

- Eunsol Choi, He He, Mohit Iyyer, Mark Yatskar, Wen-tau Yih, Yejin Choi, Percy Liang, and Luke Zettlemoyer. 2018. Quac: Question answering in context. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2174–2184.
- Jeffrey Dalton, Chenyan Xiong, and Jamie Callan. 2020. Trec cast 2019: The conversational assistance track overview. *arXiv preprint arXiv:2003.13624*.
- Jeffrey Dalton, Chenyan Xiong, and Jamie Callan. 2021. Cast 2020: The conversational assistance track overview. Technical report.
- Leon Derczynski, Jun Wang, Robert Gaizauskas, and Mark A Greenwood. 2008. A data driven approach to query expansion in question answering. In *Coling 2008: Proceedings of the 2nd workshop on Information Retrieval for Question Answering*, pages 34–41.
- Ahmed Elgohary, Denis Peskov, and Jordan Boyd-Graber. 2019. Can you unpack that? learning to rewrite questions-in-context. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 5918–5924.
- Jianfeng Gao, Chenyan Xiong, Paul Bennett, and Nick Craswell. 2022. Neural approaches to conversational information retrieval. *arXiv preprint arXiv:2201.05176*.
- Helia Hashemi, Hamed Zamani, and W Bruce Croft. 2020. Guided transformer: Leveraging multiple external sources for representation learning in conversational search. In *Proceedings of the 43rd international acm sigir conference on research and development in information retrieval*, pages 1131–1140.
- Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2019. Billion-scale similarity search with gpus. *IEEE Transactions on Big Data*, 7(3):535–547.
- Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6769–6781.
- Sungdong Kim and Gangwoo Kim. 2022. Saving dense retriever from shortcut dependency in conversational search. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 10278–10287. Association for Computational Linguistics.
- Vaibhav Kumar and Jamie Callan. 2020. Making information seeking easier: An improved pipeline for conversational search. In *Empirical Methods in Natural Language Processing*.
- Jimmy Lin, Xueguang Ma, Sheng-Chieh Lin, Jheng-Hong Yang, Ronak Pradeep, and Rodrigo Nogueira. 2021a. Pyserini: A python toolkit for reproducible information retrieval research with sparse and dense representations. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2356–2362.
- Sheng-Chieh Lin, Jheng-Hong Yang, and Jimmy Lin. 2021b. Contextualized query embeddings for conversational search. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 1004–1015.
- Sheng-Chieh Lin, Jheng-Hong Yang, Rodrigo Nogueira, Ming-Feng Tsai, Chuan-Ju Wang, and Jimmy Lin. 2020. Conversational question reformulation via sequence-to-sequence architectures and pretrained language models. *arXiv preprint arXiv:2004.01909*.
- Kelong Mao, Zhicheng Dou, Haonan Chen, Fengran Mo, and Hongjin Qian. 2023a. Large language models know your contextual search intent: A prompting framework for conversational search. *arXiv preprint arXiv:2303.06573*.
- Kelong Mao, Zhicheng Dou, and Hongjin Qian. 2022a. Curriculum contrastive context denoising for few-shot conversational dense retrieval. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 176–186.
- Kelong Mao, Zhicheng Dou, Hongjin Qian, Fengran Mo, Xiaohua Cheng, and Zhao Cao. 2022b. Contrans: Transforming web search sessions for conversational dense retrieval. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 2935–2946.
- Kelong Mao, Hongjin Qian, Fengran Mo, Zhicheng Dou, Bang Liu, Xiaohua Cheng, and Zhao Cao. 2023b. Learning denoised and interpretable session representation for conversational search. In *Proceedings of the ACM Web Conference 2023*, pages 3193–3202.
- Yuning Mao, Pengcheng He, Xiaodong Liu, Yelong Shen, Jianfeng Gao, Jiawei Han, and Weizhu Chen. 2021. Generation-augmented retrieval for open-domain question answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4089–4100.
- Fengran Mo, Jian-Yun Nie, Kaiyu Huang, Kelong Mao, Yutao Zhu, Peng Li, and Yang Liu. 2023. Learning to relate to previous turns in conversational search. *arXiv preprint arXiv:2306.02553*.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca

- Antiga, Alban Desmaison, Andreas Köpf, Edward Z. Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. Pytorch: An imperative style, high-performance deep learning library. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 8024–8035.
- Chen Qu, Liu Yang, Cen Chen, Minghui Qiu, W Bruce Croft, and Mohit Iyyer. 2020. Open-retrieval conversational question answering. In *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval*, pages 539–548.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, Peter J Liu, et al. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21(140):1–67.
- Deepak Ravichandran and Eduard Hovy. 2002. Learning surface text patterns for a question answering system. In *Proceedings of the 40th Annual meeting of the association for Computational Linguistics*, pages 41–47.
- Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. How much knowledge can you pack into the parameters of a language model? *arXiv preprint arXiv:2002.08910*.
- Svitlana Vakulenko, Shayne Longpre, Zhucheng Tu, and Raviteja Anantha. 2021a. Question rewriting for conversational question answering. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, pages 355–363.
- Svitlana Vakulenko, Nikos Voskarides, Zhucheng Tu, and Shayne Longpre. 2021b. A comparison of question rewriting methods for conversational passage retrieval. In *European Conference on Information Retrieval*, pages 418–424. Springer.
- Christophe Van Gysel and Maarten de Rijke. 2018. Pytrec_eval: An extremely fast python interface to trec_eval. In *SIGIR*. ACM.
- Nikos Voskarides, Dan Li, Pengjie Ren, Evangelos Kanoulas, and Maarten de Rijke. 2020. Query resolution for conversational search with limited supervision. In *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval*, pages 921–930.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, and Jamie Brew. 2019. [Huggingface’s transformers: State-of-the-art natural language processing](#). *CoRR*, abs/1910.03771.
- Zequ Wu, Yi Luan, Hannah Rashkin, David Reitter, and Gaurav Singh Tomar. 2021. Conqrr: Conversational query rewriting for retrieval with reinforcement learning. *arXiv preprint arXiv:2112.08558*.
- Lee Xiong, Chenyan Xiong, Ye Li, Kwok-Fung Tang, Jialin Liu, Paul N Bennett, Junaid Ahmed, and Arnold Overwijk. 2020. Approximate nearest neighbor negative contrastive learning for dense text retrieval. In *International Conference on Learning Representations*.
- Shi Yu, Jiahua Liu, Jingqin Yang, Chenyan Xiong, Paul Bennett, Jianfeng Gao, and Zhiyuan Liu. 2020. Few-shot generative conversational query rewriting. In *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval*, pages 1933–1936.
- Shi Yu, Zhenghao Liu, Chenyan Xiong, Tao Feng, and Zhiyuan Liu. 2021. Few-shot conversational dense retrieval. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 829–838.

A More Detailed Experimental Setup

A.1 Datasets

The statistics of each dataset are presented in Table 7 and the details are in the following:

QReCC focuses on the query rewriting problem within conversational scenarios by approaching the human-rewritten query. Thus, it provides an oracle query for each conversation turn. We argue that it might not be the optimal one.

TopiOCQA focuses on the challenge of the topic switch under conversational settings, whose sessions are longer than QReCC and thus present more difficulties for query reformulation. Different from QReCC, it does not provide human-rewritten queries.

CAsT-19 and **CAsT-20** are two standard conversational search benchmarks provided in the TREC Conversational Assistance Track (CAsT). The gold answers to each query are the same as their relevant passages. The newer one (CAsT-20) is known to be more challenging.

A.2 Implementation

We implement all models by PyTorch ([Paszke et al., 2019](#)) and Huggingface’s Transformers ([Wolf et al., 2019](#)).

ConvGQR The experiments are conducted on one Nvidia A100 40G GPU. For generative PLMs training, we use Adam optimizer with $1e-5$ learning rate and set the batch size as 8. The loss balance weight α is set to 0.5, which is the best according to the hyper-parameter selection of our experiments. For training ConvGQR on QReCC, we use its provided human-rewritten query q^* and gold answer r^* as generation ground-truth for two PLMs. We discard the samples without positive passages for both training and inference as Wu et al. (2021). For TopiOCQA, as it does not provide human-rewritten query q^* , we only use the ground-truth answer r^* to train one generative model for query expansion, and the rewritten query is generated by the model trained on QReCC. Aiming for a fair comparison, we set the maximum generation length (32) the same as CONQRR, which is the current state-of-the-art. The zero-shot evaluation is also based on the generative models trained on QReCC. Following the previous works (Yu et al., 2021; Lin et al., 2021b; Mao et al., 2022a), we set the relevance judgment threshold at 1 and 2 for CAsT-19 and CAsT-20, respectively.

Baselines We implement baselines based on our experimental setting and their open-source code and material. For the normal evaluation, we train QuReTeC, GPT2QR, and T5QR on the corresponding datasets rather than using external resources. Since CONQRR has not released the code and its experimental setting is similar to ours, we directly quote their experimental results on QReCC. The human-rewritten queries are provided in the datasets as annotations but are not available for TopiOCQA. For the zero-shot setting, the Query Rewriter is quoted from the original paper (Yu et al., 2021), and the T5QR is implemented on our own as the query rewriting part. The reformulated queries by Transformer++ and QuReTeC are provided in Vakulenko et al. (2021b).

B Additional Case Study

We provide two additional cases in Table 8 for analysis. The first one is a successful case where the generated expansion terms “motor”, “object”, “kinetic”, and “potential energy” occur in the relevant passage. Thus, they can further boost the retrieval performance although the model has already rewritten the query as the human-rewritten

Dataset	Split	#Conv.	#Turns(Qry.)	#Collection
QReCC	Train	10,823	63,501	54M
	Test	2,775	16,451	
TopiOCQA	Train	3,509	45,450	25M
	Test	205	2,514	
CAsT-19	Test	50	479	38M
CAsT-20	Test	25	208	38M

Table 7: Statistics of conversational search datasets.

one. The second one is a failure case where the generated answer cannot act as useful expansion terms and even hurt the retrieval results. The possible reason is that the PLM generated a redundant answer and there are no co-occurring and semantic related terms contained in the relevant passage. Thus, the expansion terms are harmful. This is a case that we should improve in the future.