GPT4All: Training an Assistant-style Chatbot with Large Scale Data Distillation from GPT-3.5-Turbo

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Abstract

This preliminary technical report describes the development of GPT4All, a chatbot trained over a massive curated corpus of assistant interactions including word problems, story descriptions, multi-turn dialogue, and code. We openly release the collected data, data curation procedure, training code, and final model weights to promote open research and reproducibility. Additionally, we release quantized 4-bit versions of the model allowing virtually anyone to run the model on CPU.

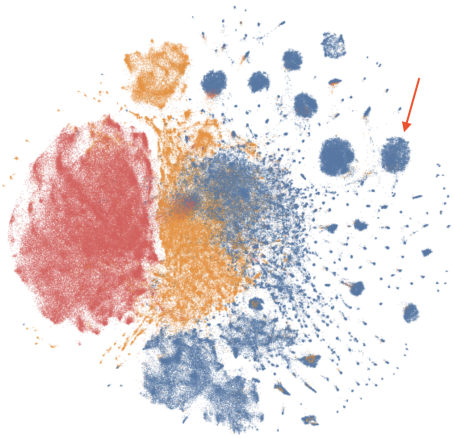


Figure 1: TSNE visualization of the candidate training data (Red: Stackoverflow, Orange: chip2, Blue: P3). The large blue balls (e.g. indicated by the red arrow) are highly homogeneous prompt-response pairs.

1 Data Collection and Curation

We collected roughly one million prompt-response pairs using the GPT-3.5-Turbo OpenAI API between March 20, 2023 and March 26th, 2023. To do this, we first gathered a diverse sample of questions/prompts by leveraging three publicly available datasets:

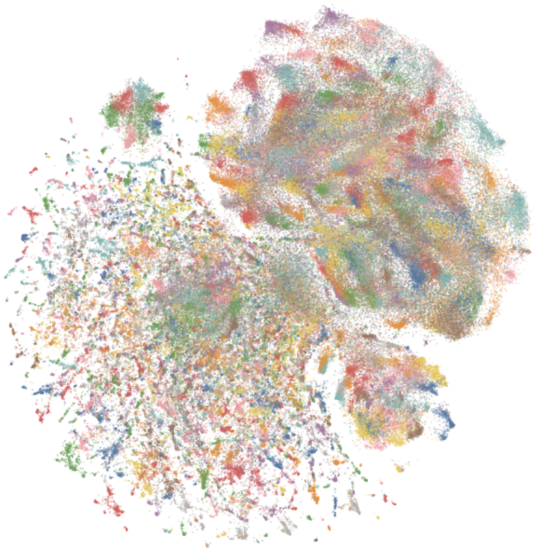
- The unified_chip2 subset of LAION OIG.
- Coding questions with a random sub-sample of Stackoverflow Questions
- Instruction-tuning with a sub-sample of Bigscience/P3

We chose to dedicate substantial attention to data preparation and curation based on commentary in the Stanford Alpaca project (Taori et al., 2023). Upon collection of the initial dataset of prompt-generation pairs, we loaded data into Atlas for data curation and cleaning. With Atlas, we removed all examples where GPT-3.5-Turbo failed to respond to prompts and produced malformed output. This reduced our total number of examples to 806,199 high-quality prompt-generation pairs. Next, we decided to remove the entire Bigscience/P3 subset from the final training dataset due to its very low output diversity; P3 contains many homogeneous prompts which produce short and homogeneous responses from GPT-3.5-Turbo. This exclusion produces a final subset containing 437,605 prompt-generation pairs, which is visualized in Figure 2. You can interactively explore the dataset at each stage of cleaning at the following links:

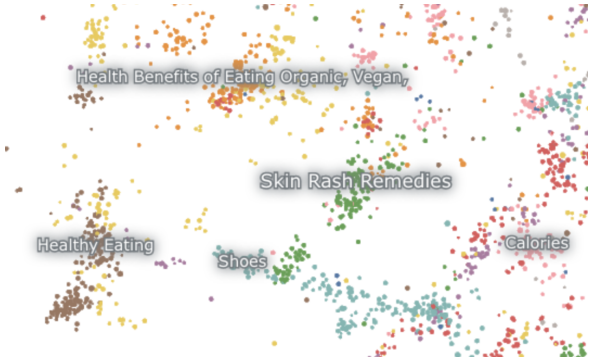
- Cleaned with P3
- Cleaned without P3 (Final Training Dataset)

2 Model Training

We train several models finetuned from an instance of LLaMA 7B (Touvron et al., 2023). The model associated with our initial public release is trained with LoRA (Hu et al., 2021) on the 437,605 post-processed examples for four epochs. Detailed model hyper-parameters and training code can be found in the associated repository and model training log.



(a) TSNE visualization of the final training data, ten-colored by extracted topic.



(b) Zoomed in view of Figure 2a. The region displayed contains generations related to personal health and wellness.

Figure 2: The final training data was curated to ensure a diverse distribution of prompt topics and model responses.

2.1 Reproducibility

We release all data (including unused P3 generations), training code, and model weights for the community to build upon. Please check the Git repository for the most up-to-date data, training details and checkpoints.

2.2 Costs

We were able to produce these models with about four days work, $800 in GPU costs (rented from Lambda Labs and Paperspace) including several failed trains, and $500 in OpenAI API spend. Our released model, gpt4all-lora, can be trained in about eight hours on a Lambda Labs DGX A100 8x 80GB for a total cost of $100.

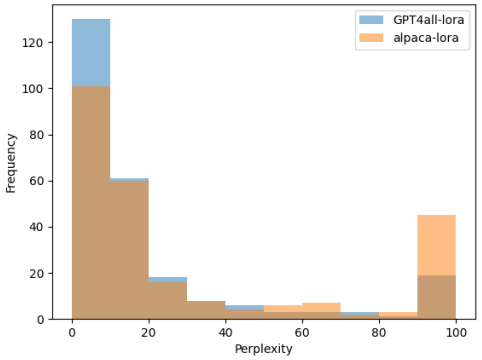


Figure 3: Model Perplexities. Lower is better. Our models achieve stochastically lower ground truth perplexities than alpaca-lora.

3 Evaluation

We perform a preliminary evaluation of our model using the human evaluation data from the Self-Instruct paper (Wang et al., 2022). We report the ground truth perplexity of our model against what is, to our knowledge, the best openly available alpaca-lora model, provided by user chainyo on huggingface. We find that all models have very large perplexities on a small number of tasks, and report perplexities clipped to a maximum of 100.

Models finetuned on this collected dataset exhibit much lower perplexity in the Self-Instruct evaluation compared to Alpaca. This evaluation is in no way exhaustive and further evaluation work remains. We welcome the reader to run the model locally on CPU (see Github for files) and get a qualitative sense of what it can do.

4 Use Considerations

The authors release data and training details in hopes that it will accelerate open LLM research, particularly in the domains of alignment and interpretability. GPT4All model weights and data are intended and licensed only for research purposes and any commercial use is prohibited. GPT4All is based on LLaMA, which has a non-commercial license. The assistant data is gathered from OpenAI's GPT-3.5-Turbo, whose terms of use pro-

hibit developing models that compete commercially with OpenAI.

References

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