching questions could appear (Adlakha et al., 2022). Thus, we claim that the proper ways to take the shortcut could improve the overall score with performance gains at the *first* and *switch* turns while keeping them at the *no-switch*.

4 Experiments

We hypothesize random in-batch negatives promote the shortcut dependency of the vanilla DPR model because of their easy-to-distinguish nature. Thus, we examine hard negative mining as one of the solutions to push the retriever to exploit the shortcut properly. We mainly evaluate it on two CS benchmarks, QReCC and OR-QuAC (Anantha et al., 2021; Qu et al., 2020).[4]

4.1 Training Dense Retriever

DPR consists of two encoders, E_Q and E_P, for encoding conversational input and passages, respectively. Each encoders takes the X_t and p, a passage in the $\mathcal{C}$, to represent d dimensional vector. Then, we can compute the similarity between the representations via dot product.

$$sim(X_t, p) = E_Q(X_t)^T E_P(p)$$

Given the input X_t, the encoders are trained in a contrastive manner with the negative passages

[3]More details for each question type are in Appendix A.

[4]More details of dataset are in Appendix B.

$P_t^- = \{p_{t1}^-, p_{t2}^-, ..., p_{t|P^-|}^-\}$ and its corresponding positive passage p_t^+.

$$L = -log \frac{e^{sim(X_t, p_t^+)}}{e^{sim(X_t, p_t^+)} + \sum_j e^{sim(X_t, p_{tj}^-)}}$$

Basically, we adopt in-batch negatives to obtain the P_t^- (Karpukhin et al., 2020). For each query representation, it computes the similarity score with other $(B-1)$ number of passage representations except for its gold relevant passage in the same batch, where the B is batch size.

4.2 Hard Negative Mining

The in-batch negative is one of the intuitive options to construct the negative examples while reducing memory consumption. However, it is often easy to distinguish from the p_t^+ and consequently encourages shortcut dependency. To reduce the dependency, we include a hard negative passage p_{t*}^- in the P_t^-. We first construct k number of negative passages N_t^- for each training instance. Then, we randomly sample a passage from the N_t^- to include it in P_t^- as the p_{t*}^-. We denote off-the-shelf retriever to obtain top-k passages in $\mathcal{C}$ from given input query x as $\mathcal{F}(x, \mathcal{C}, k)$. Specifically, we compare three strategies for hard negative mining:

BM25 Negs De-facto strategy is BM25-based negative mining following Karpukhin et al. (2020). We mine the N_t^- using whole conversational input X_t, i.e., $N_t^- \leftarrow \text{BM25}(X_t, \mathcal{C}, k)$.

CQR Negs If gold standalone question $q_t^{'}$ is available for each X_t, we can leverage it to find the negative passages with off-the-shelf retriever as in Yu et al. (2020); Lin et al. (2021b), i.e., $N_t^- \leftarrow \mathcal{F}(q_t^{'}, \mathcal{C}, k)$. For this, we employ another DPR pretrained on Natural Questions (NQ) (Kwiatkowski et al., 2019) as the $\mathcal{F}$.

Model Negs Lastly, we explore model-based hard negative mining proposed by Xiong et al. (2020). First, we train vanilla DPR model on the target dataset using only in-batch negative as in § 3. Then, we employ the model as $\mathcal{F}$ to select negative passages, i.e., $N_t^- \leftarrow \mathcal{F}(X_t, \mathcal{C}, k)$.

4.3 Implementation Details

DPR pre-trained on NQ dataset (Kwiatkowski et al., 2019) of Karpukhin et al. (2020) is used for the initial checkpoint of our dense retrievers. It consists of two BERT encoders and 220M of learnable parameters (Devlin et al., 2019). We set maximum sequence length to 128 and 384 for X_t and p, respectively. All history is concatenated with a `[SEP]` token in between. We retrain the first question and truncate tokens from the left side up to the maximum length of 128 for X_t.

We train the models for 10 epochs with 3e-5 of learning rate (lr). For optimization, AdamW is used with 0.1 warming up ratio for linear lr decay scheduling (Kingma and Ba, 2017). We build top 100 passages for the hard negatives N_t^-, i.e., $k = 100$. Batch size is set to 128 for OR-QuAC and 256 for QReCC. We choose the best performing model based on dev set. We use Pyserini (Lin et al., 2021a) to implement BM25 and IndexFlatIP index of FAISS (Johnson et al., 2019) to perform dense retrieval.[5]

4.4 Baselines

In QReCC, we include BM25 and BM25$^{\otimes}$ take X_t and $X_t \backslash \{q_t\}$ as input query, respectively. For CQR baselines less dependent on the shortcut, we include GPT2QR and CONQRR (Anantha et al., 2021; Wu et al., 2021). They use standalone question instead of directly encoding a conversation for the input of off-the-shelf retriever such as BM25 or T5-DE (Ni et al., 2022) finetuned on ODQA dataset. Anantha et al. (2021) propose GPT2QR as baseline model which is GPT-2 (Radford et al., 2019) based CQR model. We only perform BM25 inference based on released model predictions by authors instead of re-training it. CONQRR is based on T5 (Raffel et al., 2020) for the CQR (Wu et al., 2021). Especially, Wu et al. (2021) train the CONQRR using reinforcement learning against retrieval metrics (MRR, Recall) as reward signals. We also include DPR and DPR$^{\otimes}$ without hard negative mining to represent shortcut-dependent model.

In OR-QuAC, we compare our models with previously proposed dense retrieval approaches in conversational search, CQE (Lin et al., 2021b) and ConvDR (Yu et al., 2020). Both of them utilize the standalone question $q_t^{'}$ to mine hard negatives and knowledge distillation from off-the-shelf retrievers trained on ODQA, regarding it as a teacher model. Although they were not tested on QReCC, we can indirectly compare them with others using DPR with CQR Negs instead.

[5] All our experiments is based on NSML platform (Sung et al., 2017; Kim et al., 2018) and Transformers library (Wolf et al., 2020) using {4, 8} 32GB V100 GPUs.

	All			first			switch			no-switch		
Model	MRR	R@10	R@100	MRR	R@10	R@100	MRR	R@10	R@100	MRR	R@10	R@100
BM25	0.47	65.1	82.8	0.32	56.1	**99.1**	0.18	36.3	70.5	**0.78**	**90.8**	**97.9**
BM25$^{\otimes}$	0.43	58.4	63.9	-	-	-	0.16	32.8	65.3	0.76	90.3	96.5
DPR$^{\otimes}$	0.28	46.5	65.9	-	-	-	0.14	30.2	56.7	0.54	75.5	88.4
GPT2QR	0.32	50.5	82.3	0.32	56.1	**99.1**	0.30	52.8	88.0	0.46	65.7	88.9
CONQRR	0.42	65.1	84.7	-	-	-	-	-	-	-	-	-
DPR	0.39	59.1	77.6	0.36	55.7	77.6	0.29	50.3	71.5	0.60	80.8	90.8
w. CQR Negs	0.50	71.6	86.0	0.42	64.0	82.2	0.34	57.9	80.8	0.70	86.7	94.2
w. BM25 Negs	0.51	73.5	86.3	0.46	65.5	85.7	0.38	61.8	82.3	0.68	85.5	92.9
w. Model Negs	**0.53**	**76.1**	**88.3**	**0.48**	**70.9**	87.1	**0.40**	**63.0**	**84.1**	0.72	88.1	94.1

Table 1: Experimental results on QReCC test set (All) and its sub-splits by three question types discussed in § 3. The $^{\otimes}$ indicates the model takes only $X_t \backslash \{q_t\}$ as input.

4.5 Results

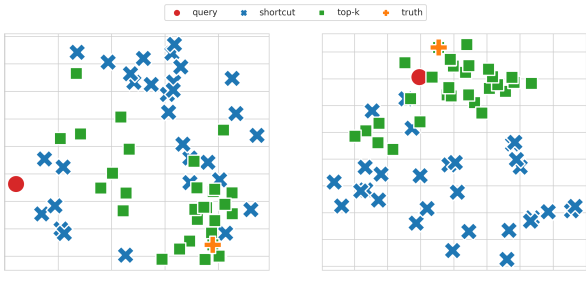
We report scores among Mean Reciprocal Rank (MRR) and Recall (R@K, K $\in \{5, 10, 100\}$).[6] Table 1 shows the retrieval performances of baseline models and hard negative mining methods on QReCC, and our findings are summarized:

Overall performances are not enough to distinguish robust methods in CS. We find lexical baselines, BM25 and BM25$^{\otimes}$, outperform CQR-based models, GPT2QR and CONQRR (Anantha et al., 2021; Wu et al., 2021) and vanilla DPR in MRR of overall retrieval performances (All). However, as we discussed in § 3, the most performances are from *no-switch* questions which can benefit from the shortcut.

Hard negatives could mitigate shortcut dependency of dense retrievers. We observe the vanilla DPR underperforms the GPT2QR in *first* and *switch* questions. Also, there is a relatively smaller gap between DPR$^{\otimes}$ and DPR in *no-switch* type of questions. Compared to the vanilla DPR, all three negatives effectively improve the overall performance. Especially, the history-independent types, *first* and *switch*, are improved at most 12.7-15.2 in R@10 indicating relaxed shortcut dependency of the model. Figure 3 shows T-SNE visualizations (Van der Maaten and Hinton, 2008) to compare DPR models with and without negatives in embedding space. Different from the vanilla DPR that fails to identify a gold passage from other irrelevant passages, DPR trained with negatives more clearly discriminates it from the distractors.

Among the negative mining methods, the model-based hard negative consistently outperforms others. We observe consistent results in other CS dataset, OR-QuAC (Qu et al., 2020) compared to previous works (Please see Appendix C). Moreover, our model achieves a new state-of-the-art with improvements of 11.0% point R@10.

[6]We use updated evaluation script, which does not consider when there is no ground truth, by Vakulenko et al. (2022).



(a) DPR w/o. Negs (b) DPR w. Negs

Figure 3: T-SNE visualization of query and passage embeddings based on two DPR models with and without hard negative training. The shortcut (blue multiply) passages are obtained by BM25$^{\otimes}$. The example is from 5th turn of conversation 1935 in QReCC test set, which is one of *switch* questions. Please see Appendix E for the corresponding qualitative example.

5 Conclusion

In this work, we show the presence of the shortcut in conversational search, which causes dense retriever often heavily relies on it when trained on in-batch negatives. We find that shortcut dependency hurts the generalization ability of dense retrievers. To save the model from relying on the shortcut, we study various hard negative mining strategies. The retriever trained with hard negatives appropriately takes beneficial information of the shortcut only when needed and achieves the state-of-the-art performance on multiple CS benchmarks.

Limitations

Even if we explain the existence of shortcut in conversational search, we could not suggest specific solutions to the shortcut dependency of dense retrievers. In the preliminary study, we tried other methods, e.g., history masking to promote the model attending more to the current question, but we found those methods are not effective as the hard negative mining in terms of shortcut dependency. However, we believe our work is an important step toward more robust conversational search.

Another limitation is the implementation cost to perform the model-based hard negative mining, i.e., indexing and inference of dense retriever over huge passages collection. Please see Appendix D for the details. Especially, the cost is increased notoriously according to the number of passage collections. We expect a more efficient method to balance shortcut dependency in future works.

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A Details of Question Types

We classify the *no-switch* and *switch* questions using dot product score between BM25 vectors of p_{t-1}^{+} and p_t^{+} as threshold in QReCC dataset. This is similar with division of *topic-concentrated* and *topic-shifted* questions in Wu et al. (2021) while we take them only when $t > 1$ to distinguish them from *first* questions. The number of subsets is 267, 279, and 573 for the *first*, *no-switch*, and *switch* respectively. Please note that the sum of each subset is not equal to the number of *all* (8209) since we take the question types from only NQ and TREC subdomains in the QReCC dataset as in Wu et al. (2021).

B Details of Dataset

Dataset		Train	Dev	Test	$\mathcal{C}$
OR-QuAC	# C	4,383	490	771	11M
	# Q	31,526	3,430	5,571	
QReCC	# C	8,823	2,000	2,775	54M
	# Q	51,928	11,573	16,451	

Table 2: Dataset statistics used in our experiments. The # C and # Q indicate the number of conversations and questions, respectively.

We mainly conduct experiments on recent CS benchmarks, OR-QuAC and QReCC (Qu et al., 2020; Anantha et al., 2021). We briefly describe the procedures of data construction and features of each dataset. Table 2 shows dataset statistics we used.

OR-QuAC Qu et al. (2020) extend one of the popular CQA datasets, QuAC (Choi et al., 2018) to the open-domain setting by aligning relevant passages with the questions in QuAC. [7] Moreover, they facilitate CQR as a subtask by reusing examples in CANARD (Elgohary et al., 2019). For retrieval, they construct passage collections from Wikipedia. However, the dataset has limitations in that all questions in the same conversation share the same gold passage. In other words, most of the questions in OR-QuAC are *no-switch* type. Thus, it is vulnerable to the shortcut. Even though it is far from the real world scenario, we include OR-QuAC to compare previous dense retrieval approaches (Lin et al., 2021b; Yu et al., 2021). We use smaller collections $\mathcal{C}_{dev}$ (6.9k) provided by the authors for the development.

[7] github.com/prdwb/orconvqa-release

Model	MRR	R@5
BM25($q_1, \mathcal{C}$)	0.216	30.6
BM25($q_t, \mathcal{C}$)	0.043	5.6
BM25($Q_{t-1}, \mathcal{C}$)	0.170	21.3
BM25($Q_t, \mathcal{C}$)	0.198	24.9
ALBERT (Qu et al., 2020)	0.225	31.4
CQE$^\diamond$ (Lin et al., 2021b)	0.266	36.5
ConvDR (Yu et al., 2021)	0.616	75.0
DPR	0.525	63.9
w. Model Negs	**0.633**	**75.9**

Table 3: Experimental result on OR-QuAC. Please note that all models take only multi-round questions $Q_t = \{q_1, q_2, ..., q_t\}$ instead of X_t as input following previous works. The $^\diamond$ indicates the CQE model performs zero-shot inference and dimensionality reduction (Lin et al., 2021b).

QReCC Anantha et al. (2021) construct QReCC dataset based on three existing datasets, QuAC, Natural Questions (NQ), and TREC (Choi et al., 2018; Kwiatkowski et al., 2019; Dalton et al., 2019). [8] To annotate gold passage, they reuse conversational questions in QuAC and CAsT as in Qu et al. (2020), while collecting new questions for the NQ dataset. Given a question randomly selected from NQ, each crowdworker alone generates not only the following questions but also their corresponding answers. Even though it contains more diverse and realistic questions than the OR-QuAC, most of the questions (78%) still belong to the QuAC, causing models to exploit the shortcut. We newly select the development set by sampling 2k conversations from the train set, since Anantha et al. (2021) combined them into the train set when the dataset is released. We also choose 7.3k number of corresponding dev passages for the development collections $\mathcal{C}_{dev}$. We only regard the examples that contain ground truth relevant passages. Thus, the actual number of training examples is 24,283.

C Experimental Results on OR-QuAC

Table 3 shows results on OR-QuAC where most of the questions are *no-switch* type. First, we observe another retrieval shortcut on the first question, which is not observed in QReCC. Even if we input only first question to BM25, BM25($q_1, \mathcal{C}$), it achieves competitive results with ALBERT baseline by Qu et al. (2020). We presume the lexi-

[8] zenodo.org/record/5115890#.YgCWNfVBxhF

Data	Training	Indexing	Inference
OR-QuAC	2h	8h	40m
QReCC	2h	28h	11h

Table 4: Summarized computational cost (run-time) for each training, indexing, and inference of dense retrieval. The target of each function is train set, passages collection, and test or dev set.

cal cues from the first question are caused by preproccesing for the questions, rewriting to the standalone questions (Qu et al., 2020).

Our DPR with model-based hard negatives consistently outperforms the previous dense retrievers (Yu et al., 2020; Lin et al., 2021b). Even though it is not fair comparison since their different backbones and setups, we can compare the models in terms of hard negative mining strategies. Both CQE and ConvDR utilize CQR-based negatives requiring gold human rewrite q_t' (CQR Negs). Similar to result in Table 1, our model with model-based negatives (Model Negs) achieves better performances without any usage of query rewriting.

D Computational Cost

Overall computational cost is summarized in Table 4. Please note that the number of passages collection and test set of QReCC is much larger than the other. Thus, we allocate 8 GPUs for QReCC and 4 GPUs for OR-QuAC to perform training and indexing. We conduct training and inference once for all experiments because of the expensive computational cost.

E Qualitative Examples

Conversation (id: 1935_5)
q_1 : when was a view to a kill made? a_1 : a view to a kill is a 1985 spy film and the fourteenth in the james bond series produced by eon productions q_2 : who directed the film? a_2 : a view to kill was the third james bond film and was directed by john glen q_3 : who played the main character? a_3 : roger moore played james bond, mi6 agent 007, in a view to kill q_4 : how old was the actor? a_4 : roger **moore** starred in his **final bond film** , a view to a kill at the age of 58. moore was **the oldest actor** to have played bond q_5 : **in how many films did the actor play the character?**
DPR without Negatives
In the Bond movie universe, **Moore** is the proud holder of three noteworthy records: 1. At age 45 in 1973, he was the oldest actor to take over the role. 2. At 57, he was again **the oldest actor play** the role in 1985's A View To a Kill, his seventh and **final Bond film** . 3. With seven appearances as 007, he starred in the most official Bond films. $\cdots$
DPR with Negatives
$\cdots$ British actor Sir **Roger Moore** KBE Moore in 1973 Born Roger George Moore (1927-10-14) 14 October 1927 Stockwell, London, England Died 23 May 2017 (2017-05-23) (aged 89) Crans-Montana, Switzerland [1] Burial place Monaco Cemetery Alma mater Royal Academy of Dramatic Art Occupation Actor Years active 1945–2013 Known for **James Bond in seven feature films** from 1973 to 1985 $\cdots$

Table 5: An example of top-1 predictions from vanilla DPR (without Negatives) and DPR trained with model-based hard negatives (with Negatives). The vanilla DPR without hard negatives fails to predict a gold passage since it heavily relies on shortcut, i.e., previous answer a_4. On the other hand, the DPR successfully predicts a gold passage with comprehending whole conversational context up to q_5 when the retriever is trained with hard negatives.