A Survey on Cross-Domain Sequential Recommendation

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Recommender Systems Based on Information (1/2)

- **OCCF** (One-Class Collaborative Filtering): The available information is limited to **whether a user interacts with an item.**
- **SOCCF** (Sequential One-Class Collaborative Filtering): It places greater emphasis on **the order relationships between items** within a sequence.
- **CD-OCCF** (Cross-Domain One-Class Collaborative Filtering): The interaction information is **expanded from a single domain to multiple domains**, yet it lacks sequential information.

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

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

Recommender Systems Based on Information (2/2)

- **CD-SOCCF** (Cross-Domain Sequential One-Class Collaborative Filtering, also called Cross-Domain Sequential Recommendation, **CDSR**): It combines all of the aforementioned directions and further incorporates **sequential information based on CD-OCCF** and **cross-domain information based on SOCCF**.

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

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

CDSR

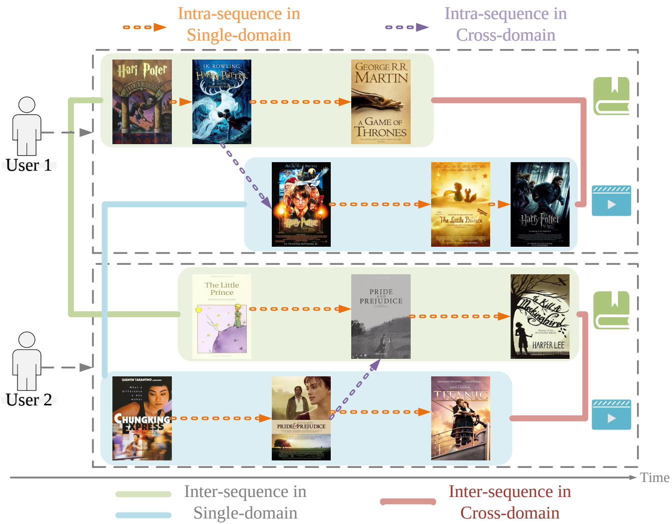


Figure: Illustration of CDSR.

Problem Definition (1/2)

As temporal information and cross-domain information are incorporated, the interaction data between users and items in CDSR undergoes a gradual expansion into **a four-dimensional data tensor**, consisting of dimensions about **users, items, time, and domains**.

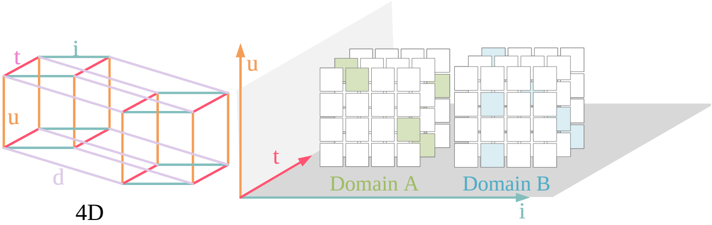


Figure: A visualization of a four-dimensional data tensor in CDSR scenarios.

Problem Definition (2/2)

The four-dimensional tensor is denoted with $\Gamma \in \mathbb{R}^{n \times m \times s \times k}$, where n and m is the number of users and items in all domains, s is the number of 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.)

The goal of CDSR is to estimate the probability for all candidate items $\hat{i} \in I^d$ in each domain to be recommended to each user. The estimated probability can be formalized as follows,

$$P(\ \hat{i} \mid \Gamma\ ) \sim f(\ \Gamma\ ) \tag{1}$$

where $f(\ \Gamma\ )$ indicates the learned function to estimate $P(\ \hat{i} \mid \Gamma\ )$.

Multidirectional Dimensionality Reduction (1/5)

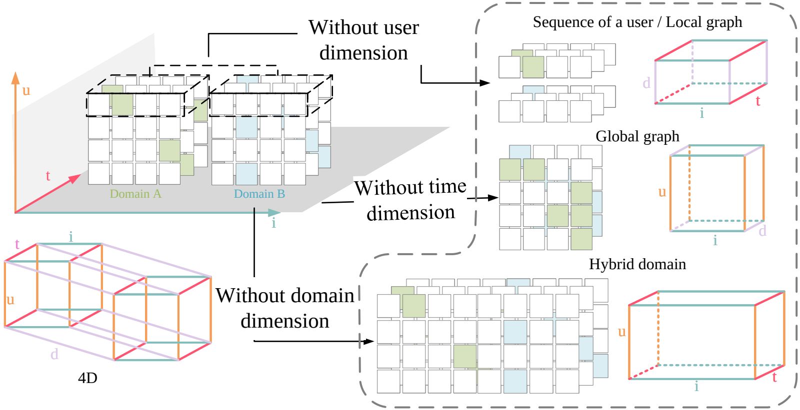
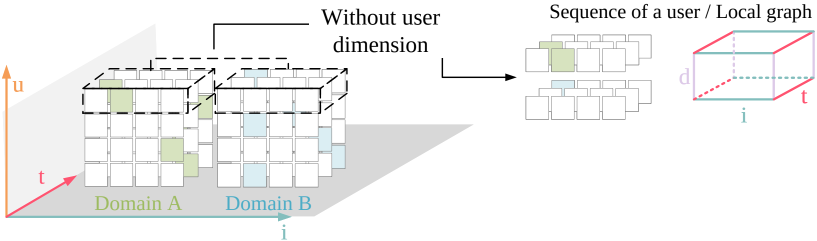


Figure: A visualization of dimensionality reduction for a four-dimensional data tensor in CDSR scenarios.

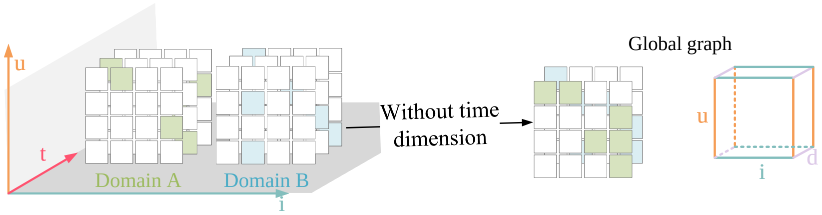
Multidirectional Dimensionality Reduction (3/5)

- **W/o User Dimension.** We have **a single user**, and his or her interactions in chronological order can form **a sequence** in each domain, which can further serve as the basis for constructing **a local graph** in subsequent work.



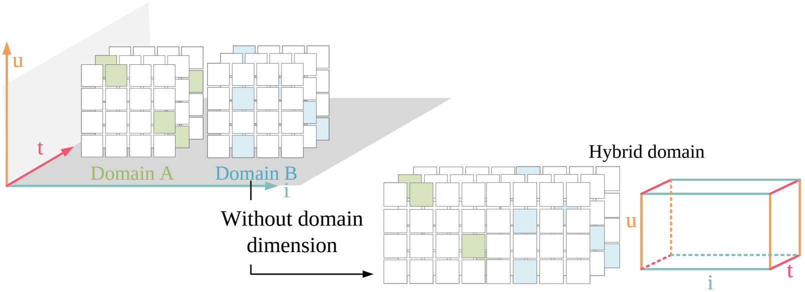
Multidirectional Dimensionality Reduction (4/5)

- **W/o Time Dimension.** Mapping the tensor along the temporal dimension and aggregating interactions within a time lays the groundwork for **a global graph** in each domain. It allows models to learn user-to-user and user-to-item connections, which are more skewed toward users' global preferences.



Multidirectional Dimensionality Reduction (5/5)

- **W/o Domain Dimension.** Blending two or more domains into **a hybrid domain**, a model can clarify the passing relationships between items originally in different domains. Many existing studies treat the hybrid domain as an independent domain, and design model fusion structures that incorporate the original domains and the new hybrid domain in parallel.



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 and analyze unconventional inputs.

- Conventional Input Representations
  - **Pure Sequential Representation**
  - **Graph-Encoded Sequential Representation**
- Unconventional Inputs
  - **Side Information**
    - Time.
    - User/Item Contexts and Reviews.
    - Knowledge Graph.
  - **Pre-trained Features**

Pure Sequential Representation

For each user u, we define $S_u^A = \{i_1^A, i_2^A, \ldots\}$ and $S_u^B = \{i_1^B, i_2^B, \ldots\}$ as his or 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., $S_u^{hybrid} = \{i_1^A, i_1^B, i_2^A, i_3^A, i_2^B, \ldots\}$), which is viewed as a sequence of 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,

$$P(\,\hat{i}\mid\Gamma\,) \rightarrow \quad P(\,\hat{i}\mid S^A, S^B) \sim f(S^A, S^B) \tag{2}$$

Graph-Encoded Sequential Representation

Some researchers 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. [Guo et al., 2021, Zheng et al., 2022, Cao et al., 2022, Zhang et al., 2023b]

- **Local graphs**: It is constructed based on a user's sequence within a domain or a sequence within a session [Zheng et al., 2022, Chen et al., 2021].
- **A global graph**: V consists of both users and items and 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,

$$P(\hat{i} \mid \Gamma) \rightarrow \quad P(\hat{i} \mid G_l, G_g) \sim f(G_l, G_g) \tag{3}$$

Side Information (1/2)

More and more researchers consider incorporating side information to enrich the semantic representation of users' historical behaviors.

- **Time.**
  - To **order** the interacted items
  - To model **time interval** of the interaction [Xiao et al., 2023, Wang et al., 2022, Guo et al., 2022]
  - To investigate **periodicity and duration** of the interaction, etc.
- **Text.**
  - **User Contexts**: e.g., city, age, etc. [Ouyang et al., 2020]
  - **Item Contexts**: e.g., categories, tags, keywords, etc. [Xiao et al., 2023, Ouyang et al., 2020, Zhuang et al., 2020]
  - **Review**: to associate users and items

Side Information (2/2)

- **Knowledge Graph.**
  A knowledge graph defines an entity set E^{KG} and a relation set R^{KG}, which consists of multiple entity-relation-entity triples $< e_i, r, e_j >$ (e.g., $< e_{i_1^A}, Is\_the\_same\_category, e_{i_1^B} >$ meaning that the entity $e_{i_1^A}$ from domain A has the same category as entity $e_{i_1^B}$ from domain B). [Bi et al., 2020, Ma et al., 2022]

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

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

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

Pre-trained Features

Considering the **privacy issues** in two or more domains, some works [Ding et al., 2023, Zhang et al., 2023a, Lei et al., 2021] **use model-trained features as the input** from the source domain, instead of the raw data.

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

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

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

Multi-Level Cross-Domain Fusion Structures

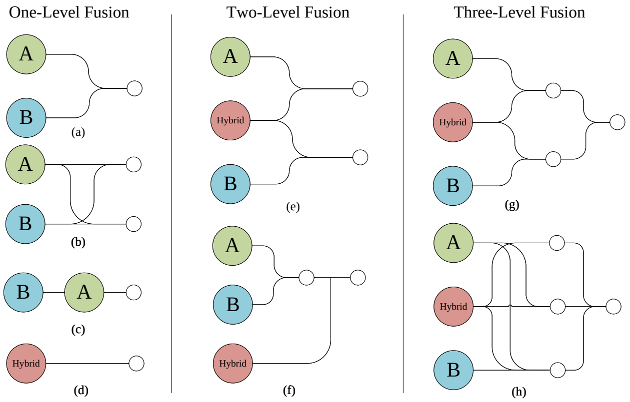
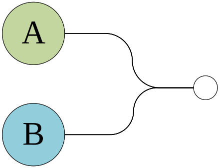


Figure: The overview of multi-level fusion structures that are divided into three levels. “A” and “B” represent domain A and domain B, respectively, and “H” denotes a combination of two domains in chronological order.

One-Level Fusion Structures (1/3)

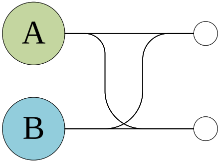
- In earlier works, to combine the cross-domain information, there are a lot of works that **first learn user preferences from domain A and domain B separately, and then fuse the representations of the two domains** using various operations (as shown in Figure(a)). These operations include, but are not 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], and some attention mechanisms [Ouyang et al., 2020, Li et al., 2021].



(a)

One-Level Fusion Structures (2/3)

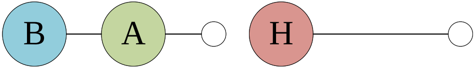
- Additionally, some works employ **transfer learning** to transfer knowledge from a source domain to a target domain [Chen et al., 2021, Liu and Zhu, 2021], or train a discriminator to bridge the representations of two domains with the idea of **adversarial learning** [Li et al., 2022], as shown in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



(b)

One-Level Fusion Structures (3/3)

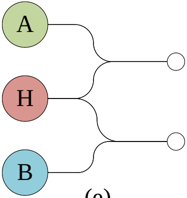
- In contrast to the above **juxtaposed structures**, there are also works utilizing a **tandem structure** to fuse information [Alharbi and Caragea, 2022] (i.e., Figure(c)).
- Some works directly tackle the problem from the perspective of **a hybrid-domain view** (i.e., Figure(d)). For instance, some works [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] choose to learn the item transition patterns in the hybrid sequences S^{hybrid}.



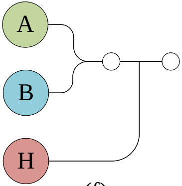
(c) (d)

Two-Level Fusion Structures

- As shown in Figure(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, Wang et al., 2022] or **the bridge** [Zheng et al., 2022] to transfer knowledge from the nother domain.
- There are also some works [Ye et al., 2023] that choose to **combine domain A and domain B first and then fuse the hybrid information** (i.e., Figure(f)).



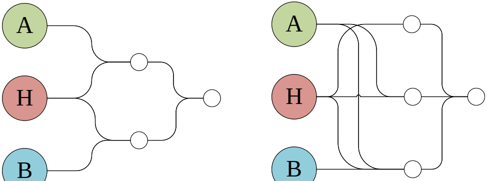
(e)



(f)

Three-Level Fusion Structures

- To delve further into the fusion structures, some researchers continue to extend the hierarchy, as illustrated in Figure(g) [Xu et al., 2023c], which **aggregates the representations again** after combining the hybrid domain information on the basis of Figure(e).
- Figure(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.



(g) (h)

Discussion (1/2)

Although there are various multi-level fusion structures, it does not mean that a more complex structure will perform better.

- Limited by the degree of fusion, **the simple fusion structures**, i.e., one-level fusion structures, are **easy to implement** but may **not comprehensively model** the domain-specific and domain-generic features.
- While **improving effectiveness**, **multi-level fusion structures** bring **increased complexity and reduced interpretability**.

Discussion (2/2)

Considering **the symmetry and asymmetry** of the structures, researchers focus on each domain greatly affects the design of a cross-domain fusion structure.

- 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 simultaneously**, making the fusion structure designed tend to be more symmetric.

Bridges for Cross-Domain Fusion

For the bridges shown in the figure below, the first (i.e., the same users) is prevalent in scenarios with overlapping users, while the latter two (i.e., contexts and clusters/groups) are applied in scenarios without overlapping users.

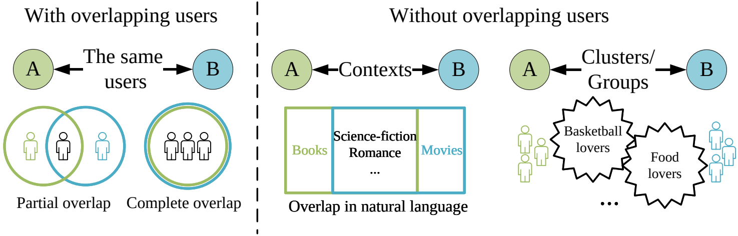


Figure: Examples of building cross-domain bridges relying on different information.

Bridges for Cross-Domain Fusion

- **Same Users.** If some same users exist, then they are often the first choice as the bridge.
- **Contexts.** If there are no common users, it is feasible to leverage the semantic similarity of natural language [Liu et al., 2023].
- **Clusters/Groups.** Further restricting the condition to no overlapping users and no side information, the clusters/groups may be another entry point since a specific group of users could have similar preferences [Lin et al., 2023a].

Works relying on overlapping users often perform well but their application scenarios may face limitations due to the sparse real-world data. Conversely, works built on non-overlapping users can be applied to a broader range of scenarios but may have limited performance. In fact, cross-domain information can be built on more than one type of bridge.

A Systematic Overview

Data Structure	Basic Technology			Auxiliary Learning			Paper
	GNN	RNN	Attention	Contrastive Learning	Transfer Learning	Others	
Sequence		✓					π-Net [Ma et al., 2019], CDHRM [Wang et al., 2020], SCLSTM [Yang et al., 2020], PSJNet [Sun et al., 2023]
Sequence		✓			✓		CDNST [Zhuang et al., 2020]
Sequence		✓	✓		✓		DASL [Li et al., 2021], TJAPL [Xu et al., 2024]
Sequence		✓	✓	✓			CMVCDR [Zang et al., 2023]
Sequence			✓	✓			SEMI [Lei et al., 2021], DREAM [Ye et al., 2023], P-CDSR [Xiao et al., 2023], Tri-CDR [Ma et al., 2023], CGRec [Park et al., 2023], LCN [Hou et al., 2023], MACD [Xu et al., 2023a]
Sequence			✓				MiNet [Ouyang et al., 2020], CD-ASR [Alharbi and Caragea, 2021], CD-SASRec [Alharbi and Caragea, 2022], MAN [Lin et al., 2023a]
Sequence			✓		✓		SATLR [Liu and Zhu, 2021]
Sequence			✓			Adversarial Learning	RecGURU [Li et al., 2022], TPUF [Ding et al., 2023], DA-DAN [Guo et al., 2023a]
Sequence			✓			Reinforcement Learning	RL-ISN [Guo et al., 2023c], O-SCDR [Nanthini and Kumar, 2024]
Sequence			✓			Prompt Learning	PLCR [Guo et al., 2023b]
Sequence							MSECDR [Hong and Jung, 2023], AMID [Xu et al., 2023b]
Graph	✓	✓					DCDIR [Bi et al., 2020], MIFN [Ma et al., 2022]
Graph	✓	✓	✓				AGNNGRU-CDR [Qu et al., 2021]
Graph	✓		✓		✓		DAT-MDI [Chen et al., 2021], SGCross [Li et al., 2023]
Graph	✓		✓				DA-GCN [Guo et al., 2021], TiDA-GCN [Guo et al., 2022]
Graph	✓		✓	✓			C^2DSR [Cao et al., 2022], EA-GCL [Wang et al., 2023], MGCL [Xu et al., 2023c]
Graph	✓		✓	✓		Federated Learning	FedDCSR [Zhang et al., 2023a]
Graph	✓		✓	✓			DDGHM [Zheng et al., 2022]
Graph	✓		✓				LEA-GCN [Zhang et al., 2023b], IESRec [Liu et al., 2023]
Graph	✓						CsrGCF [Wang et al., 2022]

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

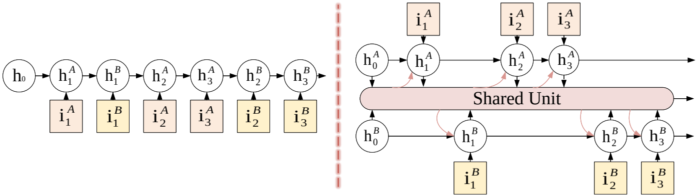
Basic Technologies

According to multi-type input representations in CDSR, the cross-domain information is always considered as a pure sequential representation or a graph-encoded sequential representation. So we illustrate the utilization of sequence modeling technologies and graph structure modeling technologies in CDSR, respectively.

- Sequence Modeling Technologies
  - **Recurrent Neural Networks in CDSR**
  - **Attention Mechanisms in CDSR**
- Graph Structure Modeling Technologies
  - **Graph Neural Networks in CDSR**

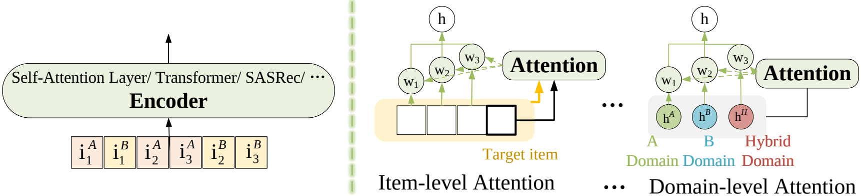
Recurrent Neural Networks in CDSR

- To employ RNNs as **an encoder** (e.g., GRUs) [Li et al., 2021, Chen et al., 2021, Zang et al., 2023]
- To incorporate **a shared unit** into each step of RNNs (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].)



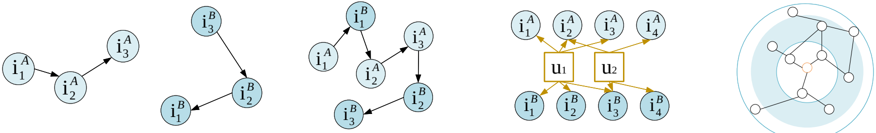
Attention Mechanisms in CDSR

- To use **an attention-based encoder** (e.g., Transformer, SASRec 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]
- To obtain **learnable attention weights** thus aggregating cross-domain information at multiple levels [Ouyang et al., 2020, Cao et al., 2022, Ma et al., 2023, Lin et al., 2023a]



Graph Neural Networks in CDSR

- To construct **a local graph** per session [Chen et al., 2021] or per domain [Cao et al., 2022, Xu et al., 2023c]
- To construct **a global graph** [Guo et al., 2021, Zhang et al., 2023b] based on the hybrid domain of all users
- To construct **a knowledge graph** to encompass more semantic information [Bi et al., 2020, Ma et al., 2022]



A-Domain Graph | B-Domain Graph | Hybrid Domain Graph | Global Graph | Knowledge Graph

Key Technical Framework

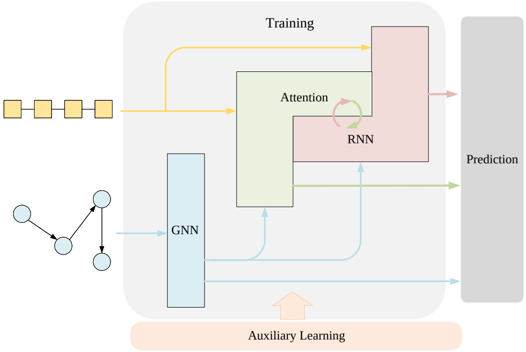


Figure: A schematic overview of the key technical framework. The color of the arrows represents the output after passing through the components represented by different colors. While models represented via graph structures require encoding with GNN, the relationship between RNN and attention can be used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

Discussion (1/2)

- While **RNNs** are easy to implement and are capable of modeling the temporal relationships in sequences, they still suffer from issues such as vanishing and exploding gradients during training.
- However, **attention mechanisms** need to use the interaction of all the positions when calculating the weights, so it contains a large number of parameters and may suffer from the issue of data sparsity.
- **GNNs** supplementally learn 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 in most cases.

Discussion (2/2)

Moreover, 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. Most works **combine graph encoders** (i.e., GNNs) **and sequence encoders** (i.e., RNNs or attention mechanisms) **as complementary parts in CDSR.**

Auxiliary Learning

In addition to the aforementioned key technologies, the utilization of auxiliary learning technologies to facilitate the integration of cross-domain information garners significant attention. Below, we provide examples of common applications.

- Transfer Learning
- Contrastive Learning
- Other Auxiliary Learning Technologies
- Discussion

Transfer Learning

Transfer learning (TL) [Pan and Yang, 2009] is primarily employed to transfer knowledge learned from one task to another task.

- 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**.
- DAT-MDI [Chen et al., 2021] combines a dual transfer model with slot attention to **self-adapt item embedding** from different domains.
- DASL [Li et al., 2021] applies **a dual embedding component** to unify the learning process of user representations.

Contrastive Learning

Contrastive learning (CL) [Jing et al., 2023] is also a widely applied technique that leverages the similarities and differences between samples to extract useful information.

- Tri-CDR [Ma et al., 2023] closes three **domains' sequence representations of the same user** and assumes that 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 works aggregate the sequences and then combine **those processed sequences** with CL.

Other Auxiliary Learning Technologies

In addition to transfer learning and contrastive learning, there are other auxiliary learning technologies.

- **Adversarial Learning**: 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.
- **Federated Learning**: FedDCSR [Zhang et al., 2023a] leverages it [Yang et al., 2019] to preserve data privacy.
- **Reinforcement Learning**: RL-ISN [Guo et al., 2023c] utilizes rewards 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.

Discussion

Incorporating auxiliary learning technologies aims to enhance a 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, i.e., there is vulnerability to negative transfer [Zhang et al., 2023c].
- Moreover, adversarial learning can unify representations from different domains but its training process is more complex.

Datasets

In this section, we summarize a list of commonly used datasets of CDSR, including their corresponding domains, data types, and scales.

Datasets	Domains		Data types	Scale
HVIDEO [Ma et al., 2019]	V-domain: family videos		user ID, item ID, time	0.4 million +
	E-domain: educational videos			
Douban [Zhu et al., 2021]	Movies		user ID, item ID, ratings, labels, reviews, time, users contexts	1 millions +
	Musics			
	Books			
Amazon [McAuley et al., 2015]	Books		user ID, item ID, ratings, time, reviews, item contexts	100 millions +
	Movies			
	Foods			
	Kitchens			
	...			
Tenrec [Yuan et al., 2022]	Videos	QK-video	user ID, item ID, multiple-behavior interactions, video category, watching times, user gender, user age	100 millions +
		QB-video		
	Articles	QK-article	user ID, item ID, multiple-behavior interactions, read percentage, item contexts, read time	
		QB-article		
Mybank-CDR [Xu et al., 2023b]	Loan		user ID, interactive sequences	100 millions +
	Fund			
	Account			

Table: A summary of commonly used datasets for CDSR.

Experimental Results

We quote the results of some representative models. It shows that **with the increase in information and advancements in methods, the results gradually improve**.

		Foods						Kitchens					
		MRR	NDCG		HR			MRR	NDCG		HR		
		@10	@5	@10	@1	@5	@10	@10	@5	@10	@1	@5	@10
OCCF	BPRMF [Rendle et al., 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 et al., 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 et al., 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 et al., 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 et al., 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 et al., 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)	π-Net [Ma et al., 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 et al., 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^{2}DSR [Cao et al., 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 et al., 2023]	**9.87**	9.57	10.72	**6.66**	12.34	15.94	4.78	4.37	5.08	2.69	6.06	8.27
	DREAM [Ye et al., 2023]	9.33	**10.05**	**11.25**	6.08	**13.75**	**17.45**	**4.82**	**5.19**	**6.15**	**2.74**	**7.52**	**10.51**

Table: 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.

Future Directions (1/3)

- **Multi-Domain Simultaneous Improvement.** 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 above, there is a large amount of relevant heterogeneous information in real-world applications. For example, users are likely to transfer from browsing short videos to purchasing items mentioned in the videos. 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 CDSR.

Future Directions (2/3)

- **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 rich semantic information that is 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 [Lin et al., 2023b].

Future Directions (3/3)

- **Fairness and Interpretability.** Fairness and interpretability are crucial research topics in recommender systems. In CDSR, it is essential to reduce the bias between different domains and to interpret CDSR results to users.
- **More Advanced Technologies.** We analyze the technologies used in existing CDSR models from a micro view. However, achieving greater leaps in performance demands more advanced technologies. For instance, exploring the application of large language models (LLMs) [Wu et al., 2023] in the CDSR scenario is also a promising direction.

Conclusions

Cross-domain sequential recommendation (CDSR) extends traditional recommender systems by incorporating sequential and cross-domain information, aiming to address the data sparsity issue.

- We first **formulate the CDSR** problem and modeling tasks, considering **various dimensionality reductions** and **different input representations**.
- **From a macro view**, we present an overview of **multi-level fusion structures**, discussing how to fuse information 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 works that are categorized into **basic and auxiliary learning technologies**.
- Furthermore, we list the **datasets** commonly used in CDSR and the representative **experimental results** as well as provide some insights into **potential future directions**.

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