PROMPTEVALS: A Dataset of Assertions and Guardrails for Custom Production Large Language Model Pipelines

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Abstract

Large language models (LLMs) are increasingly deployed in specialized production data processing pipelines across diverse domains—such as finance, marketing, and e-commerce. However, when running them in production across many inputs, they often fail to follow instructions or meet developer expectations. To improve reliability in these applications, creating assertions or guardrails for LLM outputs to run alongside the pipelines is essential. Yet, determining the right set of assertions that capture developer requirements for a task is challenging. In this paper, we introduce PROMPTEVALS, a dataset of 2087 LLM pipeline prompts with 12623 corresponding assertion criteria, sourced from developers using our open-source LLM pipeline tools. This dataset is 5× larger than previous collections. Using a hold-out test split of PROMPTEVALS as a benchmark, we evaluated closed- and open-source models in generating relevant assertions. Notably, our fine-tuned Mistral and Llama 3 models outperform GPT-4o by 20.93% on average, offering both reduced latency and improved performance. We believe our dataset can spur further research in LLM reliability, alignment, and prompt engineering.

1 Introduction

Large language models (LLMs) have become increasingly popular for various data processing tasks. An open-source tool for building LLM pipelines, developed by some of the authors, now has over 3 million weekly downloads. Its community has created thousands of specialized prompts for diverse fields like medicine, finance, and sports, leveraging LLMs' impressive zero-shot and few-shot performance [1, 22, 14, 45].

A common desire for developers using LLMs is to meet specific constraints on outputs, such as adhering to a particular structure or qualitative criteria [27]. One approach to address this need is to collect large amounts of human preference data [15, 23, 49], and improve models through alignment techniques like supervised fine-tuning and reinforcement learning from human feedback [4, 32, 44]. However, these methods have a high barrier to entry, requiring dataset collection, model fine-tuning, and serving infrastructure, which is more complex than simply manipulating prompts for LLM calls. More importantly, fine-tuning isn't supervised at the constraint level—meaning that even fine-tuned LLMs often fail to consistently follow instructions that correspond to constraints in detailed prompts [17, 33, 12].

An alternative solution involves implementing developer-specified *assertions* on LLM outputs [27, 37, 35]. This approach typically follows two steps: first, defining binary evaluation criteria to represent the desired constraints; second, implementing these criteria as assertions to evaluate LLM outputs and resample these outputs when assertions fail. However, developing effective assertion criteria is challenging—primarily due to the complexity of defining and conceptualizing these criteria, rather than their technical implementation [21, 38]. The complexity of coming up with assertions arises due to multiple factors: criteria can differ significantly between developers due to specific data, use cases, and end-user requirements [8]; criteria must account for both user preferences and LLM-specific failure modes [38]; and developers may need to incorporate qualitative or subjective criteria that require LLMs themselves to perform the evaluation [6, 21].

To improve custom and task-specific alignment for LLM pipelines, we need an approach that can examine developers' prompts and identify assertion criteria. These assertions can then be bolted onto the end of the LLM pipeline, allowing for automatic retrying of the pipeline if assertions fail. Developing such an approach requires substantial, diverse data on real-world LLM applications and

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their associated constraints. Fortunately, our open-source tool provides unique access to a diverse set of use-cases with associated prompts.

In this paper, we present PROMPTEVALS, a dataset created using our unique collection of real-world LLM prompts and use-cases. This dataset consists of 2087 human-contributed prompt templates for custom tasks and 12623 comprehensive assertion criteria. PROMPTEVALS has a median prompt template size of 191 tokens and is *more than five times larger than previous collections* [34, 52]. Our dataset and corresponding benchmark (20% of the dataset) are hosted on HuggingFace[1]. Using this benchmark, we evaluate GPT-4o and two open-source models, Llama 3-8b and Mistral-7b, on generating task-specific assertion criteria, and find that GPT-4o performs reasonably well out of the box, but its cost and latency to run for every prompt edit or pipeline update can be prohibitive in production environments—especially as prompts become increasingly complex and specialized. To address this, for our prompt engineering tools, we fine-tuned open-source models on our dataset (using Mistral-7b and Llama 3-8b architectures [16, 41]), and these models exceeded GPT-4o's F1 performance in identifying desirable assertions by 20.93% on average. These fine-tuned models are made available to the community[2], offering a faster, more cost-effective solution for generating high-quality assertions.

2 Related Work

This section reviews recent developments in prompt engineering, LLM evaluation methods, and assertions for LLM outputs.

2.1 Prompt Engineering

Prompt engineering is essential for steering LLMs towards following instructions for specific tasks or bespoke applications of LLMs. Techniques like chain-of-thought and few-shot prompting improve model performance [46, 1]. Methods to learn good prompts [24, 26] or select few-shot examples [18] also contribute to this goal. Despite these advancements, LLMs can still hallucinate and make other mistakes [13, 36]. No technique ensures consistent adherence to instructions, especially in diverse production environments. Liu et al. identify constraints like output length and semantic consistency that developers want enforced, which can aiding robust assertion criteria [27]. As developers frequently iterate on prompts in integrated development environments (IDEs) or utilize code-completion tools, the ability to quickly generate and update assertion criteria becomes crucial. The computational cost and time required to use large models like GPT-4 to generate assertion criteria for each prompt modification can significantly slow down the development process and increase operational costs.

2.2 Evaluating LLMs

Traditional LLM evaluation compares outputs against human-generated benchmarks across tasks like coding and reasoning [2, 10, 40, 5], including specialized architectures like retrieval-augmented generation and agentic systems [54, 3, 28]. However, benchmarks often miss task-specific needs, such as conciseness or clarity [20]. Human pairwise comparison of LLM outputs improves alignment holistically but does not provide insight into specific criteria that defines a good output [20, 50].

Even with explicit instructions provided in prompts, LLMs often fail to adhere to them consistently [44, 52, 39]. Existing benchmarks that evaluate the ability of LLMs to follow instructions are limited in scope, typically involving a small set of instructions either generated by LLMs or meticulously curated by researchers [34, 52]. To address these limitations, we introduce PROMPTEVALS, a comprehensive dataset that is five times larger than previous datasets. PROMPTEVALS features developer-contributed real-world prompts, often containing dozens of instructions, coupled with the corresponding assertion criteria.

2.3 Assertions and LLM-based Evaluation

In instruction-following and constraint-following evaluations, such as those presented by Zhou et al. [52] and Rebedea et al. [35], assertion criteria are typically evaluated using code-based assertions, often implemented as functions that check whether the output matches specific patterns or requirements (e.g., using regular expressions). These code-based assertions often struggle to evaluate more nuanced or "fuzzy" criteria [7, 35, 37]. Recent approaches have employed LLMs themselves as judges to evaluate outputs [50, 42]. Some approaches even develop specialized judge LLMs

[1] https://huggingface.co/datasets/reyavir/PromptEvals

[2] https://huggingface.co/reyavir/promptevals_mistral and https://huggingface.co/reyavir/promptevals_llama

Prompt Template Domain: academic writing assistance

Please assist in drafting a paper about {your topic}. Generate one sentence at a time, presenting 3 options for each sentence, numbered 1 through 3. I will respond with the number of the sentence to use, or the word 'quit'. You will respond with the full draft compiled so far, and will then generate the next sentence using the same process, continuing until the draft is finished or I type 'quit'. Don't add any other response or comments to your messages, only the current draft, and the options for the next sentence.

Low Semantic Similarity Score (Base Mistral - 0.34)

"[Concepts for Assertion Checks in LLM Responses\n1. Coherence: 'The response maintains a logical and consistent flow of thought.',
2. Relevance: 'The response directly addresses the given prompt or question.',
3. Completeness: 'The response provides a full and complete answer to the question asked.',
4. Politeness: 'The response is friendly, courteous, and does not contain rude or offensive language.',
5. Accuracy: 'The information provided by the response is factually correct.',
6. Clarity: 'The response is written in clear, concise, and easily understandable language.',
7. Grammar: 'The response is free of grammatical errors.',
8. Spelling: 'The response is free of spelling mistakes.',
9. Tone: 'The tone of the response matches the required level of formality or informality.',
10. Length: 'The response is neither too short nor too long to answer the question adequately.",
11. Formatting: 'The response is properly formatted and easy to read.',
12. Citation: 'If necessary, the response

Medium Semantic Similarity Score (GPT-4o - 0.67)

[Output must include 3 numbered options for each sentence generated, numbered 1 through 3.|multiple_choice,
Output must not include any commentary or additional responses except the full draft compiled so far and the options for the next sentence.|adhere_instructions,
Output should stay on the topic specified in the placeholder {your topic}.|stay_on_topic]

High Semantic Similarity Score (Fine-tuned Mistral - 0.80)

["Output must follow the format of presenting 3 options for each sentence. |structured_output",
"Output must include the full draft compiled so far after generating options for a sentence. |structured_output",
"Output must not include any additional response or comments outside of presenting options and the full draft. |adhere_instructions",
"Output must continue generating sentences until the draft is finished or 'quit' is typed. |adhere_instructions"]

Figure 1: Examples of criteria pairs and their semantic similarity scores. High-scoring pairs typically represent constraints that are explicitly stated or logically derived from the prompt, while low-scoring pairs often include vague, generic, or difficult-to-measure constraints.

that are fine-tuned on human preference data [51, 43, 53, 25, 20]. LLM-based validators can be productionized as assertions in addition to code-based guardrails [37, 38, 27, 21].

While LLMs as judges offer scalable evaluation, they struggle to align with human preferences across diverse tasks [47]. Developing domain-specific assertions and guardrails (e.g., for education [30] or medicine [9]) is one approach, but it does not scale easily across thousands of domains and applications. Even within domains, criteria may vary; for instance, judging code conciseness differs between educational and professional settings. In another related research effort, Kim et al. developed LLM-generated evaluation criteria and fine-tuned a judge LLM [19, 20], but their approach focuses on general (e.g., "humorous", "inspiring") rather than task-specific criteria. Our work complements this by providing assertion criteria grounded in real-world prompts and constraints, essential for production environments [27].

3 PROMPTEVALS Dataset

This section describes the PROMPTEVALS dataset, its construction process, and its characteristics. We begin by discussing the relevant background, then detail the dataset's composition and the process for generating ground-truth assertion criteria for each prompt template in our dataset.

3.1 Background: LLM Pipelines and Assertions

An *LLM pipeline* typically consists of three main components: a prompt template, input data, and the LLM itself. A prompt template is a string that includes instructions for the LLM to perform a specific task, as well as placeholders for the input data—which will be provided at runtime. For example, a template for a basic summarization task might look like this: "Summarize the following text in three sentences: {text_to _summarize}". Here, "{text_to_summarize}" is a placeholder that will be replaced with actual text when the pipeline is run. LLM pipelines are designed to be flexible and reusable, capable of handling a variety of different inputs for the same type of task.

An assertion, in the context of LLM pipelines, is a programmatic check or evaluation criterion applied to the LLM's output. For example, an assertion criterion for the summarization task might verify that the output indeed contains exactly three sentences, as specified in the prompt. This assertion could be implemented as a function that counts the number of sentences in the LLM's response and returns true if the count is three (false otherwise).

Developers implementing LLM pipelines care about a wide variety of assertions, depending on their specific use cases and requirements. Some examples of good and bad assertion criteria for a prompt template are shown in Table 1. To better understand developers' needs, a recent study

Prompt Template (Domain: financial analysis)

You are a financial analyst and you are required to summarize the key insights of given numerical tables. {table} Please list important, but no more than five, highlights in the given table. Please write in a professional and business-neutral tone. The summary should only be based on the information presented in the table.

Criteria	Good/Bad	Explanation
Response Length: The response should not list more than five highlights as requested.	Good	Mentioned in the prompt, and easy to measure.
Professional Tone: The response should maintain a professional and business-neutral tone throughout.	Good	Mentioned in the prompt template as a rule that the output should follow.
No Repetition: The response should avoid repeating the same highlight or presenting the same information in different ways.	Good	While the criterion was not explicitly mentioned in the prompt, it can be tied back to the prompt.
Specificity: The highlights should be specific and not overly broad or generic.	Bad	Vague, and difficult to measure.
Grammar and Spelling: The response should be free from grammatical errors and spelling mistakes.	Bad	Not uniquely relevant to the task or prompt.

Table 1: Examples of Good and Bad Assertion Criteria

by Liu et al. [27] interviewed 51 developers about their desired output constraints for LLMs. Based on their findings, they developed a taxonomy that includes six categories of output constraints: low-level constraints that include structured output, multiple choice and length constraints, and high level constraints that include semantic constraints, stylistic constraints, and hallucination prevention. The complete taxonomy is presented in Table 3. We employ this taxonomy in our dataset construction process to ensure the quality and relevance of our assertions. A distribution of the criteria types generated by GPT-4o is in Figure 4.

3.2 Dataset Composition

The PROMPTEVALS dataset is derived from the LangChain Prompt Hub, a publicly available, dynamic collection of prompt templates shared by members of our developer community. Developers can add a prompt to the public collection via our Python package, knowing that their prompts can be run or modified by others, and browse the collection on our website. We froze a snapshot of the prompt templates in May 2024 to create the PROMPTEVALS dataset: we selected prompt templates that could have one or more assertion criteria (i.e., they were not empty or trivial strings; they actually described a task and included some placeholders for data). An example of a prompt template that we omitted from PROMPTEVALS is: *System Message: You are a helpful assistant. Human Message: {input}*.

PROMPTEVALS includes 2087 prompt templates, their corresponding domains, and assertion criteria. The prompt templates span a wide range of fields, including IT and programming, finance, healthcare, and education. To organize the prompt templates, we implemented a hierarchical categorization process assisted by GPT-4o, resulting in a three-level categorization system. Appendix A.1 describes this categorization process in more detail. Table 2 shows the overall distribution of the highest level domains, including the domain name, number of prompt templates with that domain, and the percentage of prompts with this domain. The top three domains represented are "general-purpose chatbots", "question-answering", and "workflow automation"—the last of which assists in automating or improving processes based on a user's input. For instance, one prompt in this domain is *"Create a sequential workflow based on the users query. Create a plan represented in JSON by only using*

the tools listed below. The workflow should be a JSON array containing only the sequence index, function name and input... Tools: {tools} Only answer with the specified JSON.".

3.3 Assertion Criteria Construction Process

For each prompt template in PROMPTEVALS, we generated a set of ground truth criteria—representing assertion criteria that developers would care about, specific to the LLM pipeline. Generating ground truth criteria followed a three-step process: a first step to generate initial criteria, a second pass to add any criteria that might have been omitted in the first step, and a third pass to remove any criteria that were incorrect, redundant, irrelevant, or difficult to validate.

1. **Generate Initial Criteria:** We used GPT-4o, a state-of-the-art LLM, to generate an initial list of assertion criteria for each prompt template. Our prompt consisted of the following instructions: *(a)* We provided GPT-4o with the prompt template to be analyzed. *(b)* We also gave GPT-4o the taxonomy of LLM output constraints defined by Liu et al. [27] (see Section 3.1), explaining each constraint type. *(c)* We then instructed GPT-4o to generate assertion criteria relevant to the given prompt template, ensuring each criterion aligned with one of the constraint types from the taxonomy. GPT-4o output these criteria in a JSON list format, with each assertion tagged with its corresponding constraint type. This approach ensured that the criteria were both relevant to the specific prompt template and grounded in a structured framework of output constraints that developers typically care about. We call this the *initial criteria*.

2. **Add Missing Criteria:** Two authors conducted a manual review of 200 criteria in total, with 50 criteria examined by both reviewers. Our review uncovered criteria in the prompt templates that were initially missed by GPT-4o, averaging 1.35 missing criteria per prompt. The review process included criteria that were both unique and aligned with the taxonomy categories. To assess reliability, we calculated Cohen's Kappa on the overlapping set, achieving a score of 0.91—indicating strong inter-reviewer agreement. To address these missing elements, we added a verification step where GPT-4o re-examined the prompt templates to identify any explicitly stated criteria that were absent from its initial analysis.

3. **Refine Criteria:** In the final step, we prompted GPT-4o to refine the list by removing any criteria that were incorrect, redundant, irrelevant, or difficult to validate.

Appendix A.2 details the prompts for each step.

Validating the Generated Assertion Criteria. To assess the quality of our generated assertion criteria for PROMPTEVALS, we manually verified a sample of 200 prompt templates' generated criteria. In our verification process, we tracked, for each prompt template, how many criteria we added, and how many criteria we removed. We observed strong agreement with the LLM generated outputs, with < 0.02 criteria added and < 0.2 criteria removed per list on average by the human evaluator. This 3-step process resulted in higher agreement, in comparison to the initial criteria list, which had an average of 1.35 criteria added and 1.1 criteria removed per list for a sample of 20 prompts.

4 PROMPTEVALS Benchmark

We split PROMPTEVALS into three categories: 60% of the tasks (1252 prompts) for our training set, 20% (418 prompts) for our validation set, and 20% (419 prompts) for our test set. The PROMPTEVALS benchmark evaluates an LLM's effectiveness at generating accurate assertion criteria given a prompt template, using four key metrics defined below. The benchmark can be run by following the instructions in our Github repository [3].

4.1 Benchmark Metrics

To evaluate LLM-generated assertion criteria, we developed metrics to assess the relevance and specificity of the criteria, inspired by the approach used in BERTScore [48]. We describe two metrics: Semantic F1 and the number of criteria.

`Semantic F1.` The primary metric we use addresses a challenge in evaluating generated criteria: the fact that semantically equivalent assertions can be expressed in various ways. For example, "The response should be concise" and "The output should be brief" convey essentially the same constraint but use different words. The Semantic F1 score overcomes this limitation by measuring the

[3] https://github.com/reyavir/promptevals

Domain	Count	Percentage
General-purpose chatbots	181	8.67%
Question-answering	91	4.36%
Workflow automation	63	3.02%
Text summarization	57	2.73%
Education	40	1.92%
Prompt engineering	33	1.58%
Information retrieval	31	1.49%
Horse racing analytics	29	1.39%
Programming	20	0.96%
Customer support	18	0.86%
Database querying	18	0.86%
Journalism	17	0.81%
Task automation	15	0.72%

Table 2: Distribution of domains in the PROMPTEVALS dataset. The top three domains are general-purpose chatbots, question-answering, and workflow automation. Unexpectedly, "horse racing" is in this list: we double-checked its validity and included an example prompt template from this category in Appendix B.1.

semantic similarity between predicted and ground truth criteria.

To compute the Semantic F1 score, we first transform each criterion (both predicted and ground truth) into vector representations using OpenAI's *text-embedding-3-large* model. We then calculate recall and precision scores based on the cosine similarity between these embedding vectors.

The recall score quantifies how well the predicted criteria cover the semantic content of the ground truth criteria. It is computed as follows:

$$\text{sem\_recall} = \frac{1}{N}\sum_{i=1}^{N}\max_{j}\cos(z_i, \hat{z}_j) \quad (1)$$

where N is the number of predicted criteria, z_i is the embedding of the i-th ground truth criterion, $\hat{z}_j$ is the embedding of the j-th predicted criterion, and $\cos(z_i, \hat{z}_j)$ denotes the cosine similarity between these embeddings.

The max operation in this formula finds the most similar predicted criterion for each ground truth criterion—allowing each ground truth criterion to be "matched" with its best corresponding predicted criterion, even if they are not expressed identically. The average of these maximum similarities then gives us a measure of how well the predicted set covers the ground truth set.

The precision score measures how accurately the predicted criteria align with the ground truth:

$$\text{sem\_precision} = \frac{1}{M}\sum_{j=1}^{M}\max_{i}\cos(z_i, \hat{z}_j) \quad (2)$$

where M is the number of ground truth criteria. Here, the max operation performs the reverse matching: for each predicted criterion, it finds the most similar ground-truth criterion. This helps us assess whether the predicted criteria are meaningful, without extraneous or irrelevant assertions.

These scores are then combined into the F1 score:

$$\text{sem\_F1} = 2 \times \frac{\text{sem\_precision} \times \text{sem\_recall}}{\text{sem\_precision} + \text{sem\_recall}} \quad (3)$$

Figure 1 shows examples of criteria pairs with varying degrees of semantic similarity.

`Number of criteria.` A secondary metric that we evaluate is the number of criteria generated per prompt template. We calculate the average, median, and 75th percentile values for the number of criteria generated by each model. These statistics are compared against the ground truth values, as shown in Table 6. Ground truth values are italicized, and the closest model-generated values are bolded for comparison. For reference, the distribution of the number of ground truth criteria can be found in Table 6.

5 Benchmarking LLMs for Assertion Generation

In this section, we present our methodology for evaluating LLMs with the PROMPTEVALS benchmark. We assess the performance of baseline and fine-tuned models.

5.1 Methodology

We establish baselines for our evaluation using three models: GPT-4o [31], Llama-3-8b [41], and Mistral-7b [16]. We selected Llama-3-8b and Mistral-7b as our open-source baseline models due to their relatively compact size (8 billion and 7.3 billion parameters, respectively)—which leads to faster inference times. For each model, we generate assertion criteria based on the prompt templates in our test set and evaluate them against the ground truth criteria using the metrics described in Section 4.1: Semantic F1 and number of criteria. We compare results on the PROMPTEVALS test set.

Category	Description
Low-level constraints	
Structured Output	Adhere to specific formats (e.g., markdown, HTML, DSL); Ensure valid data structures (e.g., JSON with custom schema)
Multiple Choice	Select response from a predefined list of options
Length Constraints	Specify target length for output (e.g., character count, word count, number of items in a list)
High-level constraints	
Semantic Constraints	Control content by excluding/including specific terms; Maintain topic relevance; Adhere to specified grammar or linguistic context
Stylistic Constraints	Maintain consistent style, tone, or persona in the output
Prevent Hallucination	Ensure factual accuracy and truthfulness; adhere to instructions (without improvising unrequested actions)

Table 3: Taxonomy for Assertion Criteria [27], used to create assertions for LLM pipelines in PROMPTEVALS.

5.1.1 Fine-tuning Process

Initial results revealed suboptimal performance from baseline models (we will describe this more in Section 5.2). To address this, we fine-tuned the same Mistral and Llama base model architectures on a dataset comprising of LLM pipeline prompts as reference inputs and ground truth criteria as reference outputs. The dataset is derived from the `train` split of the PROMPTEVALS dataset, where the ground truth assertions are the result of the 3-step labeling workflow defined in Section 3.3. An input and output is demonstrated as follows:

> Input: *[INST] Here is the prompt template {sample_prompt_template} Based on the prompt template, I want to write assertions for my LLM pipeline to run on all pipeline responses. Give me a list of concepts to check for in LLM responses. This should be formatted as a comma-separated list, surrounded in brackets, and each item in the list should contain a string description of a concept to check for. This list should contain as many assertion concepts as you can think of, as long are specific and reasonable. [/INST]*
>
> Output: `["constraint": "Answer should be concise and limited to three sentences.", "category": "length_constraints", "constraint": "Answer should stay truthful and indicate 'I don't know' if the answer is not in the context.", "category": "preventing_hallucination (staying grounded and truthful)"]`

For fine-tuning Mistral-7b and Llama3-8b, we used a sequence length of 4096 and trained for 4 epochs with a batch size of 8, AdamW [29] optimizer, learning rate of 0.0001, and a cosine learning rate scheduler. We used Low-Rank Adaptation (LoRA) [11], with a rank of 16, alpha of 32, and dropout of 0.05. The training process for each model was completed in under one hour with two 80GB A100 GPUs, and we did not employ any hyperparameter search. Our fine-tuned models can be found on HuggingFace[4].

5.2 Quantitative Results

Fine-tuning our models on PROMPTEVALS resulted in substantial improvements in the quality of generated assertion criteria, as evidenced by higher semantic F1 and precision scores in Table 5. The fine-tuned Mistral model achieved an average semantic F1 score of 0.8199, which is 20.43% higher than the single-step GPT-4o's average score of 68.08%, and 100.32% higher than its base model (without any fine-tuning). Similarly, the fine-tuned Llama3 model achieved a semantic F1 score of 0.8240—outperforming GPT-4o by 21.03% and its base model by 128.42%.

5.3 Qualitative Results

We analyzed our base and fine-tuned model outputs for a set of 25 randomly selected prompt templates, observing significant improvements in 5 main categories.

Format Adherence. Base models struggled with formatting consistency. Llama3 outputs frequently contained formatting errors in nearly all cases, including issues such as missing or multiple structured lists and missing closing brackets. While

[4] https://huggingface.co/reyavir/promptevals_mistral and https://huggingface.co/reyavir/promptevals_llama

	Mistral (FT)	Llama (FT)	GPT-4o
p25	**1.8717**	2.3962	6.5596
p50	**2.3106**	3.0748	8.2542
Mean	**2.5915**	3.6057	8.7041
p75	**2.9839**	4.2716	10.1905

Table 4: Latency for criteria generation. We report runtime for the mean, 25th percentile, 50th percentile, and 75th percentile in seconds. We found that our fine-tuned Mistral model had the lowest runtime for all metrics.

the base Mistral model showed better format alignment, errors still occurred in fewer than half of the outputs, particularly with the closing brackets. **Relevance.** Base models frequently included extraneous or unrelated content. Llama3 outputs often contained inappropriate casual phrases like *"I hope this helps!"* or unnecessary meta-commentary such as *"It's also worth noting that some of these concepts may be difficult or impossible to automatically assess."* Fine-tuned models maintained strict focus on the requested criteria. **Conciseness.** As shown in Table 6, base models significantly overgenerated assertions. Llama and Mistral produced redundant or overlapping criteria—for instance, one Mistral output included both *"Check if the response starts with an emoji"* and *"Check if each summarized sentence starts with a unique emoji."* Fine-tuned models generated more distinct, non-overlapping assertions. **Completeness.** Base models often produced incomplete outputs, frequently due to exceeding token limits. For example, Mistral outputs sometimes ended mid-sentence ("Grammar and Spelling: Check if"), while Llama3 would leave thoughts unfinished ("These concepts can be used to evaluate the"). Fine-tuning effectively addressed these completion issues. **Output Length.** The ground truth PROMPTEVALS test set contained about 6 assertions per prompt template. Base models significantly exceeded this—Mistral averaged 14.5 assertions while Llama generated 28.24 assertions per template. In contrast, as shown in Table 6, GPT-4o (7.59 assertions) and our fine-tuned models produced outputs more aligned with ground truth, with fine-tuned Mistral achieving the closest match at 6.29 assertions. Additionally, our fine-tuned models demonstrated improved latency, outperforming GPT-4o in generation speed when served on two A100 GPUs.

5.4 Discussion and Implications

Our smaller, fine-tuned models achieve assertions comparable to the three-phase GPT-4o process (detailed in Section 3.3), while significantly outperforming single-phase GPT-4o. This is a meaningful finding for several reasons. First, it demonstrates that carefully curated datasets and targeted fine-tuning can enable smaller models to match or exceed the performance of much larger models in specific tasks. Second, it underscores the importance of multi-step refinement when using state-of-the-art general-purpose LLMs for generating assertion criteria, as evidenced by the low single-step GPT-4o performance. This refinement process, while effective, can lead to increased latency in non-interactive settings. Our approach offers a more resource-efficient solution for assertion generation without compromising on quality.

The ability to generate high-quality assertion criteria quickly and cost-effectively has significant implications for LLM pipeline development and deployment: it enables more frequent iterations, faster debugging, and more robust quality assurance processes without incurring prohibitive costs or delays. This is particularly valuable as prompts become longer and more complex, making the use of GPT-4o to generate assertions for every iteration on a prompt increasingly impractical. We are integrating these fine-tuned assertion generation models into our LLM pipeline development tools, particularly focusing on evaluation and monitoring capabilities. This will allow developers to automatically generate task-specific assertion criteria for any given prompt or pipeline, continuously monitor the quality of outputs in live deployments, and receive real-time feedback on output quality, all while maintaining efficiency and scalability in production environments.

While our fine-tuned models show significant improvements, we observed occasional generation of vague or redundant criteria. For example, criteria like "Output must avoid any ambiguity or confusion" and "Output must use clear and unambiguous language" could be consolidated. One idea is to directly incorporate a notion of criteria uniqueness into the training process—e.g., penalize models if, for an output, they generate two or more criteria with high semantic similarity. Another idea is to collect more data to supplement PROMPTEVALS. Future work will focus on refining the model to produce more concise and non-overlapping criteria,

	Base Mistral	Mistral (FT)	Base Llama	Llama (FT)	GPT-4o
p25	0.3608	0.7919	0.3211	**0.7922**	0.6296
p50	0.4100	0.8231	0.3577	**0.8233**	0.6830
Mean	0.4093	0.8199	0.3607	**0.8240**	0.6808
p75	0.4561	0.8553	0.3978	**0.8554**	0.7351

Table 5: Semantic F1 scores for generated assertion criteria. Percentiles and mean values are shown for base models, fine-tuned (FT) versions, and GPT-4o. Bold indicates highest scores.

	Average	Median	p75	p90
Base Mistral	14.5012	14	18.5	23
Mistral (FT)	**6.28640**	**5**	**8**	**10**
Base Llama	28.2458	26	33.5	46
Llama (FT)	5.47255	**5**	**6**	9
GPT-4o	7.59189	6	10	14.2
Ground Truth	*5.98568*	*5*	*7*	*10*

Table 6: Number of Criteria Generated by Models. Metrics show average, median, and percentile values. p75 and p90 represent the 75th and 90th percentiles, respectively. Bold indicates closest to ground truth.

and generally improve the semantic F1 score. We also intend to explore the capabilities of smaller models to determine if we can reduce latency further, while still retaining good accuracy and alignment with developers' intents.

6 Conclusion

This study introduces PROMPTEVALS, a new benchmark comprising over 2,000 human-contributed prompt templates and 12,000 assertion criteria. PROMPTEVALS is more than five times larger than previous prompt collections [34, 52]. This diverse dataset represents a significant contribution to the field of LLM pipeline development, offering a robust tool for evaluating and improving task-specific output constraints. Using PROMPTEVALS, we benchmarked several models, including GPT-4o, and additionally fine-tuned open-source models for assertion generation. Our experiments demonstrate PROMPTEVALS' utility in assessing and comparing performance across different approaches to generating relevant assertions. By making PROMPTEVALS and our fine-tuned models publicly available, our goal is to encourage the development of more reliable and task-specific LLM applications across various domains.

7 Limitations

We describe a few limitations in this section: First, benchmark scores rely on OpenAI's *text-embedding-3-large* model, released on January 25, 2024. Our reliance on a proprietary embedding model introduces a risk of inconsistency in results over time due to potential model updates. Establishing a versioning system or exploring alternative and more stable embedding methods could mitigate this issue. Moreover, currently, the benchmark is restricted to text prompts, excluding other modalities such as images and audio. Expanding the dataset to incorporate multi-modal inputs would increase its applicability and better reflect the diverse range of real-world LLM tasks.

Finally, it's important to note that while our criteria are grounded in a taxonomy derived from developer preferences, they are ultimately generated by an LLM. This approach, while efficient, may not capture the full nuance of developer intentions for every specific use case. Ideally, criteria would be developed through direct collaboration with developers for each prompt template, ensuring maximum relevance and accuracy.

8 Ethics

PROMPTEVALS is open-source and is intended to be used as a dataset and benchmark to evaluate models' ability to identify and generate assertion criteria for prompts. However, because it is open-source, it may be used in pre-training models, which can impact the effectiveness of the benchmark. PROMPTEVALS data and derivatives of this data should not be used outside of research or prompt engineering contexts. Additionally, PROMPTEVALS consists of prompts contributed by a variety of developers. In our data collection process, we did not collect any personally identifiable information (PII) on the developers, and we looked through the data to confirm that developers did not submit PII in their prompts. Since we did not control the developer population we sampled prompts from, prompts may not represent all domains equally. However, we believe that despite this, our benchmark still provides value and can be useful in evaluating models on generating assertion criteria.

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In this appendix, we include additional information on our work. This includes the prompts used in generating the dataset, distributions of domains and assertion criteria categories, example prompts in our dataset, a datasheet, and model cards.

A Prompt Template Analysis

In this section, we describe the prompts we used to identify the domain for each prompt template, the prompts used to generate the assertion criteria for each step of our workflow, and the distributions of our LLM-generated assertion criteria.

A.1 Prompts and Analysis for Domain Categorization

To categorize the prompt templates in PROMPTEVALS, we used the following prompts for querying GPT-4o. First, `DOMAIN_CATEGORIZE_1` was applied to each prompt template in parallel to generate fine-grained level 1 categories, resulting in 974 unique domains. Next, GPT-4o was queried once to consolidate these into 50 aggregate level 2 categories, which were sanity-checked for accuracy. Then, `DOMAIN_CATEGORIZE_2` was used to map each prompt template to one of the 50 predefined level 2 categories. We queried GPT-4o once more to come up with a set of level 3 categories (the highest level), and we manually assigned each level 2 category to a good level 3 category.

DOMAIN_CATEGORIZE_1

Here is my prompt template for a specialized task:

```
```json
{prompt_template}
```
```

What domain does this prompt template pertain to? Limit your response to a single word or phrase, and be as specific and fine-grained as possible. Avoid generic domains like ‘natural language processing‘ and ‘artificial intelligence.‘ Return your response as a JSON object in “‘json “‘ markers, with the key “field” and the value being the word or phrase.

DOMAIN_CATEGORIZE_2

Here is my prompt template for a specialized task:

```
```json
{prompt_template}
```
```

The domain of this prompt template is:

`{field}`

Given the following higher level domains: General-Purpose Chatbots, Workflow and Task Automation, Question-Answering Systems, Education and Academic Assistance, Content Summarization and Extraction, Information Retrieval and Management, Programming and Software Development, Customer Support and Service, Data Analysis and Visualization, Content Creation and Writing, Project Management, Psychotherapy and Mental Health, Entertainment and Gaming, Healthcare and Medicine, Financial Services and Analysis, E-Commerce and Retail, Legal and Compliance, Marketing and Sales, Coaching and Personal Development, AI Evaluation and Optimization, Translation and Multilingual Services, Creative Arts and Media, Data Management and Databases, Text Analysis and Processing, Customer Experience and Feedback, Technology and IT Support, Evaluation and Quality Assurance, Real Estate and Property Management, Research and Information Synthesis, Insurance and Risk Management, Interactive Assistance and Support, Business Intelligence and Strategy, Human Resources and Recruitment, Knowledge and Information Synthesis, Task Execution and Management, Evaluation of AI Systems, Data Visualization and Reporting, Entertainment and Interactive Systems, Question Generation and Optimization, Automation and Orchestration, Translation and Language Services, Digital Marketing and SEO, Financial Services and Advising, Programming and Development Assistance, Creative and Content Writing, Healthcare and Medical Services, Customer Experience and Support, Business and Strategy Development, Evaluation and Quality Assurance, Human Resources and Recruitment
What higher level domain does this prompt template pertain to? You must pick one from the list above. Return only a JSON object in “‘json “‘ markers, with the key “domain” and the value being the word or phrase from the list above.

While our dataset in HuggingFace https://huggingface.co/datasets/reyavir/PromptEvals includes the finest-grained level 1 domains for each prompt template, Figure 2 shows the distribution of level 2 and level 3 domains across the dataset. Most prompt templates relate to AI systems and automation, as they are mainly prompt templates that generically evaluate or grade the quality of other LLM outputs,

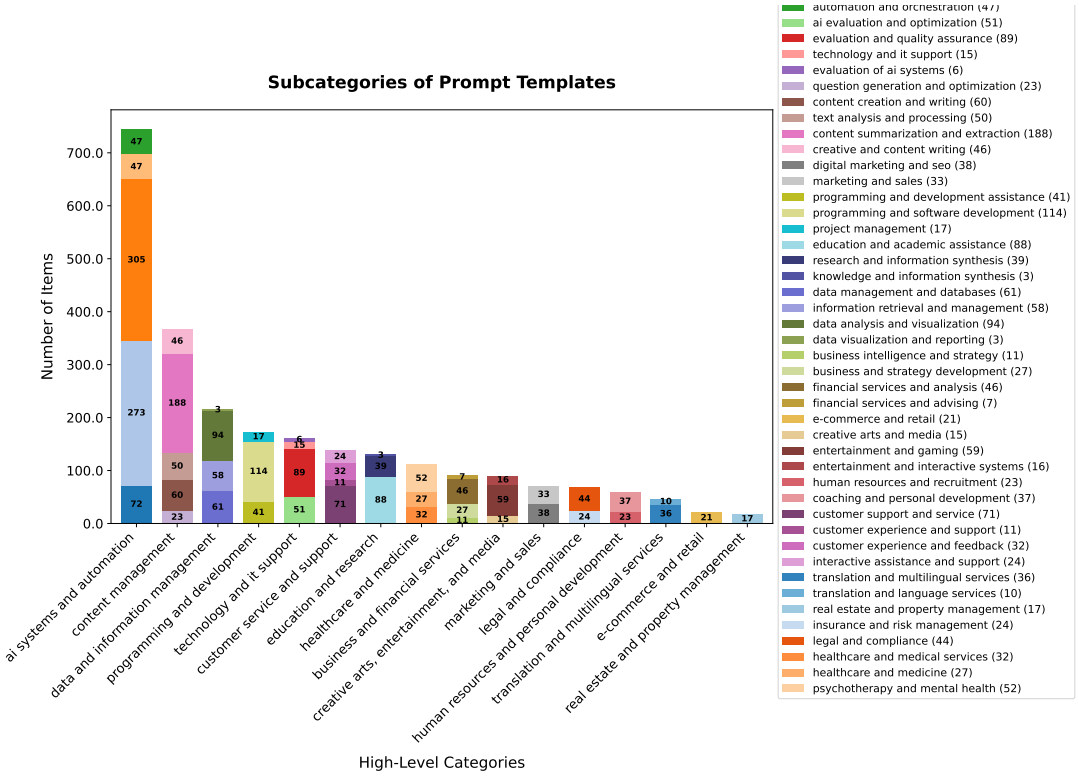

Figure 2: Distribution of Domains and Subdomains of Tasks Represented in PROMPTEVALS.

or they generically improve prompts to be more clear. The largest application of prompt templates is in content management (e.g., text summarization, creative writing), followed by data and information management (e.g., text to SQL).

A.2 Prompts for LLM-Generated Criteria

For each prompt template in the PROMPTEVALS, we use GPT-4o to generate a set of custom criteria that each LLM output should follow, or assertion criteria. Note that we use the term "constraints" here to match the terminology in Liu et al. [27]. We refer the reader to their paper to read detailed descriptions of each constraint type.

Our prompt to generate the criteria is as follows:

Prompt for Generating Custom Criteria

Here is my prompt template for a specialized task:

```json
{prompt_template}
```

I want to write assertions for my LLM pipeline to run on all pipeline outputs. Here are some categories of constraints I may want the outputs to follow:
- **Structured Output**: Is there a requirement for the output to follow a standardized or custom format, such as markdown, HTML, or a JSON object? - **Multiple Choice**: Does the output need to select from a predefined list of options? - **Length Constraints**: Are there instructions regarding the targeted length of the output, such as the number of characters, words, or items in a list? - **Semantic Constraints**: - **Excluding specific terms, items, or actions**: Are there terms, items, or actions that should be excluded from the output? - **Including or echoing specific terms or content**: Are there specific terms or content that should be included or echoed in the output? - **Covering or staying on a certain topic or domain**: Should the output cover or stay on a specific topic or domain? - **Following certain (code) grammar / dialect / context**: Are there requirements to follow certain (code) grammar, dialect, or context in the output? - **Stylistic Constraints**: Are there requirements for the output to follow a certain style, tone, or persona? - **Preventing Hallucination (Staying grounded and truthful)**: Should the output stay grounded and truthful, avoiding opinions, beliefs, or hallucinated outputs? - **Preventing Hallucination (Adhering to Instructions without improvising unrequested actions)**: Should the output strictly adhere to any specific instructions provided, without including content that is not explicitly requested?
{step}
Return only your answer as a numbered list of strings.

We updated the "step" input with a different prompt for each step of the workflow.

For step 1 (Generate initial criteria), the input was: *Give me a list of constraints to implement for verifying the quality of my LLM output. Each item in the list should contain a string description of a constraint to check for and its corresponding type. Type names are: structured_output, multiple_choice, length_constraints, exclude_terms, include_terms, stay_on_topic, follow_grammar, stylistic_constraints, stay_truthful, adhere_instructions.*

For step 2 (Add missing criteria), the input was:

Here are some assertion constraints I want the outputs to follow: {constraints}
Add assertion constraints to the provided list. Add constraints that are stated in the prompt template and not already covered by an existing constraint. Return the combined list. Make sure the constraints are also followed by their corresponding categories.

Where "constraints" was the output from the previous step.

For step 3 (Refine criteria), the input was:

Here are some assertion constraints I want the outputs to follow: {constraints}
Remove any assertion constraints that are incorrect, redundant (or already covered by another constraint), not relevant to the prompt template, or difficult to validate. Make sure the constraints are also followed by their corresponding categories.

Where "constraints" was the output from the previous step.

A.3 Analysis of LLM-Generated Criteria

We report distributions of the constraint types identified by GPT-4o in Figure 4, using the taxonomy from Liu et al. [27]. Figure 4 shows the distribution of constraints across different categories, illustrating the prevalence of `structured_output` type constraints. Additionally, Figure 3 shows a constraint type co-occurrence matrix. The top 5 co-occurring types are: `structured_output` and `adhere_instructions`, `structured_output` and `stay_on_topic`, `adhere_instructions` and `stay_on_topic`, `structured_output` and `include_terms`, and `stay_truthful` and `adhere_instructions`.

B Example Prompt Templates

B.1 Horse Racing Analytics

Prompt Template: "SystemMessagePromptTemplate
ROLE: You are a horse race analytic agent that explain a race detail with data and insight. You will receive

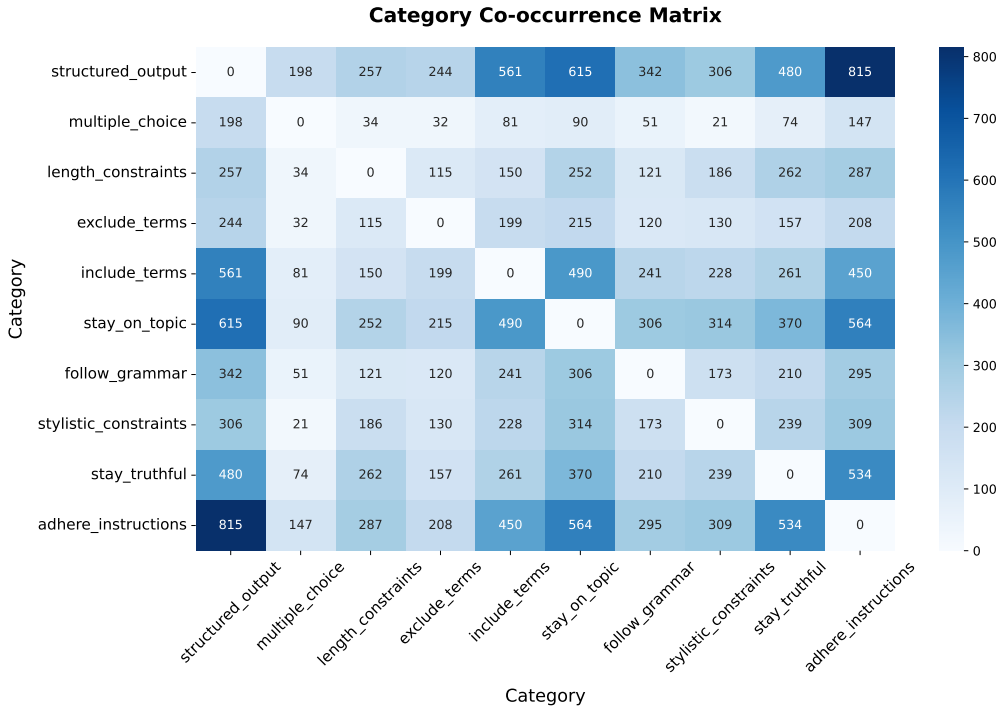

Figure 3: Constraint Type Co-Occurrence Matrix

user's question about a few horses' data, normally in numeric form. You have to first distinguish each horse's data, then answer user's question with the input and some professional's comments, your final output should be a decision of which horse is performing good or bad.
CONCEPTS: You have to note these custom attributes before answering the question: "Reborn" means that the horse has an insignificant drop in win odds, indicating that there are investment towards this horse when the win odds is not favourable. Showing that there are great increase in bettor's bet and confidence on this horse. "SpeedPro" means the attribute given from a rating system on the horse's past running strategy. "Cold Door" means the comment rating on the horse from professional horse race commentor.
ACTION: You have to analyze the separate horses and compare them with the data provided only, show which horse has the highest confidence with explanation.
HumanMessagePromptTemplate
I have a horse race with three horses participating, they has the record with : {question}. Now with the data supplied, summarize their potential performance."

C Datasheet

1. Why was the dataset created? (e.g., was there a specific intended task gap that needed to be filled?)
   The dataset was created to be used in training or fine-tuning models in generating higher quality assertion criteria.

2. Who funded the creation of the dataset?
   Lab sponsors.

3. What preprocessing/cleaning was done? (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances)
   The prompt template was extracted from the metadata and was added to the dataset. We removed any rows that resulted in 0 assertion criteria after the first step of our 3 step workflow.

4. If it relates to people, were they told what the dataset would be used for and did they consent? If so, how? Were they provided with any mechanism to revoke their consent in the future or for certain

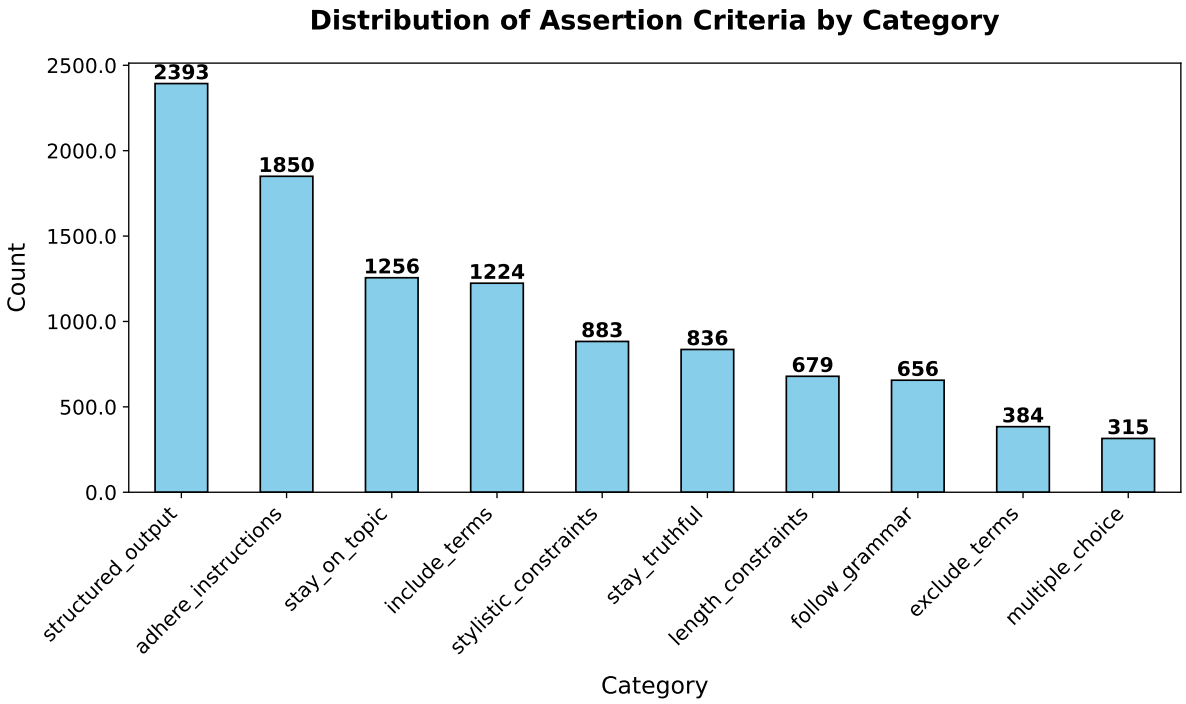

Figure 4: Distribution of Ground Truth Criteria by Type

uses?
Yes, the prompts are all from developers who consented to make their prompts public via a form. They can delete their prompts by submitting a delete request. We will semi-regularly update the Prompt Evals dataset to support the delete requests.

5. Will the dataset be updated? How often, by whom?
We plan to update the dataset yearly.

D Model Cards

D.1 Fine-tuned Mistral

1. Model Details. Basic information about the model.
– Person or organization developing model: MistralAI, and fine-tuned by the authors of this paper
– Model date: Base model released in September 2023, fine-tuned in July 2024
– Model version: version 3
– Model type: decoder-only Transformer
– Information about training algorithms, parameters, fairness constraints or other applied approaches, and features: 7.3 billion parameters, fine-tuned by us using Axolotl (https://github.com/axolotl-ai-cloud/axolotl)
– Paper or other resource for more information: https://arxiv.org/abs/2310.06825
– Citation details: https://openreview.net/forum?id=kW8wIpTgHF
– License: Apache 2.0 license
– Where to send questions or comments about the model: Reach out to the authors with any questions or comments

2. Intended Use. Use cases that were envisioned during development. (Primary intended uses, Primary intended users, Out-of-scope use cases)
Intended to be used by developers to generate high quality assertion criteria for LLM outputs, or to benchmark the ability of LLMs in generating these assertion criteria.

3. Factors. Factors could include demographic or phenotypic groups, environmental conditions, technical attributes, or others listed in Section 4.3.
   We don't collect any demographic, phenotypic, or others listed in Section 4.3, data in our dataset.

4. Metrics. Metrics should be chosen to reflect potential realworld impacts of the model. (Model performance measures, Decision thresholds, Variation approaches)
   Metrics are defined in Section 4.1

5. Evaluation Data: Evaluated on PROMPTEVALS test set

6. Training Data: Fine-tuned on PROMPTEVALS train set

7. Quantitative Analyses (Unitary results, Intersectional results): See Table 7

Domain	Similarity	Precision	Recall
General-Purpose Chatbots	0.8171	0.8023	0.8338
Question-Answering	0.8216	0.8183	0.8255
Text Summarization	0.8785	0.8863	0.8725
Database Querying	0.8312	0.8400	0.8234
Education	0.8599	0.8636	0.8564
Content Creation	0.8184	0.8176	0.8205
Workflow Automation	0.8304	0.8258	0.8351
Horse Racing Analytics	0.8216	0.8109	0.8336
Data Analysis	0.7865	0.7793	0.7952
Prompt Engineering	0.8534	0.8330	0.8755

Table 7: Fine-Tuned Mistral Score Averages per Domain (for the 10 most represented domains in our test set)

8. Ethical Considerations: See Section 8

9. Caveats and Recommendations: None

D.2 Fine-tuned Llama

1. Model Details. Basic information about the model.
   – Person or organization developing model: Meta, and fine-tuned by the authors of this paper
   – Model date: Base model was released in April 18 2024, and fine-tuned in July 2024
   – Model version: 3.1
   – Model type: decoder-only Transformer
   – Information about training algorithms, parameters, fairness constraints or other applied approaches, and features: 8 billion parameters, fine-tuned by us using Axolotl (https://github.com/axolotl-ai-cloud/axolotl)
   – Paper or other resource for more information: https://arxiv.org/abs/2310.06825
   – Citation details: https://openreview.net/forum?id=kW8wIpTgHF
   – License: Meta Llama 3 Community License
   – Where to send questions or comments about the model: Reach out to the authors with any questions or comments

2. Intended Use. Use cases that were envisioned during development. (Primary intended uses, Primary intended users, Out-of-scope use cases)
   Intended to be used by developers to generate high quality assertion criteria for LLM outputs, or to benchmark the ability of LLMs in generating these assertion criteria.

3. Factors. Factors could include demographic or phenotypic groups, environmental conditions, technical attributes, or others listed in Section 4.3.
   We don't collect any demographic, phenotypic, or others listed in Section 4.3, data in our dataset.

4. Metrics. Metrics should be chosen to reflect potential realworld impacts of the model. (Model performance measures, Decision thresholds, Variation approaches) Metrics are defined in Section 4.1

5. Evaluation Data: Evaluated on PROMPTEVALS test set

6. Training Data: Fine-tuned on PROMPTEVALS train set

7. Quantitative Analyses (Unitary results, Intersectional results): See Table 7

Domain	Similarity	Precision	Recall
General-Purpose Chatbots	0.8140	0.8070	0.8221
Question-Answering	0.8104	0.8018	0.8199
Text Summarization	0.8601	0.8733	0.8479
Database Querying	0.8362	0.8509	0.8228
Education	0.8388	0.8498	0.8282
Content Creation	0.8417	0.8480	0.8358
Workflow Automation	0.8389	0.8477	0.8304
Horse Racing Analytics	0.8249	0.8259	0.8245
Data Analysis	0.7881	0.7940	0.7851
Prompt Engineering	0.8441	0.8387	0.8496

Table 8: Fine-Tuned Llama Score Averages per Domain (for the 10 most represented domains in our test set)

8. Ethical Considerations: See Section 8

9. Caveats and Recommendations: None