Large Language Model and their application in treating ADHD

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1 Overview

This paper explores the possibility of applying Large Language Model (LLM) to help people with ADHD. Moreover, it seeks to evaluate 3 main approaches that can improve the default solutions that the LLM provides. One approach is to conduct rule-based prompt engineering before a user enters a prompt. Second can be prompt tuning, which designs a custom embedding of the prompt that yields better answers. This embedding can be created by combining relevant and scientifically supported literature with the prompt. Third, we can train the model on ADHD literature to customize the model itself to provide relevant solutions.

For context, ADHD is a condition that causes following disabilities in a person [1]. Time blindness or near-sighted vision of the future that checks one's ability to look ahead in the future and plan ahead. Lack of self-inhibition leading to impulsive behavior, distractions, and inattentiveness. Restricted working memory which reduces daily functioning such as exploring different scenarios in a situation, which causes poor decision making. Finally it inhibits the executive function, that allows one to act on their plans. Apart from medications, the strategies to overcome this disability include: structuring the day ahead, making decisions based on evaluating pros and cons, time-budgeting the tasks, working backwards from the goal to the daily actionable targets.

Here is where ChatGPT comes to play. It can define a basic structure for an activity with certain specific steps, it can evaluate a scenario considering its pros and cons, it can generate different ideas to approach a problem, and it can act as a working memory to store a complicated scenario. However, it is trained on a larger dataset from the internet and its solutions are not specifically designed to help counter ADHD. So, we seek to evaluate different methods to improve its performance. First can be to craft prompts manually from the literature to tune the model for enhanced performance. Second, to tune the prompt embeddings based on latest ADHD literature to output custom solutions that are backed by current research. Third we can tweak the model by re-training it on the current literature or by adding adaptive layers to tune the model so that it aligns it's output with the relevant domain.

2 Literature Survey

Although the field of LLMs has become mainstream in recent years, applying LLMs to domain specific tasks is still an open challenge. Though there are certain approaches that are gaining steam. Literature that discusses application of LLMs in a specific domain are as follows.

A recent paper surveyed major techniques to make LLMs domain specific[5]. it classified approaches into 3 main classes. First is "External Augmentation" or "Black Box" approach where the query is

not only passed to the LLM but also to a retriever model that looks at domain knowledge to extract the relevant information. The original query and the output of the retriever are then concatenated and passed to the LLM to generate an output. Second method is called "Prompt crafting" for instance, discrete prompts entered manually to the query. In this paper we seek to apply few-shot prompt crafting whereby each query is augmented by a few prompts relevant to ADHD and create a chain-of-thought so that the model output is restricted to this certain domain. Third approach is to change the model itself. This can be done by either training the LLM on domain specific literature or by creating Adapter-based fine-tuning where certain layers are added in the model that restrict the output to the domain we desire. This requires access to the model and thus not applicable to services like ChatGPT.

Using Large Language Models like ChatGPT for assisting people with ADHD is an area of ongoing research. People with ADHD have found various use cases to help with their day to day activities using GPT [3]. Some of those use-cases are:

- Task Management[2]: ChatGPT has been utilized as a task manager where it helps in organizing and prioritizing to-do lists, breaking down tasks into manageable steps, and providing time estimates for each step. Such as ReAct[6] proposed by S. Yao Moreover, it suggests approaches to enhance productivity and manage time more effectively.

- Memory Aid: By logging and labeling past conversations, ChatGPT serves as a memory aid, allowing users to refer back to previous interactions as notes.

- Job Search: LLMs can help in accelarating the process for applying to jobs. They can provide very specific cover letters and resumes based on the job description. This is especially useful for people with ADHD as they struggle maintaining focus on such mundane tasks.

- Educational Assistance: LLMs can explain a concept in different ways which can be quite useful. Prompts like ELI5 (Explain Like I am 5) can be useful to get a high level overview of the topic in a short amount of time and then topics can be deep-dived based on the requirements.

- Financial Planning: ChatGPT assists in financial planning by creating budgets based on input regarding monthly expenses, income, and financial goals. It also suggests ways to modify spending patterns to achieve financial objectives.

College Students with ADHD are usually said to have poor working memories [4]. LLMs can really help with providing a second brain which can store all the essential data, freeing the adhd mind for more creative thinking

The myriad ways in which ChatGPT has been employed to assist individuals with ADHD as per the ADDitude article, showcase the potential of large language models in augmenting support for individuals facing challenges in executive functions due to ADHD. However, the limitations in terms of outdated or inaccurate information highlight the importance of continuous development and possibly the integration of real-time information updating mechanisms to make such tools more reliable and effective in providing assistance.

3 Description of potential datasets and evaluation to use for the experiments

To evaluate the three approaches for improving the performance of Large Language Models (LLMs) in assisting individuals with ADHD, we will need suitable datasets and evaluation methods for each of the three approaches.

3.1 Datasets - Due date: Oct 26, 2023

Historical Prompt Data: Collect data on user interactions with the LLM where individuals with ADHD have used the system and ADHD Prompt Guidelines: Gather input from ADHD experts or clinicians to create a set of guidelines or rules for constructing effective prompts tailored to ADHD-related tasks. ADHD literature Corpus: Build a comprehensive dataset containing the latest scientific literature on ADHD. User-generated Prompts: Gather prompts created by individuals with ADHD of their caregivers. These prompts can be used to generate custom embeddings.

3.2 Evaluation

3.2.1 Rule-Based Prompt Engineering - Due Date: Nov 9

Prompt Effectiveness: Measure the performance of rule-based prompts by assessing their ability to elicit relevant and helpful response from the LLM.

3.2.2 Prompt Tuning with Custom Embeddings - Due Date: Nov 12

Embedding quality: Access the quality of custom embedding by measuring semantic similarity to ADHD literature and their impact on LLM performance.

3.2.3 Training the LLM with ADHD Literature - Due Date: Nov 16

Response Relevance and Accuracy: Compare the relevance and accuracy of LLM responses before and after fine-tuning with ADHD literature. Use metrics like precision, recall and F1 score.

4 Plan of activities

Deliverables by the Midway Report: Our initial focus will be on gathering relevant data and literature on ADHD. The we will be exploring few-shot learning across our dataset using a selection of Large Language Models (LLMs) including Flan T5, GPT 3.5, and Llama. We will explore and assess the impact of techniques such as the Chain of Thought (CoT) on model performance, and to understand the correlation between the model size and its efficacy. We will also settle on the evaluation metrics that are suitable for this project since the output is subjective.

Following this, we intend to delve into few-shot prompting techniques and model fine-tuning to gauge the extent of performance enhancement these methods can offer. The challenges we anticipate are: quality of our data; computing challenges given the size and complexity of LLMs; and conducting evaluation of different approaches in an unbiased manner.

Akansha will be investigating the capabilities of Flan T5, focusing on its utility in zero-shot learning and chain of thought prompting. Similarly, Somansh, Quynh and Charles will be exploring the capabilities of Llama, GPT 3.5 and Claude respectively.

References

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