Generating Complex Question Decompositions in the Face of Distribution Shifts

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Abstract

Question decomposition has been found to help large language models' (LLMs) performance on complex question answering (QA) by breaking these questions into simpler sub-questions for answering. Nonetheless, performance on the task remains dominated by supervised approaches, suggesting room for making LLMs better decomposers. One way of improving LLM training and fine-tuning is to leverage synthetic training data, but the superior performance of supervised approaches collapses in the face of distribution shifts, making them unsuitable for generating synthetic data across new domains and at scale. To address this, we propose an approach to generate synthetic decomposition data with only five annotated examples; we do this by (i) extending recent advancements in using LLM-as-judge and for reranking in novel ways, as well as (ii) using a panel of smaller-sized LLMs for data generation instead of resource-intensive larger models. Through careful validation of our approach over two benchmark datasets, we show that our data generation and modelling approaches bring consistent improvements over using few-shot prompting with LLMs for the task. Our code and models can be found at https://github.com/hankelvin/complex_question_decomposition.

1 Introduction

The ability of large language models (LLMs) to perform on tasks not seen at training, especially reasoning-related ones, is a keen subject of research recently (Brown et al., 2020; Wei et al., 2024; Wang et al., 2023a). However, a "compositionality gap" remains as models scale in size, i.e. even as LLMs with larger parameter sizes show improvements on answering single-hop questions, their improvements towards answering complex multi-hop questions lag meaningfully behind the former (Press et al., 2023). To address this, decomposition-based approaches (Press et al., 2023; Zhou et al., 2023; Khot et al., 2023; Dua et al., 2022) have been proposed, whereby an LLM is prompted to break a complex question or task into smaller sub-problems that are incrementally solved,[1] the benefits of which include: (i) these simpler tasks are performed relatively well by LLMs, and (ii) they facilitate extensions into retrieval, functions calling and tool usage that can aid the search for the solution (Press et al., 2023). When these sub-questions are used with LLMs to answer the complex question, it has been referred to as 'Chain-of-Questions' (CoQ) (Dua et al., 2022; Zhu et al., 2023) and there are indications of increased internal reasoning consistency when LLMs are made to answer complex queries in this way (Radhakrishnan et al., 2023).

Despite the promising performance of decomposition-based complex question answering (QA) approaches using LLMs, the current state-of-the-art (SOTA) for the associated task of question decomposition (i.e. to produce a sequence of sub-questions such as the one in Footnote 1) is achieved with supervised approaches. On the other hand, as we discuss in Table 1 (see caption there), the performance of supervised models collapses in the face of a distribution shift (i.e. changes in the domain, types of questions, etc.). This makes neither zero-/few-shot LLMs approaches nor supervised models perfectly suitable for the task of question decomposition – the latter suggests the benefit of a more general-purpose modelling approach, while the former suggests that there is room for LLMs to become better at decomposing complex questions. One direction for improving LLM capabilities is through training/fine-tuning with synthetic LLM-generated data (Gunasekar et al., 2023; Li et al., 2023a), which is what we

[1] For instance, the same answer to the complex question *"When did Allied troops land in the region where Semitic Phoenicians settled?"* could be obtained by answering these two simpler questions: *"Where did the Semitic Phoenicians settle?"* and *"When did allied troops land in #1?"*.

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explore in this work.

Dataset	Model	EM ↑	SARI ↑	GED ↓
break	F-T5 (B)	0.1845	0.8094	0.2098
	F-T5 (M)	0.0000 ↓	0.4512 ↓	0.5901 ↓
	F-T5 (2)	0.0000 ↓	0.4316 ↓	0.6070 ↓
musique	F-T5 (M)	0.1618	0.7429	0.2283
	F-T5 (B)	0.0000 ↓	0.5421 ↓	0.4616 ↓
	F-T5 (2)	0.0108 ↓	0.4949 ↓	0.5549 ↓
2wiki	f-T5 (2)	0.8735	0.9865	0.0197
	f-T5 (B)	0.0000 ↓	0.5706 ↓	0.5458 ↓
	f-T5 (M)	0.2150 ↓	0.7419 ↓	0.4346 ↓

Table 1: Performance for supervised question decomposition models (F-T5 is a model fine-tuned on Flan-T5-large, see Appendix A for details). **(B)**, **(M)**, **(2)** denotes models that were fine-tuned on the training sets of the `break`, `musique` and `2wiki` datasets (see Section 4 and dataset examples in Table B in the appendix). When tested on data with a different distribution (e.g. F-T5 (M) on `break`), supervised models' performance drops significantly (denoted by a ↓) compared to one trained on the same distribution. EM, SARI and GED are automatic metrics used to evaluate decomposition quality, see Section 5.1 for details. ↑ indicates higher the better, ↓ indicates lower the better. Implementation details for these models can be found in Appendix A.

In this work, we focus on the task of decomposing English complex questions for machine reading comprehension (MRC), into a sequence of sub-questions (Wolfson et al., 2020). Our contributions are: **(i)** an approach to generate decompositions with smaller-sized models – of between three and nine billion parameters, or "compact" LLMs (CLLMs) as we refer to them in this work – that are more resource-efficient; **(ii)** novel extensions of recent advances in using LLM-as-judge (Zheng et al., 2024) and LLM-as-rankers (Pradeep et al., 2023a), together with panel voting (Verga et al., 2024), in our approach that allows us to derive synthetic training data with only five annotated decomposition examples; and **(iii)** an extensive evaluation comparing against supervised approaches and few-shot prompting of LLMs, showing that using the generated data to fine-tune CLLMs brings about question decomposition performance comparable with or better than larger models.

Our work is novel in the using of panels of CLLMs to both produce the synthetic complex question data and also to rank the generated decompositions for quality. Being able to do so with CLLMs is meaningful as being able to create a human-annotated decomposition dataset at scale requires substantial resources and comes with restrictions.[2] Being able to do so with only five annotated examples for a given dataset allows the automatic creation of question decomposition data for new question types and new domains.

2 Related work

Complex question decomposition Decomposition-based approaches for answering complex MRC questions have been proposed – and found to improve QA performance – from before the time of LLMs; going back as far as to linguistically-based question splitting methods such as those of (Kalyanpur et al., 2012). However, question decomposition (Perez et al., 2020; Dua et al., 2022; Patel et al., 2022) is almost always done in service of QA as the end goal and seldom directly investigated on its own. In addition, many proposed solutions also often assume access to either annotated decompositions (Wolfson et al., 2020) or to a question decomposition model (Guo et al., 2022; Zhu et al., 2023).

Synthetic data for improving LLMs Recent improvements in LLM training for instruction-following and alignment with human preferences (Wei et al., 2022a; Ouyang et al., 2024; Rafailov et al., 2024) have brought about new opportunities to use LLMs for generating synthetic data, and research has shown (Zelikman et al., 2022; Gunasekar et al., 2023; Li et al., 2023a; Wang et al., 2023b; Kumar et al., 2024) that training on such synthetic data drive further model performance. The current approach is to produce such synthetic data using a single LLM of the largest sizes (e.g. GPT-4, Llama 70B/405B, PaLM (Agrawal et al., 2023)); however, this entails significant resources (compute and runtime) and, as we show, do not yet bring about substantially better question decomposition performance over smaller-sized LLMs. Some work has focused on reducing the resource-intensiveness of the process via knowledge distillation (Rosenbaum et al., 2022; Zhang et al., 2023; Li et al., 2024a) from large models to smaller ones.

Initial efforts have also mainly focused on generating class-conditioned text data used for classification tasks (e.g. movie review sentiment analysis) (Li et al., 2023b; Yu et al., 2024; Ding et al., 2023) and for instruction-following training data (Hon-

[2] Many closed-sourced (and even those with open-sourced weights) LLMs contain usage terms that restrict the use of the models for annotating data at scale. see https://huggingface.co/blog/synthetic-data-save-costs

ovich et al., 2023). For QA, (Agrawal et al., 2023) used a 540B-parameter model to generate multilingual questions that can be answered from a single passage; whereas the datasets in our work are multi-hop across two or more documents. In computer vision, (Li et al., 2024b) used templates to generate decompositions of complex visual questions as a way to obtain training data to improve LLM complex visual QA performance; though the complex questions they work with are focused on a narrow context (a visual chart) unlike the open-domain nature of the complex questions encountered in the MRC datasets we investigate.

Our approach and findings align with contemporaneous work (Bansal et al., 2024) showing that under a fixed compute budget constraint, the use of smaller (and weaker) LLMs for generating synthetic training data to fine-tune models for math reasoning tasks leads to outcomes that outperform doing the same using costly larger models. It can also be seen as generalising existing methods that generate synthetic data by sampling repeatedly (Singh et al., 2024) from the same model to obtain wider coverage and diversity of generations before selecting the optimal solution.

LLM as judges and rankers (Zheng et al., 2024) examined the use of a single large chat LLM for judging LLM outputs. (Verga et al., 2024) recently extended this to using the majority vote of a panel of three smaller-sized LLMs to judge and identify the best candidate for a task, with the motivation that doing so alleviates the need for using a single resource-intensive LLM for evaluation. The tasks they examined include single- and multi-hop QA, and they found that all of the largest-sized LLMs they investigated (GPT-4, Command-R and Haiku) give results that have lower correlations with human judgements of answer correctness compared to using a panel of CLLMs. Another line of research has shown that LLMs show promise for use in ranking tasks in information retrieval (Sun et al., 2023; Pradeep et al., 2023a,b), finding that it is possible to use few-shot prompting of LLMs, for ranking a collection of documents for their relevance to a search query, to obtain performance that is competitive with supervised approaches.

3 Approach

In this section, we describe (i) our approach for generating synthetic decomposition data; and (ii) how we fine-tune CLLMs with this data to bring about more robust decomposition performance.

The task we explore involves decomposing a complex question q_c (without any additional context) into an ordered sequence of simpler sub-questions $q_s \in Q_s$ (Wolfson et al., 2020). Depending on the structure of q_c, each q_s may contain a referring variable (i.e. a placeholder) that points to the answer of a preceding question. In this way, by successively substituting the obtained answers and answering each q_s in sequence, the final answer obtained gives the same as answering q_c directly.

3.1 Generating synthetic decompositions

There are three main steps in our approach to generate synthetic question decomposition training data for any X, a given dataset of complex questions. Figure 1 contains an illustration giving an overview of our approach.

Multiple candidate generation First, we use a series of CLLMs (we denote these as CLLM$_{dqg}$) to obtain candidate decompositions. In our experiments, we use four different CLLM$_{dqg}$ and by doing so, we obtain multiple solutions for the decomposition instead of relying on a single LLM's output (e.g. via repeated sampling with temperature). Since the datasets we work on have different forms of representing the decomposed sub-questions (see Section 4 and examples in Appendix B), we use five-shot and chain-of-thought (CoT) (Wei et al., 2022b) prompting (example prompt in Appendix G) to help ensure the CLLM generate decompositions of the desired form. We only use the complex questions from a given dataset X (plus the same five randomly chosen exemplars from the training sets of each dataset for the CoT prompts).

Ranking decomposition candidate quality The second step involves assessing the quality of the decomposition candidates. To do so, we use a panel of CLLMs (that we denote as CLLM$_{rank}$ each) for ranking all of the candidate decompositions from the first step; this is in a similar vein as what (Verga et al., 2024) did for QA. Specifically, we prompt each CLLM$_{rank}$ to rank the quality of the candidate decomposition that each CLLM$_{dqg}$ produced for a given q_c. In order to do this, we: (i) extended `RankLLM`[3] (Pradeep et al., 2023a,b) to the novel task of ranking question decomposition quality.

`RankLLM` was however designed for zero-shot

[3] https://github.com/castorini/rank_llm

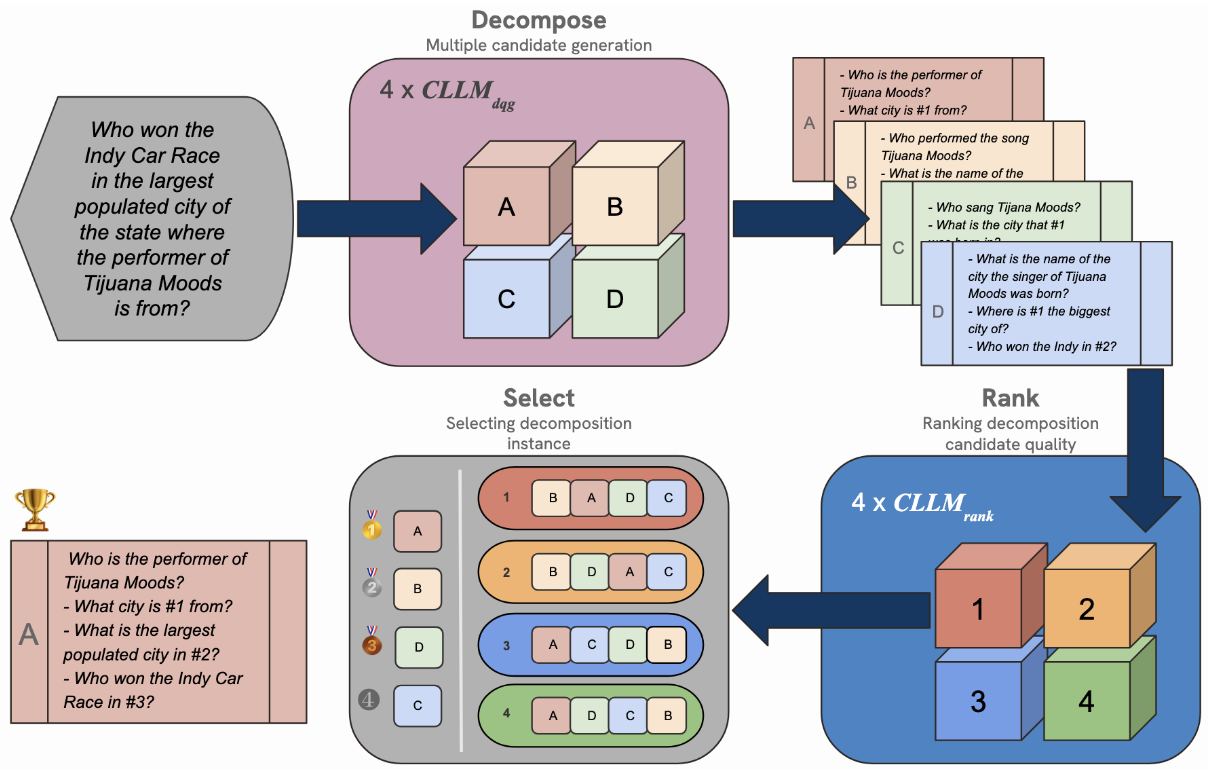

Figure 1: Overview of our approach for generating synthetic question decomposition data.

passage ranking with an LLM fine-tuned for that task;[4] as such, instead of using their model, we use a CLLM with two-shot prompting. This two-shot prompting (Figure 5 in Appendix G) is necessary to provide the CLLM$_{rank}$ with exemplars of our new ranking task. However, since there is no annotated data for the task, we obtained the exemplars by using GPT-4o (`gpt-4o-2024-08-06`) to systematically introduce errors to a set of (q_c, Q_s) tuples drawn from the training set of X. We do this by designing a scoring scheme and using it to instruct GPT-4o (see Figure 6 in Appendix G) to add combinations of various types of errors to a Q_s so that the errors sum to a certain score. We do this multiple times to the Q_s for a given q_c so that the scores for all its modified Q_s fall into even intervals. This allows us to compose sets of rank-able instances by sampling from the bins and using these as exemplars. We use the same set of exemplars for every ranking task for a given dataset X. We also use the same set of CLLMs that were used in the first step (we explore other CLLM combinations in Section 6 below). To mitigate the effects of positional bias (Zhao et al., 2021), we randomly shuffled the order of the CLLM$_{dqg}$s presented in each ranking task.

[4]i.e. Given a $query$ and a set of documents $doc \in D$ that is presented in a listwise manner to an LLM tuned for the task, it returns a sequence r that orders D by each of its doc's relevance for answering $query$.

Selecting decomposition instance Finally, from the rankings of the decompositions obtained from step two above, we identify the decomposition candidate that is preferred by the panel of CLLM$_{rank}$s. We refer to the data obtained here as **PANEL**. Since we extend from the binary score setting investigated by (Verga et al., 2024) into ranked preferences, we use Single Transferable Vote (STV) (Tideman, 1995) to select the top-ranked decomposition candidate for each q_c in the training set of X.[5] Borrowing an analogy from electoral methods, we can view each CLLM$_{rank}$ as an agent being prompted to express a preference order for the pool of candidates – an instance of q_c corresponds to an electoral seat, the set of CLLM$_{dqg}$s' outputs for q_c are the candidates for the 'seat' and the set of CLLM$_{rank}$ ranks are the votes cast for each candidate.

The four CLLMs that we use for both decomposition (CLLM$_{dqg}$) and ranking (CLLM$_{rank}$), are the smallest models of the Llama 3.1 (8B) (Dubey et al., 2024), Gemma 2 (9B) (Team et al., 2024),

[5]STV allows for more representative winning candidates for cases of ties or for a multi-seat election, by taking each voter's expressed preference into consideration; the surplus votes of declared loser(s) and/or winner(s) are successively proportionally reassigned to the remaining candidates until a winner is chosen/all seats have been filled.

Phi-3.5 (3.8B) (Abdin et al., 2024) and Qwen-2.5 (7B) (Qwen Team, 2024) model families,[6] which were the highest-ranked at the time of this work.[7]

To summarise, since the input for the decomposition only requires a complex question without the need for gold decompositions and their answers (other than a few exemplars that can be easily obtained), the approach can be easily applied on a collection of unseen complex queries to obtain new synthetic training data.

3.2 Question decomposition models

We then use the generated decompositions (i.e. **PANEL**) to fine-tune CLLMs (Llama 3.1 (8B) and Qwen 2.5 (7B)) to give improved models for question decomposition. When fine-tuning the CLLMs, we use LoRA adapters (Hu et al., 2022) with a rank of 32 for all of the model's linear layers,[8] and RSLoRA (Kalajdzievski, 2023) for controlling the α parameter for the LoRA adapters. Here, we use a three-shot CoT prompt (an example of the prompt is in Figure 4 of Appendix G) and fine-tune all the models for two epochs, which took about 8 hours for one model on an Nvidia A100 GPU.

4 Data

We focus our work on MRC datasets (examples in Appendix B) whose complex questions have the answers to their sub-questions distributed across multiple documents, which are harder to answer and whose open-domain nature has the most potential benefit from decomposition-based QA with LLMs (compared to complex questions answerable from a single document that can already be performed well by existing reader models).

- **`break` (Wolfson et al., 2020)** is a dataset designed specifically for the task of question decomposition. We use the "high-level" version that contains questions encountered in machine reading comprehension (MRC) and which was collected by drawing upon complex questions q_c from three existing datasets. Each q_c in `break` comes with its Q_s – annotated in the QDMR formalism with the help of crowd workers – but does not contain any answers. We evaluate on the portion of `break` drawn from HotpotQA (Yang et al., 2018) (about 45%) which is the only one of the three where the answers to the complex questions are distributed over two text documents.[9]

- **`musique` (Trivedi et al., 2022)** was designed to have complex questions that are harder for MRC models to derive a correct answer via reasoning shortcuts. It was constructed in a "bottom-up" manner with single-hop questions that were drawn from five other datasets, whereby sets (of sizes between two and four) of single-hop questions with bridge entities between them are put together and presented to crowd-workers to compose a complex question covering the set. We use the "answerable" version of the dataset where each q_c in `break` comes with its Q_s, which are in natural language (NL) and come with their answers.[10]

- **`2wikimultihop` (Ho et al., 2020)** was constructed using a set of templates based on questions from HotpotQA. New multi-hop questions were instantiated from these templates using entity pairs drawn from Wikidata, with steps taken to ensure that the supporting information (Wikipedia pages for the entities) require multi-hop reasoning by an MRC model. Since this dataset was constructed from a relatively small set of templates, the distribution of question types in it is constrained, making it easier to learn; so we only use it for evaluating supervised models' out-of-distribution performance (Table 1) and we focus our subsequent experiments on the other two datasets above.

5 Evaluation

Existing work on decomposition-based approaches with LLMs (Khot et al., 2023) focus on the QA aspect of the task and treat decomposition (in the form of CoT, CoQ, tree-of-thought etc) as a means for additional computation to allow the model to derive better performance on the answering of q_c; as such they focus evaluation on the token F1 of the final answer obtained for q_c. We evaluate on the development sets of `break` and `musique` (Section 6)

[6] The model checkpoints are (i) `google/gemma-2-9b-it`, (ii) `meta-llama/Llama-3.1-8B-Instruct`, (iii) `microsoft/Phi-3.5-mini-instruct` and (iv) `Qwen/Qwen2.5-7B-Instruct` on `https://huggingface.co/`

[7] Based on rankings here: `https://huggingface.co/spaces/open-llm-leaderboard/open_llm_leaderboard`

[8] The q, k, v, o, down_proj, gate_proj, and up_proj layers.

[9] The other two datasets in the high-level version of `break` are (i) ComplexWebQuestions (Talmor and Berant, 2018) for knowledge base QA, and (ii) DROP (Dua et al., 2019) whose answers are in a single paragraph (i.e. document).

[10] A portion of its q_s was originally from the Zero Shot RE dataset (Levy et al., 2017), where the single-hop questions are represented as knowledge graph triples (the subject and predicate form the single-hop question and the object forms the answer to the question). We wrote a set of templates for each predicate found in `musique` and used this to convert the Zero Shot RE triples into NL questions.

and include QA (Section 5.2) and we also investigate the generated decompositions (Section 5.1).

5.1 Automatic metrics

Following (Wolfson et al., 2020), we evaluate generated decompositions $\hat{Q}_s$ from `musique` and `breakeval` using these automatic metrics that compare between the $\hat{Q}_s$ against the reference decompositions (Q_s) for each dataset: (i) exact match (EM), (ii) SARI (Xu et al., 2016), and (iii) graph edit distance (GED).[11] Higher scores are better for EM and SARI, lower scores are better for GED.

▪ **EM** measures whether a $\hat{Q}_s$ is phrased and structured in exactly the same way as the reference in the dataset.

▪ **SARI** was originally applied towards evaluating text simplification – it measures how much of the tokens of a reference text have been added, deleted and kept when comparing a generated text against it. To evaluate the quality of $\hat{Q}_s$, (i) the added, deleted or kept n-grams between the Q_s and q_c are computed, and (ii) the same is done between $\hat{Q}_s$ and q_c. The difference between the added, deleted and kept sets of tokens for Q_s and $\hat{Q}_s$ are then used in computing the SARI score.

▪ **GED** measures the structure of $\hat{Q}_s$ against Q_s by using an alignment-based approach to measure the cost required for the minimal set of operations (addition or deletion of nodes and edges, and the substitution of nodes) to transform one to the other. Here, each q_s (or $\hat{q_s}$) is a node and an edge is an alignment between q_s^i and $\hat{q_s^i}$. The GED score provides an indication of the granularity of a generated decomposition against a reference; for instance, a three-hop question could be decomposed into two questions (of two-hop and one-hop), or three questions (of one-hop each).

5.2 QA evaluation

We also assess whether the decompositions can give the same answer as q_c by answering the generated sub-questions with an LLM using CoQ prompting (LLM-CoQ) for both `break` and `musique` (see Appendix G for prompt example), as well as a supervised model for `musique`. For the LLM-CoQ evaluation, we use two CLLMs, Llama and Qwen (from their public checkpoints, i.e. not our fine-tuned decompositions models) and prompt the model to answer the sub-questions successively based on the supporting passages in the original datasets, giving us the upper-bound performance in a retrieval-augmented generation (RAG) setting. For `musique`, we also extend (Zhang et al., 2024)'s code (which was used to achieve SOTA on the `musique` leaderboard) to train a supervised QA model for it. Their initial model was not intended for single-hop QA, but since `musique` is comprised of complex questions of between two and four hops and since we have their decompositions in the training set, we add all of the single-hop sub-questions for training this model. We also use the same templates (see Footnote 10) to realise the Zeroshot RE instances in it. For `break`, since there are no answers annotated for its sub-questions, we were not able to use a similar supervised QA model to evaluate it.

6 Results and analysis

Dataset	Model	EM ↑	SARI ↑	GED ↓
`break`	GPT-4o	0.0181	0.6314	0.3666
	Llama 3.1 70B	0.0289	0.6675	0.3366
	Few-shot			
	Llama 3.1 8B	0.0188	0.6391	0.3557
	Gemma 2 9B	0.0195	0.6325	0.3561
	Phi 3.5-mini	0.0051	0.5818	0.4684
	Qwen 2.5 7B	0.0072	0.5946	0.4104
	PANEL	0.0166	0.6919	0.3649
	FT-PANEL			
	Llama 3.1 8B	**0.0217**	**0.6728**	**0.3290**
	Qwen 2.5 7B	**0.0145**	**0.6352**	**0.3543**
`musique`	GPT-4o	0.0066	0.6050	0.3233
	Llama 3.1 70B	0.0083	0.6349	0.3136
	Few-shot			
	Llama 3.1 8B	0.0149	0.6079	0.3786
	Gemma 2 9B	0.0161	0.5505	0.4757
	Phi 3.5-mini	0.0165	0.5985	0.4077
	Qwen 2.5 7B	0.0070	0.5778	0.3994
	PANEL	0.0132	0.6553	0.3699
	FT-PANEL			
	Llama 3.1 8B	**0.0223**	**0.6332**	**0.3296**
	Qwen 2.5 7B	**0.0149**	**0.6211**	**0.3559**

Table 2: Question decomposition performance (Automatic metrics). **FT-PANEL** denotes LLM fine-tuned on PANEL synthetic data (last row of each section). In **bold** is top-performing across row.

We compare between using (i) few-shot CoT prompting of the (C)LLM (**Few-shot**), (ii) the rank and panel voting procedure corresponding to Steps 1 to 3 in Section 3.1 to select decomposition candidates (**PANEL**), and (iii) our decomposition mod-

[11] We use the script `https://github.com/allenai/break-evaluator` from (Wolfson et al., 2020), but lowercase as well as strip question marks and trailing whitespace in every question to standardise across datasets.

	break				musique			
	QA: Llama		QA: Qwen		QA: Llama		QA: Qwen	
	EM	F1	EM	F1	EM	F1	EM	F1
GPT-4o	0.4436	0.6580	0.5065	0.6983	0.4638	**0.6376**	**0.4737**	**0.6380**
F-**T5**	0.4226	0.6285	0.4689	0.6529	0.4253	0.5862	0.4373	0.5897
Few-shot								
Llama 3.1 8B	0.4045	0.6131	0.4682	0.6523	0.4154	0.5735	0.4220	0.5811
Gemma 2 9B	**0.4479**	0.6640	**0.5145**	0.6998	0.3678	0.5023	0.4137	0.5620
Phi 3.5-mini	0.3632	0.5524	0.4624	0.6484	0.4146	0.5591	0.4286	0.5778
Qwen 2.5 7B	0.4052	0.6261	0.4638	0.6547	0.4249	0.5798	0.4328	0.5874
FT-PANEL								
Llama 3.1 8B	**0.4479**	**0.6671**	**0.5145**	**0.7072**	**0.4667**	0.6343	0.4679	0.6290
Qwen 2.5 7B	0.4211	0.6359	0.4682	0.6583	0.4497	0.6088	0.4485	0.6022

Table 3: QA performance on generated decompositions, with few-shot CoQ prompting using Llama 3.1 8B and Qwen 2.5 7B. Fine-tuning with data from **PANEL** always leads to improvements on the CLLM. The highest score for each dataset is in **bold**.

els (**FT-PANEL**) that involve fine-tuning a CLLM with the generated decompositions obtained on the training sets of break/musique (i.e. **PANEL**). The models we compare with under **Few-shot** include the same four models that we use in our data generation procedure (Gemma 2 (9b), Llama 3.1 (8B), Phi-3.5 (3.8B) and Qwen 2.5 (7)). For comparison, we also include larger models GPT-4o and Llama 3.1 (70B). [12] The decomposition performance for each of these can be found in Table 2, and the results for the QA evaluation can be found in Table 3 (LLM-CoQ) as well as Table 6 in Appendix D (supervised QA for musique).

6.1 Panel of CLLMs performance

While it can be meaningful to examine EM performance for question decomposition under a supervised setting (where the training and test-time data are drawn from the same distribution and EM indicates the ability of such models to learn from the distribution of the training data), it is less so for few-shot prompting of LLMs for the task, i.e. the LLMs have not been trained to match the distribution of the original datasets and are unlikely to produce decompositions with the exact phrasing (despite those decompositions being valid ones). As such, we focus our attention on SARI and GED performance (Table 2); and note that to assess the quality of a decomposition, these two metrics have to be viewed holistically, together with the QA evaluation performance (Table 6).

[12] The OpenAI GPT-4o checkpoint we use is gpt-4o-2024-08-06 and the Llama model checkpoint is https://huggingface.co/meta-llama/Llama-3.1-70B-Instruct; we load the latter in 4bit for inference.

▪ **PANEL improves on single CLLM$_{dqg}$ performance** Despite our use of in-dataset exemplars for the few-shot prompting, we observe that CLLM performance varies between different data (e.g. the Phi model's performance relative to the other CLLMs differs substantially between break and musique, potentially due to a combination of factors such as parameter size, training data and preference tuning). Without advance knowledge of a CLLM's decomposition performance on a given collection of complex questions, using the approach to obtain **PANEL** (Steps 1 to 3 of Section 3.1) allows us to aggregate over the performance possible of each CLLM$_{dqg}$. Using **PANEL** almost always leads to better performance than single CLLMs – (i) in the case of break, only the Llama and Gemma models (0.3557, 0.3561) have better GED than **PANEL** (0.3649) and **PANEL** outperforms elsewhere for SARI and GED; and (ii) in the case of musique, **PANEL** clearly outperforms every single CLLM.

▪ **Fine-tuning with data from PANEL consistently brings improved performance** Our decomposition models **FT-PANEL** constantly outperforms few-shot prompting of the same CLLM they were based on. This gives between 2.53 (0.6332 vs 0.6079) and 4.33 points (0.6211 vs 0.5778) increase in SARI as well as between 2.67 (0.3290 vs 0.3557) and 5.61 (0.3543 vs 0.4104) points improvement in GED. The QA evaluation further validates this, with token F1 gains of up to 5.49 points for break and 6.08 points for musique with LLM-CoQ and, and up to 4.49 points for musique using the supervised QA model.

■ **Comparable performance with larger LLMs** While CLLMs generally underperform larger LLMs (first set of column in Table 2), **FT-PANEL** gives results that are comparable or better than that of a large LLM (GPT-4o) on SARI, GED as well as in the QA evaluation. This shows that our near-zero-shot synthetic data generation procedure, as well as fine-tuning, can be used as a means to obtain better decomposition models.

6.2 Analysis: CLLMs for ranking decomposition

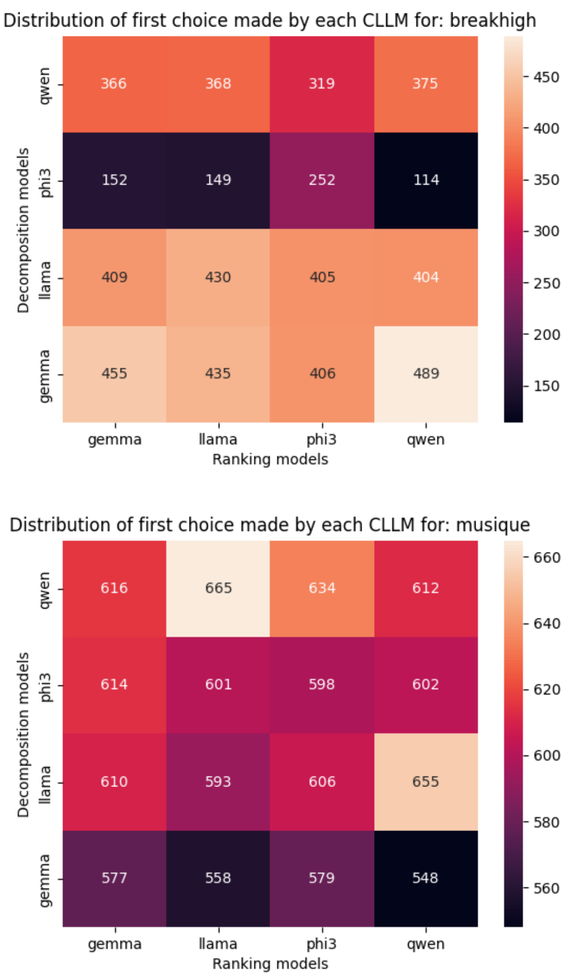

Figure 2: Voting distribution for `break` (top) and `musique` (bottom). The horizontal axes of the heatmaps show the CLLM$_{dqg}$ models whereas the vertical axes show the CLLM$_{rank}$ models; they show the number of times a CLLM$_{rank}$ picks CLLM$_{dqg}$'s decompositions as its top choice.

In this section, we evaluate the LLM-as-judge and panel voting methods that we extend to ranking question decompositions and situate them against concerns raised recently about LLM self-preference (Liu et al., 2024; Koo et al., 2024).

■ **Mitigating self-preference** It has been shown recently (Panickssery et al., 2024) that, when they are deployed for evaluating generated outputs, LLMs show *"non-trivial accuracy at distinguishing themselves from other LLMs and human"* and that there is a correlation between an LLM recognising its own outputs and preferring these over others (referred to as "self-preference"), which raises concerns as self-evaluation is increasingly used in data generation for LLM training and fine-tuning, such as for reward modelling (Wang et al., 2024) and self-correction (Madaan et al., 2023). Our approach naturally mitigates this by aggregating preferences collected from multiple CLLMs instead of relying on the same (or a single) LLM to evaluate the generated decomposition. A purely self-preferring ranking choice made by a model, unless sufficiently supported by other models, would not be chosen in the STV process we used.

■ **CLLM$_{rank}$ preferences corresponds with eventual QA performance** Besides the consistent improvement of **ST-PANEL** over that of each CLLM$_{dqg}$ (Table 2), another indicator supporting the use of CLLMs for ranking question decompositions $\hat{Q}_s$, is found in the preference patterns of the panel broken down by CLLM$_{rank}$ (Figure 2). Most notably, for `break`, all CLLM$_{rank}$ models consistently favour Phi's decompositions the least (see Figure 2 top), which the QA evaluation also validates – those Phi decomposition candidates go on to obtain the lowest QA scores amongst the four CLLMs$_{dqg}$ (see 'Few-shot' rows in Table 3). Similarly, for `musique`, the decomposition outputs of the Gemma model were favoured the least, and its decompositions likewise performed the worst in the QA evaluation. There is also a general consensus on the quality of the Gemma model's decompositions for `break` and Qwen's (three out of four) decompositions for `musique`, which are also broadly corroborated by their QA evaluation performance.

■ **Composition of the CLLM$_{rank}$ panel matters** We find that not all CLLMs may be suitable for use in the task of ranking question decompositions. Another way to further address the issue of self-preference may be to use a different set of CLLMs for the ranking task instead of the same ones that were used for question decomposition. We explore this using the Aya 23 (8B) (Aryabumi et al., 2024), Mistral v0.3 (7B) (Jiang et al., 2023), Nvidia-Llama (8B)[13] and Olmo (7B) (Groeneveld et al., 2024) models. These models are, however, all weaker compared to the four we used in our main experiments. We find that using these weaker models for ranking leads to candidates of lower quality being picked (consistently lower SARI and GED scores, see Table 4). Even when taking STV over the preferences expressed by all eight models together, it does not give better results; this suggests that the added CLLMs do not have sufficient capabilities to perform that task well, and their imperfect preferences act instead to skew the candidate choices. This is broadly reflected in the more dispersed voting patterns of these models (Figure 3 in Appendix E)

Dataset	Model	EM	SARI	GED
break	4x stronger	0.0153	0.6820	0.4099
	4x weaker	0.0150	0.6724	0.4327
	8x	0.0166	0.6811	0.4184
musique	4x stronger	0.0132	0.6553	0.3699
	4x weaker	0.0128	0.6507	0.3915
	8x	0.0141	0.6543	0.3751

Table 4: Varying the composition of the panel of CLLM rankers. **4x stronger** is the use of the Gemma, Llama, Phi and Qwen models for ranking, **4x weaker** is the use of the Aya, Mistral, Nvidia-Llama and Olmo models. **8x** is the use of all eight of these models.

6.3 Out-of-distribution performance

We also go on to investigate the out-of-domain performance of the fine-tuned CLLMs (i.e. **FT-PANEL**). We refer to this as **FT-PANEL (OOD)** and test these two settings: (i) train on `musique` & test on `break` (*Train-Br/Test-Mu*), as well as (ii) train on `break` & test on `musique` (*Train-Mu/Test-Br*). We ran the full evaluation suite (EM, SARI, GED and downstream QA) and provide the results in Tables 7-8 in Appendix F. Compared to **Few-shot** (which gives a baseline), the performance of **FT-PANEL (OOD)** is varied, and is tied to (i) the test dataset (i.e. the nature of the OOD distribution), and (ii) the model that is fine-tuned.

▪ **Test dataset differences** While *Train-Mu/Test-Br* generally brings improvements over the baseline, it is less clear for the opposite setting i.e. *Train-Br/Test-Mu*. The *Train-Br/Test-Mu* results are also broadly consistent with the much larger OOD drops for `break` than for `musique` in the supervised setting (Table 1). These are likely due to the nature of the sub-questions in the `break` dataset – there, annotators were instructed to use a restricted set of words when writing the sub-questions, giving them a specialised form with limited linguistic variability.[14] While this facilitates parsing, it means that training/tuning on it for decomposition will not be as helpful when the resulting model is applied to a dataset like `musique` where sub-questions are in natural language.

▪ **Underlying CLLM differences** We find that fine-tuning Llama 3.1 (8B) with the synthetic data brings improved or comparable OOD performance (both `break` and `musique`), but this is not the case for Qwen 2.5 (7B), which we also found across all our experiments to be generally weaker in question decomposition. Furthermore, despite being fine-tuned with the more specialised synthetic data we produce from `break`, Llama 3.1 (8B) is still able to perform on `musique` (i.e. **FT-PANEL (OOD)**) with (i) >2% and >4% improvement in SARI and GED and (ii) >1.5% improvement or comparable performance in F1 in the downstream QA evaluations. This provides an indication of the usefulness of our approach (subject to LLM performance).

7 Conclusion

We propose an approach for producing synthetic complex question decomposition data using only five annotated examples and novel extensions of LLM-as-judge/rankers as well as LLM panel voting for the task of ranking complex question decompositions. We then fine-tune smaller-sized "compact" LLMs (CLLMs) with the generated data and show – with validation over two benchmark datasets and comparisons against supervised models and few-shot LLM prompting – that it leads to consistently improved question decomposition performance. Notably, the improvements give the CLLMs performance on the decomposition task that is comparable to or better than larger LLMs. Having CLLMs that decompose questions better improves their abilities for decomposition-based QA, which has been shown to be promising for closing the "compositionality gap" that they face in answering complex questions. It can also serve as a means to produce synthetic data that can be used to train and fine-tune CLLMs (potentially for larger ones as well) for further improvements.

[13] https://huggingface.co/nvidia/Llama3-ChatQA-1.5-8B

[14] See "QDMR Annotation" in (Wolfson et al., 2020)

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9 Limitations

Notwithstanding the promising performance of LLM-as-rankers, one unresolved challenge lies with the observation that current LLMs, when prompted often produce outputs that vary when the order of the information in the prompt is shuffled (Zhao et al., 2021); this includes rank predictions that are not internally consistent when the order of the input set is shuffled; a phenomenon generally referred to as 'position bias'. This refers to situations where, given a set of N choices to be ranked, an LLM often makes a ranking prediction R_i when the input ordering is O_i, but R_j when the ordering is shuffled and presented as O_j; i.e. the rank preferences expressed in R_i are not fully respected in R_j. These position biases will have an impact on the selection of the preferred decomposition candidate, and while we took care to shuffle the order of the CLLM$_{rank}$ and the panel of LLM approach we use may help to mitigate this, methods such as using repeated sampling with order shuffling to find a "central" ranking (Tang et al., 2024) more directly addresses this (but require additional resources for the repeated sampling).

In this work, we focus on MRC complex questions that are multi-hop and whose answers to their sub-questions are across multiple documents, since such questions are the most challenging to address in QA and likely to be so for question decomposition too. We expect similar findings for decomposing complex questions that can be answered from a single document as these are easier to answer (i.e. the information sought and the hops in the complex question have a natural proximity to each other since they are expressed in the same document) and therefore likely easier to decompose.

10 Ethics statement

Our proposed approach is for the generation of synthetic question decomposition data, with the view that they can be used to improve LLM performance on the task. On the one hand, clear gains have been obtained from the use of synthetic data for LLM training/fine-tuning – from performance on benchmarks as well as validation through the production-usage of LLMs that have been trained partly on synthetic data (e.g. the Phi family of models (Gunasekar et al., 2023; Li et al., 2023a)). On the other hand, a singular reliance on synthetic LLM-generated data (without being complemented with human-produced data) for training models is expected to lead to 'model collapse' (Shumailov et al., 2024). This refers to a phenomenon when models (including LLMs) are cyclically trained/fine-tuned on synthetic data (i.e. trained with synthetic data, used to generate new data, which is then used to train the next generation of the model and so on) to the effect that they no longer learn the true distributions of human-produced data (including the long-tails) and 'collapse' to the distributions represented by the synthetic data (with their own sets of errors and biases). The risk is that, with an anticipated widespread adoption and reliance on LLMs, 'model collapse' could lead to societal harms such as those arising from stereotypes, misinformation or inaccuracies being propagated at scale. Research on the topic is, however, nascent, and it is not yet clear (i) the extent (Dohmatob et al., 2024) of the risk, (ii) the boundaries where using synthetic training data tip over to cause harm, and (iii) what methods may be identified to mitigate the phenomenon.

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A Contextualising supervised models and few-shot LLMs

For investigating the performance of supervised methods in the face of distribution shifts (Table 1), we train one model for each of the datasets that we use in this work (Section 4). Of these, only `break` (Wolfson et al., 2020) was designed with the task of question decomposition in mind and is the only one that has a public leaderboard tracking decomposition performance.[15] The current SOTA for it is held by a model that was fine-tuned on Flan-T5-large[16]; and so we do the same for each of the datasets to obtain supervised decomposition models for them.

B Dataset examples

Examples from each of the datasets can be found in Table 5.

[15] https://leaderboard.allenai.org/break_high_level/submissions/public

[16] https://huggingface.co/google/flan-t5-large

Dataset	Complex Question	Reference decomposition / evidences
break	How many yards did all offensive touchdowns combine for?	return yards of offensive touchdowns; return the sum of #1
	The football club FC Nürnberg is loaning Lucas Hufnagel from is based in what city?	return the football club that FC Nürnberg is loaning Lucas Hufnagel from; return the city that #1 is based in
musique	When did Allied troops land in the region where Semitic Phoenicians settled?	Where did the Semitic Phoenicians settle?; when did allied troops land in #1
	Who established the first Committee of Correspondence in the city where a member of the Original Memphis Five was born, and why?	Original Memphis Five » has part; #1 » place of birth; who established the first committee of correspondence in #2 in 1772 and why *
2wikimultihop	Who is the mother of the director of film Polish-Russian War (Film)?	⟨Polish-Russian War, director, Xawery Żuławski⟩, ⟨Xawery Żuławski, mother, Małgorzata Braunek⟩ **
	Which film has the director who was born later, El Extraño Viaje or Love In Pawn?	⟨El extraño viaje, director, Fernando Fernán Gómez⟩, ⟨Love in Pawn, director, Charles Saunders⟩, ⟨Fernando Fernán Gómez, date of birth, 28 August 1921⟩, ⟨Charles Saunders (director), date of birth, 8 April 1904⟩ **

Table 5: Examples of complex questions and their reference decompositions in `break` and `musique`; or in the case of `2wikimultihop` their evidences. *:We converted the `musique` instances which had sub-questions taken from Zero Shot RE (in the form of entity-predicate tuples) into natural language questions (see Section 4). For instance, the first two sub-questions were converted to: *"Who has a part in Original Memphis Five"* and *"What is the birth place of #1"*. **: We converted the evidences provided in `2wikimultihop` to NL questions and added sub-questions where necessary (e.g for comparison questions) to complete the reasoning chains to obtain the final answers; see Appendix C.

C Natural language questions for Zeroshot RE instances in `2wiki`

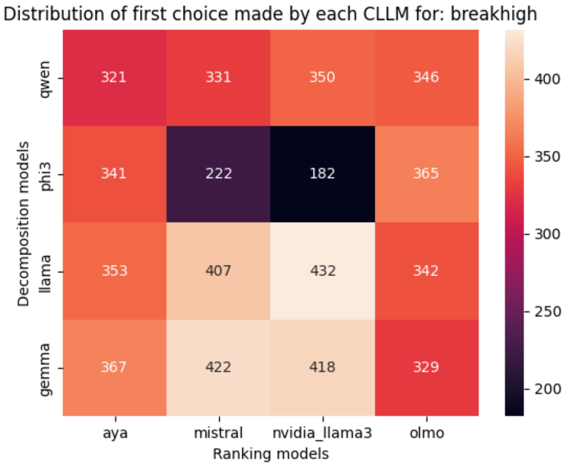
We wrote a set of templates to convert the triples (corresponding to a simple question (SQ)) here into NL questions. In addition, for 'comparison' and 'bridge comparison' types of questions in `2wikimultihop` where the evidence alone does not constitute a complete reasoning chain, we identified the templates within these two sets and wrote rules to add SQs to complete the reasoning chain. For instance, the CQ *"Which film has the director who died earlier, The Marseille Contract or Strangers Of The Night?"* with the answer "Strangers Of The Night" in the dataset is paired with evidence that allows us to construct this set of SQs: *"Who directed The Marseille Contract"*, *"Who directed Strangers of the Night"*, *"When did #1 die"*, *"When did #2 die"*. Our rules added *"Which is first/earlier #3 or #4?"*, *"Which director died on #5?"*, and *"What film did #6 direct?"* to complete the reasoning chain and allow a reader model to be able to obtain the final answer.

D QA Evaluation: supervised

	musique EM	musique F1
GPT-4o	0.4915	0.5931
F-**T5**	0.4741	0.5702
Few-shot		
Llama 3.1 8B	0.4617	0.5610
Gemma 2 9B	0.4117	0.4919
Phi 3.5-mini	0.4808	0.5771
Qwen 2.5 7B	0.4758	0.5726
FT-PANEL		
Llama 3.1 8B	**0.5060**	**0.6059**
Qwen 2.5 7B	0.4894	0.5877

Table 6: QA performance on generated decompositions. Fine-tuning with the synthetic decomposition always leads to improvements on the CLLM (i.e. FT variants with the few-shot results). The highest score for each dataset is in bold.

E Using weaker CLLM$_{rank}$ models



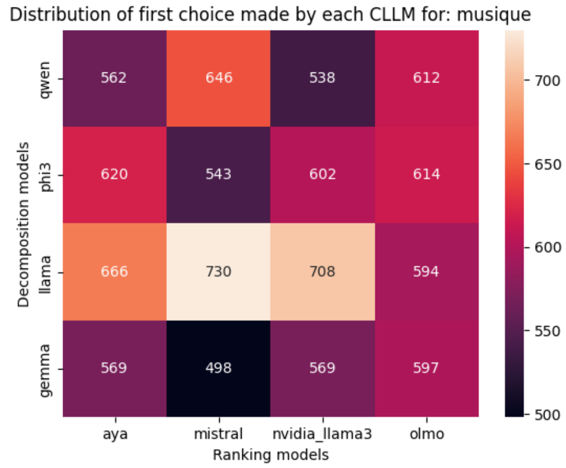


Figure 3: Voting distribution for `break` (top) and `musique` (bottom). The horizontal axes of the heatmaps show the CLLM$_{dqg}$ models whereas the vertical axes show the CLLM$_{rank}$ models; they show the number of times a CLLM$_{rank}$ picks CLLM$_{dqg}$'s decompositions as its top choice.

F Out-of-domain application: FT-PANEL (OOD)

		break: *Train-Mu/Test-Br*			musique: *Train-Br/Test-Mu*		
	Decomposer model	EM ↑	SARI ↑	GED ↓	EM ↑	SARI ↑	GED ↓
Few-shot	Llama 3.1 8B	0.0188	0.6391	0.3557	0.0149	0.6079	0.3786
	Qwen 2.5 7B	0.0072	0.5946	0.4104	0.0070	0.5778	0.3994
FT-PANEL (OOD)	Llama 3.1 8B	**0.0260**	**0.6517**	0.3626	**0.0174**	**0.6210**	**0.3620**
	Qwen 2.5 7B	**0.0224**	**0.6390**	**0.4000**	0.0050	**0.5812**	0.4420

Table 7: Question decomposition performance (Automatic metrics). **Few-shot** is an off-the-shelf application of the model with few-shot prompting (i.e. same as Table 2). **FT-PANEL (OOD)** is the out-of-distribution setting where the model has been fine-tuned on synthetic data generated on the another dataset. In bold are cases where **FT-PANEL (OOD)** outperforms the corresponding **Few-shot**.

		break: *Train-Mu/Test-Br*				musique: *Train-Br/Test-Mu*			
	Decomposer Model	QA: Llama		QA: Qwen		QA: Llama		QA: Qwen	
		EM	F1	EM	F1	EM	F1	EM	F1
Few-shot	Llama 3.1 8B	0.4045	0.6131	0.4682	0.6523	0.4154	0.5735	0.4220	0.5811
	Qwen 2.5 7B	0.4052	0.6261	0.4638	0.6547	0.4249	0.5798	0.4328	0.5874
FT-PANEL (OOD)	Llama 3.1 8B	**0.4457**	**0.6446**	**0.5007**	**0.6875**	**0.4274**	**0.5835**	**0.4282**	0.5802
	Qwen 2.5 7B	**0.4175**	**0.6367**	0.4602	**0.6622**	0.3666	0.5061	0.3736	0.5125

Table 8: QA performance on generated decompositions, with few-shot CoQ prompting using Llama 3.1 8B and Qwen 2.5 7B. **Few-shot** is an off-the-shelf application of the model with few-shot prompting (i.e. same as Table 3). **FT-PANEL (OOD)** is the out-of-distribution setting where the model has been fine-tuned on synthetic data generated on the another dataset. In bold are cases where **FT-PANEL (OOD)** outperforms the corresponding **Few-shot**.

G Prompt examples

Prompt	<|im_start|>system You are an intelligent assistant who decomposes complex questions into simpler sub-questions.<|im_end|> <|im_start|>user I will provide you with one complex multi-hop question. Decompose it into a set of simpler sub-questions so that it will be easier to identify and retrieve the information for answering them instead of the complex question. It is important that the sub-questions (i) are not ambiguously worded, (ii) are logically connected, and (iii) that they cover all the necessary information and steps to answer the original complex question. It is very important that the decompositions must be as simple as possible, i.e. (i) there should only be as many sub-questions as absolutely necessary; and (ii) each sub-question and its answer should cover only a single atomic fact. Please provide the sub-questions in a single line, in the order that you would like them to be answered. They should be separated from each other by a ";". When composing a sub-question, you must ensure that answers of earlier sub-questions are properly referred to whenever possible; when you need to do this, use a variable (e.g. "#1") for referring to the previous answer. It is very important to get the numbering for the answer variable correct. A sub-question should never refer to the answer of a sub-question that comes after it. Start your reply with your reasoning (in less than 50 words), and then immediately give the sequence of sub-questions, and stop immediately after; do not say anything else.<|im_end|> <|im_start|>assistant I understand the instructions and I will decompose the complex question into simpler sub-questions. <|im_end|> <|im_start|>user Let's do some examples of how to decompose the complex question into simpler sub-questions: Complex question: When did Allied troops land in the region where Semitic Phoenicians settled?<|im_end|> <|im_start|>assistant Let's think step-by-step. To decompose this complex question, first, I will want to ask: "Where did the Semitic Phoenicians settle?". Finally, based on the answer to the previous question #1 (North Africa), I will be able to get to the complex question's answer by answering this question: "when did allied troops land in North Africa?". Therefore the sequence of sub-questions should be: [SQ1] Where did the Semitic Phoenicians settle?[SQ2] when did allied troops land in #1<|im_end|> <|im_start|>user Complex question: Who wrote the national anthem of the country of Bahamas Ministry of Tourism and Aviation?<|im_end|> <|im_start|>assistant Let's think step-by-step. To decompose this complex question, first, I will want to ask: "What is the country Bahamas Ministry of Tourism and Aviation is in/from?". Finally, based on the answer to the previous question #1 (The Bahamas), I will be able to get to the complex question's answer by answering this question: "who wrote the national anthem of the The Bahamas?". Therefore the sequence of sub-questions should be: [SQ1] What is the country Bahamas Ministry of Tourism and Aviation is in/from[SQ2] who wrote the national anthem of the #1<|im_end|> <|im_start|>user Complex question: What did the business that published StarTropics rely primarily on for its support?<|im_end|> <|im_start|>assistant Let's think step-by-step. To decompose this complex question, first, I will want to ask: "What business published StarTropics?". Finally, based on the answer to the previous question #1 (Nintendo), I will be able to get to the complex question's answer by answering this question: "Nintendo relied primarily on what for its support?". Therefore the sequence of sub-questions should be: [SQ1] What business published StarTropics?[SQ2] #1 relied primarily on what for its support?<|im_end|> <|im_start|>user Complex question: Who won the Indy Car Race in the largest populated city of the state where the performer of Tijuana Moods is from?<|im_end|> <|im_start|>assistant
Target	Let's think step-by-step. To decompose this complex question, first, I will want to ask: "Who is the performer of Tijuana Moods?". Then, based on the answer to the previous question #1 (Charles Mingus), I will look for the answer to: "What city is Charles Mingus from?". Then, based on the answer to the previous question #2 (Arizona), I will look for the answer to: "What is the largest populated city in Arizona ?". Finally, based on the answer to the previous question #3 (Phoenix), I will be able to get to the complex question's answer by answering this question: "who won the indy car race in Phoenix?". Therefore the sequence of sub-questions should be: [SQ1] Who is the performer of Tijuana Moods[SQ2] What city is #1 from?[SQ3] What is the largest populated city in #2 ?[SQ4] who won the indy car race in #3<|im_end|>

Figure 4: Few-shot Chain-of-Thought prompt used in complex question decomposition.

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|>

Cutting Knowledge Date: December 2023
Today Date: 26 Jul 2024

You are an intelligent assistant that can rank the quality of a set of decompositions (simpler sub-questions) for a given complex multi-hop question.<|eot_id|><|start_header_id|>user<|end_header_id|>

I will provide you with 4 attempts that were made at decomposing a complex multi-hop question into a sequence of simpler sub-questions. Each attempt is indicated by a numerical identifier [] in front of it. Rank the attempts based on their quality with respect to the complex multi-hop question. You should rank the attempts by scoring each of them using the following criteria (the maximum attainable score by an attempt is 10 points):
(i) the sub-questions are grammatically sound (1 point),
(ii) the sub-questions are not ambiguously phrased or overly general such that it becomes difficult to find their answers (2 points),
(iii) the sequence of sub-questions should be as simple as possible and only contains the absolutely necessary number of steps to get to the answer of the complex multi-hop question, i.e. each sub-question and its answer must correspond to only one atomic fact and there should be as few sub-questions as possible (2 points),
(iv) each sub-question in the sequence does not logically contradict the sub-question(s) that comes before it (2 points), and
(v) as a whole, the sub-questions cover all the necessary information and steps that will allow us to arrive at the same answer as the original complex question (3 points).

Complex Multi-hop Query: 'If he were poor, would Christopher Reeve have lived?'.

Decomposition Attempts:
[01] [SQ1] What injury did Christopher Reeve suffer from? [SQ2] What equipment is required for someone with #1 in order to live? [SQ3] What would be the cost of #2? [SQ4] Would a poor person be able to afford #3?
[02] [SQ1] What injury did Christopher <unk> suffer from? [SQ2] What equipment is needed by Christopher Reeve for living with a portable ventilator? [SQ3] How much does #2 typically cost? [SQ4] Could someone with limited means afford #3?
[03] [SQ1] What serious spinal cord injury did Christopher Reeve suffer, leaving him quadriplegic? [SQ2] What equipment does an individual with #1 need to survive? [SQ3] How much does the cost of #2 amount to? [SQ4] Can a poor person afford #3?
[04] [SQ1] What type of injury did Christopher Reeve sustain? [SQ2] Which devices would a person with #1 need to survive? [SQ3] What would be cost of #2? [SQ4] Could a person without money afford #3?

Rank the 4 attempts above based on their quality with respect to the complex multi-hop question. All the attempts should be included and listed using identifiers, in descending order of quality. If there are several attempts that are equally good amongst themselves, order their ranking by their index number (smallest first). The output format should be [] > [], e.g., [02] > [01], Only respond with the ranking results, do not say any word or explain.<|eot_id|><|start_header_id|>assistant<|end_header_id|>

[1] > [4] > [2] > [3]<|eot_id|><|start_header_id|>user<|end_header_id|>

Complex Multi-hop Query: 'Is Rosemary outclassed as plant found in most song titles?'.

Decomposition Attempts:
[01] [SQ1] What is the number of songs with "Rosemary" in their titles? [SQ2] How many songs include the plant "rose" in the title? [SQ3] Is #1 fewer than?
[02] [SQ1] How many songs have "rosemary" in the title? [SQ2] How many songs have the plant "rose" in the title? [SQ3] Is #1 fewer than #2?
[03] [SQ1] What is count of songs with 'rosemary' in the title? [SQ2] How many song titles include the plant 'rose'? [SQ3] Are the titles in #1 fewer than those in #2?
[04] [SQ1] What is the number of songs with 'rosemary' in the title? [SQ2] Name two popular songs mentioning rosemary. [SQ3] How many songs feature 'rose' the plant in their titles? [SQ4] Does the number in question #2 fewer than in #3?

Rank the 4 attempts above based on their quality with respect to the complex multi-hop question. All the attempts should be included and listed using identifiers, in descending order of quality. If there are several attempts that are equally good amongst themselves, order their ranking by their index number (smallest first). The output format should be [] > [], e.g., [02] > [01], Only respond with the ranking results, do not say any word or explain.<|eot_id|><|start_header_id|>assistant<|end_header_id|>

[2] > [3] > [4] > [1]<|eot_id|><|start_header_id|>user<|end_header_id|>

Complex Multi-hop Query: 'can children become lieutenants?'.

Decomposition Attempts:
[01] [SQ1] what is the minimum age requirement to become a lieutenant? [SQ2] what is the maximum age for children? [SQ3] is the minimum age requirement for becoming a lieutenant greater than #2?
[02] [SQ1] what is the rank of a lieutenant? [SQ2] at what age can children legally enter into contracts or assume responsibilities? [SQ3] is #1 less than #2?
[03] [SQ1] what is the minimum age requirement to become a lieutenant in a typical military or law enforcement organization? [SQ2] what is the typical minimum age for children? [SQ3] is #1 less than or equal to #2?
[04] [SQ1] what is the minimum age to become a lieutenant? [SQ2] what is the age of a child? [SQ3] is #2 greater than #1?

Rank the 4 attempts above based on their quality with respect to the complex multi-hop question. All the attempts should be included and listed using identifiers, in descending order of quality. If there are several attempts that are equally good amongst themselves, order their ranking by their index number (smallest first). The output format should be [] > [], e.g., [02] > [01], Only respond with the ranking results, do not say any word or explain.<|eot_id|><|start_header_id|>assistant<|end_header_id|>
```

Figure 5: Few-shot Chain-of-Thought prompt used in ranking the quality of candidate complex question decomposition.

You are presented with a complex question (CQ) and an ordered sequence of subquestions (SQs). The SQs have been verified as being simpler decomposed questions of the CQ, i.e. when the SQs are correctly answered, the answer obtained for the final one will be the same as that for the CQ. The references to the answer of an earlier SQ is marked with a # followed by a number that is 1-indexed, e.g. in the SQ "SQ3 >> When was the company in #1 founded?", "#1" refers to the answer to the first SQ in the sequence; it is very important that you make sure to maintain this format when modifying the SQs. Your task is to paraphrase the SQs, and then introduce one or more faults into them as instructed.

Complex question (CQ): {}
{}
Subquestions (SQs): {}
{}

Do the following steps:
Step 1: Please paraphrase at least half of the SQs. When paraphrasing an SQ, try to give it a different syntactic structure. It is very important to keep the meaning of the original SQ intact. Do not add or remove any information from any of the SQs at this step.

Step 2: Please introduce the following faults into the SQs. It is very important: (i) To follow each of the instructions carefully. (ii) That you must not add or remove any SQs unless one of the instructions specifically asks you to do so. {}
{}

Step 3: Return the results in json_schema format with the following keys: (i) "modified_SQs" - is a list holding the SQs after the modifications, (ii) "index_modsSQs" - is a list holding the indices of the SQs that were modified, (iii) "mod_desc" - a list that corresponds with "index_modsSQs" with a short description (of 7 words or less) of what was modified for that SQ. Only return the modifed SQs, i.e. you MUST NOT include the prefix (e.g. "SQ1 >> ") from the input. Only return this json line, do not say anything else before or after it.

1: 'Introduce one or two syntactic and grammatical errors to SQ{0}; make sure that it causes the SQ to be less fluent but does not change its meaning, i.e. the errors should not cause the SQ to be unanswerable or change its answer. (0.5 points)',

2: 'Introduce one or two typographical errors to one of the entity/entities mentioned in SQ{0}, but make sure that the errors do not cause the SQ to be unanswerable or change its answer. (0.5 points)',

3: 'Randomly pick one of the words in SQ{0} and repeat it. (0.5 points)',

4: 'Randomly pick a word in SQ{0} that is (i) more than five characters long, and (ii) part of a named entity; split this word into two parts and replace one part with the span "<unk>" (e.g. the named entity "Montréal" becomes "Mont<unk>")". (0.5 points)',

5: 'Add a new SQ after SQ{0}; this new SQ should have some relation to the answer of any of the preceding SQs; make sure that answering this additional SQ is totally unnecessary for obtaining the final answer, but answering it will not affect whether the final answer is obtainable. Because there is now one more SQ, you must make sure to update the answer variable number of any subsequent SQs that referred to the answers of SQs coming before the new SQ you added. (1 point)',

6: 'Modify every SQ so that every one of them has one or two grammatical errors in them that are typical of non-native English speakers. Make sure that they are still barely understandable, and that the errors do not cause any of the SQs to be unanswerable or change their answers. (1 point)',

7: 'Rewrite SQ{0} so that its answer is leaked in it; example: given the SQ "SQ0 >> Who is the president of France?" whose answer is "Emmanuel Macron", a possible modification to the SQ could be: "What is the name of France\'s President Macron?" (1 point)',

8: 'Replace SQ{0} and SQ{1} with a new SQ that merges the both of them; example: given these SQs "... SQ2 >> Which street can the tallest building in #1 be found on?; SQ3 >> Which famous actress lives on #2?; SQ4 >> What is the birthplace of #3? ", a possible merger between SQ2 and SQ3 could be: "Which famous actress lives on the street where the tallest building in #1 is located on?". Because there is now one less SQ, you must make sure to update the answer variable number of any subsequent SQs that referred to the original SQ{0} or SQ{1} (e.g. SQ4 in the example should be updated to "What is the birthplace of #2?") (2 points) ',

9: 'Remove some information from SQ{0} so that it is now ambiguously worded, i.e. there is insufficient information to answer it easily. (2 points)',

10: 'Make semantic errors that change the meaning of SQ{0} so that its answer is no longer correct (2 points)',

11: 'Change SQ{0} to ask for something different, i.e. after this point in the modified sequence of SQs the reasoning chain is disconnected. DO NOT add new SQs. It is important that the answer to the modified SQ is not the same as the final answers to the CQs or SQs, but make sure that it is still somewhat related to one of the entities mentioned in the CQ. (3 points)',

12: 'Add a final boolean SQ that makes some comparison between the answers to SQ{0} and SQ{1}. (3 points)',

13: 'Change the CQ to ask for an answer that is entirely different. Rewrite all of the SQs as decompositions of this new CQ. Make sure that all the SQs remain as simple questions asking for one single fact. (3 points)',

14: 'Completely change all the SQs so that they are now all unrelated to the CQ and all of the orignal SQs. Make sure that none of the answers to the new SQs are the same as the original answers. (3 points)'

Figure 6: Scoring scheme, error typology and prompt used for generating question decomposition ranking data with GPT-4o.

<|begin_of_text|><|begin_of_text|><|start_header_id|>system<|end_header_id|>

Cutting Knowledge Date: December 2023
Today Date: 26 Jul 2024

You are an intelligent assistant that can get to the answer of a complex question by answering a sequence of simpler sub-questions that are decompositions of the complex question.<|eot_id|><|start_header_id|>user<|end_header_id|>

I will provide you with a complex question. Give me its answer by breaking it down and reasoning through it before giving me the final answer. Give me the intermediate and final answers surrounded by these markers: "[ANS_S]" and
"[ANS_E]".<|eot_id|><|start_header_id|>assistant<|end_header_id|>

I understand the instructions and I will answer the complex question.<|eot_id|><|start_header_id|>user<|end_header_id|>

Complex question: What was the 2004 novel-turned-film adaptation that Freddie Highmore starred
in?<|eot_id|><|start_header_id|>assistant<|end_header_id|>

Decomposed sub-question: return what Freddie Highmore starred in
Answer to sub-question: [ANS_S]Finding Neverland, Charlie and the Chocolate Factory, Arthur and the Invisibles, August Rush, and The Spiderwick Chronicles[ANS_E]
Decomposed sub-question: return Finding Neverland, Charlie and the Chocolate Factory, Arthur and the Invisibles, August Rush, and The Spiderwick Chronicles that was a 2004 novel-turned-film adaptation
Answer to sub-question: [ANS_S]Five Children and It[ANS_E]<|eot_id|><|start_header_id|>user<|end_header_id|>

Complex question: Which team did Tadas Simaitis's team win to end a 5-game losing
streak?<|eot_id|><|start_header_id|>assistant<|end_header_id|>

Decomposed sub-question: return the team of Tadas Simaitis
Answer to sub-question: [ANS_S]Football Club Jonava[ANS_E]
Decomposed sub-question: return the team that Football Club Jonava win to end a 5-game losing streak
Answer to sub-question: [ANS_S]Suduva[ANS_E]<|eot_id|><|start_header_id|>user<|end_header_id|>

Complex question: Who is the eldest son of the republican rival of Governor Bill Clinton of Arkansas in the 1992 presidential
election?<|eot_id|><|start_header_id|>assistant<|end_header_id|>

Decomposed sub-question: return republican rival of Governor Bill Clinton of Arkansas in the 1992 presidential election
Answer to sub-question: [ANS_S]George H. W. Bush[ANS_E]
Decomposed sub-question: return eldest son of George H. W. Bush
Answer to sub-question: [ANS_S]George W. Bush[ANS_E]<|eot_id|><|start_header_id|>user<|end_header_id|>

Complex question: The Dachau Trials and the division of Germany happened due to
what?<|eot_id|><|start_header_id|>assistant<|end_header_id|>

Figure 7: Few-shot Chain-of-Question prompt used in QA evaluation.