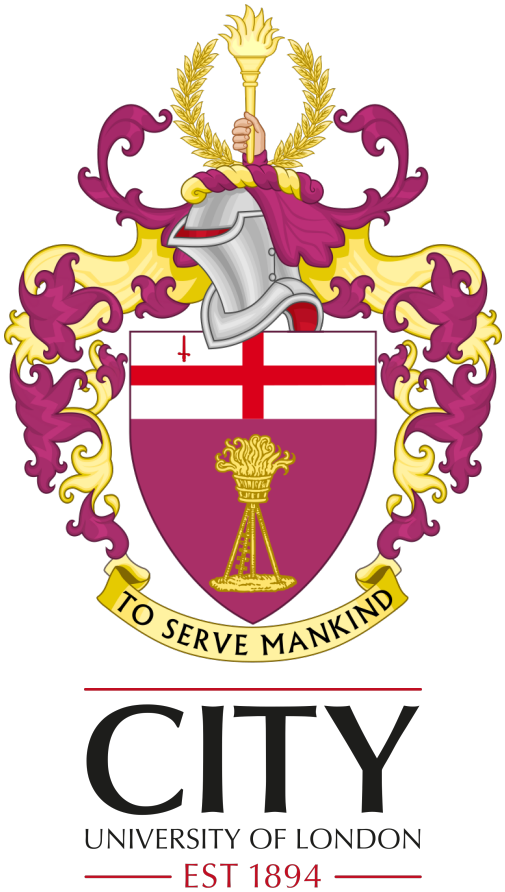

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Knowledge Grounding in Language Models: An Empirical Study

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Declaration

By submitting this work, I declare that this work is entirely my own except those parts duly identified and referenced in my submission. It complies with any specified word limits and the requirements and regulations detailed in the assessment instructions and any other relevant programme and module documentation.

In submitting this work I acknowledge that I have read and understood the regulations and code regarding academic misconduct, including that relating to plagiarism, as specified in the Programme Handbook. I also acknowledge that this work will be subject to a variety of checks for academic misconduct.

Signed: *Martin Fixman*

Acknowledgements

Abstract

In recent years large language models have exploded in quality and prevalence, and they have become crucial for work in a wide range of areas. However, their tendency to produce hallucinations presents a critical challenge in contexts where accuracy is crucial.

Retrieval-Augmented Generation (RAG), which leverages external information to provide more accurate and contextually appropriate responses, has been proposed as a solution to this issue. However, this solution is far from perfect as it's unclear when a large language model will choose the information provided by the RAG model over its learned, parametric knowledge.

This thesis explores the *Knowledge Grounding* of various large language models. In particular, it attempts to answer a simple research question: **How does a large language model respond when given information that contradicts its inherent knowledge, and why?**

To investigate this, we develop a diverse dataset comprising questions from various topics and globally representative data. We use this dataset to construct queries with counterparametric context across four models of different architectures and sizes, and later analyse the perplexity of these answers to give us a clue to *why* the model chose an answer over the other.

Our findings suggest that, when using RAG-enhanced systems, smaller and simpler models might produce fewer hallucinations. In particular, the smaller models `Meta-Llama-3.1-8B` and `Flan-T5-XL` tend to have better knowledge grounding and fewer hallucinations than their larger versions. Additionally, when adding RAG context the simpler Seq2Seq models tend to outperform the newer and more complex Decoder-only models.

As an extra analysis we investigate methods for determining whether a given response originates from the RAG context or the model's internal memory using its resulting perplexity, which may indicate a potential hallucination.

This thesis forms the foundational part of a broader project aimed at publishing a comprehensive study on knowledge grounding in retrieval-augmented language models, as outlined in the preprint "Knowledge Grounding in Retrieval-Augmented LMs: An Empirical Study" (Whitehouse et al. 2023). We build on existing literature, incorporating the use of counterparametric context in queries, to advance our understanding of this phenomenon.

Contents

1 Introduction and Objectives

1.1 Problem Background

In recent years, Large Language Models (LLMs) have become ubiquitous in solving general problems across a wide range of tasks, from text generation to question answering and logic problems. However, recent research suggests that using these models alone might not be the most effective way to solve problems that are not directly related to text generation (Yao et al. 2023).

One approach to improving the performance on knowledge problems for LLMs is Retrieval-Augmented Generation (RAG) (Lewis et al. 2020). RAG involves retrieving relevant context related to a query and incorporating it into the model's input, enhancing the model's ability to generate accurate and contextually appropriate responses.

As RAG-enhanced systems become more widespread, studies on the performance of different retrieval systems and their interaction with LLMs have become crucial. Many explore the performance of these downstream tasks depending on both the retriever and the generator (Ghader et al. 2023, Brown et al. 2020), examining whether the knowledge is *grounded* in the context. Retrieval-Augmented models, such as Atlas (Izacard et al. 2022) and Retro (Borgeaud et al. 2022), use this approach to fine-tune a model on both a large body of knowledge and an existing index for context retrieval.

This project aims to understand the performance of various large language models with added context by measuring their *knowledge grounding* on a dataset consisting of a large variety of questions across a wide range of topics. We follow the approach by Yu et al. of running queries with counterparametric context to understand whether a particular answer originates from the model's inherent knowledge (i.e., its training data) or from the provided context (i.e., the context retrieved by RAG).

This thesis builds on this knowledge and improve our understanding of how different LLMs interact with the given context in the problem of question answering. Specifically, we investigate whether these interactions vary depending on the type of question being answered, contributing to a more nuanced understanding of LLM performance in diverse knowledge domains.

1.2 Research Question

How do we know what large language models really know? This thesis attempts to answer this question by asking a different but related question:

How does a large language model respond when given information that contradicts its inherent knowledge, and why?

The rest of this section gives an overview of the steps we take to answer this question.

1.3 Research Objectives

This thesis is structured around three different sub-objectives to deepen our understanding knowledge grounding in large language models.

1. **Creating a representative dataset of questions.**
   This is necessary as existing Q&A datasets are not suitable for our objectives.
2. **Building an experimental framework to understand the source of an LLM's answer.**
   This will give us information about which models prefers which type of answers, whether it depends on the question asked, and more.
3. **Enhancing the framework to understand the reasoning behind each answer**
   We use the perplexity of a model's response on both answers to understand *why* a certain answer was chosen.

1.4 Overview of Methods

1.4.1 Creating a representative dataset of questions

We require a dataset of questions that's useful for answering our research question. This dataset should allow us to understand the responses of the models to know whether they came from the model's parametric memory or from the RAG context, and should be reasonably representative of the world to prevent biases.

In particular, the questions should allow us to easily create counterparametric answers to later add as context to our queries. We follow the example of Yu et al. on creating questions that can be easily answered with short responses, and later using these answers to create counterparametric context.

We also enhance this work by adding a much larger set of questions of a variety of topics.

1.4.2 Building an experimental framework to understand the source of an LLM's answer

Currently, little is understood about the factors and mechanisms that control whether an LLM will generate text respecting either the context or the memorised information.

Previous research found out that, when the context of a query contradicts the ground knowledge of a model, the final answer depends on the size and architecture of the model used (Yu et al. 2023).

This thesis extends this research by testing the representative set of questions and counterfactuals described in the previous section with both Seq2Seq and Decoder-only models of various sizes. We also research the cases when the answer doesn't correspond

to either the parametric or contextual knowledge, and why the model chooses a third type of answer when adding counterfactual context.

1.4.3 Enhancing the framework to understand the reasoning behind each answer

Yu et al. showed that there is a correlation between the probability of a large language model choosing a parametric answer over a counterfactual contextual answer and the amount of times this answer appears in the ground truth data of the model. This gives us clues on whether the result of a query came from parametric or contextual knowledge if we have access to this ground truth, as is the case in models like Pythia (Biderman et al. 2023).

Unfortunately, most so-called open-source large language models do not give us access to the source data being used to train it and therefore do not allow this kind of analysis.

The **perplexity** score of answer gives a measure of how "certain" a large language model is of its answer (Jiang et al. 2021). We hypothesise that we can use this metric to serve as a reliable indicator of whether a particular answer was memorised by the LLM or was derived from the provided context.

2 Context

This research is the latest on a long line of academic articles on the topics of retrieval-augmented generation, counterparametric and contextual data, and how to enhance knowledge on large language models.

This section summarizes key articles that informed this research.

2.1 Foundational Papers on Large Language Models

Large language models have exploded in popularity since the development of the transformer architecture (Vaswani et al. 2017). This architecture relies entirely on self-attention mechanisms rather than recurrent or convolutional layers, which allow the model to weigh the importance of different words in a sequence relative to each other, irrespective of their position. This mechanism enables the model to capture complex dependencies and relationships across long sequences more effectively than traditional models.

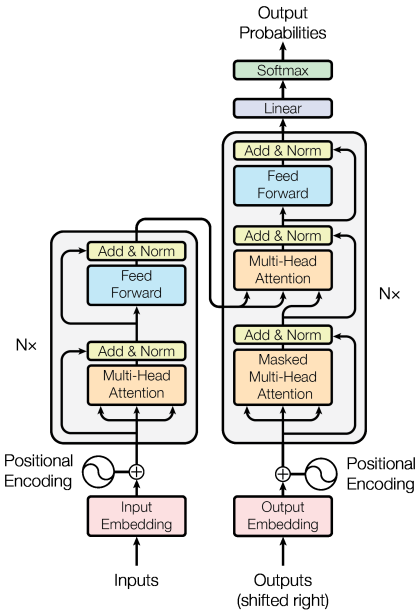


Figure 1: Transformer Architecture, from "Attention is all you need" (Vaswani et al. 2017).

GPT models (Radford & Narasimhan 2018) improve upon this architecture by running a supervised task-specific fine-tuning round after the unsupervised pre-training on large amount of test data. Later models, starting from GPT-2, use zero-shot transfer learning to improve their performance (Radford et al. 2019). Zero-shot learning (Norouzi et al. 2014) trains a model to perform a task without having been explicitly trained on examples of that task; instead, it leverages knowledge gained from pre-training to infer and generalise to new tasks with the context on the prompt.

By adding only a few examples of the task at hand, a model can use few-shot learning to

improve generalisation to new tasks with a limited amount of labelled data. GPT-3 uses this to understand the structure and nature of a task with a few examples (Brown et al. 2020)

Despite these improvements, the models themselves are still uncalibrated and not very good at question answering (Jiang et al. 2021). Hallucinations are common, even for short Q&A tasks

2.2 Architectures of Large Language Models

TODO: Talk about T5, Flan-T5, and Llama here.

2.3 Retrieval-Augmented Generation

Large pre-trained language models store factual knowledge in their parameters. Their ability to access this knowledge is limited, which affects their performance on knowledge-intensive tasks.

Retrieval-Augmented Generation (RAG) attempts to solve this problem by adding extra non-parametric context gathered from an index with a retriever that's trained independently (Lewis et al. 2020). This retrieved context is fed back to the original query by adding context, which generates a combined representation which contains both the query and the original context. An overview of this method is presented in Figure 2.

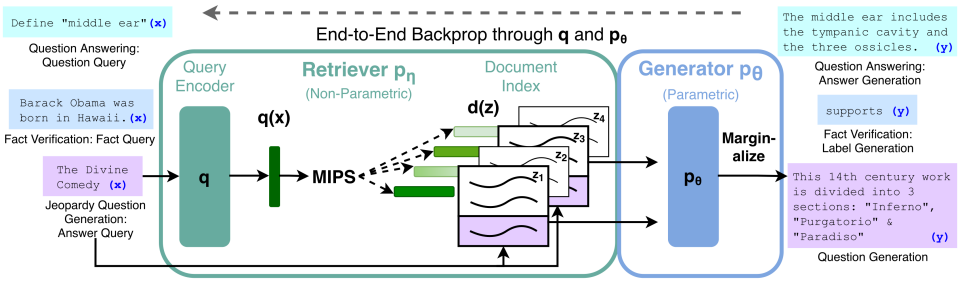


Figure 2: An overview of the RAG approach, combining a pre-trained retriever with a pre-trained model. From "Retrieval-Augmented Generation for Knowledge-Intensive NLP tasks" (Lewis et al. 2020)

RAG can be effective in preventing hallucinations by incorporating relevant external information into the generation process, ensuring that responses are more grounded in factual data from a knowledge base. However, this is not perfect and an even after adding a correct context the model could answer data from its internal memory.

2.4 Knowledge Grounding on Queries with Added Context

Knowledge grounding is the process of ensuring that information generated by a language model is consistent with a reliable external source of knowledge. In the context of RAG-enhanced queries, this can include ensuring that answers are consistent with the knowledge in the index rather than in the model's inherent knowledge.

Various attempts have been made at understanding how good the knowledge grounding of a RAG system is, and on what is the optimal configuration of RAG.

In "RAGGED: Towards Informed Design of Retrieval Augmented Systems" (Hsia et al. 2024), the authors create a framework to evaluate these systems and find that different models suit substantially varied RAG setups. In particular, the performance of the models decreases strongly in Decoder-only models such as Llama when the context passages provides more context, while this does not happen on Seq2Seq models such as Flan.

"Characterizing Mechanisms for Factual Recall in Language Models" (Yu et al. 2023), which is one of the main sources for this thesis, finds that when there is disagreement between the model's knowledge and the provided context then the architecture and size of the large language model will greatly affect the probability of the model choosing to use the context (which is much less prone to hallucinating) as an answer.

This paper also introduces a novel way to test this hypothesis by creating a dataset with questions and counterfactual context, an example of which is shown in Listing 1.

```
The capital of {country} is {in context city}
Q: What is the capital of {country}?
A:
```

Listing 1: Example of queries used in (Yu et al. 2023). These queries form the basis and inspiration for the dataset creation done in this thesis

By adding counterparametric information to the context, this method allows us to understand whether an answer came is parametric (that is, came from the memory of the model) or contextual (that is, came from the provided context).

3 Methods

How does a large language model respond when given information that contradicts its inherent knowledge, and why?

To understand this, we need to build a new framework for testing a model's answers when presented with contradictory information. This framework must be tested with models of various architectures and sizes to get insights about our responses.

Following the example set in Section 1.3, we split the work into three sub-objectives.

3.1 Creating a representative dataset of questions

As argued in Section 1.4.1, the research of this thesis requires a large dataset of questions from a variety of categories to test large language models.

3.1.1 Dataset Description

The dataset we aim to create for this research is designed to be a comprehensive and versatile tool for evaluating large language models. By choosing this criteria when selecting questions, we ensure that the dataset will provide meaningful insights of the knowledge grounding of large language models across a wide spectrum of domains.

Our dataset should have the following properties.

1. **Questions should have short, unambiguous answers.**
   Our goal is to compare these results for both equality and perplexity. Longer answers make this objective more complicated since two long, correct answers might be equivalent. Shorter answers reduce the space of possible answers that are equivalent, but not equal.

2. **Questions must cover a large and diverse set of topics.**
   The parametric knowledge of a model comes from a pre-existing dataset of training data, which might be biased towards certain topics or groups of people. For example, it is known that Wikipedia contains a significant geographical bias on biographies (Beytía 2020), and that this affects the probability of giving a correct answer without context (Yu et al. 2023). We require a large and diverse and set of topics to counteract potential biases.

3. **Questions must allow for the creation of counterparametric answers.**
   Part of the requirements of this thesis is to allow some tests of contextual versus inherent knowledge. A simple way to do this is to repeat and enhance the approach used by Yu et al. of adding counterparametric answers to a query context. This allows us to to easily disambiguate whether an answer came from the model's memory or from the context. This approach is only possible if the set of answers allows us to create a set of alternative answers that are plausibly correct and have the same format as the parametric answer, but are still counterparametric.

The existing literature uses various existing question-and-answer datasets. We believe that none of these datasets are a good fit for this research for not following some of the three desired properties. However, understanding them can be useful when designing the final dataset.

Natural Questions Dataset Created by Google Research (Kwiatkowski et al. 2019), and commonly used in research related to understanding the answers of LLMs in question-and-answer problems (Hsia et al. 2024, Mallen et al. 2023, Ghader et al. 2023). While the dataset provides an excellent range of questions and existing literature to compare these results to, the lack of categorisation is an obstacle in our objective to generate counterparametric answers.

Human-Augmented Dataset Sometimes used in research related to quality control of large language models (Kaushik et al. 2020). However, the high cost associated with this dataset would limit the size of our questions.

Countries' Capitals Question Dataset Used in "Characterizing Mechanisms for Factual Recall in Language Models" (Yu et al. 2023), this dataset contains a single question about the capital city of certain countries which can be easily transformed to a counterparametric question. This format is ideal for the research done in this thesis, but having a single question pattern will not allow a deep dive into the source of each answer in a general question.

3.1.2 Dataset Creation

Instead of using an existing dataset, this research takes inspiration from the paper by Yu et al. to create a similar but larger dataset of questions and answers from a wide range of topics, where questions can be grouped by question pattern to ensure that their formats are similar. This way, we can emulate the approach of that paper of using the answer from a certain question as the counterfactual question of another.

This dataset will be used to test the remaining questions of this thesis. Since it might be useful for future research, it will also be presented as its own result.

To address these items, we follow the approach done by Yu et al. in creating base questions that refer to a specific object, so all the answers for the same base question have a similar format and creating counterparametric answers is easy.

Since this thesis requires a set of questions that covers a large set of topics, eras, and places, we enhance this method by creating a set of categories, each of which has a large set of base questions and another set of objects that can be matched. An example of this approach is shown in Table 1.

This list of questions will enable the research on whether the answers given by large language models depend on the category and the format of the questions.

Category	Base Questions	Object	Queries
Person	Q: What is the date of birth of {person}? A: The date of birth of {person} is Q: In what city was {person} born? A: {person} was born in	Che Guevara Confucius	Q: What is the date of birth of Che Guevara? A: The date of birth of Che Guevara is Q: What is the date of birth of Confucius? A: The date of birth of Confucius is Q: In what city was Che Guevara born? A: Che Guevara was born in Q: In what city was Confucius born? A: Confucius was born in
City	Q: What country is {city} in? A: {city} is in	Cairo Mumbai Buenos Aires London	Q: What country is Cairo in? A: Cairo is in Q: What country is Mumbai in? A: Mumbai is in Q: What country is Buenos Aires in? A: Buenos Aires is in Q: What country is London in? A: London is in

Table 1: Some examples of the base-question and object generation that are fed to the models for finding parametric answers.

3.2 Building an experimental framework to understand the source of an LLM's answer

3.2.1 Model Selection

In order to get a general understanding of large language models with added context, we test the queries generated in Section 3.1 into four models of different architectures and sizes, which are listed in Table 2.

	Seq2Seq Model	Decoder-Only Model
Smaller	`Flan-T5-XL`	`Meta-Llama-3.1-8B-Instruct`
Larger	`Flan-T5-XXL`	`Meta-Llama-3.1-70B-Instruct`

Table 2: The four large language models chosen for this research.

Both Sequence-to-Sequence models are based on T5 models (Raffel et al. 2020), which employ an encoder-decoder architecture: while an encoder processed the input sequence into a context vector, and an decoder generates an input sequence from this vector. The `Flan-T5` models are fine-tuned to follow instructions, and have improved zero-shot performance compared to the original T5 models (Chung et al. 2022).

`Flan-T5-XL` contains approximately 3 billion parameters, and is considerably bigger than the base Flan-T5 model, which should improve the accuracy of its parametric answers.

`Flan-T5-XXL` contains 11 billion parameters, so it should have higher accuracy on the parametric answers as the `XL` model. However, how the higher amount of parameters

will affect the experiments that we are running is still unknown.

Unlike Seq2Seq models, Decoder-only models focus on the generation of text based on the previous tokens. In a sense, given a sequence of tokens they solve the problem of predicting the following token, repeating sequentially until some final token is found.

These architectures leverages autoregressive attention (Vaswani et al. 2017), where each token attends to its preceding tokens, maintaining the temporal order of the sequence. This approach allows them to generate coherent and contextually relevant text by sampling from this learned distribution, while also capturing long-range dependencies and complex patterns in language.

The Llama models (Dubey et al. 2024) use this architecture and fine-tune it to tasks of instruction-following, and are specially adept at complex prompts.

The Decoder-only model `Meta-Llama-3.1-8B-Instruct` has 8 billion parameters, while `Meta-Llama-3.1-70B-Instruct` has 70 billion. Meta provides an even larger model, `Meta-Llama-3.1-405B-Instruct`, that is too large to easily experiment with. However, we expect the difference between this model and the `70B` model to be roughly the same as the difference between the `70B` and `8B` models.

The properties of the models are summarised in Table 3.

Model	Architecture	Developer	Parameters	Context
`Flan-T5-XL`	Seq2Seq	Google Brain	3 Billion	512 Tokens
`Flan-T5-XXL`	Seq2Seq	Google Brain	11 Billion	512 Tokens
`Meta-Llama-3.1-8B-Instruct`	Decoder-Only	Meta AI	8 Billion	128k Tokens
`Meta-Llama-3.1-70B-Instruct`	Decoder-Only	Meta AI	70 Billion	128k Tokens

Table 3: Model cards of the large language models used in this research.

3.2.2 What type of answer does each model select for each question?

The first step to understanding the knowledge grounding of large language models is to create queries that contain counterparametric data as part of the context. By comparing the result to the existing answers it becomes trivial to understand whether an answer came from the model's memory, the queries' context, or neither of these.

Following the approach of Yu et al., for every query we randomly sample from the set of answers of the same base question for answers that are different to the parametric answer which is given by the original query. An example of this shuffling is in Table 5.

Later, we add this *counterparametric answer* to the context, to form a new query and query the same model again; this is exemplified in Table 4.

To ensure that the results are simple to interpret and minimise the effect of randomness, once we select the queries we follow the example of Hsia et al. and use Greedy Decoding to find the answer. While beam search with a short beam width tends to produce more

accurate results for long answers (Sutskever et al. 2014, Wu et al. 2016) and there are many other sampling methods that produce better results (Holtzman et al. 2020), this is likely to not have an effect on experiments that result in shorter answers (Raffel et al. 2020).

We compare the parametric answer to the previous values to come to one of three cases:

Parametric answers are equal to the answer given by the model when queried without context. This answer would come from the parametric memory of the model, and could potentially include hallucinations not fixed by RAG.

Contextual answers are equal to the context given in the query.

Other answers are neither of these, and this answer comes from a mis-interpretation of the input by the model or from some other source.

To minimise the amount of problems caused by large language models generating extra information, we define two strings to be equal by removing all text after a period or an `<EOS>` token, removing punctuation and stop words, and finding whether one is a subsequence of another.

This approach to compare strings is not enough, and understanding whether two answers are identical is an ongoing problem. This is explained in the Future Work section in Section 6.1.1.

The approach to finding out the source of knowledge of each query is specified in Figure 3.

Question with counterparametric context	Model Answer	Category
Context: [the nearest major body of water to Windhoek is the Rio de la Plata] Q: What is the nearest major body of water to Windhoek? A: The nearest major body of water to Windhoek is	the Atlantic Ocean	Parametric
Context: [the date of birth of Che Guevara is 965 AD]. Q: What is the date of birth of Che Guevara? A: The date of birth of Che Guevara is	965 AD	Contextual
Context: [Rome is in Georgia] Q: What country is Rome in? A: Rome is in	the United States	Other

Table 4: Example for results with **Parametric**, **Contextual**, and **Other** values. Note that, in the third query, the model is interpreting the question as asking about Rome in the US State of Georgia, rather than the country of Georgia.

Base Question	Object	Parametric Answer	Counterparametric Answer	Question with Counterparametric Context
Q: What is the date of birth of {person}? A: The date of birth of {person} is	Che Guevara	June 14, 1928	965 AD	Context: [the date of birth of Che Guevara is 965 AD]. Q: What is the date of birth of Che Guevara? A: The date of birth of Che Guevara is
	Ibn al-Haytham	965 AD	June 14, 1928	Context: [the date of birth of Ibn al-Haytham is June 14, 1928]. Q: What is the date of birth of Ibn al-Haytham? A: The date of birth of Ibn al-Haytham is
	W.E.B Du Bois	February 23, 1868	June 14, 1928	Context: [the date of birth of W.E.B Du Bois is June 14, 1928]. Q: What is the date of birth of W.E.B Du Bois? A: The date of birth of W.E.B Du Bois is
Q: What country is {city} in? A: {city} is in	Cairo	Egypt	India	Context: [Cairo is in India]. Q: What country is Cairo in? A: Cairo is in
	Mumbai	India	Egypt	Context: [Mumbai is in Egypt]. Q: What country is Mumbai in? A: Mumbai is in

Table 5: Using the same question format allows us to repurpose previous parametric answers as counterparametric ones.

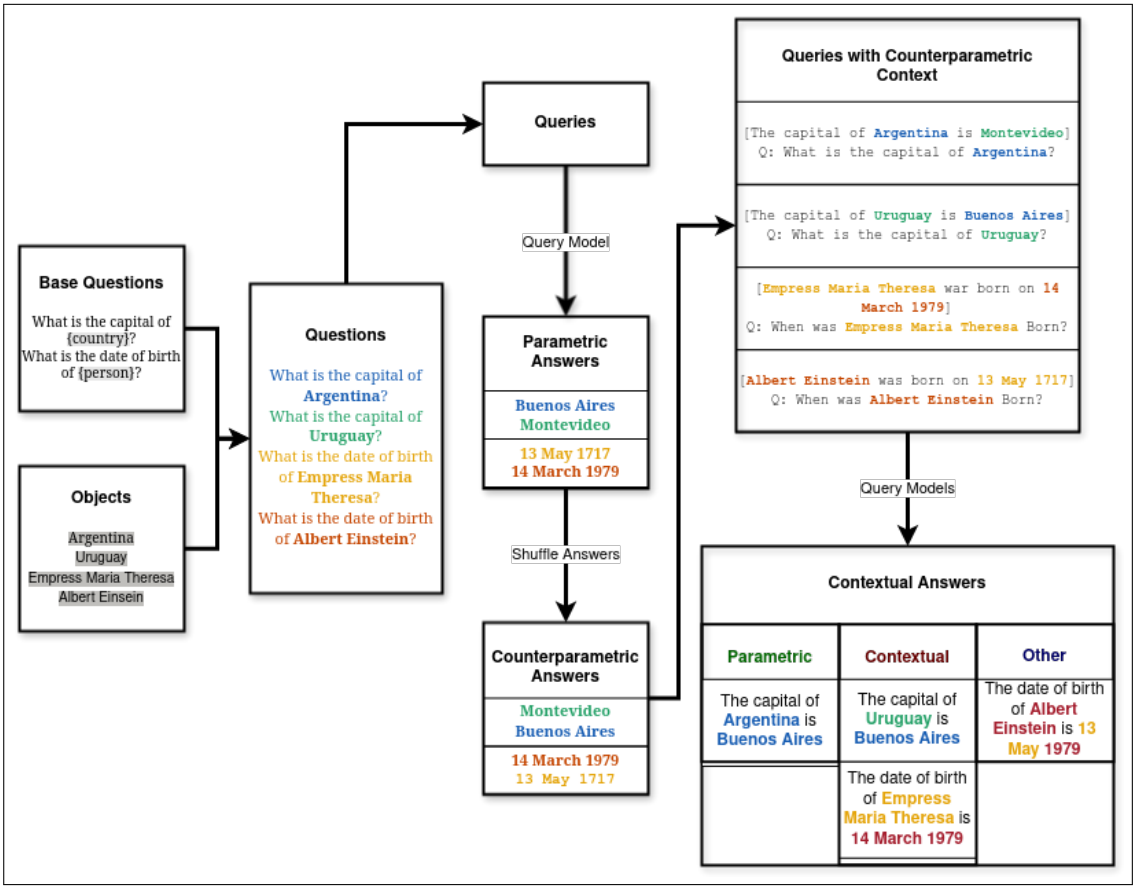


Figure 3: Example diagram of steps used to calculate the two sets of answers, *parametric* and *contextual*, and to compare them to answer the question in this objective. Many of the terms in this diagram are explained in the Glossary.

3.2.3 Understanding the result by finding the mean attention of the context and question areas

For comparing different architectures, it's useful to understand how much attention they give to the context compared to the rest of the query.

Since all our model architectures employ attention mechanisms (Chung et al. 2022, Dubey et al. 2024), we can estimate the relative importance of tokens in the context and the query by calculating the average self-attention each token receives within its respective section. Specifically, we compute the mean self-attention weights, which serve as a proxy for the emphasis the model places on different parts of the input.

This approach is formalized in Equation (1), where we define the mean self-attention for tokens in the context and query sections.

$$
\begin{aligned}
A &: \mathbb{R}^{\text{batch}\times|\text{layer}|\times|\text{attn\_head}|\times Q\times K} \\
m_{b,q,k} &= \frac{1}{|\text{layer}| \times |\text{attn\_head}|} \sum_{\substack{i=0 \\ j=0}}^{\substack{\text{layer} \\ \text{attn\_head}}} A_{b,i,j,q,k} \\
d_{b,q} &= m_{b,q,q} \\
s_{b,i} &= \left(d_{b,i} - \min\left(d_b\right)\right) / \left(\max\left(d_b\right) - \min\left(d_b\right)\right) \\
\text{attn}_{\text{ctx}} &= \frac{1}{|\text{ctx}|} \sum_{i\in\text{ctx}} s_{b,i} \qquad \text{attn}_{\text{rest}} = \frac{1}{|\text{rest}|} \sum_{i\in\text{rest}} s_{b,i}
\end{aligned}
\tag{1}
$$

In this equation, A is the 5-tensor representing the attention weights. $m_{b,q,k}$ represents the mean attention all layers and heads, while d_b represents the diagonal of these attentions which correspond to the self-attentions.

We normalise those values for s_i and average then among the context tokens and the rest of the query, respectively.

3.3 Enhancing the framework to understand the reasoning behind each answer

3.3.1 Perplexity Score

The Perplexity score of an answer is normally used to measure the inverse of the certainty that the model has of a particular answer (Brown et al. 2020, Borgeaud et al. 2022). In a sense, it's the "surprise" of a model that a certain answer is correct.

We can define the probability of a model choosing a token x_n with context $x_1, \ldots, x_{n-1}$ from a query Q by calculating the softmax value of all the logits for the possible words for this token.

The probabilities of the tokens if an answer can be accumulated to calculate the negative log-likelihood NLL, which is used to calculate the perplexity PPL using the formulas from Equations (2) and (3).

$$\mathrm{NLL}\left(x_1, \ldots, x_n \mid Q\right) = -\frac{1}{n} \sum_{i=1}^{n} \log_2 P\left(x_i \mid Q, x_1, \ldots, x_{i-1}\right) \tag{2}$$

$$\mathrm{PPL}\left(x_1, \ldots, x_n \mid Q\right) = 2^{\mathrm{NLL}(x_1, \ldots, x_n \mid Q)} \tag{3}$$

3.3.2 Perplexity of the parametric answer with counterparametric context and vice-versa

Note that the token x_n does not necessarily have to be the result of applying the query $x_1, \ldots, x_{n-1}$ to a model.

Therefore, it becomes necessary to use teacher-forcing (Lamb et al. 2016) to feed some answer to the model regardless of what's the answer to this particular query. This allows us to calculate the perplexity scores of the parametric answers for both the regular query and the one with counterparametric context, and the perplexity scores of the contextual answers for these two queries.

For a given parametric answer $p_1, \ldots, p_n$ and randomly sampled counterparametric answer $q_1, \ldots, q_m$, a query without context Q, and a query with this counterparametric context Q' we can calculate four different perplexity scores as shown in Table 6.

Since the parametric answer is by definition the response of the model to the regular query, $P_0 \leq P_1$. In fact, the perplexity of the parametric value is lower than the perplexity of any other answer on query Q.

Figure 4 contains an example of the calculation of the perplexity values for a particular query.

		Tokens	
		Parametric p	Counterparametric q
Context	Base Query	$P_0 = \text{PPL}\,(p_1, \ldots, p_n \mid Q)$	$P_1 = \text{PPL}\,(q_1, \ldots, q_m \mid Q)$
	Counterparametric Context	$P_2 = \text{PPL}\,(p_1, \ldots, p_n \mid Q')$	$P_3 = \text{PPL}\,(q_1, \ldots, q_m \mid Q')$

Table 6: Four different perplexity values: one for each set of tokens, and one for each query context.

3.3.3 Predicting whether an answer came from memory or from context

One question remains: if the response of the query with counterparametric context Q' is a certain answer $x_1, \ldots, x_n$, how can we predict whether this answer is came from the model's memory p or from the given context q without requiring an extra query?

We propose investigating the value of the perplexity $\text{PPL}\,(x_1, \ldots, x_n \mid Q')$ and comparing it to the distribution of perplexities on the answers with added parametric context P_2 and P_3. For simplicity reasons, we are obviating the case when the preferred answer is neither of these; instead, we focus on whether the parametric or counterparametric answer are more likely.*

*TODO: Maybe include a KDE or a K-S test here.

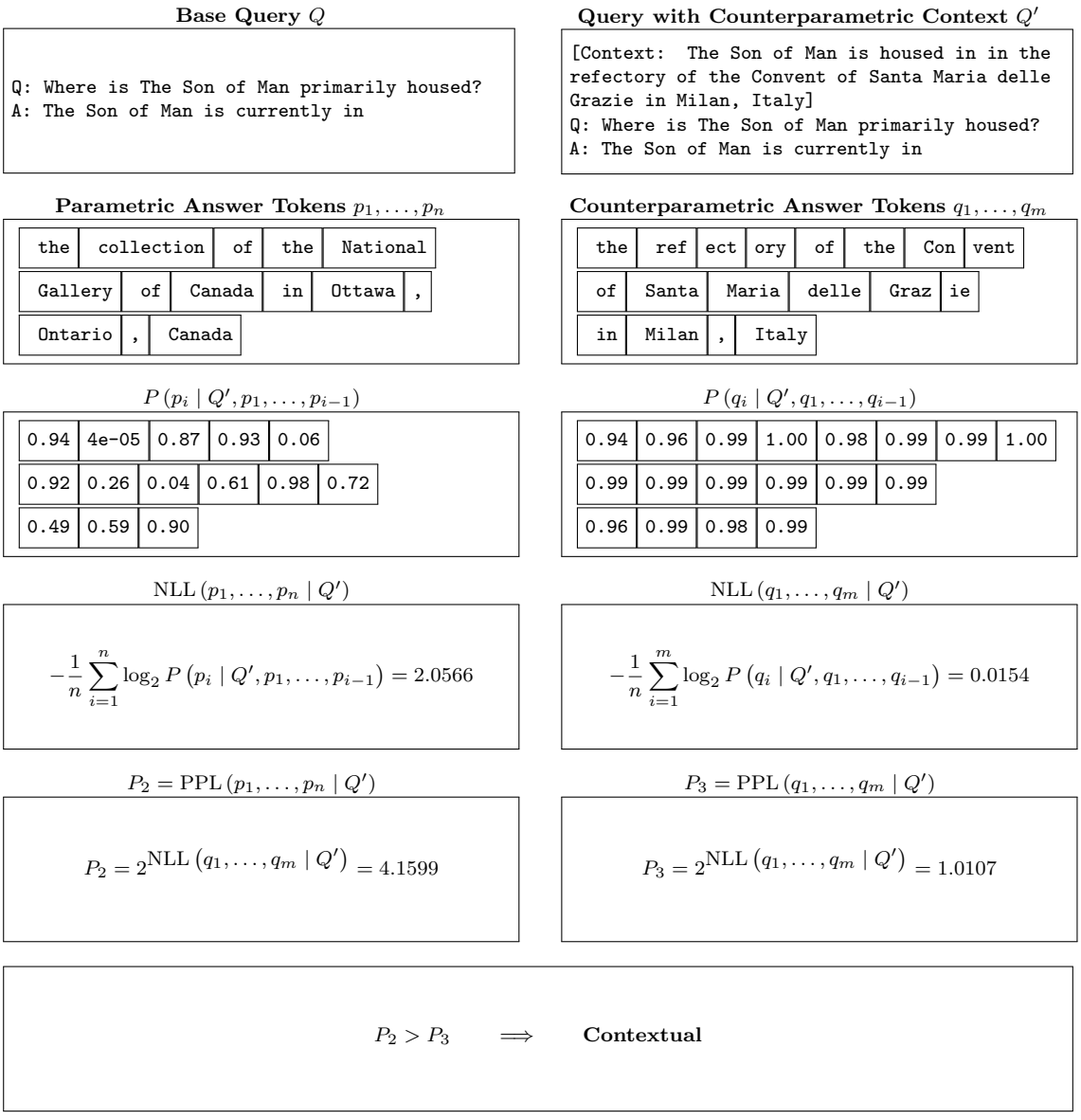


Figure 4: Example of perplexity calculation for the parametric and counterparametric answers in a query with the counterparametric context. Note that, due to teacher forcing, the calculation finds the probability of the next token p_i *given the previous tokens of the searched answer* $p_1, \ldots, p_{i-1}$ rather than given the most likely tokens. For example, once we feed the string "`National Gallery of Canada in`", the probability of the next token being "`Ottawa`" is very high.

4 Results

We followed the methods explained in Section 3 to create a new dataset and run the listed models in Section 3.2.1 in order to measure the knowledge grounding of each one of these models.

This section presents the results from these runs.

4.1 Creating a representative dataset of questions

As described in Section 1.4.1 and explained in Section 3.1, we require a new and diverse dataset in order to run this data and answer the research question.

We manually create a set of 4760 questions using the method explained in Section 3.1.

In order to be able to reuse objects for different questions, we separated the questions and objects in 9 different categories.

1. **Person** Historical people living from early antiquity to the present day from all around the globe. The questions have short, unambiguous answers, such as date of birth or most famous invention.
2. **City** Cities from all over the globe. Questions may include population, founding date, notable landmarks, or geographical features.
3. **Principle** Scientific principles, discovered from the 16th century forward. Questions about their discovery, use, and others.
4. **Element** Elements from the periodic table. Questions may cover discovery, atomic number, chemical properties, or common uses.
5. **Book** Literary works from various genres, time periods, and cultures. Questions may involve authors, publication dates, plot summaries, or literary significance.
6. **Painting** Famous artworks from different art movements and periods. Questions may cover artists, creation dates, styles, or current locations.
7. **Historical Event** Significant occurrences that shaped world history, from ancient times to the modern era. Questions may involve dates, key figures, causes, or consequences.
8. **Building** Notable structures from around the world, including ancient monuments, modern skyscrapers, and architectural wonders. Questions may cover location, architect, construction date, or architectural style.
9. **Composition** Musical works from various genres and time periods. Questions may involve composers, premiere dates, musical style, or cultural significance.

Each one of these categories has a number of questions that are assigned one of the objects, enhancing the done by Yu et al..

The full list of base questions and objects for all categories can be found in Appendix A. The total amount of these and composition of the 4760 questions can be found in Table 7.

Category	Base Questions	Objects	Total Questions
Person	17	57	969
City	17	70	1190
Principle	5	37	185
Element	15	43	645
Book	11	49	539
Painting	12	44	528
Historical Event	4	64	256
Building	9	22	198
Composition	10	25	250
Total	100	411	4760

Table 7: The amount of base questions, objects, and the total amount of questions in each category on the final dataset.

4.2 Building an experimental framework to understand the source of an LLM's answer

4.2.1 Building and running the framework

The code used for running this framework is present in Appendix D. This code roughly follows the diagram on Figure 3 to run the following steps.

1. Generate questions from base questions and objects: `combine_questions`.
2. Gather the parametric answers for each model: `QuestionAnswerer.answerChunk`.
3. Shuffle them to create counterfactual answers: `sample_counterfactual_flips`.
4. Build new queries with these counterfactual answers as context: `Question.format`.
5. Run the models again, and gather the corresponding answer type for each answer from the results: `QuestionAnswerer.answerCounterfactuals`.

The models were run on a server with 48 Intel(R) Xeon(R) CPU 3GHz CPUs, 376GB of RAM, and 2 NVIDIA A100 GPUs with 80GB of VRAM each that was kindly provided by City, University of London.

We estimate that it's possible to run this framework on all but the largest model, `Meta-Llama-3.1-70B`, using a single A100 GPU.

Appendix C explains the many options that can be run on `knowledge_grounder.py` to re-run this experiment or run similar ones.

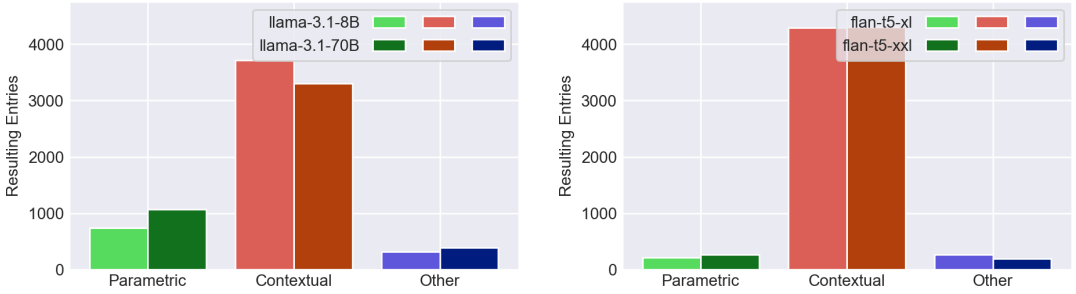
4.2.2 Framework Results

The results of running the queries created in Section 3.1 with added counterparametric context on each of the four models the four models can be found in Table 8 and Figure 5.

Model	Parametric	Contextual	Other
`llama-3.1-8B`	745	3662	353
`llama-3.1-70B`	1070	3303	387
`flan-t5-xl`	248	4284	228
`flan-t5-xxl`	242	4304	214

Table 8: Results when running all entries on a decoder-only model.

.



(a) Decoder-only models

(b) Seq2Seq models

Figure 5: Results by type depending on which model; these are the same results as Table 8.

As hypothesised in Section 1.4.2, there are vast differences on how the models of different types and sizes act when presented with a context that contradicts their knowledge. This is investigated further in Section 5.

A similar pattern emerges in most (but not all) of the categories, which can be seen in Tables 9 and 10 and Figures 6 and 7.

4.2.3 Calculating the attention of the contextual and question part of each query

Using the method described in Section 3.2.3, we can find how much attention each model gives, on average, to the context part of the query and to the rest. The results are present in Table 11.

Figure 6: Results of running decoder-only models on the queried data, grouped by category. This plots the information shown in Table 9.

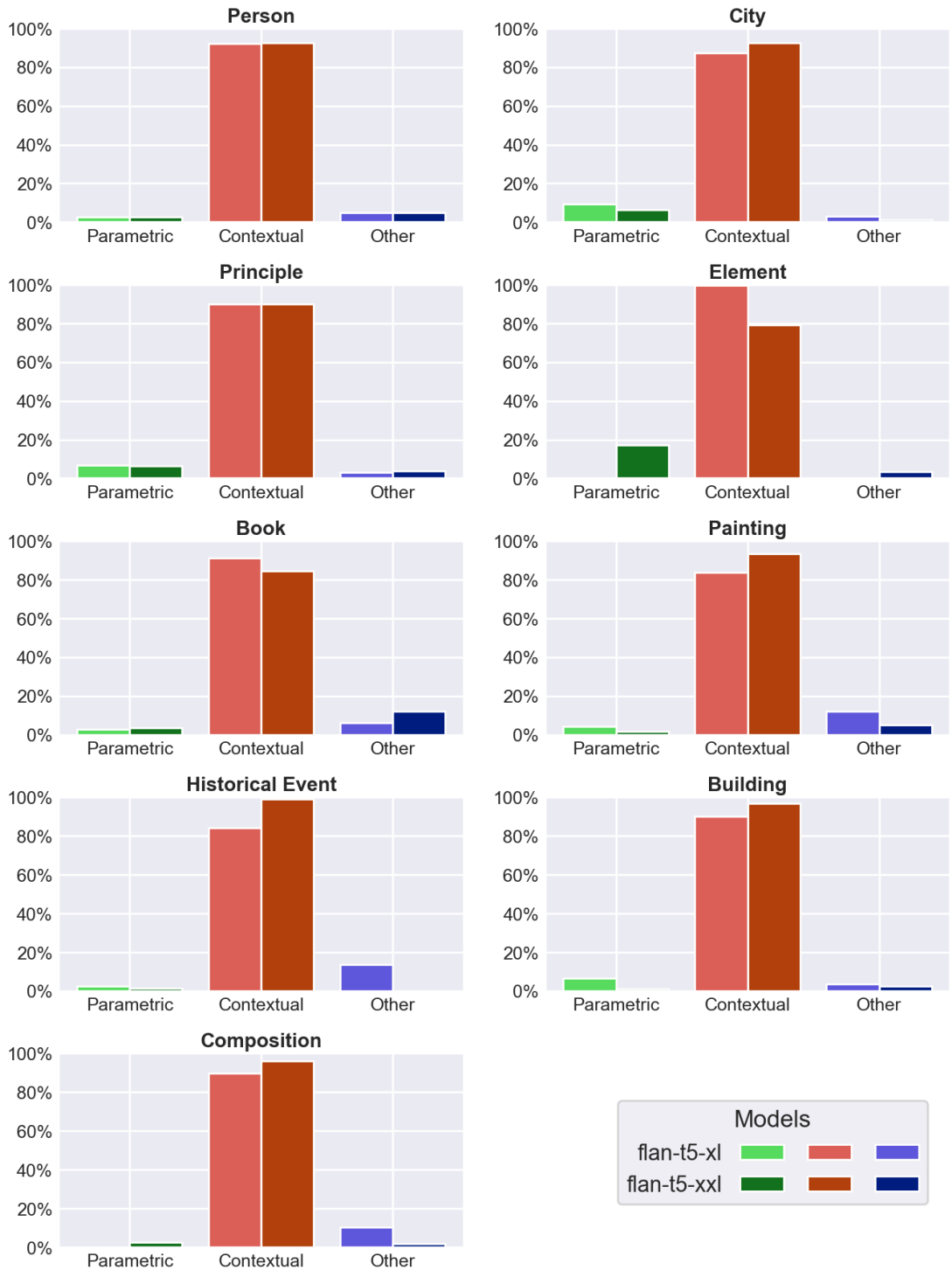


Figure 7: Results of running Seq2Seq models on the queried data, grouped by category. This plots the information shown in Table 10.

	llama-3.1-8B			llama-3.1-70B		
	Parametric	Contextual	Other	Parametric	Contextual	Other
Person	40	833	96	209	614	146
City	117	1007	66	166	966	58
Principle	44	118	23	44	117	24
Element	218	385	42	275	347	23
Book	135	344	60	154	318	67
Painting	47	458	23	49	445	34
Historical Event	81	154	21	117	118	21
Building	27	163	8	31	159	8
Composition	36	200	14	25	219	6

Table 9: Results for running each one of the 10 categories separately on the Decoder-only models.

	flan-t5-xl			flan-t5-xxl		
	Parametric	Contextual	Other	Parametric	Contextual	Other
Person	32	900	37	23	890	56
City	120	1030	40	78	1093	19
Principle	13	164	8	9	168	8
Element	6	637	2	102	515	28
Book	26	488	25	18	457	64
Painting	26	446	56	4	498	26
Historical Event	11	217	28	1	254	1
Building	14	174	10	0	189	9
Composition	0	228	22	7	240	3

Table 10: Results for running each one of the 10 categories separately on the Seq2Seq models.

Query Part	flan-t5-xl	flan-t5-xxl	Meta-Llama-3.1 -8B-Instruct	Meta-Llama-3.1 -70B-Instruct
Context	0.18		0.08	
Rest	0.38		0.29	

Table 11: Average normalised attention of the query on the tokens corresponding to the context of the query, and to the tokens corresponding to the rest.

4.3 Enhancing the framework to understand the reasoning behind each answer

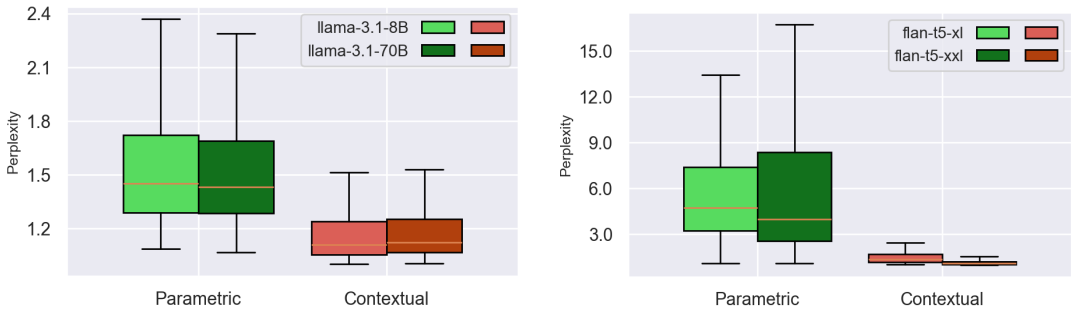
We calculate the resulting perplexity of each query as explained in Section 3.3. These are accumulated in three distributions, depending on answer type, which are summarised in Tables 12 and 13 and Figure 8.

	llama-3.1-8B		llama-3.1-70B	
	Parametric	Contextual	Parametric	Contextual
count	313	4447	383	4377
mean	1.67	1.20	1.56	1.22
std	0.79	0.32	0.46	0.31
25%	1.28	1.05	1.28	1.06
50%	1.43	1.10	1.43	1.12
75%	1.78	1.23	1.68	1.25

Table 12: Distribution of perplexity values for Decoder-only models

	flan-T5-XL		flan-T5-XXL	
	Parametric	Contextual	Parametric	Contextual
count	651	4109	507	4253
mean	6.38	1.56	11.75	1.27
std	9.07	0.56	18.47	0.75
25%	3.21	1.19	2.41	1.02
50%	4.71	1.39	3.89	1.09
75%	7.14	1.71	7.70	1.24

Table 13: Distribution of perplexity values for Seq2Seq models



(a) Decoder-only models

(b) Seq2Seq models

Figure 8: Perplexity distribution according to model architecture and size. These represent the same distributions as Tables 12 and 13.

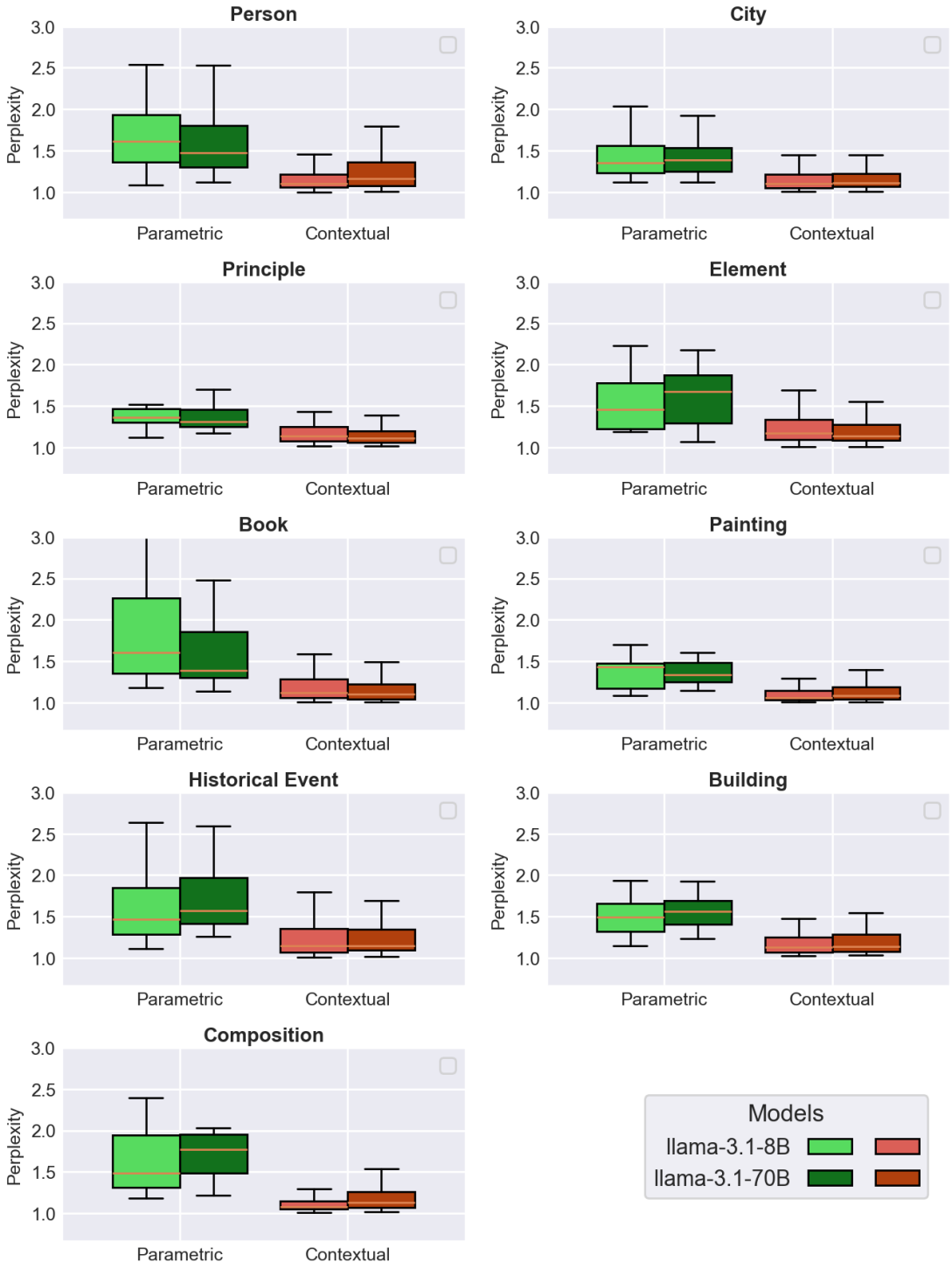


Figure 9: Box plots representing the distribution of the perplexities when running both Llama models, grouped by category.

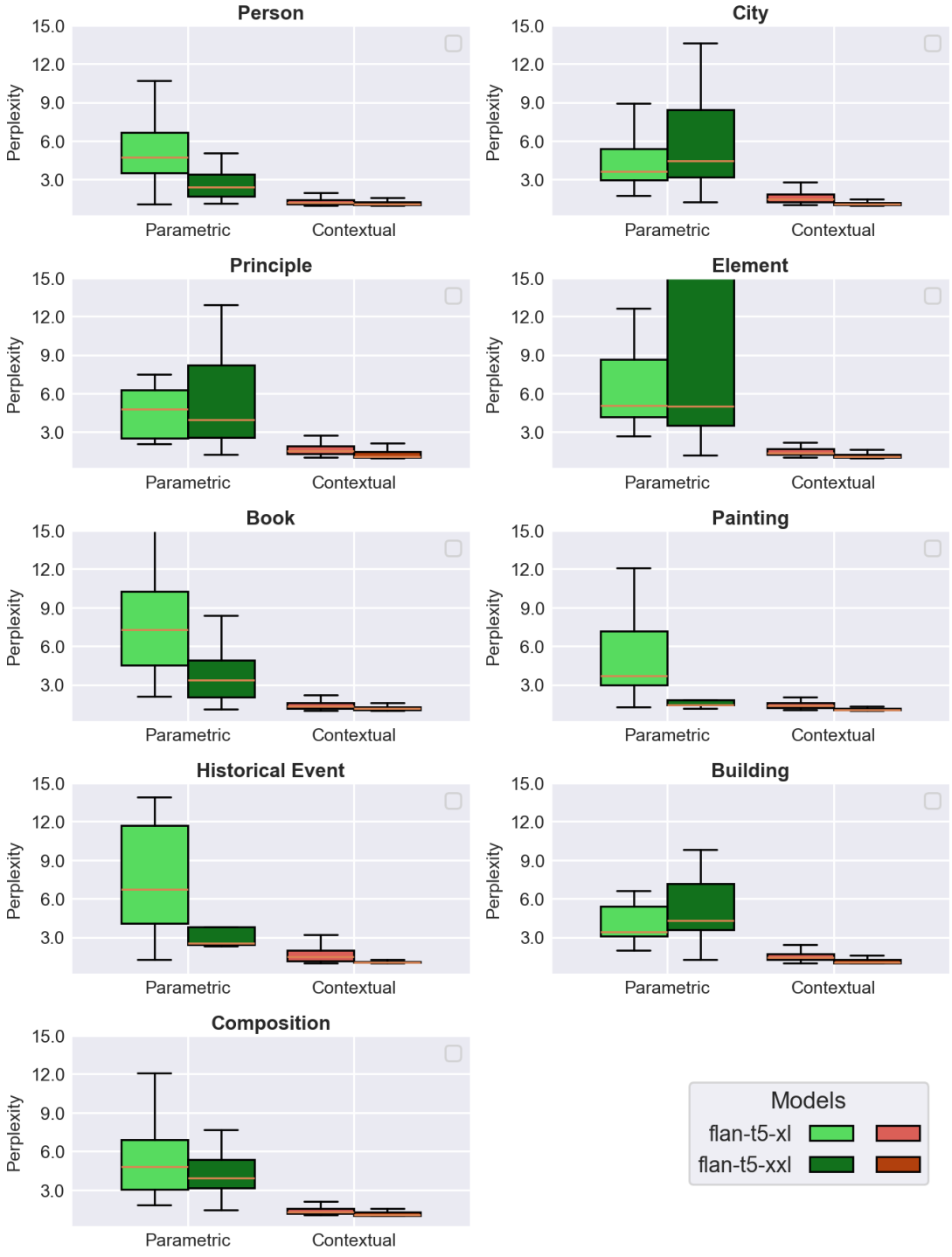


Figure 10: Box plots representing the distribution of the perplexities when running both Flan-T5 models, grouped by category.

5 Discussion

Section 4 presented several results from generating the question dataset and running the framework to understand the role of parametric knowledge in question answering with a context.

This section attempts to explain these results, and discusses what they mean for our research question.

5.1 Model architecture and memorised knowledge

Section 4.2.2 presents the results of running our framework on the provided questions on two different model architectures: Seq2Seq models and Decoder-only models. Tables 9 and 10 show these results split by category of question.

The results are clear: **Seq2Seq models tend to answer questions from their contextual knowledge rather than from their inherent knowledge more often than Decoder-only models**. These results are the same regardless of the category of the question, and are consistent among many types and lengths of answers.

This results shows that, in the framework of question-answering when using RAG to fetch contextual data from an index, Seq2Seq models will have fewer hallucinations that contradict this index than Decoder-only models.

We present several hypotheses which might cause the difference in these results.

5.1.1 Encoder-Decoder Architecture

As described in Section 2.2, Seq2Seq models such as `Flan-T5` are encoder-decoder models that process the entire context of the query in the encoder component before passing it to the decoder, which could increase the weight given to the context itself.

We can test this hypothesis by finding the average attention of the context section of each query and of the question section for each model, using the method discussed in Section 3.2.3.

5.2 Model size and memorised knowledge

Section 4.2.2 also shows differences in how models of different sizes process information in queries with counterparametric context.

5.2.1 Seq2Seq Models

While the average results are very similar, which is likely due to the properties of Seq2Seq models discussed in Section 5.1, the models seem to be significantly different for queries of category `element`, `historical_events`, and a few others. **??** presents some cases where the results are different.

5.3 What are all of these Others?

Section 4.2 showed that a significant minority of responses to queries with counterfactual context are **Other**: answers that aren't equal to either the parametric nor the contextual data. The numbers of these entries, per model, are presented in Table 14.

	Flan-T5-XL	Flan-T5-XXL	Meta-Llama-3.1 -8B-Instruct	Meta-Llama-3.1 -70B-Instruct
Other	260	192	312	387

Table 14: Amount of **Other** entries, that is, results where the answer was not either the parametric or contextual answer.

By manually checking these results, we can understand the reason why the model chose these answers.

1. **Different phrasing of a parametric answer**
   There are many answers where the parametric chooses a certain way to phrase some answer, while the contextual information biases it to give the parametric answer with a different context.

2. **Plain incorrect answers**
   Sometimes, adding counterfactual context to the model just causes it to produce an incorrect answer that's different the answers given by both the model and the context.

3. **Question misinterpretation due to the context**
   Some questions can be ambiguous or have a low probability of another answer. By adding a context with a counterfactual answer, the model can misinterpret the question and answer something different.

4. **Negating the context**
   This is an interesting one: if the model has an answer in its parametric knowledge that contradicts the data on its context, then it interpret the context as part of the question and adds its negation as part of the answer.

5. **Different phrasing of the context**
   Much less common than point 1, models sometimes give the same answer as the context but in the format of the parametric answer.

6. **Correct answer, just different than the parametric answer**
   Some question have multiple correct answers, and adding counterfactual context can cause the model to give a different one.

7. **Mixing elements of both parametric answer and context**
   Elements of the parametric answer are mixed with elements of the context in the model's answer. This produces an incorrect answer, but it's easy to understand where it came from. The cause of this is likely the greedy decoding used to find the answers, as explained in Section 3.2.2.

Examples of each one of these types can be found in Table 16.

Does the architecture and size of the model affect the distribution of each type of **Other** answer? Table 15 contains the amount of answers per architecture for each one of the models, and there does not seem to be a particular distribution.

Type	Flan-T5-XL	Flan-T5-XXL	Meta-Llama-3.1 -8B-Instruct	Meta-Llama-3.1 -70B-Instruct
(Parametric)	248	242	745	1070
(Contextual)	4284	4304	3662	3303
1.	0	0	116	234
2.	6	3	50	15
3.	0	0	13	8
4.	0	0	20	61
5.	241	170	33	38
6.	7	16	63	23
7.	6	3	17	8

Table 15: Different types of **Other** answers per model (with amount of **Parametric** and **Contextual** added for comparison). The two most notable groups are **1.**, which contains parametric answers with different phrasing, and **5.**, which contains counterfactual answers with different phrasing.

Surprisingly, there is a large difference in the distribution of answers that don't come either from the model or from the given context.

In the case of Seq2Seq models, the vast majority of **Other** answers are **Contextual** answers which have a different format due to model mangling. This is consistent with the previous result, where the vast majority of their answers came from the query's context.

The majority of **Other** answers in Decoder-only models are the opposite: **Parametric** answers that keep the format of the context. However, the reasons are much more varied and this would be an interesting topic of discussion in future research.

Part of the reason for many of these answers, particularly on the Seq2Seq models, is due to the strict comparison function we use to define answer type. This is an area that should be improved; Section 6.1.1 gives more information and various suggestions on how to compare results that might be relevant on future work.

5.4 Differences in perplexity scores for larger and smaller models

5.4.1 Can we use this to predict from where an answer came from?

5.5 Differences in distributions for different categories and questions.

Reason	Question	Parametric	Counterfactual	Contextual
1.	Who was the primary leader associated with The Reforms of Diocletian?	Diocletian Himself	Caracalla, a Roman Emperor	Diocletian, a Roman Emperor
	In which city is Louvre Pyramid located?	Paris, France	the city of Valladolid, in the state of Yucatan, Mexico	the city of Paris, in the country of France
2.	In which period of the periodic table is Silver located?	5 of the periodic table	3 of the periodic table	4 of the periodic table
3.	What was the duration of Queen Elizabeth II's Platinum Jubilee?	12 months	approximately 100 years	approximately 70 years
	What is the nearest major body of water to Cusco?	Lake Titicaca	the North Sea	the Pacific Ocean
4.	What is the name of the main protagonist in One Flew Over the Cuckoo's Nest?	Randle McMurphy	Achilles	Not Achilles
	What is Frida Kahlo primarily known for?	her self-portraits and her depiction of Mexican culture	his theories on communism and his critique of capitalism	her artwork and her life story, not for his theories on communism or critique of capitalism
5.	How many pages are in One Flew Over the Cuckoo's Nest?	320 pages	480 pages in a standard edition	480 pages
6.	Who is credited with the discovery of Conservation of Energy?	Julius Robert Mayer	Alfred Wegener	James Joule[1]
	What is the name of the main protagonist in The Great Gatsby?	Nick Carraway	Liesel Meminger	Jay Gatsby[2]
	What educational institution did Srinivasa Ramanujan attend?	The University of Madras	The University of Vienna	the University of Cambridge[3]
7.	What is the date of death of Vladimir Lenin?	January 21, 1924	March 28, 1941	March 21, 1924
	What's the main nationality of Mozart?	Austria	English-Born American	American-born English-born Austrian

[1] Discovery of the conservation of energy is credited to both Julius Robert Mayer and James Joule.
[2] Nick Carraway and Jay Gatsby are co-protagonists in The Great Gatsby.
[3] Srinivasa Ramanujan attended both the University of Madras and the University of Cambridge.

Table 16: Examples of different types of **Other** answers when running the `Meta-Llama-3.1-8B-Instruct` model. Other models have similar reasons for these kinds of answers.

6 Evaluations, Reflections, and Conclusions

6.1 Future Work

6.1.1 Better Categorisation of the Answers

To test whether two answers are equal and to know whether an answer came from parametric or contextual knowledge, the code in this thesis checks for string equality among after removing a few stop simple words such as 'the'.

This solution might not be enough, and some answers classified as **Other** should have been classifier as something else. Table 17 provides some examples of answers where this is the case.

Query	Parametric Answer	Query Answer	Comparison	Expected
[Context: The primary leader associated with The Construction of Hadrian's Wall was Napoleon Bonaparte] Q: Who was the primary leader associated with The Construction of Hadrian's Wall? A: The primary leader associated with The Construction of Hadrian's Wall was	Emperor Hadrian	Hadrian, the Roman Emperor	**Other**	**Parametric**
[Context: Che Guevara was born in Kensington, London, England] Q: In what city was Che Guevara born? A: Che Guevara was born in	Rosario, Argentina	London	**Other**	**Contextual**

Table 17: Example of incorrectly-categorised answers. These were categorised as "**Other**", since their answer strings are different from both parametric and contextual answers. However, a closer look reveals that this is just either answer with a slight formatting difference.

A more complete solution might include using another LLM to compare whether two answers are truly equal.

6.1.2 Knowledge Grounding in Retrieval-Augmented LMs

This thesis was originally based on a preprint, "Knowledge Grounding in Retrieval-Augmented LMs: An Empirical Study" (Whitehouse et al. 2023), and contains work towards understanding how large language models retrieve data which can ultimately help prevent hallucinations.

We plan to continue this work and complete the paper created by the preprint by running the methods outlined on this thesis on retrieval-augmented LMs such as Atlas (Izacard

et al. 2022) and RETRO (Borgeaud et al. 2022) and creating a full evaluation framework that specifically focuses on their grounding. A well-grounded model should demonstrate the capability to adapt its generation based on the provided context, specially in cases like the ones experimented in this thesis when the context contradicts the model's parametric memorisation.

6.1.3 Further Memory Locator Prediction

The results of Section 4.3 show a clear difference in perplexity value between answers that come from the parametric memory of a model and those that come from a context.

This could be used to create a predictor where, given a certain answered query, it could give you a probability of the source the model used for this answer by using the perplexity of the answer and comparing against the distribution of perplexities for this model on similar questions.

In RAG-enhanced models, where the RAG context might contradict the parametric knowledge of a model, this might prevent hallucinations.

6.1.4 Fine-tuning a LLM for a RAG Context

Existing retrieval-augmented LMs, such as ATLAS and RETRO, are trained on existing models along with an index. In the fast-moving world of large language models, this might not be ideal: the generator part of models is based on T5, a model created in 2019. Meanwhile, between the time I started writing this thesis and this moment Meta launched a new Llama model.

The current dataset and experiments might be useful for being able to fine-tune a modern model to prefer the context generated by RAG when it contradicts its parametric knowledge. This might improve retrieval-augmented models, and make it easier to use them with newer models.

Glossary

Base Questions

Objects

Queries

Parametric Answers

Counterparamteric answers

Queries with counterfactual/counterparametric context

Contextual Answer

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Appendices

A Questions and objects used to form the queries

```
What is the date of birth of {person}? The date of birth of {person} is
In what city was {person} born? {person} was born in
What is the date of death of {person}? The date of death of {person} is
What is the primary profession of {person}? The primary profession of {person} is
What is {person} primarily known for? {person} is primarily known for
What's the main nationality of {person}? {person} is
What educational institution did {person} attend? {person} attended
What was the native language of {person}? The native language of {person} was
Who was {person}'s most influential mentor? The most influential mentor of {person} was
What was {person}'s religious affiliation? The religious affiliation of {person} was
What was {person}'s primary field of study? The primary field of study of {person} was
What was {person}'s most famous work or invention? The most famous work or invention of {person} was
What historical period did {person} live in? {person} lived during the
What was {person}'s family's social class? {person}'s family belonged to the
What was {person}'s political ideology? The political ideology of {person} was
What was {person}'s preferred artistic or scientific medium? The preferred medium of {person} was
What was {person}'s cultural background? The cultural background of {person} was

What country is {city} in? {city} is in
What's the highest administrative subdivision {city} is part of? {city} is part of
In what year was {city} founded? {city} was founded in
What major river is nearest to {city}? The nearest major river to {city} is
What is the time zone of {city}? The time zone of {city} is
What is the current population of {city}? The current population of {city} is
What is the altitude of {city} above sea level? {city} is at an altitude of
What is the primary language spoken in {city}? The primary language spoken in {city} is
What is the predominant architectural style in {city}? The predominant architectural style in {city} is
What is the main economic industry of {city}? The main economic industry of {city} is
What is the average annual temperature in {city}? The average annual temperature in {city} is
What is the nearest major body of water to {city}? The nearest major body of water to {city} is
What is the most famous landmark in {city}? The most famous landmark in {city} is
What is the primary mode of public transportation in {city}? The primary mode of public transportation in
     {city} is
What is the name of the airport serving {city}? The airport serving {city} is
What is the sister city of {city}? The sister city of {city} is
What is the traditional cuisine {city} is known for? The traditional cuisine {city} is known for is

Who is credited with the discovery of {principle}? {principle} was discovered by
Which scientific discipline encompasses {principle}? {principle} is encompassed by
What is the primary application of {principle}? The primary application of {principle} is
In which year was {principle} first formulated? {principle} was first formulated in
What is the SI unit most commonly associated with {principle}? The SI unit most commonly associated with
     {principle} is

What's the chemical formula for {element}? The chemical formula for {element} is
When was {element} first isolated? {element} was first isolated in
What's the atomic number of {element}? The atomic number of {element} is
What is the melting point of {element}? The melting point of {element} is
In which group of the periodic table is {element} found? {element} is found in group
What's the standard atomic weight of {element}? The standard atomic weight of {element} is
What's the electron configuration of {element}? The electron configuration of {element} is
What's the most common oxidation state of {element}? The most common oxidation state of {element} is
What's the crystal structure of {element} at room temperature? The crystal structure of {element} at room
     temperature is
What's the primary isotope of {element}? The primary isotope of {element} is
What's the electronegativity value of {element}? The electronegativity value of {element} is
What's the ionization energy of {element}? The ionization energy of {element} is
What's the atomic radius of {element}? The atomic radius of {element} is
What's the boiling point of {element}? The boiling point of {element} is
In which period of the periodic table is {element} located? {element} is located in period

What genre does {book} belong to? The genre of {book} is
Who's the author of {book}? {book} was written by
In what year was {book} first published? {book} was first published in
How many pages are in the original publication of {book}? The original publication of {book} has
What is the name of the main protagonist in {book}? The main protagonist in {book} is

What is the original language of {book}? The original language of {book} is
Who is the original publisher of {book}? The publisher of {book} is
What is the highest award {book} won? The highest award won by {book} is
What is the opening line of {book}? The opening line of {book} is
How many chapters are in {book}? {book} has
How many pages are in {book}? {book} has

Who painted {painting}? {painting} was painted by
```

```
When was {painting} completed? {painting} was completed in
What artistic movement does {painting} belong to? {painting} belongs to
What materials were used to create {painting}? {painting} was created with
Where is {painting} primarily housed? {painting} is currently in
What are the dimensions of {painting}? The dimensions of {painting} are
In which museum was {painting} first exhibited? {painting} was first exhibited in
What is the dominant color in {painting}? The dominant color in {painting} is
Who commissioned {painting}? {painting} was commissioned by
What is the estimated value of {painting}? The estimated value of {painting} is
What is the subject matter of {painting}? The subject matter of {painting} is
In which country was {painting} created? {painting} was created in

What year did {historical_event} happen? {historical_event} happened in the year
Who was the primary leader associated with {historical_event}? The primary leader associated with
     {historical_event} was
What was the duration of {historical_event}? {historical_event} lasted for
In which country did {historical_event} primarily take place? {historical_event} primarily took place in

What is the height of {building}? The height of {building} is
Who was the main architect of {building}? The main architect of {building} was
In which year was {building} completed? {building} was completed in
In which city is {building} located? {building} is located in
What architectural style is {building}? The architectural style of {building} is
How many floors does {building} have? {building} has
What is the primary construction material of {building}? The primary construction material of {building} is
What is the total floor area of {building}? The total floor area of {building} is
How long did it take to construct {building}? The construction of {building} took

Who composed {composition}? {composition} was composed by
In what year was {composition} first performed? {composition} was first performed in
What is the musical genre of {composition}? The musical genre of {composition} is
What is the opus number of {composition}? The opus number of {composition} is
What is the key signature of {composition}? The key signature of {composition} is
How many movements does {composition} have? {composition} has
What is the tempo marking of {composition}? The tempo marking of {composition} is
What is the duration of {composition}? The duration of {composition} is
For which instrument(s) was {composition} written? {composition} was written for
In which city was {composition} premiered? {composition} was premiered in
```

Listing 2: All base questions used in this work. Each one of these will get combined with data from Listing 2 as detailed in Section 3.1.

```
Ada Lovelace,person
Alan Turing,person
Albert Einstein,person
Alexander Fleming,person
Aristotle,person
Billie Jean King,person
Boyan Slat,person
Catherine the Great,person
Che Guevara,person
Cleopatra,person
Confucius,person
Ernest Rutherford,person
Florence Nightingale,person
Freddie Mercury,person
Frida Kahlo,person
Greta Thunberg,person
Harriet Tubman,person
Ibn al-Haytham,person
Isaac Newton,person
Karl Marx,person
Leonardo da Vinci,person
Mahatma Gandhi,person
Malala Yousafzai,person
Mansa Musa,person
Marie Curie,person
Martin Luther King Jr.,person
Michelangelo,person
Mohandas Gandhi,person
Mozart,person
Muhammad Ali,person
Neil Armstrong,person
Nelson Mandela,person
Nikola Tesla,person
Pablo Picasso,person
Rosalind Franklin,person
Shirin Ebadi,person
Simon Bolivar,person
Srinivasa Ramanujan,person
Stephen Hawking,person
```

```
Sun Yat-sen,person
Virginia Woolf,person
Vladimir Lenin,person
Wangari Maathai,person
W.E.B. Du Bois,person
William Shakespeare,person
Wu Zetian,person
Yuri Gagarin,person
Amelia Earhart,person
Galileo Galilei,person
Genghis Khan,person
Joan of Arc,person
Lise Meitner,person
Marcus Aurelius,person
Maya Angelou,person
Queen Nzinga,person
Socrates,person
Voltaire,person
Alexandria,city
Amsterdam,city
Antananarivo,city
Athens,city
Baghdad,city
Berlin,city
Buenos Aires,city
Bukhara,city
Cairo,city
Cape Town,city
Cartagena,city
Chicago,city
Cusco,city
Cuzco,city
Delhi,city
Dubrovnik,city
Fez,city
Havana,city
Istanbul,city
Jerusalem,city
Kyoto,city
La Paz,city
Lhasa,city
Lisbon,city
London,city
Luang Prabang,city
Marrakech,city
Mexico City,city
Montevideo,city
Moscow,city
Mumbai,city
Muscat,city
New York,city
Nur-Sultan,city
Paris,city
Petra,city
Prague,city
Quebec City,city
Reykjavik,city
Rome,city
Sao Paulo,city
Sarajevo,city
Shanghai,city
Singapore,city
St. Petersburg,city
Sydney,city
Tbilisi,city
Tenochtitlan,city
Thimphu,city
Timbuktu,city
Tokyo,city
Ulaanbaatar,city
Varanasi,city
Venice,city
Vienna,city
Wellington,city
Windhoek,city
Xi'an,city
Yogyakarta,city
Zanzibar City,city
Addis Ababa,city
Bangkok,city
Dubai,city
Helsinki,city
Machu Picchu,city
```

```
Nairobi,city
Rio de Janeiro,city
Samarkand,city
Toronto,city
Yangon,city
Archimedes' Principle,principle
Bernoulli's Principle,principle
Boyle's Law,principle
Cell Theory,principle
Conservation of Energy,principle
DNA Replication,principle
Electromagnetism,principle
Entropy,principle
Evolution by Natural Selection,principle
Evolution,principle
General Relativity,principle
Germ Theory of Disease,principle
Gravity,principle
Hardy-Weinberg Principle,principle
Heliocentrism,principle
Hubble's Law,principle
Kepler's Laws of Planetary Motion,principle
Le Chatelier's Principle,principle
Mendel's Laws of Inheritance,principle
Newton's Laws of Motion,principle
Pauli Exclusion Principle,principle
Periodic Law,principle
Photosynthesis,principle
Plate Tectonics,principle
Principle of Least Action,principle
Quantum Mechanics,principle
Relativity,principle
Superconductivity,principle
Thermodynamics,principle
Uncertainty Principle,principle
Avogadro's Law,principle
Coulomb's Law,principle
Faraday's Laws of Electrolysis,principle
Heisenberg Uncertainty Principle,principle
Ohm's Law,principle
SchrÃ¶dinger Equation,principle
Special Relativity,principle
Aluminum,element
Barium,element
Bismuth,element
Bromine,element
Calcium,element
Carbon,element
Chlorine,element
Chromium,element
Copper,element
Gold,element
Helium,element
Hydrogen,element
Iodine,element
Iron,element
Lead,element
Lithium,element
Magnesium,element
Manganese,element
Mercury,element
Neon,element
Nitrogen,element
Oxygen,element
Phosphorus,element
Plutonium,element
Potassium,element
Radon,element
Silicon,element
Silver,element
Sodium,element
Sulfur,element
Thorium,element
Tin,element
Titanium,element
Uranium,element
Zinc,element
Argon,element
Boron,element
Cobalt,element
Fluorine,element
Gallium,element
Krypton,element
```

```
Nickel,element
Xenon,element
1984,book
Anna Karenina,book
Beloved,book
Brave New World,book
Catch-22,book
Crime and Punishment,book
Don Quixote,book
Fahrenheit 451,book
Frankenstein,book
Jane Eyre,book
Midnight's Children,book
Moby-Dick,book
One Flew Over the Cuckoo's Nest,book
One Hundred Years of Solitude,book
Pride and Prejudice,book
Slaughterhouse-Five,book
The Alchemist,book
The Art of War,book
The Book Thief,book
The Brothers Karamazov,book
The Catcher in the Rye,book
The Chronicles of Narnia,book
The Color Purple,book
The Count of Monte Cristo,book
The Grapes of Wrath,book
The Great Gatsby,book
The Handmaid's Tale,book
The Hitchhiker's Guide to the Galaxy,book
The Hobbit,book
The Hunger Games,book
The Kite Runner,book
The Little Prince,book
The Lord of the Rings,book
The Metamorphosis,book
The Name of the Rose,book
The Odyssey,book
The Picture of Dorian Gray,book
The Pillars of the Earth,book
The Stranger,book
The Sun Also Rises,book
The Wind-Up Bird Chronicle,book
To Kill a Mockingbird,book
Ulysses,book
War and Peace,book
Wuthering Heights,book
The Iliad,book
The Tale of Genji,book
Things Fall Apart,book
To the Lighthouse,book
American Gothic,painting
Christina's World,painting
Girl with a Pearl Earring,painting
Guernica,painting
Les Demoiselles d'Avignon,painting
Liberty Leading the People,painting
Mona Lisa,painting
School of Athens,painting
Starry Night,painting
The Absinthe Drinker,painting
The Anatomy Lesson of Dr. Nicolaes Tulp,painting
The Arnolfini Portrait,painting
The Astronomer,painting
The Birth of Venus,painting
The Calling of Saint Matthew,painting
The Card Players,painting
The Death of Marat,painting
The Fighting Temeraire,painting
The Garden of Earthly Delights,painting
The Gross Clinic,painting
The Hay Wain,painting
The Kiss,painting
The Last Supper,painting
The Nighthawks,painting
The Night Watch,painting
The Ninth Wave,painting
The Persistence of Memory,painting
The Potato Eaters,painting
The Raft of the Medusa,painting
The Scream,painting
The Sleeping Gypsy,painting
The Son of Man,painting
```

```
The Swing,painting
The Third of May 1808,painting
The Tower of Babel,painting
The Treachery of Images,painting
The Triumph of Galatea,painting
The Wanderer above the Sea of Fog,painting
Water Lilies,painting
The Creation of Adam,painting
The Girl with a Pearl Earling,painting
The Great Wave off Kanagawa,painting
The Thinker,painting
Venus de Milo,painting
Decimalisation in the UK,historical_event
Queen Elizabeth II's Platinum Jubilee,historical_event
Queen Victoria's Coronation,historical_event
The Act of Union between England and Scotland,historical_event
The Battle of Adrianople,historical_event
The Battle of Adwa,historical_event
The Battle of Agincourt,historical_event
The Battle of Hastings,historical_event
The Battle of Sekigahara,historical_event
The Battle of Teutoburg Forest,historical_event
The Battle of the Milvian Bridge,historical_event
The Battle of Waterloo,historical_event
The Brexit Referendum,historical_event
The Codification of Roman Law by Justinian,historical_event
The Construction of Hadrian's Wall,historical_event
The Construction of the Great Pyramid of Giza,historical_event
The Conversion of Constantine,historical_event
The Council of Chalcedon,historical_event
The Crisis of the Third Century,historical_event
The Defeat of the Spanish Armada,historical_event
The Discovery of the Americas by Columbus,historical_event
The Dissolution of the Soviet Union,historical_event
The Division of the Roman Empire,historical_event
The Dunkirk Evacuation,historical_event
The Edict of Caracalla,historical_event
The Fall of Constantinople,historical_event
The Fall of the Aztec Empire,historical_event
The Fall of the Western Roman Empire,historical_event
The First Circumnavigation of the Earth,historical_event
The First Council of Nicaea,historical_event
The First Crusade,historical_event
The Founding of Constantinople,historical_event
The Founding of Rome,historical_event
The Founding of the British Broadcasting Corporation,historical_event
The Founding of the League of Nations,historical_event
The French Revolution,historical_event
The Glorious Revolution,historical_event
The Gothic War in Italy,historical_event
The Great Fire of London,historical_event
The Indian Independence Act,historical_event
The Industrial Revolution,historical_event
The London 7/7 Bombings,historical_event
The Meiji Restoration,historical_event
The Plague of Justinian,historical_event
The Reforms of Diocletian,historical_event
The Reunification of the Empire by Aurelian,historical_event
The Sack of Rome by Alaric,historical_event
The Sack of Rome by the Vandals,historical_event
The Signing of the Good Friday Agreement,historical_event
The Signing of the Magna Carta,historical_event
The Suez Crisis,historical_event
The Treaty of Westphalia,historical_event
The UK Abolition of the Slave Trade Act,historical_event
The Unification of Italy,historical_event
The Wedding of Prince Charles and Lady Diana,historical_event
The Year of the Four Emperors,historical_event
The American Revolution,historical_event
The Black Death,historical_event
The Cuban Missile Crisis,historical_event
The Fall of the Berlin Wall,historical_event
The Moon Landing,historical_event
The Renaissance,historical_event
The Russian Revolution,historical_event
The Signing of the Declaration of Independence,historical_event
Angkor Wat,building
Buckingham Palace,building
Burj Khalifa,building
Chichen Itza,building
Chrysler Building,building
Colosseum,building
Eiffel Tower,building
```

```
Empire State Building,building
Forbidden City,building
Guggenheim Museum,building
Hagia Sophia,building
Louvre Pyramid,building
Machu Picchu,building
Neuschwanstein Castle,building
Parthenon,building
Petra,building
Petronas Towers,building
Potala Palace,building
Sears Tower,building
St. Basil's Cathedral,building
Sydney Opera House,building
Taj Mahal,building
Adagio for Strings,composition
Billie Jean,composition
Bohemian Rhapsody,composition
Canon in D,composition
Carmina Burana,composition
Clair de Lune,composition
Eine kleine Nachtmusik,composition
FÃ¼r Elise,composition
GymnopÃ©dies,composition
Imagine,composition
In the Mood,composition
Like a Rolling Stone,composition
Lovesong,composition
Mbube (The Lion Sleeps Tonight),composition
Nessun Dorma,composition
Purple Rain,composition
Raga Malkauns,composition
Rhapsody in Blue,composition
Rhapsody on a Theme of Paganini,composition
Symphony No. 5,composition
The Blue Danube,composition
The Four Seasons,composition
The Planets,composition
The Rite of Spring,composition
Toccata and Fugue in D minor,composition
```

Listing 3: All objects which will be conbined with the questions in Listing 1.

B Full Results for Each Question

C Grounder Usage and Documentation

D Source Code of the Experiments

The latest version of the source code, including the input data generated in Section 3.1, is available in `https://github.com/mfixman/rag-thesis`[†].

```python
import warnings
warnings.simplefilter(action = 'ignore', category = FutureWarning)

from argparse import ArgumentParser
import csv
import logging
import random
import ipdb
import os
import sys
import wandb

from Models import Model_dict
from QuestionAnswerer import QuestionAnswerer
from Utils import print_parametric_csv, LogTimeFilter, combine_questions

def parse_args():
    parser = ArgumentParser(
        description = 'Combines questions and data and optionally provides parametric data'
    )

    parser.add_argument('--debug', action = 'store_true', help = 'Go to IPDB console on exception.')
    parser.add_argument('--lim-questions', type = int, help = 'Question limit')
    parser.add_argument('--device', choices = ['cpu', 'cuda'], default = 'cuda', help = 'Inference device')
    parser.add_argument('--models', type = str.lower, default = [], choices = Model_dict.keys(), nargs = '+', metavar = 'model', help = 'Which model or models to use for getting parametric data')
    parser.add_argument('--offline', action = 'store_true', help = 'Tell HF to run everything offline.')
    parser.add_argument('--rand', action = 'store_true', help = 'Seed randomly')
    parser.add_argument('--max-batch-size', type = int, default = 120, help = 'Maximimum size of batches. All batches contain exactly the same question.')

    parser.add_argument('--per-model', action = 'store_true', help = 'Write one CSV per model in stdout.')
    parser.add_argument('--output-dir', help = 'Return one CSV per model, and save them to this directory.')

    parser.add_argument('--runs-per-question', type = int, default = 1, help = 'How many runs (with random counterfactuals) to do for each question.')

    parser.add_argument('base_questions_file', type = open, help = 'File with questions')
    parser.add_argument('things_file', type = open, help = 'File with things to combine')

    args = parser.parse_args()

    args.base_questions = [x.strip() for x in args.base_questions_file if any(not y.isspace() for y in x)]
```

[†]TODO: Move all of this to a new repo.

```
    args.things = [{k: v for k, v in p.items()} for p in
    csv.DictReader(args.things_file)]

    del args.base_questions_file
    del args.things_file

    if args.per_model and args.output_dir:
        raise ValueError('Only one of --per-model and --output-dir can be
    specified.')

    return args

def main(args):
    logging.getLogger('transformers').setLevel(logging.ERROR)
    logging.basicConfig(
        format='[%(asctime)s] %(message)s',
        level=logging.INFO,
        datefmt='%Y-%m-%d %H:%M:%S'
    )
    logging.getLogger().addFilter(LogTimeFilter())

    if args.offline:
        os.environ['TRANSFORMERS_OFFLINE'] = '1'
    else:
        wandb.init(project = 'knowledge-grounder', config = args)

    logging.info('Getting questions')
    questions = combine_questions(args.base_questions, args.things,
    args.lim_questions)

    if args.output_dir:
        try:
            os.mkdir(args.output_dir)
        except FileExistsError:
            pass

    logging.info(f'About to answer {len(questions) * len(args.models) *
    args.runs_per_question * 2} questions in total.')
    answers = {}
    for model in args.models:
        if not args.rand:
            random.seed(0)

        qa = QuestionAnswerer(
            model,
            device = args.device,
            max_length = 20,
            max_batch_size = args.max_batch_size,
            runs_per_question = args.runs_per_question,
        )
        model_answers = qa.answerQueries(questions)
        del qa

        if args.output_dir:
            empty = lambda s: sum([x == '' for x in model_answers[s]])
            count = lambda s: sum([x == s for x in model_answers['comparison']])
            logging.info(f"{model}:\t{empty('parametric')} empty parametrics,
    {empty('counterfactual')} empty counterfactuals, {empty('contextual')} empty
    contextuals")
            logging.info(f"\t{count('Parametric')} parametrics,
    {count('Contextual')} contextual, {count('Other')} others")

```

```
            model_filename = os.path.join(args.output_dir, model + '.csv')
            with open(model_filename, 'w') as out:
                print_parametric_csv(out, model_answers)

        elif args.per_model:
            print_parametric_csv(sys.stdout, model_answers)
        else:
            answers |= model_answers

    if answers:
        logging.info('Writing CSV')
        print_parametric_csv(sys.stdout, answers)

if __name__ == '__main__':
    args = parse_args()
    if not args.debug:
        main(args)
    else:
        with ipdb.launch_ipdb_on_exception():
            main(args)
```

Listing 4: `knowledge_grounder.py` is the main entry point and contains mostly argument parsing and output printing.

```
import warnings
warnings.simplefilter(action = 'ignore', category = FutureWarning)

import logging
import math
import torch
import typing

from Models import Model
from typing import Optional, Union, Any
from Utils import Question, sample_counterfactual_flips, chunk_questions

from collections import defaultdict
from transformers import BatchEncoding

import ipdb

FloatTensor = torch.Tensor
LongTensor = torch.Tensor
BoolTensor = torch.Tensor

# A QuestionAnswerer is the main class to answer queries with a given model.
# Example Usage:
#   qa = QuestionAnswerer('llama', device = 'cuda', max_length = 20,
    max_batch_size = 75)
#   output = qa.answerQueries(Utils.combine_questions(base_questions, objects))
# The list of models can be found in `Model_dict` in `Models.py`.
class QuestionAnswerer:
    device: str
    max_length: int
    max_batch_size: int
    runs_per_question: int
    llm: Model

    def __init__(
        self,
        model: Union[str, Model],
```

```
        device: str = 'cpu',
        max_length: Optional[int] = None,
        max_batch_size: Optional[int] = None,
        runs_per_question: Optional[int] = None,
    ):
        self.device = device
        self.max_length = max_length or 20
        self.max_batch_size = max_batch_size or 120
        self.runs_per_question = runs_per_question or 1

        if type(model) == str:
            model = Model.fromName(model, device = device)

        model = typing.cast(Model, model)
        self.llm = model

        # Generated list of stop tokens: period, newline, and various different end tokens.
        stop_tokens = {'.', '\n'}
        self.stop_token_ids = torch.tensor([
            v
            for k, v in self.llm.tokenizer.get_vocab().items()
            if
                k in ['<start_of_turn>', '<end_of_turn>', self.llm.tokenizer.special_tokens_map['eos_token']] or
                not stop_tokens.isdisjoint(self.llm.tokenizer.decode(v))
        ]).to(self.device)

    # Query data related to a list of questions, and return a dict with information about these runs.
    # Output elements:
    #  parametric: Parametric answer, as a string.
    #  base_proba: Perplexity of parametric answer in base query.
    #  counterfactual: Randomly selected counterfactual answer.
    #  base_cf_proba: Perplexity of counterfacutal answer in base query.
    #  contextual: Contextual answer, as a string.
    #  ctx_proba: Perplexity of contextual answer.
    #  ctx_param_proba: Perplexity of parametric answer when running contextual query.
    #  ctx_cf_proba: Perplexity of counterfactual answer when running contextual query.
    #  comparison: Comparison between parametric and contextual answer. Where does this answer come from?
    #  preference: Comparison between perplexity of paramertic and counterfactual answer on contextual query. Which one is the least surprising?
    def answerChunk(self, questions: list[Question]) -> dict[str, Any]:
        output: defaultdict[str, list[Any]] = defaultdict(lambda: [])

        base_tokens = self.tokenise([q.format(prompt = self.llm.prompt) for q in questions])
        parametric = self.generate(base_tokens)

        parametric_output = self.decode(parametric)
        base_proba_output = self.perplexity(base_tokens, parametric)
        for run in range(self.runs_per_question):
            run_output: dict[str, list[Any]] = dict(
                parametric = parametric_output,
                base_proba = base_proba_output,
            )

            run_output['question'] = questions
            flips = sample_counterfactual_flips(questions,
```

```
    run_output['parametric'])
91          counterfactual = parametric[flips]
92
93          run_output['counterfactual'] = self.decode(counterfactual)
94          run_output['base_cf_proba'] = self.perplexity(base_tokens,
    counterfactual)
95
96          run_output |= self.answerCounterfactuals(questions,
    run_output['counterfactual'], parametric, counterfactual)
97
98          run_output['comparison'] = [
99              'Parametric' if self.streq(a, p) else
100             'Contextual' if self.streq(a, c) else
101             'Other'
102             for p, c, a in zip(run_output['parametric'],
    run_output['counterfactual'], run_output['contextual'])
103         ]
104
105         run_output['preference'] = [
106             'Parametric' if pp > cp else
107             'Contextual'
108             for pp, cp in zip(run_output['ctx_proba'],
    run_output['ctx_cf_proba'])
109         ]
110
111         for k, v in run_output.items():
112             output[k].extend(v)
113
114     return output
115
116 # Given a list of questions with assigned counterfactuals, run contextual
    queries and return
117 # a dictionary containing information about these runs.
118 # Parameter list:
119 #  questions: list of questions to ask.
120 #  counterfactuals: counterfactual answers, as string.
121 #  parametric: parametric answer, as set of tokens.
122 #    This will be used to calculate the perplexity of this answer with the
    counterfactual context.
123 #  counterfactual: counterfacutal answers, as a set of tokens.
124 #    This is necessary since the same string might have several encodings,
    but we need exactly the same one generated by the model
125 #    in the first place.
126 def answerCounterfactuals(self, questions: list[Question], counterfactuals:
    list[str], parametric: LongTensor, counterfactual: LongTensor) -> dict[str,
    Any]:
127     output: dict[str, Any] = {}
128     ctx_tokens = self.tokenise([
129         q.format(prompt = self.llm.cf_prompt, context = context)
130         for q, context in zip(questions, counterfactuals)
131     ])
132
133     contextual = self.generate(ctx_tokens)
134
135     output['contextual'] = self.decode(contextual)
136     output['ctx_proba'] = self.perplexity(ctx_tokens, contextual)
137
138     output['ctx_param_proba'] = self.perplexity(ctx_tokens, parametric)
139     output['ctx_cf_proba'] = self.perplexity(ctx_tokens, counterfactual)
140
141     output['context_attn'], output['question_attn'] =
    self.avgSelfAttentions(ctx_tokens)
```

```
142
143         return output
144
145     # Answer a list of Questions: run the queries, gather counterfactual values, run the queries
146     # with counterfactual context, and return a `dict` with information to print.
147     @torch.no_grad()
148     def answerQueries(self, questions: list[Question]) -> dict[str, Any]:
149         output: defaultdict[str, list[Any]] = defaultdict(lambda: [])
150
151         chunks = chunk_questions(questions, max_batch_size = self.max_batch_size)
152         logging.info(f'Answering {len(questions)} queries in {len(chunks)} chunks.')
153
154         for e, chunk in enumerate(chunks, start = 1):
155             logging.info(f'Parsing chunk ({e} / {len(chunks)}), which has size {len(chunk)}.', extra = {'rate_limit': 20})
156
157             chunk_output = self.answerChunk(chunk)
158
159             for k, v in chunk_output.items():
160                 output[k] += v
161
162         return dict(output)
163
164     def fakeTokens(self) -> BatchEncoding:
165         return self.tokenise(['[Context: Montevideo is located in Egypt] Q: What country is Montevideo located in? A: Montevideo is located in'])
166
167     # Gets the scaled mean self-attentions of the context section of a query and
168     # of the section after the context.
169     @torch.no_grad()
170     def avgSelfAttentions(self, queries: BatchEncoding) -> tuple[list[float], list[float]]:
171         attentions = self.llm.attentions(queries)
172         attention_mean = attentions.mean(dim = (1, 2))
173         diag = attention_mean.diagonal(dim1 = 1, dim2 = 2)
174         scaled = (diag - diag.min(dim = 1, keepdims = True)[0]) / (diag.max(dim = 1, keepdims = True)[0] - diag.min(dim = 1, keepdims = True)[0])
175
176         context_left = ((queries.input_ids == self.llm.tokenizer.pad_token_id) | (queries.input_ids == self.llm.tokenizer.eos_token_id))
177         context_right = ((queries.input_ids == self.llm.tokenizer.convert_tokens_to_ids(']')) | (queries.input_ids == self.llm.tokenizer.convert_tokens_to_ids('].')))
178
179         context_area = ~context_left & (context_right.cumsum(dim = 1) == 0)
180         later_area = context_right.cumsum(dim = 1) > 0
181
182         context = scaled.clone()
183         context[~context_area] = torch.nan
184
185         later = scaled.clone()
186         later[~later_area] = torch.nan
187
188         return context.nanmean(dim = 1).cpu().tolist(), later.nanmean(dim = 1).cpu().tolist()
189
190     # Tokenise a list of phrases.
191     # [n] -> (n, w)
192     def tokenise(self, phrases: list[str]) -> BatchEncoding:
193         return self.llm.tokenizer(
```

```
            phrases,
            return_tensors = 'pt',
            return_attention_mask = True,
            padding = True,
        ).to(self.device)

    # Generate an attention mask for a sequence of tokens.
    # (n, w) -> (n, w)
    def batch_encode(self, tokens: LongTensor) -> BatchEncoding:
        attention_mask = tokens != self.llm.tokenizer.pad_token_id
        return BatchEncoding(dict(
            input_ids = tokens,
            attention_mask = attention_mask,
        ))

    # Use Greedy decoding to generate an answer to a certain query.
    # (n, w) -> (n, w)
    def generate(self, query: BatchEncoding) -> LongTensor:
        generated = self.llm.model.generate(
            input_ids = query.input_ids,
            attention_mask = query.attention_mask,
            max_new_tokens = self.max_length,
            min_new_tokens = self.max_length,
            tokenizer = self.llm.tokenizer,
            do_sample = False,
            temperature = None,
            top_p = None,
            return_dict_in_generate = True,
            pad_token_id = self.llm.tokenizer.pad_token_id,
            eos_token_id = self.llm.tokenizer.eos_token_id,
            bos_token_id = self.llm.tokenizer.bos_token_id,
        )

        # Ensure that all the sequences only contain <PAD> after their first stop token.
        sequences = generated.sequences[:, -self.max_length:]
        ignores = torch.cumsum(torch.isin(sequences, self.stop_token_ids), dim = 1) > 0
        sequences[ignores] = self.llm.tokenizer.pad_token_id

        return sequences

    # Return the perplexity of a certain sequence of tokens being the answer to a
    # certain query, as a list of floats in CPU.
    # (n, w0), (n, w1) -> (n)
    def perplexity(self, query: BatchEncoding, answer: LongTensor) -> list[float]:
        probs = self.batch_perplexity(query, self.batch_encode(answer))
        return probs.cpu().tolist()

    # Return the perplexity of a certain sequence of tokens being the answer to a
    # certain query.
    # (n, w0), (n, w1) -> (n)
    @torch.no_grad()
    def batch_perplexity(self, query: BatchEncoding, answer: BatchEncoding) -> FloatTensor:
        entropies = self.llm.logits(query, answer).log_softmax(dim = 2)
        entropies /= math.log(2)
        probs = torch.where(
            answer.input_ids == self.llm.tokenizer.pad_token_id,
            torch.nan,
            entropies.gather(index = answer.input_ids.unsqueeze(2), dim = 2).squeeze(2),
```

```
        )

        return torch.pow(2, -torch.nanmean(probs, dim = 1))

    # Decode a sequence of tokens into a list of strings.
    # (n, w) -> [n]
    def decode(self, tokens: LongTensor) -> list[str]:
        decoded = self.llm.tokenizer.batch_decode(
            tokens,
            skip_special_tokens = True,
            clean_up_tokenization_spaces = True,
        )
        return [x.strip() for x in decoded]

    # Compare strings for equality to later check whether an answer is parametric
    or contextual.
    # For simplicity, we remove stop words and gather only the subset of words.
    @staticmethod
    def streq(a: str, b: str) -> bool:
        a = a.lower().replace('the', '').replace(',', '').strip()
        b = b.lower().replace('the', '').replace(',', '').strip()
        return a[:len(b)] == b[:len(a)]
```

Listing 5: `QuestionAnswerer.py` contains the `QuestionAnswerer` class which deals with the logic of answering parametric and counterfactual questions from a model

```
import logging

from transformers import AutoTokenizer, AutoModelForCausalLM,
    AutoModelForSeq2SeqLM, BatchEncoding
from torch import nn, tensor
from torch import FloatTensor, Tensor
import torch

# Dictionary of models, containing all of the models aliases and their respective
    models.
Model_dict = {
    'llama': 'meta-llama/Meta-Llama-3.1-8B-Instruct',
    'llama-70b': 'meta-llama/Meta-Llama-3.1-70B-Instruct',
    'llama-405b': 'meta-llama/Meta-Llama-3.1-405B-Instruct',
    'flan-t5': 'google/flan-t5-base',
    'flan-t5-small': 'google/flan-t5-small',
    'flan-t5-base': 'google/flan-t5-base',
    'flan-t5-large': 'google/flan-t5-large',
    'flan-t5-xl': 'google/flan-t5-xl',
    'flan-t5-xxl': 'google/flan-t5-xxl',
    'gemma': 'google/gemma-2-9b-it',
    'gemma-27b': 'google/gemma-2-27b-it',
    'falcon2': 'tiiuae/falcon-11b',
    'falcon-180b': 'tiiuae/falcon-180b-chat',
    'falcon-40b': 'tiiuae/falcon-40b-instruct',
    'falcon-7b': 'tiiuae/falcon-7b-instruct',
    'distilbert': 'distilbert/distilbert-base-uncased-distilled-squad',
    'roberta': 'FacebookAI/roberta-base',
    'roberta-large': 'FacebookAI/roberta-large',
    'roberta-squad': 'deepset/roberta-base-squad2',
    'mixtral': 'mistralai/Mixtral-8x22B-Instruct-v0.1',
    'dummy': '',
}

# Virtual class containing a model.
```

```
# Derived classes should reimplement __init__ and logits.
class Model(nn.Module):
    name: str
    model_name: str
    device: str

    tokenizer: AutoTokenizer
    model: AutoModelForCausalLM

    # Construct a model from a certain name.
    # This should be the main constructor of models.
    @staticmethod
    def fromName(name: str, device: str = 'cpu') -> 'Model':
        if name == 'dummy':
            return DummyModel()

        if name in ('llama-70b', 'gemma-27b'):
            return LargeDecoderOnlyModel(name, device)

        if 't5' in name:
            return Seq2SeqModel(name, device)

        return DecoderOnlyModel(name, device)

    def __init__(self, name: str, device: str = 'cuda'):
        super().__init__()
        self.name = name
        self.model_name = Model_dict[name]
        self.device = device

    @torch.no_grad()
    def logits(self, query: BatchEncoding, answer: BatchEncoding) -> FloatTensor:
        raise NotImplementedError('logits called from generic Model class')

# Decoder-only model, such as llama.
class DecoderOnlyModel(Model):
    def __init__(self, name: str, device: str = 'cuda'):
        super().__init__(name, device)

        # self.prompt = 'Answer the following question in a few words and with no formatting.'
        # self.cf_prompt = 'Answer the following question using the previous context in a few words and with no formatting.'
        self.prompt = ''
        self.cf_prompt = ''

        kwargs = {}
        if 'llama' in name:
            kwargs = dict(
                pad_token = '<|reserved_special_token_0|>',
                padding_side = 'left',
            )
        elif 'gemma' in name:
            kwargs = dict(
                padding_side = 'right',
            )

        self.tokenizer = AutoTokenizer.from_pretrained(
            self.model_name,
            clean_up_tokenization_spaces = True,
            **kwargs,
        )
```

```
94
95          logging.info(f'Loading model for {self.model_name} using
    {torch.cuda.device_count()} GPUs.')
96          self.model = AutoModelForCausalLM.from_pretrained(
97              self.model_name,
98              device_map = 'auto' if self.device == 'cuda' else self.device,
99              torch_dtype = torch.bfloat16,
100             pad_token_id = self.tokenizer.pad_token_id,
101             bos_token_id = self.tokenizer.bos_token_id,
102             eos_token_id = self.tokenizer.eos_token_id,
103             low_cpu_mem_usage = True,
104         )
105         self.model.eval()
106
107     @torch.no_grad()
108     def logits(self, query: BatchEncoding, answer: BatchEncoding) -> FloatTensor:
109         w0 = query.input_ids.shape[1]
110         w1 = answer.input_ids.shape[1]
111
112         input_ids = torch.cat([query.input_ids, answer.input_ids], dim = 1)
113         attention_mask = torch.cat([query.attention_mask, answer.attention_mask],
    dim = 1)
114
115         return self.model(input_ids, attention_mask = attention_mask).logits[:,
    w0 - 1 : w0 + w1 - 1]
116
117     @torch.no_grad()
118     def attentions(self, queries: BatchEncoding) -> FloatTensor:
119         outputs = self.model(**queries, output_attentions = True).attentions
120         return torch.stack(outputs, dim = 1)
121
122 # Seq2Seq model, such as Flan-T5.
123 class Seq2SeqModel(Model):
124     def __init__(self, name: str, device: str = 'cpu'):
125         super().__init__(name, device)
126
127         self.prompt = ''
128         self.cf_prompt = ''
129
130         kwargs = dict(
131             padding_side = 'right',
132         )
133         self.tokenizer = AutoTokenizer.from_pretrained(
134             self.model_name,
135             clean_up_tokenization_spaces = True,
136             **kwargs,
137         )
138
139         logging.info(f'Loading Seq2Seq model for {self.model_name} using
    {torch.cuda.device_count()} GPUs.')
140         self.model = AutoModelForSeq2SeqLM.from_pretrained(
141             self.model_name,
142             device_map = 'auto' if self.device == 'cuda' else self.device,
143             torch_dtype = torch.bfloat16,
144             pad_token_id = self.tokenizer.pad_token_id,
145             bos_token_id = self.tokenizer.bos_token_id,
146             eos_token_id = self.tokenizer.eos_token_id,
147             low_cpu_mem_usage = True,
148         )
149         self.model.eval()
150
151     @staticmethod
```

```
    def pad(tensor: Tensor, length: int, value) -> Tensor:
        right = torch.full((tensor.shape[0], length - tensor.shape[1]), value)
        return torch.cat([tensor, right.to(tensor.device)], dim = 1)

    @torch.no_grad()
    def logits(self, query: BatchEncoding, answer: BatchEncoding) -> FloatTensor:
        length = max(query.input_ids.shape[1], answer.input_ids.shape[1])

        input_ids = self.pad(query.input_ids, length, self.tokenizer.pad_token_id)
        attention_mask = self.pad(query.attention_mask, length, 0)
        decoder_input_ids = self.pad(self.model._shift_right(answer.input_ids),
    length, self.tokenizer.pad_token_id)

        return self.model(
            input_ids = input_ids,
            attention_mask = attention_mask,
            decoder_input_ids = decoder_input_ids,
        ).logits[:, : answer.input_ids.shape[1]]

    @torch.no_grad()
    def attentions(self, queries: BatchEncoding) -> FloatTensor:
        outputs = self.model(
            **queries,
            output_attentions = True,
            decoder_input_ids = torch.full_like(queries.input_ids,
    self.tokenizer.pad_token_id).to(self.device),
        ).decoder_attentions
        return torch.stack(outputs, dim = 1)

# Large decoder-only model.
# Similar to DecoderOnlyModel, but eagerly deletes the model when the class is
    deleted.
# Assumes you need 2 GPUs to run this.
class LargeDecoderOnlyModel(DecoderOnlyModel):
    def __init__(self, name, device: str = 'cuda'):
        if torch.cuda.device_count() < 2:
            raise ValueError(f'At least two GPUs are needed to run {name}')

        super().__init__(name, device)

    def __del__(self):
        logging.info(f'Deleting large model {self.name}')
        del self.model
        torch.cuda.empty_cache()

# Dummy model, used for testing.
class DummyModel(Model):
    def __init__(self):
        nn.Module.__init__(self)
        self.name = 'dummy'
        self.tokenizer = self
        self.model = self
        self.sequences = ['dummy']
        self.logits = tensor([[[1., 2., 3.]]])

        self.bos_token_id = 0
        self.eos_token_id = 1
        self.pad_token_id = 2

    def to(self, *args, **kwargs):
        return self

```

```
    def __call__(self, *args, **kwargs):
        return self

    def generate(self, *args, **kwargs):
        return self

    def __getitem__(self, key):
        return self

    def decode(self, *args, **kwargs):
        return 'Dummy text'

    def batch_decode(self, *args, **kwargs):
        return ['Dummy Text 1', 'Dummy Text 2']

    def shape(self):
        return (1, 2, 3)

# If called separately, just print the names of the models.
def main():
    print(f'{"Model Name":>15} | {"Huggingface Model":<40}')
    print((15 + 1) * '-' + '|' + (40 + 1) * '-')
    for name, model in Model_dict.items():
        print(f'{name:>15} | {model:<40}')

if __name__ == '__main__':
    main()
```

Listing 6: `Models.py` contains the list of models and includes code that differentiates them.

```
import csv
import logging
import itertools
import random
import time
import typing

from collections import defaultdict
from dataclasses import dataclass
from typing import Optional, Any

# Custom filter that does not print a log if it printed another one at most
    `rate_limit` seconds ago.
class LogTimeFilter(logging.Filter):
    def __init__(self):
        super().__init__()
        self.last_log = defaultdict(lambda: 0)

    def filter(self, record):
        if not hasattr(record, 'rate_limit'):
            return True

        current_time = time.time()
        if current_time - self.last_log[record.lineno] >= record.rate_limit:
            self.last_log[record.lineno] = current_time
            return True

        return False

# A question contains combines a base_question and an object into something that
    can be queried.
```

```python
@dataclass
class Question:
    category: str
    obj: str
    base_question: str

    # Static constructor: return a question combining an object and an object if the category
    # matches; return None otherwise.
    @staticmethod
    def orNothing(obj: str, category: str, base_question: str) -> Optional['Question']:
        if not f'{{{category}}}' in base_question:
            return None

        return Question(obj = obj, category = category, base_question = base_question)

    # Return a query from the format of this Question.
    def format(self, *, prompt: Optional[str] = None, context: Optional[str] = None, use_question: bool = True, use_later: bool = True) -> str:
        [question, later] = self.base_question.format_map({self.category: self.obj}).split('?', 1)
        question += '?'

        formatted = ''
        if use_question:
            formatted = f'Q: {question.strip()}'

        if use_later:
            formatted = f'{formatted} A: {later.strip()}'

        if prompt is not None:
            formatted = f'{prompt} {formatted}'

        if context is not None:
            formatted = f'Context: [{later.strip()} {context}]. {formatted}'

        return formatted.strip()

# Returns the set product of a list of base question with the respective set of objects.
def combine_questions(base_questions: list[str], objects: list[dict[str, str]], lim_questions: Optional[int] = None) -> list[Question]:
    questions = []
    for bq in base_questions:
        for obj in objects:
            q = Question.orNothing(obj = obj['object'], category = obj['category'], base_question = bq)
            if q is None:
                continue

            questions.append(q)

    if lim_questions is None:
        return questions

    keep_nums = {x: e for e, x in enumerate(random.sample(range(len(questions)), lim_questions))}
    short_questions = [questions[x] for x in keep_nums.keys()]

    return short_questions
```

```
83
84  # Given a list of questions and a list of answers, produce a list of integers
        that would provide the
85  # index to a randomly sampled counterfactual.
86  def sample_counterfactual_flips(questions: list[Question], answers: list[str]) ->
        list[int]:
87      flips = [-1 for _ in questions]
88
89      for q, es_iter in itertools.groupby(range(len(questions)), key = lambda e:
        questions[e].base_question):
90          es = set(es_iter)
91
92          for e in es:
93              rest = [x for x in es if answers[x] != answers[e]]
94              if not rest:
95                  logging.error(f'Unitary question "{q}". This means that all
        answers in this chunk are identical, and the results will be incorrect.')
96                  flips[e] = e
97                  continue
98
99              flips[e] = random.choice(rest)
100             assert answers[flips[e]] != answers[e]
101
102     assert all(x != -1 for x in flips)
103     return flips
104
105 # Chunk a list of question into batches of size or at most `max_batch_size`.
106 def chunk_questions(questions: list[Question], max_batch_size: int) ->
        list[list[Question]]:
107     result: list[list[Question]] = []
108
109     for q, chunk_iter in itertools.groupby(questions, key = lambda x:
        x.base_question):
110         chunk = list(chunk_iter)
111         if not result or len(chunk) + len(result[-1]) > max_batch_size:
112             result.append([])
113
114         result[-1].extend(chunk)
115
116     return result
117
118 # Prints a CSV file with the questions and resulting answers.
119 def print_parametric_csv(out: typing.TextIO, answer: dict[str, list[Any]]):
120     fieldnames = ['Num', 'Category', 'Base_Question', 'Thing', 'Question',
        'Prefix'] + list(answer.keys())
121
122     writer = csv.DictWriter(
123         out,
124         fieldnames = fieldnames,
125         extrasaction = 'ignore',
126         dialect = csv.unix_dialect,
127         quoting = csv.QUOTE_MINIMAL,
128     )
129     writer.writeheader()
130
131     for e, answers in enumerate(zip(*answer.values())):
132         param = dict(zip(answer.keys(), answers))
133
134         question = param['question']
135         param.pop('question')
136
137         writer.writerow(
```

```
            {
                'Num': str(e),
                'Category': question.category,
                'Base_Question':
    ''.join(question.base_question.partition('?')[0:2]),
                'Object': question.obj,
                'Question': question.format(use_later = False),
                'Prefix': question.format(use_question = False)
            } | param
        )
```

Listing 7: `Utils.py` contains various useful functions

```
import unittest
from unittest import TestCase
from unittest.mock import MagicMock

import torch
from torch import tensor

from QuestionAnswerer import QuestionAnswerer

pad = 128002
class QuestionAnswererTests(unittest.TestCase):
    def setUp(self):
        self.qa = QuestionAnswerer('dummy', 'cpu', None)
        # self.qa.llm.tokenizer = MagicMock()
        self.qa.llm.tokenizer.pad_token_id = pad
        self.qa.llm.tokenizer.batch_decode = MagicMock(
            return_value = ['Hello how are you', 'Newline here', 'No stop
    string', '']
        )

    def test_winner(self):
        logits = tensor([
            [[0.0900, 0.2447, 0.6652], [0.6652, 0.2447, 0.0900], [0.2447, 0.6652,
    0.0900]],
            [[0.2119, 0.2119, 0.5761], [0.2119, 0.2119, 0.5761], [0.2119, 0.2119,
    0.5761]],
            [[0.6652, 0.2447, 0.0900], [0.2119, 0.5761, 0.2119], [0.5761, 0.2119,
    0.2119]],
        ])

        expected_path = tensor([[2, 0, 1], [2, 2, 2], [0, 1, 0]])
        expected_probs = tensor([
            [0.6652, 0.6652, 0.6652],
            [0.5761, 0.5761, 0.5761],
            [0.6652, 0.5761, 0.5761],
        ])

        path, probs = self.qa.winner(logits)
        self.assertTrue(torch.equal(path, expected_path), msg = (path,
    expected_path))
        self.assertTrue(torch.allclose(probs, expected_probs), msg = (probs,
    expected_probs))

    def test_decode(self):
        path = tensor([
            [128000, 9906, 1268,  527,  499,    13,  358, 1097, 3815, 7060, 9901,
     499,   13],
            [128000, 3648, 1074, 1618,  198, 54953,    0,   13, 1234, 1234, 1234,
```

```
    1234, 1234],
42          [128000, 2822, 3009,  925, 1234,  1234, 1234, 1234, 1234, 1234, 1234,
    1234, 1234],
43          [128000,   13, 1234, 1234, 1234,  1234, 1234, 1234, 1234, 1234, 1234,
    1234, 1234],
44      ])
45      probs = tensor([
46          [1., 3., 5., 7., 9., 11., 13., 15., 17., 19., 21., 23., 25.],
47          [1., 3., 5., 7., 9., 11., 13., 15., 17., 19., 21., 23., 25.],
48          [1., 3., 5., 7., 9., 11., 13., 15., 17., 19., 21., 23., 25.],
49          [1., 3., 5., 7., 9., 11., 13., 15., 17., 19., 21., 23., 25.],
50      ])
51
52      expected_result = [
53          'Hello how are you',
54          'Newline here',
55          'No stop string',
56          '',
57      ]
58      expected_mean_probs = [5., 4., 13., 1.]
59
60      result, mean_probs = self.qa.decode(path, probs)
61      self.assertListEqual(expected_result, result)
62      self.assertListEqual(expected_mean_probs, mean_probs)
```

Listing 8: `test_QuestionAnswerer.py` is used to test some of the complicated bits of logic in QuestionAnswerer.