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Knowledge Grounding in Language Models: An Empirical Study

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Declaration

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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.

*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).

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

1. The 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 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 counterfactual 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.

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.

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.

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 4.1 into four 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 2: 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?

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 (given by the original query). Later, we add this “counterfactual” answer to the context, to form a new query and query the same model again.

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.

We compare the parametric answer to the previous values to come to one of three cases: either this answer is identical to the **Parametric** answer and the model inferred it from its grounded knowledge, to the **Counterparametric** answer and the model inferred it from the context, or the answer is different to these two and the model inferred it from some **Other** place.

This approach is detailed in Figure 1, and Table 3 contains an example of the shuffling done for this experiment.

Base Question	Object	Parametric Answer	Counterparametric Answer	Question with counterparametric context
Q: What is the date of birth of <code>{person}</code> ? A: The date of birth of <code>{person}</code> 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
Q: What country is <code>{city}</code> in? A: <code>{city}</code> 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 3: Using the same question format allows us to repurpose previous parametric answers as counterparametric ones.

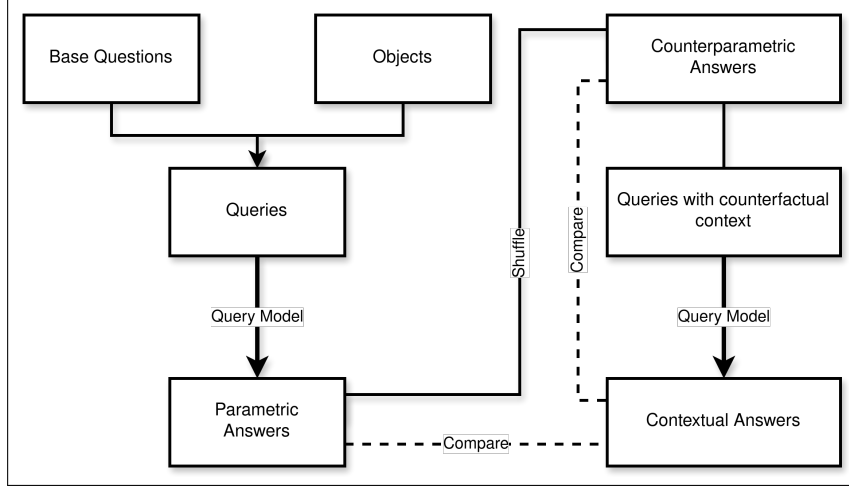


Figure 1: Example diagram of steps used to calculate the two sets of answers, *parametric* and *contextual*, and to compare them to answer the question in this objective. Many of the terms in this diagram are explained in the Glossary.

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 a model choosing a token x_n with context x_1, \dots, 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 (1) and (2).

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

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

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.

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 counterfactual context, and the perplexity scores of the contextual answers for these two queries.

For a given parametric answer p_1, \dots, p_n and randomly sampled counterparametric answer q_1, \dots, 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 4.

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

Table 4: Four different perplexity values: one for each set of tokens, and one for each query context.

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 .

The question in Section 3.2 is equivalent to asking whether $P_2 \stackrel{\leq}{\geq} P_3$, or whether there is a different sequence of tokens that has any lower perplexity of these two.

3.3.3 Predicting whether an answer came from memory or from context

One question remains: if the response of the query with counterfactual context Q' is x_1, \dots, x_n , how can we predict whether this answer is came from the model's memory p , from the given context q , or something else?

We propose investigating the value of the perplexity $\text{PPL}(x_1, \dots, x_n \mid Q')$ and comparing it to the distribution of perplexities on parametric and contextual answers. TODO: Maybe include a KDE or a K-S test here.

4 Results

4.1 Creating a representative dataset of questions

We manually create a set of 4760 questions using the method explained in Section 4.1.

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 5.

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

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

The results of running the queries created in Section 4.1 with added counterfactual context on each of the four models the four models can be found in Table 6 and Figure 2.

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

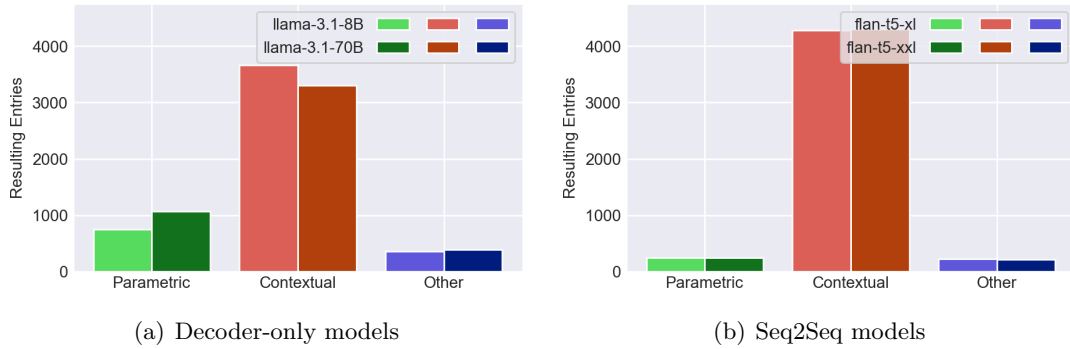


Figure 2: Results by type depending on which model; these are the same results as Table 6.

As hypothesised in Section 1.2.2, 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 6.

A similar pattern emerges in most (but not all) of the categories, which can be seen in Tables 7 and 8 and Figures 3 and 4.

	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 7: 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 8: Results for running each one of the 10 categories separately on the Seq2Seq models.



Figure 3: Results of running decoder-only models on the queried data, grouped by category. This plots the information shown in Table 7.

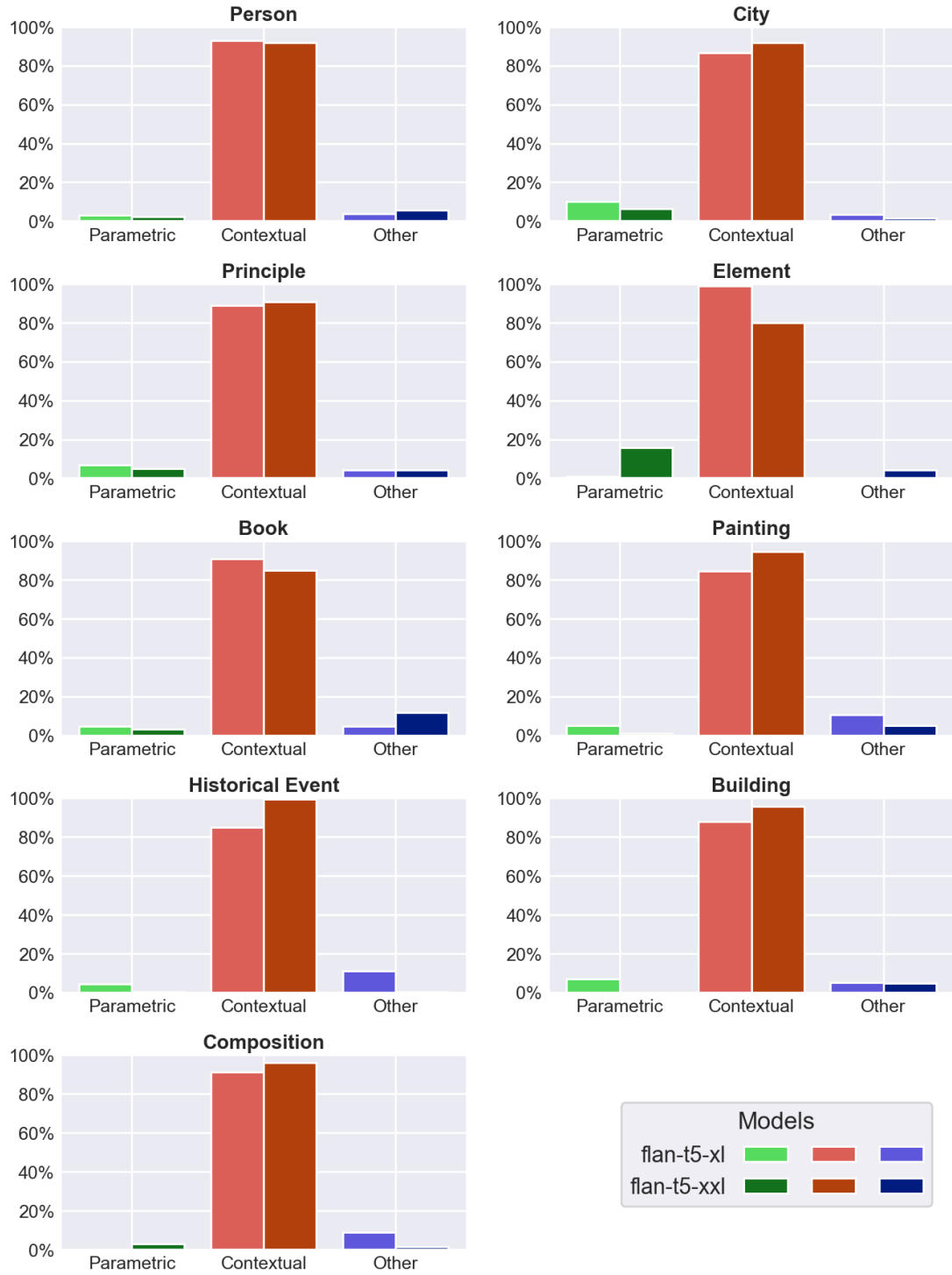


Figure 4: Results of running Seq2Seq models on the queried data, grouped by category. This plots the information shown in Table 8.

5 Results (old)

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 significative results.
- Interesting “*Other*” results.
- **Anything else?**

5.1 Comparing the amounts of each type of answer

5.2 Comparing the perplexity distribution for each type of answer

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.

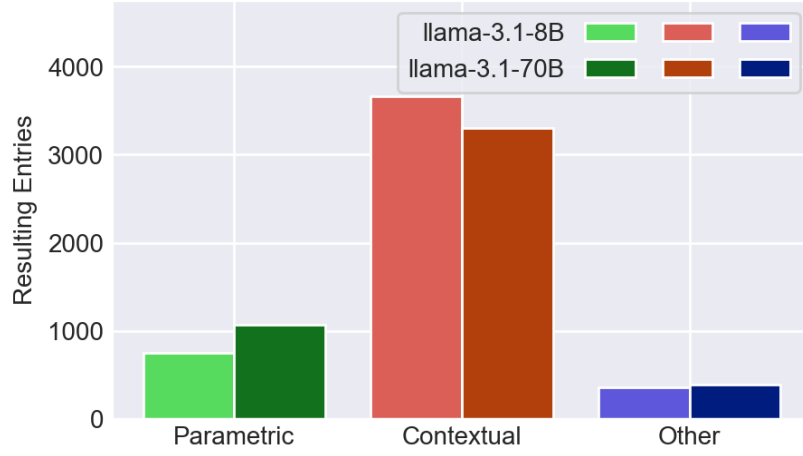


Figure 5: Amount of entries for each result after applying counterfactual context to Llama models. Generally, larger models tend to prefer parametric to contextual knowledge; this is further discussed in Section 6.2.

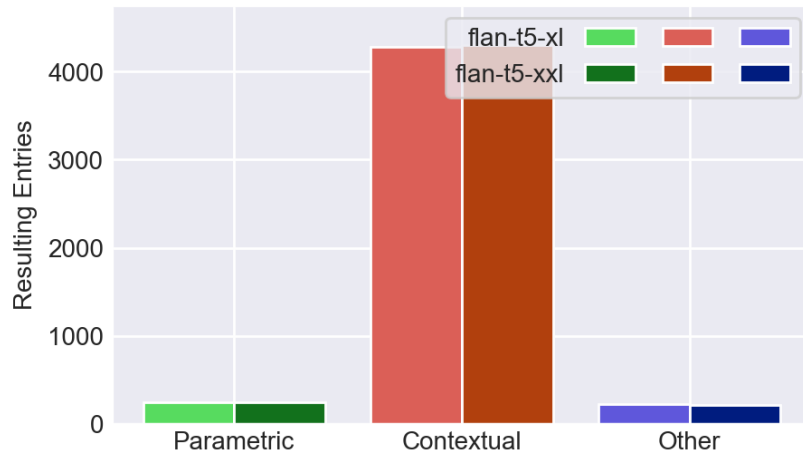


Figure 6: Same results for the Seq2Seq models FLAN-T5. While these models tend to be more biased towards contextual knowledge, as discussed in Section 6.1, larger models still are biased towards parametric knowledge.

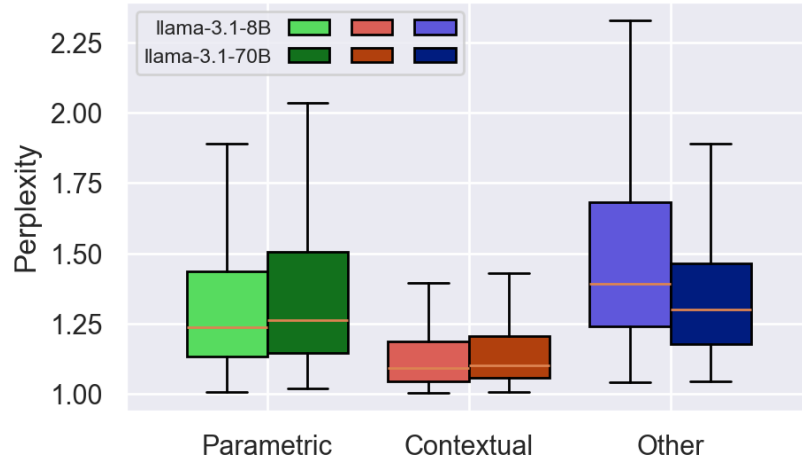


Figure 7: Perplexity box plots for Decoder-only Llama models.

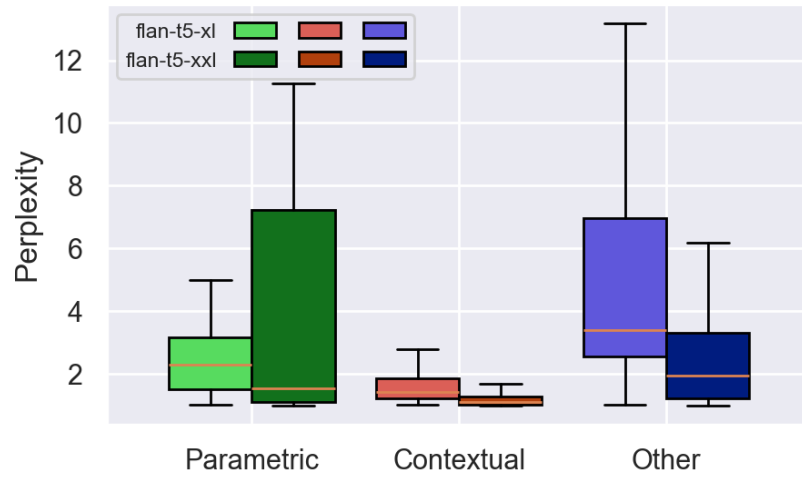


Figure 8: Perplexity box plots for Seq2Seq Flan models.

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

Glossary

Base Questions

Objects

Queries

Parametric Answers

Counterparamteric answers

Queries with counterfactual/counterparametric context

Contextual Answer

Bibliography

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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

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

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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

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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
Potlatch 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**