Pre-train, Prompt and Recommendation: A Comprehensive Survey of Language Modelling Paradigm Adaptations in Recommender Systems

Peng Liu[1] , **Lemei Zhang**[1] , **Jon Atle Gulla**[1]
[1]Norwegian University of Science and Technology
{peng.liu, lemei.zhang, jon.atle.gulla}@ntnu.no

Abstract

The emergency of Pre-trained Language Models (PLMs) has achieved tremendous success in the field of Natural Language Processing (NLP) by learning universal representations on large corpora in a self-supervised manner. The pre-trained models and the learned representations can be beneficial to a series of downstream NLP tasks. This training paradigm has recently been adapted to the recommendation domain and is considered a promising approach by both academia and industry. In this paper, we systematically investigate how to extract and transfer knowledge from pre-trained models learned by different PLM-related training paradigms to improve recommendation performance from various perspectives, such as generality, sparsity, efficiency and effectiveness. Specifically, we propose an orthogonal taxonomy to divide existing PLM-based recommender systems w.r.t. their training strategies and objectives. Then, we analyze and summarize the connection between PLM-based training paradigms and different input data types for recommender systems. Finally, we elaborate on open issues and future research directions in this vibrant field.

1 Introduction

As an important part of the online environment, Recommender Systems (RSs) play a key role in discovering users' interests and alleviating information overload in their decision-making process. Recent years have witnessed tremendous success in recommender systems empowered by deep neural architectures and increasingly improved computing infrastructures. However, deep recommendation models are inherently data-hungry with an enormous amount of parameters to learn, which are likely to overfit and fail to generalize well in practice when their training data (i.e., user-item interactions) are insufficient. Such scenarios widely exist in practical RSs when a large number of new users join in but have fewer interactions. Consequently, the data sparsity issue becomes a major performance bottleneck of the current deep recommendation models.

With the thriving of pre-training in NLP[Qiu *et al.*, 2020], many language models have been pre-trained on large-scale unsupervised corpora and then fine-tuned in various downstream supervised tasks to achieve state-of-the-art results, such as GPT [Brown *et al.*, 2020], and BERT [Devlin *et al.*, 2019]. One of the advantages of this pre-training and fine-tuning paradigm is that it can extract informative and transferrable knowledge from abundant unlabelled data through self-supervision tasks such as masked LM [Devlin *et al.*, 2019], which will benefit downstream tasks when the labelled data for these tasks is insufficient and avoid training a new model from scratch. A recently proposed paradigm, prompt learning [Liu *et al.*, 2023], further unifies the use of pre-trained language models (PLMs) on different tasks in a simple yet flexible manner. In general, prompt learning relies on a suite of appropriate prompts, either hard text templates [Brown *et al.*, 2020], or soft continuous embeddings [Qin and Eisner, 2021], to reformulate the downstream tasks as the pre-training task. The advantage of this paradigm lies in two aspects: (1) It bridges the gap between pre-training and downstream objectives, allowing better utilization of the rich knowledge in pre-trained models. This advantage will be multiplied when very little downstream data is available. (2) Only a small set of parameters are needed to tune for prompt engineering, which is more efficient.

Motivated by the remarkable effectiveness of the aforementioned paradigms in solving data sparsity and efficiency issues, adapting language modelling paradigms for recommendation is seen as a promising direction in both academia and industry, which has greatly advanced the state-of-the-art in RSs. Although there have been several surveys on pre-training paradigms in the fields of CV [Long *et al.*, 2022], NLP [Liu *et al.*, 2023] and graph learning [Liu *et al.*, 2022c], only a handful of literature reviews are relevant to RSs. [Zeng *et al.*, 2021] summarizes some research on the pre-training of recommendation models and discusses knowledge transfer methods between different domains. But it only covers a small number of BERT-like works and does not go deep into the training details of pre-trained recommendation models. [Yu *et al.*, 2022a] give a brief overview of the advances of self-supervised learning in RSs. However, its focus is on a purely self-supervised recommendation setting, which means the supervision signals used to train the model are semi-automatically generated from the raw data itself. While our

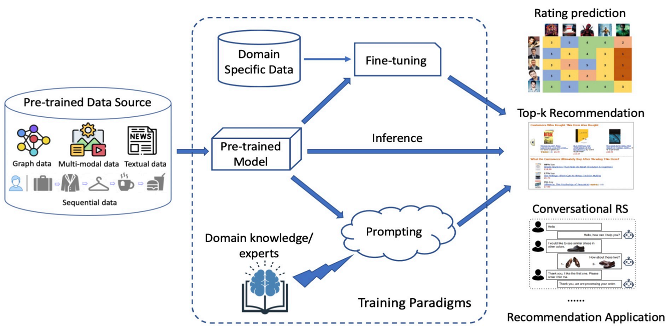

Figure 1: A generic architecture of language modelling paradigm for recommendation purpose.

work does not strictly focus on the self-supervised training strategies but also incorporates the adaptation and exploration of supervised signals and data augmentation techniques in the pre-training, fine-tuning and prompting process for various recommendation purposes. Furthermore, none of them systematically analyzed the relationship between different data types and training paradigm choices in RSs. To the best of our knowledge, our survey is the first work that presents an up-to-date and comprehensive review of **L**anguage **M**odelling Paradigm Adaptations for **R**ecommender **S**ystems (LMRS)[1]. The main contributions of this paper are summerized as follows:

- We survey the current state of PLM-based recommendation from perspectives of training strategy, learning objective and related data types, and provide the first systematic survey, to the best of our knowledge, in this nascent and rapidly developing field.
- We comprehensively review existing research works on adapting language modelling paradigms to recommendation tasks by systematically categorizing them from two perspectives: pre-training & fine-tuning and prompting. For each category, several subcategories are provided and explained along with their concepts, formulations, involved methods, and their training and inferencing process for recommendations.
- We shed light on limitations and possible future research directions to help beginners and practitioners interested in this field learn more effectively with the shared integrated resources.

2 Generic Architecture of LMRS

LMRS provides a new way to conquer the data sparsity problem via knowledge transfer from Pre-trained models (PTMs). Figure 1 gives a high-level overview of the LMRS from the perspective of data input, pre-training, fine-tuning/prompting and inference to different recommendation tasks. In general, the types of input data objects can be relevant w.r.t. both the training and inference stages. After preprocessing the input into desired forms, such as graphs, ordered sequences and aligned text-image pairs, the training process will start to take in such preprocessed data and perform either "*pre-train, fine-tune*" or "*pre-train, prompt*" flow. If the inference is barely based upon the pre-trained model, it can be seen as an end-to-end manner but leveraging LM-based learning objectives. Then the trained model can be used to infer different recommendation tasks.

3 Data Types

Encoding input data as embeddings is usually the first step in recommendations. The recommender system's input is more diverse than most NLP tasks. Therefore, the encoding techniques and processes may be differentiated and adjusted to align with different input types. This section will outline several input data types before delving into training technologies for recommendations.

Textual data As a powerful medium of spreading and transmitting knowledge, culture and thoughts, people use texts to express opinions, dialogue, narrate, and describe things. Textual data has also become one of the most common inputs for recommendations. In this paper, textual data includes reviews, comments, summaries, news, and conversations and codes.

Sequential data User-item interaction, as the basic unit of the recommender system, is originally an input sequence with chronological order. In this paper, we only classify user interactions strictly arranged chronologically or in a specific order as sequential input. This data type is commonly seen as inputs of sequential and session-based recommender systems.

Graphs Graphs usually contain different semantic information from other types of data inputs. At different phases of PLMRS training, graph construction and learning play different roles in improving recommendation performance. They can be user-user social graph, user-item interaction graph, or heterogeneous knowledge graph.

Multi-modal data Graphs usually contain different semantic information from other types of data inputs. At different phases of PLMRS training, graph construction and learning play different roles in improving recommendation performance. They can be a user-user social graph, a user-item interaction graph, or a heterogeneous knowledge graph.

4 LMRS Training Strategies

Given the significant impact that PLMs have had on NLP tasks in the pre-train and fine-tune paradigm, there has been a surge recently in adapting such paradigms to multiple recommendation tasks. As illustrated in Figure 1, there are mainly two classes regarding different training paradigms: pre-train, fine-tune paradigm and prompt learning paradigm. Each class is further classified into subclasses regarding different training efforts on different parts of the recommendation model. This section will go through various training strategies w.r.t. specific recommendation purposes. Figure

[1]It is worth noting that most of the existing literature reviews on pre-trained models focus on the architecture of large-scale language models (such as Bert, T5, UniLMv2, etc.), while our survey mainly discusses training paradigms, which are not limited to pre-trained language model architectures. It can also be other neural networks, such as CNN [Chen *et al.*, 2021], and GCN [Liu *et al.*, 2022b].

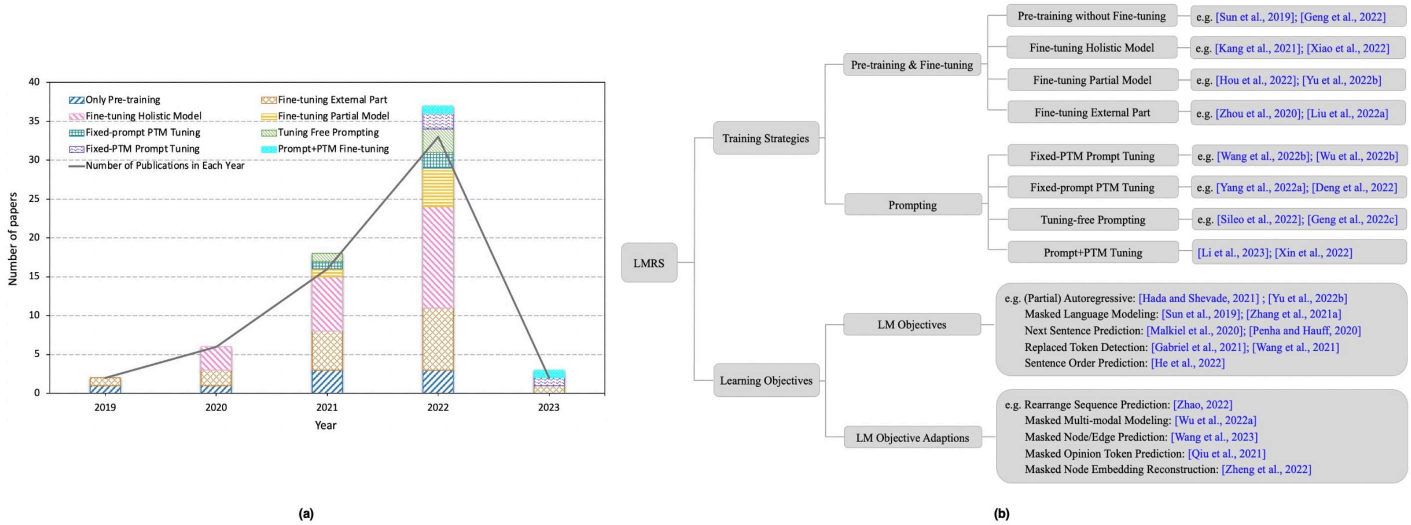

Figure 2: LMRS structure with representatives and statistics on different training strategies and the total number of publications per year.

2(b) shows the taxonomy and some corresponding representative LMRSs. Figure 2(a) statistics of recent publications of LMRSs grouped by different training strategies and the total number of the published research works each year. Table 1 distinguishes some representative LMRSs in more detail.

4.1 Pre-train, fine-tune paradigm

The "*pre-train, fine-tune*" paradigm attracts increasing attention in the recommendation field of researchers due to the advantages of 1) pre-training provides a better model initialization, which usually leads to better generalization on different downstream recommendation tasks, improves recommendation performance from various perspectives, and speeds up convergence on the fine-tuning stage; 2) pre-training on huge source corpus can learn universal knowledge which can be beneficial for the downstream recommenders; 3) pre-training can be regarded as a kind of regularization to avoid overfitting on low-resource, and small datasets [Erhan *et al.*, 2010].

Pre-train

This training strategy can be seen as traditional end-to-end training with domain input. Differently, we only focus on research works adapting LM-based learning objectives into the training phase. Many typical LM-based RSs fall into this category, such as BERT4Rec [Sun *et al.*, 2019], which modelled sequential user behaviour with a bidirectional self-attention network through Cloze task, and Transformers4Rec [Gabriel *et al.*, 2021] who adopted haggingface transformer-based architecture as the base model for next-item prediction and also explored Causal LM, MLM, Permutation LM, and Replacement Token Detection four different LM tasks while training. These two models laid the foundation for LM-based recommender systems and have become popular baselines for their successors.

Pre-train, fine-tune holistic model

Under this category, the model is pre-trained and fine-tuned with different data sources, and the fine-tuning process will go through adjusting the whole model parameters. The learning objectives can also be different from the pre-training and fine-tuning stage. Pre-training and fine-tuning with different domains of data source, also called cross-domain recommendation, can refer to the works of [Kang *et al.*, 2021; Qiu *et al.*, 2021]. [Kang *et al.*, 2021] adopted segmented source API code to pre-train the GPT model and then leveraged API code snippets from another library to fine-tune the pre-trained GPT model for cross-library recommendation. [Wang *et al.*, 2022a] fine-tuned the pre-trained DialoGPT model for conversational recommendation with domain-specific dataset together with an R-GCN model to inject knowledge from DBpedia to enhance recommendation performance. [Xiao *et al.*, 2022] fine-tuned the PTM to learn news embedding together with a user embedding part in an auto-regressive manner for news recommendation. They also explored different fine-tuning strategies like tuning part of the PTM and tuning the last layer of the PTM but empirically found fine-tuning the whole model resulted in better performance, which gives us an insight into balancing the recommendation accuracy and training efficiency.

Pre-train, fine-tune partial model

Since fine-tuning the whole model is usually time-consuming and less flexible, many LMRSs choose to fine-tune partial parameters of the model to achieve a balance between training overhead and recommendation performance [Hou *et al.*, 2022; Yu *et al.*, 2022b; Wu *et al.*, 2022a]. For instance, to deal with the problem that BERT induces a non-smooth anisotropic semantic space for general texts resulting in a large language gap for texts from different domains of items, [Hou *et al.*, 2022] applied a linear transformation layer to transform BERT representations of items from different domains followed by an adaptive combination strategy to derive a universal item representation to deal with domain bias problem. Meanwhile, considering the seesaw phenomenon that learning from multiple domain-specific behavioural patterns can be a conflict, they proposed sequence-item and sequence-

sequence contrastive tasks for multi-task learning during the pre-training stage. They found only fine-tuning a small proportion of model parameters could still quickly adapt the model to unseen domains with cold-start or new items.

Pre-train, fine-tune extra part of the model

With the increase in the depth of PTMs, the representation captured by them makes the downstream recommendation easier. Apart from the aforementioned two fine-tuning strategies, some work to leverage a task-specific layer on top of the PTMs for recommendation tasks. Fine-tuning barely goes through such extra parts of the PTMs by optimizing the parameters of the task-specific layer. [Shang *et al.*, 2019] pre-trained a GPT and a BERT model to learn to visit embeddings of patients' historical visits, which were then as input to fine-tune the extra prediction layer for medication recommendation. Another way is to use the PTM to initialize a new model with similar architecture in fine-tuning stage, and the fine-tuned model is used for recommendations. [Zhou *et al.*, 2020] first pre-trained a bidirectional Transformer-based model on four different learning objectives (associated attribute prediction, masked item prediction, masked attribute prediction and segment prediction) in a self-supervised manner to learn item embeddings. Then, the learned model parameters were adopted to initialize a unidirectional Transformer-based model for fine-tuning with pairwise rank loss for recommendation.

4.2 Prompting paradigm

Instead of adapting PLMs to different downstream recommendation tasks by designing specific objective functions, "*pre-train, prompt, and inference*" reformulating downstream recommendations through hard/soft prompts recently has a rising trend to replace "*pre-train, fine-tune and inference*" to become a vital training paradigm for multiple recommendation tasks. In this paradigm, fine-tuning can even be avoided with domain-specific training objectives. The pre-trained model itself can directly be employed to predict next items, generate recommendation explanations, make conversations, recommend similar math problems or library for programmers while coding, or even output subtasks related to recommendation targets such as explanation [Li *et al.*, 2023].

Prompt learning breaks through the problem of data constraints and bridges the gap of objective forms between pre-training and fine-tuning. Prompts can be classified as hard/discrete prompts or soft continuous prompts. The former usually uses manually carefully designed text templates that are human-readable, while the latter is composed of several continuous learnable embeddings.

Fixed-PTM prompt tuning

Prompt-tuning only needs to tune a small set of parameters for the prompts and labels, which is efficient for especially few-shot recommendation tasks. Despite the promising results via constructing prompt information without changing the structure and parameters of PTMs significantly, it also calls for the necessity of choosing the most appropriate prompt template and verbalizer, which may greatly impact recommendation performance. Prompt tuning can be both discrete textual template [Penha and Hauff, 2020], which is more human readable, and soft continuous vectors [Wang *et al.*, 2022b; Wu *et al.*, 2022b]. For instance, [Penha and Hauff, 2020] manually designed several prompt templates to test the performance of movie/book recommendations on a pre-trained BERT model with similarity measure. [Wu *et al.*, 2022b] proposed a personalized prompt generator tuned to generate soft prompt as a prefix before user behaviour sequence for sequential recommendation.

Fixed-prompt PTM tuning

Fixed-prompt PTM tuning tunes the parameters of PTMs similar to the "pre-train, fine-tune" strategy but additionally uses prompts with fixed parameters to steer the recommendation task. The prompts can be one or several tokens indicating different tasks, including recommendations. [Deng *et al.*, 2022] different unified goals, such as chit-chat, conversational recommendation and question&answer, to the same sequence-to-sequence model and designed prompt tokens to shift/lead the conversation from various tasks seamlessly. The model was trained in a multi-task learning scheme, and the parameters were optimized with the same objective. [Yang *et al.*, 2022] designed a *[REC]* token as prompt to indicate the start of the recommendation process and to summarize the dialogue context for the conversational recommendation.

Tuning-free prompting

This training strategy can be referred to *zero-shot recommendations* that directly generates the results of recommendation or/and related subtasks without changing the parameters of the PTMs but based only on the input prompts. Zero-shot recommendation has been verified by a few research works on its ability to deal with new user/item in one domain or cross-domain settings [Sileo *et al.*, 2022; Geng *et al.*, 2022b] compared with state-of-the-art baselines. Specifically, [Geng *et al.*, 2022b] learned multiple tasks such as sequential recommendation, rating prediction, explanation generation, review summarization and direct recommendation in a unified way with the same Negative Log-likelihood (NLL) training objectives during pre-training. At the inference stage, a series of carefully designed discrete textual template prompts were taken as input, including the ask for recommending items in the new domain (not appearing in the pre-training phase) and the trained model output the preferable results without fine-tuning stage. The reason for the ability of zero-shot recommendation is that the training data and the pre-training tasks are able to distil the rich knowledge of semantics and correlations from diverse modalities into the user and item tokens which are able to comprehend the user preferences behaviours w.r.t. item characteristics [Geng *et al.*, 2022b].

Prompt+PTM tuning

In this setting, parameters include two parts: the prompt-relevant parameters and the model parameters. The tuning phase is performed by optimizing all parameters for specific recommendation tasks. Different from "pre-train, fine-tune the holistic model", Prompt+PTM tuning can provide the additional prompts that can provide additional bootstrapping at the start of model training. For example, [Li *et al.*, 2023] proposed a continuous prompt learning approach by first fixing

PTM, tuning prompt to bridge the gap between the continuous prompts and the loaded PTM, and then fine-tuning both prompt and PTM, resulting in higher BLUE score on empirical results. They combined both discrete prompts (three user/item feature keywords, such as gym, breakfast and Wi-Fi) and soft prompts (user/item embedding) to generate recommendation explanations. The case studies showed the improvement of the proposed prompts on readability and fluency of generated explanations. Note that Prompt+PTM tuning stage does not necessarily mean the fine-tuning stage but can be any possible stage for tuning parameters from both sides for specific data input. [Xin *et al.*, 2022] adapt reinforcement learning framework as a Prompt+PTM tuning strategy by learning reward-state pair as a soft prompt encoding w.r.t. the observed action during training. At the inferencing stage, the trained prompt generator could directly generate soft prompt embedding for recommendation model to generate action (item).

Despite some improvements that "*pre-train, fine-tune*" and "*pre-train, prompt*" training strategies have achieved in recommendation field, research is still in its infancy stage, and more work should be done to compare the performance of the different training strategies on recommendation tasks on the same platform.

5 Training Objectives

Given the significant impact of the language modelling paradigm in recommendation tasks, there are a lot of research works adopt language training strategies or/and training objectives for specific targets. This section will overview several typical learning tasks and objectives of language models and their adaptation for different recommendation purposes.

5.1 Language modelling objectives

Due to the expensive manual efforts on annotated datasets, many language learning objectives adopt self-supervised label and convert to a classic probabilistic density estimation problem. Particularly, language modelling objectives include auto-regressive or partial auto-regressive modelling, Masked Language Modelling (MLM), Next Sentence Prediction (NSP), and Replaced Token Detection(RTD).

Partial/ Auto-regressive Modelling (P/AM) Given a text sequence $\mathbf{X}_{1:T} = [x_1, x_2, \cdots x_T]$, the joint probability can be factorized as a product of conditionals

$$p(\mathbf{X}_{1:T}) = \prod_{t=1}^{T} p(x_t|\mathbf{X}_{1:t-1}) \tag{1}$$

where the probability of each variable is dependent on the previous variables. And the following formula summerizes the training objective of AM as:

$$\mathcal{L}_{AM} = -\sum_{t=1}^{T} log\, p(x_t|\mathbf{X}_{<t-1}) \tag{2}$$

Representative examples of modern LMRS adopt popular pre-trained left-to-right LMs such as GPT-2 [Hada and Shevade, 2021] and DialoGPT [Wang *et al.*, 2022a; Wang *et al.*, 2022b] as backbone for explainable recommendation and conversational recommendation respectively, to avoid ponderous work of pre-training from scratch. Auto-regressive objectives can model the context dependency well, but the modelling context can only be accessed from one direction (mostly left-to-right). Therefore, partially autoregressive LM (PAM) is proposed to extend AM by enabling the factorization step to be a span. For each input $\mathbf{X}$, one factorization order M will be sampled. UniLMv2 [Bao *et al.*, 2020] is a popular PTM that takes PAM as one of its objectives, and the pre-trained UniLMv2 model can be used to initial news embedding model for news recommendation [Yu *et al.*, 2022b].

Masked Language Modelling (MLM) Taking a sequence of textual sentence as input, MLM first masks a token or multi-tokens with a special token such as $[MASK]$. Then the model is trained to predict the masked tokens taking the rest of the tokens as context. The objective is as follows:

$$\mathcal{L}_{MLM} = -\sum_{\hat{x} \in m(\mathbf{X})} log\, p(\hat{x}|\mathbf{X}_{M(\mathbf{X})}) \tag{3}$$

where $M(\mathbf{X})$ and $\mathbf{X}_{M(\mathbf{X})}$ represent the masked tokens in the input sequence $\mathbf{X}$ and the rest of the tokens in $\mathbf{X}$ respectively. A typical example of MLM training strategy can be found on BERT, which is leveraged as backbone in [Zhang *et al.*, 2021] to enhance news representations and capture user-news matching signals for news recommendation.

Concurrently, some research works propose multiple enhanced versions of MLM. RoBERTa [Liu *et al.*, 2019] improves BERT by dynamic masking instead of static manner and can be used to initiate word embedding for conversations [Wang *et al.*, 2022b] and news articles [Wu *et al.*, 2021] for different recommendation scenarios.

Next Sentence Prediction (NSP) It is a binary classification loss for predicting whether two segments follow each other in the original text. The training can be performed in a self-supervised way by taking positive examples from consecutive sentences from the input text corpus and creating negative examples by pairing segments from different documents. A general loss of the NSP is as follows:

$$\mathcal{L}_{NSP} = -\,log\, p(c|\mathbf{x}, \mathbf{y}) \tag{4}$$

where $\mathbf{x}$ and $\mathbf{y}$ represent two segments from the input corpus, and $c = 1$ if $\mathbf{x}$ and $\mathbf{y}$ are consecutive, otherwise $c = 0$. The NSP objective requires reasoning about the relationships between pairs of sentences, which can be used for better representation learning for textual items such as news, item descriptions, and conversations for recommendation purposes. Still, it also can be leveraged to model the intimate relationships between two components. In [Malkiel *et al.*, 2020], the NSP is used to model the relationship between the title and the description of an item for next item prediction. Besides, model pre-trained with the NSP (e.g. BERT) can also be used to probe the learned knowledge with prompts, which is then infused in the fine-tuning stage to improve the ability of model training adversarial data for conversational recommendation [Penha and Hauff, 2020].

Another variation of the NSP is the Sentence Order Prediction (SOP). The differences lie in that the latter takes two consecutive segments from the same document as positive examples, but the same two segments with swapped order as negative examples [Lan *et al.*, 2020]. In [He *et al.*, 2022], the

Training Strategy	Paper	Learning Objective	Recommendation Task	Data Type	Source Code
Pre-training & Fine-tuning					
Pre-training w/o Fine-tuning	[Sun *et al.*, 2019]	Pre-train: MLM	Sequential RS	Sequential data	https://shorturl.at/ioxGP
	[Geng *et al.*, 2022a]	Pre-train: AM	Explainable RS	Graph	N/A
	[Gabriel *et al.*, 2021]	Pre-train: AM + MLM + PLM + RTD	Session-based RS	Textual + Sequential data	https://shorturl.at/ehqHV
Fine-tuning Holistic Model	[Kang *et al.*, 2021]	Pre-train: cross-entropy Fine-tune: cross-entropy	Cross-library API RS	Textual data (code)	https://shorturl.at/JLOQ0
	[Wang *et al.*, 2022a]	Pre-train: AM Fine-tune: AM + cross-entropy	Conversational RS	Textual data + Graph	https://shorturl.at/luBX1
	[Xiao *et al.*, 2022]	Pre-train: AM + MLM Fine-tune: AM	News RS	Textual + Sequential data	https://shorturl.at/giPQR
	[Zhang *et al.*, 2022a]	Pre-train: MLM + NT-Xent Fine-tune: Negative Sampling Loss	Social RS	Textual data	https://shorturl.at/aegQW
	[Wang *et al.*, 2023]	Pre-train: MNP + MEP + cross-entropy + Contrastive Loss; Fine-tune: cross-entropy	Top-N RS	Graph	N/A
Fine-tuning Partial Model	[Hou *et al.*, 2022]	Pre-train: Contrastive Loss Fine-tune: cross-entropy	Cross-domain RS Sequential RS	Textual + Sequential data	https://shorturl.at/kMVXZ
	[Yu *et al.*, 2022b]	Pre-train: MLM + AM Fine-tune: cross-entropy + MSE + InfoNCE	News RS	Textual + Sequential data	https://shorturl.at/biow4
	[Wu *et al.*, 2022a]	Pre-train: MMM + MAP Fine-tune: cross-entropy	News RS	Sequential + Multi-modal data	https://shorturl.at/lKLMQ
Fine-tuning External Part	[Zhou *et al.*, 2020]	Pre-train: MIM Fine-tune: Pairwise Ranking Loss	Sequential RS	Textual + Sequential data	https://shorturl.at/BDLM2
	[Liu *et al.*, 2022a]	Pre-train: MTP + cross-entropy Fine-tune: cross-entropy	News RS	Textual + Sequential data	https://shorturl.at/ADERU
	[Shang *et al.*, 2019]	Pre-train: binary cross-entropy Fine-tune: cross-entropy	Medication RS	Graph	https://shorturl.at/kuIZ8
	[Liu *et al.*, 2022b]	Pre-train: binary cross-entropy Fine-tune: BPR + binary cross-entropy	Top-N RS	Textual data + Graph	https://shorturl.at/tHJOR
Prompting					
Fixed-PTM Prompt Tuning	[Wang *et al.*, 2022b]	Pre-train: AM + MLM + cross-entropy Prompt-tuning: AM + cross-entropy	Conversational RS	Textual data	https://shorturl.at/cuCOT
	[Wu *et al.*, 2022b]	Pre-train: Pairwise Ranking Loss Prompt-tuning: Pairwise Ranking Loss + Contrastive Loss	Cross-domain RS Sequential RS	Textual + Sequential data	N/A
Fixed-prompt PTM Tuning	[Yang *et al.*, 2022]	Pre-train: AM + MLM PTM Fine-tune: AM + cross-entropy	Conversational RS	Textual data	https://shorturl.at/cuCOT
	[Deng *et al.*, 2022]	Pre-train: AM; PTM Fine-tune: AM	Conversational RS	Textual data	https://shorturl.at/dlAY1
Tuning-free Prompting	[Sileo *et al.*, 2022]	Pre-train: AM	Zero-Shot RS	Textual data	https://shorturl.at/glmqA
	[Geng *et al.*, 2022b]	Pre-train: AM	Zero-Shot RS Cross-domain RS	Textual + Sequential data	https://shorturl.at/wHJR4
Prompt+PTM Tuning	[Li *et al.*, 2023]	Pre-train: AM; Prompt-tuning: NLL Prompt+PTM tuning: NLL + MSE	Explainable RS	Textual data	https://shorturl.at/opS15
	[Xin *et al.*, 2022]	Prompt+PTM tuning: cross-entropy	Next Item RS	Sequential data	N/A

Note: NT-Xent: Normalized Temperature-scaled Cross Entropy Loss; MMM: Masked Multi-modal Modelling; MAP: Multi-modal Alignment Prediction; MIM: Mutual Information Maximization Loss; MTP: Masked News/User Token Prediction; NLL: Negative Log-likelihood Loss.

Table 1: A list of representative LMRS methods with open-source code.

SOP is used to learn the inner coherence of title, description, and code for tag recommendation on StackOverflow.

One potential uncertainty of the NSP and the SOP is that its necessity and effectiveness for downstream tasks have been questioned by some researchers [He *et al.*, 2022], which should be further verified in recommendation scenario.

Replaced Token Detection(RTD) It is used to predict whether a token is replaced given its surrounding context. The objective is as follows:

$$\mathcal{L}_{RTD} = -\sum_{t=1}^{T} log\, p(y_t|\hat{\mathbf{X}}) \tag{5}$$

where $y_t = \mathbf{1}(\hat{x}_t = x_t)$, $\hat{\mathbf{X}}$ is corrupted from the input sequence $\mathbf{X}$. [Gabriel *et al.*, 2021] leveraged a Transformer-based architecture model to train on RTD task for session-based recommendations and empirically achieved the best performance compared with MLM and AM learning objectives on the same model architecture, which is probably because RTD takes the whole user-item interaction sequence as input and model the context from the bidirectional way.

5.2 Adaptive objectives to recommendation

A variety of several per-training or fine-tuning objectives take inspiration from LM objectives and are successfully adapted to specific downstream tasks according to different input data types and recommendation purposes.

A natural motivation in sequential recommendations is to model an ordered input sequence from left to right in an auto-regressive way. [Zheng *et al.*, 2022; Xiao *et al.*, 2022] took user clicked news history as input text sentence and proposed to model user behaviour in an auto-regressive manner for next user clicking prediction. Considering that the sequential dependency may not be strictly held in terms of user preference for recommendations as verified in [Yuan *et al.*, 2020a], modifications can be made based on MLM objectives. [Yuan *et al.*, 2020b] randomly masked a certain percentage of historical user records and predicted the masked items at the masked position in training. Auto-regressive learning tasks can also be adapted to other types of data. For instance, [Geng *et al.*, 2022a] took a series of paths sampled from a knowledge graph as input sequences, which were then modelled in an auto-regressive way, and recommendation was made by generating the end node from the pre-trained model. [Zhao, 2022] observed the significant importance of the item interaction order in a user's interaction history in capturing the user's true preferences according to the analysis of the real-word e-commercial data and reordering the interaction sequence might not make full use of the order information. Based on this, they propose pre-training the Rearrange Sequence Prediction task by predicting whether the user interaction history had been rearranged to learn the sequence-level information of the user's entire interaction history, which is similar to Permuted Language Modelling (PLM) [Yang *et al.*, 2019]. The empirical results showed superior performance on sequential recommendation, which is not sensitive to the rearrangement probability.

MLM, also called *Cloze Prediction*, can be adapted to learn graph representations for different recommendation purposes. [Wang *et al.*, 2023] proposed to pre-train a transformer with Masked Node Prediction (MNP), Masked Edge prediction (MEP) and meta-path type prediction on the reconstructed subgraph from user-item-attribute heterogeneous graph by taking node id embedding, node type embedding, slot embedding and precursor embedding as inputs. MNP was performed by randomly masking a proportion of nodes in a heterogeneous subgraph and then predicting the masked nodes based on the remaining contexts by maximizing the distance between the masked node and the irrelevant node. Similarly, MEP was to recover the masked edge of two adjacent nodes based on the surrounding context. MLM can also be adapted to multi-modal data called Masked Multi-modal Modelling (MMM) [Wu *et al.*, 2022a]. MMM was performed by predicting the semantics of masked news and news image regions given the unmasked inputs and indicating whether a news image and news content segment correspond for news recommendation.

NSP/SOP can be adapted to CTR prediction as Next K Behaviors Prediction (NBP), which was proposed to learn user representations in the pre-training stage by inferring whether a candidate behaviour is the next i-th behaviour of the target user based on their past N behaviours and to capture the relatedness between past and multiple future behaviours.

6 Formulating Training with Data Types

To associate different training strategies and objectives with different types of input data, in Table 1, we summarize representative research works in this domain and list their training paradigms according to various training inputs for different recommendation tasks. The listed training strategies and objectives are carefully selected and are typical in existing work. For the page limit, we only selected part of recent research on LMRS. For more research progress and related resources, please see https://github.com/liupeng9966/LMRS.

7 Conclusion

In this survey, we presented an overview of LMRSs. We discuss the generic architecture and propose a comprehensive taxonomy of pre-training & fine-tuning, and prompting. For each category, we briefly introduce its concepts and the training and inferencing process for recommendations. We review different LM learning objectives and adaptations to RS. Despite the effectiveness of LM training paradigms has been verified in various recommendation tasks, there are still several challenges that could be the direction of future research.

Language bias and fact-consistency in language generation tasks of recommendation. While generating free-form responses of conversational recommender systems or explanations of the recommended results using language models, the pre-trained model tends to predict generic tokens to make sentences fluent or repeat certain universally applicable "safe" sentences (e.g. "the hotel is very nice" generated from PETER [Li *et al.*, 2021]). Therefore, one of the future research directions is how to enhance the diversity and pertinence of generated explanations and replies based on ensuring language fluency instead of "Tai Chi" responses. Meanwhile, how to generate sentences that are consistent with the facts is also an urgent research problem that needs to be solved but lacks attention [Xie *et al.*, 2022].

Knowledge transmission and injection for downstream recommendations. To transfer knowledge from the pre-trained model, improper training strategy may cause problems of varying degrees. [Zhang *et al.*, 2022b] point out the catastrophic forgetting problem in continuously-trained industrial recommender systems. Understanding how much domain knowledge the pre-trained models have and how to transfer and inject the learned domain knowledge for recommendation purposes are both open questions.

Scalability of pre-training mechanism in recommendation. With the continuous development of the pre-trained model with large-scale data sources as inputs, model parameters are getting larger and larger, and the stored knowledge is also increasing. Despite the great success of the pre-trained model in recommendation tasks, what should be paid more attention to is how to maintain and update such complex and large-scale models without affecting the efficiency and accuracy of recommendations in reality. Some works propose to improve model updating efficiency by fine-tuning partial pre-trained models or extra part with parameters far less than the model magnitude. However, efforts are still needed in this rapidly developing field.

Privacy issue and ethical state. [Yuan *et al.*, 2020b] revealed that the user representations learned by pre-trained models could infer user profiles (e.g. gender, age, and marital status), which could help to improve the quality of recommendation tasks but also raise concerns about privacy protection. Indeed, recent pre-training processes are performed on large-scale corpus crawled from the web without fine-grained filtering, which may perceive users' sensitive information. Therefore, developing LMRS ensuring trade-offs between privacy and the high performance of recommendation algorithms is still an open issue.

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