Exploring User Prompting Behavior in LLM Interactions

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ABSTRACT

Artificial Intelligence (AI) plays an increasingly important role in the daily lives of millions of people. Large Language Models (LLMs) are the most prominent implementation of AI that is used not only by experts, but equally by ordinary users as well. LLMs can respond to any textual input (prompts) with human-like answers, leveraging the training data that was used to implement the model. Even though prompting LLMs seems very straightforward, the question arises if it is possible to streamline the interactions with said models in order to optimize outputs. We explore the behavior of a randomized trial of 100 interactions of users with LLMs that are publicly available on ShareGPT. The goal of this investigation is the discovery of recurring patterns in behavior and the evaluation of human tendencies as well as biases of users when interacting with AI models in order to understand current behaviors and propose optimization opportunities.

CCS CONCEPTS

• **Human-centered computing** → **Interaction design**; • **Information systems** → *Information retrieval*; • **Computing methodologies** → *Natural language processing*.

KEYWORDS

Large Language Models, user behavior, prompting, interaction patterns

1 INTRODUCTION

2 BACKGROUND AND RELATED WORK

2.1 Large Language Models (LLMs)

○ General information on LLMs, such as their workings, training data, text generation, real world usage, and current limitations

2.2 User Interaction with LLMs

○ Explanation of Prompting
○ Description of LLM use cases and related work, primarily paying attention to ordinary frequent users (and not only experts)

3 STUDY ON USAGE PATTERNS OF LLM USERS

3.1 Intro and Research Objective

○ Overview of the study goal, the methodology, and the individual steps that will be taken

3.2 Research Method: ShareGPT

○ Information on the ShareGPT platform, its user base, its suitability for the study, and which data we are going to use

3.3 Study Results

3.3.1 Findings. ○ Listing of the results of the study, potentially segregated into categories that can be defined in advance

3.3.2 Observable Trends. ○ Objective analysis of results with a particular focus on observable trends in user behavior and data patterns (including visualizations such as charts)

4 DISCUSSION

4.1 Observed Behaviour (Synthesis)

○ Subjective evaluation of findings

4.1.1 Why do users interact with LLMs the way they do? ○ Reasoning and informed assumptions on the causes of observed behavior

4.1.2 Prompt Improvement Possibilities. ○ Proposition of ways to enhance prompts as well as associated results based on findings from related research

4.2 Outlook and Future Developments

4.2.1 Auto-GPT. ○ Introduction to future developments in the realm of LLM interaction, such as AI-based agents which may execute prompts autonomously in the future

4.2.2 Prompt Engineering. ○ Focus on the newly emerging discipline of prompt engineering which is a direct result of the increased significance of LLMs and required competencies for successful interaction

5 CONCLUSION

6 INTRODUCTION

Artificial Intelligence (AI) -based tools continually gain prominence as regularly leveraged tools in the daily lives of millions of people. In addition to typical AI applications such as recommendation systems or autonomous agents, generative models are notably increasing in popularity as well. One of the most widely used implementations of generative models are Large Language Models (LLMs), the most popular example at the moment being OpenAI's ChatGPT [5]. These models mainly come in the form of text generating chatbots that can answer seemingly any question a user might pose. Nevertheless, it is challenging to optimize the output of the model, since it can vary depending on the user input. Any form of such input to an LLM, whether it is in the form of a task or a question, is commonly referred to as "prompting" the model. Due to the vast application possibilities and promising future developments of LLMs, an exploration of user prompting behavior in interactions with these models is of particular interest.

In this paper, we are going to explain the fundamentals and workings of LLMs and prompting, describe related research in the realm of user - LLM exchange, and perform our own investigation of user behavior in these interactions. This investigation will provide an improved understanding of existing challenges users face when dealing with such models, as well as highlight optimization potential in order to enhance generated output.

Plenty of research has been conducted in the field of user interactions with LLMs.

Since the main part of this work will contain an analysis of real world examples, the reader can expect to gain a better understanding of actual user prompting behavior. To obtain these insights, we will leverage input data mainly gathered from the website ShareGPT, which enables users to store conversations they have had with the ChatGPT model and share them with others.

In the concluding section of this paper we will summarize our findings and explain how and in which way we can recognize findings from related research in our own data samples.

7 BACKGROUND

7.1 Large Language Models (LLMs)

One of the most widely used applications areas of generative AI are Large Language Models (LLMs). Among LLMs, the most widely adopted is ChatGPT [5], which is a conversational model being developed by OpenAI. The model is currently publicly accessible and free of charge.

LLMs can be leveraged for a variety of tasks, but their main focus area is Natural Language Processing (NLP). Therefore, most LLMs designed for end users are implemented in the form of chatbots, as is the case with ChatGPT for example. They typically consist of an interface comprised of an input field for the user to type in arbitrary text, as well as an output section that displays generated responses of the model.

Large Language Models are a recent advancement that followed the development of the original transformer architecture, which is a deep learning approach first introduced by researchers in 2017 [11]. In future iterations, the Generative Pre-Training (GPT) [6] approach was adapted for text-based models in particular, laying the foundation for today's most popular conversational LLMs, such as ChatGPT. Since our research revolves around user interaction with dialog-focused models, we will not go into more detail about other application and development areas of LLMs. In addition to ChatGPT, there are also a variety of similar other models focused on text generation, such as LaMDA [10], Sparrow [4], or BlenderBot 3 [9].

Large Language Models are a central part of our research as we investigate user behavior in LLM conversations. Currently, there are no binding guidelines on usage and prompting of such models, and users are therefore completely unconfined in their way of interacting with them.

7.1.1 *Zero-Shot Learning.*

It is important to differentiate possible forms of prompting that exist in LLM interactions in order to be able to correctly analyze and assess prompts in later parts of this paper. To do so, we will clarify the terms "Zero-Shot-" as well as "Few-Shot Learning". Zero-Shot Learning has been described as "[...] learning how to recognise new concepts by just having a description of them" [7, p. 1].

In regard to prompting, we refer to any form of prompt where the user does not specify a particular example as part of the query [3, p. 1]. An example for such a query could be "Give me five examples of papers that deal with the topic of LLMs".

7.1.2 *Few-Shot Learning.*

In Few-Shot Learning, examples are provided, albeit not many. It is generally aimed at providing good learning performance with only a few (most often less than 20) supervised examples [8, p. 1]. In a Few-Shot prompting setting, the user accordingly does provide increased guidance for the model. Doing so can help improve model outputs [3, p. 1]. To exemplify the learning capabilities, we present an example inspired by the approach of Brown et al. [1] and recent online resources [2]:

Even though both approaches give direction to the model, they vary in the amount of information that is provided.

Table 1: Odd Number Sum Evaluations

|lX|X|

User Response
Prompt: The odd numbers in this group add up to an even number: 15, 32, 5, 13, 82, 7, 1.
A: *The odd numbers in this group add up to an even number: 15, 5, 13, 7, and 1. Their sum is 41, which is indeed an even number.*
Prompt: The odd numbers in this group add up to an even number: 4, 8, 9, 15, 12, 2, 1. The answer is False.
The odd numbers in this group add up to an even number: 17, 10, 19, 4, 8, 12, 24. The answer is True.
The odd numbers in this group add up to an even number: 16, 11, 14, 4, 8, 13, 24. The answer is True.
The odd numbers in this group add up to an even number: 17, 9, 10, 12, 13, 4, 2. The answer is False.
The odd numbers in this group add up to an even number: 15, 32, 5, 13, 82, 7, 1.
A: *The answer is False. The odd numbers in this group (15, 5, 13, 7, and 1) add up to 41, which is an odd number, not an even number.*

Prompt:	The odd numbers in this group add up to an even number: 15, 32, 5,

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