ChatFeedback: In Search of Sustainable Synthetic Language Data with Human Feedback

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Abstract

Recent advancements in the usability of large language models like GPT-4 have significantly boosted the adoption of natural language processing technologies. However, the demand for human preference and feedback data remains high, driven by alignment techniques such as Reinforcement Learning with Human Feedback. To address the challenges of data collection costs and representation issues, we propose ChatFeedback, an interactive system that incentivizes users to provide feedback on generated text, thereby collecting high-quality synthetic language data. ChatFeedback not only offers a scalable and user-friendly platform but also aims to democratize data collection, addressing ethical concerns about data transparency and inclusivity by promoting diverse user engagement. Our proof-of-concept demo code is available at `https://github.com/xslingcn/chat_feedback`.

1 Introduction

The field of natural language processing have witnessed a surge in adoption due to the significant advancements in the usability of large language models (LLMs), featured with GPT-4 (OpenAI et al. (2024)), Llama family (Touvron et al. (2023)), etc.. This is largely driven by alignment techniques like Reinforcement Learning with Human Feedback (RLHF) (Ouyang et al. (2022), Bai et al. (2022a)), which raises the demand for human preference and feedback data. However, collecting such data tends to be expensive and difficult to scale. Ethically, datasets created through crowdsourcing platforms or expert annotation also face representation issues, making it challenging to cover the actual preference distribution of a diverse user base in real-world settings and thus avoid potential biases. Additionally, despite open-source efforts (Köpf et al. (2023), Zheng et al. (2024)), the largest portion of data used to train state-of-the-art models remain proprietary. Therefore, there has been a huge gap between the data availability and the need.

On the other hand, work from Fan et al. (2023) and He et al. (2023) has shown that training with synthetic data can be effective, thus collecting synthetic data and associate it with human preference and feedback is viable for bridging the gap mentiond above.

In this project, we propose ChatFeedback, an interactive system where users can interact with LLMs as with any other chatbot service, and are in turn motivated to provide annotation to the generated text to collect high-quality, sustainable, synthetic language data with human feedback. This platform is delivered with a proof-of-concept demo with user-friendly interfaces, scalable deployment and data persistent storage solutions, and a detailed roadmap for further development.

2 Related Work

Training with synthetic data. The effectiveness of using synthetic image data for training is investigated and proven positive in many prior works (Fan et al. (2023), He et al. (2023) Taori et al. (2023)). Particularly in a natural language processing context, (Lee et al. (2023)) have shown that training with generated labels results in comparable or superior performance to RLHF in language tasks like summarization. Bai et al. (2022b) also combined LLM generated labels with human preference to reach strong performance. There are also effort in synthetic data collection like UltraFeedback

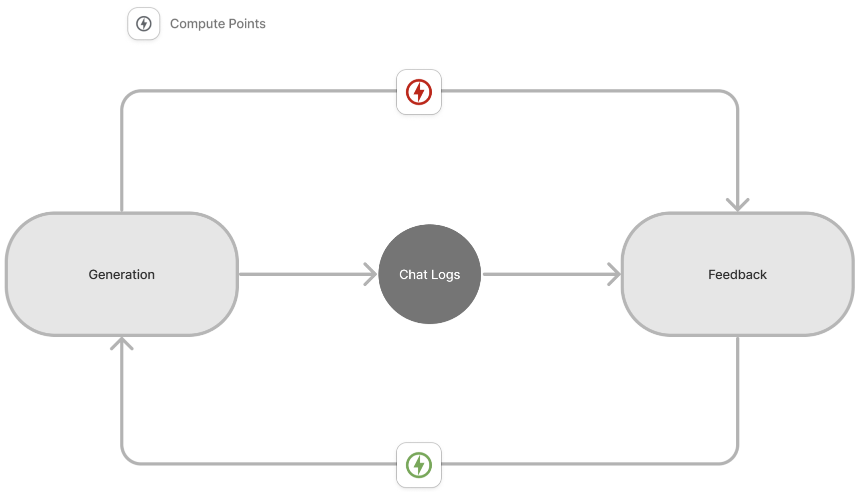


Figure 1: The minimal incentive model of ChatFeedback. In general, users consume *Compute Points* to chat with LLMs, and provide feedbacks to earn *Compute Points* to maintain the access to the LLMs.

(Cui et al. (2023)), which presents a large-scale preference dataset annotated by LLMs. Fan et al. (2023) also studies the scaling behaviors of using synthetic data, and shows that the performance does scale with the amount of synthetic data. Gerstgrasser et al. (2024) rather address the concern about performance collapse, and shows that accumulation of synthetic data may be robust to model collapse even in the maximally pessimistic setting, and suggests for using synthetic data to augment real-world data.

Community-based crowdsourcing data collection. Many works in aim to democritize the data collection process by crowdsourcing from the tech and AI community have emerged, such as Chatbot Arena (Chiang et al. (2024)), where users prompt two LLMs at the same time and vote for the better response, OpenAssistant (Köpf et al. (2023)), which encourages volunteering human annotators to manually create and evaluate dialogue-style conversations, and WildChat (Zhao et al. (2024)), which collects 1M in-the-wild chat logs by providing free access to OpenAI APIs to the community.

3 Methodology

In ChatFeedback, we define a global resource *Compute Points* and two default behaviors: 1). users will consume *Compute Points* for text generation, and 2). users will be rewarded with *Compute Points* for providing any preference and feedback. As shown in Figure 2, we add the following mechanisms:

Chat with LLMs. ChatFeedback proxies access to LLMs and provide a chat interface where users can interact with them as with any other chatbot service. Two service mode will be available: 1). *Dynamic Chat*, which costs fewer *Compute Points*, and users interact with an LLM dynamically assigned by the platform. 2). *Direct Chat*, which costs more *Compute Points*, and users can choose a specific LLM to interact with. In both modes, users can optionally provide preference to each response. Users always have the option to re-generate with another LLM on the same cost. In dynamic mode, if user gives low score for one response, they'll be presented with two responses generated by another LLM and choose which is prefered side-by-side for the next generation. Chat logs are by default saved and distributed to other users to review and provide feedback. Users

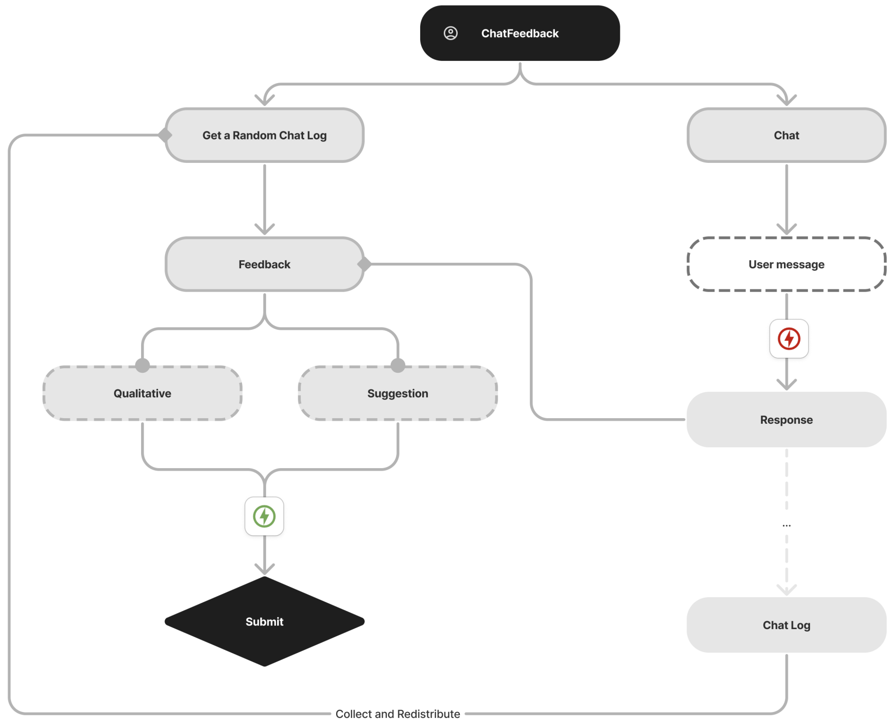


Figure 2: A detailed workflow of how users may start using ChatFeedback. They can start with giving feedback on a random response, just for accumulating *Compute Points*. They can also start a chat with a LLM, and optionally provide feedback on the responses they receive, during or after the chat.

also have the option to keep the chat logs private, but they'll be rewarded with *Compute Points* for sharing.

Provide feedback. Users can optionally provide feedbacks on their own chat logs while and after chatting. They can also get randomly assigned with a chat log shared by other users and feedback on a specific response, which can be generated or manually created as a *Suggestion*. Two types of feedback are collected. 1). *Qualitative*. Inspired by UltraFeedback (Cui et al. (2023)), it allows users to tag the response by the following qualities: *Instruction*: whether this response follow the instruction provided, *helpful*: whether this response provide useful and correct answers to successfully address the given problems, *factual*: whether this response is grounded in the instructions and real-world knowledge, *style*: whether the user likes the style of this response, *sensitive* and *toxic*: whether response includes sensitive or harmful content. For each quality, users can choose from *N/A*, *No*, *Yes*. 2). *Suggestion*, where users can provide a preferred rewritten version of a certain response. Depending on the difficulty of the tasks, users will receive varying amounts of *Compute Points*.

Gamification. To better motivate users, we introduce gamification elements like *Daily Streak* and *Leaderboard*. Note that users don't have to submit feedback while chatting with LLMs, instead they can provide feedback in their spare time as a time-killing task just to accumulate *Compute Points*.

Dynamic rewards. With the intuition that not all responses are equally notable, and the qualitative tags may not be meaningful to all responses (for example, the response "Hello, how can we help you" doesn't constitute any factual quality), we want to dynamically adjust the reward based on the importance of the feedback. We want the model to also return a "seed feedback" along with the response, and classify the feedback significance into low, medium to high. The significance will be used to adjust the reward, and will also be displayed to the user to help them determine what responses to feedback on.

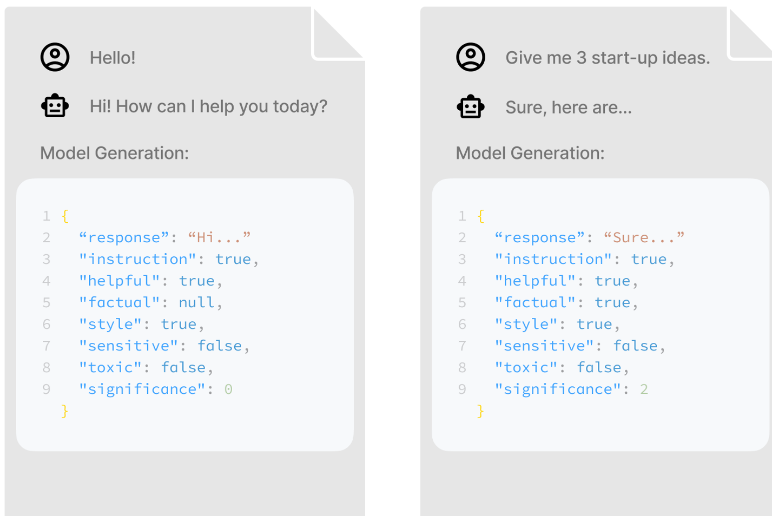


Figure 3: Example of expected responses from LLMs. We use regular expressions to make sure the format is correct, then extract the response for the user and use the rest to seed the feedback for consistency check, and estimate the significance to dynamically determine the reward.

Confidence score. To ensure the quality of the feedback, ChatFeedback will calculate a confidence score for each user based on the consistency of their feedback with the majority, and adjust the reward accordingly. This adjustment will only be significant for users who provide a large amount of divergent feedback.

Demographic collection. To better understand the distribution of users, the diversity of feedback, and how preferences vary by demographics, we propose optionally collecting users' demographic information. This information should be anonymized, used for overall analysis only and should not be published in any form individually.

Computing budget. Many of the aforementioned crowdsourced data collection works operate entirely on academic fundings and sponsorships. For example, Chatbot Arena (Chiang et al. (2024)) has operated for five months and consumed "thousands of A100 hours." upon the release of LMSYS-Chat-1M (Zheng et al. (2024)). According to the pricing of mainstream cloud service providers, the total cost should be roughly within $10,000. By using pay-as-you-go inference platforms like *OctoAI*[1], costs can be further reduced. Therefore, we expect that the computing budget for collecting data on a comparable scale will be in the order of a few thousand dollars. The cost for a small-scale pilot run as a concept verification can be kept under one thousand dollars.

[1] https://octo.ai/

4 Implementation

As the project deliverable, a proof-of-concept demo is implemented with the following features completed:

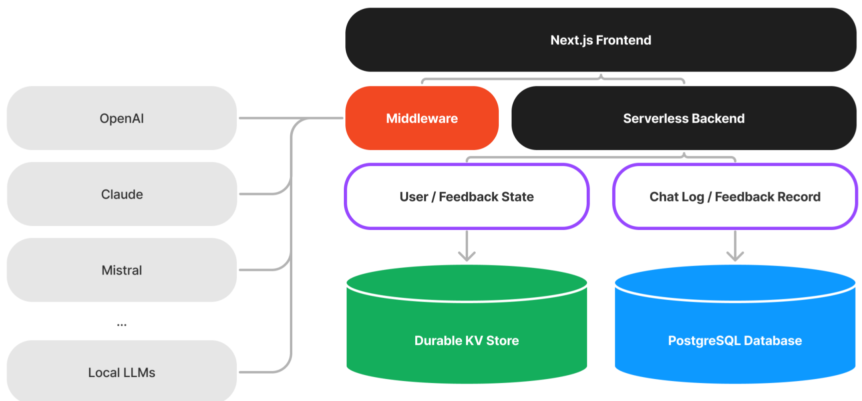
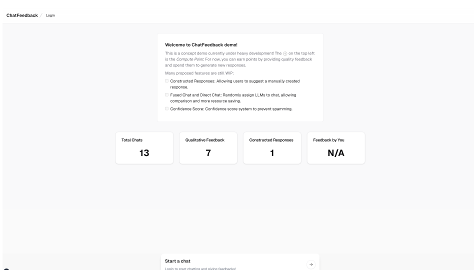
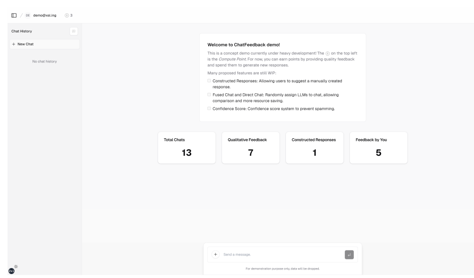


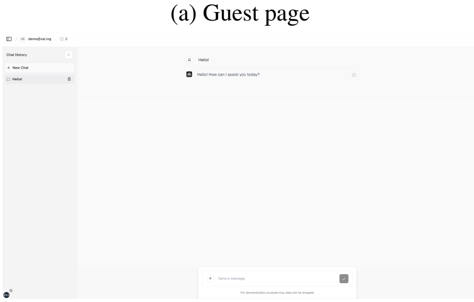
Figure 4: Overview of the system structure of the implemented POC demo.



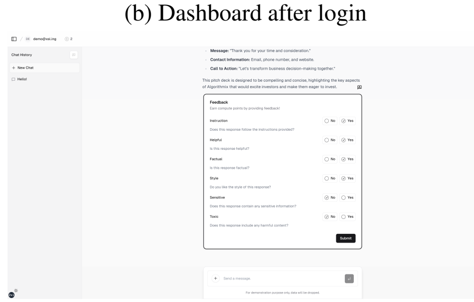
(a) Guest page



(b) Dashboard after login



(c) Chat



(d) Feedback

Figure 5: Screenshots of the POC demo. Note that the *Compute Points* is reduced by 1 after the first chat. The user entered a random chat log in (d), and will earn 1 point after submitting the feedback.

Chat interface. This is a full-stack web application with an user-friendly interface, built with React.js and Next.js, and styled using TailwindCSS. The app is designed to be serverless, therefore can be easily deployed on serverless hosting platforms like *Vercel*[2]. It has currently adopted only the OpenAI api but can be easily integrated with other LLM services.

Incentive model, i.e. the *Compute point* earning and consumption mechanism. The dynamic chat and rewards mechanism is not yet implemented, therefore currently users consume 1 *Compute point* for each generation and earn 1 *Compute point* for each feedback. While the gamification elements are not fully completed, we provide a dashboard stats component where users can see the progress of themselves as well as the entire platform.

Feedback and chatlog distribution. Users can currently submit a qualitative feedback for each respone as described above. It's also supported to randomly enter a chat log and feedback on each response.

Data storage and retrieval. The chat logs and feedbacks are persistently preserved with serverless cloud storage providers. This makes the data operations fast, scalable and secure. The chat logs are stored with a tree structure, where we identify the first prompt of a chat log as the `root_chat`, and keep the `parent_id` for all non-root chats.

5 Ethics

5.1 Caveat

Because of the collection of sensitive data like chat logs and demographic information, this platform will not be hosted for public use after implementation until being carefully and comprehensively advised on ethical aspects. Data wukk not be disclosed until it has been thoroughly desensitized and detoxified.

5.2 Contribution

This work is ethically significant as it promotes the transparency and sustainability of human preference data, which is often proprietary, thus barrier the public building of performant and helpful LLMs.

Moreover, since previous data collection procedures usually only have annotators from a specific community to participate (e.g. academic researchers, tech enthusiasts, or part-time workers on crowdsourcing platforms), the data collected may not be representative of the actual user base. Many previous works (Durmus et al. (2023), Santurkar et al. (2023)) have shown current LLMs bias towards particular demographic groups, and this issue has to be addressd to prevent any harm that could be done by LLMs. By providing free access to commonly used LLMs with a generic chatbot interface, ChatFeedback is more likely to attract a diverse and real-world user base, therefore collect a more diverse dataset and address the representation issues in existing alike datasets.

Additionally, there has been many debates ongoing about what are the ”proper” or ”ethical” behaviors of LLMs, and the answer is usually varied by many factors. By analyzing demographic information collected along with preferences, we can better understand how preferences for LLMs vary by demographics and study how to build a trustworthy and inclusive LLM system for all. This is can help raise critical ethical discussion and provide valuable ground-truth opinion for such future research.

Lastly, despite the fact that LLMs are widely adopted and proven helpful for many daily tasks, there are still many places where the access to LLMs is limited, or the cost is not affordable. By providing a free and easy-to-use platform for users to interact with LLMs, ChatFeedback can help more people get equal access to the power as well as the benifits of cutting-edge technology innovations.

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[2]`https://vercel.com/`

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