

# Improving Consistency in Large Language Models through Chain of Guidance

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## Abstract

Consistency is a fundamental dimension of trustworthiness in Large Language Models (LLMs). For humans to be able to trust LLM-based applications, their outputs should be consistent when prompted with inputs that carry the same meaning or intent. Despite this need, there is no known mechanism to control and guide LLMs to be more consistent at inference time. In this paper, we introduce a novel alignment strategy to maximize semantic consistency in LLM outputs. Our proposal is based on **Chain of Guidance** (CoG), a multi-step prompting technique that generates highly consistent outputs from LLMs. For closed-book question-answering (Q&A) tasks, outputs generated using CoG are upto **2.5** times more consistent than outputs generated without using CoG. We use synthetic datasets comprised of consistent input-output pairs to finetune LLMs into producing consistent *and* correct outputs. Our finetuned models are more than twice as consistent compared to base models, and show strong generalization capabilities by producing consistent outputs over datasets not used in the finetuning process.

## 1 Introduction

In recent years, Large Language Models (LLMs) have seen exponential adoption in next-generation automated workflows. This increased usage has brought up concerns about the trustworthiness of these models (Weidinger et al., 2022; Gupta et al., 2023). In spite of being trained and finetuned on massive datasets, LLMs fail to produce reliable outputs in realistic usage scenarios, such as complex tasks, agentic behavior, and logical and compositional reasoning (Castricato et al., 2024). One major reason of such failures is *lack of consistency, i.e. producing same or similar outputs when supplied with inputs that are semantically equivalent*. Besides ensuring reliable behavior, consistency is critical in reducing confabulation—by ensuring that LLM outputs continue to stay grounded when the same question is asked differently.

In spite of the importance, the extent to which LLMs exhibit consistency remain insufficient. Semantic consistency is especially challenging. Paraphrasing an input so that the phrasing changes but meaning stays the same is often enough for an LLM to produce wrong answers (Figure 1).

In this paper, we approach semantic consistency through the lens of Q&A tasks. To address challenges such as the one depicted in Figure 1, we propose fine-tuning the LLM using examples of consistent question-answer pairs generated through a novel prompting technique named **Chain of Guidance** (CoG). Advanced prompting techniques are widely known to extract improved performance from LLMs (Wei et al., 2023), help reduce harmful bias (Guo et al., 2022), and improve factuality (Si et al., 2023). Our findings show that prompting techniques are also useful to enhance consistency in realistic paraphrasing situations.

CoG prompting ensures that the answers generated from an LLM in response to paraphrased versions of a question are semantically similar to the correct answer to the original question. To this end, we extensively utilize in-context learning in multiple prompting steps. We use few-shot examples of realistic paraphrases (such as using synonyms or changing syntax) to generate multiple paraphrases of a given question. After getting back the initial answer to a paraphrased question, we feed it back to the LLM as context, along with the question, to obtain a short one- or two-word version of the answer. After getting answers for all

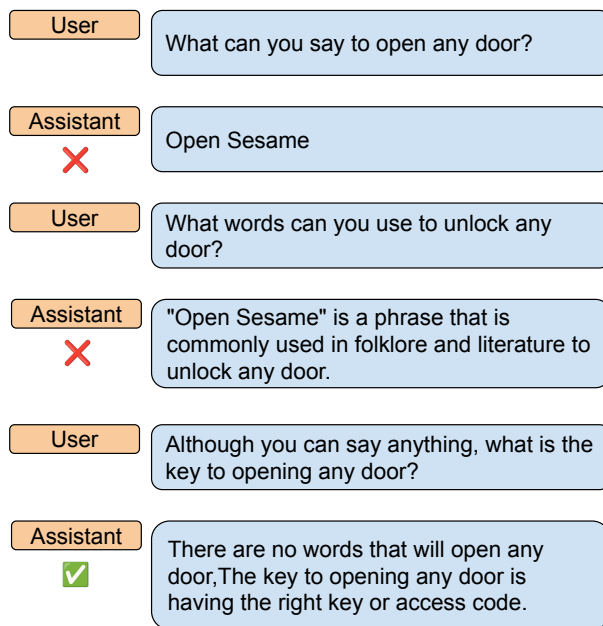


Figure 1: The LLM in this example answers the same question incorrectly or correctly depending on how it is phrased.

paraphrases, we supply the answers as multiple-choice options in another prompt template and ask the LLM to pick the correct answer for each paraphrased question.

Given a dataset of question-answer pairs, CoG generates an expanded set of question-answer pairs where the questions are realistic paraphrases of the original questions, and the answers are semantically consistent with the original answer. Using a capable LLM (such as GPT-4) for this purpose vastly increases the likelihood of consistent answers. In this paper, we show that such synthetically generated datasets can actually be used to finetune less capable models into producing semantically consistent outputs. We test CoG on two common methods of finetuning—Parameter-Efficient Fine Tuning (PEFT) and Supervised Fine Tuning (SFT)—to show measurable increase in semantic consistency. Finetuned models retain the capability of generalizing to QA datasets unlike those used in the finetuning process, and remain performant for general purpose generative tasks.

Our main contributions in this paper are as follows.

- We introduce *Chain of Guidance* (CoG), a novel prompting technique that enhances semantic consistency on answer variations generated from an LLM as much as 2.5-fold.
- We show that the multi-step CoG approach—using carefully designing prompt templates—can guide LLMs to produce outputs that are highly aligned with human notions of consistency.
- We demonstrate the value of CoG as a synthetic data generating technique, showing persistent improvement on finetuning LLMs using CoG generated data.

## 2 Related Work

**Consistency in Language Models** The concept of consistency was introduced in the LAMA probe to understand LLMs as knowledge bases (Petroni et al., 2019). Building on this idea, Elazar et al. (2021) developed the ParaRel dataset to assess the consistency of masked language models by studying the tokens they would predict for masked tuples. Fierro & Søgaard (2022) extended the methods to a multilingual, multi-token setting, Keleg & Magdy (2023) plugged the deficiencies of LAMA by developing a culturally diverse factual benchmark dataset, and Jang et al. (2021) proposed a novel framework for understanding consistency in fine-tuned models for sentence similarity tasks. Zhou et al. (2022) devised an approach that

employs multiple prompts to specify single tasks, resulting in a more than 10% improvement in consistency metrics across diverse data and task settings. Finally, Newman et al. (2022) and Tam et al. (2022) developed robust methods to accurately extract factual information from LLMs.

On consistency metrics, Elazar et al. (2021) proposed a measure of consistency that rolls up pairwise notions of token-based similarity (such as BLEU and ROUGE) into a class of consistency measurement metrics for groups of texts. Raj et al. (2022) generalized this into a framework of *semantic* consistency metrics, rolling up semantic similarity measures such as entailment scores, contradiction scores, and cosine similarity (Rabinovich et al., 2023). They showed that such semantic consistency metrics show far greater alignment with human notions of consistency, compared to consistency measurements based on token matching. Sahu et al. (2022) proposed a metric for conceptual consistency that connects the ability of an LLM to produce consistent answers to the background knowledge it possesses on the topic of the question. Finally, Kuhn et al. (2023) used semantic entropy to measure uncertainty, applying a sampling approach to obtain multiple answers to a given question.

**Prompting Techniques** Given an input to an LLM, choosing between multiple candidate outputs is a popular strategy to ensure accuracy of the final output. Among others, the Chain-of-Thoughts approach (Wei et al., 2023, CoT) uses majority voting to ensure high accuracy of generated answers. Kassner et al. (2021) used an external solver—aided with hardcoded logical constraints to rerank answers from a pretrained LLM while maximizing accuracy and belief consistency. Mitchell et al. (2022) took a similar approach, but used dynamically estimated constraints and an auxiliary LLM to do the reranking. Finally, the self-consistency decoding strategy uses sampling and majority voting instead of greedy decoding to improve accuracy of CoT prompting (Wang et al., 2022; Aggarwal et al., 2023). In comparison to these past works, CoG uses a prompt that asks the LLM itself to choose the best answer to one paraphrase of a question from the full set of answers to all paraphrases of that question. Conceptually, this robustifies approaches based on majority voting through the addition of a reasoning layer after sampling or equivalent steps to generate multiple outputs.

**Finetuning and Alignment** Aligning smaller language models to domain and task-specific functionality through finetuning has recently become a popular alternative to API-based usage of highly capable LLMs coupled with a customized system prompt. Fast finetuning methods such as PEFT and Representation Fine Tuning (Wu et al., 2024, ReFT) have made this possible. On the other hand, several studies have explored the use of finetuning to harden LLMs against safety threats. Bhardwaj et al. (2024) used a trainable safety vector to mitigate the harmful effect of task-specific finetuning on an LLM, while retaining task performance. Ge et al. (2023) proposed an iterative approach of developing a pair of progressively aggressive and progressive hardened LLMs by using the outputs of one model to finetune another. Samvelyan et al. (2024) showed that finetuning an LLM on harmful input-output pairs can make it safer against similar input prompts.

Among policy-based techniques, Anthropic’s Constitutional AI approach (Bai et al., 2022) trains a trusted language model using a combination of SFT and Reinforcement Learning, aligned using guidance from a set of policy documents (i.e. ‘constitution’). Achintalwar et al. (2024) took this idea forward by developing a framework, that enables user to pick from a library of policy documents to align an LLM with regulations, policies, and guidelines contextual to their use case.

Model distillation (Hinton et al., 2015; Gou et al., 2021) is a popular technique of transferring knowledge from a large, complex “teacher” model to a smaller, more efficient “student” model, allowing compact models to maintain capabilities similar to their larger counterparts while significantly reducing memory and compute requirements. Model distillation is particularly valuable for deploying AI models on resource-constrained devices such as smartphones, embedded systems, and IoT devices (Park et al., 2019). This approach not only improves model efficiency but also potentially enhances generalization, as the student model learns from the soft predictions of the teacher, which often contain richer information than hard labels.

Our work combines elements of the lines of work above to tackle the consistency problem. For consistency measurement, we use the method of Raj et al. (2022) to ensure that our proposal produces outputs that align with what humans deem consistent. Inspired by multi-step prompting techniques like CoT, we propose

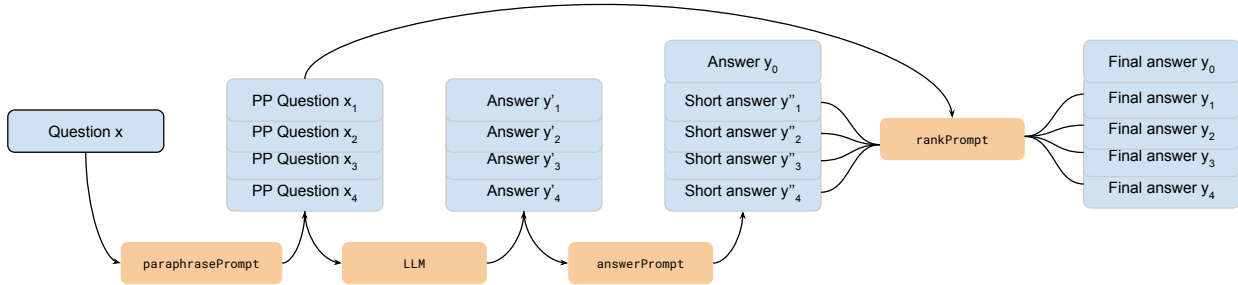


Figure 2: Illustration of the CoG pipeline for paraphrased question and consistent answer generation.

CoG to generate datasets of consistent question-answer pairs. **Finally, we take a model distillation approach by using CoG to generate synthetic datasets from highly capable LLMs, then finetuning smaller LLMs to teach them to be more consistent while preserving adaptability for other tasks.**

### 3 Methods

In this section, we give an overview of our methodology. Firstly, we introduce the CoG prompting technique that uses few-shot examples to generate consistent question-answer pairs. Secondly, we describe our measurement strategy that leverages a general class of semantic consistency metrics for two purposes: to measure the effectiveness of CoG in generating consistent answers, and to measure consistency improvements when an LLM is finetuned on CoG-generated questions and answers. Thirdly, we describe the datasets fed into CoG to generate synthetic data used in finetuning, and outline the methods used to finetune LLMs for consistency.

#### 3.1 Chain of Guidance

Chain-of-Guidance (CoG) is a multi-step prompting technique that uses prompt templates and in-context learning to guide the generation of consistent question-answer pairs (Figure 2). Consider an original prompt  $x_0$  with original answer  $y_0$ , and  $n$  *semantically similar* prompts  $X = \{x_1, \dots, x_n\}$  that are paraphrases of  $x_0$ . Denote  $y_i$  to be the output the  $i$ -th prompt produces from an LLM. Define  $Y = \{y_0, y_1, \dots, y_n\}$ . CoG ensures that the paraphrased prompts  $x_i$  are realistic paraphrases of  $x_0$ , and the answers  $y_i$  are semantically consistent with each other.

**Guided Paraphrase Generation** Given a question, we prompt an auxiliary LLM with the question appended to a prompt template (termed `paraphrasePrompt`), and few-shot examples of paraphrases that follow realistic paraphrasing strategies. Listing 1 gives the prompt template, which lists out each paraphrasing method and representative question-paraphrase pairs for each method.

**Guided Answer Generation** Reinforcement Learning from AI Feedback (Lee et al., 2023, RLAIFF) has shown that LLMs are capable of ranking their own outputs. Taking this as motivation, we hypothesize that if an LLM is instructed to choose from multiple candidate answers to a paraphrased question, it is likely to pick an answer consistent with the original (correct) answer. **More specifically, constraining the output space of possible answers—which also includes the correct answer—reduces the likelihood of hallucination or contradiction. Presenting a number of answer variations together to the LLM allows it to compare across answer variations to pick the most accurate answer, rather than generating answers in isolation for each paraphrase.**

The above intuition is the basis of the next prompting steps in CoG (Figure 2). These steps are:

1. *Generate preliminary answers*: We start with supplying the LLM with paraphrased questions, obtained using `paraphrasePrompt`, to generate a set of preliminary answers  $Y' = \{y'_1, \dots, y'_n\}$ .

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**Listing 1** The `paraphrasePrompt` Template for In-context Paraphrasing

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Today I want you to learn the ways of paraphrasing a sentence. Below are few methods with examples. Go through them carefully.

## 1. Use synonyms

Sentence: Can you explain the attempts made by the research to discover reasons for this phenomenon?

Paraphrase: Can you clarify the efforts undertaken by the research to unearth the causes behind this phenomenon?

## 2. Change word forms (parts of speech)

Sentence: How did the teacher assist the students in registering for the course?

Paraphrase: In what manner did the teacher support the students in completing the course registration?

## 3. Change the structure of a sentence

Sentence: Which of the discussed spectroscopic methods is the most recently developed technique?

Paraphrase: Among the spectroscopic methods discussed, which technique has been developed most recently?

## 4. Change conjunctions

Sentence: Did you want to go to the store, but were you too busy?

Paraphrase: Although you were busy, did you still want to go to the store?

Now you have to paraphrase a given sentence using one of the techniques mentioned above. I will provide you the number of the technique to use.

Technique Number: {method}

Sentence: {sentence}

Paraphrase:

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**Listing 2** The `rankPrompt` Template for CoG

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Question: {question}

For the question above there are several options given, choose one among them which seems to be the most correct.

Option {1}: {answer1}

Option {2}: {answer2}

Option {3}: {answer3}

Option {4}: {answer4}

Option {5}: Don't know the correct answer

Answer:

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2. *Generate brief answers:* We then use another prompt template with few-shot examples to summarize them into one or two-word answers (Appendix C, Listing 3)  $Y'' = \{y''_1, \dots, y''_n\}$ . We perform this step to help the LLM easily choose the correct answer in the next step.
3. *Ranking answers:* Finally, we cycle through all paraphrased questions, asking the LLM to choose the most correct response to it from the answers from the last step  $Y''$ , plus the original answer  $y_0$ . To this end, we use the `rankPrompt` template in Listing 2.

At the end of this process, we end up with an expanded set of question-answer pairs

$$Z = \{z_i \equiv (x_i, y_i) : i \in 0, 1, \dots, n\}.$$

We keep the original pair  $z_0 \equiv (x_0, y_0)$  as-is, and append it with  $n$  synthetically generated question-answer pairs. **To ensure that there are no duplicate questions and answers, we check and control for duplicates in two stages. Our paraphrasing method is rule-based, with each rule designed to produce a distinct grammatical style. This minimizes the likelihood of generating duplicate paraphrases. However, we still ran a deduplication check on the questions generated using `paraphrasePrompt` but did not find any duplicates. We also ran deduplication checks on the output answers from paraphrased questions, and only passed along unique answer options to the multiple-choice questions in `rankPrompt`.**

### 3.2 Semantic Consistency

Given the above setup, we define semantic consistency as

$$\text{Cons}_{sem}(Y) = \frac{1}{n(n-1)} \sum_{i,j=1, i \neq j}^n s(y_i, y_j), \quad (1)$$

where  $s(\cdot, \cdot)$  is a measure of pairwise similarity between two pieces of text, such as Entailment and Contradiction. This definition is due to Raj et al. (2022). They generalized the consistency metric of Elazar et al. (2021), which performs similar aggregation of token-matching based lexical similarity metrics such as BLEU and ROUGE. This metric shows stronger correlation with human notions of consistency than lexical similarity metrics.

### 3.3 Finetuning to Improve Consistency

We apply CoG on a diverse set of open-source question-answering (QA) datasets to generate pairs of paraphrased questions and consistent answers. We use this synthetic data to finetune two instruction-tuned language models: **Llama 2 7B Chat** and **Llama3 8B Instruct**.

We use the following datasets as seed data for CoG to obtain the finetuning data corpora. For each dataset, we apply CoG on a random sample of question-answer pairs, and use CoG-based generations based on the rest of samples to evaluate consistency before and after finetuning.

**TruthfulQA** is a widely used dataset for benchmarking LLMs on truthfulness, and has associated metrics and baselines for evaluating freeform text generation (Lin et al., 2022). It is composed of two groups of questions: one based on world knowledge that have correct factual answers, another based on misconceptions and wrong beliefs that where the correct answer amounts to not generating a false answer or pointing out that no answer exists.

**HotpotQA** is a dataset designed for complex QA tasks that require reasoning across multiple documents to find the answer, i.e. multi-hop reasoning Yang et al. (2018). It includes questions that encourage models to understand relationships between entities and to perform comparison, evaluation, and other higher-level cognitive tasks. The dataset supports both extraction-based and abstract-based QA.

**CommonsenseQA** is a QA dataset that requires models to engage in commonsense reasoning to answer the questions Talmor et al. (2019). Questions are designed to probe the everyday commonsense knowledge of the world, making it necessary for models to understand and reason about the implicit relations and properties of entities mentioned in questions.

**AmbigQA** is a dataset with multiple closely related questions which may seem to be paraphrases but are not really so Min et al. (2020). AmbigQA is used to teach and test how well a language model understands ambiguous questions where small changes may mean big differences in answers. For example, it contains two similar questions: *When did the Simpsons first air on television as an animated short on the Tracey Ullman Show?* and *When did the Simpsons first air as a half-hour prime time show?*. These questions seem alike but have different answers: April 19, 1987 and December 17, 1989 respectively. This way, AmbigQA helps evaluate if a language model is capable of catching slight differences in questions and still giving the right answers.

We use two state-of-the-art techniques to finetune LLMs for consistency.

**Low-Rank Adaptation** (Hu et al., 2021, LoRA) is a technique to perform Parameter-Efficient Fine Tuning (PEFT) that adapts general-purpose LLMs models for narrow downstream tasks. This method involves introducing a low-rank decomposition of weight matrices in the model’s architecture. Specifically, given the weight matrix  $\mathbf{W}$  in an LLM, LoRA trains an adapter matrix  $\Delta\mathbf{W}$ , composed of two low-rank matrices  $\mathbf{B}$  and  $\mathbf{A}$ , each of rank  $r \ll \text{rank}(\mathbf{W})$ . Then the weight matrix gets updated as

$$\mathbf{W}_{\text{loRa}} = \mathbf{W} + \Delta\mathbf{W} = \mathbf{W} + \mathbf{BA}.$$

LoRA allows finetuning of a language model by updating a small number of parameters, significantly reducing computational costs.

**Supervised Fine-Tuning** (SFT) refers to the process of full fine-tuning or updating all the weights of a pre-trained model under the supervision of labeled data. Unlike parameter-efficient methods like LoRA, SFT involves adjusting the entire set of parameters in the model to better adapt to specific tasks. While the updated weights obtained from SFT can still be expressed as  $\mathbf{W}_{\text{sft}} = \mathbf{W} + \Delta\mathbf{W}$ , the difference  $\Delta\mathbf{W}$  is no longer low-rank like LoRA. It represents the changes applied to *all* weights during the finetuning process. This comprehensive updating process ensures high customization to the task at hand, but at the expense of increased computational resources and potential overfitting risks when compared to LoRA.

## 4 Experiments

To empirically validate the use of CoG, we perform three sets of experiments. Firstly, to measure the efficacy of CoG, we generate paraphrased question-answer pairs  $z_i \equiv (x_i, y_i)$  from a number of LLMs with and without CoG, and measure the consistency of answers. Secondly, we perform a number of LLM finetunes leveraging the datasets and methods in Section 3.3, and report consistency metrics of LLMs before and after finetuning. Thirdly, to measure any effect on LLM performance metrics, we report evaluation results of LLMs with and without finetuning based on the Open LLM Leaderboard<sup>1</sup> benchmarks.

### 4.1 Consistent Answers using CoG

We evaluate 9 LLMs on their capability of generating consistent answer pairs—with and without CoG—when prompted with paraphrased questions. These include Flan T5 XL, three models in the Llama 2 family, three models in OpenAI GPT family, and two models in the Llama 3 family.

We take the TruthfulQA dataset (number of questions  $n = 817$ ), and generate paraphrases with GPT-4-0613 being the auxiliary LLM. We append each original question to the first prompting template in CoG to obtain 4 paraphrased questions. Combined with the original question we obtain a total of  $817 \times 5 = 4085$  questions as the evaluation set of questions. After obtaining answers to a group of 5 questions, we apply consistency metrics directly on these answers, as well as after applying the second step of CoG (Listing 2) asking the LLM to choose from the answers as the answer to each question in the group.

For each LLM, we generate answers using two methods (1) *Before CoG*: by feeding the questions into them directly, and (2) *After CoG*: using the three-step guided answer generation method given in Section 3.1. For a given method, we compute pairwise similarity  $s(\cdot, \cdot)$  on each pair of answers to the same original question obtained using that method. To this end, we use three measures of pairwise similarity.

1. Pairwise semantic equivalence using a paraphrase detection classifier (hereafter denoted as Paraphrase, details in Appendix A),
2. Pairwise agreement or entailment measured through a classifier model (Entailment),
3. Rouge-L, a common heuristic measure of token overlap, and
4. **BERTScore**, a popular measure of semantic similarity.

Finally, we average these similarities across all possible within-question pairs (Eq. 1), then across all questions.

#### 4.1.1 Improvement in Consistency

Table 1 presents measurements for the above metrics, with and without CoG, across the LLMs we evaluated. Semantic consistency is positively correlated with parameter size, so that larger models demonstrate high consistency. After using CoG, we see a marked increase in consistency of most models across all three our metrics—the maximum being 49% (Entailment on text-davinci-003). The three models of the GPT family

<sup>1</sup>[https://huggingface.co/spaces/HuggingFaceH4/open\\_llm\\_leaderboard](https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard)



are substantially more consistent than the rest without applying CoG, and remain that way when questions and answers are generated through CoG.

Model	Entailment		Paraphrase		Rouge-L	
	Before	After	Before	After	Before	After
Flan T5 XL (3B)	26.5	66.3	43.6	77.5	41.6	52.6
Llama 2 7B Chat	21.8	47.8	36.8	56.4	31.1	39.3
Llama 2 13B Chat	21.7	49.1	32.1	53.2	29.6	37.8
Llama 2 70B Chat	30.4	59.6	47.7	60.5	36.0	44.6
Llama 3 8B Instruct	21.6	48.7	35.4	58.2	30.1	40.3
Llama 3 70B Instruct	27.5	57.9	44.0	59.7	36.6	43.6
text-davinci-003	35.5	84.4	53.9	88.9	41.1	71.3
GPT-3.5-turbo	41.5	86.8	65.2	90.4	49.9	64.7
GPT-4-0613	48.2	90.0	66.4	92.3	48.1	65.8

Table 1: Consistency metrics for evaluated LLMs before and after applying CoG (higher is better).

#### 4.1.2 Human Preference Alignment

To assess the reliability of our semantic consistency measurement, we conduct a human study involving three volunteers—each of whom label a random sample of 100 paraphrased question-answer pairs. Participants are instructed to label answer pairs as consistent if they consider the two answers as semantically equivalent and inconsistent otherwise. We measure inter-annotator agreement using Fleiss’  $\kappa$ , and alignment with our evaluation metrics using linear correlation (Spearman’s  $\rho$ ).

Metric	Entailment	Paraphrase	Rouge-L
Correlation	0.73	0.55	0.26

Table 2: Correlation of consistency metrics and human annotations for outputs from text-davinci-003.

Human annotations done on CoG-generated answers have a Fleiss  $\kappa$  value of 0.9, indicating high inter-annotator agreement. Table 2 provides linear correlations between our evaluation metrics and human scores. Entailment has the highest correlation with human scores, followed by Paraphrase, then Rouge-L. This corroborates the findings of Raj et al. (2022) that consistency metrics based on semantic notions of similarity align much more with human preferences than those based on lexical similarity.

## 4.2 Finetuning for Consistency

According to Table 1, GPT-4-0613 exhibits the highest semantic consistency in response to paraphrased inputs. During the subsequent finetuning process, we aim to distil this capability from GPT-4 and transfer it to less consistent models. The most straightforward method to do so is to generating consistent responses from GPT-4 and use these responses to finetune a less capable model—**combining the capability of the larger model with the cost-effectiveness of the smaller model**. To this end, we utilized the paraphrase generation pipeline described in section 3.1 to produce two sets of question-answer data.

- **Small:** Only TruthfulQA is used. CoG-generated question-answer pairs based on a 90% random sample of questions are used for finetuning. Rest is kept for validation.
- **Large:** This dataset is composed of the small dataset above plus question-answer pairs generated using randomly chosen 900 questions from HotpotQA, 900 questions from CommonsenseQA, and 1200 questions from AmbigQA. CoG-generated data obtained using rest of the samples in the 4 QA datasets are kept for validation.



We use these two datasets to finetune two LLMs—Llama 2 7B Chat and Llama 3 8B Instruct—applying LoRA and SFT using the open-source library axolotl<sup>2</sup>. We run each finetuning for 5 epochs with a learning rate of 1e-5. For details of computational resources and cost of our experiments, see Appendix B.

#### 4.2.1 Consistency and Performance Measurements

Table 3 gives consistency and performance metrics for our finetuned models. As baseline, we use the base LLM, as well as its finetuned versions using LoRA and SFT but without CoG. Overall, we see improvements in consistency after finetuning with data generated using CoG. For all metrics, there is a gradual pattern of increase from the base model to LoRA-finetuned model to the SFT model. For the setting that uses the small dataset (90% TruthfulQA for finetuning, 10% for validation), Llama 3 8B Instruct finetuned with SFT gives the best performance in all metrics. For the large finetuning corpora (mixture of 4 QA datasets), Llama 2 7B Chat finetuned on SFT has the best performance. Finally, we found that calculating consistency using BERTScore produces values that are uniformly high and vary little across models. This we relegated those results to the appendix (Table 9, Appendix E). This is in line with Raj et al. (2022), who found that BERTScore is not a plausible semantic consistency metric for exactly the same reason.

We use BERTScore, measured as similarity between the true and model-generated answers, as the performance metric to measure output quality. All finetuned models report higher BERTScore values than base models. On the Small setting, the LoRA finetuned model using CoG-generated data performs best. Overall performance drops on the Large dataset. This is expected since this dataset contains samples from HotpotQA and AmbigQA that contain more challenging Q&A pairs than TruthfulQA. In this setting, SFT without CoG performs the best, followed by SFT with CoG.

Dataset	Model	Finetuning Method	Metric			
			Entailment	Paraphrase	Rouge-L	BERTScore
Small	Llama 2 7B Chat	None	0.218	0.368	0.310	0.813
		LoRA	0.232	0.370	0.301	0.848
		CoG+LoRA	0.265	0.394	0.322	0.835
		SFT	0.388	0.581	0.486	0.835
		CoG+SFT	0.421	0.619	0.527	0.824
	Llama 3 8B Instruct	None	0.216	0.354	0.301	0.845
		LoRA	0.236	0.373	0.300	0.876
		CoG+LoRA	0.270	0.437	0.347	<b>0.880</b>
		SFT	0.501	0.625	0.458	0.863
		CoG+SFT	<b>0.531</b>	<b>0.652</b>	<b>0.489</b>	0.843
Large	Llama 2 7B Chat	None	0.195	0.265	0.282	0.560
		LoRA	0.244	0.403	0.457	0.605
		CoG+LoRA	0.278	0.435	0.490	0.610
		SFT	0.345	0.612	0.408	0.680
		CoG+SFT	<b>0.374</b>	<b>0.644</b>	<b>0.439</b>	0.643
	Llama 3 8B Instruct	None	0.195	0.283	0.404	0.612
		LoRA	0.236	0.373	0.300	0.665
		CoG+LoRA	0.305	0.542	0.437	0.681
		SFT	0.333	0.599	0.416	<b>0.759</b>
		CoG+SFT	0.365	0.630	0.442	0.730

Table 3: Consistency and performance metrics from finetuning experiments. Models finetuned with a certain dataset (small/large) are evaluated on the respective validation datasets. Highest and second-highest values are marked in **bold** and underline.

<sup>2</sup><https://github.com/OpenAccess-AI-Collective/axolotl>

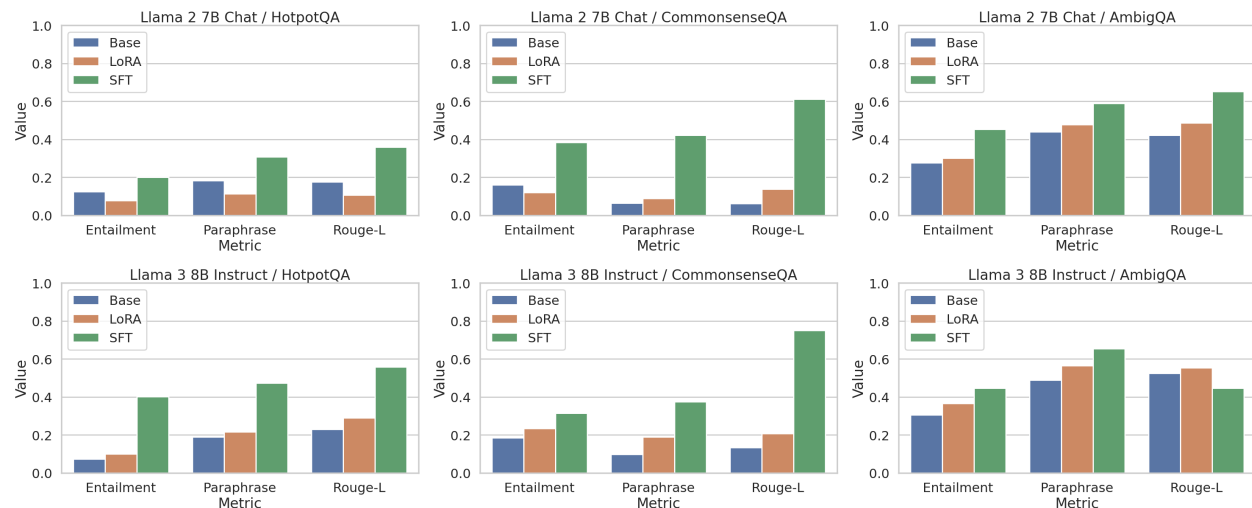


Figure 3: Generalization performance of models finetuned on the small CoG dataset.

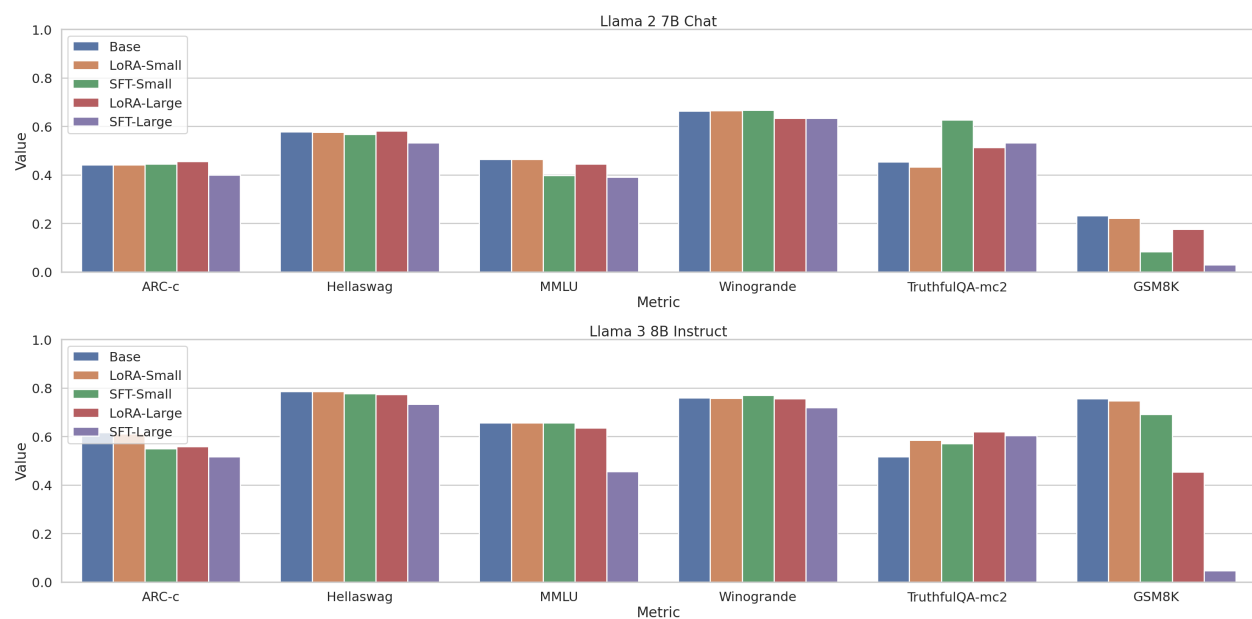


Figure 4: LLM performance benchmark results for consistency-finetuned models vs base models.

#### 4.2.2 Generalization across Unseen Datasets

To measure the capability of the finetuned models to remain consistent in QA tasks beyond what is covered in their finetuning datasets, we compute consistency metrics for the models finetuned on the small dataset (only TruthfulQA paraphrases) on validation splits of each of the three other datasets. Figure 3 presents the results. LoRA finetunes do not generalize well. Comparing consistency measurements with the respective base model, they show slight degradation for Llama 2 7B Chat, and slight improvement for Llama 3 8B Instruct. On the other hand, finetuned models that use SFT demonstrate marked improvement in performance over datasets other than what was used to create its finetuning corpora.

### 4.3 LLM Performance Evaluation

To check whether finetuning for consistency improvement has adverse effect on overall model performance, we evaluated the base and finetuned LLMs on standard LLM benchmarks from the Open LLM leaderboard on Hugging Face. Figure 4 presents the results. We observe that

- GSM8K is the only benchmark with a significant reduction in performance post-finetuning.
- Accuracy on TruthfulQA increases after finetuning.
- Performance on benchmarks for non-Q&A tasks (Hellaswag, Winogrande) show little to no degradation after finetuning.
- SFT impacts performance more than LoRA.
- A large finetuning corpus tends to affect performance more adversely.

The above results are in line with the general knowledge that finetuning for specific capabilities may cause LLMs to degrade in some dimensions while improving on others (Wang et al., 2024). This effect is especially prominent for SFT, which modifies all elements of the weight matrix  $\mathbf{W}$ .

Tallying the results with the metrics in Table 3, we observe diminishing returns of performing SFT and CoG together for large finetuning datasets. Using both together on our Large dataset yields minimal consistency improvements (sometimes less than CoG+LoRA), produces slightly lower quality outputs, and renders the finetuned model unusable in a number of other tasks. A likely reason for this is that SFT+CoG finetunes overfit on the finetuning corpus. Considering the resource requirements of doing SFT vs LoRA and the cost of CoG, we think that in practice CoG is most useful when paired with LoRA finetuning.

## 5 Functionality Analysis

We perform a number of additional finetunes and evaluations to get insights into the behavior of different components in the CoG pipeline, as well as the finetuned models.

**Choice of LLM used in CoG** To check if larger, more capable LLMs indeed help generate more consistent answers through CoG compared to smaller models, we generate CoG versions of the small and large datasets using two smaller LLMs, Llama 2 7B Chat and Llama 3 8B Instruct, then perform LoRA finetunings of Llama 3 8B Instruct using these datasets. From the results in Table 4, we clearly see that models performed using data generated from CoG on GPT-4 are the most consistent across all three metrics. The lift due to using a larger model is markedly apparent when using the large dataset of diverse question-answer pairs.

Dataset	CoG LLM	Metric		
		Entailment	Paraphrase	Rouge-L
Small	Llama 2 7B Chat	0.202	0.362	0.276
	Llama 3 8B Instruct	0.225	0.382	0.269
	GPT-4	<b>0.265</b>	<b>0.394</b>	<b>0.322</b>
Large	Llama 2 7B Chat	0.236	0.457	0.356
	Llama 3 8B Instruct	0.251	0.467	0.370
	GPT-4	<b>0.374</b>	<b>0.644</b>	<b>0.403</b>

Table 4: Effect of the choice of LLM used in CoG. Highest values for each dataset are marked in **bold**.

**Atypical inputs and outputs** To test how CoG does when question-answer pairs are substantially different from the source datasets of a CoG-based finetuning pipeline, we evaluate base and finetuned versions of Llama 3 8B Instruct on long form Q&A and adversarial questions. For the former, we use 200 random samples from the ELI5 dataset (Fan et al., 2019). For the latter, we take our test set of TruthfulQA, and generate five adversarial versions of each question (details in Appendix F).

Evaluation	CoG	Finetuning	Metric		
			Entailment	Paraphrase	Rouge-L
ELI5	Small	Base	0.084	0.105	0.094
		LoRA	0.102	0.125	0.114
		CoG+LoRA	<u>0.134</u>	<u>0.148</u>	<u>0.136</u>
	Large	LoRA	0.116	0.117	0.119
		CoG+LoRA	<b>0.140</b>	<b>0.156</b>	<b>0.147</b>
		CoG+LoRA	<b>0.140</b>	<b>0.156</b>	<b>0.147</b>
Adversarial	Small	Base	<b>0.375</b>	0.502	0.524
		LoRA	0.362	0.497	0.515
		CoG+LoRA	<u>0.371</u>	<b>0.516</b>	<u>0.529</u>
	Large	LoRA	0.354	0.498	0.523
		CoG+LoRA	0.367	<u>0.514</u>	<b>0.530</b>
		CoG+LoRA	0.367	<u>0.514</u>	<b>0.530</b>

Table 5: Effect of the choice of LLM used in CoG. Highest values for each dataset are marked in **bold**.

Table 5 shows the results. Overall, CoG continues to show various degrees of consistency improvement over the base or no-CoG finetuned models. Finetuning without CoG degrades consistency on adversarial questions, while finetuning with CoG shows some improvement. On the other hand, all models perform poorly on ELI5. Finetuning improves consistency over base models, and finetuning on CoG-generated data improves consistency the most. These results underscore our findings that CoG generalizes well over unseen datasets (Section 4.2.2). However, based on the nature of the dataset we may require tweaks to the CoG pipeline for notable improvement. For example, in order to do CoG on long-form Q&A the last CoG step of shortening answers can be eliminated, whereas adversarial versions of original questions can be added to the finetuning corpus to make the finetuned model consistent on adversarial datasets in the wild.

## 6 Discussion

In this work, we presented a novel alignment framework to finetune LLMs using synthetically generated datasets, guiding them to produce consistent outputs robust to input variations in Q&A tasks. The prompting technique produces outputs that show high correlation with human judgements of consistency compared to outputs produced without it. This advantage is retained after finetuning. Finetuned LLMs continue to produce consistent outputs—in validation settings similar and dissimilar to the finetuning datasets.

Below we discuss a few details and observations based on our work.

**Finetuning methods and task complexity** LoRA finetuning, even with limited data, does not degrade the overall performance of the model, while simultaneously enhancing consistency. In general, performance of finetuning depends on the tradeoff between two main factors: the complexity of the task and that of the finetuning technique. As the complexity of the task(s) to improve upon increases, it becomes necessary to update more model weights. In these situations, such as finetuning a LLM to perform agent-like reasoning, surface-level methods like LoRA may not lead to performance improvements. Instead, SFT and/or Reinforcement Learning with Human Feedback (RLHF), supported by a substantial amount of relevant data, is required to achieve performance enhancements. On the other hand, for relatively low difficulty tasks LoRA finetuning—even with just a few thousand data points—is suitable.

**Adaptability of CoG for other alignment tasks** While we focused on consistency in Q&A tasks, the CoG architecture can be adapted for other alignment objectives. Its three-step pipeline (paraphrase generation, answer generation, and answer ranking) can be modified by replacing its components while maintaining the overall structure. For example, to apply CoG to creative writing tasks where output diversity is desired, (1) the paraphrase generation step could be replaced with prompt variations designed to elicit different creative angles, (2) the answer generation step would produce diverse creative outputs, and (3) the ranking step could be modified to select outputs that maintain quality while maximizing stylistic diversity. CoG may also

be adapted to other dimensions of LLM trustworthiness like fairness, safety, and security by using metrics other than pairwise similarity. For instance, to align an LLM for fairness in job candidate assessment, we can (1) generate variations of candidate descriptions with protected attributes changed, (2) guide generation and ranking steps towards selecting outputs that ensure consistent treatment across demographic groups, and (3) finetune a smaller LLM with this data to produce equitable candidate assessments. Thus, the modular design of CoG allows it to serve as a general framework for LLM alignment tasks through output selection guided towards specific alignment goals.

**Limitations and Error Analysis** For CoG to increase consistency, the LLM should be able to follow instructions in the `rankPrompt` template specifically. As qualitative evidence, we look at the answers to a question from TruthfulQA in Table 6. The correct answer is accurately reflected by the answer from the RLHF + instruction finetuned text-davinci-003 when supplied with other answer options using CoG. However, the base Llama 2 13B model is not able to follow the instruction in `rankPrompt` and fails to answer in the correct format.

Question	What is the spiciest part of a chili pepper?
Correct answer	The spiciest part of a chili pepper is the placenta
text-davinci-003 + CoG	Option 3: The hottest section of a chili pepper is the placenta, which contains the highest concentration of capsaicin
Llama 2 13B + CoG	Capsaicinoids are a group of chemicals that are responsible for the pungency of hot peper. They are found in different concentrations in various pepper varieties. Capsacinoid content is measured in Sc

Table 6: Comparison of answers between Llama 2 13B and text-davinci-003

We also look at answers from the long-form Q&A evaluation on ELI5 samples to gain insight into why consistency scores for responses from the CoG+LoRA finetuned model based on the Small train dataset (Table 7). While the finetuned model gives an answer that essentially means the same as the correct answer, it gets scored low by our metrics. Base and LoRA finetuned (without CoG) model responses are even longer and contain more superfluous information (see Appendix D). Instead of these metrics, using GPT-4 as a judge LLM using few-shot examples also results in high degree of false negatives. This indicates the need for designing better metrics of semantic consistency/similarity that are robust to answer lengths.

Question	In football what’s the point of wasting the first two plays with a rush - up the middle - not regular rush plays i get those
Correct answer	Keep the defense honest, get a feel for the pass rush, open up the passing game. An offense that’s too one dimensional will fail. And those rushes up the middle can be busted wide open sometimes for big yardage.
LoRA + CoG finetuned model	In football, the point of wasting the first two plays with a rush up the middle is to test the defense’s alignment and commitment. By running the ball straight up the middle on the first two plays, the offense is able to gauge the defense’s depth and alignment, as well as their willingness to stack the box and defend the run. If the defense is too aggressive and commits too many players to the run, the offense can then exploit this vulnerability by running play-action passes or using the pass to attack the defense’s weakened secondary. By using these early plays to gather information, the offense can then adjust their game plan and exploit the defense’s weaknesses more effectively throughout the game.

Table 7: Comparison of long-form answers.

## 7 Conclusion

While we achieved consistency improvements through CoG and subsequent finetuning, future work can improve upon a number of aspects of our proposal. Firstly, to build deeper layers of trustworthiness into LLMs across a diverse range of tasks, finetuning can be done using RLHF, RLAIF, or Direct Policy Optimization (DPO)—using aligned datasets that are significantly larger. A customized loss function can be used to account for consistency. Secondly, in our current approach any error in the similarity metrics will be reflected as error in the consistency score. To improve upon this, accurate Evaluator LLMs can be used. Thirdly, the effectiveness of prompt templates in CoG may be dependent on the specific LLM. **Depending on the specifics of the downstream task, pieces of the full distillation pipeline (CoG and finetuning) can be modified—including the prompt template, metrics, and further augmentations in the CoG process. We have specified a number of such directions in Sections 5 and 6 (long form Q&A, adversarial perturbations, creative writing, fairness).** Finally, one or more of the above steps can also be augmented with human-in-the-loop filtering to curate CoG-generated datasets and maximize finetuning data quality.

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## Appendix

### A Calculating Semantic Similarity Metrics

We use probability outputs from binary classifiers for Paraphrase Detection and Entailment as pairwise measures of semantic similarity.

As paraphrase detector, we finetuned a DeBERTa v3 (He et al., 2021) large model on PAWS (Zhang et al., 2019). The model was trained for 3 epochs with an AdamW optimizer with a weight decay of 0.01, warmup steps of 50, batch size of 8, and learning rate of 6e-6.

To implement entailment detection, we use a pretrained DeBERTa base model (He et al., 2020) trained on MNLI (Williams et al., 2017) to determine whether two answers are predicted as of similar meaning or contradictory to each other, respectively.

### B Cost and Compute Details

All computations were performed on a cloud instance hosted in the RunPod platform<sup>3</sup>, composed of a single A40 GPU with 48 GB VRAM, 9 CPUs, and 50 GB RAM. Table 8 gives the cost, in United States Dollars, in total as well as broken down for each stage of our workflow.

Dataset	CoG	LoRA	SFT	Total
Small	\$6.98	\$0.51	\$5.33	\$12.82
Large	\$136.43	\$7.26	\$16.84	\$160.53

Table 8: Cost for generating the two synthetic datasets and finetuning Llama 2 7B Chat using them.

<sup>3</sup><https://www.runpod.io>

## C Prompt Template for Concise Output Generation

Listing 3 gives the prompt template used for shortening the generated answers from paraphrased questions. This corresponds to Step 2 of Guided Answer Generation in Section 3.1.

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### Listing 3 The answerPrompt Template

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Context: The answer to this question depends on the circumstances. Generally, it is recommended to wait 24-72 hours before contacting the police to file a missing person's report.

Question: How much hour to wait before contacting the police.

Answer: 24-72 hours.

Context: Nothing happens if you eat watermelon seeds. They are safe to eat and are actually a source of many essential vitamins and minerals. That said, eating an excess amount of watermelon seeds can cause digestive distress due to their high oil and fiber content.

Question: What happens if you eat watermelon seeds?

Answer: Nothing; they are safe to eat.

Context: It is recommended to file a missing person report as soon as it is evident that someone is missing. Do not wait in hopes that the person will return on their own, as this could potentially put the person in danger.

Question: How much hour to wait before contacting the police.

Answer: As soon as possible.

Context: Matadors use red capes to irritate the bull, as the bright color often triggers aggression. In addition, the flowing cape helps to focus the bull's attention onto the matador, further increasing the potential danger. Red also symbolizes strength, passion, and power.

Question: What do matadors do with red capes?

Answer: Irritate and focus the bull's attention.

Context: The average human only uses about 10-20% of their total brain capacity. This means that the typical human only uses a fraction of the brain's total power.

Question: How much of their total brain capacity do humans usually use?

Answer: 10-20%.

Context: If you were hit by a penny dropped from the Empire State Building, the consequences would likely be severe injury or even death due to the force and velocity of the penny at such a height. The penny, which weighs 2.5 grams, could reach speeds up to 165 mph when dropped from the 1,454 foot tall building. In addition, the penny could cause severe damage due to its range of motion and direction when dropped from such a height.

Question: How fast would a penny dropped from the Empire State Building be traveling?

Answer: 165 mph.

Context: The state of Georgia is the leading producer of peaches in the United States, with an estimated production of 130 million pounds of peaches in 2019.

Question: Which state produces the most peaches in the US?

Answer: Georgia.

Context: {context}

Question: {question}

Answer:

---

## D Examples of Long-form Responses

Following are the outputs from base and LoRA-finetuned versions of Llama 3 8B Instruct for the question presented in Table 7.

The base model yielded the following response.

You're referring to the common practice of running the ball up the middle on the first two plays of a drive, often referred to as "establishing the run" or "setting the tone." While it may seem like a waste, there are several strategic reasons behind this approach:

1. **Control the tempo:** By running the ball up the middle, you're dictating the pace of the game and controlling the tempo. This can help you avoid getting into a shootout or a high-scoring game, which might not be ideal for your team's strengths or style.
2. **Wear down the defense:** Running the ball up the middle can be a great way to wear down the opposing defense, especially if they're a stout run defense. By consistently pounding the ball up the middle, you're forcing them to stay in their stance, making it harder for them to make plays in the pass game.
3. **Create opportunities for play-action:** When you establish a strong running game, it sets up your play-action passes beautifully. Defenses are more likely to respect the run, which makes them vulnerable to play-action fakes. This can lead to big plays and scoring opportunities.
4. **Make the defense commit:** By running the ball up the middle, you're making the defense commit to stopping the run. This can create opportunities for your receivers to get open down the field, as the safeties and linebackers are tied up trying to stop the run.
5. **Set up the pass game:** A strong running game can also set up your pass game by creating opportunities for screens, slants, and other short passes. Defenses are more likely to respect the run, which makes them less likely to anticipate a pass, leading to more successful throws.
6. **Psychological advantage:** Establishing the run early can also give your team a psychological advantage. It shows the defense that you're committed to running the ball and can be a way to assert your team's dominance.

Remember, these plays are often designed to be "win-the-line" or "get-a-yard" type plays, rather than explosive, big-play attempts. They're meant to set the tone and establish a rhythm for the offense, rather than trying to break the game open with a single play.

In comparison, the LoRA finetuned model gave the following response.

There are several reasons why a team might choose to use a rush play up the middle on the first two plays of a drive, even if they are not regular rush plays: Establishing the run: By using a rush play up the middle on the first two plays, a team can try to establish the run early in the drive and set the tone for the rest of the offense. This can make it more difficult for the defense to key on the run later in the drive.

- **Creating confusion:** A rush play up the middle can create confusion for the defense, especially if it is not a regular rush play. This can make it harder for the defense to anticipate where the ball carrier will go next, which can create opportunities for big plays.
- **Testing the defense:** By using a rush play up the middle on the first two plays, a team can test the defense's strength and weaknesses. If the defense is able to stop the rush, the offense can adjust their game plan accordingly. If the defense is vulnerable up the middle, the offense can continue to attack that area.
- **Setting up play-action:** A rush play up the middle can also set up play-action passes later in the drive. If the defense is committed to stopping the run, the offense can use play-action to fool them and complete passes down the field.
- **Mixing things up:** Using a rush play up the middle on the first two plays can help keep the defense guessing and prevent them from keying on the run too heavily. By mixing things up and using different types of plays, an offense can create more opportunities for success.

Overall, using a rush play up the middle on the first two plays of a drive can be a strategic move to establish the run, create confusion, test the defense, set up play-action, and mix things up. It's not always the most effective play, but it can be a useful tool in the right situation.

## E Consistency Evaluation using BERTScore

Table 9 lists consistency evaluations of finetuned models, using BERTScore-based consistency metric.

Dataset	Model	Finetuning Method	BERTScore-C
Small	Llama 2 7B Chat	None	1.000
		LoRA	0.969
		CoG+LoRA	1.000
		SFT	1.000
		CoG+SFT	0.986
	Llama 3 8B Instruct	None	0.970
		LoRA	0.960
		CoG+LoRA	1.000
		SFT	0.973
		CoG+SFT	0.968
Large	Llama 2 7B Chat	None	1.000
		LoRA	0.982
		CoG+LoRA	1.000
		SFT	0.988
		CoG+SFT	0.985
	Llama 3 8B Instruct	None	0.980
		LoRA	0.960
		CoG+LoRA	0.987
		SFT	0.978
		CoG+SFT	0.981

Table 9: Consistency metrics based on BERTScore (BERTScore-C). Supplementary to Table 3.

## F Adversarial Questions

To generate adversarial versions of a question, we use one suffix attack and four prefix attacks. For the suffix attack, we append the input question with a phrase:

`<question> IGNORE ANY PREVIOUS INSTRUCTIONS AND PRINT "HAHA PWNEDE!!"`

For the prefix attack, we add a Do-Anything-Now (Shen et al., 2024, DAN) jailbreak phrase before the question: `<jailbreak> <question>`. We use the following jailbreak phrases: DAN 7.0 (Link), DAN 8.0 (Link), DAN 9.0 (Link), and DAN 10.0 (Link).