Bridging Time and Domains: A Time-aware Framework for Cross-Domain Sequential Recommendation

Zemu Liu
School of Computer Science, Beijing Institute of Technology
Beijing, China
zemu_liu@bit.edu.cn

Zhida Qin*
School of Computer Science, Beijing Institute of Technology
Beijing, China
zanderqin@bit.edu.cn

Pengzhan Zhou
School of Computer Science, Chongqing University
Chongqing, China
pzzhou@cqu.edu.cn

Tianyu Huang
School of Computer Science, Beijing Institute of Technology
Beijing, China
huangtianyu@bit.edu.cn

Gangyi Ding
School of Computer Science, Beijing Institute of Technology
Beijing, China
dgy@bit.edu.cn

Abstract

Cross-domain sequential recommendation (CDSR) aims to utilize users' interactions across multiple domains to alleviate the problem of interaction sparsity that is prevalent in web platforms, thereby providing more accurate personalized recommendations. Although current CDSR methods have made some progress, they suffer from two main limitations: (i) *assuming uniformly distributed interactions over time;* and (ii) *neglecting temporal influences during cross-domain transfer.* In order to address the above issues, we propose a novel **T**ime-**A**ware **C**ross-**D**omain **S**equential **R**ecommendation framework (**TA-CDSR**). First, we design a time-sensitive attention which captures user preferences over time by decoupling interaction sequences and time sequences. Second, we propose a time-guided preference generator that can reconstruct the lacking interactions in the target domain by taking the source domain interactions time as guidance information. Finally, we design a multi-scale time windows based domain transfer module, which can dynamically identify the temporal interaction density and thus adaptively assign the weights of cross-domain information. Extensive experiments on three real-world datasets indicate that TA-CDSR achieves competitive time complexity while outperforming other baselines.

CCS Concepts

• **Information systems** → **Recommender systems**.

Keywords

Cross-Domain Sequential Recommendation; Attention Network; Diffusion Model; Recommender Systems

*Corresponding author

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1 INTRODUCTION

With the exponential growth of information on the Internet, recommendation systems have been widely used in many web services such as news, e-commerce, entertainment, etc., effectively improving the users experience [8, 9, 13, 60]. However, the problem of interaction sparsity arises along with the huge amount of information in the web network, which limits the performance of recommendation[31, 38, 39, 55]. To address this problem, Cross-domain sequential recommendation (CDSR) is proposed and has been proven to be effective [47, 53, 57]. CDSR aims to learn more accurate users preferences by utilizing data from multiple domains, so as to improve recommendation performance.

Classical CDSR models rely on completely overlapping users to explicitly model inter-domain behavioral dependencies. Specifically, these methods separately model user preferences for each domain and transfer knowledge through cross-domain modules [34, 35, 59]. Benefiting from the effectiveness of Transformer in sequential recommendation [19, 51], CDSR methods generally utilize self-attention for modeling, e.g., C^2DSR [6], Tri-CDR [33], MAN [28]. In addition, most existing approaches directly transfer complete cross-domain knowledge, ignoring the users heterogeneity. However, in real-world scenarios, the percentage of fully overlapping users is usually small, resulting in a low model coverage. Therefore, recent researches explore partially or non-overlapping user scenarios, such as IESRec [30] with a joint multi-interest and domain alignment framework and AMID [52] with a multi-interest module with doubly robust estimation for open-world recommendations.

Despite the advancements, these approaches ignore the temporal distribution of user preferences, thus hindering the models' ability to accurately capture user evolving preferences. Specifically, these methods suffer from two major limitations: (i) *They rely on an*

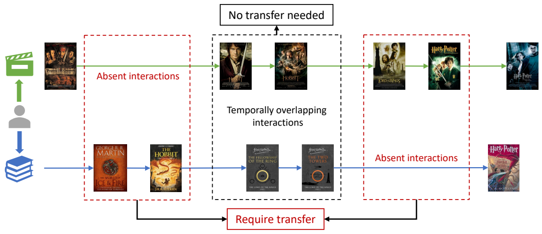


Figure 1: Illustrative example of a representative user interaction sequence.

oversimplified assumption that the interactions in sequences are uniformly distributed over time; and (ii) *They ignore temporal influences in the process of cross-domain transfer.* These limitations may result in a biased recommendation from the users true interest, as well as an inefficient cross-domain knowledge transfer. Therefore, it is important to incorporate temporal information into CDSR models to improve the accuracy of recommendations. However, effectively addressing both limitations faces the following two challenges.

- **How to alleviate the highly irregular and sparse user interactions?** As shown in Figure 1, user interactions are not uniformly distributed over time. Specifically, users frequently concentrate their interactions in short periods of time with long periods of lacking interactions, which further exacerbates the interaction sparsity. Previous researches [11, 14] have shown that non-uniform distribution is not beneficial for capturing user preferences because of the preference drift problem, i.e., user preferences may drift over time. Most of the current approaches alleviate this problem by cross-domain knowledge transfer, but still fail to capture preferences for time periods when both domains lack interactions.
- **How to model the impact of temporal information on cross-domain transfer?** Due to the inherent user heterogeneity, it is not optimal to employ a consistent cross-domain transfer mechanism for all users. Specifically, when a user exhibits abundant interactions in both domains, the model should reduce cross-domain preference transfer during this period to mitigate potential interference from domain-specific information. Conversely, when interactions in the target domain are sparse, the model should actively transfer relevant preferences from the source domain to compensate for lacking interactions and assist the recommendation of the target domain. As shown in Figure 1, since the absence of recent interactions in the book domain, the model should mainly migrate the movie domain preferences during this period so as to correctly recommend *Harry Potter* for the user. Therefore, the model should be able to recognise users temporal patterns and adaptively regulate cross-domain preference transfer.

In order to address the above challenges, we propose a novel **T**ime-**A**ware **C**ross-**D**omain **S**equential **R**ecommendation framework (**TA-CDSR**). First, we design a time-sensitive attention as a sequence encoder. In particular, we model users preferences over time by calculating the correlation of interaction sequences with time sequences. Then, we propose a time-guided preference generator to alleviate the problem of uneven sequences distribution by generating sparse interactions. Specifically, we take the user source domain interactions time as guidance information to assist the diffusion model in generating the lacking target domain interactions. Furthermore, we align the preferences between the original and augmented sequences through contrastive learning to enhance representation consistency. In addition, we design a multi-scale time windows based domain transfer module, which enables the model to adaptively recognize interaction density and assign cross-domain information weights based on the temporal distribution of user interactions. Therefore, the model can perform effective cross-domain transfer. We conduct extensive experiments on three real-world datasets to demonstrate that TA-CDSR achieves competitive time complexity while outperforming other baselines.

The contributions of this paper are summarized as follows:

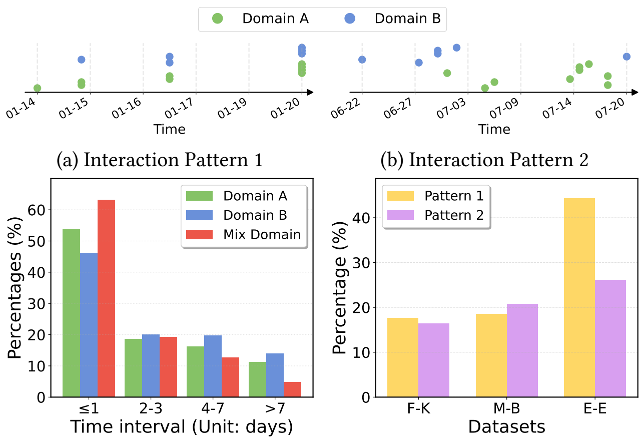
- We propose TA-CDSR, a novel CDSR framework that introduces temporal information in three complementary aspects: sequence encoding, preference generation, and cross-domain transfer for efficient recommendation.
- We propose a diffusion generator which employs source domain interactions time as guidance information to generate absent target domain user interactions, thereby mitigating the interaction sparsity.
- We employ multi-scale time windows to capture the temporal distribution of user interactions, enabling adaptive identification of interaction density and dynamic allocation of cross-domain weights.
- We perform extensive experiments on three real-world datasets that outperform all baselines, proving the effectiveness of TA-CDSR.

2 DATA ANALYSIS

In this section, we perform extensive data analysis to illustrate two issues that are prevalent but neglected in cross-domain sequential data: (i) temporally irregular and sparse interactions, and (ii) temporal heterogeneity of users during cross-domain transfer. For this study, we utilize three datasets, with the detailed information in the Appendix A.1.

In order to better illustrate these issues, we visualize the results of data analysis, as shown in Figure 2: Figure 2(a) and Figure 2(b) show the interaction distributions of two representative users in the Movie-Book dataset; Figure 2(c) displays the time intervals between neighboring interactions of the Movie-Book dataset; and Figure 2(d) quantitatively presents the prevalence of the two interaction temporal patterns described above in the three datasets. From these data analysis figures, we can observe the following two issues:

Temporally irregular and sparse interactions. As shown in Figure 2(a) and Figure 2(b), the distribution of interactions for both users is highly irregular, i.e., a large number of interactions are concentrated in a very short period of time. Furthermore, Figure 2(c) reflects the uniformity of the interaction distribution, with larger intervals indicating a more uneven distribution. In the single domain, while a large number of interaction intervals are within 1 day, half of the interactions still have longer time intervals. Notably, over 10% of interaction intervals exceed one week, suggesting these interactions may lack correlation. Mixing the interactions of both domains significantly mitigates the non-uniformity of the interactions, proving the effectiveness of our time-guided preference



(a) Interaction Pattern 1 (b) Interaction Pattern 2

(c) Percentage of Time Intervals (d) Percentage of Two Patterns

Figure 2: Data analysis on three datasets.

generator. However, previous works ignore temporal information in modeling by simply assuming that user interactions are uniformly distributed, failing to distinct between immediate and delayed interactions, consequently unable to capture the temporal evolution of user preferences.

Temporal heterogeneity of users during cross-domain transfer. Figure 2(a) and Figure 2(b) reflect two typical patterns in which the two domain interactions are either temporally simultaneous or separated. During cross-domain transfer, the patterns of Figure 2(b) can convey more effective information from the source domain for the target domain, since it complements the absent parts of the target domain. In contrast, in the patterns of Figure 2(a), the knowledge transferred from the source domain often exhibits significant overlap with the existing information in the target domain. The target domain preferences may even be disturbed by the transferred specific features of the source domain and introduce additional noise. Previous methods treat source-domain preferences equally with target-domain preferences during cross-domain transfer, ignoring the temporal heterogeneity of users.

Figure 2(d) demonstrates the prevalence of the above two interaction patterns. Our statistical shows that both distribution patterns account for nearly 20% in three datasets, with pattern 1 even over 40% in the E-E dataset. It indicates that the two temporal patterns discussed above are prevalent enough to impact the recommendation quality, therefore it is necessary to consider the temporal heterogeneity of users during cross-domain transfer.

3 PRELIMINARY

We consider a typical CDSR scenario. Specifically, given a user u, who interacts in two domains, defined as domain A and domain B. We can represent the user's chronological interaction sequences in domains A and B with $S^A = (i_1^A, i_2^A, \ldots, i_n^A)$ and $S^B = (i_1^B, i_2^B, \ldots, i_m^B)$, where $i_i^A \in I^A$, $i_i^B \in I^B$ denote the interacted items. I^A and I^B denote the item sets of domain A and domain B. The corresponding time sequence can be denoted as $T^{S^A} = (t_1^A, t_2^A, \ldots, t_n^A)$ and $T^{S^B} = (t_1^B, t_2^B, \ldots, t_m^B)$, where $t_i^A, t_i^B \in T$ denote the interaction time. T denote the whole time set of domain A and domain B. Moreover, we merge the interaction and time sequences of both domain chronologically into S^M, T^{S^M} to better learn the domain-shared features. In addition, the timestamps for the target interactions are t_{n+1}^A, t_{m+1}^B, which are used for prediction. The objective is to predict the user's next interaction in domains A and B, i.e., i_{n+1}^A and i_{m+1}^B.

4 METHOD

In this section, we present the details of TA-CDSR, as shown in Figure 3. First, we feed the initialized embeddings into a time-aware sequence encoder. Then, we complement the user lacking interactions by using a time-guided preference generator and leverage contrastive learning to align user preferences. Finally, we design a multi-scale time windows module that captures the users interaction density over time to adaptively assign cross-domain weights.

4.1 Embedding Layer

In this section, we transform raw item IDs and timestamps into dense vector representations. Crucially, we design a dual temporal embedding that models both the cyclical patterns of long-term interests and the interest decay of short-term behaviors, thereby addressing the inadequate modeling of users temporal patterns.

4.1.1 Item Embedding. We randomly initialize the domain-specific embedding matrices $\boldsymbol{M}^A \in \mathbb{R}^{|I^A|\times d}$, $\boldsymbol{M}^B \in \mathbb{R}^{|I^B|\times d}$ and domain-shared embedding matrix $\boldsymbol{M}^M \in \mathbb{R}^{|I^A+I^B|\times d}$. Where $|I^A|$, $|I^B|$ denote the number of items. We can get the corresponding embeddings as: $\boldsymbol{E}^A$, $\boldsymbol{E}^B$, $\boldsymbol{E}^M$. Note that we pad the sequence embeddings shorter than L with zero vectors for all domains.

4.1.2 Dual Temporal Embedding. We design dual temporal embeddings to capture the cross-domain sequential patterns:

Absolute Time Embedding. We randomly initialize an embedding matrix $\boldsymbol{M}^{at} \in \mathbb{R}^{|T|\times d}$ with an index mapping $I\colon T \to \{1, 2, \ldots, |T|\}$, where $|T|$ denotes the number of timestamps. Given a time sequence $T = (t_1, t_2, \ldots, t_n)$, we can obtain the embedding $\boldsymbol{E}_{at} = [\boldsymbol{M}_1^{at}, \boldsymbol{M}_2^{at}, \ldots, \boldsymbol{M}_n^{at}]$.

Relative Time Embedding. Given a time sequence $T = (t_1, t_2, \ldots, t_n)$, the time interval can be formulated as:

$$T^R = (\Delta_1, \Delta_2, \ldots, \Delta_n) = (0, t_2 - t_1, \ldots, t_n - t_{n-1}). \quad (1)$$

We then apply a logarithmic transformation to model the natural decay of user interests over time:

$$\text{pos}_i = \lfloor a \log(\Delta_i + 1) \rfloor, \quad (2)$$

where a is a scaling parameter. Similarly, we initialize an embedding matrix $\boldsymbol{M}^{rt} \in \mathbb{R}^{|pos|\times d}$, where $|pos|$ denotes the number of time intervals. Then the relative time embedding can be represented as $\boldsymbol{E}_{rt} = [\boldsymbol{M}_1^{rt}, \boldsymbol{M}_2^{rt}, \ldots, \boldsymbol{M}_n^{rt}]$.

The final temporal representation is obtained by non-linearly combining both embeddings through a MLP:

$$\boldsymbol{E}_t = \text{MLP}(\boldsymbol{E}_{at} + \boldsymbol{E}_{rt}). \quad (3)$$

4.2 Time-Aware Sequence Encoder (TASE)

In this section, we design a new sequence encoder. First, we conduct a triple-graph convolution that enriches item representations through structural semantics. Then, we design a time-sensitive attention, which models the temporal distribution of user preferences

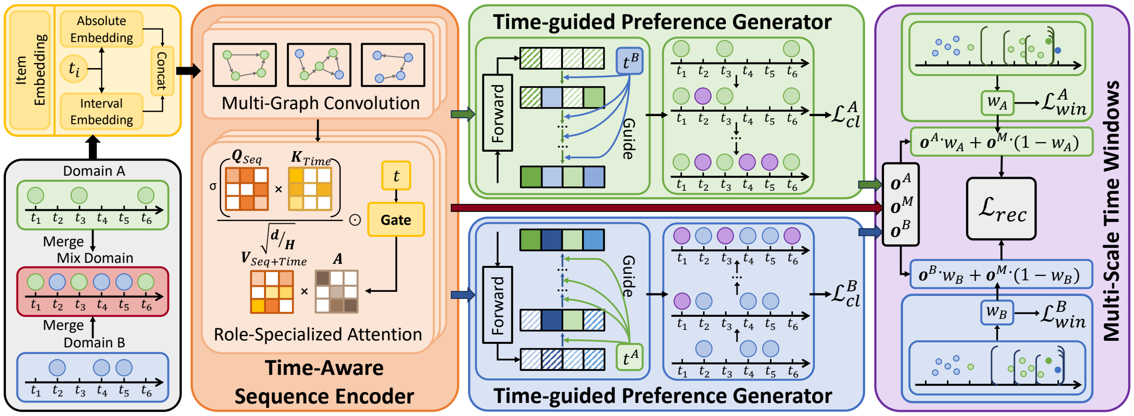


Figure 3: The overall architecture of our proposed method.

by decoupling interaction and time sequences as well as introducing a time gating module. We take domain A as an example in the later description.

4.2.1 Triple-Graph Convolution. In order to capture the correlation between items, we consider encoding with a multi-layers graph convolution network. Similar to C^{2}DSR[6], we respectively construct an item-item matrix for each domain: $G^A \in \{0,1\}^{|I^A|\times|I^A|}$, $G^B \in \{0,1\}^{|I^B|\times|I^B|}$ and $G^M \in \{0,1\}^{(|I^A|+|I^B|)\times(|I^A|+|I^B|)}$. The outputs of graph convolution are:

$$Z^A = \mathrm{GCN}(E^A)+E^A, Z^B = \mathrm{GCN}(E^B)+E^B, Z^M = \mathrm{GCN}(E^M)+E^M. \tag{4}$$

4.2.2 Time-Sensitive Attention. Previous approaches typically employ SASRec[19] as the sequence encoder, which fails to capture the temporal distribution of user preferences, consequently limiting model performance. In order to model users' complex preferences over time, we design a novel time-sensitive attention, which simultaneously decouples interaction sequences and temporal sequences while incorporating a time gating mechanism.

We take the triple-graph convolution output Z^A, Z^B, Z^M as input. Unlike standard self-attention, we assign different roles to Q, K, and V to capture the user preferences and temporal patterns simultaneously. Specifically, Q preserves content semantics to model stable user preferences, K processes temporal signals exclusively to capture temporal patterns, V fuses both modes to enhance the diversity of representations. The process are formulated as:

$$Q^A = Z^A W_Q^A, \quad K^A = E_t^A W_K^A, \quad V^A = (Z^A + E_t^A) W_V^A, \tag{5}$$

where E_t^A denotes the temporal embedding and $W_Q^A, W_K^A, W_V^A \in \mathbb{R}^{d\times d}$ are learnable parameter matrices. Furthermore, to capture fine-grained temporal patterns, we design a time gating module that adaptively calibrates attention scores. The time-gated attention mechanism is formulated as:

$$O^A = \mathrm{softmax}\left(\frac{(Q^A)(K^A)^\top}{\sqrt{d}} \odot A^A\right) V^A, \tag{6}$$

$$A^A = \sigma(E_t^A W_t^A)\sigma(E_t^A W_t^A)^\top, \tag{7}$$

where $A^A \in \mathbb{R}^{L\times L}$ denotes the time gating matrix, W_t^A denotes a learnable parameter matrix, $\odot$ denotes element-wise multiplication and σ denotes the sigmoid function. We stack K layers of attention, which can be formulated as:

$$O_k^A = \mathrm{ATT}(O_{k-1}^A, E_t^A, O_{k-1}^A + E_t^A), \tag{8}$$

when $k=1$, $O_0^A = Z^A \in \mathbb{R}^{L\times d}$ and O_K^A is the final output. Note that we utilize similar positional encoding and feed-forward layers to Transformer's. We conduct the same process in domain B and the mix domain.

4.3 Time-guided Preference Generator (TGPG)

Since user interactions are sparse, it is difficult to capture complete user preferences. Moreover, due to the uneven distribution of user interactions over time, the sparsity is further aggravated. Generative data augmentation is an effective approach to alleviate this issue. In light of the superior performance of diffusion models in data generation, we design a new time-guided preference generator to complement the user lacking interactions. Specifically, we employ source domain timestamps as anchors for user behavioral states, indicating when preference loss may occur in the target domain. The generator combines user preferences and these temporal anchors to produce plausible target domain interactions aligned with the correct time. This time-guided preference generation not only reflects user preferences in the target domain, but also explicitly aligns the generated data distribution with the true temporal pattern, thus reducing both interaction sparsity and temporal distribution bias. In the following, we take domain A as an example.

4.3.1 Cross-Domain Time-guided Diffusion Process. We first utilize sequence embeddings $O_K^A, O_K^B, O_K^M \in \mathbb{R}^{L\times d}$ to obtain the holistic user preferences as diffusion target:

$$\begin{aligned} o^A &= \mathrm{AvgPool}(O_K^A) + \mathrm{AvgPool}(\{o_{K,l}^M : i_l \in I^A\}), \\ o^B &= \mathrm{AvgPool}(O_K^B) + \mathrm{AvgPool}(\{o_{K,l}^M : i_l \in I^B\}). \end{aligned} \tag{9}$$

In order to accurately capture the time of user interactions, we design a temporal embedding encoder to obtain the time guidance for the diffusion model. Specifically, we encode the timestamps by varying frequencies of Cosine to get the time guidance representation:

$$e_t = [\cos(2\pi\omega_1 t + b_1), \ldots, \cos(2\pi\omega_d t + b_d)]. \tag{10}$$

Specifically, the forward process is consistent with the standard diffusion model. We organize a K_1-step noise addition process and

$\boldsymbol{\alpha}_0 = \boldsymbol{o}^A$. In the reverse process, we aim to restore the time-specific user preference guided by the learned time embedding $\boldsymbol{e}_t$:

$$p_\theta(\boldsymbol{\alpha}_{k-1}|\boldsymbol{\alpha}_k, \boldsymbol{e}_t) = \mathcal{N}(\boldsymbol{\alpha}_{k-1}; \boldsymbol{\mu}_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k), \Sigma_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k)), \quad (11)$$

where $\boldsymbol{\mu}_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k)$, $\Sigma_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k)$ denote the mean and covariance functions parameterized by the neural network. We optimize the reverse process through the Evidence Lower Bound (ELBO). The detailed diffusion process is shown in the Appendix A.4.

4.3.2 Time-guided Preference Inference. After training the time-guided diffusion model, a key challenge is how to gradually generate users lacking interactions. As discussed in the data analysis, user interactions are sparse over time, preventing the model from learning accurate domain-specific preferences. Considering that users usually interact with only one domain over a period of time, we can utilize the source domain time information to generate absent interactions in the target domain. Thus, the interaction sparsity problem is effectively mitigated while not altering the users true temporal distribution.

Time-guided Interaction Generation. Since user preferences are constantly evolving over time, the interaction timestamps in the source domain can be taken as guidance information which reflects the user interest in the target domain in this period. For domain A, we can regard the time sequence $T^{S^B} = (t_1^B, \dots, t_m^B)$ of domain B as the potential interaction time, then generate the user's lacking interactions via time-guided preference generator. Specifically, for any $t_i^B \in T^{S^B}$, we can obtain the time-specific embedding $\hat{\boldsymbol{\alpha}}_0$ based on $\boldsymbol{o}^A$ and $\boldsymbol{e}_{t_i}$ from the reverse diffusion process. Then the generated interaction can be denoted as:

$$\hat{i}_i^A = \text{top1}(\hat{\boldsymbol{\alpha}}_0(\boldsymbol{M}^A)^\top), \quad (12)$$

where $\boldsymbol{M}^A$ denotes the items embedding matrix of domain A. By iterating over T^{S^B}, we generate lacking interactions $(\hat{i}_1^A, \dots, \hat{i}_m^A)$ and merge them with S^A chronologically to form the augmented sequence $\hat{S}^A = (i_1^A, \hat{i}_1^A, \dots, \hat{i}_m^A, i_n^A)$. Note that conduct similar process for domain B to get $\hat{S}^B$.

Latent Preference Augmentation. We encode both the original sequence S^A and diffusion-augmented sequence $\hat{S}^A$, then aggregate them via average pooling to obtain user preference representations: $\boldsymbol{o}^A$, $\hat{\boldsymbol{o}}^A$. Considering that $\hat{\boldsymbol{o}}^A$ captures more comprehensively domain-specific preferences, we design a contrastive learning module to align the preferences of the original and augmented sequences. We treat $(\boldsymbol{o}^A, \hat{\boldsymbol{o}}^A)$ as positive pair and other embeddings in the same batch as negative samples. The contrastive loss is:

$$\mathcal{L}_{cl}^A = -\log \frac{\exp(sim(\boldsymbol{o}^A, \hat{\boldsymbol{o}}^A)/\tau)}{\sum_{\boldsymbol{o}^{A'} \in \mathcal{N}(\boldsymbol{o}^A)} \exp(sim(\boldsymbol{o}^A, \boldsymbol{o}^{A'})/\tau)}, \quad (13)$$

where $sim(\cdot)$ denotes the inner product, τ denotes the temperature parameter and $\mathcal{N}(\cdot)$ denotes the set of negative samples. The contrastive loss $\mathcal{L}_{cl}^B$ can be obtained by the same operation.

4.4 Multi-Scale Time Windows Based Domain Transfer (MTDT)

While the time-guided preference generator refines the specific preferences of each domain, effective cross-domain knowledge transfer is still non-trivial. Moreover, most of the previous works directly concatenate or add domain-specific and domain-shared embeddings for prediction, ignoring user heterogeneity and leading to inefficient domain transfer. Therefore, we propose a time-dependent weight assignment mechanism. To be specific, we design a multi-scale time windows module that captures the interaction density based on user temporal patterns. Then, it adaptively assigns domain transfer weights based on the interaction density. It models diverse temporal patterns observed in data analysis and transfers preferences that are not present in the target domain from the source domain, aiming to capture temporal heterogeneity in a stable and interpretable way.

4.4.1 Time-Dependent Weight Assignment. Given a user's interaction sequences S^A, S^B, along with the target interaction timestamps t_{n+1}^A, t_{m+1}^B, we construct multi-scale time windows centered at the target timestamps. The window sizes are dynamically determined based on the average time duration of all sequences in the dataset, ensuring adaptability to varying interaction patterns.

Unlike a single fixed-scale window, our multi-scale approach accommodates diverse user interaction density, thereby reducing random noise in temporal modeling. For example, a fine-grained time window captures active user interactions, while a coarse-grained time window is more suitable for low-frequency users. Meanwhile, a fine-grained time window measures recent interactions that are more consistent with current preferences, while a coarse-grained time window reflects a more comprehensive view of user preferences. This hierarchical design ensures robust preference inference across different time patterns. We design three scales of time windows: coarse-grained, middle-grained, and fine-grained.

Within each time window, we calculate the interaction counts for domains A and B, denoted as num^A and num^B. The domain-specific interaction density is quantified by their relative ratio. For domain A, it can be formulated as: $c^A = num^A/(num^A + num^B)$, yielding a density vector $[c_c^A, c_m^A, c_f^A]$ across coarse-, middle-, and fine-grained windows. Then the domain-specific weight is formulated as:

$$w^A = \left[\sigma\left(\text{MLP}(c_c^A, c_m^A, c_f^A)\right)\right]_a^b, \quad (14)$$

where $\sigma(\cdot)$ denotes the sigmoid function and $[\cdot]_a^b$ represents truncation to the interval $[a, b]$. This bounded transformation prevents: (i) loss of domain-specific information caused by insufficient weights, and (ii) lack of domain-shared information resulting from excessive weights. The domain-shared weight of cross-domain is $1 - w^A$. The weight of domain B w^B can be obtained similarly.

4.4.2 Weight Consistency Penalty Mechanism. Based on the above discussion, a smaller c^A indicates lack of recent interactions in domain A as well as more recent interactions in domain B, necessitating reduced weight allocation to the embeddings of domain A. Conversely, the weighting strategy is inverted when c^A gets larger, i.e., $w^A \propto c^A$. To ensure the model accurately captures the correlation between w^A and c^A, we propose a novel weight consistency penalty mechanism. Specifically, for each pair (w_i^A, c_i^A), we randomly sample a negative pair (w_j^A, c_j^A) from the mini-batch and get their disparity $(\Delta w_i^A, \Delta c_i^A)$. The optimization objective is:

$$\mathcal{L}_{\text{win}}^A = \frac{1}{|\mathcal{B}|} \sum_{i \in |\mathcal{B}|} \text{ReLU}\left(\Delta w_i^A \cdot \text{sign}\left(-\Delta c_i^A\right)\right), \quad (15)$$

where $|\mathcal{B}|$ denotes the size of mini-batch. The penalty mechanism selectively penalizes cases where Δw^A and Δc^A exhibit opposing

Table 1: Performance of our model with all baselines on the three datasets.

Datasets	Metrics	Transformer Method				Diffusion Method				CDSR Method				TA-CDSR	impro.
		SASRec	TiSASRec	CL4SRec	IOCRec	DreamRec	DiffuRec	ADRec	InDiRec	C^2DSR	EA-GCL	Tri-CDR	ABXI		
Food	MRR	0.0917	0.0951	0.0949	0.1260	0.0185	0.1312	0.1376	0.1383	0.1246	0.1119	0.1195	0.1260	**0.1789**	29.36%
	N@5	0.0915	0.0943	0.0928	0.1282	0.0123	0.1327	0.1387	0.1408	0.1250	0.0731	0.1141	0.1277	**0.1779**	26.35%
	N@10	0.1063	0.1080	0.1085	0.1375	0.0170	0.1400	0.1481	0.1503	0.1338	0.0748	0.1311	0.1390	**0.1846**	22.82%
	H@1	0.0475	0.0546	0.0513	0.0902	0.0067	0.0981	0.1002	0.0981	0.0889	0.1055	0.0682	0.0836	**0.1537**	45.69%
	H@5	0.1337	0.1319	0.1320	0.1614	0.0193	0.1626	0.1723	0.1783	0.1570	0.1199	0.1560	0.1673	**0.1999**	12.11%
	H@10	0.1800	0.1744	0.1812	0.1901	0.0354	0.1852	0.2019	0.2078	0.1843	0.1255	0.2087	0.2027	**0.2206**	5.70%
Kitchen	MRR	0.0588	0.0640	0.0661	0.0973	0.0152	0.0965	0.0907	0.0917	0.0830	0.0745	0.0713	0.0833	**0.1153**	18.50%
	N@5	0.0541	0.0604	0.0614	0.0957	0.0088	0.0952	0.0883	0.0896	0.0794	0.0481	0.0662	0.0821	**0.1121**	17.14%
	N@10	0.0670	0.0715	0.0738	0.1018	0.0142	0.1008	0.0970	0.0978	0.0880	0.0486	0.0782	0.0908	**0.1179**	15.82%
	H@1	0.0269	0.0321	0.0341	0.0770	0.0041	0.0765	0.0627	0.0647	0.0569	0.0720	0.0320	0.0514	**0.0954**	23.90%
	H@5	0.0805	0.0879	0.0877	0.1129	0.0147	0.1123	0.1116	0.1123	0.1008	0.0779	0.0993	0.1110	**0.1275**	12.93%
	H@10	0.1210	0.1225	0.1262	0.1322	0.0316	0.1297	0.1383	0.1376	0.1276	0.0795	0.1367	0.1382	**0.1458**	5.42%
Movie	MRR	0.0673	0.0744	0.0710	0.0889	0.0143	0.0968	0.0885	0.0971	0.0719	0.0786	0.0712	0.0923	**0.1337**	37.69%
	N@5	0.0612	0.0690	0.0639	0.0863	0.0087	0.0930	0.0839	0.0932	0.0670	0.0506	0.0623	0.0880	**0.1299**	39.38%
	N@10	0.0742	0.0822	0.0769	0.0950	0.0121	0.1018	0.0964	0.1041	0.0749	0.0516	0.0795	0.1007	**0.1363**	30.93%
	H@1	0.0333	0.0387	0.0350	0.0581	0.0044	0.0704	0.0526	0.0650	0.0490	0.0756	0.0272	0.0563	**0.1126**	48.94%
	H@5	0.0891	0.0983	0.0911	0.1130	0.0142	0.1147	0.1137	0.1193	0.0837	0.0820	0.0959	0.1186	**0.1460**	22.38%
	H@10	0.1295	0.1393	0.1314	0.1400	0.0261	0.1421	0.1529	0.1530	0.1081	0.0851	0.1491	0.1580	**0.1661**	5.13%
Book	MRR	0.0457	0.0537	0.0561	0.0768	0.0101	0.0851	0.0806	0.0781	0.0673	0.0592	0.0617	0.0728	**0.1012**	18.92%
	N@5	0.0433	0.0513	0.0523	0.0744	0.0059	0.0818	0.0789	0.0732	0.0649	0.0386	0.0545	0.0685	**0.0978**	19.56%
	N@10	0.0499	0.0577	0.0601	0.0784	0.0078	0.0844	0.0828	0.0766	0.0694	0.0389	0.0646	0.0747	**0.1021**	20.97%
	H@1	0.0236	0.0320	0.0339	0.0634	0.0019	0.0738	0.0631	0.0643	0.0506	0.0564	0.0314	0.0490	**0.0880**	19.24%
	H@5	0.0628	0.0694	0.0704	0.0845	0.0100	0.0889	0.0943	0.0809	0.0778	0.0629	0.0769	0.0864	**0.1070**	13.47%
	H@10	0.0834	0.0890	0.0950	0.0970	0.0158	0.0967	0.1064	0.0918	0.0917	0.0638	0.1081	0.1056	**0.1203**	11.29%
Entertainment	MRR	0.4296	0.4348	0.3611	0.4717	0.0598	0.4469	0.4643	0.4265	0.5916	0.4036	0.5117	0.4398	**0.7430**	25.59%
	N@5	0.4461	0.4484	0.3773	0.4882	0.0534	0.4666	0.4846	0.4477	0.6184	0.2991	0.5414	0.4583	**0.7491**	21.13%
	N@10	0.4878	0.4862	0.4196	0.5224	0.0631	0.5010	0.5188	0.4858	0.6437	0.3240	0.5788	0.4957	**0.7619**	18.36%
	H@1	0.2950	0.3120	0.2250	0.3493	0.0339	0.3168	0.3326	0.2889	0.4682	0.2955	0.3583	0.3057	**0.6974**	48.95%
	H@5	0.5848	0.5729	0.5173	0.6117	0.0718	0.6008	0.6178	0.5915	0.7500	0.5461	0.7010	0.5962	**0.7950**	6.00%
	H@10	0.7135	0.6895	0.6479	0.7168	0.1043	0.7140	0.7233	0.7091	0.8280	0.6267	0.8161	0.7117	**0.8345**	0.79%
Education	MRR	0.5522	0.5523	0.5052	0.7792	0.6916	0.7810	0.7937	0.7895	0.7188	0.6471	0.5870	0.6432	**0.8439**	6.32%
	N@5	0.5888	0.5898	0.5349	0.7898	0.6927	0.7899	0.8047	0.8002	0.7428	0.4488	0.6208	0.6735	**0.8511**	5.77%
	N@10	0.6224	0.6214	0.5708	0.8028	0.6966	0.8033	0.8165	0.8127	0.7586	0.4600	0.6553	0.6959	**0.8579**	5.07%
	H@1	0.3976	0.3962	0.3547	0.7206	0.6735	0.7247	0.7358	0.7321	0.6184	0.5534	0.4367	0.5169	**0.8094**	10.00%
	H@5	0.7569	0.7584	0.6935	0.8486	0.7082	0.8434	0.8615	0.8571	0.8436	0.7701	0.7817	0.8074	**0.8865**	2.90%
	H@10	0.8591	0.8544	0.8033	0.8885	0.7205	0.8848	0.8981	0.8957	0.8921	0.8065	0.8875	0.8762	**0.9074**	1.04%

signs, ensuring that the weights are properly assigned. The loss $\mathcal{L}^B_{\text{win}}$ can be obtained by the same operation.

4.5 Prediction and Optimization

Based on the outputs of time-aware sequence encoder $\boldsymbol{O}^A_K$, $\boldsymbol{O}^B_K$, $\boldsymbol{O}^M_K \in \mathbb{R}^{L\times d}$ and the weights of multi-scale time windows w^A, w^B, we predict the target item with the following equation:

$$\begin{aligned}\hat{\boldsymbol{y}}^A &= \text{softmax}\left((w^A\boldsymbol{o}^A_K + (1-w^A)\boldsymbol{o}^M_K)\boldsymbol{W}^A\right),\\ \hat{\boldsymbol{y}}^B &= \text{softmax}\left((w^B\boldsymbol{o}^B_K + (1-w^B)\boldsymbol{o}^M_K)\boldsymbol{W}^B\right),\end{aligned} \tag{16}$$

where $\boldsymbol{o}^A_K$, $\boldsymbol{o}^B_K$, $\boldsymbol{o}^M_K$ denote the last item embeddings and $\boldsymbol{W}^A \in \mathbb{R}^{d\times|I^A|}$, $\boldsymbol{W}^B \in \mathbb{R}^{d\times|I^B|}$ denote the learnable parameter matrices. $\hat{\boldsymbol{y}}^A$, $\hat{\boldsymbol{y}}^B$ denote the probability of interacting with each item.

We optimize the main task by employing the cross-entropy loss function, the formula is:

$$\mathcal{L}^A = -\sum_{S^A\in\mathcal{S}^A}\log(\hat{y}^A_i), \quad \mathcal{L}^B = -\sum_{S^B\in\mathcal{S}^B}\log(\hat{y}^B_j), \tag{17}$$

where i, j denote the index of ground truth and $\mathcal{S}^A$, $\mathcal{S}^B$ denote the overall interaction sequence sets. Except for the domain-specific loss, we also design the domain-shared loss:

$$\begin{aligned}\hat{\boldsymbol{y}}^A_m &= \text{softmax}(\boldsymbol{o}^M_K\boldsymbol{W}^A), \quad \hat{\boldsymbol{y}}^B_m = \text{softmax}(\boldsymbol{o}^M_K\boldsymbol{W}^B),\\ \mathcal{L}^A_m &= -\sum_{S\in\mathcal{S}}\log(\hat{y}^A_{m,i}), \quad \mathcal{L}^B_m = -\sum_{S\in\mathcal{S}}\log(\hat{y}^B_{m,j}).\end{aligned} \tag{18}$$

Therefore, the total loss function is:

$$\mathcal{L}_{rec} = \mathcal{L}^A+\mathcal{L}^B+\mathcal{L}^A_m+\mathcal{L}^B_m+\lambda_1\cdot(\mathcal{L}^A_{cl}+\mathcal{L}^B_{cl})+\lambda_2\cdot(\mathcal{L}^A_{\text{win}}+\mathcal{L}^B_{\text{win}}), \tag{19}$$

where λ_1, λ_2 denote the hyper-parameters which control the losses weights, respectively. In order to better improve the performance of model, we alternately update $\mathcal{L}_{rec}$ and $\mathcal{L}_{diff}$.

5 EXPERIMENTS

In this section, we conduct extensive experiments on three real-world datasets with the aim of answering the following questions:

- **RQ1:** Does TA-CDSR achieve optimal results in all domains?
- **RQ2:** How does each module of TA-CDSR affect overall performance?
- **RQ3:** Does the TGPG achieve the expected performance?
- **RQ4:** Does the MTDT achieve the expected performance?
- **RQ5:** How about the time complexity of TA-CDSR?

5.1 Experimental Settings

5.1.1 Datasets. We conducted extensive experiments on three datasets: (i) Food-Kitchen, (ii) Movie-Book, (iii) Entertainment-Education. We refer to C^2DSR [6] for the data classification. The details of the datasets are given in the Appendix A.1.

5.1.2 Baselines. We compare TA-CDSR with various types of baselines: (i) the transformer methods (**SASRec** [19], **TiSASRec** [22], **CL4SRec** [51], **IOCRec** [24]); (ii) the diffusion methods (**DreamRec** [56], **DiffuRec** [27], **ADRec** [7], **InDiRec** [40]); (iii) the CDSR methods (**C^2DSR** [6], **EA-GCL** [49], **Tri-CDR** [33], **ABXI** [4]). More details about these baselines are provided in Appendix A.2.

5.1.3 Implementation Details. For all methods, we set the embedding dimension d to 256, the batch size to 256. Since the original interactions are extremely sparse, we set the training step K_1 to 5 and the sampling step to 1. The time window scales vary depending on the dataset. For instance, we set it to {15, 30, 60} (days) for the

Table 2: Ablation Study.

Variants	Food MRR	Food N@10	Food H@10	Kitchen MRR	Kitchen N@10	Kitchen H@10
w/o Single	0.1433	0.1514	0.1971	0.0814	0.0850	0.1192
w/o Cross	0.1644	0.1674	0.1937	0.1056	0.1058	0.1244
w/o TASE	0.1748	0.1804	0.2167	0.1133	0.1145	0.1384
w/o TGPG	0.1782	0.1835	0.2165	0.1149	0.1171	0.1443
w/o MTDT	0.1750	0.1793	0.2108	0.1144	0.1165	0.1425
TA-CDSR	**0.1789**	**0.1846**	**0.2206**	**0.1153**	**0.1179**	**0.1458**

Variants	Movie MRR	Movie N@10	Movie H@10	Book MRR	Book N@10	Book H@10
w/o Single	0.0893	0.0925	0.1280	0.0679	0.0697	0.0921
w/o Cross	0.1263	0.1271	0.1495	0.0927	0.0921	0.1040
w/o TASE	0.1312	0.1334	0.1606	0.0955	0.0951	0.1073
w/o TGPG	0.1325	0.1355	0.1644	0.1005	0.1005	0.1159
w/o MTDT	0.1298	0.1330	0.1637	0.0968	0.0972	0.1129
TA-CDSR	**0.1337**	**0.1363**	**0.1661**	**0.1012**	**0.1021**	**0.1203**

Food-Kitchen dataset. We set λ_1 to 0.1 and λ_2 are chosen from {0.1, …, 0.9}. More details are provided in Appendix A.3.

5.2 Performance Comparison (RQ1)

In this section, we perform a comprehensive performance comparison with other baselines. Table 1 shows the results of all models on the three datasets, yielding the following observations:

TA-CDSR achieves the best results in all domains. TA-CDSR achieves optimal performance in all six domains of the three datasets with high improvements. It is mainly attributed to the three temporal modules complementing each other: TASE accurately captures user preferences, TGPG fills in the users missing interactions, and MTDT properly assigns the weights of cross-domain transfer. It demonstrates that temporal information is important for cross-domain sequence recommendations.

Diffusion-based models outperform other baselines. Since the interactions are sparse, models are unable to capture accurate user preferences. As a generative approach, diffusion-based models can generate unobserved but plausible interaction sequences.TA-CDSR benefits from the powerful generation capability of diffusion models to mitigate interaction sparsity , therefore performing better than other CDSR methods.

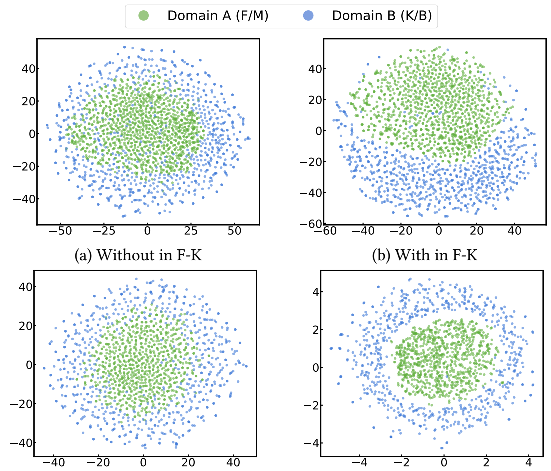
Cross-domain information can enhance model performance. Single-domain SR methods cannot provide satisfactory results compared to TA-CDSR since they fail to utilize the auxiliary information in the source domain. It indicates that cross-domain information can effectively alleviate interaction sparsity and improve recommendation performance.

Transformer effectively captures sequential preferences. A lot of Diffusion and CDSR methods, such as DiffuRec, InDiRec, C^2DSR, TriCDR, also utilize Transformer as encoder and achieve competitive performances, highlighting the practicality and superiority of Transformer for modeling sequential problems.

5.3 Ablation Study (RQ2)

In this section, we design different variants to evaluate the impact of each module in TA-CDSR on performance:

- **w/o Single:** Remove domain-specific embeddings , only use domain-shared embeddings for prediction.
- **w/o Cross:** Remove domain-shared embeddings , only use domain-specific embeddings for prediction.



(a) Without in F-K (b) With in F-K (c) Without in M-B (d) With in M-B

Figure 4: The visualization of TGPG module's effect.

- **w/o TASE:** Replace time-sensitive attention with standard self-attention.
- **w/o TGPG:** Remove time-guided preference generator.
- **w/o MTDT:** Remove multi-scale windows based domain transfer module.

Table 2 displays the comparative results of TA-CDSR and all variants on the two datasets, which can be observed:

From the results of the variants "w/o Single" and "w/o Cross", lacking either single- or cross-domain information significantly decreases the model performance, which shows the importance of cross-domain information when recommending.

The results from the variant "w/o TASE" demonstrate the effectiveness of time-sensitive attention in capturing user preferences. By decoupling temporal and interaction features, the encoder effectively models the temporal distribution of user preferences.

The results from the variant "w/o TGPG" indicate the practicality of the diffusion model in generating user absent interactions. By utilizing our designed source domain time-guided strategy, the generator can successfully enrich user lacking interactions, thereby capturing user preferences more accurately.

The results from the variant "w/o MTDT" illustrate the usefulness of adaptively merging domain-specific and domain-shared embeddings according to different users. The multi-scale time windows accurately identify the interaction density over time, thus improving the efficiency of cross-domain transfer.

5.4 Visualization of TGPG module (RQ3)

In this section,we present a comparative visualization of the domain-specific embedding distributions obtained by TA-CDSR with and without the TGPG module on two datasets, as shown in Figure 4. It can be noticed that the two-domain point clouds are highly mixed and lack a clear demarcation without the TGPG module. While it can be observed that the two-domain point clouds form a notable separation and the boundary clarity is significantly improved with TGPG module. It indicates that due to the uneven distribution and interaction sparsity of the original sequences, the model struggles to learn accurate domain-specific features and is susceptible to noise. In contrast, the TGPG module notably mitigates these two

Table 3: Comparison of different scales of time window.

Scales	Food			Kitchen		
	MRR	N@10	H@10	MRR	N@10	H@10
fine	**0.1795**	0.1839	0.2163	**0.1165**	**0.1181**	0.1429
middle	0.1794	0.1831	0.2137	0.1159	0.1173	0.1437
coarse	0.1789	0.1836	0.2160	0.1147	0.1162	0.1411
multi	0.1789	**0.1846**	**0.2206**	0.1153	0.1179	**0.1458**
Scales	**Movie**			**Book**		
	MRR	N@10	H@10	MRR	N@10	H@10
fine	0.1308	0.1341	0.1670	0.1004	0.1007	0.1166
middle	0.1322	0.1353	**0.1675**	0.1005	0.1009	0.1165
coarse	0.1324	0.1358	0.1637	0.1007	0.1009	0.1162
multi	**0.1337**	**0.1363**	0.1661	**0.1012**	**0.1021**	**0.1203**

problems by generating user lacking interactions, which improves the accuracy of capturing domain-specific features.

5.5 Multi-Scale Time Windows Study (RQ4)

In this section, we first compare the results of different scales of time windows to verify the superiority of multi-scale. Then, we visualize the relationship between domain-specific embeddings weights and interaction density to confirm the inference from the data analysis.

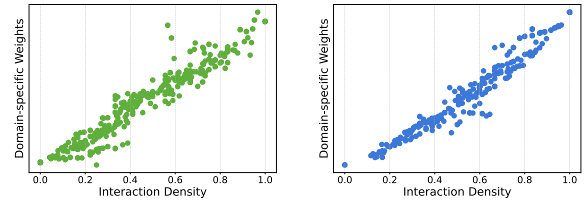
Table 3 shows the results for different scales of time windows on the two datasets. We design three scales of time windows: coarse-grained, middle-grained, and fine-grained. It can be observed that multi-scale achieves the optimal results in most cases while worse than single-scale in a few cases. This is due to the fact that different datasets have different temporal patterns.

For example, in the Food-Kitchen dataset, the user sequences have an average interaction span of 6 months. Users interests may change over time, and recent interactions are more reflective of current preferences, thus fine-grained time windows perform better. Coarse-grained time windows may introduce excessive irrelevant historical interactions and dilute the key signals. While the average interaction span of the Movie-Book dataset is only half a month, which differs from the time patterns of the Food-Kitchen dataset, therefore presenting different results. In general, multi-scale time windows are able to quantify the users interaction density over time, adaptively adjusting the weights.

Next, we visualize the relationship between the domain-specific embedding weights and the interaction density of this domain. In Section 4.4, we consider that their relationship should be proportional, since a smaller interaction density indicates more lack of recent interactions in the target domain and more plentiful recent interactions in the source domain. Figure 5 presents the results of the visualization, which are in line with our expectations. It suggests that the multi-scale time windows are able to identify low interaction density users in the target domain and adaptively take more account of source domain information, which is beneficial to improve the recommendation performance.

5.6 Time Complexity Analysis (RQ5)

Given that the efficiency bottleneck of TA-CDSR is predominantly associated with the TGPG module, we therefore compare the time complexity with other diffusion-based methods in this section, as shown in Table 4. Since the selected methods are single-domain sequential recommendation models, we sum their time for processing both domains to get the CDSR time. Because ADRec employs



(a) Domain A (a) Domain B

Figure 5: The relationship between the domain-specific embedding weights and the interaction density.

Table 4: Training and inference time per epoch (Unit: seconds) and GPU memory occupation (Unit: GB) comparison.

Datasets		DreamRec	DiffuRec	InDiRec	TA-CDSR
F-K	Training	63.8	**52.2**	91.5	65.1
	Inference	63.7	24.2	7.0	**3.9**
	Memory	5.13	2.41	**1.77**	7.64
M-B	Training	98.6	**86.0**	128.5	123.3
	Inference	58.5	22.5	8.4	**4.3**
	Memory	6.18	2.63	**1.83**	10.98
E-E	Training	820.0	451.4	966.4	**378.7**
	Inference	51.8	19.7	**3.2**	3.5
	Memory	3.92	2.19	**1.5**	6.07

a pre-training method and the time complexity is related to the pre-trained model, we do not compare with it.

It can be observed that TA-CDSR consumes similar time as other models in training, even less on the larger dataset (E-E). When inferring, TA-CDSR takes almost the shortest time. In conclusion, TA-CDSR achieves the best results with similar time complexity as the other models. The time consumption of diffusion models mainly comes from the forward and reverse processes. Since there is inherent noise (e.g., false clicks) in the interactions, we set a small number of forward and backward steps. However, the time-guided preference generator has to perform multiple diffusion processes for a single sequence, which greatly increases the time consumption. In summary, the overall time efficiency of TA-CDSR is still acceptable. Additionally, as TA-CDSR is designed to handle Domain A, Domain B, and the mix domain simultaneously, it theoretically contains 2 to 3 times the parameters of a single-domain model. Consequently, TA-CDSR consumes more memory.

6 CONCLUSION

In conclusion, this paper proposes a new time-aware cross-domain sequential recommendation framework. Specifically, this paper considers three aspects of cross-domain temporal characterization. First, we design a time-sensitive attention to model the temporal features of user preferences. Then, we design a time-guided preference generator to generate the users lacking interactions. Finally, we adaptively transfer cross-domain information based on multi-scale time windows. Extensive experiments on three datasets prove that TA-CDSR has competitive time complexity while outperforming other baselines.

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A APPENDIX

A.1 Dataset Description

In this paper, we select three real-world datasets for our experiments, which are widely used in CDSR tasks. The details of the datasets are shown in Table 5.

A.2 Details of Baselines

In order to evaluate the performance of the model, we perform comparisons with some classical and state-of-the-art models. Specifically, baselines can be divided into the following three categories:

The Transformer Methods:

- **SASRec** [19] utilizes self-attention to effectively capture sequential patterns and dependencies in user-item interactions.
- **TiSASRec** [22] enhances sequential recommendation by incorporating time interval information into self-attention.
- **CL4SRec** [51] uses SASRec as encoder and performs self-supervised pre-training with three sequential-level contrastive learning to improve recommendation results.
- **IOCRec** [24] designs a contrastive learning framework based on multi-intention learning by using transformer encoding.

The Diffusion Methods:

- **DreamRec** [56] reshapes sequential recommendation into a generative paradigm that directly portrays the user's real preferences via the Diffusion model.
- **DiffuRec** [27] models items and user interests as distributions , progressively restores target item representations for recommendation.

Table 5: Statistics of datasets.

Datasets	#Users	#Items	#Train	#Valid	#Test	Sparsity
Food Kitchen	16,579	29,207 34,886	34,117	8,173	8,406	99.94% 99.95%
Movie Book	15,352	36,845 63,937	58,515	7,644	7,708	99.92% 99.96%
Entertainment Education	13,714	8,367 11,404	120,635	6,929	6,785	98.14% 98.79%

- **ADRec** [7] applies the noising process to each token and captures the correlations between the tokens through autoregression.
- **InDiRec** [40] guides the diffusion model to generate interactions through user target intentions, which provides a more reliable augmented view for contrastive learning.

The CDSR Methods:

- **C^{2}DSR** [6] utilizes SASRec to encode intra- and inter-domain user preferences and enhance the preferences representation by maximizing mutual information.
- **EA-GCL** [49] designs an external attention encoder that effectively mitigates the bias interference from batch-based methods.
- **Tri-CDR** [33] implements a triple cross-domain attention-based encoding framework and captures more accurate multi-domain representations via multi-granularity modeling.
- **ABXI** [4] utilizes two types of LoRAs to adaptively learn user representations and align different domains by using a task-guided approach.

A.3 Evaluation Protocol and Implementation Details

In this section, we introduce the detailed evaluation protocol and experimental setting. Following previous works, we utilize the leave-one-out method to validate the model performance. We also use cross-validation with a ratio of 8:1:1 for the training, validation, and test sets. To guarantee an unbiased evaluation, we randomly select 999 negative samples and 1 ground truth for each case and evaluate the rankings.

The max epoch is set to 100, the learning rate is set to 0.001, and using the Adam optimizer for optimization.The layer of graph convolution is set to 1 and the layer of attention is set to 2. For the Movie-Book dataset, we set the time window scale to {4, 7, 10} (days); for the Entertainment-Education dataset, we set the time window scale to {7, 15, 30} (days). In addition, we conduct all experiments on a 24G NVIDIA GeForce RTX 3090.

A.4 Time-guided Diffusion Process

In this section, we introduce the time-guided diffusion process in detail. We initialize the Gaussian process with $\boldsymbol{\alpha}_0 = \boldsymbol{o}^A$ and progressively destroy the embedding by adding Gaussian noise over K_1 steps, known as forward process. The transition follows:

$$q(\boldsymbol{\alpha}_{K_1}|\boldsymbol{\alpha}_0) = \mathcal{N}(\boldsymbol{\alpha}_{K_1}; \sqrt{\bar{\beta}_{K_1}}\boldsymbol{\alpha}_0, (1-\bar{\beta}_{K_1})\boldsymbol{I}), \tag{20}$$

where $\bar{\beta}_{K_1} = \prod_{k=1}^{K_1} \beta_k$, $\beta_{K_1} = 1 - \gamma_{K_1}$. γ_{K_1} controls the scale of the Gaussian noise added at each step K_1, and $1 - \bar{\beta}_{K_1} \propto K_1$, ensuring

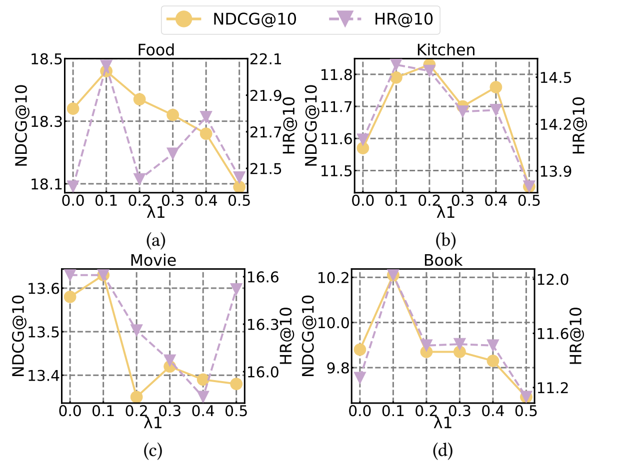

Figure 6: The effect of the hyper-parameter λ_1.

that the noise increases linearly with step. Therefore, Eq. (14) can be reparameterized as: $\boldsymbol{\alpha}_{K_1} = \sqrt{\bar{\beta}_{K_1}}\boldsymbol{\alpha}_0 + \sqrt{1-\bar{\beta}_{K_1}}\boldsymbol{\epsilon}, \boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{I})$.

After the forward process, we aim to restore the time-specific user preference guided by the learned time embedding $\boldsymbol{e}_t$. Specifically, we start from $\boldsymbol{\alpha}_{K_1}$ and gradually remove the noise introduced into the holistic user preference:

$$p_\theta(\boldsymbol{\alpha}_{k-1}|\boldsymbol{\alpha}_k, \boldsymbol{e}_t) = \mathcal{N}(\boldsymbol{\alpha}_{k-1}; \boldsymbol{\mu}_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k), \Sigma_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k)), \tag{21}$$

where $\boldsymbol{\mu}_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k)$, $\Sigma_\theta(\boldsymbol{\alpha}_k, \boldsymbol{e}_t, k)$ denote the mean and covariance functions parameterized by the neural network.

We optimize the reverse process through the Evidence Lower Bound (ELBO), expressed as:

$$\begin{aligned} \mathcal{L}_k &= D_{KL}(q(\boldsymbol{\alpha}_{k-1}|\boldsymbol{\alpha}_k, \boldsymbol{\alpha}_0) \| p_\theta(\boldsymbol{\alpha}_{k-1}|\boldsymbol{\alpha}_k, \mathbf{e}_t)), \\ &= \frac{1}{2}\left(\frac{\bar{\beta}_{k-1}}{1-\bar{\beta}_{k-1}} - \frac{\bar{\beta}_k}{1-\bar{\beta}_k}\right) \|\hat{\boldsymbol{\alpha}}_\theta(\boldsymbol{\alpha}_k, \mathbf{e}_t, k) - \boldsymbol{\alpha}_0\|_2^2, \end{aligned} \tag{22}$$

where $\hat{\boldsymbol{\alpha}}_\theta(\boldsymbol{\alpha}_k, \mathbf{e}_t, k)$ denotes the predicted $\boldsymbol{\alpha}_0$ based on the input $\boldsymbol{\alpha}_k$ and the time embedding $\mathbf{e}_t$ at step k. In summary, the loss function is:

$$\mathcal{L}_{diff} = \mathbb{E}_{k \sim \mathcal{U}(1,K_1)} \mathbb{E}_{q(\boldsymbol{\alpha}_k|\boldsymbol{\alpha}_0)} \mathcal{L}_k. \tag{23}$$

A.5 Hyper-parameters Study

In this section, we explore the effect of hyper-parameters on the experimental results. We select three hyper-parameters: contrastive learning loss weight λ_1 based on time-guided preference generators, loss weight λ_2 for the multi-scale time windows module, and truncation interval $[a, b]$ for the adaptive weights in multi-scale time windows.

Figure 6 shows the results of the hyper-parameter λ_1. Comparing the results of both domains, it can be noticed that the model achieves optimal performance when $\lambda_1 = 0.1$. It indicates that the augmented sequences generated by the time-guided preference generator indeed improve the source sequences representation. However, due to the selection of negative samples, high weights will excessively suppress the other sequences within the batch, destroying their original distributions.

Figure 7 illustrates the results of the hyper-parameter λ_2. It can be noticed that different datasets obtain the best results with different λ_2. Comparing both domains, the Food-Kitchen dataset reaches the

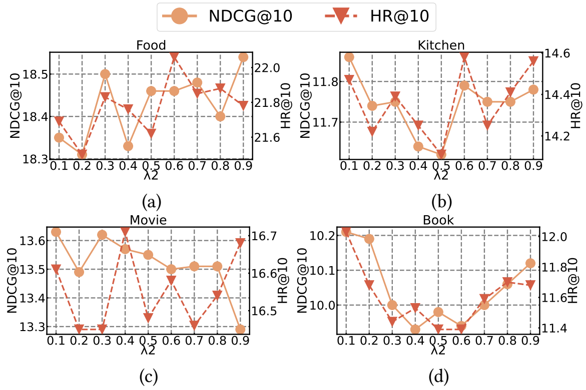

Figure 7: The effect of the hyper-parameter λ_2.

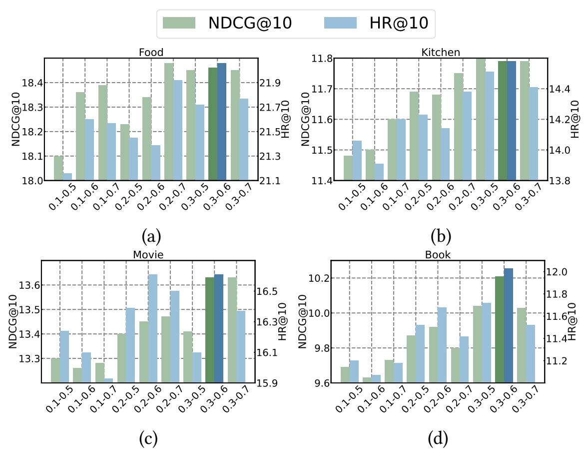

Figure 8: The effect of the hyper-parameter $[a, b]$.

best result at $\lambda_2 = 0.6$, and the Movie-Book dataset reaches the best result at $\lambda_2 = 0.1$. This is due to the fact that various datasets have various time patterns, hence requiring different weights.

Figure 8 demonstrates the results of the hyper-parameter $[a, b]$. We can find that the model performs optimally when the truncation interval is set to $[0.3, 0.6]$. which is consistent with our consideration. It is consistent with our consideration that low-weights in source domain result in the lack of domain-specific information and high-weights result in the lack of domain-shared information.

A.6 Related Work

In this section, we briefly review the related work, which primarily includes cross-domain sequential recommendation and diffusion models.

A.6.1 Cross-Domain Sequential Recommendation. Cross-domain recommendation (CDR) aims to utilize information from more than one domain to alleviate the interaction sparsity problem which is prevalent in recommendation tasks [21, 45, 50, 61], thereby improving the accuracy of recommendations. Cross-domain sequential recommendation (CDSR) combines CDR and sequential recommendation with the objective of addressing the same problem [34, 36, 37].

The classical CDSR models rely on completely overlapping users, i.e., users interacting in both domains, by modeling users preferences in each domain separately, and then transforming preferences by using a cross-domain transfer module [1, 3, 16, 62]. For example, π-Net [35] utilizes gated recurrent units to generate user preferences within each domain and extracts useful information between domains via cross-domain transfer units. PSJNet [46] extends π-Net by proposing a parallel split-join framework. DA-GCN [17] introduces graph neural networks to model user preferences by constructing multiple graphs. RL-ISN [18] converts the CDSR task into a layered reinforcement learning task.

Recent researches begin to explore utilizing partially overlapping users or non-overlapping users for recommendations. IESRec [30] proposes a joint internal multi-interest exploration and external domain alignment framework by selecting typical anchors for domain alignment. MAN [28] designs a multiple attention network that can recommend by utilizing non-overlapping users. AMID [52] proposes a framework based on a multi-interest information module and a doubly robust estimator which is able to recommend in open-world environments.

All of the above methods present competitive results in cross-domain sequence recommendation tasks, but they all focus on modeling sequence preferences, ignoring the important users time patterns.

A.6.2 Diffusion Models. In recent years, diffusion models have performed outstandingly in tasks such as computer vision [2, 5, 32, 41], natural language processing [26, 42, 58], and time series prediction[12, 43, 44], better than GAN [15] and VAE [20] networks. In recommendation tasks, diffusion models also gain a lot of attention from researchers due to the excellent denoising and generative capabilities. For example, DiffRec [48] introduces diffusion modeling to collaborative filtering for the first time , which learns the generation process of user interactions through denoising. In sequential recommendation, DreamRec [56] utilizes a diffusion model to generate target embeddings that are consistent with user preferences, removing negative samples. DiffuASR [29] proposes a diffusion-based pseudo sequence generation framework and utilizes U-Net Network to adapt the discrete sequence generation task. CaDiRec [10] employs a context-guided diffusion model to replace some of the items in sequences to generate augmented views for contrastive learning. DimeRec [23] designs a new noise space that optimizes both the classification loss and the reconstruction loss, while introducing a separate guidance loss next to the diffusion module.

Recently, some researchers explore the potential of diffusion models in cross-domain recommendation (CDR). DiffCDR [54] designs a diffusion module to generate user embeddings in the target domain, thereby mitigating the cold-start problem. DMCDR [25] takes user interactions in the source domain as guiding signals to generate personalized user representations in the target domain. Different from existing approaches, we generate potential interactions for the target domain by utilizing source domain interactions time as guidance information to augment the users domain-specific representations.