

Multi-Task Deep Recommender Systems: A Survey

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Multi-task learning (MTL) aims at learning related tasks in a unified model to achieve mutual improvement among tasks considering their shared knowledge. It is an important topic in recommendation due to the demand for multi-task prediction considering performance and efficiency. Although MTL has been well studied and developed, there is still a lack of systematic review in the recommendation community. To fill the gap, we provide a comprehensive review of existing multi-task deep recommender systems (MTDRS) in this survey. To be specific, the problem definition of MTDRS is first given, and it is compared with other related areas. Next, the development of MTDRS is depicted and the taxonomy is introduced from the task relation and methodology aspects. Specifically, **the task relation is categorized into parallel, cascaded, and auxiliary with main, while the methodology is grouped into parameter sharing, optimization, and training mechanism**. The survey concludes by summarizing the application and public datasets of MTDRS and highlighting the challenges and future directions of the field.

ACM Reference Format:

Yuhao Wang, Ha Tsz Lam, Yi Wong, Ziru Liu, Xiangyu Zhao, Yichao Wang, Bo Chen, Huifeng Guo, and Ruiming Tang. 2023. Multi-Task Deep Recommender Systems: A Survey. 14 pages.

1 INTRODUCTION

The development of the Internet industry has led to a tremendous increase in the information volume of online services, such as social media and online shopping platforms [1]. The Recommender Systems (RS), which match different types of items with users based on their hidden patterns, has made significant influences on improving the online experience for users in a variety of scenarios, such as product matching in online shopping and movie recommendation [42, 54]. For recommendation problems, the input data typically consists of categorical features and sparse identity information [42]. The common recommendation tasks can be divided into score prediction and generation. Score prediction is usually formulated as a classification or regression problem predicting the likelihood of a user to perform an action, such as click through rate (CTR) prediction. Generation task focuses on providing explanations for recommendations [39].

In practice, the RS should be endowed with the capability to conduct various recommendation tasks simultaneously, so as to cater to multiple and diverse demands of user. For example, in video recommendation, users exhibit different behaviors towards a single video, such as clicks, likes, and retweets. Consequently, the development of multi-task recommendation (MTR) is prompted in both

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Conference acronym

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ACM ISBN 978-1-4503-XXXX-X/18/06...\$15.00

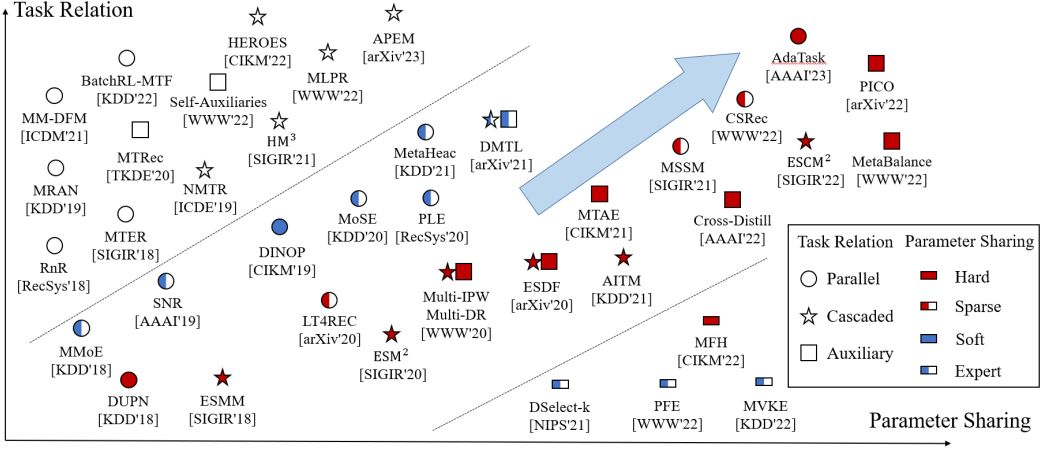


Fig. 1. Trend of MTDRS. Shapes denote different task relations, colors represent parameter sharing patterns. They have works overlapped.

research and application fields [56]. MTR is applied in various domains for more personalized and relevant recommendations based on multiple aspects of user behaviors. Based on the capability of deep neural networks (DNN) to learn high-order feature interactions and model complex user-item interaction behaviors, multi-task deep recommender systems (MTDRS) incorporate multi-task learning (MTL) paradigm and have demonstrated superior performance compared to traditional MTR frameworks.

Compared with tackling multiple recommendation tasks separately, MTDRS offers two main benefits. On the one hand, by exploiting data and knowledge across multiple tasks, MTDRS can achieve mutual enhancement among the tasks. On the other hand, it obtains higher efficiency of computation and storage. Despite these advantages, MTDRS also face three challenges. First, MTDRS must effectively and efficiently capture useful information and relevance among tasks. Second, the data sparsity, e.g., in the conversion signal, presents a challenge. Third, the unique sequential dependency, i.e., the sequential pattern of user actions across tasks in recommendations, is another challenge faced by MTDRS.

In the rest of the survey, the problem definition and analysis of MTDRS are presented in Section 2, including the comparison with three similar areas in recommendation and MTL in CV and NLP. Next, the trend (Figure 1) and the taxonomy of MTDRS are detailed in Section 3. Afterward, the application of MTDRS and public datasets are introduced in Section 4. Finally, its challenges and future directions are summarized in Section 5 and Section 6 concludes the survey.

2 PROBLEM DEFINITION AND ANALYSIS

In this section, the formulation and loss function of MTDRS is given. Next, MTR is compared with related fields in recommendation, and the MTL techniques in CV and NLP areas.

2.1 Formulation of MTDRS

Given a K -task recommendation dataset with $D := \{\mathbf{x}_n, (y_n^1, \dots, y_n^K)\}_{n=1}^N$, which consists of N user-item interaction records and the corresponding feature vector of observed impression, where \mathbf{x}_n represents the concatenation of the n -th user-item ID pair and feature vector. Each data record has K labels y^1, \dots, y^K for the corresponding task. The objective is to learn the MTL model with task-specific parameters $\{\theta^1, \dots, \theta^K\}$ and shared parameter θ^s , which outputs the K task-wise predictions

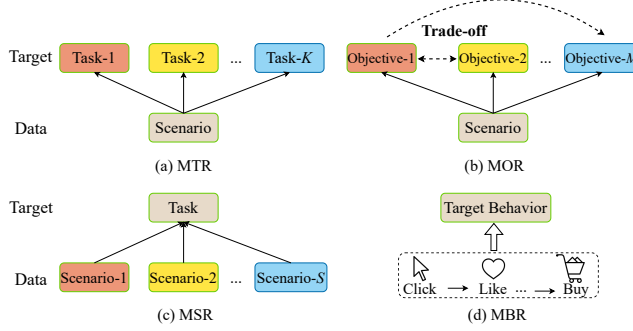


Fig. 2. Comparison of MTR, MOR, MSR, and MBR according to the target and data. K , M , and S denotes the number of task, objective, and scenario, respectively.

by extracting the hidden pattern of user-item feature interactions. The loss function for multi-task training is commonly defined as a weighted sum of losses, e.g., Binary Cross-Entropy (BCE). The above modeling process can be written as the following optimization problem:

$$\arg \min_{\{\theta^1, \dots, \theta^K\}} \mathcal{L}(\theta^s, \theta^1, \dots, \theta^K) = \arg \min_{\{\theta^1, \dots, \theta^K\}} \sum_{k=1}^K \omega^k L^k(\theta^s, \theta^k) \quad (1)$$

where $L^k(\theta^s, \theta^k)$ is the loss function for k -th task with parameter θ^s, θ^k , and ω^k is the loss weight for k -th task.

- The objective functions for most existing MTL works are typically linear scalarizations of the multiple-task loss functions, which fix the weight with a constant. However, the PLE model [54] proposes an updatable loss weight: given an initial loss weight ω_0^k for task k , the loss weight is updated based on a constant ratio γ_k :

$$\omega_t^k = \omega_0^k \cdot \gamma_k^t \quad (2)$$

This setting is based on the observation that tasks may have different importance for the specific training period.

- Since MTDRS usually conducts score prediction task, the general assumption of loss function $L^k(\theta^s, \theta^k)$ for the k -th task with parameter θ^s, θ^k is the BCE loss:

$$L^k(\theta^s, \theta^k) = - \sum_{n=1}^N [y_n^k \log(\hat{y}_n^k) + (1 - y_n^k) \log(1 - \hat{y}_n^k)] \quad (3)$$

where \hat{y}_n^k is the prediction value for task k at the n -th data parameterized by θ^s, θ^k .

2.2 Comparison with Related Recommendation Directions

This section aims to compare the MTR against related areas in recommendation, i.e., multi-objective recommendation (MOR), multi-scenario recommendation (MSR) and Multi-behavior recommendation (MBR). Meanwhile, their comparison is depicted in Figure 2.

2.2.1 Comparison with Multi-objective Recommendation. Multi-objective optimization (MOO) focuses on Pareto efficiency [51], which is regarded as an optimal state where no objective could be improved without hurting others. The Pareto frontier is constructed by combing all Pareto-efficient situations. Based on MOO, multi-objective recommendation (MOR) focuses on the trade-off and balance among multiple objectives, e.g., diversity [38] and fairness [68] from the optimization perspective. Interested readers can refer to the existing surveys on MOR [29, 85]. Furthermore, the

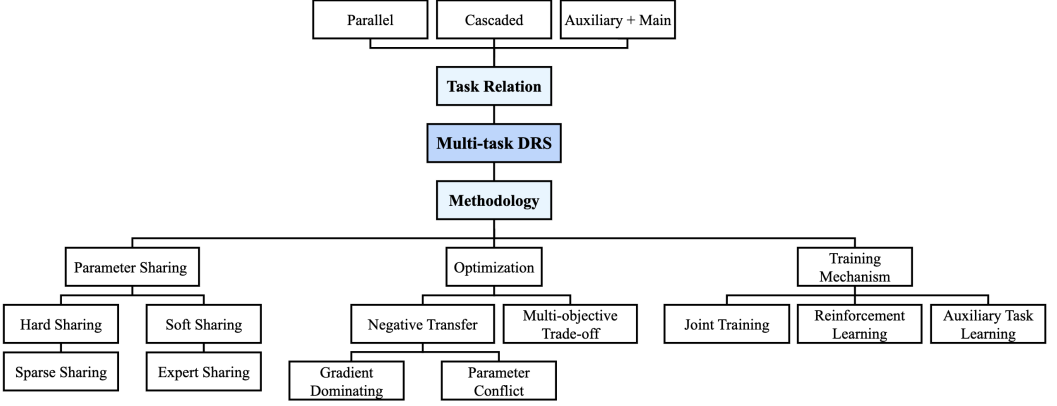


Fig. 3. An overview of taxonomy.

connections between MOR and MTR are two-fold. On the one hand, MOO can be a solution to MTDRS, since minimizing task losses in multi-task learning can be formulated as MOO problem [52], e.g., Lin et al. [35] achieve improvement simultaneously on CTR and GMV task in the online experiment. On the other hand, the multi-objective trade-off under MTDRS setting is a new direction. It presents a multi-dimensional Pareto frontier and we will further detail it in Section 3.3.2.

2.2.2 Comparison with Multi-scenario Recommendation. Multi-scenario recommendation (MSR) aims at improving recommendation performance simultaneously in multiple scenarios such as the different categories of products on Amazon and different spots to present items on Taobao. MSR uses all-scenario data with a unified model to tackle the data sparsity problem. It is also referred to as multi-target cross-domain recommendation in the research community. Similarly, both MSR and MTR require generating adaptive representations among multiple scenarios or tasks in a fine-grained manner and modeling complex inter-dependency. Meanwhile, MTDRS models can be applied for MSR simply regarding different scenarios as different tasks like HMoE [32]. However, these two problems are at different levels. Specifically, MSR focuses on the same task whose label space is the same while the data distribution is distinctive in different scenarios. By contrast, MTDRS has different label spaces of different tasks.

2.2.3 Comparison with Multi-behavior Recommendation. Multi-behavior recommendation (MBR) focuses on predicting the probability that a user will interact with an item under the target behavior as single-task learning, given the multi-behavior interaction history. It is inspired by the fact that other types of behavior and feedback contain mutual inter-dependency and contextual signals, leading to a better understanding of target behavior. Similarly, the prediction of different behaviors can be explicitly modeled as different tasks in MTDRS [14, 17, 26].

2.3 Comparison with MTL in CV&NLP

By contrast, the focus of MTL is different in computer vision (CV) and natural language processing (NLP). Specifically, the MTL problem in CV can be defined as the multi-target segmentation and further classification for each object. Most existing methods utilize feature transformation [81] to represent common features based on a multi-layer feed-forward network. Besides, the existing MTL models in NLP mostly focus on the design of MTL architectures [5], e.g., based on recurrent neural network (RNN), since the data exhibits the sequence pattern. Meanwhile, the NLP tasks can be divided into word-, sentence-, and document-level by granularity.

3 TAXONOMY

In this section, the trend of MTDRS is first depicted in Figure 1. Next, the taxonomy is depicted in Figure 3, then it is detailed from the perspective of task relation and methodology.

3.1 Trend of MTDRS

We differentiate MTDRS models by two dimensions, i.e., task relation and methodology. Specifically, we depict the development of MTDRS in Figure 1 and existing models are divided into three groups: purely on task relation, purely on parameter sharing, and both.

To begin with, as for the methods considering task relation only, parallel and cascaded relations are in the majority. Meanwhile, among the methods concerned with parameter sharing only, most works target at improving expert sharing. Finally, the mainstream MTDRS models simultaneously consider these two factors. Among them, more than half of the works focus on hard sharing, which indicates the widespread use of shared bottom architecture [3]. Besides, expert sharing is the hot spot, while they are mainly discussed under the parallel task relation setting.

3.2 Task Relation

Considering the relation of tasks, MTDRS can be systematized as: parallel, cascaded, and auxiliary with main tasks.

3.2.1 Parallel. A parallel task relation indicates that various tasks are independently calculated without the sequential dependency of their results. The objective function of parallel task relation MTDRS is usually defined as the weighted sum of losses with constant loss weights. Existing methods under parallel task relation can be grouped by their target and challenge.

As for the target, RnR [21] merges the ranking and rating prediction tasks along with a two-phase decision process for personalized recommendation in video recommendation. Additionally, MTER [60] and CAML [8] focus on recommendation and explanation tasks. Besides, DINOP [70] is proposed specifically for e-commerce online promotions by considering multiple sales prediction tasks.

Meanwhile, several works try to tackle the challenge of feature selection and sharing among parallel tasks, since a static sharing strategy may fail to capture the complex task relevance. Existing studies mainly adopt attention mechanisms. DUPN [45] integrates multi-task learning, attention along with RNNs to extract general features that will be shared among the associated tasks. MRAN [82] proposes to use an attention mechanism for feature interaction and task-feature alignment. RevMan [33] uses an attentive adaptive feature sharing mechanism for different tasks. MSSM [14] applies a feature-field sparse mask within the input layer and the connection control between a set of more fine cells in sub-networks of multiple layers. Recently, CFS-MTL [9] proposes to select the stable causal features via pseudo-intervention from a causal view.

3.2.2 Cascaded. A cascaded task relationship refers to the sequential dependency between tasks. In other words, the computation of the current task depends on the previous ones, e.g., CTCVR derived by multiplying CTR and CVR. It can be considered as a general MTL problem with the assumption on prediction scores for specific task k :

$$\hat{y}_n^k(\theta^s, \theta^k) - \hat{y}_n^{k-1}(\theta^s, \theta^k) = P(\epsilon_k = 0, \epsilon_{k-1} = 1) \quad (4)$$

where ϵ_k is the indicator variable for task k . This assumption implies the difference of $\hat{y}_n^k(\theta^s, \theta^k)$ and \hat{y}_n^{k-1} is the probability of the task k not happening while the task $k - 1$ is observed. Besides, the formulation above is equivalent to the sequential dependence MTL (SDMTL) in [55].

We summarize the methods under the cascaded task relation setting in Table 1 with respect to the problem and behavior sequence. They basically aim at CVR prediction task on the e-commerce

Table 1. Summary of models with cascaded task relation in MTDRS

Model	Problem	Behavior Sequence
ESMM [42]	SSB & DS	impression → click → conversion
ESM ² [65]	SSB & DS	impression → click → D(O)Action → purchase
Multi-IPW & DR [80]	SSB & DS	exposure → click → conversion
ESDF [62]	SSB & DS & time delay	impression → click → pay
HM ³ [64]	SSB & DS & micro and macro behavior modeling	impression → click → micro → macro → purchase
AITM [67]	sequential dependence in multi-step conversions	impression → click → application → approval → activation
MLPR [66]	sequential engagement & vocabulary mismatch in product ranking	impression → click → add-to-cart → purchase
ESCM ² [57]	inherent estimation bias & potential independence priority	impression → click → conversion
HEROES [30]	multi-scale behavior & unbiased learning-to-rank	observation → click → conversion
APEM [55]	sample-wise representation learning in SDMTL	impression → click → authorize → conversion

platform, except AITM [67] and APEM [55] are proposed for advertising and financial service, respectively. Meanwhile, they mainly target at tackling sample selection bias (SSB) and data sparsity (DS) issues caused by sparse training data of conversion. Besides, their assumed sequential patterns are based on “impression → click → conversion” and its extension following ESMM [42], which adopts shared embedding and models over entire space.

3.2.3 Auxiliary with Main Task. Auxiliary with main task refers to the circumstance that a task is specified as the main task while others, i.e., associated auxiliary tasks help to improve its performance. The probability estimation for the main task is calculated based on the probability of auxiliary tasks, which is estimated on the entire space with richer information.

On the one hand, some works simply adopt the original recommendation tasks as auxiliaries [26, 62, 83, 83]. Specifically, Multi-IPW and Multi-DR [80] introduce an auxiliary CTR task with main CVR and imputation task. ESDF [62] treats CTR and CTCVR as auxiliaries of time delay task. DMTL [83] models CTR as auxiliary of duration task.

On the other hand, some works design various auxiliary tasks under specific settings [31, 36, 73, 75]. Specifically, MTRec [31] takes link prediction for network dynamic modeling as an auxiliary of the recommendation task. PICO [36] considers task relevance between CTR and CVR as auxiliary. MTAE [75] predicts the winning probability as auxiliary. Cross-Distill [73] proposes ranking-based task as auxiliary containing cross-task relation. Specially, CSRec [2] and PICO [36] adopt contrastive learning as the auxiliary task to extract task relevance better.

Nevertheless, the frameworks above are manually-auxiliary, since the design of auxiliary tasks usually requires specific domain knowledge. Recently, Wang et al. [63] propose under-parameterized self-auxiliaries to achieve better generalization.

3.3 Methodology

For methodology, existing MTDRS can be categorized into: parameter sharing, optimization, and training mechanism.

3.3.1 Parameter Sharing. Considering the parameter sharing pattern and sharing levels, existing methods can be categorized into hard sharing, sparse sharing, soft sharing, and expert sharing. Their illustrations are shown in Figure 4 with two tasks as an example.

Hard Sharing. Hard parameter sharing refers to the shared bottom layers extracting the same information for different tasks, while the task-specific top layers are trained individually. On the one hand, it can improve computation efficiency and alleviate over-fitting. However, it may suffer from the limited capacity of the shared parameter space, especially for weakly related tasks and noise.

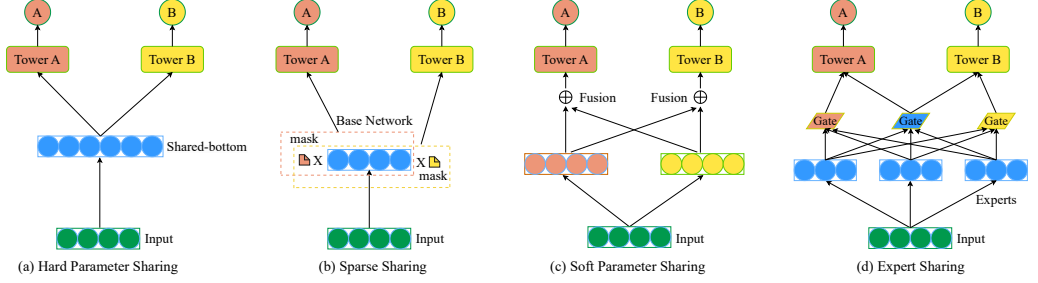


Fig. 4. The illustration of hard sharing, sparse sharing, soft sharing, and expert sharing with task A and B. Blue represents the shared parameters. Red and yellow represent the task-specific parameters.

Many studies simply follow the shared bottom structure of hard parameter sharing [26, 37, 74]. Notably, MFH [37] proposes an efficient cooperative learning with heterogeneity, which consists of nested hierarchical MTL trees for multi-dimension task relation from the macro perspective and switcher networks in different levels from the micro perspective.

Sparse Sharing. Sparse sharing extracts sub-networks for each task by parameter masks from a base network in the shared parameter space. It is a special case of hard sharing because the parameters are shared in neuron or layer level. Specifically, it usually extracts subnets and trains with the fixed sharing strategy in parallel for each task. Compared with hard sharing, it has the advantage of coping with the weakly related tasks flexibly.

In MTDRS, LT4REC [69] proposes neuron-level mask based on Lottery Ticket Hypothesis. MSSM [14] adopts sparse connection in field-level for task-aware feature selection and in cell-level for determining the connection among cells in subnets of different layers. However, these methods may suffer from negative transfer when updating shared parameters. Recently, CSRec [2] proposes contrastive pruning in contrastive sharing network to learn better parameter masks among tasks.

Soft Sharing. In contrast to the hard sharing method extracting information from the shared bottom layer, soft parameter sharing also builds separate models for tasks but the information among tasks is fused by weights of task relevance, e.g., from the attention mechanism. This structure could equip the model with relatively high flexibility in parameter sharing compared to hard sharing methods. However, it can not reconcile the flexibility and computation cost of the model.

In MTDRS, DINOP [70] incorporates dynamic target user profiles into the attention-based pooling, so as to learn universal item representation for different tasks. It also fuses the dynamic features and static properties with the framework on RNN.

Expert Sharing. Expert sharing model first employs multiple expert networks to extract knowledge from the shared bottom layer. Then the knowledge is fed into task-specific modules like gates to learn useful information. Finally, the assembled information is passed into the task-specific tower. Notably, expert sharing is a special case of soft sharing since expert knowledge is shared but fused by task-specific weights.

Inspired by Mixture of Experts (MoE) [28], MMoE [41] proposes to use softmax gates from gating networks to assemble experts with different weights for each task, and it acts as a milestone in MTDRS. Based on MMoE, further improvements have been proposed subsequently. SNR [40] propose to split the shared bottom layer into sub-networks allowing sparse connection and replace the gating network with latent variable. PLE [54] utilizes a novel Customized Gate Control (CGC) module which could explicitly separate shared and task-specific experts. Meanwhile, it adopts multi-level extraction networks with progressive separation routing.

Afterward, more works have been proposed based on MMoE. DMTL [83] proposes to distill information to a student model learned from the teacher model, which employs the MMoE framework to model CTR and CVR. DSelect-k [24] proposes a continuously differentiable sparse gate to tackle the lack of smoothness. Meanwhile, MetaHeac [86] introduces a hybrid structure that combines a critic network with an expert network. Recently, PFE [71] adapts prototype feature extraction into the MMoE framework. MVKE [72] proposes a virtual kernel structure for expert and gate for better user profiling.

However, the models above only consider non-sequential input features. By contrast, MoSE [46] models sequential user behaviors by using sequential experts and applying Long Short-Term Memory (LSTM) to the shared bottom layer and task-specific towers.

3.3.2 Optimization. From the optimization aspect, in MTL, the joint optimization of different tasks needs to tackle two issues: (i) the conflict across the performance of multiple tasks, e.g., accuracy, and (ii) the trade-off between objectives with respect to each task. The former is related to negative transfer while the latter corresponds to multi-objective trade-off.

Negative Transfer. Negative transfer is a situation that transferring unrelated information among tasks could result in performance degradation and seesaw phenomenon. When the performance of some tasks is improved but at the cost of others' result, the seesaw phenomenon is observed. Since most of the existing methods seek better recommendation accuracy, they focus on this problem. Specifically, there are mainly two reasons causing negative transfer in MTDRS from the shared parameters θ . The first is gradient dominating and the second is parameter conflict.

Gradient dominating denotes the magnitude imbalance of gradient $\|\nabla_{\theta} L^k(\theta)\|$ of different tasks, and some works try to tackle this problem [7, 76]. In the recommendation community, AdaTask [74] proposes to quantifying task dominance of shared parameters, and calculating task-specific accumulative gradients for adaptive learning rate methods. MetaBalance [26] proposes to flexibly balance the gradient magnitude proximity between auxiliary and target tasks by a relax factor.

Besides, parameter conflict indicates that the shared parameter θ has opposite directions of gradient $\nabla_{\theta} L^k(\theta)$ in different tasks. PLE [54] discusses seesaw phenomenon and propose Customized Gate Control (CGC) that separates shared and task-specific experts to explicitly alleviate parameter conflicts. CSRec [2] applies an alternating training procedure and contrastive learning on parameter masks to reduce the conflict probability.

Multi-objective Trade-off. The trade-offs among objectives under MTDRS setting is a new topic. Specifically, the corresponding objectives in each task are usually optimized by a single model regardless of the potential conflict. Some study the trade-off between group fairness and accuracy across multiple tasks [61] and afterward, the trade-off between minimizing task conflicts and improving multi-task generalization in a higher level [63].

3.3.3 Training Mechanism. Training mechanism refers to the specific training process and learning strategy of different tasks in MTDRS model. Existing works on MTDRS can be grouped into: joint training, reinforcement learning, and auxiliary task learning.

Joint Training. Most MTL models adopt joint training among tasks in a parallel manner, and the majority of the above-mentioned MTDRS models belong to this category. Specially, some works simply jointly learn different tasks, such as session-based RS [44, 47, 53], route RS [11], knowledge graph enhanced RS [58], explainability [39, 60], and graph-based RS [59]. Besides, some works adopt an alternating training procedure, e.g., contrastive pruning [2].

Reinforcement Learning. Reinforcement Learning (RL) algorithms have recently been applied in DRS, which models the sequential user behaviors as Markov Decision Process (MDP) and utilizes

Table 2. Summary of datasets for MTDRS

Datasets	Stage	Tasks	Website
Ali-CCP [42]	Ranking	CTR, CVR	https://tianchi.aliyun.com/dataset/408/
Criteo [13]	Ranking	CTR, CVR	https://ailab.criteo.com/criteo-attribution-modeling-bidding-dataset/
AliExpress [32]	Ranking	CTR, CTCVR	https://tianchi.aliyun.com/dataset/74690/
MovieLens [23]	Recall & Ranking	Watch, Rating	https://grouplens.org/datasets/movielens/
Yelp	Recall & Ranking	Rating, Explanation	https://www.yelp.com/dataset/
Amazon [25]	Recall & Ranking	Rating, Explanation	http://jmcauley.ucsd.edu/data/amazon/
Kuairand [18]	Recall & Ranking	Click, Like, Follow, Comment, ...	https://kuairand.com/
Tenrec [77]	Recall & Ranking	Click, Like, Share, Follow, ...	https://github.com/yuangh-x/2022-NIPS-Tenrec/

RL to generate recommendations at each decision step [43]. By setting user-item features as state and continuous score pairs for multiple tasks as actions, the RL-based MTL method is capable of handling the sequential user-item interaction and optimizing long-term user engagement. Zhang et al. [79] formulate MTF as Markov Decision Process and use batch Reinforcement Learning to optimize long-term user satisfaction. Han et al. [22] propose to use an actor-critic model to learn the optimal fusion weight of CTR and the bid rather than greedy ranking strategies to maximize the long-term revenue.

Auxiliary Task Learning. As discussed in Section 3.2.3, adding auxiliary tasks aim at helping to enhance the performance of primary tasks. Specifically, the auxiliary tasks are usually trained along with the primary tasks in a joint training manner. By contrast, ESDF [62] employs Expectation-Maximization (EM) algorithm for optimization. Besides, self-auxiliaries are trained with task-specific sub-networks while they are discarded in the inference stage.

4 APPLICATION AND DATASETS

In this section, the application of MTDRS on different fields and multi-task fusion is first introduced. Next, the public datasets of MTR is summarized.

4.1 Application Fields

Apart from e-commerce, MTDRS has been applied to various fields such as advertising and social media. On the one hand, for an advertisement, to jointly and accurately estimate the utility and cost are essential for determining its success. In MTDRS, MM-DFM [27] performs multiple conversion prediction tasks in different observation duration. MetaHeac [86] is proposed for audience expansion tasks on content based mobile marketing. MVKE [72] is proposed for user tagging for online advertising.

On the other hand, social media is a more complex field since the users interact with both items and users. Multiple MTDRS models validate their effectiveness on social media by online A/B test, including MMoE [84] on YouTube considering engagement and satisfaction, LT4REC [69] on Tencent Video, and BatchRL-MTF [79] on Tencent short video platform.

4.2 Multi-task Fusion

In real-world multi-task recommender systems, after predicting various recommendation tasks, a Multi-Task Fusion (MTF) model is usually applied to combine the multi-task outputs into one ranking score considering user satisfaction and produces the final ranking. Several works try to search for fusion weight, such as Grid Search [20, 50], Evolutionary Algorithm [49], and Bayesian Optimization [16]. A state-of-the-art solution is RL [22, 79], as discussed in Section 3.3.3.

4.3 Datasets

We summarize the public datasets in MTDRS in Table 2 according to their stage of recommendation applied and the used frequency. Meanwhile, it is notable that the ratings can be categorized into binary classification task, i.e., to predict whether a rating ranging from 1 to 5 is greater than 3. For MovieLens dataset, the common two tasks are to predict whether the user watches the movie and to predict the rating.

5 CHALLENGES AND FUTURE DIRECTIONS

In this section, we summarize the challenges and future directions of MTDRS including negative transfer, multi-task with multi-scenario modeling, using large pre-trained model, AutoML, explainability, and task-specific biases.

Negative Transfer. As discussed in Section 3.3.2, previous works try to tackle negative transfer in MTDRS from either gradient or separating shared and specific parameters. However, how to extract the complex inter-task correlation needs further research, e.g., from the causal relation [9]. Meanwhile, what, where, and when to transfer to alleviate negative transfer is still under-explored in MTDRS.

Multi-task with Multi-scenario Modeling. There is a new trend to tackle multi-task and multi-scenario problems in a unified model in an end-to-end manner. For example, M2M [78] proposes to use meta learning to extract specific information from scenario knowledge as dynamic weights considering inter-scenario correlations. AESM² [87] proposes to adaptively select shared and specific experts by calculating relevance score via gating mechanism, and stack multiple layers to model hierarchical scenario structure. However, these methods are restricted to the MMoE framework, and the tasks with sequential dependency are not considered.

Using Large Pre-trained Model. Large pre-trained model has achieved great success, and it is promising to conduct MTR by the large pre-trained language model, which is able to unify different recommendation tasks in a single sequence-to-sequence framework. Geng et al. [19] propose P5 with pre-training and personalized hard prompts. It covers five recommendation task families based on T5 backbone [48]. Similarly, M6-Rec [10] is proposed upon M6 [34] and UniMIND [12] is proposed for multi-goal conversational recommendation. However, they all rely on prompt design or tuning for each specific task, which is inefficient and different from the common MTDRS model.

AutoML. For MTDRS, different tasks may require different neural network architectures and hyper-parameters, and it is exhausting to design and tune different components of MTDRS manually for each task. Recently, automated machine learning (AutoML) [4] is emerging for automating the components of DRS and enhancing generalization. Under MTDRS setting, SNR [40] proposes to automatically learn the connection routing for flexible parameter sharing by Neural Architecture Search (NAS). Besides, MTNAS [6] proposes to search for the suitable sparse sharing route for MTDRS by NAS. However, they only focus on the parameter sharing routing, while other components and hyper-parameters are still under-explored.

Explainability. Explainable recommendation is proposed to improve the transparency and user satisfaction in trustworthy RS [15]. Most existing DRS models employ DNN, whose prediction mechanism is difficult to explain, suffering from vulnerability and unreliability. MTDRS faces more challenges with explainability due to its complex task relevance. Works such as [8, 60] address the issue but only for single score prediction tasks, not multiple recommendation tasks. Consequently, it is worth paying more attention to this topic, leading to a better trustworthy MTDRS.

Task-specific Biases. MTDRS may be prone to the task-specific biases, which are caused by different behavior patterns in different tasks. They can lead to an unfair or sub-optimal experience for users and result in poor performance on certain tasks. Most existing models only focus on one specific bias, such as sample selection bias [42], implicit selection bias [84], and inherent estimation bias [57]. Consequently, how to tackle biases among different tasks needs further study.

6 CONCLUSION

Multi-task recommendation (MTR) is an important topic in the recommendation community. In this survey, we are the first to conduct a comprehensive survey on the existing multi-task approaches in DRS, namely multi-task deep recommender systems (MTDRS). Based on our formulation and comparison with similar directions in recommendations, we categorize MTDRS methods into task relation and methodology and depict its trend. Next, the application and public datasets of MTDRS are summarized. Finally, the challenges and future directions are introduced. We hope this survey would shed light on the future study in MTDRS.

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