Supplementary Material for Uncovering ChatGPT's Capabilities in Recommender Systems

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1 RELATED WORK

Large Language Models Pioneering studies [4, 22] demonstrated that LLMs can perform a diverse range of tasks without requiring gradient updates, solely based on textual instructions or a few examples. This has drawn significant attention towards improving the capabilities of LLMs. Previous studies [15] have investigated the performance limits of pre-trained language models (PLMs) by training larger models, as they have noted that augmenting the model or data size typically enhances the model's ability on downstream tasks, such as Megatron-turing NLG [27] with 530B parameters, Gopher [23] with 280B parameters, Ernie 3.0 Titan [31] with 260B parameters, BLOOM [25] with 175B parameters, and PaLM [7] with 540B parameters. These LLMs have exhibited exceptional performance on challenging tasks, showcasing new abilities that were not apparent in smaller pre-trained language models (PLMs). For a more comprehensive overview of LLMs, we would recommend referring to [36].

Existing Evaluation of ChatGPT As ChatGPT continues to gain worldwide popularity, more studies are focusing on evaluating it since it is perhaps one of the strongest LLMs to date. Bang et al. [2] propose to quantitatively evaluate ChatGPT from a multitask, multilingual, and multimodal perspective by analyzing their performance on 8 common NLP tasks. Their study reveals that while ChatGPT performs well on most tasks but may also have limitations and biases in

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reasoning, hallucination, and interactivity. Qin et al. [21] empirically show that ChatGPT possesses some zero-shot capabilities as a generalist model on 7 NLP tasks and conclude that ChatGPT performs poorly in solving specific tasks such as sequence tagging. Other researchers also do evaluations and case studies on ChatGPT's robustness [5, 30], ethics [13, 37] and its applications in education [10, 17, 19], medicine [1, 3, 24], recommender[8, 16], search[29] and law [6]. To the best of our knowledge, there has been no comprehensive evaluation of probing the ChatGPT's capabilities in recommender systems from different ranking perspectives. Therefore, we conducted an exhaustive evaluation of ChatGPT (as well as other GPT-3.5 series LLMs) on four recommendation domain benchmarks to fill this research gap.

Language Models for Recommendation The remarkable success of pre-trained LMs in NLP community has motivated researchers in recommender systems to explore their potential in recommendation tasks. Existing works can be categorized into two types: (i) utilizing LMs training strategies to reformulate and model recommendation tasks, such as BERT4Rec (*masked language modeling*) [28], UnisRec (*pre-train and finetune*)[12], P5 (*pre-train and prompting*) [9] and (ii) using LMs to obtain better representations of users, items and context based on textual information [14, 32, 34]. More recently, some researchers have explored leveraging off-the-shelf pre-trained LMs as recommender systems by reformulating the recommendation tasks with prompts as multi-token cloze tasks [20, 26, 35]. In this paper, we aim to conduct a preliminary evaluation of ChatGPT's potential and limitations in recommender systems.

2 EXPERIMENTAL DETAILS AND MORE EXPERIMENTAL RESULTS

2.1 Dataset

To better probe the different capabilities of ChatGPT and GPT-3.5s (text-davinci-002 and text-davinci-003) on personalized recommendation, we conducted evaluations on datasets from four different domains.

Movie: We use the widely-adopted MovieLens-1M[1] dataset that contains 1M user ratings for movies.

Book: We use the "Books" subset of Amazon Reviews[2] dataset that contains 1.8M user ratings for books.

Music: We use the "CDs & Vinyl" subset of Amazon Reviews[2] to conduct experiments on the music domain.

News: We use the MIND-small[3] dataset as the benchmark for news domain.

Following the common practices [11, 18, 33], for the Movie, Book, and Music datasets, we treat ratings above 3 as positive feedbacks (labeled as 1) and otherwise as negative feedbacks (labeled as 0). For the News dataset, we used the original binary feedback labels. For more details about the processing of datasets, please refer to the link[4].

2.2 Performance of Zero-shot Prompt

A natural question on the off-the-shelf LLMs for recommendation is whether LLMs can work without examples (i.e., $M = 0$). However, with the original 0-shot learning approach, we found that more than 50% of cases were invalid and difficult to evaluate in practice. Fortunately, OpenAI provides an API[2] that allows us to control the logits bias of output tokens. We were able to upweight the logit bias of the indexes of answers, which improved the compliance rate. For instance, for pair-wise ranking, we increased the probabilities of both outputs 'A' and 'B' by the same magnitude, while ensuring that their relative order remains unchanged. Under this setting, we conduct the zero-shot example experiments and the results are shown in Table 1. These findings demonstrate the potential of LLMs as recommendation systems, as

[1] https://grouplens.org/datasets/movielens/1m/

[2] http://jmcauley.ucsd.edu/data/amazon/

[3] https://msnews.github.io/

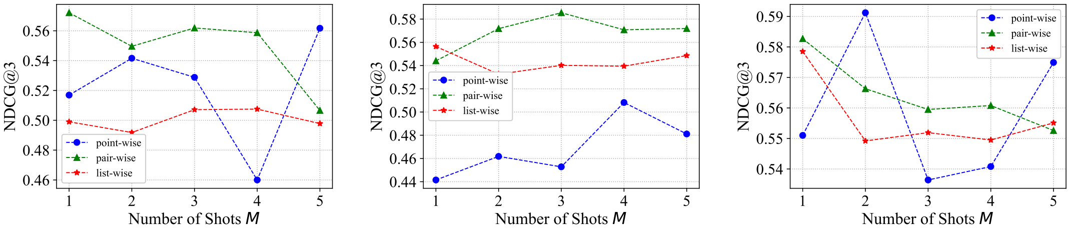
[4] https://github.com/rainym00d/LLM4RS/tree/main/data

[1] For zero-shot setting, valid outputs are derived by manipulating the 'logit_bias' and 'top_p' parameters of the API. However, it should be noted that due to a limitation in gpt-3.5-turbo's control over the 'top_p' parameter, there are currently no available experimental results in this regard.

[2] https://platform.openai.com/docs/api-reference/completions/create#completions/create-logit_bias

Table 1. Performance of different LLMs with zero-shot and few-shot examples on Movie dataset. Bold indicates the best result for each row and '_' indicates the best result for each wise of each LLM.

Model	Metric	random	pop	point-wise		pair-wise		list-wise	
				zero-shot	few-shot	zero-shot	few-shot	zero-shot	few-shot
text-davinci-002	NDCG@3	0.4264	0.4761	0.5168	0.5416	0.5253	**0.5728**	0.4544	0.4990
	MRR@3	0.3667	0.4103	0.4519	0.4824	0.4643	**0.5071**	0.3950	0.4363
text-davinci-003	NDCG@3	0.4264	0.4761	0.4674	0.4618	0.5249	**0.5441**	0.5062	0.5564
	MRR@3	0.3667	0.4103	0.4092	0.3998	0.4633	**0.4763**	0.4450	0.4950
gpt-3.5-turbo (ChatGPT)	NDCG@3	0.4264	0.4761	0.5413	**0.5912**	0.5833	0.5827	N/A[1]	0.5785
	MRR@3	0.3667	0.4103	0.4742	**0.5260**	0.5243	0.5162		0.5167



(a) text-davinci-002

(b) text-davinci-003

(c) gpt-3.5-turbo (ChatGPT)

Fig. 1. Impact of the number of shots prompts in LLMs on Movie dataset.

they perform better than a random policy and a popularity-based policy under the zero-shot setting. Furthermore, as expected, LLMs under few-shot settings outperform those under zero-shot settings in most cases, demonstrating the effectiveness of few-shot prompts in-context learning.

2.3 Performance Under Different Shots Examples

Previous studies in natural language processing (NLP) have emphasized that the number of examples M is very important for in-context learning. To assess the impact of M in LLMs for recommendation, we conducted experiments on Movie dataset by varying M from 1 to 5. Figure 1 illustrates the performances of different M in terms of the $NDCG@3$ of ChatGPT and GPT3.5s. Surprisingly, we observe that the best results did not always correspond to the maximum number of examples. One possible explanation is that while more example shots can provide more context and information for LLMs to understand the recommendation task, they may also introduce more noise, causing the models to learn unhelpful patterns. Therefore, the optimal number of prompt shots may depend on the specific LLM, task, and dataset.

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