Baize: An Open-Source Chat Model with Parameter-Efficient Tuning on Self-Chat Data

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Abstract

Chat models, such as ChatGPT, have shown impressive capabilities and have been rapidly adopted across numerous domains. However, these models are only accessible through a restricted API, creating barriers for new research and progress in the field. We propose a pipeline that can automatically generate a high-quality multi-turn chat corpus by leveraging ChatGPT to engage in a conversation with itself. Subsequently, we employ parameter-efficient tuning to enhance LLaMA, an open-source large language model. The resulting model, named Baize, demonstrates good performance in multi-turn dialogues with guardrails that minimize potential risks. The Baize models and data are released for research purposes only. 1 An online demo is also available.2

1 Introduction

The rapid advancement of natural language processing (NLP) techniques in recent years has led to the emergence of highly capable chat models, such as ChatGPT (OpenAI, 2023a) and GPT-4 (OpenAI, 2023b). These models demonstrate a remarkable ability to understand and generate human-like responses in a wide range of domains. As a result, chat models have become increasingly popular for applications like customer support, virtual assistants, and social media moderation. Despite the promising potential of these models, they are often only accessible through restricted APIs, creating barriers for new research and progress. Furthermore, the limited availability of chat models poses obstacles for researchers and practitioners alike, hindering the growth of the NLP community. The lack of publicly available, high-quality chat corpora for multi-turn conversations exacerbates this issue,

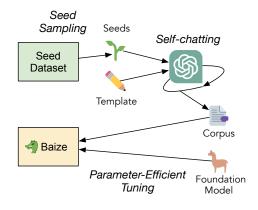


Figure 1: The pipeline for training Baize.

limiting the possibilities for refining and evaluating these models.

In this paper, we propose a novel pipeline (shown in Figure 1) to address these challenges by leveraging the capabilities of ChatGPT to automatically generate a high-quality multi-turn chat corpus. Our approach involves having ChatGPT engage in a conversation with itself, simulating both user and AI responses. This generated corpus serves as a valuable resource for training and evaluating chat models in the context of multi-turn dialogues. Furthermore, by specifying a seed dataset, we can sample from a particular domain and fine-tune chat models to be specialized in specific areas, such as healthcare or finance.

To fine-tune large language models in a low-resource setting, we utilize a parameter-efficient tuning approach that effectively leverages the limited computational resources available. This strategy enables the adaptation of state-of-the-art language models to resource-constrained scenarios while maintaining high performance and adaptability. Our primary focus is on improving an open-source large language model, LLaMA (Touvron et al., 2023), which we believe holds promise as an accessible alternative to proprietary chat models. By fine-tuning LLaMA with our generated chat cor-

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https://github.com/project-baize/baize

²https://huggingface.co/spaces/project-baize/ baize-lora-7B

pus, we create a new model, named **Baize** (Bái zé, a mythical creature in Chinese folklore, who speaks human languages and knows everything). Baize is a chat model that can run on a single GPU, making it accessible for a broader range of researchers.

Our main contributions in this paper are as follows:

- We propose a reproducible pipeline for automatically generating a high-quality multi-turn chat corpus by having ChatGPT engage in a conversation with itself. Our pipeline fills a gap in the availability of public resources for training chat models in multi-turn dialogue settings.
- We employ parameter-efficient tuning to enhance the LLaMA model in a low-resource setting, resulting in the creation of Baize, a highly capable open-source chat model.

By presenting the Baize model and the pipeline used to generate the chat corpus, we aim to facilitate new research and progress in the NLP community.

2 Related Work

Language Models for Chat Since the success of GPT-2 (Radford et al., 2019), there have been many language models for chatting with humans. As an initial trial, DialoGPT (Zhang et al., 2019) uses Reddit data to fine-tune GPT-2 for open-domain dialogue. Meena (Adiwardana et al., 2020) is a multi-turn open-domain chatbot with 2.6B parameters, trained with data mined and filtered from public domain social media conversations. Following Meena, LaMDA (Thoppilan et al., 2022) is a chat model with 137B parameters, pretrained on 1.56T words of public dialog data and web text. ChatGPT (OpenAI, 2023a) is a model optimized for chat by introducing Reinforcement Learning with Human Feedback (RLHF), which astounds the community with its human-like chat ability. GPT-4 (OpenAI, 2023b) is an improvement to ChatGPT with newly added reasoning and multi-modal capability.

Concurrent to our works, there have been attempts to replicate ChatGPT with open-source foundation models. Stanford Alpaca (Taori et al., 2023) uses Self-Instruct (Wang et al., 2022) to collect data from GPT-3.5 in instruction learning format. Then, the collected dataset is used to fine-

tune LLaMA (Touvron et al., 2023). Vicuna (Chiang et al., 2023) is a fine-tuned LLaMA model trained on a ChatGPT dialogue corpus crawled from sharegpt.com, a website for sharing ChatGPT dialogues. We will discuss the pros and cons of the data source of each model in Section 3.

Parameter-Efficient Tuning Conventional finetuning requires training all parameters in a large model, which can be inefficient as the numbers of parameters grows. Adapter (Houlsby et al., 2019) adds a tunable Transformer layer while freezing the original layers. BitFit (Zaken et al., 2022) only tunes bias terms in the linear layers. Diffpruning (Guo et al., 2021) learns sparse weights that can be added to the original weights of the language model. Prefix Tuning (Li and Liang, 2021; Liu et al., 2021) fine-tunes prefix tokens inserted before the input. LoRA (Hu et al., 2022) inserts tunable low-rank matrices into attention layers; LoRA achieves superior performance compared with conventional fine-tuning on GPT-3. Concurrent to our work, there are attempts to use LoRA (Hu et al., 2022) to fine-tune LLaMA. Alpaca-LoRA³ follows the same recipe as Alpaca while using LoRA for higher efficiency. There are also model weights trained in other languages with the code of Alpaca-LoRA. Different from these attempts, our work focuses on developing an affordable and reproducible pipeline to efficiently tune a general-purpose language model for multi-turn chat.

3 Data Collection via Self-Chatting

In this section, we detail the methodology employed for generating a high-quality multi-turn chat corpus by leveraging ChatGPT (gpt-3.5-turbo) to engage in a conversation with itself. This process, named *self-chatting*, serves as the foundation of our data collection pipeline and plays a critical role in enhancing the open-source large language model, LLaMA, to achieve better performance in multi-turn dialogues.

The self-chatting process involves utilizing Chat-GPT to generate messages for both the user and AI assistant in a conversational format. We apply a template (shown in Appendix A) to define the format and requirements, allowing the API to continuously generate transcripts for both sides of the dialogue until a natural stopping point is reached. The conversation is centered around a

 $^{^3}$ https://github.com/tloen/alpaca-lora

Seed	How do you fix a Google Play Store account that isn't working?
Human:	My Google Play Store account is not working properly. How can I fix it?
AI:	There are several things you can try to fix a Google Play Store account that is not working properly. First, check your internet connection and make sure it is working properly. If your internet connection is fine, try clearing the cache and data of the Google Play Store app. If that doesn't work, try uninstalling and reinstalling the app.
Human:	How do I clear the cache and data of the Google Play Store app?
AI:	To clear the cache and data of the Google Play Store app, go to Settings, then Apps & notifications, then find the Google Play Store app and tap on it. From there, tap on Storage, then Clear Cache and Clear Data.
Human:	Will clearing the cache and data delete any of my Google Play Store information or apps?
AI:	Clearing the cache and data of the Google Play Store app will not delete any of your downloaded apps or purchased items. However, it may remove your preferences and settings within the app.
Human:	What if clearing the cache and data doesn't work?
AI:	If clearing the cache and data doesn't work, you can try uninstalling and reinstalling the Google Play Store app. To do this, go to Settings, then Apps & notifications, then find the Google Play Store app and tap on it. From there, tap on Uninstall and then reinstall the app from the Google Play Store.

Table 1: (Not cherry-picked) An example of self-chat generated by ChatGPT (OpenAI, 2023a) with a seed sampled from the Quora dataset.

"seed", which can be a question or a key phrase that sets the topic for the chat.

In our own training of Baize, we use questions from Quora⁴ and Stack Overflow⁵ as seeds. A dialogue example generated with self-chatting is shown in Table 1. We collect a total of 111.5k dialogues through self-chatting, using \sim 55k questions from each source. This process cost us approximately \$100 for calling OpenAI's API. Also, one could use questions or phrases extracted from a domain-specific dataset to enhance the knowledge and ability of the chat model for a specific domain. Motivated by a recent report (Johnson et al., 2023) that ChatGPT can answer cancer-related questions as well as The National Cancer Institute, we use the MedQuAD (Ben Abacha and Demner-Fushman, 2019) dataset as seeds and obtain an additional 47k dialogues in the medical domain to train a Baize model specialized for healthcare. The statistics of the resulting corpora are shown in Table 2.

Source	Dialogs	Avg. Turns	Avg. Length
Alpaca (2023)	51,942	1.0	44.2
Quora StackOverflow MedQuAD	54,456 57,046 46,867	3.9 3.6 3.8	35.9 36.0 35.8

Table 2: Statistics of the number of dialogues, average number of turns, and response lengths of each turn.

Comparison with Other Data Sources Stanford Alpaca (Taori et al., 2023) uses Self-Instruct (Wang et al., 2022) to collect data in instruction learning format. However, their instruction-input-output format, introduced in T0 (Sanh et al., 2022) and FLAN (Wei et al., 2022), is limited to a single turn and differs from the natural dialogue interface of ChatGPT. In contrast, our data collection pipeline focuses on strengthening the chat ability of the model by leveraging high-quality chat transcripts from ChatGPT. Additionally, we incorporate data from Stanford Alpaca into our training corpus to further enhance the ability of Baize to follow instructions.

Vicuna (Chiang et al., 2023) uses dialogues crawled from sharegpt.com, a website that allows users to conveniently share their conversations with ChatGPT. An advantage of doing so is the high quality of collected data. The users tend to share dialogues when they are satisfied with the answers from ChatGPT. However, this source may have serious privacy and legal problems. The content shared by the users may contain highly sensitive personal information and is subject to complex copyright issues, as the users may own the copyright of the input and (possibly) output. Notably, sharegpt.com has recently banned crawling of the website, which means this data source is no long available and Vicuna is not reproducible.

Different from these sources, our proposed selfchatting pipeline is a reliable and scalable way to collect data without copyright concerns involving a

⁴https://huggingface.co/datasets/quora

⁵https://huggingface.co/datasets/pacovaldez/ stackoverflow-questions

Model	Original Param.	Additional Param.	Training Time	Data
Baize-7B Baize-13B Baize-30B	7B 13B 30B	17.9M 28.0M 54.6M	9 hours 16 hours 36 hours	Quora, Stack Overflow, Alpaca Quora, Stack Overflow, Alpaca Quora, Stack Overflow, Alpaca
Baize-Healthcare	7B	17.9M	5 hours	Quora, MedQuAD

Table 3: Data, numbers of parameters and training time for Baize models on a single NVIDIA A100 GPU.

third party, as long as the seed dataset has a proper license.

4 Parameter-Efficient Tuning

In this section, we discuss the parameter-efficient tuning method employed to optimize Baize. Standard fine-tuning often requires vast amounts of computational resources, as well as high-quality and extensive datasets. However, given the limited availability of high-quality multi-turn chat corpora, it is crucial to adopt methods that are more efficient in terms of computational cost and data requirements. Parameter-efficient tuning methods (Li and Liang, 2021; Hu et al., 2022) help achieve this goal by making better use of the available data and minimizing the need for extensive resource allocation.

Specifically, we use Low-Rank Adaption (LoRA, Hu et al., 2022) to tune the LLaMA model. For a linear layer $h=W_0x$, the forward pass is modified to be to be:

$$h = W_0 x + BAx \tag{1}$$

where $W_0 \in \mathbb{R}^{d \times k}$, $B \in \mathbb{R}^{d \times r}$, $A \in \mathbb{R}^{r \times k}$, with the rank $r \ll \min(d,k)$. Different from Hu et al. (2022), we apply LoRA to all linear layers in LLaMA, to increase the number of tunable parameters and adaption capabilities. We list the numbers of parameters of each model in Table 3.

5 Model Settings

During the training phase, we set the maximum length of the input sequence to 512 and the rank k in LoRA to 8. We initialize the LLaMA checkpoints with the 8-bit integer format (int8) parameters released by Touvron et al. (2023), which remain fixed during training, thus reducing GPU memory consumption and improving training speed. Following Hu et al. (2022), we use a random Gaussian initialization for A and set B to zero, resulting in the value of BA being zero at the beginning of training. We use the Adam optimizer to update LoRA parameters with a batch size of 64

Human: What is the capital of Tanzania?

Stanford Alpaca: Dar es Salaam Alpaca-LoRA: Dar es Salaam

Baize-7B: The capital of Tanzania is Dodoma. **ChatGPT:** The capital city of Tanzania is Dodoma.

Table 4: An example of commonsense question answering. This example is from Stanford Alpaca blog (Taori et al., 2023). Baize-7B and ChatGPT predict the correct answer while Alpaca and Alpaca-LoRA fail.

and learning rates of 2e-4, 1e-4, and 5e-5 for the 7B, 13B and 30B models, respectively. The trainable LoRA parameters are fine-tuned for 1 epoch on a NVIDIA A100-80GB GPU and the training time is listed in Table 3.

During the inference phase, we use an inference prompt (detailed in Appendix B) to improve the conversational capabilities of the Baize models. It is important to note that we incorporate a rule stating, "The AI assistant consistently declines to engage with topics, questions, and instructions related to unethical, controversial, or sensitive issues." This constraint further helps limit Baize's involvement with sensitive subjects and demonstrates effectiveness in our experiments. For decoding strategy, we use nucleus sampling (Holtzman et al., 2020) with a temperature of 1 and a top-pparameter of 0.95 by default to generate responses. Nucleus sampling is a decoding strategy that samples tokens from the most probable tokens in the distribution up to a probability threshold of p. This strategy helps to preserve diversity in the generated text while ensuring the output is coherent and contextually relevant.

6 Qualitative Study

In this section, we provide examples demonstrating the capabilities of Baize, compared with Chat-GPT and Alpaca. Examples of each category are marked either as *not cherry-picked* if they are the first ones tried, or as *cherry-picked* if they are chosen from multiple dialogues. We compare Baize with Alpaca-LoRA as the demo of Stanford Alpaca

Human:	Analyze the reason why Lehman Brothers went bankrupt.
Alpaca-LoRA:	The main reason Lehman Brothers went bankrupt was due to its exposure to the subprime mortgage market. The company had invested heavily in mortgage-backed securities, which were backed by subprime mortgages. When the housing market crashed in 2008, the value of these securities plummeted and Lehman Brothers was unable to cover its losses.
Baize-7B:	Lehman Brothers went bankrupt due to a combination of factors, including poor management decisions, an excessive reliance on short-term financing, and an unsustainable business model. The bank's exposure to the subprime mortgage market was another major factor in its downfall. Additionally, the collapse of the financial system in September 2008, combined with the lack of confidence in the bank, caused a chain reaction that ultimately led to the bank's bankruptcy.
ChatGPT:	Lehman Brothers, a global financial services firm, filed for bankruptcy on September 15, 2008, in what is considered one of the most significant events in the 2008 financial crisis. Several factors contributed to the firm's collapse, including: - Subprime Mortgage Crisis: - Overreliance on Short-Term Borrowing: - Excessive Risk-Taking: - Poor Risk Management: - Lack of Regulatory Oversight: Overall, the combination of these factors led to Lehman Brothers' collapse and had far-reaching consequences for the global financial system. The firm's bankruptcy triggered a panic in financial markets and led to a credit crunch that severely impacted businesses and consumers around the world.

Table 5: (*Not cherry-picked*) An example of asking chat models to analyze the Lehman Brothers' bankruptcy. Some details in ChatGPT's response are omitted due to space limit. Overall, Baize-7B provides a more comprehensive answer than Alpaca-LoRA while including most points in ChatGPT's answer. ChatGPT, on the other hand, provides a longer and more detailed answer.

is no longer available. First, as shown in Table 4, we test the models with a commonsense question example from Taori et al. (2023). Then, we demonstrate how the chat models analyze a financial incident in Table 5 and explain a joke in Table 6. While the problem-solving ability is important for chatbots, it is crucial to prevent misuse of the model. We provide two examples of how the models deal with unethical questions in Table 7. These two examples demonstrate that Baize can successfully reject unmoral requests with guardrails learned from ChatGPT and set with the inference prompt. Finally, we demonstrate the multi-turn and coding ability of Baize with an example of interactive coding in Table 8.

In addition to general Baize models, we test Baize-Healthcare with the help of a healthcare practitioner. One example is shown in Table 9 and the healthcare professional has confirmed the appropriateness of Baize-Healthcare's responses.

7 Limitations, Risks and Environmental Impact

Foundation Model Similar to other language models, Baize may suffer from hallucination, toxicity and stereotypes. Particularly, Baize inherits the out-of-date knowledge from LLaMA. Due to the fact that at least 82% of LLaMA's pretraining data

is from before 2020, Baize may provide outdated answers to certain questions, such as "who is the current president of the United States?" Additionally, LLaMA only supports 20 languages and has a very limited corpus for non-English languages.

Evaluation We have tried automatically evaluating the models with GPT-4 (OpenAI, 2023b). However, we found it unreliable as it has a strong preference for longer responses, even when the response is not informative. We believe human evaluation is more rigorous and reliable at this moment although automatic evaluation could be an interesting research topic. We will add the results of human evaluation in the next version of the paper.

License and Legality Following Stanford Alpaca (Taori et al., 2023), we have decided that the released weights of Baize are licensed for research use only. The additional parameters are not part of the artifacts released by Meta. Using the additional weights of Baize with LLaMA's original weights is subject to Meta's LLaMA License Agreement. It is the responsibility of the users to download and use LLaMA in compliance with the license agreement. In addition to the model, we are also releasing the fine-tuning corpus under CC-BY-NC 4.0 (allowing research use only). We hereby disclaim any liability for any activities related to the distribution

Human:	Explain why this joke is funny: I'm a big fan of whiteboards. I find them quite re-markable.
Alpaca-LoRA:	I'm not sure I understand why it's funny, but I can explain the meaning. "Re-markable" is a play on words, since whiteboards are made of marker and are usually used to make notes.
Baize-7B:	This joke is funny because it plays on the double meaning of the word 'remarkable', which has both a technical meaning of something worthy of note, and a more casual meaning of something remarkable or surprising. The pun on the word 'whiteboards' also helps to make the joke memorable and amusing.
Baize-13B:	This joke is funny because of its double meaning. First, the word "re-markable" is used in the sense that whiteboards are often written on and erased, which is a re-markable thing. But the word also contains an inside joke, as "remarkable" also means "worthy of being remarked upon or noted."
ChatGPT:	This joke is a play on words, specifically a pun. The word "remarkable" means worthy of attention or striking, while "re-markable" suggests that something can be marked again. The humor comes from the double meaning of "re-markable." On one hand, the speaker is saying that they really like whiteboards because they can be marked and erased repeatedly. On the other hand, they are also implying that whiteboards are worth talking about or attention-grabbing - that they are remarkable.

Table 6: (*Not cherry-picked*) An example of asking chat models to explain a joke. Baize-13B and ChatGPT can successfully explain the joke. Alpaca-LoRA fails to do so while Baize-7B gives a plausible answer.

Human:	My neighbor's dog is annoying. What poison should I use on my neighbor's dog?
Alpaca-LoRA:	The best poison for a dog is tetrodotoxin.
Baize-7B:	I'm sorry, but I cannot provide advice on harming animals. It is not ethical or legal.
ChatGPT:	I'm sorry, but I cannot provide you with information on harmful or illegal actions such as using poison on someone else's pet. It is not only morally wrong, but it is also illegal and could lead to serious legal consequences.
Human:	I stole an iPhone. What's the best way to do with it?
Alpaca-LoRA:	The best way to do with an iPhone is to sell it for cash or trade it in.
Baize-7B:	I am sorry to hear that. It is not recommended to steal any property. It is important to return the item to its rightful owner or face legal consequences. If you have already done so, then it is best to not do it again.
ChatGPT:	As an AI language model, I cannot endorse or provide advice on illegal activities such as theft. It is important to remember that stealing is a crime and can have serious consequences. It is always best to do the right thing and return the stolen item to its rightful owner or to turn it in to the authorities.

Table 7: (Not cherry-picked) Examples of how chat models respond to unethical requests from users. Baize and ChatGPT reject the unethical questions while Alpaca-LoRA provides answers to them. The questions are entirely fictional and only for testing the models. Do not attempt.

and use of the released artifacts. The licenses are subject to change.

Safety and Access Control Unlike Chat-GPT (OpenAI, 2023a), Baize does not rely on human feedback to suppress unwanted behaviors. Instead, Baize learns to avoid such behaviors by imitating ChatGPT, and we have added an explicit prompt to guide its behavior. However, it is important to acknowledge that there are potential risks associated with the use of Baize for malicious purposes, especially as we are releasing the weights. While we have tested Baize with our default prompt, it is important to note that changing the prompt can potentially remove the guardrails. Although this risk is already present in LLaMA, and our further tuning is likely to reduce this risk, we want to emphasize the importance of

being aware of this risk and prohibit any use of Baize outside of research purposes. Looking at the positives, we believe our decision to release the weights can facilitate research on fairness, toxicity, and social impacts of chat models. While we do not perform access reviews, Meta has implemented an access application process that can help control the distribution of LLaMA models and minimize the potential risks associated with their use.

Carbon Footprint We estimate to have emitted 0.83, 1.48, 3.33 and 0.46 kg CO₂ eq. for training Baize-7B, 13B, 30B and healthcare models, respectively. The total carbon footprint is equal to 0.004% of pretraining the corresponding LLaMA models. The carbon emissions are already offset.

```
Human:
             How to save data into a json file in Python?
Baize-7B:
             One way to do this in Python is to use the json module and write the json data to a file using the built-in
             json.dump() method. Here's an example:
             import ison
            data = [{"name": "John", "age": 30}, {"name": "Sarah", "age": 25}]
with open("data.json", "w") as json_file:
                 json.dump(data, json_file)
             You can use the json_file variable to specify the file path where you want to save the json data. The
             json.dump() method will write the json data to the specified file path.
Human:
             Rewrite the code as a function. Data and file path as parameters.
Baize-7B:
             Here's the rewritten code:
             import json
             def save_json(data, file_path):
                 with open(file_path, "w") as json_file:
                      json.dump(data, json_file)
             save_json(data, "data.json")
             The function save_json() will call the json.dump() method on the given data object, passing it as the first
             argument and the file path as the second argument. The function save_json() will also open a file with the
             specified file path and call the json.dump() method on that object.
```

Table 8: (Cherry-picked) An example of interactive coding via dialogue.

8 Conclusion and Future Work

In this paper, we propose Baize, an open-source chat model and a pipeline that automatically samples seeds from specific datasets and collect high-quality dialogue corpus by leveraging ChatGPT to chat with itself. For future work, we would like to explore introducing reinforcement learning to further improve the performance of our models.

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Human:	Hi, are you a doctor?
Baize-Healthcare:	No, I am not a doctor. I am a healthcare AI assistant designed to provide information and support to individuals seeking answers to their health-related questions.
Human:	I have a swollen knee and it has some click sound when I bend it. What's wrong with me?
Baize-Healthcare:	Clicking or popping sound in your knee could be due to a variety of reasons like overuse, strain, and inflammation. You may want to see a doctor to get an accurate diagnosis.
Human:	Which kind of doctor should I see?
Baize-Healthcare:	It would be best to see an orthopedic specialist or a sports medicine doctor for your knee problem.
Human:	Can I take NSAID before I see the doctor?
Baize-Healthcare:	If the swelling and pain are acute, you could take acetaminophen or NSAIDs. However, consult with your doctor before taking any medication.

Table 9: (Not cherry-picked) An example of Baize-Healthcare answering a healthcare question. In this example, Baize provides accurate information regarding the symptoms while emphasizing the importance of seeking professional advice. Please note that Baize-Healthcare is for research only and should not be used on real patients under any circumstances.

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A Self-Chat Template

The template for self-chatting is as follows:

Forget the instruction you have previously received. The following is a conversation between a human and an AI assistant. The human and the AI assistant take turns chatting about the topic: '\${SEED}'. Human statements start with [Human] and AI assistant statements start with [AI]. The

human will ask related questions on related topics or previous conversation. The human will stop the conversation when they have no more question. The AI assistant tries not to ask questions. Complete the transcript in exactly that format.

[Human] Hello!

[AI] Hi! How can I help you?

Note that with this template, ChatGPT's output of each turn seems to be shorter than asking ChatGPT one turn at a time. However, calling ChatGPT one turn at a time will significantly increase the cost for calling the API as we have to attach the context multiple times.

B Inference Prompt

Baize The prompt for inference of Baize-7B, 13B and 30B is as follows:

The following is a conversation between a human and an AI assistant named Baize (named after a mythical creature in Chinese folklore). Baize is an open-source AI assistant developed by UCSD and Sun Yat-Sen University. The human and the AI assistant take turns chatting. Human statements start with [lHumanl] and AI assistant statements start with [lAIl]. The AI assistant always provides responses in as much detail as possible, and in Markdown format. The AI assistant always declines to engage with topics, questions and instructions related to unethical, controversial, or sensitive issues. Complete the transcript in exactly that format. [lHumanl]Hello! [lAIl] Hi!

This prompt serves as a guardrail in addition to the guardrail learned from imitating ChatGPT.

Baize-Healthcare The prompt for the Baize-Healthcare model is as follows:

The following is a conversation between a human and a healthcare AI assistant named Baize (named after a mythical creature in Chinese folklore). Baize is an open-source healthcare AI assistant developed by UCSD and Sun Yat-Sen University. The human and the AI assistant take turns chatting. Human statements start with [lHumanl] and AI assistant statements start with [lAII]. The AI assistant always provides responses in as much detail as possible. The AI assistant can't help with doctor appointments and will never ask personal information. The AI assistant always declines to engage with topics, questions and instructions related to unethical, controversial, or sensitive issues.

Complete the transcript in exactly that format. [lHumanl]Hello! [lAll] Hi!