Generative Query Reformulation Using Ensemble Prompting, Document Fusion, and Relevance Feedback

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Abstract

Query Reformulation (QR) is a set of techniques used to transform a user's original search query to a text that better aligns with the user's intent and improves their search experience. Recently, zero-shot QR has been a promising approach due to its ability to exploit knowledge inherent in large language models. Inspired by the success of ensemble prompting strategies which have benefited other tasks, we investigate if they can improve query reformulation. In this context, we propose two ensemblebased prompting techniques, GenQREnsemble¹ and GenQRFusion which leverage paraphrases of a zero-shot instruction to generate multiple sets of keywords to improve retrieval performance ultimately. We further introduce their post-retrieval variants to incorporate relevance feedback from a variety of sources, including an oracle simulating a human user and a "critic" LLM. We demonstrate that an ensemble of query reformulations can improve retrieval effectiveness by up to 18% on nDCG@10 in pre-retrieval settings and 9% on post-retrieval settings on multiple benchmarks, outperforming all previously reported SOTA results. We perform subsequent analyses to investigate the effects of feedback documents, incorporate domain-specific instructions, filter reformulations, and generate fluent reformulations that might be more beneficial to human searchers. Together, the techniques and the results presented in this paper establish a new state of the art in automated query reformulation for retrieval and suggest promising directions for future research.

1 Introduction

Users searching for relevant documents might not always be able to express their information needs in their initial queries accurately. This could result in queries being vague or ambiguous or lacking the necessary domain vocabulary. Query Reformulation (QR) is a set of techniques used to transform a user's original search query to a text that better aligns with the user's intent and improves their search experience. Such reformulation alleviates the vocabulary mismatch problem by expanding the query with related terms or paraphrasing it into a suitable form by incorporating additional context.

Recently, with the success of large language models (LLMs) (Brown et al., 2020; Peng et al., 2023), a plethora of QR approaches have been developed. The generative capabilities of LLMs have been exploited to produce novel queries (Nogueira et al., 2019), as well as useful keywords to be appended to the users' original queries (Wang et al., 2023c). By gaining exposure to enormous amounts of text during pre-training, prompting has become a promising avenue for utilizing knowledge inherent in an LLM for the benefit of subsequent downstream tasks (Srivastava et al., 2023) especially QR (Jagerman et al., 2023; Weller et al., 2023a).

Unlike training or few-shot learning, zero-shot prompting does not rely on any labeled examples. The advantage of a zero-shot approach is the ease with which a standalone generative model can be used to reformulate queries by prompting a templated piece of instruction along with the original query. Particularly, zero-shot QR can be used to generate keywords by prompting the user's original query along with an instruction that defines the task of query reformulation in natural language like Generate useful search terms for the given query: 'List all the pizzerias in New York'.

However, such a zero-shot prompting approach is still contingent on the exact instruction appearing in the prompt providing plenty of avenues of improvement. While LLMs have been known to vary significantly in performance across different prompts (Zhao et al., 2021; Dhole et al., 2023a) and generation settings (Wiher et al., 2022), many

¹The extended work of Dhole and Agichtein (2024), European Conference on Information Retrieval, 2024

Instruction	Generations
Increase the search efficacy by offering beneficial	age goldfish grow outsmart outlive ageing species
expansion keywords for the query	goldfish grows diet
Enhance search outcomes by recommending ben-	Goldfish breed sizes What kind of goldfish grows
eficial expansion terms to supplement the query	the fastest Do goldfish have scales
Optimize search results by suggesting meaningful	Goldfish genus Betta bonsai or Fancy goldfish also
expansion terms to enhance the query	known as Loachyodidae Family

Table 1: Reformulations generated for the query ("do goldfish grow") differ drastically when generated from three paraphrastic instructions prompted to flan-t5-xxl.

natural language tasks have benefited by exploiting such variation via ensembling multiple prompts or generating diverse reasoning paths (Li et al., 2023c; Arora et al., 2022; Wang et al., 2022). Whether such improvements also transfer to tasks like QR is yet to be determined. We hypothesize that QR might naturally benefit from prompt variation – An ensemble of zero-shot reformulators with paraphrastic instructions can be tasked to look at the input query in diverse ways to elicit different expansions. This work proposes the following contributions:

- We propose two novel pre-retrieval methods, GenQREnsemble and GenQRFusion zero-shot Ensemble based Generative Query Reformulator and Document Fusion which exploit multiple zero-shot instructions for QR generating more effective query reformulations than possible with a single instruction.
- We further introduce their post-retrieval extensions GenQREnsemble-RF and GenQRFusion-RF to incorporate Relevance Feedback from a variety of sources, including human searchers and "critic" LLMs
- We evaluate the proposed methods over four standard IR benchmarks, demonstrating significant relative improvements vs. recent state of the art, of up to 18% on nDCG@10 in preretrieval settings, and of up to 9% nDCG@10 on post-retrieval (feedback) settings, demonstrating increased generalizability of our approach. Further analysis shows how performance is influenced by the number of feedback documents, the number of instructions and domain-specific instructions, and the generation of fluent reformulations.

Next, we summarize the prior work to place our contributions in context.

2 Related Work

Query reformulation is effective in many settings (Carpineto and Romano, 2012). It can be used pre-retrieval, or post-retrieval, via incorporating evidence from feedback, obtained either from a user (relevance feedback) or from top-ranked results (pseudo-relevance feedback) in both sparse (Li et al., 2023a) and dense retrieval settings (Wang et al., 2023d; Yu et al., 2021).

Recently, zero-shot approaches to query reformulation have received considerable attention. Wang et al. (2023c) design a query reformulator by zero-shot prompting an instruction tuned model, FlanT5 (Chung et al., 2022) to generate keywords for query expansion and Pseudo-Relevance Feedback (PRF) incorporation. Jagerman et al. (2023) demonstrate that LLMs can be more powerful than traditional methods for query expansion. Mo et al. (2023) propose a framework to reformulate conversational search queries using LLMs. (Gao et al., 2023)'s framework performs retrieval through fake documents generated by prompting LLMs with user queries. Dhole et al. (2023b, 2024) demonstrate an interactive zero-shot query generation and reformulation interface. Mackie et al. (2023) vary the types of keywords to be generated by prompting for entities, news articles, essays, etc. Dhole and Agichtein (2024) introduce GenQREnsemble by leveraging an ensemble of multiple prompts to generate a combined reformulation.

However, using a single query reformulation can often degrade performance compared to the original query. To address this drawback, prior efforts have incorporated ensemble strategies via keywords from numerous sources or fusing documents from different queries. Gao et al. (2012) combine features extracted from various translation models to generate better query rewrites. Si et al. (2006) perform QR by utilizing multiple external biomedical resources. Hsu and Taksa (2005)

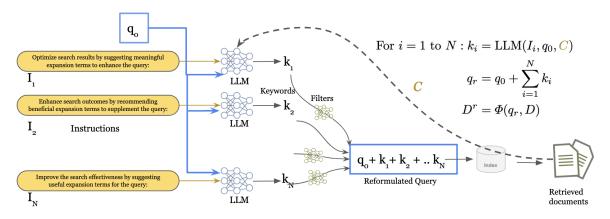


Figure 1: The complete flow and algorithm of GenQREnsemble and GenQREnsemble-RF (dotted).

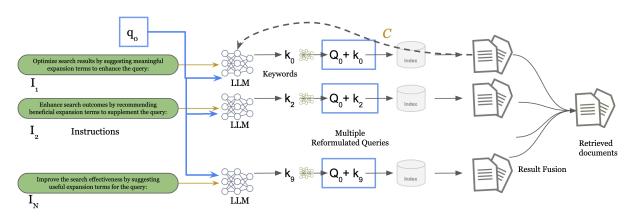


Figure 2: The complete flow of GenQRFusion. GenQRFusion-RF is shown with the dotted line.

present a data fusion framework suggesting that diverse query formulations represent distinct evidence sources for inferring document relevance. Later, Mohankumar et al. (2021) generated diverse queries by introducing a diversity-driven reinforcement learning algorithm. For other tasks, recent works demonstrated the benefits of ensemble strategies for prompting LLMs, including self-consistency (Wang et al., 2022) for arithmetic and common sense tasks, Chain of Verification (Dhuliawala et al., 2023) for improving factuality, and Diverse (Li et al., 2023c) for question answering.

However, zero-shot based ensemble methods for LLMs have hardly been explored for the Query Reformulation task, as we propose in this paper. Mackie et al. (2023) manually create different instructions by invoking different kinds of textual units i.e. news, documents, keywords, essays, etc., and find that combining keywords from above all improves retrieval performance in a traditional setting. Li et al. (2023b) describe an ensemble approach by splitting individual keywords generated from a single LLM pass to generate multiple reformulations and show their benefits for the cross-

encoder based re-rankers.

3 Proposed Approaches

In this section, we describe two variations of our proposed approach, pre- and post-retrieval settings. In the pre-retrieval setting, $q_r = R.q_0$, where a Query Reformulation R transforms a user's expressed query q_0 into a novel reformulated version q_r to improve retrieval effectiveness for a given search task (e.g., passage or document retrieval). We also consider the post-retrieval setting, wherein the reformulator can incorporate additional context like document or passage-level feedback.

3.1 Pre-retrieval

We introduce **GenQREnsemble** and **GenQRFusion** – two ensemble prompting-based query reformulators that use N diverse paraphrases of a QR instruction to enhance retrieval. Specifically, we first use an LLM to paraphrase the instruction I_1 to create N instructions with different surface forms viz. I_1 to I_N . This is done offline once. Each instruction is then prompted along with the user's query q_0 to generate instruction-specific key-

words. These keywords are then optionally passed to another LLM to filter out irrelevant keywords.

- 1. In GenQREnsemble, all the keywords are then appended to the original query, resulting in a reformulated bag-of-words query, which is then executed against a document index D to retrieve relevant documents D^r . The complete process and algorithm are shown in Figure 1.
- 2. In GenQRFusion, each of the multiple keywords generated from the individual instructions are appended one by one to create N reformulations. These are then executed against a document index D to produce N sets of relevant documents D_i . The sets are then fused to create a single ranked list of documents D^r (e.g. score fusion between BM25 scores or reciprocal rank fusion). The complete process is shown in Figure 2.

3.2 Post-retrieval

To assess how well our method can incorporate additional context like document feedback, we introduce GenQREnsemble-RF and GenQRFusion- \mathbf{RF} . Here, we prepend the N instructions described earlier with a fixed context capturing string "Based on the given context information {C}," used² in Wang et al. (2023c) to create their PRF counterparts – where C is a space (' ') delimited concatenation of feedback documents $C = d_1 + \ldots + d_m$, obtained either as pseudorelevance feedback from first-stage retrieval, or human-feedback.

Experiments

We now describe the experiments and analysis performed for different retrieval settings.

4.1 Prompts

To instruct the LLM to generate query reformulations, we start with an instruction empirically chosen by Wang et al. (2023c) - as our base QR instruction I_1 . We use this instruction to generate N paraphrases (N = 10). To this aim, we invoke the ChatGPT API (OpenAI, 2023) with the paraphrase generating prompt, namely, I_p = "Generate 10 paraphrases for the following instruction:"- and the base QR instruction I_1 to obtain I_2 to I_{10} . These paraphrases,

shown in Figure 3 serve as our instruction set for all subsequent experiments.

We further resort to a domain-specific instruction for each of the datasets described in the upcoming section which is paraphrased similarly.

- Improve the search effectiveness by suggesting expansion terms for the query

- Recommend expansion terms for the query to improve search results Improve the search effectiveness by suggesting useful expansion terms for the query Maximize search utility by suggesting relevant expansion phrases for the query
- Enhance search efficiency by proposing valuable terms to expand the query Elevate search performance by recommending relevant expansion phrases for the query Boost the search accuracy by providing helpful expansion terms to enrich the query Increase the search efficacy by offering beneficial expansion keywords for the query
- Optimize search results by suggesting meaningful expansion terms to enhance the query Enhance search outcomes by recommending beneficial expansion terms to supplement the query

Figure 3: The N reformulation instructions used for GenQREnsemble and GenQRFusion

4.2 Generation Models

For reformulations, generating the query we employ two models, flan-t5-xxl and Llama-2-7b-chat-hf. FlanT5 (Chung et al., 2022) is a set of models are created by fine-tuning the text-to-text transformer model, T5 (Raffel et al., 2020) on instruction data of a variety of NL tasks. We use the checkpoint³ provided through HuggingFace's Transformers library(HF) (Wolf et al., 2020). Nucleus sampling is performed with a cutoff probability of 0.92 keeping top 200 tokens (top_k) and a repetition penalty of 1.2.

We also investigate the use of Llama-2-7b-chat-hf (Touvron et al., 2023), an auto-regressive language model, which is RLHF fine-tuned and optimized for dialog use cases. We chose the LLama2 series of models as they have shown state-of-the-art performance across multiple benchmarks. We use the HF checkpoint⁴ keeping the same generation settings as above with a repetition penalty of 2.1. We use the prompt template shown in Figure 4 where the instruction variable is the concatenation of the actual instruction and the query provided at run-time. We appended "And do not explain yourself." to minimize the conversational jargon that the model could generate.

4.3 Retrieval Evaluation

For evaluation, we use four popular benchmarks through IRDataset (MacAvaney et al., 2021)'s interface.

1) TP19: TREC 19 Passage Ranking which uses the MSMarco dataset (Nguyen et al., 2016;

²We found prepending this string performs better than appending it at the end during prompting

³huggingface.co/google/flan-t5-xxl

⁴huggingface.co/meta-llama/Llama-2-7b-chat-hf

	Reformulation	TREC Pa	assage 19		TREC Robus	st 04	Webis	Fouche	DBpedia	Entity
Model	Name	nDCG@10	RR(rel=2)	P@10	nDCG@10	RR(rel=2)	nDCG@10	RR(rel=2)	nDCG@10	RR(rel=2)
	BM25	.480	.642	.426	.434	.154	.260	.454	.321	.297
GPT3-curie	Query2Doc (Wang et al., 2023a)	.551	-	-	-	-	-	-	-	-
	GenQR	.477	.593	.473	.483	.151	.315	.511	.342	.345
	$GenQR_{\beta=.05}$.511	.621	.469	.477	.150	.276	.476	.353	.339
	GenQR+FL	.489	.653	.439	.446	.151	.262	.459	.326	.305
	GenQR (Wang et al., 2023c)	.556	.707	-	.461	-	-	-	-	-
flan-t5-xxl	GenQREnsemble (Dhole and Agichtein, 2024)	.564 [†]	.706	.500 [†]	.513 [†]	.159	.317	.555	.374 [†]	.376 [†]
	GenQREnsemble _{$\beta=.05$}	.575 [†]	.714	.502 [†]	.512 [†]	.159	.292	.489	.377 [†]	.380 [†]
	GenQREnsemble+FL	.537 [†]	.694	.482 [†]	.492 [†]	.151	.272	.467	.361 [†]	.341 [†]
	GenQRFusion	.565 [†]	.717 [†]	.502 [†]	.513 [†]	.160	.302	.529	.373	.379
	GenQRFusion+FL	.558	.698 [†]	.493	.503	.155	.278	.489	.370 [†]	.360
	GenQR	.496	.678	.451	.461	.156	.268	.462	.328	.304
	GenQR+FL	.493	.666	.449	.459	.156	.267	.464	.329	.304
	KEQE (Lei et al., 2024)	.571	-	-	-	-	-	-	-	-
llama-2-7b	GenQREnsemble	.580 [†]	.703 [†]	.504 [†]	.513 [†]	.173	.319 [†]	.579 [†]	.370 [†]	.372 [†]
	GenQREnsemble+FL	.575 [†]	.744	.510 [†]	.519 [†]	.166	.314 [†]	.543	372 [†]	$.372^{\dagger}$
	GenQRFusion	.503	.679	.453	.461	.158	.268	.465	.328	.304
	GenQRFusion+FL	.497	.673	.448	.457	.157	.268	.463	.326	.304

Table 2: Performance of GenQREnsemble and GenQRFusion on the four benchmarks with two underlying models. † denotes significant improvements (paired t-test with Holm-Bonferroni correction, p < 0.05) over GenQR.

You are a helpful assistant who directly provides comma separated keywords or expansion terms. Provide as many expansion terms or keywords as possible related to the query. And do not explain yourself. instruction: query

Figure 4: The prompt used for all the Llama-2 Query reformulators.

Jagerman et al., 2023) consisting of search engine queries. 2) **TR04**: TREC Robust 2004 Track, a task intended for testing poorly performing topics. In our experiments, we use title as our choice of query. And two tasks from the BEIR (Thakur et al., 2021) benchmark 3) **WT**: Webis Touche (Bondarenko et al., 2020) for argument retrieval and 4) **DE**: DBPedia Entity Retrieval (Hasibi et al., 2017), a test collection for entity search.

4.4 Baselines

We compare our work against the following using the Pyterrier (Macdonald et al., 2021) framework. For all the post-retrieval experiments, we used 5 documents as feedback.

4.4.1 Experiments with BM25 Retriever

Here, we compare with the following approaches.

- 1. BM25: Here, we retrieve using raw queries without any reformulation
- 2. GenQR: We implement a single-instruction zero-shot QR (Wang et al., 2023c) which is also a specific case of our approach when N=1 with flan-t5-xxl and llama-2-7b.
- 3. Query2Doc (Wang et al., 2023a)'s reformulation generated via a GPT3-curie model

- (6.7B), which is the closest in size to flan-t5-xxl (11.3B) and llama-2-7b (7B).
- 4. BM25+RM3 (Abdul-Jaleel et al., 2004): BM25 retrieval with RM3 expanded queries (#feedback terms=10)
- 5. BM25+GenPRF (Wang et al., 2023c): BM25 retrieval with GenPRF expanded queries
- 6. GenQREnsemble: The ensemble query reformulation introduced by Dhole and Agichtein (2024) which used a FlanT5 generator.
- 7. GenQREnsemble-RF: The corresponding PRF variant.

4.4.2 Experiments with Neural Reranking

Here, we re-evaluate the above settings in conjunction with a MonoT5 neural reranker with all other parameters constant. We use the MonoT5 base version castorini/monot5-base-msmarco through the PyTerrier_t5 plugin⁵.

- 1. BM25+MonoT5: BM25 retrieval using raw queries, re-ranked with MonoT5 model (Pradeep et al., 2021)
- {GenQREnsemble\GenQR}+MonoT5: BM25 retrieval with GenQREnsemble\ GenQR reformulations, re-ranked with MonoT5 model
- 3. BM25+RM3+MonoT5: BM25 retrieval with RM3 expanded queries, re-ranked with MonoT5 model

⁵https://github.com/terrierteam/pyterrier_t5

4. BM25+{GenQREnsemble-RF\GenPRF}+MonoT5: BM25 retrieval with GenQREnsemble-RF\ GenPRF expanded queries, re-ranked with MonoT5 model

5 Results and Analysis

We now report the results of query reformulation for all the settings and present further analysis.

5.1 Pre-Retrieval Performance

We first compare the retrieval performances of raw queries and the reformulations from GenQR, with GenQREnsemble and GenQRFusion in Table 2. Both GenQREnsemble and GenQRFusion outperform the raw queries as well as generate better reformulations than GenQR's queries across all four benchmarks over a BM25 retriever. GenQREnsemble improves performance over the single instruction setting through keywords generated from both the underlying generators, FlanT5 and Llama-7-b with Llama-7-b showing better gains. The performance also gradually improves with more number of instructions as seen in Figure 6.2. This indicates the usefulness of paraphrasing initial instructions and exploiting the model's sensitivity. On TP19, nDCG@10 and MAP improve significantly with relative improvements of 18% and 24% respectively. This is further validated through the querywise analysis shown in Figure 6.1 – Relative to BM25, nDCG@10 scores of GenQREnsemble are overall better than GenQR.GenQREnsemble seems more robust too as it avoids drastic degradation in at least 6 queries on which GenQR fails. Example reformulations are shown in Figure 5, where crucial keywords are produced through GenQREnsemble's paraphrasing.

We further look at GenQREnsemble under the neural reranker setting shown in Table 3. In three of the four settings, viz., TP19, WT, and DE, GenQREnsemble is preferable to its zero-shot variant, GenQR. Evidently, the gains of both the zero-shot approaches in the traditional setting are stronger vis-à-vis the neural setting. We hypothesize this could be due to GenQREnsemble and GenQR both expanding the query by incorporating semantically similar but lexically different keywords. Comparatively, neural models are adept at capturing notions of semantic similarity and might benefit less from QR. This also is in line with Weller et al. (2023b)'s recent analysis on the non-ensemble variant.

5.2 Post-Retrieval Performance

We now investigate if GenQREnsemble-RF and GenQRFusion-RF can effectively incorporate PRF in Table 4. While GenQRFusion-RF improves recall, we find that GenQREnsemble-RF improves retrieval performance across all metrics as compared to other PRF approaches and is able to incorporate feedback from a BM25 retriever better than RM3 as well as its zero-shot counterpart. To assess if GenQREnsemble-RF and GenPRF can at all benefit from incorporating relevant documents, we perform oracle testing by providing the highest relevant gold documents as context. We find that GenQREnsemble-RF is able to improve over GenQREnsemble (without feedback) showing that it is able to capture context effectively as well as benefit from it. It can incorporate relevant feedback better than its single-instruction counterpart GenPRF. We notice improvements even under the neural setting as GenQREnsemble-RF outperforms RM3 and GenPRF. Besides, the oracle improvements are higher with only a BM25 retriever as compared to when a neural reranker is introduced.

6 Analysis

Our complete ensemble pipeline has multiple directions in which performance can be improved. In this section, we attempt to vary the number of feedback documents, relative influence of the keywords and incorporate domain specific instructions to seek additional gains.

6.0.1 Increasing Feedback Documents

We further evaluate the effect of varying the number of feedback documents from 0 to 5. We notice that resorting to an ensemble approach is highly beneficial as seen in Figure 6.2. In the BM25 setting, the ensemble approach seems always preferable. Under the neural reranker setting too,GenQREnsemble-RF almost always outperforms GenPRF.

6.0.2 Relative Influence of Reformulation

We vary the relative influence of the reformulated query by upweighting its terms as compared to the original query. We use the constant $\beta \in [0,1]$ to denote the proportional of reformulated query terms. When $\beta=0$, the query consists of original query terms, and when $\beta=1$, the query consists of terms from the original query as well as the generated keywords. We plot the nDCG@10 scores on MS-Marco for GenQR and GenQREnsemble

Original Query what is theraderm used for GenQR Generated Keywords ...is a topical and external painkilling patch which was first registered as Tradexedrine in Japan... Theraderm is a medicated cream used to treat open wounds such as leg ulcers diabetic foot ulcers or pressure ulcers... GenQREnsemble Generated Keywords Theraderm is a topical and external painkilling patch ... is a registered brand name of products a ..a medicated cream used to treat open wounds .. Its application on toe areas has been described in a preclinical... ...antiviral immunosuppressant used in combination with a dose of lamivudine to reduce mortality ... is a low dose topical anesthetic cream that relieves itching ... which helps treat non specific skin infections ... used for topical treatment of patients after enucleation for skin defects ... is an amino acid derivative used in medicine and cosmetics The use of contraceptive patches ... This article refers to topical anesthetics available in the US ... Intensive Care is a medication approved for treating ... and it may leave a thin film that will eventually go well ... Because immune system suppressor

Figure 5: Query Reformulations generated from the Single Instruction Setting and the Ensemble Setting. The grey highlights depict the terms present in the highest relevant (gold) documents.

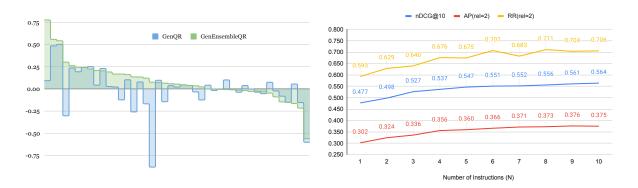


Figure 6: 1) Relative nDCG@10 scores of GenQREnsemble as compared to GenQR on TP19 benchmark 2) On TP19, GenQREnsemble improves as the number of instructions are increased.

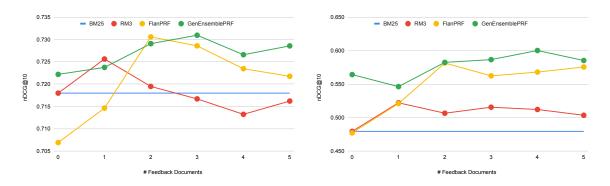


Figure 7: Effect of PRF with increasing feedback on the sparse (BM25) and the neural (MonoT5) setting on TP19.

Reformulation		TREC Passage 19		TREC Robust 04			Webis Touche		DBpedia Entity	
Model	Name	nDCG@10	RR(rel=2)	P@10	nDCG@10	RR(rel=2)	nDCG@10	RR(rel=2)	nDCG@10	RR(rel=2)
	BM25+MonoT5	.718	.881	.492	.513	.173	.299	.525	.414	.444
GPT3-curie	Query2Doc (Wang et al., 2023a)	.687	-	-	-	-	-	-	-	-
-	HyDE (Gao et al., 2023)	.613	-	-	-	-	-	-	-	-
-	Doc2Query (Nogueira et al., 2019)	.627	-	-	-	-	-	-	-	-
-	Doc2Query- (Gospodinov et al., 2023)	.670	-	-	-	-	-	-	-	-
	T5QR (Wang et al., 2023c)	.696	.831	-	.474	-	-	-	-	-
	$GenQR^M$.707	.847	.490	.510	.170	.292	.530	.415	.446
	$GenQR^M+FL$.720	.881	.491	.511	.170	.299	.530	.415	.438
flan-t5-xxl	GenQR ^M (Wang et al., 2023c)	.727	.908		.473	-	-	-	-	-
	GenQREnsemble ^M (Dhole and Agichtein, 2024)	.722	.862	.484	.506	.170	.298	.548	.420	.450
	GenQREnsemble ^M +FL	.725	.867	.488	.509	.170	.297	.528	.418	.438
	GenQRFusion M	.723	.875	.404	.422	.157	.301	.529	.403	.433
	GenQRFusion ^M +FL	.729	.881	.438	.455	.163	.296	.528	.411	.439
	$GenQR^M$.729	.881	.490	.510	.170	.300	.530	.414	.442
	$GenQR^M+FL$.719	.858	.488	.510	.170	.300	.528	.419	.448
llama-2-7b	$GenQREnsemble^M$.730	.869	.488	.510	.170	.300	.532	.415	.444
	GenQREnsemble ^M +FL	.729	.869	.490	.511	.169	.299	.527	.415	.441
	GenQRFusion M	.728	.881	.470	.487	.168	.300	.528	.412	.440
	GenQRFusion ^M +FL	.721	.881	.470	.488	.166	.300	.528	.413	.441

Table 3: Performance of GenQREnsemble and GenQRFusion under the neural setting and compared with other neural approaches. The superscript M denotes reranking through a MonoT5 reranker.

		With BM25	Retriever		With Neural Reranking			
Setting	nDCG@10	nDCG@20	MAP	MRR	nDCG@10	nDCG@20	MAP	MRR
BM25	.480	.473	.286	.642	.718	.696	.477	.881
RM3	.504	.496	.311	.595	.716	.699	.480	.858
GenPRF	.576	.553	.363	.715	.722	.703	.486	.874
GenPRF (Wang et al., 2023c)	.628	-	.404	.809	-	-	-	-
GenQREnsemble-RF	.585 +2 %	.560+1%	.373+3%	.753+5%	.729+1%	.706+1%	.501+3%	.894+2%
GenQRFusion-RF	.566	.548	.368	.725	.718	.707	.488	.882
GenPRF (Oracle)	.753	.728	.501	.936	.742	.734	.545	.881
GenQREnsemble-RF (Oracle)	$.820^{\circ} + 9\%$.773+6%	.545+9%	.977+4%	.756+2%	.751+2%	.545	.897+2%
GenQRFusion-RF (Oracle)	.708	.672	.465	.938	.748	.731	.532	.887

Table 4: Comparison of PRF performance on the TP19 benchmark using queries generated from flan-t5-xxl

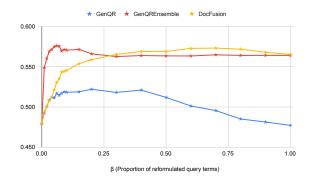


Figure 8: Effect on TP19 nDCG@10 on varying the relative influence of the reformulated query as compared to the original query.

in Figure 8. We notice that the performance peaks for β values of less than 0.2. We use terrierql query language and linearly interpolate between the original query and the reformulated query.

Besides, the performance of the single instruction setting tends to decrease with the increasing influence of reformulated terms while in the ensemble setting, the performance remains constant. This entails that ensemble prompting can not only produce more useful keywords but also reemphasize the crucial ones through different instructions.

6.1 Incorporating Domain Information

The enhanced effectiveness of the ensemble approach can be attributed to the sensitivity of LLMs to inputs with minor differences (Zhao et al., 2021; Dhole et al., 2023a). Investigating if the models are equally responsive to paraphrastic instructions that emphasize domain-specific keywords might be beneficial to improve performance over specific target domains. We hence measure if domain-specific instructions can further improve the retrieval effectiveness of the target benchmark. We modify the initial instruction I_1 to instruct the model to take into consideration the target domain. For instance, for DBPedia Entity Retrieval, we define I_1 as shown in Figure 10. We then paraphrase as before to generate N=10 instructions and reevaluate retrieval performance.

The results are shown in Table 5. Using domain-specific instructions improves over generic instructions across all the benchmarks in the BM25 single instruction setting. In the ensemble setting, nDCG@10 improves for the three domain-specific datasets - TR04, WT, and DB. In the neural setting,

	TREC Pa	ssage 19	TREC Robust 04		Webis Touche		DBpedia	Entity
Setting	nDCG@10	RR(rel=2)	nDCG@10	RR(rel=2)	nDCG@10	RR(rel=2)	nDCG@10	RR(rel=2)
GenQR	.496	.678	.461	.156	.268	.462	.328	.304
+DSI	.504	.679	.467	.158	.271	.471	.331	.309
GenEnsembleQR	.580	.703	.513	.173	.319	.579	.370	.372
+DSI	.573	.693	.522	.169	.330	.576	.377	.378
GenQR+MonoT5	.729	.881	.510	.170	.300	.530	.414	.442
+DSI	.723	.881	.509	.171	.297	.530	.417	.437
GenEnsembleQR+MonoT5	.730	.869	.510	.170	.300	.532	.415	.444
+DSI	.732	.869	.512	.171	.299	.530	.416	.448

Table 5: Impact of using domain-specific instruction (DSI) as the initial instruction. Values in bold signify where the domain-specific instruction improves performance vis-à-vis the general instruction counterpart.

Reformulation: 12Expansion termsof Gold fish growing growthrate food size tanks health Golden Goldie s Aquatic Fish Food Growth Size Inquiry 1 size of golden fish 2 golden size limits admission tickets in an underwater setting 3 compilation records from aquatic plants about growth statistics 4 information on food required 1 Aquarium care tip sheet growth rate chart ATSolutions MidCoastUtePlymDump FASTBACCP 13 keyworssgrowth development increase in length aquarium pets water body size environment food diet care exercise breeding habitat lifespan Post Filtering: Goldfish growing, growth rate, food, size, health, Aquatic Fish Food Growth Size, size of golden fish, information on food required, Aquarium care tip sheet growth rate chart, growth development, increase in length, aquarium pets, water body size, environment, food, diet, care, breeding, habitat, lifespan.

Figure 9: Sample Reformulation from flan-t5-xxl for the query "do goldfish grow" before and after filtering

Given a focused collection of arguments and some socially important and controversial topic, the keywords should retrieve arguments that could help an individual forming an opinion on the topic, or arguments that support/challenge their existing stance. Improve the search effectiveness of argument retrieval by suggesting related expansion terms for the query.

Figure 10: QR prompt used with 11ama-2-7b

the DB Entity Retrieval sees improvement in both single instruction and ensemble settings.

6.2 Filtering Query Reformulations

We noticed that many of the produced reformulations are verbose, and hence we perform automated filtering to keep only the most relevant keywords. For this task, we prompt the GPT-4 API to filter the query reformulations from flan-t5-xxl as well as llama-2-7b-chat-hf and measure the retrieval effectiveness of the reformulations (shown as FL in Figure 2). The results for different proportions of the reformulated and filtered queries are shown in Figure 8 and 11. With the addition of a filter layer, the performance almost remains the same but the interpretability of the queries increases drastically (described in detail in subsection 6.3).

6.3 Exploring Interpretable Reformulations

	Comparisons	nDCG@10	Interpretability
GenQR	KW vs NL	.496 vs .479	36 vs 50
GeliQK	KW vs FL	.496 vs .493	3 vs 83
GenQREnsemble	KW vs NL	.580 vs .529	37 vs 49
	KW vs FL	.580 vs .575	5 vs 81

Table 6: Comparison of Keyword reformulations (KW) with Filtered (FL) and Natural Language reformulations (NL) alongwith interpretability preferences out of 86

While keyword-based reformulations generated from LLMs improve retrieval effectiveness on multiple benchmarks, they can sometimes be messy and hard to interpret and may lack fluency to the level desired for other downstream applications like question answering. Some studies (Faruqui and Das, 2018; Chu et al., 2020; Chikkamath et al., 2024) have emphasized the importance of fluent reformulations or generated well-formed expansions (Wang et al., 2023a). In that regard, we modify the instructions to elicit natural language reformulations (shown in Figure 13) and attempt to generate comparatively fluent and interpretable reformulations rather than keywords. In addition to retrieval effectiveness, we perform a model-based evaluation using GPT-4 (OpenAI, 2023) to compare the interpretability of keyword-based queries and natural language queries through the prompt shown in Figure 12. The order of the queries being compared is reversed and evaluation (on 43 queries) is reperformed to mitigate possible position bias (Wang et al., 2023b). We find that while nDCG@10 drops slightly, reformulations are comparatively more interpretable and easy to understand. Filtered queries are also preferred against their pre-filtered counterparts. The results are shown in Table 6.

7 Conclusions

Zero-shot QR is advantageous since it does not rely on any labeled relevance judgments and allows eliciting pre-trained knowledge in the form of keywords by prompting the model with the original query and appropriate instruction. By intro-

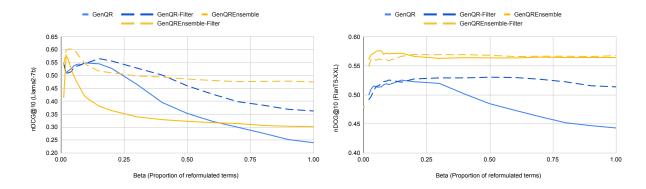


Figure 11: Effect of Filtering on Llama2 (left) and FlanT5 (right) generated keywords for TP19.

Which one of the following query reformulations for the original query ... is more interpretable and easy to comprehend and understand for a reader. First analyze both the reformulations and provide a short explanation why one is more interpretable than the other and then specify reformulation A or reformulation B as your final option

Reformulation A: ...

Reformulation B: ...

Specify either A or B.

Figure 12: Evaluation Prompt Used to Measure Interpretability of the Generated Reformulations. The evaluation was performed with the order of the placeholders reversed too.

You are a helpful assistant who directly provides a natural language reformulated query with novel keywords related to the user's original query. Do not explain yourself. Just return a natural language query.

Figure 13: Prompt Used to Generate Natural Language Reformulations

ducing GenQREnsemble and GenQRFusion, we show that zero-shot performance can be further enhanced by using multiple views of the initial instruction, both as a unified query and through document fusion. We also show that the PRF extension GenQREnsemble-RF can effectively incorporate relevance feedback, either automated or from users. With domain-specific instructions, we can further incorporate specific information to improve effectiveness over benchmarks with specific focus. A final filtration step to convert messy keywords to their fluent counterparts helps increase interpretability. Our proposed ensemble approach improves upon the state-of-the-art zero shot reformulation and can be applied to a variety of settings, for example, to address different aspects of queries or metrics to optimize, or to better control the generated reformulations, or for improving queries for retrieval augmented generation.

8 Limitations

While generative QR greatly benefits from our ensemble approach, the proposed methods come at a cost of potentially increased latency, but this is becoming less problematic with the increased availability of batch inference for LLMs.

In our work, we have presented a zero-shot approach for incorporating domain-related information through domain descriptions. There are other ways to incorporate domain information like presenting exemplar documents of the target domain or sample terms or phrases of the same. Our objective was to establish the benefits of ensembling while also presenting baselines of ancillary avenues of increasing performance. Further performance enhancement could be achieved by resorting to each of those directions.

The interpretability of not only query reformulations but even of other language phenomena is often highly subjective (Miller, 2019) and it could vary according to the intended application. Besides, it could be argued that natural language might not always be the best mode for interpretability. While natural language expressions could communicate the precise intent, keywords could also be useful for clustering or visualization – and hence both being useful for interpretability. Our work closely

adheres to the former definition of interpretability.

9 Ethical considerations

Large Language Models should be conceptualized as socio-technical subsystems (Selbst et al., 2019; Dhole, 2023). Although our research did not identify harmful outputs, it is essential to acknowledge that other instances, might produce toxic or harmful keywords. Consequently, reformulators must undergo rigorous testing before deployment to ensure that the generated content, particularly keywords, does not exhibit toxicity or bias. Such precautionary measures are critical in mitigating potential risks associated with the deployment of LLMs.

References

- Nasreen Abdul-Jaleel, James Allan, W Bruce Croft, Fernando Diaz, Leah Larkey, Xiaoyan Li, Mark D Smucker, and Courtney Wade. 2004. Umass at trec 2004: Novelty and hard. page 189.
- Simran Arora, Avanika Narayan, Mayee F Chen, Laurel Orr, Neel Guha, Kush Bhatia, Ines Chami, and Christopher Re. 2022. Ask me anything: A simple strategy for prompting language models. In *The Eleventh International Conference on Learning Representations*.
- Alexander Bondarenko, Matthias Hagen, Martin Potthast, Henning Wachsmuth, Meriem Beloucif, Chris Biemann, Alexander Panchenko, and Benno Stein. 2020. Touché: First shared task on argument retrieval. In Advances in Information Retrieval: 42nd European Conference on IR Research, ECIR 2020, Lisbon, Portugal, April 14–17, 2020, Proceedings, Part II 42, pages 517–523. Springer.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. volume 33, pages 1877–1901.
- Claudio Carpineto and Giovanni Romano. 2012. A survey of automatic query expansion in information retrieval. *Acm Computing Surveys (CSUR)*, 44(1):1–50.
- Renukswamy Chikkamath, Deepak Rastogi, Mahesh Maan, and Markus Endres. 2024. Is your search query well-formed? a natural query understanding for patent prior art search. *World Patent Information*, 76:102254.
- Zewei Chu, Mingda Chen, Jing Chen, Miaosen Wang, Kevin Gimpel, Manaal Faruqui, and Xiance Si. 2020. How to ask better questions? a large-scale multidomain dataset for rewriting ill-formed questions. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 7586–7593.

- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. arXiv preprint arXiv:2210.11416.
- Kaustubh Dhole. 2023. Large language models as SocioTechnical systems. In *Proceedings of the Big Picture Workshop*, pages 66–79, Singapore, Singapore. Association for Computational Linguistics.
- Kaustubh Dhole, Varun Gangal, Sebastian Gehrmann, Aadesh Gupta, Zhenhao Li, Saad Mahamood, Abinaya Mahadiran, Simon Mille, Ashish Shrivastava, Samson Tan, et al. 2023a. Nl-augmenter: A framework for task-sensitive natural language augmentation. Northern European Journal of Language Technology, 9(1).
- Kaustubh D. Dhole and Eugene Agichtein. 2024. Genqrensemble: Zero-shot llm ensemble prompting for generative query reformulation. In *Advances in Information Retrieval*, pages 326–335, Cham. Springer Nature Switzerland.
- Kaustubh D. Dhole, Shivam Bajaj, Ramraj Chandradevan, and Eugene Agichtein. 2024. Queryexplorer: An interactive query generation assistant for search and exploration. In 2024 Annual Conference of the North American Chapter of the Association for Computational Linguistics System Demonstration Track. Video: https://www.youtube.com/watch?v=sXBU8-uWR3o, Code: https://github.com/emory-irlab/query-explorer.
- Kaustubh D. Dhole, Ramraj Chandradevan, and Eugene Agichtein. 2023b. An interactive query generation assistant using llm-based prompt modification and user feedback.
- Shehzaad Dhuliawala, Mojtaba Komeili, Jing Xu, Roberta Raileanu, Xian Li, Asli Celikyilmaz, and Jason Weston. 2023. Chain-of-verification reduces hallucination in large language models. *arXiv preprint arXiv:2309.11495*.
- Manaal Faruqui and Dipanjan Das. 2018. Identifying Well-formed Natural Language Questions. In *Proc. of EMNLP*.
- Jianfeng Gao, Shasha Xie, Xiaodong He, and Alnur Ali. 2012. Learning lexicon models from search logs for query expansion. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 666–676.
- Luyu Gao, Xueguang Ma, Jimmy Lin, and Jamie Callan. 2023. Precise zero-shot dense retrieval without relevance labels. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1762–1777, Toronto, Canada. Association for Computational Linguistics.

- Mitko Gospodinov, Sean MacAvaney, and Craig Macdonald. 2023. Doc2query—: When less is more. In *European Conference on Information Retrieval*, pages 414–422. Springer.
- Faegheh Hasibi, Fedor Nikolaev, Chenyan Xiong, Krisztian Balog, Svein Erik Bratsberg, Alexander Kotov, and Jamie Callan. 2017. Dbpedia-entity v2: a test collection for entity search. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1265–1268.
- D. Frank Hsu and Isak Taksa. 2005. Comparing rank and score combination methods for data fusion in information retrieval. *Information Retrieval*, 8:449–480.
- Rolf Jagerman, Honglei Zhuang, Zhen Qin, Xuanhui Wang, and Michael Bendersky. 2023. Query expansion by prompting large language models. *arXiv* preprint arXiv:2305.03653.
- Yibin Lei, Yu Cao, Tianyi Zhou, Tao Shen, and Andrew Yates. 2024. Corpus-steered query expansion with large language models. *arXiv preprint arXiv:2402.18031*.
- Hang Li, Ahmed Mourad, Shengyao Zhuang, Bevan Koopman, and Guido Zuccon. 2023a. Pseudo relevance feedback with deep language models and dense retrievers: Successes and pitfalls. *ACM Trans. Inf. Syst.*, 41(3):62:1–62:40.
- Minghan Li, Honglei Zhuang, Kai Hui, Zhen Qin, Jimmy Lin, Rolf Jagerman, Xuanhui Wang, and Michael Bendersky. 2023b. Generate, filter, and fuse: Query expansion via multi-step keyword generation for zero-shot neural rankers. *ArXiv*, abs/2311.09175.
- Yifei Li, Zeqi Lin, Shizhuo Zhang, Qiang Fu, Bei Chen, Jian-Guang Lou, and Weizhu Chen. 2023c. Making language models better reasoners with step-aware verifier. pages 5315–5333.
- Sean MacAvaney, Andrew Yates, Sergey Feldman, Doug Downey, Arman Cohan, and Nazli Goharian. 2021. Simplified data wrangling with ir_datasets. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 2429–2436.
- Craig Macdonald, Nicola Tonellotto, Sean MacAvaney, and Iadh Ounis. 2021. Pyterrier: Declarative experimentation in python from bm25 to dense retrieval. In *Proceedings of the 30th acm international conference on information & knowledge management*, pages 4526–4533.
- Iain Mackie, Shubham Chatterjee, and Jeffrey Dalton. 2023. Generative relevance feedback with large language models. In Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '23, page 2026–2031, New York, NY, USA. Association for Computing Machinery.

- Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial intelligence*, 267:1–38.
- Fengran Mo, Kelong Mao, Yutao Zhu, Yihong Wu, Kaiyu Huang, and Jian-Yun Nie. 2023. ConvGQR: Generative query reformulation for conversational search. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 4998–5012, Toronto, Canada. Association for Computational Linguistics.
- Akash Kumar Mohankumar, Nikit Begwani, and Amit Singh. 2021. Diversity driven query rewriting in search advertising. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 3423–3431.
- Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. 2016. Ms marco: A human-generated machine reading comprehension dataset. In *Proceedings of the International Conference on Learning Representations (ICLR)*.
- Rodrigo Nogueira, Wei Yang, Jimmy Lin, and Kyunghyun Cho. 2019. Document expansion by query prediction. Technical report.
- OpenAI. 2023. Gpt-4 technical report.
- Baolin Peng, Chunyuan Li, Pengcheng He, Michel Galley, and Jianfeng Gao. 2023. Instruction tuning with gpt-4. *arXiv preprint arXiv:2304.03277*.
- Ronak Pradeep, Rodrigo Nogueira, and Jimmy J. Lin. 2021. The expando-mono-duo design pattern for text ranking with pretrained sequence-to-sequence models. *ArXiv*, abs/2101.05667.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, 21(1):5485–5551.
- Andrew D Selbst, Danah Boyd, Sorelle A Friedler, Suresh Venkatasubramanian, and Janet Vertesi. 2019. Fairness and abstraction in sociotechnical systems. In *Proceedings of the conference on fairness, accountability, and transparency*, pages 59–68.
- Luo Si, Jie Lu, and Jamie Callan. 2006. Combining multiple resources, evidences and criteria for genomic information retrieval. In *Text Retrieval Conference*.
- Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. 2023. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *Transactions on Machine Learning Research*.

- Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. 2021. Beir: A heterogeneous benchmark for zero-shot evaluation of information retrieval models. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Liang Wang, Nan Yang, and Furu Wei. 2023a. Query2doc: Query expansion with large language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 9414–9423, Singapore. Association for Computational Linguistics.
- Peiyi Wang, Lei Li, Liang Chen, Dawei Zhu, Binghuai Lin, Yunbo Cao, Qi Liu, Tianyu Liu, and Zhifang Sui. 2023b. Large language models are not fair evaluators. *ArXiv*, abs/2305.17926.
- Xiao Wang, Sean MacAvaney, Craig Macdonald, and Iadh Ounis. 2023c. Generative query reformulation for effective adhoc search. In *The First Workshop on Generative Information Retrieval*, SIGIR 2023.
- Xiao Wang, Craig Macdonald, Nicola Tonellotto, and Iadh Ounis. 2023d. Colbert-prf: Semantic pseudorelevance feedback for dense passage and document retrieval. *ACM Transactions on the Web*, 17(1):1–39.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2022. Self-consistency improves chain of thought reasoning in language models.
- Orion Weller, Kyle Lo, David Wadden, Dawn Lawrie, Benjamin Van Durme, Arman Cohan, and Luca Soldaini. 2023a. When do generative query and document expansions fail? a comprehensive study across methods, retrievers, and datasets. *arXiv preprint arXiv:2309.08541*.
- Orion Weller, Kyle Lo, David Wadden, Dawn J Lawrie, Benjamin Van Durme, Arman Cohan, and Luca Soldaini. 2023b. When do generative query and document expansions fail? a comprehensive study across methods, retrievers, and datasets. *ArXiv*, abs/2309.08541.
- Gian Wiher, Clara Meister, and Ryan Cotterell. 2022. On decoding strategies for neural text generators. *Transactions of the Association for Computational Linguistics*, 10:997–1012.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 conference on empirical methods in natural language processing: system demonstrations*, pages 38–45.

- HongChien Yu, Chenyan Xiong, and Jamie Callan. 2021. Improving query representations for dense retrieval with pseudo relevance feedback. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 3592–3596.
- Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. 2021. Calibrate before use: Improving few-shot performance of language models. In *International Conference on Machine Learning*, pages 12697–12706. PMLR.