Technical Appendix

QBR Demo

We have deployed QBR on CLIC, an online legal information platform, to recommend relevant legal questions and answers to users. Figure 1 illustrates the system with an example input. It provides a user-friendly interface and guides users through three key steps: describing the situation (Figure 1a), choosing relevant topics (Figure 1b), and reading/visiting recommendations (Figure 1c).

For example, a mother finds herself in an abusive relationship and wishes to pursue a divorce but she lacks knowledge about legal process. Instead of formulating precise legal questions, she can simply describe her current situation to the system (Figure 1a). After providing the input, the system prompts her to select one or more topics related to her situation (Figure 1b). Although we did not detail the topic filtering procedure in the paper, this process is designed to help users focus on the areas they wish to explore. Finally, the system presents her with a list of relevant questions that match her input (Figure 1c). Additionally, the system offers options for her to view relevant excerpts or to visit the original CLIC page for the full content. The deployment of QBR eases the users' burden by allowing them to access legal information without the need to navigate through the comprehensive and intricate CLIC website.

Contrastive Learning Model Training

For CL training, we use AdamW optimizer with a learning rate of 1e-5. We train for 5 epochs with maximum token length 128. The temperature hyper parameter τ is 0.1.

Detailed experiment results

In this section, we provide full results of the experiments.

QB quality Our QB has 38,571 questions in total. We investigate how its size $|QB|$ affects QBR's performance. We perform uniform subsampling to obtain QBs of various sizes. Tables 1 and 2 show document retrieval and scope identification performance, respectively, as we vary $|QB|$ in steps of 10k questions. From the tables, we see that QBR's performance progressively improves as we increase the QB's size. A notable point shown in Table 2 is that even with a small QB (10k), compared with no QB (0 questions), scope identification is drastically improved (acc: 0.5 $\rightarrow$ 0.719; MRR_s: 0.7061 $\rightarrow$ 0.8345). This shows that the QB provides critical information for disambiguating scopes and our CL approach is highly effective even with a small question bank.

For the legal dataset, our question bank QB consists of 15,333 human-composed questions (QB_H) and 23,238 machine-generated questions (QB_M). Generally, human questions are precise and cover almost perfectly the whole document set, while machine questions are mostly precise and give good coverage. Moreover, machine questions are cheaper to obtain and so they are more numerous. Tables 3 and 4 show QBR's performance using QB_H, QB_M, and the complete QB. MPNet's is also shown as a comparison baseline.

From Table 3, in document retrieval, we see that QB_H and QB_M give very similar performance with QB_H having a slight edge over QB_M. Also, both of them outperform MPNet by significant margins. This shows that machine questions are competitive against human ones and both are highly useful. By combining QB_H and QB_M, the final question bank QB is even richer in content, which further hoists QBR's performance. The performance numbers under QB in Table 3 are therefore significantly better than others'. This shows that human and machine can work complementarily to construct a rich question bank. Table 4 shows scope identification performance with different QBs. We see that in this case QB_M gives better performance than QB_H. This is because there are more machine questions than human questions. Therefore, QB_M helps generate more CL training examples compared with QB_H, leading to better scope identification. Other conclusions are similar to those previously mentioned: Human and machine questions complement each other and they are highly useful for QBR to achieve accurate scope identification.

QBR with different language models We have conducted experiments using different language models (in addition to MPNet) to derive the embedding function $T()$ QBR employs to demonstrate that QBR can be incorpoarted with various embedding methods. We replace the embedding function $T()$ of QBR with different embedding methods and evaluate its performance on scope identification. Recall that QBR obtains the adjusted embedding ($T'()$) through contrastive learning and LLM-augmentation. The results are reported in Table 5, where "Original" shows the performance of using $T()$ directly to perform scope identification and "QBR" shows that of using QBR's adjusted embedding ($T'()$). We observe that QBR shows significant advantage over the original embedding methods. For example, the Recall@1 scores of TinyBERT and QBR (with TinyBERT as the baseline embedding) are 0.4390 and 0.8080, respectively. QBR is therefore a general approach that can work with different representation techniques.

Medical Domain In addition to the application in legal contexts, our approach also extends to other professional fields, such as medicine. The National Institutes of Health (NIH)[1] is the primary agency of the United States government responsible for biomedical and public health research. It is composed of 27 different institutes and centers, each focuses on specific areas of health and disease investigation. We collected 100 medical pages from NIMH[2], NIAMS[3], NIAAA[4] and NEI[5]. Based on the medical documents, we obtained 10,393 MGQs (and their answer scopes) as the medical question bank. To perform CL training, we construct training examples using the bank. We generate (10,393; 63,805) positive and negative examples for MGQs. We further augment the training set using LLM-augmentation and obtained (1,848; 10,928) positive and negative examples. The final training set has (12,241;

[1]https://www.nih.gov/

[2]https://www.nimh.nih.gov/

[3]https://www.niams.nih.gov/

[4]https://www.niaaa.nih.gov/

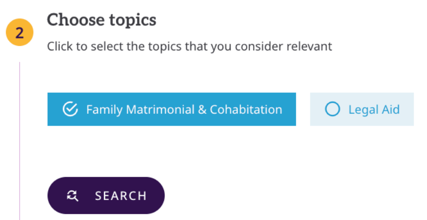
[5]https://www.nei.nih.gov/

74,733) examples in total. Finally, we sample 300 positive $(\hat{u}, s)$ examples that are not included in the training set as our test set U.

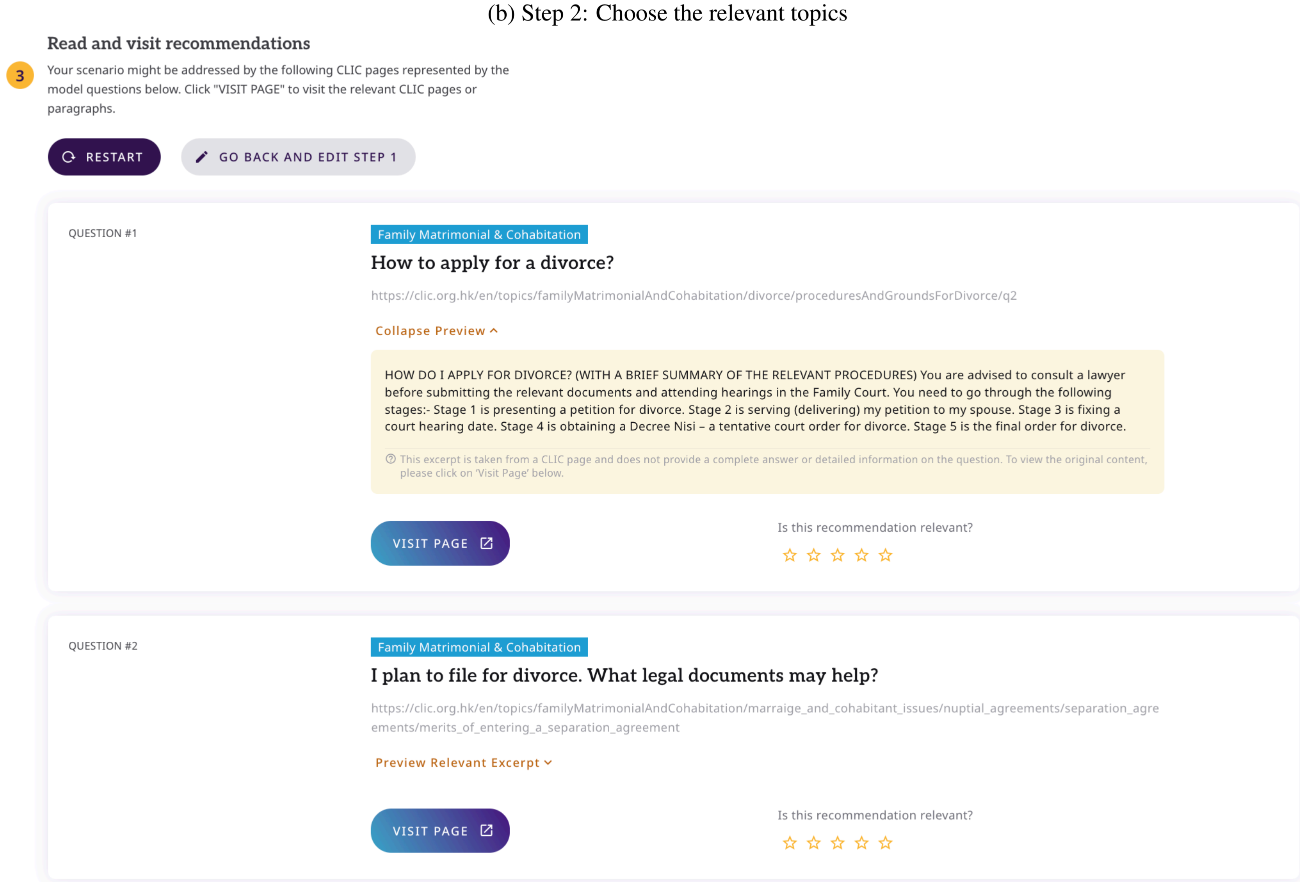
We deployed QBR with the medical data and conducted analogous experiments. Table 6 and Table 7 show the document retrieval and scope identification performance on the Medical Dataset. From the two tables, we can derive similar conclusions regarding performances on document-level and scope-level retrieval, demonstrating that the wide applicability of QBR in different domains.

Document retrieval with QB In the paper, we show the performance of baseline model in terms of document-level retrieval. Here we examine the effectiveness of combining QB with individual methods and evaluate the performance for each baseline approach. The results, illustrated in Table 8 shows a significant enhancement across all models. For example, the Recall@1 performance of BM25 is improved from 0.2540 to 0.3120. This global improvement demonstrates the effectiveness of introducing QB in the domain-specific document retrieval process irrespective of the retrieval model used. Thus, our proposed method of using QB is an effective and broadly applicable approach in improving domain-specific document retrieval.

(a) Step 1: Describe the situation using text or voice input



(b) Step 2: Choose the relevant topics



(c) Step 3: Read recommended questions, excerpts and CLIC pages

Figure 1: Demo of the deployed QBR

	0	10k	20k	30k	All (38.57k)
Recall@1	0.4500	0.4930	0.5180	0.5320	0.5400
Recall@3	0.6670	0.6690	0.7020	0.7130	0.7230
Recall@5	0.7360	0.7610	0.7840	0.7870	0.8050
MRR_d	0.5739	0.5994	0.6275	0.6379	0.6482

Table 1: Document retrieval performance vs. $|QB|$ (Legal Datset)

	0	10k	20k	30k	All (38.57k)
acc	0.5000	0.7190	0.7420	0.8130	0.8370
MRR_s	0.7061	0.8345	0.8547	0.8961	0.9100

Table 2: Scope identification performance vs. $|QB|$ (Legal Datset)

	MPNet	QBR		
		QB_H	QB_M	QB
Recall@1	0.4500	0.5160	0.5090	0.5400
Recall@3	0.6670	0.7050	0.6990	0.7230
Recall@5	0.7360	0.7760	0.7700	0.8050
MRR_d	0.5739	0.6242	0.6192	0.6482

Table 3: Document retrieval performance with different Legal QBs

	MPNet	QBR		
		QB_H	QB_M	QB
acc	0.5000	0.7450	0.7810	0.8370
MRR_s	0.7061	0.8553	0.8728	0.9100

Table 4: Scope identification performance with different Legal QBs

	TinyBERT		BERT		RoBERTa		ANCE		DPR		TAS-B		SBERT		MPNet	
	Original	QBR	Original	QBR	Original	QBR	Original	QBR	Original	QBR	Original	QBR	Original	QBR	Original	QBR
Recall@1	0.4390	0.8080	0.4650	0.8260	0.4500	0.8180	0.4410	0.8170	0.3580	0.8140	0.4390	0.8110	0.4870	0.8200	0.5000	0.8370
MRR_s	0.6638	0.8915	0.6763	0.9022	0.6683	0.8974	0.6570	0.8982	0.5964	0.8986	0.6631	0.8946	0.6963	0.8992	0.7061	0.9100

Table 5: Scope identification of QBR with different embedding methods (Legal Dataset)

	Lexical	Sparse Models		Dense Models							
	BM25	SPARTA	docT5query	TinyBERT	BERT	RoBERTa	ANCE	DPR	TAS-B	SBERT	MPNet	QBR
Recall@1	0.4067	0.2433	0.3867	0.4467	0.5067	0.3900	0.4833	0.3467	0.5033	0.5333	0.6133	**0.6467**
Recall@3	0.5867	0.4100	0.6067	0.6067	0.6700	0.5467	0.6167	0.5400	0.6700	0.7167	0.6783	**0.7733**
Recall@5	0.6933	0.5067	0.6700	0.6833	0.7333	0.6400	0.6900	0.6500	0.7333	0.7700	0.6938	**0.8333**
MRR_d	0.5193	0.3564	0.5117	0.5508	0.5995	0.4963	0.5713	0.4661	0.6019	0.6385	0.7003	**0.7244**

Table 6: Document retrieval performance on Medical Dataset

	TinyBERT	BERT	RoBERTa	ANCE	DPR	TAS-B	SBERT	MPNet	QBR	$\text{QBR}_{\neg\text{GPT}}$
acc	0.4767	0.5767	0.5233	0.5600	0.4633	0.5467	0.5967	0.6267	**0.7133**	0.6600
MRR_s	0.6635	0.7335	0.6900	0.7218	0.6403	0.7103	0.7455	0.7679	**0.8263**	0.7982

Table 7: Scope identification performance on Medical Dataset

Method		Lexical	Sparse		Dense					
		BM25	SPARTA	docT5query	TinyBERT	BERT	RoBERTa	ANCE	DPR	TAS-B	SBERT
w/o QB	Recall@1	0.2540	0.1890	0.3300	0.2770	0.3840	0.3300	0.3670	0.1920	0.3900	0.4520
	Recall@3	0.4160	0.3170	0.4950	0.4130	0.5250	0.5100	0.5540	0.3150	0.5700	0.6370
	Recall@5	0.5090	0.3820	0.5800	0.4940	0.6060	0.5750	0.6250	0.3850	0.6520	0.7180
	MRR_d	0.3584	0.2697	0.4333	0.3666	0.4763	0.4364	0.4801	0.2758	0.4993	0.5639
w/ QB	Recall@1	0.3120	0.2470	0.3990	0.3480	0.4530	0.4130	0.4150	0.2080	0.4330	0.5340
	Recall@3	0.4340	0.4090	0.5650	0.5160	0.6250	0.5730	0.5620	0.3380	0.6310	0.7090
	Recall@5	0.5010	0.4770	0.6160	0.5830	0.6890	0.6450	0.6260	0.4030	0.6840	0.7870
	MRR_d	0.3921	0.3468	0.4915	0.4521	0.5551	0.5116	0.5063	0.2922	0.5413	0.6359

Table 8: Results of document-level retrieval across all baselines with and without QB