Large Language Models for Generative Recommendation: A Survey and Visionary Discussions

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Abstract

Recent years have witnessed the wide adoption of large language models (LLM) in different fields, especially natural language processing and computer vision. Such a trend can also be observed in recommender systems (RS). However, most of related work treat LLM as a component of the conventional recommendation pipeline (e.g., as a feature extractor) which may not be able to fully leverage the generative power of LLM. Instead of separating the recommendation process into multiple stages such as score computation and re-ranking, this process can be simplified to one stage with LLM: directly generating recommendations from the complete pool of items. This survey reviews the progress, methods and future directions of LLM-based generative recommendation by examining three questions: 1) *What* generative recommendation is, 2) *Why* RS should advance to generative recommendation, and 3) *How* to implement LLM-based generative recommendation for various RS tasks. We hope that the survey can provide the context and guidance needed to explore this interesting and emerging topic.

1 Introduction

Over the years, recommender systems (RS) have undoubtedly made our daily life easier when it comes to finding things that we are interested in, such as movies, songs, and restaurants. In the meantime, the strong capability of large language models (LLM) in handling various tasks has impressed both practitioners in the field of artificial intelligence (AI) and the general public. As a result, it is natural to consider the combination of the two, i.e., RS and LLM [Geng *et al.*, 2022c]. Although natural language is an expressive medium, it can also be vague. For example, when an LLM is deployed for vehicle identification and scheduling, it would be dangerous to use vague descriptions (e.g., "a black SUV") to identify a vehicle rather than a precise identifier such as vehicle identification number (VIN) or plate number. Similarly, vagueness may also be a problem in recommendation scenarios that require precise and unique identifiers of items, because RS need to guarantee that recommendations made for users are things that factually exist so as to avoid the hallucination problem [Azamfirei *et al.*, 2023]. This also explains why an ID is usually assigned for each user/item in RS. Despite that, the current understanding of IDs is usually limited to one form. That is, most RS research considers each ID as a discrete token associated with an embedding vector. In this survey, we generalize the definition of ID as follows:

Definition 1 (ID in Recommender Systems)**.** *An ID in recommender systems is a sequence of tokens that can uniquely identify an entity, such as a user or an item. An ID can take various forms, such as a vector embedding, a sequence of numerical tokens, and a sequence of word tokens (including an item title, a description of the item, or even a complete news article), as long as it can uniquely identify the entity.*

For example, a product in e-commerce platform may be assigned the ID "item_7391" and be further represented as a sequence of tokens such as ⟨item⟩⟨_⟩⟨73⟩⟨91⟩ [Geng *et al.*, 2022c; Xu *et al.*, 2023]. Note that the ID may not necessarily be comprised of numerical tokens. As long as it is a unique identifier for an item, it may be considered as the item's ID. For example, the title of the movie "The Lord of the Rings" can be considered as the ID of the movie. The ID may even be a sequence of words that do not convey any explicit meaning, e.g., "ring epic journey fellowship adventure" [Hua *et al.*, 2023b]. Actually, IDs in conventional RS can be seen as a special case of the above definition, i.e., a sequence of just one token. Under this definition, IDs resemble token sequences as in text, and thus naturally fit natural language environment as well as LLM.

Due to the huge number of items in real-world systems, traditional RS usually take the multi-stage filtering paradigm [Covington *et al.*, 2016] – some simple and efficient methods such as rule-based filtering are used to reduce the number of candidate items from millions to a few hundred, and then advanced recommendation algorithms are applied on the remaining items to further select a few number of items for recommendation. As a result, advanced recommendation algorithms are not applied to all items, but only a few hundred of items.

The generative power of LLM has the potential to reshape the RS paradigm from multi-stage filtering to single-stage filtering. In the context of generative recommendation, an LLM itself can be the single and entire recommendation pipeline, which directly generates the items to recommend, eliminat-

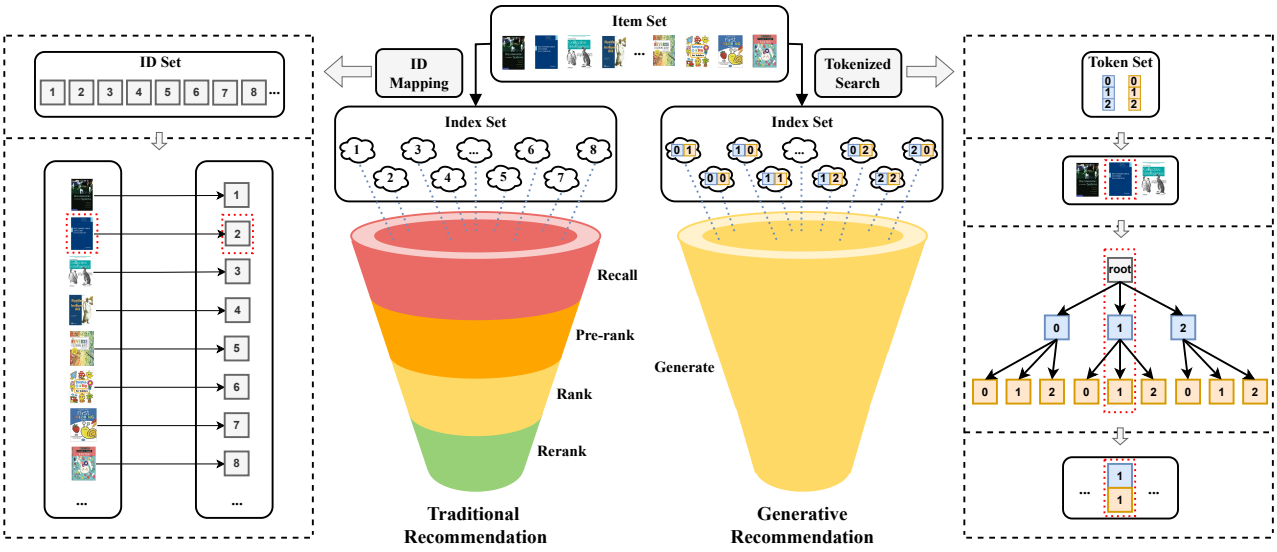

Figure 1: Pipeline comparison between traditional recommender systems and LLM-based generative recommendation.

ing the need for multi-stage filtering. In other words, advanced LLM-based recommendation algorithms are implicitly applied over all items in the system to decide which items to recommend. We term such a process *generative recommendation* and formally define it as follows:

Definition 2 (Generative Recommendation)**.** *A generative recommender system directly generates recommendations or recommendation-related content without the need to calculate each candidate's ranking score one by one for sorting and ranking.*

In a broader sense, this is in line with the trend of general AI research, which recently has been shifting from discriminative AI (such as classification and regression) to generative AI (e.g., ChatGPT[1]).

With the above definitions, we first answer why RS are developing towards generative recommendation in Section 2. In Section 3, we review ID creation approaches that could retain collaborative information in the LLM environment. Then, we show how typical recommendation tasks can be performed on LLM by providing general formulations in Section 4, and highlight opportunities in the LLM era in Section 5. At last, we conclude our survey in Section 6.

It should be noted that our survey is different from some recent surveys on LLM-based recommendation [Liu *et al.*, 2023c; Wu *et al.*, 2023; Fan *et al.*, 2023; Lin *et al.*, 2023a; Chen *et al.*, 2023] from two perspectives: 1) our survey is organized with generative recommendation as the key focus, eliminating discriminative recommendation models for clarity; 2) we develop a taxonomy for LLM-based recommendation research with strong inspiration from the recommendation community, instead of following the LLM taxonomy from the community of natural language processing (NLP).

To sum up, this survey makes the following contributions:

- To the best of our knowledge, this is the first survey that systematically summarizes research on LLM-based generative recommendation. To differentiate this topic from traditional RS, we have generalized the definition of ID for generative recommendation.
- This survey is pragmatic as we provide the formulation for different LLM-based recommendation tasks when categorizing relevant research, which provides a useful guideline for future research.
- We discuss important and promising directions to explore for LLM-based generative recommendation research, which may help broaden the scope of this under-explored research area.

2 Why Generative Recommendation

To answer why RS are developing towards generative recommendation, we first discuss problems with discriminative recommendation. When the amount of items on a recommendation platform is prohibitively large, the ranking score calculation with regard to each item would be computationally expensive. Therefore, industrial RS usually consist of multiple stages to narrow down the candidate items. At the early stage, simple models (e.g., logistic regression) or straightforward filtering strategies (e.g., feature matching) are usually adopted to filter out less relevant items. Only in the final stage can the relatively complex and advanced models be utilized. This naturally causes a gap between academic research and industrial application. In consequence, although recent recommendation models are growing more fancy and sophisticated, few have been practically employed in industry.

In the era of LLM, we see a great opportunity that could potentially bridge this gap. As both academic research and industry application may share the same backbone LLM, most research advancements on LLM may benefit its downstream applications. Regarding recommendation pipeline, the typical multiple stages could be advanced to one stage for generative recommendation, i.e., directly generating items to rec-

[1]https://openai.com/blog/chatgpt

Item ID	User ID	Related Work
Token Sequence (e.g., "*56 78*")	Token Sequence	P5 [Geng *et al.*, 2022c], UP5 [Hua *et al.*, 2023a], VIP5 [Geng *et al.*, 2023], OpenP5 [Xu *et al.*, 2023], POD [Li *et al.*, 2023c], GPTRec [Petrov and Macdonald, 2023], [Hua *et al.*, 2023b]
Item Title (e.g., "*Fast X*")	Interaction History (e.g., ["*Fast X*", "*Her*", ...])	LMRecSys [Zhang *et al.*, 2021], GenRec [Ji *et al.*, 2023], GPT4Rec [Li *et al.*, 2023a], TALLRec [Bao *et al.*, 2023b], NIR [Wang and Lim, 2023], PALR [Chen, 2023], BookGPT [Zhiyuli *et al.*, 2023], PBNR [Li *et al.*, 2023e], ReLLa [Lin *et al.*, 2023b], KnowRec [Colas *et al.*, 2023], BIGRec [Bao *et al.*, 2023a], [Dai *et al.*, 2023; Liu *et al.*, 2023a; Hou *et al.*, 2023b; Li *et al.*, 2023f; Zhang *et al.*, 2023b]
Item Title	Metadata (e.g., age)	Chat-REC [Gao *et al.*, 2023], [Zhang *et al.*, 2023a; He *et al.*, 2023]
Metadata	Metadata	M6-Rec [Cui *et al.*, 2022], LLMRec [Liu *et al.*, 2023b]
Embedding ID	Embedding ID	PEPLER [Li *et al.*, 2023b]

Table 1: Methods of representing IDs for LLM-based generative recommendation.

ommend. A graphical comparison between the two types of pipeline is shown in Fig. 1. At each step of recommendation generation, the LLM can produce a vector that represents the probability distribution on all possible ID tokens. After a few steps, the generated tokens can constitute a complete ID that stands for the target item. This process implicitly enumerates all candidate items to generate the target item for recommendation, which is different from traditional RS that draw items from a subset resulted from the previous filtering step.

The key secret of LLM for generative recommendation is that we can use finite tokens to represent (almost) infinite items. Suppose that we have 1000 tokens for representing user or item IDs, which can be numerical tokens, word tokens or even out-of-vocabulary (OOV) tokens, and each ID consists of 10 tokens, then we can use these 1000 tokens to represent as many as $1000^{10} = 10^{30}$ items (i.e., unique IDs), which is almost an astronomical number and large enough for most of real-world RS. When applying beam search algorithm for generating item IDs, the probability vector at each step is bounded by 1000 tokens, making it computationally possible to directly generate recommendations out of the item pool.

3 ID Creation Methods

When implementing generative recommendation with LLM, the input (particularly user and item IDs) should be made into the right format that is compatible with LLM. Intuitively, one would consider the metadata of users and items as an alternative, such as user name and item title. In fact, this type of ID representation is quite common in related work, as summarized in Table 1. Despite the popularity, it has two problems [Li *et al.*, 2023d]. First, when the IDs are extremely long, e.g., in the case of item description, it would be computationally expensive to conduct generation. Besides, it would be difficult to find an exact match in the database for a long ID, i.e., the hallucination problem [Azamfirei *et al.*, 2023]; and double-checking the existence of each ID would take us back to discriminative recommendation since we need to compare it with each item in the database. Second, although natural language is a powerful and expressive medium, it can also be vague in many cases. For example, two different users' names could be identical. Besides, two irrelevant items could have very similar titles, such as Apple the fruit and Apple the company, while two closely related items may have very different titles, such as the classic "beer and diaper" example in data mining.

Therefore, we need concise and unique representations of IDs in recommendation scenarios to precisely distinguish one user or item from the others. Associating each ID with an embedding vector is a common practice in traditional RS, but it would cost a lot of memory to store them, since industry-scale RS usually involve tons of users and items. In addition, these IDs are OOV tokens to LLM, and thus are not very compatible with the models.

This is why a new way of representing IDs, i.e., a sequence of tokens rather than a single embedding, is needed. The key idea is to use a small amount of tokens to represent an astronomical number of users or items as explained in the previous section. To make IDs reasonably short, similar users or items could share more tokens in their ID sequences, while the remaining tokens can be used to guarantee their uniqueness. In the following, we review three typical ID creation approaches that follow this principle. Most of these ID creation methods aim to encode the user-user, item-item, or user-item collaborative information into the ID representations, which combines the success of collaborative filtering from traditional RS with the emerging LLM for effective recommendation.

3.1 Singular Value Decomposition

[Petrov and Macdonald, 2023] acquire an item's ID tokens from its latent factors. Specifically, they first perform truncated singular value decomposition on user-item interaction data to obtain the item embedding matrix. After a set of operations, including normalization, noise-adding, quantization, and offset adjustment, each item's embedding becomes an array of integers, which serves as this item's ID sequence. In particular, the noise-adding operation can ensure that there are no identical item embeddings, and thus make each item ID unique.

3.2 Product Quantization

[Hou *et al.*, 2023a] quantize item embeddings with product quantization (PQ) [Jegou *et al.*, 2010] to obtain their IDs. For PQ, there are in total D vector sets, and each set is comprised of M centroid embeddings. They first encode an item's textual description with BERT [Devlin *et al.*, 2019] to get the item's embedding vector, which is further divided into D segments for quantization. For the i-th embedding segment, its nearest centroid embedding from the i-th vector set can be easily found. The index of this centroid embedding then becomes the item's i-th ID token. All these ID tokens together form the item's complete ID.

Rating Prediction	Top-N Recommendation	Sequential Recommendation	Explainable Recommendation	Review Generation	Review Summarization	Conversational Recommendation
P5 [Geng *et al.*, 2022c], BookGPT [Zhiyuli *et al.*, 2023], LLMRec [Liu *et al.*, 2023b], RecMind [Wang *et al.*, 2023b], [Liu *et al.*, 2023a; Dai *et al.*, 2023]	P5 [Geng *et al.*, 2022c], UP5 [Hua *et al.*, 2023a], VIP5 [Geng *et al.*, 2023], OpenP5 [Xu *et al.*, 2023], POD [Li *et al.*, 2023c], GPTRec [Petrov and Macdonald, 2023], LLMRec [Liu *et al.*, 2023b], RecMind [Wang *et al.*, 2023b], [Zhang *et al.*, 2023a; Zhang *et al.*, 2023b; Liu *et al.*, 2023a; Li *et al.*, 2023f; Dai *et al.*, 2023]	P5 [Geng *et al.*, 2022c], UP5 [Hua *et al.*, 2023a], VIP5 [Geng *et al.*, 2023], OpenP5 [Xu *et al.*, 2023], POD [Li *et al.*, 2023c], GenRec [Ji *et al.*, 2023], GPTRec [Petrov and Macdonald, 2023], LMRecSys [Zhang *et al.*, 2021], NIR [Wang and Lim, 2023], PALR [Chen, 2023], LLMRec [Liu *et al.*, 2023b], RecMind [Wang *et al.*, 2023b], BIGRec [Bao *et al.*, 2023a], [Hua *et al.*, 2023b; Liu *et al.*, 2023a; Hou *et al.*, 2023b; Zhang *et al.*, 2023b]	P5 [Geng *et al.*, 2022c], VIP5 [Geng *et al.*, 2023], POD [Li *et al.*, 2023c], PEPLER [Li *et al.*, 2023b], M6-Rec [Cui *et al.*, 2022], LLMRec [Liu *et al.*, 2023b], RecMind [Wang *et al.*, 2023b], KnowRec [Colas *et al.*, 2023], [Liu *et al.*, 2023a]	-	P5 [Geng *et al.*, 2022c], LLMRec [Liu *et al.*, 2023b], RecMind [Wang *et al.*, 2023b], [Liu *et al.*, 2023a]	M6-Rec [Cui *et al.*, 2022], RecLLM [Friedman *et al.*, 2023], Chat-REC [Gao *et al.*, 2023], [Wang *et al.*, 2023a; Lin and Zhang, 2023; He *et al.*, 2023]

Table 2: Seven typical generative recommendation tasks with LLM.

3.3 Collaborative Indexing

[Hua *et al.*, 2023b] compose an item ID with nodes on a hierarchical tree. Technically, they first construct an item graph whose edge weights denote the co-occurring frequency of any two items in all users' interaction history. Then, the graph's adjacency matrix and Laplacian matrix as well as the latter's eigenvectors can be computed. With the eigenvectors, spectral clustering [Von Luxburg, 2007] can be applied to group similar items into the same cluster. By recursively doing so, large clusters can be further divided into smaller ones. When the number of nodes in each cluster is smaller than a threshold, these clusters and their sub-clusters naturally constitute a hierarchical tree whose leaf nodes are the items. After assigning tokens to each node, each item has a unique ID sequence by following a path from the root node to the leaf node.

In addition to the above three ID creation approaches, [Hua *et al.*, 2023b] discussed other strategies such as sequential indexing based on user interaction history, and semantic indexing based on item metadata information, which are effective approaches to creating item IDs. We omit the details because they are quite simple and straightforward.

4 How to Do Generative Recommendation

With the above-defined user and item IDs, we now describe how to perform different generative recommendation tasks with LLM. A summary of relevant research on each task is given in Table 2. We can see that there are a few models that have the ability to perform multiple recommendation tasks, e.g., P5 [Geng *et al.*, 2022c]. To allow LLM to understand each task, especially those that have the same input data, we can construct a prompt template [Liu *et al.*, 2023d] that describes the task and then fill the user and item information such as their IDs in the prompt. During the inference stage, all kinds of output (e.g., predicted item IDs) are autoregressively generated as natural language generation. In the following, we introduce the general formulation of each task, followed by the recent progress. Finally, we discuss how to evaluate these tasks.

4.1 Rating Prediction

In conventional RS, the rating prediction task is formulated as follows: given a user u and an item i, a recommendation model $f(u, i)$ needs to estimate a score $\hat{r}_{u,i}$ that the user would rate the item. In the context of LLM, u and i are no longer embedding IDs, but two sequences of tokens as defined in Definition 1. The two IDs can be filled in an instruction prompt $p(u, i)$, e.g., "how would *user_1234* rate *item_5678*", such that LLM can understand this task. After feeding $p(u, i)$ into the LLM, it can generate a numerical string in the scale of 1 to 5 such as "4.12", indicating that the user is likely to interact with the item.

There are some studies [Geng *et al.*, 2022c] that tested LLM with this task, among which many [Zhiyuli *et al.*, 2023; Liu *et al.*, 2023a; Dai *et al.*, 2023; Liu *et al.*, 2023b; Wang *et al.*, 2023b] are based on ChatGPT. As users may not leave an explicit rating for each item with which they interact, the rating prediction task can be less practical for real-world systems. Instead, implicit feedback, e.g., clicking, is easier to collect. Thus, how to infer users' preferences from such implicit feedback motivates the development of top-N recommendation task.

4.2 Top-N Recommendation

The top-N recommendation task, a.k.a., ranking, aims to select N items as recommendations for a given user u. To this end, traditional RS usually compute a score $\hat{r}_{u,i}$ w.r.t. each item i in the item set $\mathcal{I}$. After filtering out those that the user already interacted with, i.e., $\mathcal{I}_u$, the top candidates can be selected as recommendations from the remaining items as $\text{Top}(u, i) := \arg\max^N_{i \in \mathcal{I}/\mathcal{I}_u} \hat{r}_{u,i}$.

However, due to the context length limit of LLM, it is impossible to feed the model all the items. As a result, the community has explored two approaches to solve the problem. One is *straightforward recommendation* [Xu *et al.*, 2023; Geng *et al.*, 2022c; Zhang *et al.*, 2023a], which uses a prompt that only contains user information (ID or user metadata) and asks the LLM to directly generate recommendations for this user. The second is *selective recommendation* [Geng *et al.*, 2022c; Hua *et al.*, 2023a; Geng *et al.*, 2023; Li *et al.*, 2023c; Petrov and Macdonald, 2023; Zhang *et al.*, 2023b; Liu *et al.*, 2023a; Li *et al.*, 2023f; Dai *et al.*, 2023; Liu *et al.*, 2023b; Wang *et al.*, 2023b], which provides both user information and a list of candidate items $\mathcal{I}_c$ in the prompt and asks the LLM to select items for recommendation out of the candidates. For example, the candidate list may consist of a testing item and a number of sampled negative items. After filling the user and candidates in a prompt $p(u, \mathcal{I}_c)$, e.g., "select one item to recommend for *user_1234* from the following candidates: *item_6783, ..., item_9312, item_2834*", the LLM can generate an item ID, e.g., "9312" as recommendation. When combined with beam search, the model can produce a number of item IDs, i.e., a list of N recommendations.

Besides generating item IDs, some recent studies [Li *et al.*,

2023e; Bao *et al.*, 2023b; Lin *et al.*, 2023b] instruct LLM to answer whether a user is going to interact with a given item by generating "yes" or "no". Although the "yes" or "no" answer is generated by LLM, these methods can be considered as discriminative recommendation since they need to generate an answer or a score (e.g., the probability of "yes") for each item.

4.3 Sequential Recommendation

The sequential recommendation task goes one step further than the top-N recommendation with the consideration of the time or order of interaction. Specifically, its objective is to predict the next item with which a user u is likely to interact based on his/her past interactions. The items interacted by the user are chronologically ordered according to their timestamps, which can be denoted as I_u. Considering the sequential nature of such data, researchers usually employ sequential models to deal with the problem, such as Markov chains, recurrent neural networks (RNN), and Transformer [Vaswani *et al.*, 2017]. Again, we can first fill the user and the item sequence in a prompt $p(u, I_u)$, e.g., "given *user_1234*'s interaction history *item_3456, ..., item_4567, item_5678*, predict the next item with which the user will interact", and then prompt LLM to generate an item ID as a prediction, e.g., "6789". To reduce the inference time, we can cut off the relatively old items before filling the item sequence in the prompt.

This task is a trending topic, as evidenced by a significant number of LLM-based models [Geng *et al.*, 2022c; Hua *et al.*, 2023a; Geng *et al.*, 2023; Xu *et al.*, 2023; Li *et al.*, 2023c; Petrov and Macdonald, 2023; Zhang *et al.*, 2021; Wang and Lim, 2023; Hua *et al.*, 2023b; Liu *et al.*, 2023a; Zhang *et al.*, 2023b; Liu *et al.*, 2023b; Wang *et al.*, 2023b]. In particular, [Bao *et al.*, 2023a] leverage LLM to generate candidates for further filtering while [Chen, 2023; Hou *et al.*, 2023b; Ji *et al.*, 2023] provide LLM with candidate items for recommendation, and [Bao *et al.*, 2023b; Lin *et al.*, 2023b] instruct LLM to answer whether a user is going to like a specific item.

4.4 Explainable Recommendation

Besides generating recommendations, explanations that allow users to know the reason behind them are equally important. There are various methods to explain a recommendation to a user, such as explicit item features [Zhang *et al.*, 2014] and visual highlights [Chen *et al.*, 2019]. We refer interested readers to the survey [Zhang *et al.*, 2020] for a comprehensive examination of explainable recommendations.

A typical LLM-based recommendation explanation task can be natural language explanation generation. That is, given a pair of user u and item i, we direct the model to generate a sentence or paragraph in natural language to explain why i is recommended for u. Ground-truth explanations can be mined from user reviews [Li *et al.*, 2020]. As the inputs (i.e., u and i) are identical to those for rating prediction, we can put them in a prompt $p(u, i)$ to inform the LLM that this is an explanation task, e.g., "explain to *user_1234* why *item_5678* is recommended." As a response, the model may generate an explanation such as "The movie is top-notch." However, using IDs alone in the prompt could be unclear as to which aspects the model should discuss in the explanation. To address this problem, we can provide some item features f as hint words in the prompt, e.g., "acting". An example prompt $p(u, i, f)$ for such a scenario could be "write an explanation for *user_1234* about *item_5678* based on the feature *acting*." Then, the LLM may generate an explanation such as "The acting in this movie is attractive."

[Geng *et al.*, 2022c; Geng *et al.*, 2023; Li *et al.*, 2023c; Liu *et al.*, 2023a; Liu *et al.*, 2023b; Wang *et al.*, 2023b] perform the explanation generation task as above; [Cui *et al.*, 2022] trigger the explanation task with the word "because"; [Li *et al.*, 2023b] make use of continuous prompt vectors instead of discrete prompt templates.

4.5 Review Generation

In addition to explanation generation, the above formulation can also be adapted to the review generation task, which may make it easier and more efficient for users to leave a comment after purchasing a product, watching a movie, taking a ride, etc. The resulting data would in turn facilitate the development of recommendation-related research, such as explainable recommendation and conversational recommendation. As usual, we can fill a user and his/her interacted item in a prompt $p(u, i)$, e.g., "generate a review for *user_1234* about *item_5678*." Then, the LLM may generate a review paragraph. For example, "the hotel is located in ...". However, we have not noticed any LLM-based recommendation research on this problem, probably because the formulation is too similar to explanation generation, except that reviews are generally longer.

4.6 Review Summarization

Reading a long review can take some time, which users may not be able to afford sometimes. A highly concise review summary can help users quickly understand the pros and cons of an item. Current LLM-based review summarization methods [Geng *et al.*, 2022c; Liu *et al.*, 2023a; Liu *et al.*, 2023b; Wang *et al.*, 2023b] mainly target how to summarize a user u's own review R for an item i, and treat the review title or tip as the summary. In this case, we can construct a prompt and fill the ternary data in $p(u, i, R)$, e.g., "summarize the following review that *user_1234* wrote for *item_5678*: *the hotel is located in ...*". Then, the LLM may generate a short summary, e.g., "great location".

However, it may be unnecessary to summarize a user's own review because the user already knows about the reviewed item. Instead, summarizing the review for another user who has never interacted with the item can be more useful. Furthermore, it is also meaningful to conduct multi-review summarization that summarizes different users' opinions towards the same item. However, the problem lies in creating such multi-review summary data, since it may take a lot of human effort to write those summaries.

4.7 Conversational Recommendation

The goal of conversational recommendation is to recommend a user some items within multiple rounds of conversation [Jannach *et al.*, 2021; Sun and Zhang, 2018; Zhang *et al.*, 2018]. Different from traditional RS which mainly rely on

users' historical interactions, in a conversational environment users can freely state their preferences in natural language and even provide negative feedback, e.g., rejecting a recommendation. However, the research community is still in the process of reaching a consensus on how to formulate this task.

[Cui *et al.*, 2022; Friedman *et al.*, 2023; He *et al.*, 2023] adopt two labels (i.e., "USER" and "SYSTEM") to mark the speaker of an utterance before feeding a dialogue session into the LLM for generating a response. [Gao *et al.*, 2023] further employ a prompt constructor to summarize the input information, such as the user's query and historical conversation, but the technical details are not fully disclosed. [Lin and Zhang, 2023] directly chat with ChatGPT, because they aim to establish principles for conversational recommendation, e.g., memory mechanism and repair mechanism, rather than developing new models. For evaluation, [Wang *et al.*, 2023a] point out the problem of current protocols. Specifically, although ChatGPT's chatting ability is undeniably impressive, its performance on existing metrics is not very good because they overly stress the matching between generated responses and annotated recommendations or utterances.

4.8 Evaluation Protocols

To evaluate the performance of LLM on these tasks, we can apply existing metrics. For rating prediction, root mean square error (RMSE) and mean absolute error (MAE) are commonly used. For the other two recommendation tasks, i.e., top-N recommendation and sequential recommendation, we can employ ranking-oriented metrics, such as normalized discounted cumulative gain (NDCG), precision, and recall. Besides offline evaluation, online A/B test can also be adopted since it is able to reflect users' actual interactions with recommended items.

As to natural language generation tasks, including explanation generation, review generation, review summarization, and conversational recommendation, the quality of LLM's generation can be estimated with BLEU [Papineni *et al.*, 2002] in machine translation and ROUGE [Lin, 2004] in text summarization. Both metrics measure the degree of matching between text segments of the generated content and those of the ground-truth. Some other learning-based metrics can also be used, e.g., BERTScore [Zhang *et al.*, 2019]. However, as pointed out in [Wang *et al.*, 2023a], it can be problematic to over-emphasize the matching with annotated data. Also, there are other aspects beyond text similarity that cannot be reflected by BLEU or ROUGE. As an early attempt, [Li *et al.*, 2020] proposed several metrics such as feature coverage ratio and feature diversity that take into account the characteristics of explicit elements for the evaluation of explanations, but they are still rudimentary. Thus, more advanced and standard metrics need to be developed. In addition to automatic evaluation, we can also conduct human evaluation to measure LLM on these generation tasks. However, it requires researchers to properly design the questionnaire and the number of participants could be limited.

5 Challenges and Opportunities

In this section, we discuss research challenges and opportunities for generative recommendation in the LLM era, especially those significant matters that need urgent care in the near future.

5.1 Hallucination

Hallucination [Azamfirei *et al.*, 2023] means that the content generated by an LLM may deviate from the facts. Hallucination is an important problem in LLM as well as their applications. In particular, for LLM-based RS, we need to guarantee that the items recommended to users really exist, otherwise it may cause user dissatisfaction and frustration, and even low user adoption of the system in real life. For example, a user may spend time traveling to a recommended restaurant, only to find out that such a restaurant does not exist at all. In high-stake recommendation domains such as drug recommendation, medical treatment recommendation, and financial investment recommendation, hallucinated recommendations may cause severe losses for users.

There are two possible approaches to addressing the hallucination problem in LLM-based RS. One is to use meticulously designed item IDs for generation. For example, [Hua *et al.*, 2023b] create item IDs and organize the IDs of all items into a prefix tree structure, which is also called a trie structure. As a result, as long as the beam search generation process follows the root-to-leaf paths in the tree, the generated items will be guaranteed to be really existing items. The other method is to apply retrieval-augmentation over the LLM [Mialon *et al.*, 2023], i.e., conditioning LLM on retrieved items, so that the recommended items match those in the item database. Furthermore, the two methods, i.e., indexing and retrieval, can be integrated to address the hallucination problem effectively and efficiently.

5.2 Bias and Fairness

There can be two types of bias for LLM-based RS, which are *content bias* and *recommendation bias*. The former refers to the bias that can be directly observed in the generated content. A typical example is gender bias. [Wang *et al.*, 2022a] find that machine-generated recommendation explanations for male users are usually longer than those for female users in the game domain. This problem may lie in the training data that are adapted from user reviews of games. In addition to recommendation data, LLM trained with a huge amount of human-generated data may reiterate or even reinforce the bias hidden in the training data. Taking linguistic bias as an example, [Zhang *et al.*, 2021] observe that LLM tend to use generic tokens when generating item titles to make them look fluent and linguistically sound, but lead to recommendations that are greatly different from users' preferred items. When adapted to downstream recommendation tasks, the bias should be mitigated or even completely removed so as to prevent the propagation of negative effects and to improve user experience.

Regarding recommendation bias, [Li *et al.*, 2023f] report that ChatGPT is prone to recommend news articles from news providers that it labeled as popular. [Zhang *et al.*, 2023a] observe that the music recommendations made by ChatGPT for people with different demographic attributes (e.g., white v.s. African American) are different. Although the results look biased, they could also be a type of personalization

since the music tastes of people under different cultural backgrounds could differ. Therefore, a question needs to be answered: *What is the boundary between bias and personalization?* [Hua *et al.*, 2023a] attempt to make LLM-based recommendation models fair with respect to sensitive attributes, such as age, marital status, and occupation, by distilling the bias into continuous prompts. As the bias and fairness issues are still open problems, more work should be done, e.g., from the perspective of fairness definition and bias mitigation for LLM-based RS.

5.3 Transparency and Explainability

Making recommendations transparent and explainable to users has always been an important problem for RS and AI in general [Zhang *et al.*, 2020]. Due to the huge size and complexity of LLM, explaining LLM-based recommendations has posed new challenges to the community. There are two types of explainability for LLM-based RS. One is to generate reasonable natural language explanations for recommended items, while the other is to really dive into the model and try to explain the internal working mechanism of LLM. While researchers have explored the first type of explainability for a while [Li *et al.*, 2021; Geng *et al.*, 2022c; Geng *et al.*, 2023; Li *et al.*, 2023c; Liu *et al.*, 2023a; Liu *et al.*, 2023b; Wang *et al.*, 2023b; Cui *et al.*, 2022; Li *et al.*, 2023b; Colas *et al.*, 2023], the second type of explainability has been largely unexplored. One possible method is to align the LLM such as its prompts with an explicit knowledge base such as a knowledge graph [Geng *et al.*, 2022b; Ye *et al.*, 2023], so that the model's decision making process is aligned with explicit paths in the knowledge graph for explanation. However, the direction is generally very preliminary and requires innovative methods and brave new ideas from the community.

5.4 Controllability

Controllability is an important problem for LLM, since we usually cannot precisely control the output of LLM. The lack of controllability may cause serious problems. For example, LLM may generate harassing content, fake content, or content that deviates from basic moral standards. For RS, the controllability issue is more complicated due to the various recommendation tasks or scenarios that require controllability [Tan *et al.*, 2023; Wang *et al.*, 2022b; Schafer *et al.*, 2002; Parra and Brusilovsky, 2015]. For example, users may want to control the feature that an explanation talks about [Li *et al.*, 2021; Li *et al.*, 2023b; Geng *et al.*, 2022c], i.e., if a user cares about the "price" of a restaurant, then the explanation should talk about its price, while if the user is concerned about "distance", then the explanation should discuss the distance. Users may also want to control the features of recommended items, such as price level, color, and brand [Tan *et al.*, 2023]. For example, the user may hope that LLM only recommend items that fall within a certain price range. Although these features can be included in the prompt to trigger LLM's generation, the recommendations provided by LLM may still fail to meet the user's requirements. Current research on the controllability of LLM-based recommendation mainly focuses on controlling the explanations [Li *et al.*, 2021; Li *et al.*, 2023b; Geng *et al.*, 2022c], while more research is urgently needed on controlling recommendations generated by LLM.

5.5 Inference Efficiency

As LLM contain a huge amount of parameters and RS are a latency-sensitive application, the efficiency of LLM-based recommendation models is vital. The training efficiency can be improved by either option tuning [Cui *et al.*, 2022] or adapter tuning [Geng *et al.*, 2023]. To reduce LLM's training time, [Li *et al.*, 2023c] propose a task-alternative training strategy to deal with multiple recommendation tasks. Since the training efficiency of LLM can be improved in an offline environment and usually an LLM does not have to be retrained too frequently, it is not as important as the inference efficiency problem. [Cui *et al.*, 2022] pre-compute the first few layers of an LLM and cache the results to improve its inference efficiency. However, this strategy may only be applicable to a specific LLM architecture that represents users and items with metadata. [Li *et al.*, 2023c] observe that LLM's inference time can be slightly reduced when the discrete prompt is removed. In summary, there is still much room to further improve the inference efficiency of LLM-based recommendation models.

5.6 Multimodal Recommendation

In addition to text, data of other modalities can also be leveraged by LLM, as long as they can be represented as a sequence of tokens that can be integrated into textual sentences. [Geng *et al.*, 2023] incorporate item images into an LLM to improve its performance on recommendation tasks. Regarding image generation, [Geng *et al.*, 2022a] generate visual explanations for recommendations based on a vision-language model, and [Cui *et al.*, 2022] synthesize images for product design. In addition to images, videos and audios can also be generated in an auto-regressive way [Rubenstein *et al.*, 2023; Yan *et al.*, 2021], which makes LLM-based multimodal recommendation a promising direction. Furthermore, when there is no available item that caters to a user's interest in the item repository, the system can directly create new items. Meanwhile, model designers should guarantee the authenticity of machine-generated content to prevent users from having negative experiences, e.g., a picture of Hawaiian attraction captioned South Korea.

5.7 Cold-start Recommendation

As LLM have learned world knowledge during the pretraining stage, they are able to perform recommendation tasks even if they are not fine-tuned on recommendation-specific datasets. A typical example is ChatGPT, which can be instructed to perform various recommendation tasks as discussed in the previous section [Liu *et al.*, 2023a]. The underlying reason is that users' preferences and items' attributes can be expressed in natural language. As a result, LLM-based recommendation models have the potential to mitigate the well-known cold-start problem in recommendation when there is limited or even no interaction regarding new users or new items. Although the interaction data is insufficient, we may still make use of their metadata for recommendation,

such as user demographic information and item description information.

6 Conclusions

In this survey, we have reviewed the recent progress of LLM-based generative recommendation and provided a general formulation for each generative recommendation task according to relevant research. To encourage researchers to explore this promising direction, we have elaborated on its advantages compared to traditional RS, generalized the definition of IDs, and summarized various ID creation methods. We have also pointed out several future prospects that might be worth in-depth exploration. We anticipate a future where LLM and RS would be nicely integrated to create personalized services of high quality for users in a variety of situations.

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