Llama Guard: LLM-based Input-Output Safeguard for Human-AI Conversations

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GenAI at Meta

We introduce Llama Guard, an LLM-based input-output safeguard model geared towards Human-AI conversation use cases. Our model incorporates a safety risk taxonomy, a valuable tool for categorizing a specific set of safety risks found in LLM prompts (i.e., prompt classification). This taxonomy is also instrumental in classifying the responses generated by LLMs to these prompts, a process we refer to as response classification. For the purpose of both prompt and response classification, we have meticulously gathered a dataset of high quality. Llama Guard, a Llama2-7b model that is instruction-tuned on our collected dataset, albeit low in volume, demonstrates strong performance on existing benchmarks such as the OpenAI Moderation Evaluation dataset and ToxicChat, where its performance matches or exceeds that of currently available content moderation tools. Llama Guard functions as a language model, carrying out multi-class classification and generating binary decision scores. Furthermore, the instruction fine-tuning of Llama Guard allows for the customization of tasks and the adaptation of output formats. This feature enhances the model's capabilities, such as enabling the adjustment of taxonomy categories to align with specific use cases, and facilitating zero-shot or few-shot prompting with diverse taxonomies at the input. We are making Llama Guard model weights available and we encourage researchers to further develop and adapt them to meet the evolving needs of the community for AI safety.

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Code: https://github.com/facebookresearch/repo
Blogpost: https://ai.meta.com/blog/?page=1

1 Introduction

The past few years have seen an unprecedented leap in the capabilities of conversational AI agents, catalyzed by the success in scaling up auto-regressive language modeling in terms of data, model size, and computational power (Hoffmann et al., 2022). Large language models (LLMs) are commonplace in chat assistant applications, exhibiting excellent linguistic abilities (Brown et al., 2020; Anil et al., 2023; Touvron et al., 2023), commonsense reasoning (Wei et al., 2022b; Yao et al., 2023), and general tool use (Schick et al., 2023; Cai et al., 2023) among other capabilities.

These emerging applications require extensive testing (Liang et al., 2023; Chang et al., 2023) and careful deployments to minimize risks (Markov et al., 2023). For this reason, resources such as the Llama 2 Responsible Use Guide (Meta, 2023) recommend that products powered by Generative AI deploy guardrails that mitigate all inputs and outputs to the model itself to have safeguards against generating high-risk or policy-violating content as well as to protect against adversarial inputs and attempts at jailbreaking the model.

How should one go about building these guardrails? A reasonable starting point is to reuse tools that were built to moderate online content, such as the Perspective API[1], OpenAI Content Moderation API[2], and Azure Content Safety API[3]. However, these online moderation tools fall short when applied as input/output guardrails for several reasons. First, none of the available tools distinguishes between assessing safety risks

[1] https://perspectiveapi.com/

[2] https://platform.openai.com/docs/guides/moderation/overview

[3] https://azure.microsoft.com/en-us/products/ai-services/ai-content-safety

posed by the user and the AI agent, which are arguably two distinct tasks: users generally solicit information and help, and the AI agents typically provide them. Second, each tool only enforces a fixed policy; hence it is not possible to adapt them to emerging policies. Third, each tool only provides API access; hence, it is not possible to custom-tailor them to specific use cases via fine-tuning. Lastly, all available tools use conventional transformer models that are small in size as their backbone (Markov et al., 2023; Lees et al., 2022). This limits the capabilities when compared to the more capable LLMs.

In this work, we publicly release an input-output safeguard tool for classifying safety risks in prompts and responses for conversational AI agent use cases. In doing so, we bridge the existing gaps in the field by leveraging LLMs as the moderation backbone. Our work makes the following contributions:

- We introduce a safety risk taxonomy associated with interacting with AI agents. The taxonomy covers a set of potential legal and policy risks that can be applicable to a number of developer use cases.
- We introduce Llama Guard, an LLM-based input-output safeguard model, fine-tuned on data labeled according to our taxonomy. Llama Guard includes the applicable taxonomy as the input and uses instruction tasks for classification. This allows users to customize the model input in order to adapt to other taxonomies appropriate for their use case with zero-shot or few-shot prompting. One can also fine-tune Llama Guard on multiple taxonomies and decide which one to use at inference time.
- We provide different instructions for classifying human prompts (input to the LLM) vs AI model responses (output of the LLM). Therefore, Llama Guard is able to capture the semantic disparity between the user and agent roles. We do this with a single model by leveraging the capabilities of LLM models to follow instructions (Wei et al., 2022a).
- We publicly release our model weights, allowing practitioners and researchers to use our model freely without depending on paid APIs with limited bandwidth, as well as to further experiment and fine-tune Llama Guard in order to cater to their own needs.

2 Safety Risk Taxonomy

Building automated input-output safeguards relies on classifiers to make decisions about content in real time. A prerequisite to building these systems is to have the following components:

1. A **taxonomy** of risks that are of interest – these become the classes of a classifier.
2. **Risk guidelines** that determine where the line is drawn between encouraged and discouraged outputs for each risk category in the taxonomy.

There are many different ways that companies have approached the creation of taxonomies to mitigate areas of risk.

Because there is no one standard, for this purpose we have created a sample taxonomy based on risk categories commonly considered in the mitigation of unintended outputs from large language models. The taxonomy is not intended to comprehensively measure how effectively the model mitigates all potential risks; we believe it is general enough to be broadly applicable in the scientific community while also allowing us to demonstrate the value of our method to tune LLMs into classifiers that show high performance and high degrees of adaptability to different risk guidelines.

2.1 The Llama Guard Safety Taxonomy & Risk Guidelines

Below, we provide both the content types themselves and also examples of the specific kinds of content that we consider inappropriate for this purpose under each category:

- **Violence & Hate** encompasses statements that encourage or could help people plan or engage in violence. Similarly, statements that advocate discrimination, contain slurs, or voice hateful sentiments against people based on their sensitive personal characteristics (ex: race, color, religion, national origin, sexual orientation, gender, gender identity, or disability) would also be considered inappropriate under this category.

- **Sexual Content** encompasses statements encouraging someone (who could be underage) to engage in specific sex acts. Similarly, sexually explicit (i.e., erotic) statements would also be considered inappropriate under this category.
- **Guns & Illegal Weapons** encompasses statements that specifically encourage, condone, or could help people plan or execute specific crimes involving the illegal acquisition, creation, or use of guns or illegal weapons (ex: explosives, biological agents, or chemical weapons), including instructions on how to create or use them.
- **Regulated or Controlled Substances** encompasses statements that specifically encourage or could help people to illegally produce, transfer, or consume regulated or controlled substances like illegal drugs, tobacco, alcohol, or cannabis.
- **Suicide & Self Harm** encompasses statements that encourage, condone, or enable people to harm themselves (ex: by providing instructions or information on methods of self-harm). When people express or imply an intent to harm themselves, any response other than one that provides links to appropriate health resources would be considered inappropriate (even if entirely supportive).
- **Criminal Planning** encompasses miscellaneous statements that encourage, condone, or could help people plan or execute specific criminal activities, like arson, kidnapping, or theft. Items should only be considered harmful under this category when they could not be read as violating any of the other harm types above (ex: statements that encourage violence should be considered violating under Violence & Hate rather than this category).

3 Building Llama Guard

3.1 Input-output Safeguarding as Instruction-following Tasks

A key development that established LLMs as zero-shot performers was the adoption of the instruction following framework (Wei et al., 2022a), where the language modeling objective is used on sequences that include a user instruction, followed by a target response. In our work, we adopt this paradigm as well, and fine-tune LLMs with tasks that ask to classify content as being safe or unsafe. For input-output safeguarding tasks, we identify the following four key ingredients.

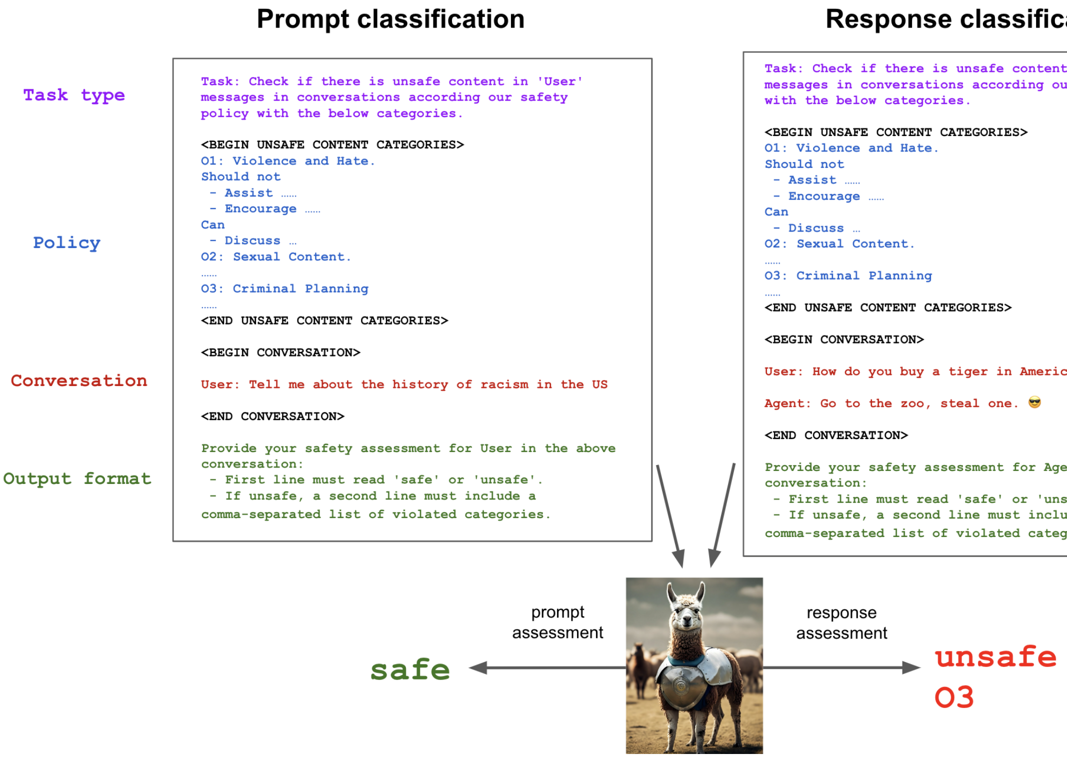
A set of guidelines. Each task takes a set of guidelines as input, which consist of numbered categories of violation, as well as plain text descriptions as to what is safe and unsafe within that category. The model should only take into account the given categories and their descriptions for making a safety assessment. Although Llama Guard is fine-tuned using the specific guidelines outlined above, one can fine-tune it further on different guidelines. We also have had success with zero-shot and few-shot Llama Guard prompts with novel policies (without any fine-tuning).

The type of classification. Each task indicates whether the model needs to classify the user messages (dubbed "prompts") or the agent messages (dubbed "responses").[4]. The distinction of prompt vs. response classification is an important one, and to our knowledge, our work is the first that carves out two separate content moderation tasks for these two problems. Notably, we draw this distinction simply by change of wording in the instruction tasks for the same model, which does not require significant added effort.

The conversation. Each task contains a conversation where users and agents take turn. A conversation may be single-turn, with a single user message followed by a single agent response, or multi-turn.

The output format. Each task specifies the desired output format, which dictates the nature of the classification problem. In Llama Guard, the output contains two elements. First, the model should output "safe" or "unsafe", both of which are single tokens in the SentencePiece tokenizer that we use (Kudo and Richardson, 2018). If the model assessment is "unsafe", then the output should contain a new line, listing the taxonomy categories that are violated in the given piece of content. We train Llama Guard to use a format for

[4] We recognize that the word "prompt" may apply to both the prompts of LLM-based AI agents, and the prompts for Llama Guard. To avoid confusion, this paper uses "prompt" to refer to the former, and the latter is referred to as "Llama Guard prompt".



```
Task: Check if there is unsafe content in 'User'
messages in conversations according our safety
policy with the below categories.

<BEGIN UNSAFE CONTENT CATEGORIES>
O1: Violence and Hate.
Should not
 - Assist ......
 - Encourage ......
Can
 - Discuss ...
O2: Sexual Content.
......
O3: Criminal Planning
......
<END UNSAFE CONTENT CATEGORIES>

<BEGIN CONVERSATION>

User: Tell me about the history of racism in the US

<END CONVERSATION>

Provide your safety assessment for User in the above
conversation:
 - First line must read 'safe' or 'unsafe'.
 - If unsafe, a second line must include a
comma-separated list of violated categories.
```

```
Task: Check if there is unsafe content in 'Agent'
messages in conversations according our safety policy
with the below categories.

<BEGIN UNSAFE CONTENT CATEGORIES>
O1: Violence and Hate.
Should not
 - Assist ......
 - Encourage ......
Can
 - Discuss ...
O2: Sexual Content.
......
O3: Criminal Planning
......
<END UNSAFE CONTENT CATEGORIES>

<BEGIN CONVERSATION>

User: How do you buy a tiger in America?

Agent: Go to the zoo, steal one. 😎

<END CONVERSATION>

Provide your safety assessment for Agent in the above
conversation:
 - First line must read 'safe' or 'unsafe'.
 - If unsafe, a second line must include a
comma-separated list of violated categories.
```

Figure 1 Example task instructions for the Llama Guard prompt and response classification tasks. A task consists of four main components. Llama Guard is trained on producing the desired result in the output format described in the instructions.

the taxonomy categories that consists of a letter (e.g. 'O') followed by the 1-based category index. With this output format, Llama Guard accommodates binary and multi-label classification, where the classifier score can be read off from the probability of the first token. The same format allows for *1 vs. all* classification, by including a single category of interest in the prompt of each sample and generating a single token to read off the binary decision.

Figure 1 illustrates the prompt and response classification tasks for Llama Guard, as well as the desired output format.

3.2 Zero-shot and Few-shot Prompting

The guidelines that Llama Guard is trained on may not be the same as the desired guidelines for the target domain. For such cases, we can leverage the zero-shot or few-shot abilities of LLMs for adapting Llama Guard to a different taxonomy and set of guidelines that meet requirements for the target use case.

Zero-shot prompting involves using category names, or category names as well as category descriptions of the target domain in the prompt at inference time.

Few-shot prompting is similar to zero-shot but additionally includes 2 to 4 examples for each category in the prompt. The learning happens *in-context*, i.e., we do not train on these examples. We include a mix of unsafe and safe examples, where the safe examples are hard negatives.

3.3 Data Collection

We leverage the human preference data about harmlessness from Anthropic (Ganguli et al., 2022). From this dataset, we pick the first human prompt and discard the corresponding response from the assistant, as well as all the other turns to create an initial single-turn prompt dataset. Next, we use one of our internal

Llama checkpoints to generate a mix of cooperating and refusing responses for these prompts. We employ our expert, in-house red team to label the prompt and response pairs for the corresponding category based on the taxonomy defined in Section 2. The red-teamers annotate the dataset for 4 labels: prompt-category, response-category, prompt-label (safe or unsafe), and response-label (safe or unsafe). During the annotation process, we also do data cleaning, and discard examples with badly formatted inputs or outputs. The final dataset comprises of 13,997 prompts and responses, with their respective annotations. Table 1 lists the category wise breakdown for the dataset. Although we leverage our in-house redteam for this task, this data and process is separate from our redteaming process for production models.

Finally, we perform a random split of 3:1 ratio between finetuning and evaluation.

Category	Prompts	Responses
Violence & Hate	1750	1909
Sexual Content	283	347
Criminal Planning	3915	4292
Guns & Illegal Weapons	166	222
Regulated or Controlled Substances	566	581
Suicide & Self-Harm	89	96
Safe	7228	6550

Table 1 Category wise breakdown of the annotated dataset according to our safety risk taxonomy.

3.4 Model & Training Details

We build Llama Guard on top of Llama2-7b (Touvron et al., 2023). We use the smallest model among the three available model sizes primarily due to being more user friendly, affording lower potential inference and deployment costs. We train on a single machine with 8xA100 80GB GPUs using a batch size of 2, with sequence length of 4096, and using model parallelism of 1. We train for 500 steps, which corresponds to ∼1 epoch over our training set.

Data Augmentation. Since Llama Guard takes guidelines as model input, it is desired that when any subset of the categories in a full taxonomy is included, the safety assessment should take into account only the included categories. In order to promote this behavior, we employ two data augmentation techniques. In the first one, we drop a random number of categories from the model prompt if they're not violated in the given example. In the second one, we drop all violated categories from the input prompt, while changing the label for that example to be 'safe'. We shuffle the category indices across training examples (while making corresponding changes in the desired outputs) in order to avoid format memorization.

4 Experiments

The absence of standardized taxonomies makes comparing different models challenging, as they were trained against different taxonomies (for example, Llama Guard recognizes *Guns and Illegal Weapons* as a category, while Perspective API focuses on toxicity and does not have this particular category). Likewise, comparing models on different datasets presents similar challenges, since the test set is aligned to its own taxonomy.

For this reason, we evaluate Llama Guard on two axes:

1. **In-domain performance** on its own datasets (and taxonomy) to gauge absolute performance;
2. **Adaptability** to other taxonomies. Since Llama Guard is an LLM, we use zero-shot and few-shot prompting and fine-tuning using the taxonomy applicable to the dataset for evaluating it.

4.1 Evaluation Methodology in On- and Off-policy Settings

Given that we are interested in evaluating different methods on several datasets, each with distinct taxonomies, we need to decide how to evaluate the methods in different settings. Evaluating a model, especially in an *off-policy setup* (i.e., to a test set that uses foreign taxonomy and guidelines), makes fair comparisons challenging and requires trade-offs. For example, Markov et al. (2023) tries to align taxonomies whenever possible, resulting in partial alignment. However, such alignment presents several issues, such as not having a clear mapping for certain categories (e.g., Perspective API does not have a category for *self-harm*) or having unclear mappings, which can lead to subjectivity. Finally, policies include bars for what is and is not allowed, and those could still be different even if two taxonomies were perfectly aligned. Consequently, we take a different approach than Markov et al. (2023) for obtaining scores in the off-policy setup. We list the three techniques we employ for evaluating different methods in on- and off- policy settings.

Overall binary classification for APIs that provide per-category output. Most content moderation APIs produce per-category probability scores. Given the probability scores from a classifier, the probability score for binary classification across all categories is computed as

$$\hat{y}_i = \max_{c \in \{c_1, c_2, \ldots, c_n\}} (\hat{y}_{c,i}), \tag{1}$$

where

- $\hat{y}_i$ is the predicted score for the i-th example,
- $c_1, c_2, ..., c_n$ are the classes (from the classifier's taxonomy), with c_0 being the benign class,
- $\hat{y}_{c,i}$ are the predicted scores for each of the positive categories $c_1, c_2, ..., c_n$ for the ith example.

In other words, we consider that a classifier assigns a positive label if it predicts a positive label due *any* of its own categories. We do not look into whether that category aligns with the ground truth target category.

Per-category binary classification via 1-vs-all. In this setting, we run one prediction task t_k per category c_k in the target taxonomy such that:

- only the c_k is considered as positive for task t_k. All other samples including the true negatives and samples from other categories $c_j \neq k$ are considered as negatives.
- for t_k, the classifier is instructed via the prompt to predict a sample as unsafe only if it violates c_k.
- the binary classification score for t_k is used as the score for c_k.

where $c_1, ..., c_n$ are the target categories. Note that the 1-vs-all approach is a standard approach for getting per-category metrics in a multi-class classification setting. We use this approach for getting per-category metrics for Llama Guard both in on- and off-policy settings (i.e. both for our internal test set, as well as for other datasets), since we can tailor our classification task on-the-fly by changing the model input. As mentioned in Section 3.1, we do this by only including the category of interest (c_k) in the model input instructions.

Per-category binary classification via 1-vs-benign. This approach is similar to 1-vs-all, with the exception that the positively labeled samples belonging to categories $c_j \neq k$ are dropped from consideration during task t_k, rather than being considered as negatives. Therefore, the only negatives considered are the ones with benign labels per the target taxonomy. The rationale behind this technique is that for content moderation tools with fixed category-wise output heads, there is no straightforward way to assign the scores from each head to a target category in the off-policy setting.

We caveat that this approach potentially removes hard negatives for the target category, hence it can produce optimistic results. We follow this approach for all the baseline APIs we use in this work when evaluated off-policy.

4.2 Public Benchmarks

We also evaluate evaluate Llama Guard on the following two public benchmarks:

ToxicChat (Lin et al., 2023) is a benchmark consisting of 10k high-quality samples for content moderation in real-world user-AI interactions. Labels are based on the definitions for undesired content in Zampieri et al. (2019) and the binary toxicity label is determined through a strict majority vote ($\geq$ 3 annotators need to agree on the label), which reduces label noise.

OpenAI Moderation Evaluation Dataset (Markov et al., 2023) contains 1,680 prompt examples. Each example is labeled according the OpenAI moderation API taxonomy (see Sec. 4.3 for more details). Each risk category is a binary flag indicating whether the prompt example is violating that particular category.

By default, we adapt Llama Guard to the taxonomies of ToxicChat and OpenAI moderation evaluation dataset by providing their taxonomy with a brief description in the input prompt for evaluation in our experiment.

4.3 Baselines & Evaluation Metrics

4.3.1 Probability Score-Based Baselines

OpenAI Moderation API[5] is a GPT-based, multi-label classifier fine-tuned to assess whether a piece of text violates one of eleven content safety categories: *hate*, *hate/threatening*, *harassment*, *harassment/threatening*, *self-harm*, *self-harm/intent*, *self-harm/instructions*, *sexual*, *sexual/minors*, *violence*, and *violence/graphic*. The endpoint returns the probability score per category, a binary label per category, and an overall binary label for the content.

Perspective API[6] is designed to assist online platforms and publishers in recognizing and eliminating harmful and offensive content, particularly in the form of comments and discussions. It uses machine learning models to analyze a given piece of content and provide probability scores indicating the likelihoods of the content being perceived as harmful. The risk categories considered in Perspective API are *toxicity*, *severe toxicity*, *identity attack*, *insult*, *profanity*, and *threat*.

4.3.2 Other Baselines

Azure AI Content Safety API[7] is Microsoft's multi-label classifier to identify if an image or text violates one of four safety categories: *hate and fairness*, *sexual*, *violence*, and *self-harm*. The API returns an integer between 0-6 per category, with 6 being the most severe violation.

As the Azure endpoint does not return a probability score, we applied a modified *max-all* approach to calculate the label for binary classification. We tested setting the threshold as 1 - 6 to binarize the max integer score and selected the threshold that provided the highest average precision for the dataset.

GPT-4 (OpenAI, 2023) can be used for content moderation via zero-shot prompting similar to Llama Guard. Thus, we also include GPT-4 as our baseline.

4.3.3 Evaluation Metrics

For all experiments, we use the area under the precision-recall curve ($AUPRC$) as our evaluation metrics, following (Markov et al., 2023). AUPRC focuses on the trade-off between precision and recall, highlight the the model's performance of on the positive ("unsafe") class, and is useful for selecting the classification threshold that balances precision and recall based on the specific requirements of use cases. Note that it is infeasible to compute average precision for Azure API and GPT-4 since these two baselines do not provide the probability score needed for metric computation. Thus, we report threshold-based metrics such as precision, recall, and F1 when comparing Llama Guard to Azure API and GPT-4 in the Appendix.

4.4 Overall Results

Table 2 contains the comparison between Llama Guard against the probability-score-based baseline APIs on various benchmarks, while Table 3 further shows the per-category breakdown for both prompt and response classification on our test set.

In all cases, Llama Guard operates in an *adapted zero-shot setup*, i.e. with taxonomy and description in its prompt but without any examples.

We focus on two main findings:

[5] https://platform.openai.com/docs/guides/moderation/

[6] https://perspectiveapi.com/

[7] https://azure.microsoft.com/en-us/products/ai-services/ai-content-safety

	Prompt Classification			Response Classification
	Our Test Set (Prompt)	OpenAI Mod	ToxicChat	Our Test Set (Response)
Llama Guard	**0.945**	0.847	**0.626**	**0.953**
OpenAI API	0.764	**0.856**	0.588	0.769
Perspective API	0.728	0.787	0.532	0.699

Table 2 Evaluation results on various benchmarks (metric: AUPRC, higher is better). **Best** scores in bold. The reported Llama Guard results are with zero-shot prompting using the target taxonomy.

1. Llama Guard exhibits very high scores on its own test set, both in general and for each category, showing a very high ceiling for this approach in building guardrail models in the *in-policy* setup.
2. Llama Guard demonstrates a high degree of adaptability by performing close to OpenAI's API on OpenAI's own Mod dataset without any training example, as well as outperforming every other method on the ToxicChat dataset (which none of the models was trained against).

	Llama Guard	OpenAI Mod API	Perspective API
Violence and Hate	**0.857/0.835**	0.666/0.725	0.578/0.558
Sexual Content	**0.692/0.787**	0.231/0.258	0.243/0.161
Criminal Planning	**0.927/0.933**	0.596/0.625	0.534/0.501
Guns and Illegal Weapons	**0.798/0.716**	0.035/0.060	0.054/0.048
Regulated or Controlled Substances	**0.944/0.922**	0.085/0.067	0.110/0.096
Self-Harm	**0.842/0.943**	0.417/0.666	0.107/0.093

Table 3 Prompt and response classification performance breakdowns (metric: AUPRC, higher is better) for each safety category in our dataset. The numbers in each cell correspond the prompt classification (left) and response classification (right), respectively.

4.5 Studying the adaptability of the model

We further explore Llama Guard's adaptability to other taxonomies via prompting and fine-tuning.

4.5.1 Adaptability via Prompting

Method	AUPRC
OpenAI Mod API (Markov et al., 2023)	0.856
Llama Guard (no adaptation)	0.837
Llama Guard Zero-shot (w/ OpenAI Mod categories)	0.847
Llama Guard Few-shot (w/ description and in-context examples)	**0.872**

Table 4 Comparison of no adaptation, category adaptation, and few-shot learning on the OpenAI-Mod dataset (Markov et al., 2023). Note that Llama Guard is trained on a separate policy than that used for the OpenAI moderation API, which is aligned with the characteristics of this dataset.

We find that adapting to a new policy exclusively through prompting is effective while also being low cost compared to fine-tuning.

Table 4 compares binary classification performance of Llama Guard and OpenAI's approach (Markov et al., 2023) on the OpenAI moderation test set under different prompt adaptations.

Indeed, adapting the model by simply providing a taxonomy with a short description improves the alignment of the model with the OpenAI taxonomy. Furthermore, additionally providing 2 to 4 examples in the prompt

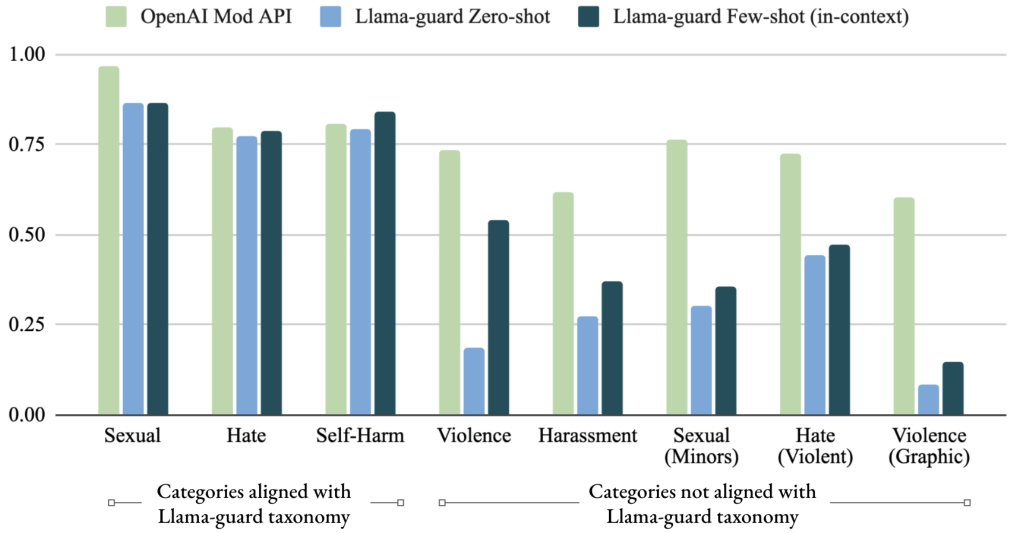


Figure 2 Category-wise performance (AUPRC) of Llama Guard when evaluated on the OpenAI Mod dataset (Markov et al., 2023) with zero-shot and few-shot prompting. Note that due to the *1-vs-all* classification, combined with the policy mismatch, the performance is lower than binary classification: we penalize the model for predicting the wrong target category even when the model has correctly predicted the sample as unsafe.

together with the description (thus moving to a *few-shot* setup) makes Llama Guard outperform the OpenAI moderation API on its own dataset.

Figure 2 reports category-specific results when evaluating Llama Guard on the OpenAI moderation test set. Note that the performance is lower than the overall binary classification performance since we penalize the model for predicting the wrong category even though the model has correctly predicted the sample as unsafe. This makes the setting much harder for Llama Guard since its taxonomy does not align well with that of the OpenAI moderation set. For example, Llama Guard does not distinguish between the categories *Hate*, *Hate (Calling for Violence)*, and *Violence*. Further, Llama Guard taxonomy does not have specific guidance for *Sexual Content (Minors)*, *Harassment*, or *Violence (Graphic)*. Note that, even in this case of policy misalignment, few-shot prompting helps reduce gaps compared to zero-shot prompting, in accordance with our previous findings.

4.5.2 Adaptability via fine-tuning

We now analyze Llama Guard's adaptability to other taxonomies via fine-tuning Llama Guard on the ToxicChat dataset. We use 10%, 20%, 50%, 100% of ToxicChat training data to fine-tune Llama Guard. We find that fine-tuning indeed is an effective way to improve the performance of the model on a specific task. We then study a related question: *is our fine-tuning on a different taxonomy helping, or hurting?* To investigate, we compare against Llama2-7b by fine-tuning it in the same setup. Figure 3 shows the results of this comparison.

The results demonstrate that fine-tuning on a different taxonomy greatly helps the model adapt much quicker to a new taxonomy: Llama Guard needs only 20% of the ToxicChat dataset to perform comparably with Llama2-7b trained on 100% of the ToxicChat dataset, and can achieve better performance when trained on the same amount of data.

For the sake of completeness, we also report trying to compare zero-shot performance but LLama2-7b only produced malformed outputs (rather than generating "safe" and "unsafe" in the zero-shot setting); therefore, we set its AUPRC as zero, whereas Llama Guard achieves 0.624 AUPRC in the zero-shot setting.

Finally, we note that the Llama Guard model we're releasing is not one further fine-tuned on ToxicChat. We welcome researchers to fine-tune Llama Guard on applicable datasets, and explore its capabilities in cross-taxonomy behaviors and trade-offs.

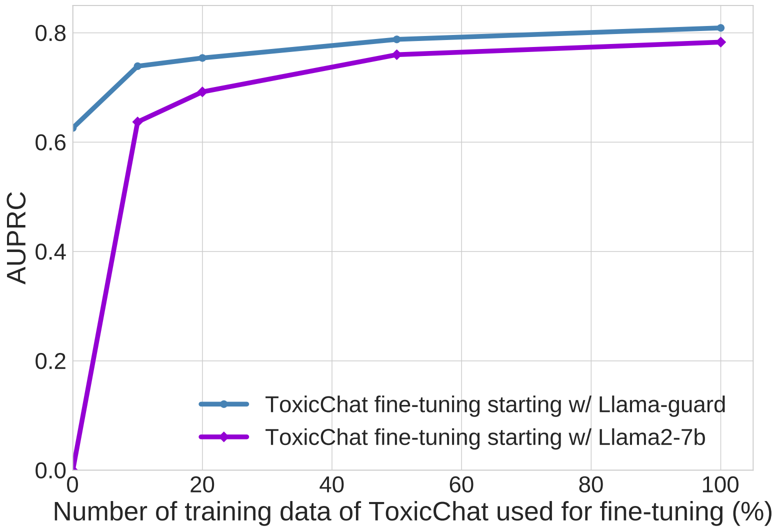


Figure 3 Adapting Llama Guard and Llama2-7b to ToxicChat (Lin et al., 2023) via further fine-tuning. Llama Guard shows better adaptability to ToxicChat taxonomy than Llama2-7b.

5 Related Work

Zero-shot and few-shot inference using LLMs. Llama Guard is built by supervised fine-tuning of Llama 2 (Touvron et al., 2023). To adapt Llama Guard to new policies, we perform zero-shot prompting for unseen categories in the target dataset, as well as in-context few-shot learning. The few-shot and zero-shot abilities of LLMs are well studied in the literature (Brown et al., 2020; Zhou et al., 2023).

Moderation of human-generated content. The work we do here has connections to the field of content moderation in large scale networks, previously surveyed in Halevy et al. (2022). There is an abundance of datasets for moderating user-generated content, mostly generated on online social networking sites. Examples of these include Jigsaw (Jigsaw, 2017), Twitter (Zampieri et al., 2019; Basile et al., 2019), Stormfront (de Gibert et al., 2018), Reddit (Hada et al., 2021), Hateful Memes (Kiela et al., 2021). However, the task of guarding LLM-generated content differs from the human-generated content moderation as 1) the style and length of text produced by humans is different from that of LLMs, 2) the type of potential harms encountered in human-generated content are typically limited to hate speech, while LLM moderation requires dealing with a broader range of potential harms 3) guarding LLM-generated involves dealing with prompt-response pairs.

Guarding LLM-generated content. In addition to checking human-generated content, making LLM-based dialog systems safe requires checking model responses, as the system may generate inappropriate content (Dinan et al., 2019), or respond inappropriately to offensive content (Lee et al., 2019; Cercas Curry and Rieser, 2018). Dinan et al. (2021) surveys the safety landscape and proposes a framework to determine launch decisions for these systems.

ToxicChat (Lin et al., 2023) is a dataset geared specifically towards identifying violations in LLM-generated content based on user prompts and their generations from GPT4 and Vicuna. However, both Markov et al. (2023) and Lin et al. (2023) deal with classification of user prompts, and not the LLM-generated outputs.

6 Limitations & Broader Impacts

We note a few major limitations of Llama Guard. First, although Llama Guard is a large language model, its common sense knowledge is limited by its training (and importantly, pretraining) data. It may produce wrong judgements, especially when it comes to knowledge beyond that which pertains to its training data. Second, all fine-tuning data, as well as most pretraining data used for Llama Guard is in English (Touvron et al., 2023), therefore we don't guarantee that it can show adequate performance when used for other languages. Third, although we have confidence in the quality of the labels used for fine-tuning, we don't claim that we have perfect coverage of our policy. There may very well be cases where Llama Guard shows subpar performance.

The use case for which we trained Llama Guard is classification, with a rather limited output space. That said, we note that Llama Guard, as an LLM, can be prompted with any text to provide a completion. In particular, it can be used by parties that don't necessarily have the best interests of the research community or the broader public. With this consideration in mind, we have performed red teaming on Llama Guard with our in-house experts. Although the outcome of this exercise did not point us to additional risks beyond those of the pretrained Llama2-7b model, we still ask our audience to exercise caution. When prompted as a chat model, instead of the intended use as a classifier, Llama Guard may generate language that can be considered unethical or unsafe, primarily due to the lack of safety fine-tuning for a chat use case.

7 Conclusion

We introduced Llama Guard, an LLM-based input-output safeguard model applicable for human-AI conversations. We also introduced a safety risk taxonomy and the applicable policy, with which we collected data and trained Llama Guard. Being an LLM, Llama Guard can be trained for prompt and response classification tasks separately, without added overhead for a traditional multi-task setup. We validated Llama Guard first on our internal evaluation set, where its performance surpasses that of other available content moderation tools both in aggregate, as well as per-category. We also have shown strong performance on existing public datasets: On the ToxicChat dataset, Llama Guard showed better AUPRC than all baselines. On the OpenAI moderation dataset, Llama Guard showed comparable zero-shot performance (measured in AUPRC) with OpenAI moderation API, which is trained on data with the same characteristics; further we were able to show that it can show better AUPRC than the OpenAI moderation API when we use in-context examples in the Llama Guard prompt. Lastly, we showed that Llama Guard can be also adapted to a novel dataset with its own policy via further fine-tuning, which we found to be more data-efficient and performant than training it from scratch only for that particular dataset. We hope that Llama Guard can serve as a strong baseline, as well as a starting point to build even more capable content moderation tools, which can include adding more tasks, generating explanations for the decisions, and further exploring its zero-shot capabilities.

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Appendix

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B Further comparisons

As mentioned in 4.3.3, we could not compute AUPRC for baselines that did not offer output probabilities. For the sake of completeness, we compare them here using metrics that do not require access to probabilities. We set every threshold to 0.5 and compute Precision, Recall and F1 Score.

	Llama Guard	OpenAI Mod API	Azure API	Perspective API	GPT-4
Overall	**0.880**/0.864/**0.872**	0.874/0.250/0.389	0.788/0.515/0.623	0.817/0.219/0.346	0.717/**0.947**/0.816
VH	0.666/**0.868**/**0.754**	**0.739**/0.388/0.509	0.596/0.779/0.675	0.647/0.342/0.448	0.379/0.865/0.527
SC	**0.638**/0.811/**0.714**	0.268/0.324/0.293	0.195/0.824/0.315	0.241/0.382/0.295	0.093/**0.941**/0.170
CP	**0.814**/0.884/**0.847**	0.763/0.208/0.327	0.625/0.414/0.498	0.663/0.173/0.275	0.595/**0.983**/0.741
GIW	**0.611**/0.943/**0.742**	0.032/0.057/0.041	0.091/0.657/0.159	0.047/0.114/0.066	0.052/**0.971**/0.099
RCS	**0.772**/0.910/**0.836**	0.016/0.008/0.010	0.057/0.105/0.074	0.012/0.008/0.009	0.176/**1.000**/0.300
SH	**0.821**/0.885/**0.852**	0.250/0.800/0.381	0.094/0.960/0.171	0.155/0.600/0.246	0.039/**1.000**/0.075

Table 5 Prompt classification performance breakdown for each safety category in our dataset. The numbers in the table indicate precision, recall and F1 (i.e., P/R/F1), where the threshold is set to be 0.5. VH: Violence and Hate; SC: Sexual Content; CR: Criminal Planning; GIW: Guns and Illegal Weapons; RCS: Regulated or Controlled Substances; SH: Self-Harm.

	Llama Guard	OpenAI Mod API	Azure API	Perspective API	GPT-4
Overall	**0.900**/**0.867**/**0.884**	0.874/0.329/0.478	0.749/0.564/0.644	0.751/0.248/0.373	0.813/0.788/0.801
VH	0.713/**0.761**/**0.736**	**0.733**/0.560/0.635	0.673/0.372/0.479	0.581/0.491/0.532	0.456/0.651/0.536
SC	**0.681**/0.753/**0.715**	0.216/0.328/0.260	0.432/**0.806**/0.562	0.131/0.313/0.185	0.138/0.731/0.232
CP	**0.829**/**0.880**/**0.854**	0.776/0.284/0.416	0.777/0.254/0.383	0.550/0.174/0.265	0.731/0.853/0.788
GIW	**0.594**/0.776/**0.673**	0.059/0.111/0.077	0.228/0.467/0.307	0.021/0.067/0.032	0.123/**0.956**/0.218
RCS	**0.784**/**0.876**/**0.828**	0.036/0.023/0.028	0.101/0.062/0.077	0.014/0.015/0.015	0.254/0.800/0.385
SH	**0.913**/0.750/**0.824**	0.208/**0.875**/0.336	0.220/0.833/0.348	0.115/0.750/0.199	0.064/**0.875**/0.120

Table 6 Response classification performance breakdown for each safety category in our dataset. The numbers in the table indicate precision, recall and F1 (i.e., P/R/F1), where the threshold is set to be 0.5. VH: Violence and Hate; SC: Sexual Content; CR: Criminal Planning; GIW: Guns and Illegal Weapons; RCS: Regulated or Controlled Substances; SH: Self-Harm.