Superhighway: Bypass Data Sparsity in Cross-Domain CF

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ABSTRACT
Cross-domain collaborative filtering (CF) aims to alleviate data sparsity in single-domain CF by leveraging knowledge transferred from related domains. Many traditional methods focus on enriching compared neighborhood relations in CF directly to address the sparsity problem. In this paper, we propose superhighway construction, an alternative explicit relation-enrichment procedure to improve recommendations by enhancing cross-domain connectivity. Specifically, assuming partially overlapped items (users), superhighway bypasses multi-hop inter-domain paths between cross-domain users (items, respectively) with direct paths to enrich the cross-domain connectivity. The experiments conducted on a real-world cross-region music dataset and a cross-platform movie dataset show that the proposed superhighway construction significantly improves recommendation performance in both target and source domains.

KEYWORDS
recommendation; data sparsity; cross-domain; knowledge transfer

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1 INTRODUCTION
Collaborative filtering (CF) in recommender systems is highly susceptible to data sparsity as the method analyzes observed user-item interactions solely. In modern e-commerce, as the number of items and users skylrockets and dwarfs the growth of user-item ratings in comparison, data sparsity takes an increasing toll on the performance of CF-based recommender systems. In response to such a vital issue, cross-domain CF is proposed to enhance recommendation quality in a given target domain by leveraging knowledge transferred from related source domains.

As data sparsity in single-domain CF remarks the lack of observed rating data, intuition suggests to alleviate the sparsity issue via explicitly populating relations in a cross-domain system. In the literature, many traditional methods have been proposed to directly enrich the compared neighborhood in CF, which, for example, attach additional intra-domain edges in target domains [3] or inter-domain edges in overlapped regions [2]. However, such methods typically require additional assumptions; for example, the source domain has to be denser than the target domain [3].

In this paper, our superhighway construction establishes a new type of relations by means of inference based on existing relations, which allows the source and the target domains to mutually improve due to the enhanced cross-domain connectivity. The construction of superhighways consists of two steps: 1) the identification of cross-domain user candidates suitable for superhighway construction, and 2) weight scaling for superhighways to optimize cross-domain space alignment. Figure 1 illustrates the connectivity enhancement brought forth by superhighways (red bold lines), which provide additional leverage of combining the source and the target domains.

2 METHODOLOGY
In collaborative filtering (CF), user-item interactions are commonly captured using a bi-adjacency matrix \( M = (m_{ij}) \in \mathbb{R}^{\lvert U \rvert \times \lvert I \rvert} \), where \( U \) and \( I \) denote the sets of users and items, respectively; \( m_{ij} = 1 \) if there exists an observed association for user \( i \) and item \( j \), and otherwise, \( m_{ij} = 0 \). The matrix \( M \) can also be represented as a bipartite graph \( G = (U, I, R) \), where \( R = \{(i, j) \mid m_{ij} = 1\} \).

Given a cross-domain system with source domain \( G_S = (U_S, I_S, R_S) \) and target domain \( G_T = (U_T, I_T, R_T) \) such that the set of shared items \( I = I_S \cap I_T \neq \emptyset \), a highway is defined as a path between user \( u_i \in U_S \) and \( u_j \in U_T \) through shared items in \( I \). To enrich the cross-domain connectivity, the superhighway construction, denoted as an operation \( \mathcal{F} \), establishes direct relations between candidate
users $u_i \in \hat{U}_S$ and $u_j \in \hat{U}_T$, where $\hat{U}_S \subseteq U_S$ and $\hat{U}_T \subseteq U_T$ are the sets of candidate users from the source and target domains, respectively. Consequently, the new graph $\mathcal{F}(G_S, G_T)$, which is more connected than the naively joined graph $G_S \cup G_T$, can then be used for CF. The candidate user sets $\hat{U}_S$ and $\hat{U}_T$ mentioned above are defined as

$$\hat{U}_d = \left\{ u \in U_d \mid \frac{|N(u) \cap \hat{I}|}{|N(u)|} \geq \alpha \right\},$$

where $d \in \{ S, T \}$, $N(u)$ is the set of neighbors of $u$, and $\alpha$ is the predefined smoothness threshold.

While many proposed cross-domain CF methods approach the data sparsity problem by directly enriching the compared neighborhood (e.g., the user-item relations in each domain), we instead enhance cross-domain connectivity. Specifically, we establish superhighways between users from each of the candidate sets defined in Eq. (1), resulting additional $|\hat{U}_S| \times |\hat{U}_T|$ superhighways. The weight between each pair of users is defined as

$$w = \beta \times |N(u_i) \cap N(u_j)|,$$

where $u_i \in \hat{U}_S$, $u_j \in \hat{U}_T$, and $\beta$ is the scaling factor for the strength of domain alignment. Notice superhighways are kept weighted to provide fine-grained alignment between the source domain and the target domain.

3 EXPERIMENTS

In order to validate the effectiveness of the proposed superhighway construction on cross-domain collaborative filtering (CF), we conducted query-based recommendation [1] and used items as queries. Our experiments employ two sets of real-world cross-domain datasets: 1) KKBOX R1–KKBOX R2, a cross-region music dataset (R denotes region); 2) Movielens–Netflix, a cross-platform movie dataset. The statistics of the datasets are listed in Table 1. The cross-domain datasets are organized into three structures for training: 1) single: denoting the original target domain, $G_T$; 2) highway: denoting the naive concatenation of the source and target domains, $G_S \cup G_T$; and 3) superhighway: denoting the naive concatenation augmented with superhighways to enhance cross-domain connectivity, $\mathcal{F}(G_S, G_T)$. With these three structures, models (i.e., user and item embedding) are trained using traditional matrix factorization and two network embedding algorithms: DeepWalk [4] and HPE [1]. In addition, transfer learning is conducted for the single structure via pre-training on the source domain and then fine-tuning on the target domain [5]. For each algorithm, we also find the best combination of $\alpha$ and $\beta$ in the interval of $(0.0, 1.0)$ and $(0.5, 1.5)$, respectively, with 0.1 increment.

Table 2 compares the performance on the target domain of the above three structures. Note that most models perform worse when training on the highway structure than on the single structure; this phenomenon is likely due to the naive combination of the two domains actually aggravates data sparsity in the system, demonstrating the mere introduction of transferable knowledge is insufficient. In contrast, the superhighway structure reduces data sparsity and facilitates structural alignment between the source and the target domains by enhancing cross-domain connectivity, thereby creating a mutually enriching relationship. Hence, superhighway improves CF-based recommendation across all algorithms, making it widely applicable. In addition, it is worth noting that superhighway, as a user-user relation, does not enrich item neighborhood. Therefore, the improvement in matrix factorization suggests superhighways "bypass" the data sparsity problem in cross-domain CF, addressing the problem indirectly by enhancing the connectivity of the cross-domain system. Moreover, as traditional cross-domain improvements are often directional, i.e., source domains facilitate target domains, superhighways also improve recommendation performances on source domains; e.g., HPE improves from 2.1 to 4.4 for the music dataset and from 4.4 to 4.6, for the movie dataset.

4 CONCLUSIONS

This paper proposes an explicit relation-enrichment procedure, superhighway construction, to bypass data sparsity in single-domain collaborative filtering by enhancing cross-domain connectivity using self-contained inference. In our approach, superhighways are generated based on suitable (interaction smoothness) highways and then scaled for domain space alignment. According to the results form cross-region music dataset and cross-platform movie dataset, the constructed superhighways not only facilitate improvements across all tested models but also lead to improvements in the source domains, making it widely applicable.

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