Disentangled Contrastive Learning for Social Recommendation

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ABSTRACT

Social recommendations utilize social relations to enhance the representation learning for recommendations. Most social recommendation models unify user representations for the user-item interactions (collaborative domain) and social relations (social domain). However, such an approach may fail to model the users' heterogeneous behavior patterns in two domains, impairing the expressiveness of user representations. In this work, to address such limitation, we propose a novel **D**isentangled **c**ontrastive learning framework for social **Rec**ommendations (**DcRec**). More specifically, we propose to learn disentangled users' representations from the item and social domains. Moreover, disentangled contrastive learning is designed to perform knowledge transfer between disentangled users' representations for social recommendations. Comprehensive experiments on various real-world datasets demonstrate the superiority of our proposed model.

CCS CONCEPTS

• **Information systems** → **Recommender systems, Social recommendation**; • **Self-supervised learning**;

KEYWORDS

Social Recommendations, Self-Supervised Learning, Disentangled Learning, Collaborative Learning.

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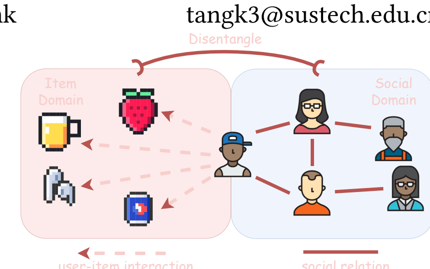

Figure 1: Users are involved in both collaborative domain and social domain, where the behavior patterns of users in two domains are semantically heterogeneous.

1 INTRODUCTION

As suggested by social correlation theories [3], users' preferences are likely to be influenced by those around them. Based on this intuition, a bunch of works have been proposed to utilize the information of social relations in modeling users' preferences for items to enhance recommendation performance in various online platforms (e.g., Facebook, WeChat, LinkedIn, etc.) [5, 13, 26], known as social recommendations [8, 10, 11, 34, 35].

In social recommendation, as shown in Figure 1, users are interacted with different objectives (i.e., items and social friends) with distinct purposes in each domain (i.e., collaborative domain and social domain) [5]. Therefore, the behavior patterns of users in two domains can be heterogeneous. In a real scenario, a user tends to connect with friends of his/her friends but he/she are not likely to purchase the items serving similar functions in a short period of time. However, off-the-shelf manners on modeling users' preferences adopt unified users' representations for user-item interactions and user-user social relationships (i.e., Diffnet++ [35] and DSCF [12]). They are insufficient to model users' heterogeneous behavior patterns towards social friends and items in social recommendations.

To address this problem, we propose to *disentangle* user behaviors into two domains, so as to learn disentangled users' representations in the social recommendations. The main challenge is how to learn such disentangled users' representations in two domains while transferring knowledge from social domain to collaborative domain for social recommendations.

Recently, Self-Supervised Learning (SSL) has been proven beneficial to the tasks in a wide range of fields [2, 6, 14, 24, 25, 30, 40]. The main idea of SSL is to utilize self-supervision signals from unlabeled data by maximizing the mutual information between different augmented views of the same instance (i.e., user or item) [31], in the representation learning process of which SSL increases the informativeness of those views and enables knowledge transferring between those views [38]. For instance, MHCN [38] constructs different hypergraphs and maximizes the mutual information between the users and the hyper-graphs to learn the hierarchical structure information and transfer it into the learned nodes' representations.

Motivated by the advantage of SSL in transferring knowledge, we develop a novel contrastive learning-based framework to solve the aforementioned issue. More specifically, domain disentangling is introduced to disentangle users' behaviors into collaborative domain and social domain. Moreover, we propose disentangled contrastive learning objectives to transfer knowledge from social domain to collaborative domain by maximizing the mutual information between disentangled representations. Notably, while DGCL [21] proposes an implicitly disentangled contrastive learning method to capture multiple aspects of graphs, we explicitly disentangle the data from different domains and propagate the representations of nodes based on independent adjacency matrices. The main contributions of this paper can be summarized as follows: (1) We introduce a principled approach to learn users' representations, where disentangled users' representations can be learned to reflect their preferences towards items and social friends in two domains. (2) We propose a novel **D**isentangled **c**ontrastive learning framework for social **Rec**ommendations (**DcRec**), which can harness the power of contrastive learning to transfer knowledge from social domain to collaborative domain. (3)We conduct comprehensive experiments on various real-world datasets to show the superiority of the proposed model.

2 METHODOLOGY

We first introduce definitions and notations used in this paper. We utilize $\mathcal{U}$ to stand for the user set and $\mathcal{I}$ to stand for the item set. Let $m = |\mathcal{U}|$ defines the number of users and $n = |\mathcal{I}|$ denotes the number of items. Then, we denote the user-item interactions matrix in the collaborative domain by $\mathbf{A}_I \in \mathbb{R}^{m\times n}$ and social relations matrix in the social domain by $\mathbf{A}_S \in \mathbb{R}^{m\times m}$. In addition, we use dense vectors to represent users and items (i.e., embeddings), where $\mathbf{P}_S \in \mathbb{R}^{m\times d}$ and $\mathbf{P}_I \in \mathbb{R}^{m\times d}$ denote users' embeddings with d dimension in social domain and collaborative domain, respectively. $\mathbf{Q}_I \in \mathbb{R}^{n\times d}$ denotes items' embeddings in the collaborative domain.

2.1 An Overview of the Proposed Framework

In this work, we propose a **D**isentangled **c**ontrastive learning framework for social **Rec**ommendations (**DcRec**), which follows the general paradigm of self-supervised contrastive learning via maximizing the representation agreement between different views on the same instance [1, 2, 18, 33].

The architecture of the proposed model is shown in Figure 2. More specifically, the proposed architecture consists of three main components: (1) **Domain Disentangling**, which is devised to disentangle the input data into two sub-domains; (2) **Encoder**, where we use different encoders on two domains to learn representations from two different views; (3) **Disentangled Contrastive Learning**, which aims to transfer the knowledge from the social domain into recommendation modeling task by jointly optimizing the disentangled contrastive learning tasks and main recommendation task.

2.2 Domain Disentangling

To mitigate the influence caused by the semantic discrepancy between social domain and collaborative domain, we disentangle the input data into two domains, which will be represented by a user-item interactions matrix $\mathbf{A}_I$ in the collaborative domain and social relations matrix $\mathbf{A}_S$ in the social domain, respectively.

After domain disentanglement, we perform data augmentation to obtain different views for the data in each domain. Since the data in social recommendations can be naturally represented as graph [10], the inputs (i.e., user-item interactions $\mathbf{A}_I$ and social relations $\mathbf{A}_S$) can be augmented via graph-based data augmentation methods [18, 36], such as *Edge Adding*, *Edge Dropout*, and *Node Dropout*, which can be formulated as follows:

$$\mathbf{A}_S^{(1)} = H_S^{(1)}(\mathbf{A}_S), \mathbf{A}_S^{(2)} = H_S^{(2)}(\mathbf{A}_S),$$
$$\mathbf{A}_I^{(1)} = H_I^{(1)}(\mathbf{A}_I), \mathbf{A}_I^{(2)} = H_I^{(2)}(\mathbf{A}_I),$$

where $H_S^{(\cdot)}$ and $H_I^{(\cdot)}$ denote the independent augmentation functions to generate two views in social domain and collaborative domain, respectively.

2.3 Encoder

To model the user-item interactions and social relations, we utilize encoders to learn representations for users and items in each domain. Furthermore, to ensure semantic consistency while conducting cross-domain contrastive learning between users' representations from two different domains, we also project the users' representations into the same semantic space. Here, we use $Rec(\cdot)$ and $F(\cdot)$ to represent the encoder in the item and social domains, respectively. Note that any Collaborative Filtering (CF) based models (*e.g.*, MF [20], NeuMF [16], and LightGCN [15].) can be set as the recommendation encoder $Rec(\cdot)$ in the collaborative domain, and we can set Graph Neural Networks (GNNs) methods [4, 7, 9] as social encoder $F(\cdot)$.

2.3.1 *Recommendation Encoder in Collaborative Domain*.

The collaborative domain encoder aims to learn the representations of users and items by encoding the user-item interactions (i.e., $\mathbf{A}_I^{(1)}$ and $\mathbf{A}_I^{(2)}$) from two augmented views. In practice, a simple yet effective GNN-based recommendation model LightGCN [15] is used as collaborative domain encoder $Rec(\cdot)$ and we can obtain users' and items' representations from two views (i.e., $\mathbf{A}_I^{(1)}$ and $\mathbf{A}_I^{(2)}$) as:

$$\mathbf{U}_I^{(1)}, \mathbf{V}_I^{(1)} = \mathrm{Rec}(\mathbf{A}_I^{(1)};\Theta_I), \mathbf{U}_I^{(2)}, \mathbf{V}_I^{(2)} = \mathrm{Rec}(\mathbf{A}_I^{(2)};\Theta_I), \quad (1)$$

where Θ_I is the parameter of the recommendation encoder. $\mathbf{U}_I^{(1)} \in \mathbb{R}^{m\times d}$, $\mathbf{U}_I^{(2)} \in \mathbb{R}^{m\times d}$, $\mathbf{V}_I^{(1)} \in \mathbb{R}^{n\times d}$ and $\mathbf{V}_I^{(2)} \in \mathbb{R}^{n\times d}$ are learned representations of users and items from two views for contrastive learning. Furthermore, we also use this encoder $Rec(\cdot)$ to train our primary task via BPR loss [15] (Eq. 7) and learn final users and items representations (i.e., $\mathbf{U} \in \mathbb{R}^{m\times d}$ and $\mathbf{V} \in \mathbb{R}^{n\times d}$) on user-item interactions (i.e., $\mathbf{A}_I$) for making predictions as follows:

$$\mathbf{U}, \mathbf{V} = \mathrm{Rec}(\mathbf{A}_I; \Theta_I).$$

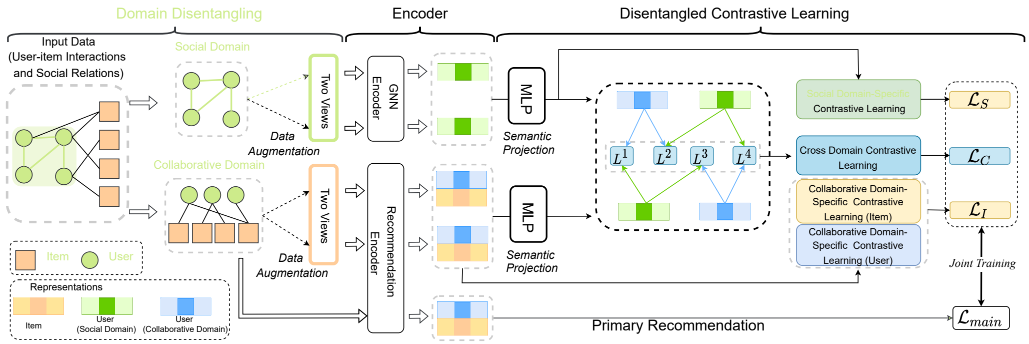

Figure 2: The overall architecture of the proposed disentangled contrastive learning for social recommendations (DcRec).

2.3.2 ***GNNs Encoder in Social Domain.*** The encoder in social domain aims at learning users' representations by capturing social relations among users. Here, due to the excellent expressiveness of GNNs in modeling graph structural data [10], we adopt a general GNNs method [19] as an encoder (i.e., $F(\cdot)$) to obtain user representations in social domain as follows:

$$\mathbf{U}_S^{(1)} = \mathrm{F}(\mathbf{A}_S^{(1)}; \Theta_S), \mathbf{U}_S^{(2)} = \mathrm{F}(\mathbf{A}_S^{(2)}; \Theta_S),$$

where $\mathbf{\Theta}_S$ denotes the parameters of GNNs encoder in the social domain. $\mathbf{U}_S^{(1)} \in \mathbb{R}^{m\times d}$ and $\mathbf{U}_S^{(2)} \in \mathbb{R}^{m\times d}$ are learned representations of users from two views for contrastive learning in social domain.

2.3.3 ***Semantic Projection.*** Since users' representations learned from collaborative domain and social domain are semantically heterogeneous, we propose to project them into the same semantic space. Specifically, in social domain, we adopt Multilayer Perceptrons (**MLPs**) to perform such projection on users' representations as follows:

$$\widetilde{\mathbf{U}}_S^{(1)} = \mathrm{MLP}(\mathbf{U}_S^{(1)}; \theta_S), \widetilde{\mathbf{U}}_S^{(2)} = \mathrm{MLP}(\mathbf{U}_S^{(2)}; \theta_S),$$

where θ_S is the set of MLPs' parameters in the social domain. Analogously, we can obtain users' representations $\widetilde{\mathbf{U}}_I^{(1)}$ and $\widetilde{\mathbf{U}}_I^{(2)}$ in the collaborative domain via MLP with parameters θ_I.

2.4 Disentangled Contrastive Learning

Disentangled contrastive learning consists of cross-domain contrastive learning and domain-specific contrastive learning. We devise cross-domain contrastive learning so as to transfer the knowledge from socia domain to collaborative domain. To extract self-supervision signals from unlabeled data [18, 33], we introduce domain-specific loss to maximize the representation agreement between different views on the same instance in each domain.

2.4.1 ***Cross-domain Contrastive Learning Loss.*** In order to transfer the knowledge from social domain to collaborative domain, we design cross-domain contrastive learning loss based on the projected users' representations (i.e., $\widetilde{\mathbf{U}}_S^{(1)}, \widetilde{\mathbf{U}}_S^{(2)}, \widetilde{\mathbf{U}}_I^{(1)}, \widetilde{\mathbf{U}}_I^{(2)}$) as follows:

$$\mathcal{L}_C = L(\widetilde{\mathbf{U}}_S^{(1)}, \widetilde{\mathbf{U}}_I^{(1)}) + L(\widetilde{\mathbf{U}}_S^{(1)}, \widetilde{\mathbf{U}}_I^{(2)}) + L(\widetilde{\mathbf{U}}_S^{(2)}, \widetilde{\mathbf{U}}_I^{(1)}) + L(\widetilde{\mathbf{U}}_S^{(2)}, \widetilde{\mathbf{U}}_I^{(2)}), \quad (2)$$

where $L(\cdot,\cdot)$ denotes a common contrastive learning loss which distinguishes the representations of the same users in these different views from other users' representations [23, 33, 41], where $L(\widetilde{\mathbf{U}}_S^{(1)}, \widetilde{\mathbf{U}}_I^{(1)})$, $L(\widetilde{\mathbf{U}}_S^{(1)}, \widetilde{\mathbf{U}}_I^{(2)})$, $L(\widetilde{\mathbf{U}}_S^{(2)}, \widetilde{\mathbf{U}}_I^{(1)})$ and $L(\widetilde{\mathbf{U}}_S^{(2)}, \widetilde{\mathbf{U}}_I^{(2)})$ are denoted by L^2, L^3, L^1 and L^4 in Figure 2, respectively.

Due to symmetric property in two contrasted views, a common contrastive learning loss $L(\cdot,\cdot)$ can be formally given by:

$$L(\mathbf{Z}^{(1)}, \mathbf{Z}^{(2)}) = \frac{1}{2w}\sum_{j=1}^{w}\left[loss(\mathbf{z}_j^{(1)}, \mathbf{z}_j^{(2)}) + loss(\mathbf{z}_j^{(2)}, \mathbf{z}_j^{(1)})\right], \quad (3)$$

where $\mathbf{Z}^{(1)} \in \mathbb{R}^{w\times d}$ and $\mathbf{Z}^{(2)} \in \mathbb{R}^{w\times d}$ are instances' representations in two different views, and $\mathbf{z}_j^{(1)}$ and $\mathbf{z}_j^{(2)}$ are corresponding representations of u-th instance (i.e., users and items) in two views and $w \in \{m, n\}$. Inspired by the design in [41], the $loss(\mathbf{z}_j^{(1)}, \mathbf{z}_j^{(2)})$ can be formulated as:

$$loss(\mathbf{z}_j^{(1)}, \mathbf{z}_j^{(2)}) = -\log \frac{e^{\Psi(\mathbf{z}_j^{(1)}, \mathbf{z}_j^{(2)})}}{e^{\Psi(\mathbf{z}_j^{(1)}, \mathbf{z}_j^{(2)})} + \sum_{v\in\{1,2\}}\sum_{k\neq j} e^{\Psi(\mathbf{z}_j^{(1)}, \mathbf{z}_k^{(v)})}}, \quad (4)$$

where $\Psi(\mathbf{z}_1, \mathbf{z}_2) = s(\mathbf{z}_1, \mathbf{z}_2)/\tau$, measuring the cosine similarity between two representations, and τ is the temperature parameter.

2.4.2 ***Domain-specific Contrastive Learning Loss.*** To enhance the expressiveness of the learned representations for each instance in each domain, we design domain-specific contrastive learning loss in the two domains:

$$\text{Collaborative Domain: } \mathcal{L}_I = L(\mathbf{U}_I^{(1)}, \mathbf{U}_I^{(2)}) + L(\mathbf{V}_I^{(1)}, \mathbf{V}_I^{(2)}), \quad (5)$$

$$\text{Social Domain: } \mathcal{L}_S = L(\widetilde{\mathbf{U}}_S^{(1)}, \widetilde{\mathbf{U}}_S^{(2)}), \quad (6)$$

where $\mathcal{L}_S$ and $\mathcal{L}_I$ are domain-specific contrastive learning losses for the social domain and collaborative domain, respectively. Note that in practice, the projected representations in the social domain are used to conduct the domain-specific contrastive learning due to the promising results in our experiments.

2.5 Model Optimization

2.5.1 ***Primary Recommendation Task.*** Given the learned representation $\mathbf{u}_u$ and $\mathbf{v}_i$ for user u and item i, we adopt a widely used inner product to predict the score for measuring how likely the user u will interact with item i as: $\hat{y}_{ui} = \mathbf{u}_u^T \mathbf{v}_i$.

To optimize the primary recommendation task, we choose Bayesian Personalized Ranking (BPR) loss [28], formulated as:

$$\mathcal{L}_{main} = \sum_{(u,i,j)\in O} -\log \sigma(\hat{y}_{ui} - \hat{y}_{uj}), \quad (7)$$

where $O = \{(u,i,j) | (u,i) \in O^+, (u,j) \in O^-\}$. Here, O^+ is the set of observed interactions and O^- is the set of unobserved ones.

Table 1: Dataset Statistics

Dataset	#Users	#Items	#Ratings	#Relations	Density
Dianping	16,396	14,546	51,946	95,010	0.022%
Ciao	7,375	105,114	284,086	111,781	0.037%

2.5.2 *Joint Training*.

To improve the recommendation performance by our proposed model with disentangled contrastive learning, we adopt a joint training strategy to optimize both the recommendation loss and contrastive learning loss:

$$\mathcal{L} = \mathcal{L}_{main} + \lambda_1(\mathcal{L}_I + \mathcal{L}_S) + \lambda_2\mathcal{L}_C + \lambda_3\|\zeta\|_2,$$

where λ_1, λ_2, and λ_3 are hyperparameters to balance the contributions of various contrastive learning losses and regularization.

3 EXPERIMENTS

Datasets. We conduct experiments on two real-world datasets: Dianping [22] and Ciao [29]. Since we aim at producing Top-K recommendations, we leave out the ratings less than 4 and utilize the rest in these two datasets, where users' ratings for items range from 1 to 5. The statistics of the datasets are shown in Table 1. For each dataset, the ratio of splitting the interactions into training, validation, and testing set is 8 : 1 : 1.

Baselines and Implementation. We conduct experiments by comparing with various kinds of baselines, including MF-based (BPR [28], SBPR [39], SoRec [27], SocialMF [17]), GNNs-based (Diffnet [35], NGCF [32], and LightGCN [15]), as well as SSL-enhanced recommendation methods (SGL [33], MHCN [38] and SEPT [37]). The baselines LightGCN+Social and SGL+Social are implemented by adding social information into their adjacency matrices for propagation via GNNs techniques in social recommendation tasks. For implementation, BPR, SBPR, SoRec, SocialMF, Diffnet, MHCN, and SEPT are from the open-source library QRec. The rest baselines are implemented based on the implementation of LightGCN [15]. For a fair comparison, we apply grid search to fine-tune the hyperparameters of the baselines, initialized with the optimal parameters reported in the original papers. We use Adam optimizer to optimize all these models.

Evaluation Metrics. For the metrics, we follow the ranking protocol used in [33] to evaluate the top-K recommendation performance and report the average *NDCG*, *Recall*, and *Precision*, where K=5. Higher values of these three metrics indicate better predictive performance.

Experiment Results. In this part, we verify the effectiveness of the proposed model DcRec for recommendation performance. The overall comparisons are given in Table 2. The baselines used for comparisons range from classical MF-based models, GNNs-based models to SSL-enhanced models. According to the results, we can draw the following findings: (1) The proposed DcRec achieves the best performance two datasets, achieving promising improvement over the strongest baselines that are marked with underlines. Compared to SSL-enhanced social recommendation baselines, our method incorporates advanced components to learn representations from social and collaborative domains by disentangled contrastive learning. (2) In most cases, SSL-enhanced methods outperform those without SSL, which demonstrates the effectiveness of SSL for recommendations and the necessity of designing the domain-specific contarstive learning part. (3) Without the MLP for semantic projection, the performance degrades on all metrics for two datasets, verifying the effectiveness of the design of semantic projection.

Table 2: Overall Performance Comparison

Dataset	Dianping			Ciao		
Metrics	NDCG	Recall	Precision	NDCG	Recall	Precision
BPR [28]	0.0188	0.0189	0.0145	0.0226	0.0155	0.0177
SBPR [39]	0.0162	0.0203	0.0217	0.0284	0.0191	0.0223
SoRec [27]	0.0149	0.0149	0.0111	0.0220	0.0147	0.0165
SocialMF [17]	0.0144	0.0148	0.0109	0.0218	0.0154	0.0166
Diffnet [35]	0.0241	0.0242	0.0181	0.0280	0.0182	0.0213
NGCF [32]	0.0287	0.0289	0.0221	0.0232	0.0157	0.0183
LightGCN [15]	0.0396	0.0384	0.0292	0.0326	0.0224	0.0253
LightGCN+Social	0.0392	0.0381	0.0289	0.0326	0.0220	0.0254
SGL [33]	0.0421	0.0414	0.0310	0.0340	0.0223	0.0266
SGL+Social	0.0405	0.0402	0.0299	0.0334	0.0221	0.0266
MHCN [38]	0.0398	0.0399	0.0296	0.0315	0.0218	0.0252
SEPT [37]	0.0378	0.0371	0.0286	0.0313	0.0212	0.0250
DcRec(w/o MLP)	0.0417	0.0409	0.0307	0.0338	0.0217	0.0263
DcRec	**0.0443**	**0.0441**	**0.0327**	**0.0366**	**0.0243**	**0.0280**
%Improv.	5.31%	6.63%	5.29%	6.46%	8.39%	5.32%

Table 3: Ablation study of λ_1 and λ_2 on dataset Ciao

✓		Metrics				✓	Metrics		
λ_1	λ_2	NDCG	Recall	Precision	λ_1	λ_2	NDCG	Recall	Precision
0	0.01	0.03488	0.02436	0.02668	0.01	0	0.03617	0.02394	0.02794
0.001	0.01	0.03498	0.02416	0.02662	**0.01**	**0.001**	**0.03657**	**0.02430**	**0.02795**
0.01	**0.01**	**0.03629**	**0.02405**	**0.02773**	0.01	0.01	0.03629	0.02405	0.02773
0.1	0.01	0.02735	0.01760	0.02191	0.01	0.1	0.03635	0.02412	0.02803
1	0.01	0.00814	0.00513	0.00681	0.01	1	0.03618	0.02398	0.02803
10	0.01	0.00103	0.00088	0.00075	0.01	10	0.03626	0.02419	0.02803

Sensitivity Study on λ_1 and λ_2. As shown in Table 3, we present the performance of DcRec with different values of λ_1 and λ_2. From the left part, studying the λ_1, we can find that setting a large value could lead to great drop on performance. We argue that this is because a large weight for domain-specific contrastive learning can lead the optimization towards instance discrimination (the objective of SSL) instead of the recommendation objective. From the right part, we found a similar phenomenon, but the best value for λ_2 is much smaller. We justify that this is because the proper amount of social information is beneficial to recommendation task but too much is harmful.

4 CONCLUSION

To model the heterogeneous behavior patterns of users in social domain and item domain, we proposed a disentangled contrastive learning framework for social recommendations, which disentangles two domains and learns users' representations in each domain, respectively. Furthermore, we devised cross-domain contrastive learning to transfer knowledge from the social domain to the item domain, so as to enhance the recommendation performance.

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