

# A Survey on Cross-Domain Sequential Recommendation

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## Abstract

Cross-domain sequential recommendation (CDSR) shifts the modeling of user preferences from flat to stereoscopic by integrating and learning interaction information from multiple domains at different granularities (ranging from inter-sequence to intra-sequence and from single-domain to cross-domain). In this survey, we initially define the CDSR problem using a four-dimensional tensor and then analyze its multi-type input representations under multidirectional dimensionality reductions. Following that, we provide a systematic overview from both macro and micro views. From a macro view, we abstract the multi-level fusion structures of various models across domains and discuss their bridges for fusion. From a micro view, focusing on the existing models, we specifically discuss the basic technologies and then explain the auxiliary learning technologies. Finally, we exhibit the available public datasets and the representative experimental results as well as provide some insights into future directions for research in CDSR.

## 1 Introduction

In real life, users constantly leave interaction traces in multiple scenarios (e.g., shopping scenarios, reading scenarios, etc.), multiple platforms (e.g., Amazon, Taobao, etc.), and even multiple boards (e.g., books and movies in Douban, etc.). Considering all these as different domains, combining information across domains and shifting the modeling of user preferences from flat to stereoscopic is a new and important direction for the development of recommender systems. As shown in Table 1, starting from traditional one-class collaborative filtering (OCCF), further progressing to sequential one-class collaborative filtering (SOCCF) and to cross-domain one-class collaborative filtering (CD-OCCF), finally to cross-domain sequential one-class collaborative filtering (CD-SOCCF, also called cross-domain sequential recommendation, CDSR), recommender systems focus on information that is becoming deeper and more comprehensive.

In the case of OCCF [Rendle *et al.*, 2012], the available information is limited to whether the user interacted with the item. As illustrated in Figure 1, we only know the items

Table 1: A table summarizing OCCF, SOCCF, CD-OCCF and CD-SOCCF (CDSR) based on information from different granularity.

Problem \ Information	Single-Domain		Cross-Domain	
	Inter-sequence	Intra-sequence	Inter-sequence	Intra-sequence
OCCF				
SOCCF	✓	✓		
CD-OCCF	✓		✓	
CD-SOCCF (a.k.a. CDSR)	✓	✓	✓	✓

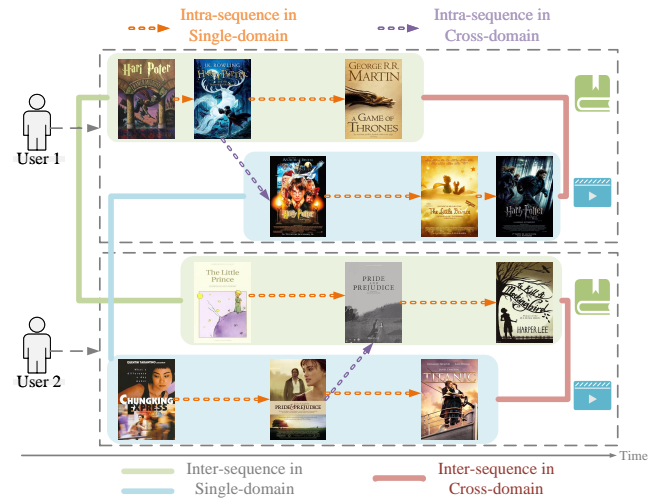


Figure 1: Illustration of CDSR.

that both user 1 and user 2 have interacted with in a single domain, without considering the sequential pattern among successive items. SOCCF [Lin *et al.*, 2020], building upon OCCF, places greater emphasis on the order relationships between items within a sequence, i.e., the information of intra-sequence in a single domain, and thus the model can capture the user's long-term interests and short-term preferences. At a large granularity, expanding from a single domain to multiple domains offers a fresh perspective to rich information for recommendation. As shown in Figure 1, users have interactions not only in the book domain but also in the movie domain and they are closely related. It constitutes CD-OCCF [Hu *et al.*, 2018] which integrates the interactions of both two domains. In this cross-domain scenario, designing models to transfer or

aggregate interaction records from multiple domains, as well as aligning representations of users or items across different domains, are critical challenges.

Indeed, CDSR combines all of the directions aforementioned and further incorporates sequential information based on CD-OCCF and cross-domain information based on SOCCF. As indicated by the purple arrows in Figure 1, CDSR especially necessitates the precise capturing of sequential relationships between items across different domains. For example, user 1, after reading two books in the *Harry Potter* series, chooses to watch the corresponding *Harry Potter* movie. On the other hand, user 2 who enjoys watching romantic movies also reads the original novels after watching the *Pride and Prejudice* movie. In addition to capturing the cross-domain sequential dependencies described above as much as possible, the challenges of CDSR include how to fuse information from different domains and how to distinguish between users’ specific preferences within a single domain and global preferences shared across multiple domains.

In this survey, we initially provide an overarching problem definition and modeling of CDSR, considering various dimensionality reductions and input representations. Then we adopt both a macro and micro view to summarize the existing works in CDSR. From a macro view, we present an overview of multi-level fusion structures, discussing how information is fused across different domains and exploring bridges for cross-domain fusion. From a micro view, we conduct a detailed analysis of various technologies employed by existing models that are categorized into basic technologies and auxiliary learning. Based on this analysis, we synthesize a comprehensive framework that provides an overview of the key technologies used in CDSR models. Furthermore, we also list the datasets commonly used in CDSR and the representative experimental results as well as provide some insights into potential future directions.

## 2 Formulation

In this section, we begin by presenting the problem definition that unifies CDSR using a four-dimensional tensor. Following that, we delve into the various directions of dimensionality reduction employed in practical modeling, as illustrated in Figure 2, along with the discussion of multi-type input representations.

### 2.1 Problem Definition

In a typical cross-domain sequential recommendation scenario, as temporal information and cross-domain information are incorporated, the interaction data between users and items undergoes a gradual expansion into a four-dimensional data tensor, consisting of dimensions pertaining to users, items, time, and domains. We denote this four-dimensional data tensor with  $\Gamma \in \mathbb{R}^{n \times m \times s \times k}$ , where  $n$  is the number of users,  $m$  is the number of items,  $s$  is the discrete time intervals, and  $k$  is the number of domains. Each element  $\gamma_{(u,i,t,d)}$  in it signifies whether there is an interaction between user  $u$  and item  $i$  at time  $t$  in domain  $d$ . Then the goal of CDSR is to estimate the probability for all the candidate items in each domain and to recommend the most probable next item to each user. The

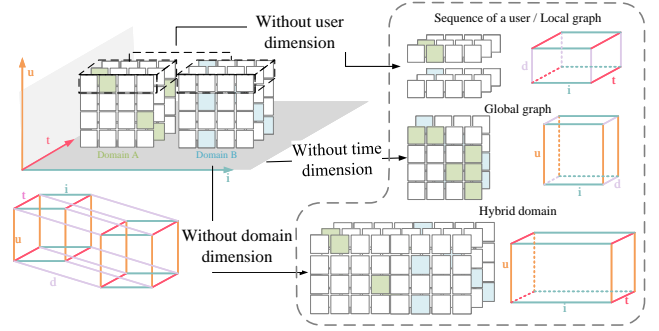


Figure 2: A visualization of dimensionality reduction for a four-dimensional data tensor in CDSR scenarios. We represent the dimensions contained in the data using wireframes and simulate tensors using blocks. The colored blocks indicate records of user interaction with items within the domain at a given moment. In this case, both domains share the same set of users, but there is no overlap in the items they interact with.

estimated probability can be formalized as follows,

$$P(\hat{i} | \Gamma) \sim f(\Gamma) \quad (1)$$

where  $\hat{i}$  is the candidate item in each domain,  $\Gamma$  is the four-dimensional tensor containing all interaction information, and  $f(\Gamma)$  is the learned function to estimate  $P(\hat{i} | \Gamma)$ .

In fact, most existing works in CDSR are primarily established on two domains, i.e.,  $k = 2$ . Therefore, for the subsequent discussion, we take two domains as an example, representing them as domain A and domain B, respectively. Some researchers [Bi *et al.*, 2020; Xu *et al.*, 2023c] also refer to the two domains as the source domain and the target domain. Moreover, some works [Ma *et al.*, 2019; Sun *et al.*, 2023; Guo *et al.*, 2021; Guo *et al.*, 2023c] introduce an additional assumption with a shared account. They assume that within a real account, there are  $q$  virtual users ( $u_j, j \leq q$ ) simultaneously active. Regarding the shared account issue, it is applicable not only in cross-domain scenarios but also in single-domain scenarios.

### 2.2 Multidirectional Dimensionality Reduction

For modeling and computational convenience, the four-dimensional tensor is often reduced dimensionally into corresponding three-dimensional tensors from various directions, as shown in Figure 2. In the following, we offer explanations for the dimensionality reduction from three different directions.

- **W/o User Dimension.** In the modeling of CDSR, focusing on a user can give rise to a cross-domain interaction sequence, which can then serve as the basis for constructing a local graph in subsequent work.
- **W/o Time Dimension.** Some involve mapping the four-dimensional tensor along the temporal dimension and aggregating all the interactions within a time, laying the groundwork for building a global graph in subsequent steps.

- **W/o Domain Dimension.** Furthermore, we blend two or more domains into a hybrid domain, encompassing users and items from all domains, along with their interactions recorded in chronological order. Many existing studies treat the hybrid domain as an independent domain, designing model fusion structures that incorporate all three domains in parallel, which is shown in Section 3.1.

Indeed, these dimensionality reduction directions are often combined and used in conjunction rather than being treated as independent. Next, we visualize those dimensionality reduction processes on different types of inputs.

### 2.3 Multi-Type Input Representations

Researchers’ considerations on dimensionality reduction directions in CDSR are first reflected in the input representations. Here, we categorize conventional input representations into pure sequential representation and graph-encoded sequential representation. Subsequently, we analyze unconventional inputs, including side information and features obtained through pre-training.

#### Pure Sequential Representation

Arranging the interacted items of a user in chronological order yields a sequence. For each user  $u$ , we define  $S_u^A = \{i_1^A, i_2^A, \dots\}$  and  $S_u^B = \{i_1^B, i_2^B, \dots\}$  as his/her interaction sequences in domain A and domain B, respectively. If  $u$  is an overlapping user who has interactions both in domain A and domain B, we can mix  $S_u^A$  and  $S_u^B$  to a hybrid sequence in chronological order (e.g.,  $S_u^{hybrid} = \{i_1^A, i_1^B, i_2^A, i_2^B, i_3^A, i_3^B, \dots\}$ ), and view it as the hybrid domain. From a pure sequential perspective, we can substitute the four-dimensional tensor in Eq. (1) with the set of sequences in each domain, as follows,

$$P(\hat{i} | S^A, S^B) \sim f(S^A, S^B) \quad (2)$$

#### Graph-encoded Sequential Representation

Some researchers [Guo *et al.*, 2021; Zheng *et al.*, 2022; Cao *et al.*, 2022; Zhang *et al.*, 2023b] turn to construct directed graphs  $G = \{V, E\}$  to model sequential information, where  $V$  is a set of items that have been interacted with and  $E$  is the edges that represent relations of the serial relationship from item to item. Constructing the user’s sequence within a domain or the sequence within a session as a local graph is a common practice [Zheng *et al.*, 2022; Chen *et al.*, 2021]. In the global graph construction scenario,  $E$  is also utilized to denote the relations between users and items [Xu *et al.*, 2023c]. We represent the raw data in its graph-encoded form to extend Eq.(1), where  $G_l$  denotes all local graphs and  $G_g$  denotes the global graph, as follows,

$$P(\hat{i} | G_l, G_g) \sim f(G_l, G_g) \quad (3)$$

#### Side Information

More and more researchers consider incorporating side information to enrich the semantic understanding of users’ historical behaviors. Here, we divide the most common side information into three categories: time, text (i.e., user/item context and review), and knowledge graph.

**Time.** Previously the timestamps are only used to order the items, but some researchers [Xiao *et al.*, 2023; Wang *et*

*al.*, 2022; Guo *et al.*, 2022] define  $t_{ij} = |t_i - t_j|$  to model the time interval and apply it to the subsequent learning of model, where  $t_i$  and  $t_j$  are the timestamps that the item  $i$  and the item  $j$  are interacted with, respectively. In addition to the time intervals, we can mine more information about time, such as periodicity and the duration of the interaction, etc.

**User/Item Context and Review.** Except for the user ID, triples composed of multiple contextual information (e.g., (“*UserID*”, “*City*”, “*Age*”,  $\dots$ )) are utilized as a basis for finding user-user relationships [Ouyang *et al.*, 2020]. Similarly, the context information that consists of categories, tags, keywords, etc, is used as a supplement to item ID [Xiao *et al.*, 2023; Ouyang *et al.*, 2020; Zhuang *et al.*, 2020]. And review is also a type of available text message that can associate users and items. A common way to encode these texts is through some pre-trained models.

**Knowledge Graph.** Knowledge graphs [Bi *et al.*, 2020; Ma *et al.*, 2022] deal with information from both entity and relationship views. It not only contains structural information between nodes but also implies some relationship description. A knowledge graph defines an entity set  $E^{KG}$  and a relation set  $R^{KG}$ , which consists of multiple entity-relation-entity triples  $\langle e_i, r, e_j \rangle$  (e.g.,  $\langle e_{a1}, Is\_the\_same\_category, e_{b1} \rangle$  meaning that the entity  $e_{a1}$  from domain A has the same category as entity  $e_{b1}$  from domain B).

Considering the mentioned side information, we can extend Eq. (1) as follows,

$$P(\hat{i} | \Gamma, D) \sim f(\Gamma, D) \quad (4)$$

where  $D$  is the side information mentioned above and often serves as supplementary data to conventional inputs.

#### Pre-trained Features

Considering the privacy issues in two or more domains, some models [Ding *et al.*, 2023; Zhang *et al.*, 2023a; Lei *et al.*, 2021] use model-trained features as the input of the source domain, instead of raw data. [Ding *et al.*, 2023] directly combines the pre-trained user features from one domain with another domain. [Zhang *et al.*, 2023a] utilizes federated learning to fetch the global representation from the server, and then injects it into the local model.

We take domain A as an example and revise Eq. (1) as follows,

$$P(\hat{i} | \Gamma^A, M^B) \sim f(\Gamma^A, M^B) \quad (5)$$

where  $M^B$  are the features of domain B after pre-training and  $\Gamma^A$  denotes the interaction data exclusively within domain A. Notice that in domain B, the equation is  $P(\hat{i} | \Gamma^B, M^A) \sim f(\Gamma^B, M^A)$ .

### 3 Macro-View: What Structure Is Used to Fuse the CDSR Information?

In CDSR, the fusion structure serves as the primary framework of the model, providing pathways for the separation and aggregation of these features. In this section, we first propose the multi-level fusion structures and then elaborate on the bridge for inter-domain fusion.

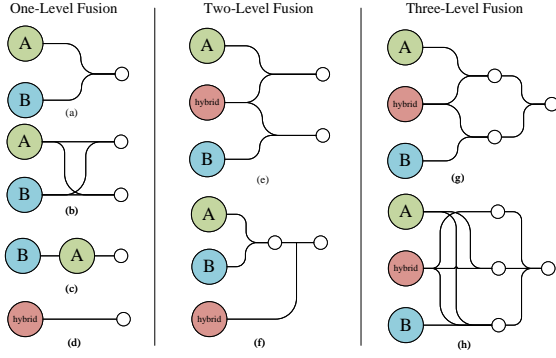


Figure 3: The overview of multi-level fusion structures that are divided into three levels. “A” and “B” represent domain A and domain B, respectively, and “hybrid” denotes a combination of two domains in chronological order.

### 3.1 Multi-Level Cross-Domain Fusion Structures

For cross-domain fusion, researchers employ various structures to aggregate information from different domains. In this section, we overview the various multi-level fusion structures shown in Figure 3. Specifically, we introduce those structures from two parts, i.e., the one-level fusion structures and the two/three-level fusion structures.

#### One-Level Fusion Structures

In earlier works, to combine the cross-domain information, there are a lot of methods that first learn user preferences from domain A and domain B separately, and then fuse the representations of the two domains using various operations (shown in Figure 3(a)). These operations are not limited to concatenation [Lei *et al.*, 2021; Guo *et al.*, 2023c], summation [Alharbi and Caragea, 2021; Ding *et al.*, 2023], multi-layer perceptron (MLP) [Bi *et al.*, 2020], or some attention mechanisms [Ouyang *et al.*, 2020; Li *et al.*, 2021].

Additionally, some researchers employ transfer learning to transfer knowledge from a source domain to a target domain [Chen *et al.*, 2021; Liu and Zhu, 2021], or train a discriminator to bridge the representation of two domains with the idea of adversarial learning [Li *et al.*, 2022], shown in Figure 3(b).

In contrast to the above-juxtaposed structures, there are also works utilizing a tandem structure to fuse information [Alharbi and Caragea, 2022] (i.e., Figure 3(c)), or tackling the problem from the perspective of a hybrid-domain view (i.e., Figure 3(d)). Some researchers [Guo *et al.*, 2021; Guo *et al.*, 2022] construct a global graph for the hybrid domain to combine the cross-domain knowledge. And others like [Ma *et al.*, 2019; Sun *et al.*, 2023] learn the item transition patterns in the hybrid sequences  $S^{hybrid}$ .

#### Two/Three-Level Fusion Structures

Considering the potential for further exploration and advancement in the field of fusion structure, researchers combine the single domain and the hybrid domain with a multi-level fusion structure. As shown in Figure 3(e), in order to predict the next item in a separate domain, the hybrid domain is utilized as the main sharer [Cao *et al.*, 2022;

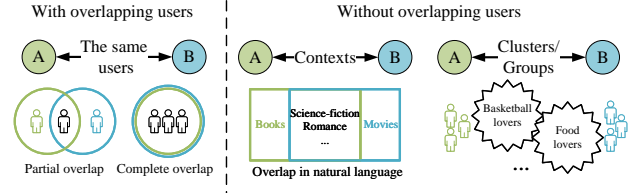


Figure 4: Examples of building cross-domain bridges relying on different information.

Wang *et al.*, 2022] or the bridge [Zheng *et al.*, 2022] to transfer knowledge from another domain. Some researchers [Ye *et al.*, 2023] choose to combine the domain A and domain B first and then fuse the hybrid information (i.e., Figure 3(f)).

To delve further into the fusion structures, some researchers continue to extend the hierarchy, as illustrated in Figure 3(g) [Xu *et al.*, 2023c] which aggregates the representations again after combining the hybrid domain information on the basis of Figure 3(e). Figure 3(h) [Zhang *et al.*, 2023b] proposes a more complex structure, which shares the coarse-grained representations of the target domain A and the hybrid domain with each other domain.

#### Discussion

Although multi-level fusion structures have been proposed, it does not mean that a more complex structure will result in a better model. The simple fusion structures, i.e., one-level fusion structures, are easy to implement but may not be conducive to comprehensive modeling of domain-specific and domain-generic features due to the limitation of the degree of fusion. While improving effectiveness, multi-level fusion structures bring increased complexity and reduced interpretability.

Focusing on the symmetry and asymmetry of the structures, the design of a cross-domain fusion structure also has a lot to do with the extent to which the researchers focus on each domain. For example, some researchers [Ouyang *et al.*, 2020; Bi *et al.*, 2020; Xu *et al.*, 2023c] consider the two domains as source and target domains and leverage the data-rich source domain to assist the data-sparse target domain, which makes the target domain dominant in the fusion structure. Other researchers [Guo *et al.*, 2021; Li *et al.*, 2021; Ma *et al.*, 2022] aim to improve the recommendation performance of both domains at the same time, which makes the fusion structure designed tend to be more symmetric.

### 3.2 Bridges for Cross-Domain Fusion

When considering the overall cross-domain fusion structure, it is important to note the bridges through which information from different domains can be shared. We categorize those bridges of the existing works into three categories, i.e., the same users, contexts, and clusters/groups, as shown in Figure 4. The first one primarily exists in scenarios with overlapping users, while the latter two can be employed in situations without any overlapping users.

- **The Same Users.** Building a bridge with overlapping users is the most common practice. Most works confine recommendation scenarios to fully overlapping users, with-



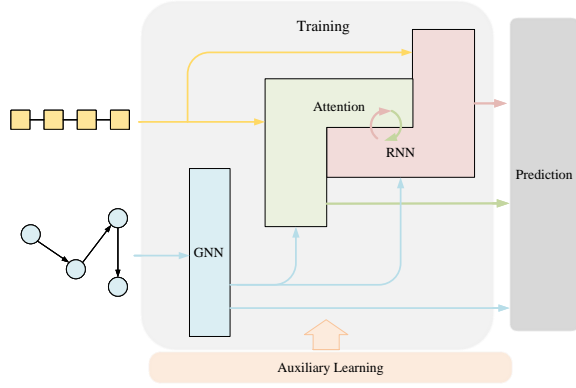


Figure 5: A schematic overview of the key technical framework. The color of the arrows represents the output after passing through the components represented by different colors. While models represented via graph structures require encoding with GNN, the relationship between RNN and attention can be used in parallel or an alternating fashion.

out considering any non-overlapping users. However, some works [Li *et al.*, 2022] consider both overlapping users and non-overlapping users.

- **Contexts.** In the absence of overlapping users, leveraging semantic similarity in natural language can also serve as a bridge to connect items between different domains. For example, using item contexts instead of traditional item ID can more easily identify similarities between items [Liu *et al.*, 2023].
- **Clusters/Groups.** If there are neither overlapping users nor side information available, the approach of using clusters/groups as a bridge can be applicable [Lin *et al.*, 2023a], due to the similarity in preferences within a certain group of people.

Different bridges exhibit distinct characteristics, each suitable for different scenarios. Methods relying on overlapping users often yield better performance but may face limitations due to sparse data in real-world scenarios. On the other hand, methods built on non-overlapping users can be applicable to a wider range of scenarios but the performance may be limited.

## 4 Micro-View: What Technologies Are Used to Address the CDSR Problem?

Utilizing an overall structural framework for CDSR modeling, we take a more tangible perspective to summarize the technologies adopted by existing models in addressing the challenges. In conjunction with Table 2 and Figure 5, we elaborate on the basic technologies and the auxiliary learning technologies, respectively.

### 4.1 Basic Technologies

According to Section 2.3, the cross-domain information is always considered as a pure sequence representation and a graph representation. So we illustrate the utilization of

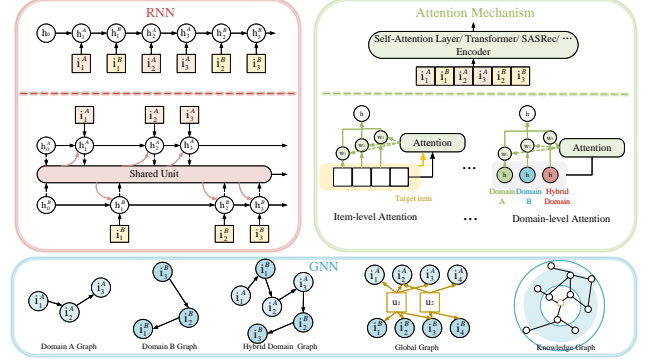


Figure 6: Some examples of basic technologies being applied to CDSR.  $\{i_1^A, i_2^A, \dots\}$  denotes the sequence of user interactions in domain A and similarly  $\{i_1^B, i_2^B, \dots\}$  denotes the sequence of interactions in domain B.  $h$  denotes the output representation of the corresponding item after being processed by the model, and  $w$  denotes the attention weight.

sequence modeling technologies (i.e., recurrent neural networks and attention mechanisms) and graph structure modeling technologies (i.e., graph neural networks) in CDSR, respectively, as shown in Figure 6. Moreover, from Figure 5, we can observe that the three basic technologies are not independent entities and can be applied interchangeably or in parallel based on the characteristics of different technologies. Notice that multi-layer perceptron (MLP) is used in almost all existing models for non-linear feature mapping or to simply aggregate cross-domain information [Xu *et al.*, 2023b; Hong and Jung, 2023], so we do not describe it separately.

### Recurrent Neural Networks in CDSR

Recurrent neural networks (RNNs) model sequences, by taking the current time step’s representation and the hidden features from the previous time step as input, and generating the output and hidden features for the current time step. Due to the issues of vanishing and exploding gradients, its variants, i.e., gated recurrent unit (GRU) and long short-term memory (LSTM) [Yang *et al.*, 2020], are more widely adopted. In CDSR, some researchers [Li *et al.*, 2021; Chen *et al.*, 2021; Zang *et al.*, 2023] directly employ GRUs as encoders of sequences to get sequential representations. While some researchers incorporate a shared unit into each step of RNNs to transfer cross-domain information. The shared unit could be a shared-account filter unit [Ma *et al.*, 2019; Sun *et al.*, 2023] or the common representations of the overlapping users [Wang *et al.*, 2020]. While RNNs are easy to implement and are capable of modeling the temporal relationships in sequences, they suffer from issues such as vanishing and exploding gradients during training.

### Attention Mechanisms in CDSR

Attention mechanisms can selectively focus on the importance of different parts and weight their contributions accordingly, enabling effective aggregation. Attention mechanisms are utilized in two main ways in CDSR modeling. One is to use an attention-based encoder (e.g., Transformer [Vaswani *et al.*, 2017], SASRec [Kang and McAuley,

Table 2: A systematic overview of the existing models for CDSR.

Data Structure	Basic Technology			Auxiliary Learning			Paper
	GNN	Attention	RNN	Contrastive Learning	Transfer Learning	Other	
Sequence		✓		✓			DREAM [Ye <i>et al.</i> , 2023]
							P-CDSR [Xiao <i>et al.</i> , 2023]
							Tri-CDR [Ma <i>et al.</i> , 2023]
							SEMI [Lei <i>et al.</i> , 2021]
							CGRec [Park <i>et al.</i> , 2023]
							LCN [Hou <i>et al.</i> , 2023]
							MACD [Xu <i>et al.</i> , 2023a]
							TPUF [Ding <i>et al.</i> , 2023]
						Adversarial Learning	RecGURU [Li <i>et al.</i> , 2022]
							DA-DAN [Guo <i>et al.</i> , 2023a]
							RL-ISR [Guo <i>et al.</i> , 2023c]
						Reinforcement Learning	PLCR [Guo <i>et al.</i> , 2023b]
						Prompt Learning	SATLR [Liu and Zhu, 2021]
					✓		MAN [Lin <i>et al.</i> , 2023a]
							MiNet [Ouyang <i>et al.</i> , 2020]
							CD-ASR [Alharbi and Caragea, 2021]
							CD-SASRec [Alharbi and Caragea, 2022]
							CMVCDR [Zang <i>et al.</i> , 2023]
							DASL [Li <i>et al.</i> , 2021]
							CDNST [Zhuang <i>et al.</i> , 2020]
							PSJNet [Sun <i>et al.</i> , 2023]
							$\pi$ -Net [Ma <i>et al.</i> , 2019]
							CDHRM [Wang <i>et al.</i> , 2020]
							SCLSTM [Yang <i>et al.</i> , 2020]
							MSECDR [Hong and Jung, 2023]
							AMID [Xu <i>et al.</i> , 2023b]
Graph	✓	✓		✓			DA-GCN [Guo <i>et al.</i> , 2021]
							TiDA-GCN [Guo <i>et al.</i> , 2022]
							EA-GCL [Wang <i>et al.</i> , 2023]
							MGCL [Xu <i>et al.</i> , 2023c]
							C <sup>2</sup> DSR [Cao <i>et al.</i> , 2022]
						Federated Learning	FedDCSR [Zhang <i>et al.</i> , 2023a]
							DDGHM [Zheng <i>et al.</i> , 2022]
							LEA-GCN [Zhang <i>et al.</i> , 2023b]
							IESRec [Liu <i>et al.</i> , 2023]
							DAT-MDI [Chen <i>et al.</i> , 2021]
							SGCross [Li <i>et al.</i> , 2023]
							AGNNGRU-CDR [Qu <i>et al.</i> , 2021]
							DCDIR [Bi <i>et al.</i> , 2020]
							MIFN [Ma <i>et al.</i> , 2022]
							CsrGCF [Wang <i>et al.</i> , 2022]
				✓			

2018] or multi-head attention blocks, etc.), replacing RNNs as a sequence encoder [Ye *et al.*, 2023; Xu *et al.*, 2023c; Alharbi and Caragea, 2022; Ding *et al.*, 2023; Park *et al.*, 2023]. The other is to obtain learnable attention weights thus aggregating cross-domain information at multiple levels. For instance, MiNet [Ouyang *et al.*, 2020] designs item-level attention and interest-level attention to learn which items are more important and which of these items better matches a certain interest of the user. With representation-level attention, C<sup>2</sup>DSR [Cao *et al.*, 2022] fuses the sequential representation and the graph representation together. By adopting domain-level attention, Tri-CDR [Ma *et al.*, 2023] learns the weights of the features from different domains and then aggregates them. And MAN [Lin *et al.*, 2023a] also proposes a group-level attention to bridge the not-aligned information. In fact, attention strategies need to be designed from multiple levels which poses a challenge to researchers. However, it needs to use the interaction of all the positions when calculating the weights, so it has a large number of parameters and suffers from the issue of data sparsity.

### Graph Neural Networks in CDSR

Aware of the structural relationships of item-item and item-user in a sequence, graph neural networks are used to model such information. The researchers construct a graph per session [Chen *et al.*, 2021] or per domain [Cao *et al.*, 2022; Xu *et al.*,

*et al.*, 2023c], or just construct a global graph [Guo *et al.*, 2021; Zhang *et al.*, 2023b] based on the hybrid domains of all users. Apart from that, DCDIR [Bi *et al.*, 2020] and MIFN [Ma *et al.*, 2022] construct a knowledge graph to encompass more semantic information. In addition to CsrGCF [Wang *et al.*, 2022], most researchers apply graph encoders (i.e., GNNs) and sequence encoders (i.e., RNNs or attention mechanisms) together as complementary parts in CDSR modeling. For instance, DA-GCN [Guo *et al.*, 2021] utilizes graph convolutional networks to learn latent users' representations and user-specific item representations and then carries the weights from the item and user neighbors to the target item in each domain with an attention matrix. C<sup>2</sup>DSR [Cao *et al.*, 2022] combines the encoded representations from GNNs with the original sequences and feeds them into the attention encoder for further modeling. It supplementally learns complex information about nodes and edges to capture more comprehensive preferences of users. However, when GNNs are applied to a large-scale data, the huge computational and storage overhead is a major drawback.

### 4.2 Auxiliary Learning

In addition to the aforementioned key technologies, the utilization of auxiliary learning technologies to facilitate the integration of cross-domain information garner significant at-

Table 3: A summary of commonly used datasets for CDSR.

Datasets	Domains		Data types	Scale	Link
HVIDEO [Ma <i>et al.</i> , 2019]	V-domain: family videos		user ID, item ID, time	0.4 million +	<a href="https://bitbucket.org/Catherine_Ma/pinet_sigir2019/src/master/HVIDEO">https://bitbucket.org/Catherine_Ma/pinet_sigir2019/src/master/HVIDEO</a>
	E-domain: educational videos				
Douban [Zhu <i>et al.</i> , 2021]	Movies	user ID, item ID, ratings, labels, reviews, time, users context	1 millions +	<a href="https://github.com/FengZhu-Jocy/GA-DTCDR/tree/main/Data">https://github.com/FengZhu-Jocy/GA-DTCDR/tree/main/Data</a>	
	Musics				
	Books				
Amazon [McAuley <i>et al.</i> , 2015]	Books	user ID, item ID, ratings, time, reviews, item context	100 millions +	<a href="https://jmcauley.ucsd.edu/data/amazon">https://jmcauley.ucsd.edu/data/amazon</a>	
	Movies				
	Foods				
	Kitchens				
	...				
Tenrec [Yuan <i>et al.</i> , 2022]	Videos	user ID, item ID, multiple-behavior interactions, video category, watching times, user gender, user age	100 millions +	<a href="https://static.qbiv.qq.com/qbiv/h5/algo-frontend/tenrec_dataset.html">https://static.qbiv.qq.com/qbiv/h5/algo-frontend/tenrec_dataset.html</a>	
	QB-video				
	Articles	user ID, item ID, multiple-behavior interactions, read percentage, item context, read time			
	QB-article				

Table 4: Experimental results (%) on two domains of Foods and Kitchen of Amazon. Notice that the results are copied from [Cao *et al.*, 2022; Xiao *et al.*, 2023; Ye *et al.*, 2023] for reference. We bold the best results and underline the second-best results.

		Foods						Kitchens					
		MRR		NDCG		HR		MRR		NDCG		HR	
		@10	@5	@10	@1	@5	@10	@10	@5	@10	@1	@5	@10
OCCF	BPRMF [Rendle <i>et al.</i> , 2012]	4.10	3.55	4.03	2.42	4.51	5.95	2.01	1.45	1.85	0.73	2.18	3.43
	ItemKNN [Sarwar <i>et al.</i> , 2001]	3.92	3.51	3.97	2.41	4.59	5.98	1.89	1.28	1.75	0.58	1.99	3.26
SOCCF	GRU4Rec [Hidasi <i>et al.</i> , 2015]	5.79	5.48	6.13	3.63	7.12	9.11	3.06	2.55	3.10	1.61	3.50	5.22
	SASRec [Kang and McAuley, 2018]	7.30	6.90	7.79	4.73	8.92	11.68	3.79	3.35	3.93	1.92	4.78	6.62
	SR-GNN [Wu <i>et al.</i> , 2019]	7.84	7.58	8.35	5.03	9.88	12.27	4.01	3.47	4.13	2.07	4.80	6.84
CD-OCCF	NCF-MLP [He <i>et al.</i> , 2017]	4.49	3.94	4.51	2.68	5.10	6.86	2.18	1.57	2.03	0.91	2.23	3.65
	CoNet [Hu <i>et al.</i> , 2018]	4.13	3.61	4.14	2.42	4.77	6.35	2.17	1.50	2.11	0.95	2.07	3.71
CD-SOCCF (a.k.a. CDSR)	$\pi$ -Net [Ma <i>et al.</i> , 2019]	7.68	7.32	8.13	5.25	9.25	11.75	3.53	2.98	3.73	1.57	4.34	6.67
	MIFN [Ma <i>et al.</i> , 2022]	8.55	8.28	9.01	6.02	10.43	12.71	4.09	3.57	4.29	2.21	4.86	7.08
	C <sup>2</sup> DSR [Cao <i>et al.</i> , 2022]	8.91	8.65	9.71	5.84	11.24	14.54	4.65	4.16	4.94	2.51	5.74	8.18
	P-CDSR [Xiao <i>et al.</i> , 2023]	<b>9.87</b>	<b>9.57</b>	<b>10.72</b>	<b>6.66</b>	<b>12.34</b>	<b>15.94</b>	<b>4.78</b>	<b>4.37</b>	<b>5.08</b>	<b>2.69</b>	<b>6.06</b>	<b>8.27</b>
	DREAM [Ye <i>et al.</i> , 2023]	<u>9.33</u>	<b>10.05</b>	<b>11.25</b>	<u>6.08</u>	<b>13.75</b>	<b>17.45</b>	<b>4.82</b>	<b>5.19</b>	<b>6.15</b>	<b>2.74</b>	<b>7.52</b>	<b>10.51</b>

tention among researchers.

### Transfer Learning

Transfer learning is primarily employed to transfer knowledge learned from one task to another task. For instance, CDNST [Zhuang *et al.*, 2020] transfers the novelty-seeking trait learned from a source domain to a target domain. SATLR [Liu and Zhu, 2021] considers transferring knowledge by multiplying the independently learned representations from one domain with an orthogonal mapping matrix. To improve the ability of knowledge transfer, some researchers propose dual transfer learning. DAT-MDI [Chen *et al.*, 2021] combines a dual transfer model with slot attention to self-adapte item embedding from different domains. DASL [Li *et al.*, 2021] applies a dual embedding component to unify the learning process of user representations and then proposes a dual attention component to incorporate user behaviors in multiple domains.

### Contrastive Learning

Contrastive learning (CL) is also a widely applied technique that leverages the similarities and differences between samples to extract useful information. In the case of Tri-CDR [Ma *et al.*, 2023], it designs two contrastive learning tasks, i.e., the coarse-grained similarity modeling and the fine-grained distinction modeling. The coarse-grained similarity modeling closes three domains' sequence representations of the same user, and the fine-grained distinction modeling assumes the distance between domain A and domain B should be larger than the distance between domain B and the hybrid domain.

MGCL [Xu *et al.*, 2023c] views the local and global item representations of a user as the positive samples and the representations from different users as the negative samples. Additionally, some methods aggregate the sequences and then combine those processed sequences with CL. DREAM [Ye *et al.*, 2023] proposes supervised contrastive learning to minimize the relevance among inter-sequences with different preferences.

### Other Auxiliary Learning Technologies

In addition to transfer learning and contrastive learning, there are other auxiliary learning technologies. For instance, RecGURU [Li *et al.*, 2022] and TPUF [Ding *et al.*, 2023] train a discriminator until it is unable to distinguish whether a feature belongs to domain A or domain B, thereby achieving the goal of adversarial feature alignment. FedDCSR [Zhang *et al.*, 2023a] leverages federated learning to preserve data privacy. RL-ISN [Guo *et al.*, 2023c] utilizes rewards in reinforcement learning to determine whether to revise the whole transferred sequence and selects which interactions should be retained, thus alleviating the noise introduced by transferring cross-domain information. PLCR [Guo *et al.*, 2023b] treats domain-specific context as the prompt and feeds them with domain-agnostic context and label features into self-attention blocks to learn prompt embedding.

### Discussion

Incorporating auxiliary learning technologies aims to enhance the model's ability to capture cross-domain information. Contrastive learning can make learned representations

more discriminative and robust, but it is sensitive to the designed contrastive strategy. Transfer learning enables the sharing of information across domains, but the effectiveness of knowledge transfer is affected by the correlation between domains. There is also adversarial learning that can unify representations from different domains but the training process is more complex.

## 5 Datasets and Experimental Results

In this section, we summarize a list of commonly used datasets in the CDSR scenario, including their corresponding domains, data types, and scales shown in Table 3.

In order to more fully represent the performance of models with different granularity of information and different technologies in CDSR, we quote the results of representative models from [Cao *et al.*, 2022; Xiao *et al.*, 2023; Ye *et al.*, 2023] in Table 4. Notice that these three papers are consistent in their treatment of this dataset. We can see that with the increase in information and advancements in methods, the results gradually improve.

## 6 Future Directions

Although certain progress has been made in addressing the CDSR problem, there is still ample room for improvement. In this section, we summarize several promising directions for potential developments from different perspectives.

### Multi-Domain Simultaneous Improvement

As mentioned in Section 3.1 and shown in Figure 3, most existing models are primarily established on two domains. In real-world applications, users tend to have interactions in multiple domains. Exploring how to integrate information from multiple domains (e.g., dozens of domains) and simultaneously improve the performance of each domain is a crucial research direction for the future of CDSR.

### Heterogeneous Information Fusion

Apart from the side information mentioned in Section 2.3, there is a large amount of relevant heterogeneous information in the real world. For example, users are likely to transfer from browsing short videos to an e-commerce platform to purchase items mentioned in the videos they watched. Therefore, it is worth investigating effective methods that combine heterogeneous information (e.g., image, video, etc.) and traditional ID-based information, to address the challenges in cross-domain recommendation. Moreover, it is also worth considering introducing heterogeneous sequential behaviors [Luo *et al.*, 2022] into cross-domain scenarios.

### Deep Utilization of Non-overlapping Information

Indeed, the majority of current models rely on overlapping users to bridge different domains, but non-overlapping data also contain hidden features that are worth exploring and extracting [Liu *et al.*, 2023]. So researchers can conduct deeper studies on non-aligned information.

### Privacy Preservation

When it comes to sensitive user information, encryption and protection of data is crucial. Particularly within the realm of

CDSR, there is a greater inclusion of user data. Therefore, designing effective federated learning methods to ensure privacy while minimizing the loss of valuable information in the cross-domain scenario is a meaningful but less studied area [Yang *et al.*, 2019; Lin *et al.*, 2023b].

### Fairness and Interpretability

Fairness and interpretability are important research topics in recommender systems. In CDSR, we also need to focus on how to reduce the bias between different domains and how to interpret cross-domain sequential recommendation results to users.

### More Advanced Technologies

In Section 4, we analyze the technologies used in existing CDSR models from a micro view. However, it is undeniable that it still requires more advanced technologies to propel models toward achieving greater leaps in performance. For instance, exploring the application of large language models [Wu *et al.*, 2023] in the CDSR scenario is also a promising direction.

## 7 Conclusions

Cross-domain sequential recommendation (CDSR) is an emerging problem that extends traditional recommender systems by incorporating both sequential and cross-domain granularities, offering the potential to effectively address data sparsity. In this paper, we approach CDSR from the perspective of a four-dimensional tensor and then provide a comprehensive overview of CDSR from both macro and micro views. From a macro view, we summarize the existing models by abstracting multi-level fusion structures. From a micro view, we focus on analyzing and summarizing the basic technologies and auxiliary learning technologies employed by the models. Finally, we also include some public datasets and experimental results for CDSR, and provide some promising future research directions.

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