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# **Knowledge Grounding in Language Models: An Empirical Study**

**Martin Fixman**

Supervised By: Tillman Weyde

Collaborators: Chenxi Whitehouse and Pranava Madhyastha

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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**

This is an abstract

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# 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 LLMs 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 counterfactual 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 Thesis Questions & Objectives

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

### 1.2.1 Creating a representative dataset of questions

The research of this thesis requires a large dataset of questions from a variety of categories to test large language models. In order to understand knowledge grounding in these models, we require a dataset with the following properties.

1. The dataset must contain questions that have short, unambiguous answers.
2. The questions must cover a large set of topics.
3. It must allow for the creation of counterfactual answers in the same format as correct ones to test contextual versus inherent knowledge.

The existing literature uses various existing question-and-answer datasets, none of which are useful for this research.\*

**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 counterfactual 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 counterfactual 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.

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 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.

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\*TODO: Maybe this entire subsection should go on Section 2 or Section 3.

### 1.2.2 When does a model choose the provided context knowledge over its inherent knowledge?

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 answer picked depends on the type and size 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.

This thesis also gathers insights from answering this question on different categories and patterns of questions to find out if this depends on what is being asked.

### 1.2.3 Can we use the perplexity score of an answer to predict whether it came from inherent or contextual knowledge?

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 presents a short summary of some of the articles that were useful in researching this topic.

### 2.1 Foundational Papers on Large Language Models

- “Language models are unsupervised multitask learners” (Radford et al. 2019).
  - The foundational paper for GPT2.
- “Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer” (Raffel et al. 2020).
  - The foundational paper for T5.
- “Language Models are Few-shot Learners” (Brown et al. 2020).
  - Introduces “in-context learning”.
- “Prompt programming for large language models: Beyond the few-shot paradigm” (Reynolds & McDonell 2021).
  - Improves the previous paper.

### 2.2 Papers working with RAG and contextual data

- “Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks” (Lewis et al. 2020).
  - Foundational paper for RAG.
- “Self-RAG: Learning to Retrieve, Generate, and Critique through Self-Reflection” (Asai et al. 2023).
  - Interesting RAG system.
- “Can Retriever-Augmented Language Models Reason? The Blame Game Between the Retriever and the Language Model” (Ghader et al. 2023).
  - Nice evaluation of RAG models.

### 2.3 Retrieval-Augmented Language Models

- “Shall We Pretrain Autoregressive Language Models with Retrieval? A Comprehensive Study” (Wang et al. 2023).

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\*This entire section is in progress — short summaries of the named papers will come soon.

- Reproduces and pretrains RETRO.
- “Atlas: Few-shot Learning with Retrieval Augmented Language Models” (Izcard et al. 2022).
  - Introduces ATLAS.
- “Improving language models by retrieving from trillions of tokens” (Borgeaud et al. 2022).
- “RAGGED: Towards Informed Design of Retrieval Augmented Generation Systems” (Hsia et al. 2024).
  - Analyses results of these systems; compares Llama to Flan-T5.

## 2.4 On disentangling parametric and context-augmented counterparametric knowledge

- “DISCO: Distilling Counterfactuals with Large Language Models” (Chen et al. 2023).
  - Does similar analysis with counterfactuals to this thesis
- “DisentQA: Disentangling Parametric and Contextual Knowledge with Counterfactual Question Answering” (Neeman et al. 2022).
  - Also does a similar analysis to this thesis.
- “Characterizing Mechanisms for Factual Recall in Language Models” (Yu et al. 2023).
  - Very simple analysis, but tries to understand WHERE in the model the contextual answers come from.
- “Can We Edit Factual Knowledge by In-Context Learning?” (Zheng et al. 2023).
- “Learning the Difference that Makes a Difference with Counterfactually-Augmented Data” (Kaushik et al. 2020).

### 3 Methods

#### 3.1 Creating a representative dataset of questions

As shown in Section 1.2.1, our codebase requires the creation of a new dataset of questions with three main properties.

1. Questions should have short and unambiguous answers.
2. They must cover a large set of topics, eras, and places.
3. They must allow for the creation of sensible counterfactuals by having sets of questions with the same answer format.

To address Items 1 and 3, we follow the approach done by Yu et al. in creating questions which have a question with a particular “object” as its nucleus. This way, it’s possible to create counterfactuals that have the same format of the original answer by randomly sampling from the set of answers, as shown in Table 1.

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
	Boyan Slat	27 January 1994	February 23, 1868	Context: [the date of birth of Boyan Slat is February 23, 1868]. Q: What is the date of birth of Boyan Slat? A: The date of birth of Boyan Slat 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

**Table 1:** Using the same question format allows us to repurpose previous parametric answers as counterparametric ones.

To address Item 2, we manually create a large of different topics, questions, and objects referred to that question in various categories. To create the questions that are being queries, every question is matched to an object of its corresponding category as shown in Table 5.

Category	Base Questions	Object	Final Questions
Person	Q: What is the date of birth of <code>{person}</code> ? A: The date of birth of <code>{person}</code> is Q: In what city was <code>{person}</code> born? A: <code>{person}</code> 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 <code>{city}</code> in? A: <code>{city}</code> is in	Cairo Mumbai	Q: What country is Cairo in? A: Cairo is in Q: What country is Mumbai in? A: Mumbai is in

**Table 2:** Some examples of the base-question and object generation that are fed to the models for finding parametric answers.

In addition to having the previous properties, it’s easy to make a long list of questions using this method.

## 3.2 When does a model choose the provided context knowledge over its inherent knowledge?

### 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 models of different types and sizes.

	Seq2Seq Model	Decoder-Only Model
Small	Flan-T5-XL	Meta-Llama-3.1-8B-Instruct
Large	Flan-T5-XXL	Meta-Llama-3.1-70B-Instruct

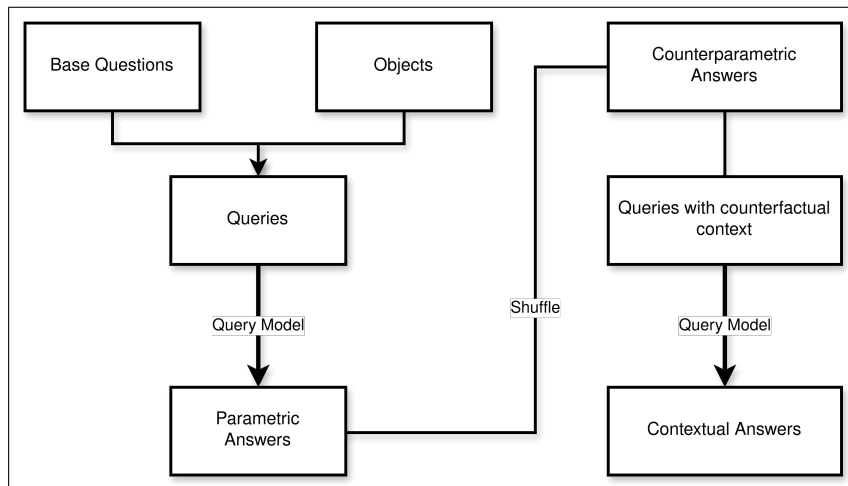
**Table 3:** The four large language models chosen for this research.

The Flan-T5 models (Chung et al. 2022) are an extension to the original Seq2Seq T5 models (Raffel et al. 2020) which are fine-tuned to particular NLP tasks framed as text-to-text problems. Compared to T5, it’s generally better at following instructions and has improved zero-shot performance.

The Llama models (Dubey et al. 2024) are Decoder-only models with a dense transformer architecture that are fine-tuned for instruction-following tasks, and are specially adept at complex prompts.

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

TODO: Maybe I should explain the whole drama with the counterparametric answers here.



**Figure 1:** 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.

To ensure that the results are simple to interpret and minimise the chance that the result is affected by 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).

## 3.3 Can we use the perplexity score of an answer to predict whether it came from inherent or contextual knowledge?

### 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 model  $Q$  choosing a token  $x_n$  with context  $x_1, \dots, x_{n-1}$  by calculating the softmax value of all the logits for the possible words for this token.

This probability of the tokens corresponding to a particular answer  $x_1, \dots, x_n$  can be accumulated to calculate the negative log-likelihood NLL, which is used to calculate the perplexity PPL using the formulas from Equations (1) and (2).

$$\text{NLL}(x_1, \dots, x_n \mid Q) = -\frac{1}{n} \sum_{i=1}^n \log_2 P(x_i \mid Q, x_1, \dots, x_{i-1}) \quad (1)$$

$$\text{PPL}(x_1, \dots, x_n \mid Q) = 2^{\text{NLL}(x_1, \dots, x_n \mid Q)} \quad (2)$$

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

Note that the token  $x_n$  does not necessarily have to be the result of applying the query  $x_1, \dots, x_{n-1}$  to a model. We can instead use teacher-forcing (Lamb et al. 2016) to calculate the perplexity values of finding the parametric answer in the query with counterfactual context, and the

## 4 Methods (Old)

### 4.1 Models and Resources Used

- Reader Models

- Llama-8B.
- Llama-70B.
- Flan-T5-XL.
- Flan-T5-XXL.
- *Atlas?*

- Questions

- Our own dataset, shown in Appendix A.
- *Maybe add Natural Questions, HotpotQA, and/or BioASQ as in RAGGED (Hsia et al. 2024).*

### 4.2 Preprocessing and Inference Methodology

#### 4.2.1 Source Data Preparation

Our source data is prepared by extending the ideas presented by Yu et al.. Instead of using one simple question, our approach consists of separating this data into 7 categories, where each category has a set of base questions and another set of objects that are paired together and presented to our models.

This work contains 7 categories in the configuration shown by Table 4, for a total of 3840 questions. The full list of questions can be found in Appendix A.

Category	Questions	Objects	Total
Person	14	47	658
City	14	60	840
Principle	10	30	300
Element	10	35	350
Book	10	45	450
Painting	14	39	546
Historical Event	6	56	336
Total	68	312	3840

**Table 4:** The amount of questions for each category. The full list of questions can be found in Appendix A. This is still a work in progress and I expect to add more questions.

We enhance the zero-shot learning prompt used by Brown et al. by using the prompt format example format presented Jiang et al. for calibrating the T5 language model by adding both the question and the first part of the answer.

### 4.2.2 Prompting

There is plenty of research that suggests that for zero-shot problems (Brown et al. 2020, Reynolds & McDonell 2021), it’s convenient to create a minimal prompt (Jiang et al. 2021, Yu et al. 2023). This is helpful when later calculating the perplexity of the answers, as it tends to bias for short answers without any extra information that might change the individual probabilities of each token.

Examples of the prompting format explained in Sections 4.2.1 and 4.2.2 can be found in Table 5. For later queries, this is enhanced with context as in ??.

Base Question	Object	Final Question
What is the date of birth of {person}?		Q: What is the date of birth of Che Guevara?
The date of birth of {person} is	Che Guevara	A: The date of birth of Che Guevara is
In what city was {person} born?	Confucius	Q: What is the date of birth of Confucius?
{person} was born in		A: The date of birth of Confucius is
What country is {city} in?	Cairo	Q: In what city was Che Guevara born?
{city} is in	Mumbai	A: Che Guevara was born in
		Q: In what city was Confucius born?
		A: Confucius was born in
		Q: What country is Cairo in?
		A: Cairo is in
		Q: What country is Mumbai in?
		A: Mumbai is in

**Table 5:** Some examples of the base-question and object generation that are fed to the models for finding parametric answers.

### 4.2.3 Generating and scoring parametric answers

We query each of the models listed in Section 4.1 with the data from the previous subsections.

To ensure results are simple to interpret and not affected by randomness, we follow the example of Hsia et. al (Hsia et al. 2024) 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).

The negative log-likelihood of an answer  $x$  is calculated in base of the conditional probability of generating each token given the prior tokens. We can use this value to calculate the perplexity, which measures the level of “surprise” of a particular answer.

$$\begin{aligned}
 \text{NLL}(x_1, \dots, x_N | Q) &= -\frac{1}{N} \sum_{i=1}^N \log P(x_i | Q, x_{i-1}, \dots, x_1) \\
 \text{PPL}(x_1, \dots, x_N | Q) &= e^{\text{NLL}(x_1, \dots, x_N | Q)}
 \end{aligned} \tag{3}$$



		Tokens	
		Parametric $p$	Counterparametric $\bar{p}$
Context	Empty $Q$	$\text{PPL}(p_1, \dots, p_N \mid Q)$	$\text{PPL}(\bar{p}_1, \dots, \bar{p}_N \mid Q)$
	Counterparametric $W$	$\text{PPL}(p_1, \dots, p_N \mid W)$	$\text{PPL}(\bar{p}_1, \dots, \bar{p}_N \mid W)$

**Figure 2:** Four different perplexity values: one for each set of tokens, and one for each query context..

We can ensure that the probabilities are calculated based on the intended tokens rather than the “most probable” generated ones by using teacher forcing (Lamb et al. 2016).

#### 4.2.4 Shuffling to generate counterparametric answers

Previous work related to finding per token probabilities of answers in large language models focus on either a pre-existing list of questions or on a single question format (Yu et al. 2023). This approach does not work for our use case for three reasons.

1. Having 68 different types of questions, rather than just 1, makes finding counterfactual answers technically challenging.
2. Our focus is not on finding *counterfactual* answers, but *counterparametric* ones. We do not care about correctness; we care about answers not being parametric.
3. Since we are measuring perplexity of these answers, we focus on answers that are generated by the same base question and the same model. This way we ensure that the format of the answer is the same.

We propose a novel way of generating counterparametric answers while focusing on these three points: rather than generating new answers for each question, counterfactual answers are randomly sampled from the parametric answers corresponding to the same base question. An example of this approach can be seen in ??.

#### 4.2.5 Counterparametric and contextual perplexity scores

This works extends the approach of analysing answers found in [citation needed] and explained in Section 4.2.3 by also calculating the perplexity of *alternative* answers to each question.

That is, we take the result of applying each model to both the answer with and without counterparametric context, and we calculate the perplexity scores of getting both the parametric and counterparametric answer to each one of these. This produces four different scores which are detailed in Figure 2: one for each answer using either empty and counterparametric context.

---

\*I am finding it hard to explain this subsubsection. Maybe I should add pseudocode here.

By definition, the tokens of the parametric answer  $p_1, \dots, p_N$  are the ones corresponding to the lowest perplexity answer for the query without any context. This is not the case for the tokens of the counterparametric answer  $\bar{p}_1, \dots, \bar{p}_{\bar{N}}$ , which produces the inequality in Equation (4).

$$\text{PPL}(p_1, \dots, p_N \mid Q) \leq \text{PPL}(\bar{p}_1, \dots, \bar{p}_{\bar{N}} \mid Q) \quad (4)$$

Finding the result of the inequality for the queries with the counterparametric context  $W$  is one of the main goals of this research. In fact, we know that if the perplexity of the parametric tokens  $p_1, \dots, p_N$  is greater than the tokens for the counterparametric answer  $\bar{p}_1, \dots, \bar{p}_{\bar{N}}$  then the answer was memorised. Otherwise, the answer was generated in-context.

$$\text{Answer Source} = \begin{cases} \text{Memory} & \text{if } P(p_1, \dots, p_N \mid W) < P(\bar{p}_1, \dots, \bar{p}_{\bar{N}} \mid W) \\ \text{Context} & \text{otherwise} \end{cases} \quad (5)$$

#### 4.2.6 Comparing the Final Answers

There is a third case that's not present in Equations (4) and (5): the case where the answer comes from neither the model's memory nor the query's context, but that instead the model generates a third answer combining both.

There are several cases where this can happen. The most interesting are explained in ??, while the full results can be found in Appendix B.

In particular, we categorise the final answers in one of three groups depending on whether the answer with minimal perplexity on the query with the counterfactual context  $W$  is equal to the parametric answer, to the counterparametric answer, or to something else.

$$\text{Group} = \begin{cases} \text{Parametric} & \text{if } (\nexists x_1, \dots, x_N) \text{ PPL}(x_1, \dots, x_N \mid W) < A \\ \text{Counterparametric} & \text{if } (\nexists x_1, \dots, x_N) \text{ PPL}(x_1, \dots, x_N \mid W) < B \\ \text{Other} & \text{otherwise} \end{cases} \quad (6)$$

where

$$\begin{aligned} A &= \text{PPL}(p_1, \dots, p_N \mid W) \\ B &= \text{PPL}(\bar{p}_1, \dots, \bar{p}_{\bar{N}} \mid W) \end{aligned}$$

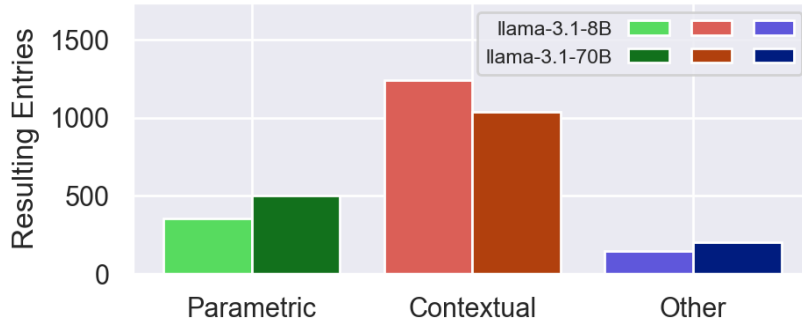
There is a correlation between Equation (6) and Equation (5): an answer in the Parametric group will come from the model's memory, and an answer in the Counterparametric group will come from the query's (counterparametric) context.

## 5 Results

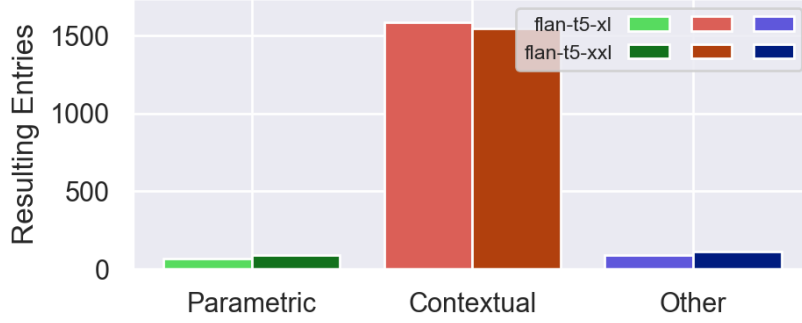
Some results I want to show.

- Larger models tend to prefer parametric knowledge over contextual knowledge.
  - This is the case in “Characterizing Mechanisms for Factual Recall in Language Models” (Yu et al. 2023), but I’m proving this on a larger set of question.
  - This is using exact match. Maybe attempting Unigram  $F_1$  would produce interesting results (Petroni et al. 2021).
- How this compares between Decoder-only models, Seq2Seq models, and Retrieval-Augmented Language Models.
- How does the perplexity between parametric answers and contextual answers compare within the same model.
  - From the perplexity alone, can we predict whether an answer came from the model’s memory or from the context?
  - It might be worth experimenting this with factual answers in the context, to simulate a RAG-difference detector.
- Is there any correlation between the perplexity of the parametric and contextual answer *without any context* and which one will be chosen when adding context?
  - This one is interesting, but I’m not sure we’ll get significant results.
- Interesting “Other” results.
- Anything else?

### 5.1 Comparing the amounts of each type of answer

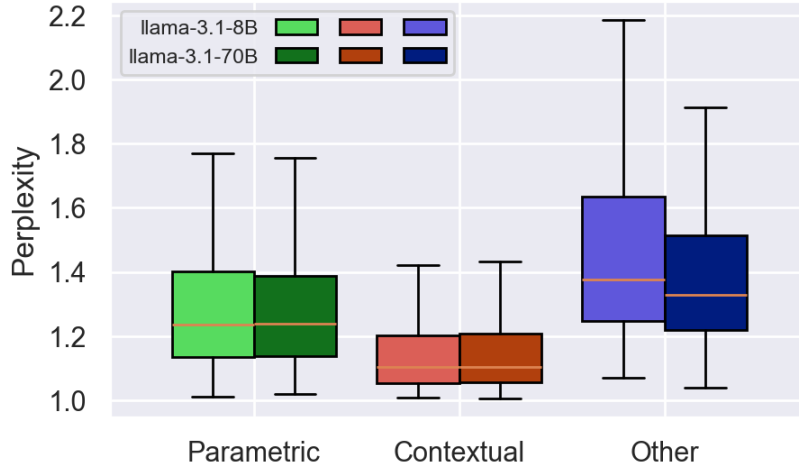


**Figure 3:** Amount of entries for each result after applying counterfactual context to Llama models. Generally, larger models tend to prefer parametric to contextual knowledge; this is further discussed in Section 6.2.



**Figure 4:** Same results for the Seq2Seq models FLAN-T5. While these models tend to be more biased towards contextual knowledge, as discussed in Section 6.1, larger models still are biased towards parametric knowledge.

## 5.2 Comparing the perplexity distribution for each type of answer

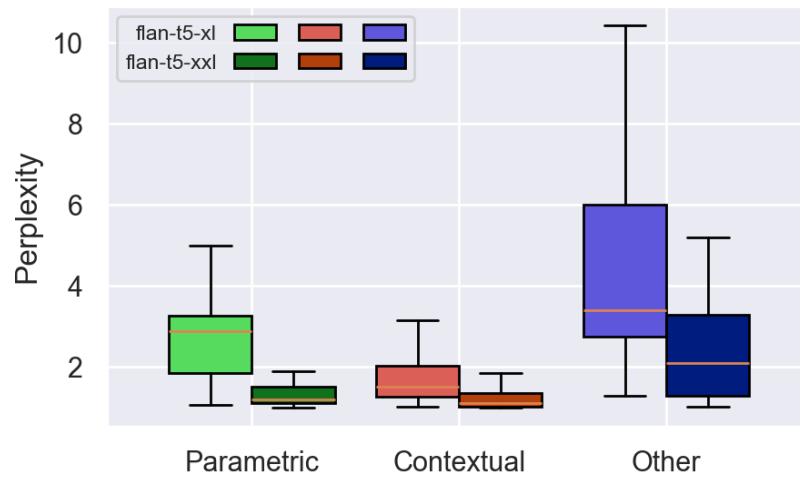


**Figure 5:** Perplexity box plots for Decoder-only Llama models.

Despite the amount for small and large Llama models being considerably different, the average values and distributions remain roughly the same. This is discussed in Section 6.

Additionally, the perplexity of contextual answers is considerably lower than the one for parametric answers.

Interestingly, the larger models tend to have a much lower perplexity for both parametric and contextual answers.



**Figure 6:** Perplexity box plots for Seq2Seq Flan models.

## 6 Discussion

6.1 Model type and memorised knowledge

6.2 Model size and memorised knowledge

6.3 Differences in perplexity scores for larger and smaller models

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

6.4 Differences in distributions for different categories and questions.

## 7 Evaluations, Reflections, and Conclusions

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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 1:** All base questions used in this work. Each one of these will get combined with data from Listing 2 as detailed in Section 4.2.1.

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  
 Schrödinger 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](#)



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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
Für Elise,composition
Gymnopédies,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

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**Listing 2:** All objects which will be combined with the questions in Listing 1.

- B Full Results for Each Question**
- C Grounder Usage and Documentation**
- D appendixD**