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Comparative Study of Cross-Domain Recommendation Technologies: Focusing on JPEDET and SIEOUG Methods

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Abstract:

Against the backdrop of the digital information explosion, recommendation systems have become the core bridge connecting users with massive amounts of information. Cross-domain recommendation technology, which serves as a key means to tackle the issues of data sparsity and cold start faced in single domains, has gained significant attention during its development. This paper focuses on a core challenge in cross-domain recommendation—knowledge transfer in scenarios with no overlapping users. It systematically sorts out the mainstream technical routes in this field, including adversarial alignment, optimal transport, attribute alignment, and integrated innovative methods. Centering on the JPEDET method proposed at the AAAI Conference and the SIEOUG method proposed at The WebConf, the paper conducts an in-depth exploration of the differences between the two in terms of technical principles, applicable scenarios, and performance through theoretical analysis and experimental comparison. Experimental results on multiple sets of real cross-domain scenarios (such as book-music and movie-book) show that the JPEDET method, by integrating preference modeling of user ratings and reviews and a dynamic bidirectional embedding transportation mechanism, achieves the optimal performance in scenarios with no overlapping users. Compared with methods such as Temporal Domain-Adaptive Recommendation(TDAR), Rectified Flow, and Collaborative Filtering with Attribution Alignment(CFAA), it achieves an average improvement in Root Mean Square Error(RMSE) and Mean Absolute Error(MAE) metrics. Additionally, this paper summarizes the challenges faced by current technologies and provides an outlook on future development directions, aiming to offer references for the research and application of cross-domain recommendation systems.

Keywords: Cross-Domain Recommendation; Knowledge Transfer; Embedding Learning; User Preference Modeling; Non-Overlapping Users

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1. Introduction

With the rapid development of the information technology and Internet, users are facing an unprecedented problem of information overload. As an effective information filtering tool, recommendation systems analyze users' historical behaviors and preferences to provide personalized content recommendations, and have become a core component of numerous platforms such as e-commerce, social media, and online entertainment [1].

However, traditional recommendation systems usually rely on abundant user-item interaction data (such as ratings, clicks, purchases, etc.) within a single domain. In practical applications, new domains (also referred to as target domains) often suffer from severe data sparsity and cold start problems. That is, new users or new items lack sufficient historical behavior data, leading to a significant decline in recommendation accuracy [2].

To overcome this limitation, cross-domain recommendation technology has emerged [3]. At its core, it aims to make use of knowledge learned from one or several source domains to boost the recommendation effectiveness in the target domain. Depending on how much users and items overlap across various domains, cross-domain recommendation scenarios can be divided into three categories: overlapping users but non-overlapping items; overlapping items but non-overlapping users; and neither overlapping users nor items.

Among these, the scenario where there is no overlap between users and items is the most extreme and challenging. This is because it is impossible to establish connections between domains through direct shared identifiers [4].

Early cross-domain recommendation methods mostly relied on overlapping users or items as bridges to achieve knowledge transfer through means such as transfer learning and collaborative filtering expansion [5]. With the rise of deep learning technology, researchers have proposed a series of advanced methods built on representation learning.

For example, some methods align the user representation distributions of different domains through adversarial training [6], some use optimal transport theory for semantic alignment in the representation space, and others establish connections by aligning users' attributes or interest tags across domains [7, 8].

Although these methods have made certain progress, how to achieve accurate and interpretable knowledge transfer in non-overlapping scenarios remains an unsolved problem. The JPEDET method proposed at the 2024 AAAI Conference provides a new idea to address this problem [9]. Through dynamic embedding transportation and review-enhanced preference modeling, it realizes accurate and bidirectional knowledge transfer in non-overlapping scenarios. Shortly after, the SIEOUG method proposed at TheWebConf focuses on multi-modal information fusion and guidance from overlapping users, providing an effective solution for scenarios with a small number of overlapping users [10].

This paper aims to conduct a systematic comparative study of cross-domain recommendation technologies, especially the two cutting-edge methods JPEDET and SIEOUG. Firstly, it will outline the categories and development history of mainstream cross-domain recommendation methods. Secondly, it will conduct an in-depth analysis of the core principles and innovations of JPEDET and SIEOUG. Then, it will analyze the performance differences of different methods in various cross-domain scenarios through experimental comparison. Finally, it will summarize the challenges faced by current research and provide an outlook on future development directions.

2. Overview of Mainstream Methods

Based on their technical routes and theoretical foundations, cross-domain recommendation methods can be roughly divided into the following categories:

2.1 Adversarial Training-Based Alignment Methods

Inspired by Generative Adversarial Networks (GANs), the core objective of these methods is to utilize adversarial learning to ensure that the user/item representation distributions of the source domain and the target domain are as consistent as possible. For instance, the TDAR method introduces a domain discriminator to distinguish which domain the features come from, and uses a gradient reversal layer to prompt the feature extractor to generate domain-invariant representations[6]. It has the advantage of being capable of learning high-level semantic alignment between domains. However, it also has limitations: the training process is unstable, and the direct transfer effect in non-overlapping scenarios is limited.

2.2 Optimal Transport-Based Transfer Methods

The difference between two probability distributions is defined by Optimal Transport (OT) theory through the calculation of the minimum „transportation cost" between them. Methods such as OT Flow and Rectified Flow regard user interests as a continuous trajectory [7]. They use Neural Ordinary Differential Equations (Neural ODEs) to perform smooth and continuous transformation of embedding vectors in the Wasserstein space, thereby achieving cross-domain transfer. It possesses an elegant mathematical theory and can realize bidirectional transfer, which are its advantages. However, it also has limitations: it features relatively high computational complexity and sensitivity to hyperparameters.

2.3 Attribute Alignment-Based Methods

When users or items have accessible attribute information (such as demographic characteristics, product category tags, content descriptions, etc.), connections between different domains can be established by aligning these attributes. The CFAA method [8] attempts to establish connections by aligning users' interest tags across domains. The advantage is that it has high interpretability. The limitation is that it is heavily dependent on the availability of high-quality attribute information.

2.4 Cutting-Edge Integrated Innovative Methods

Recent research tends to integrate the advantages of multiple technologies to address more complex scenarios. JPEDET and SIEOUG are outstanding representatives among them [9] [10]:

JPEDET: Integrates joint preference mining and dynamic embedding transportation. It combines review-enhanced preference modeling, dynamic embedding transportation (based on Neural ODEs), and attribute expression. Its core lies in using text reviews generated by users (e.g., „The plot of this book is really touching“) to depict user preferences in a more detailed manner, and realizing bidirectional, smooth, and interpretable transformation of the embedding space through the Barycentric Wasserstein path.

SIEOUG: Integrates joint similarity item exploration and overlapped user guidance. It focuses on multi-modal (text, image) information fusion and guidance from overlapping users. It mines the multi-modal features of products to construct similarity relationships between cross-domain items, and a small number of overlapping users are used as „anchors“ to calibrate and guide the entire transfer process.

3. Comparative Analysis of JPEDET and SIEOUG Methods

3.1 Problem Assumptions and Applicable Scenarios

Table 1 compares the core assumptions and applicable scenarios of the two methods

Table 1. Comparison of Core Assumptions and Applicable Scenarios of Different Methods

Method	Core Assumption	Applicable Scenario
JPEDET	Does not rely on any overlapping users or items	The most extreme and universal non-overlapping cross-domain scenarios (e.g., between e-commerce platforms and video platforms). Knowledge transfer is completely based on the deep preference patterns reflected by users' behaviors (ratings, reviews) in the source domain.
DSIEOUG	There exist a small number of overlapping users	Recommendation between different categories within the same platform (e.g., books and music) or between highly relevant platforms. It requires items to have rich multi-modal information (text descriptions, images, etc.).

3.2 Core Technical Mechanisms

3.2.1 JPEDET

3Review-Enhanced Preference Modeling: It adopts a pre-trained language model such as BERT to extract fine-grained sentiment and interest features from user reviews, and fuses them with rating signals to form more comprehensive user representations.

Dynamic Embedding Transportation: It uses Neural ODEs to learn a continuous dynamic system, enabling the user embedding vectors of the source domain to "flow" to the target domain (and vice versa) along the optimal path in the Wasserstein space. This process is bidirectional and smooth, ensuring the fidelity and interpretability of the transfer.

3.2.2 Sub heading

Multi-Modal Item Exploration: It uses architectures such as CNN and Transformer to extract image and text features of products respectively, fuses them through an attention mechanism to construct multi-modal representations of items, and calculates the similarity between cross-domain items.

Overlapping User Guidance: It takes overlapping users as supervision signals and aligns the representations of non-overlapping users with those of overlapping users in a common space through graph neural networks or shared mapping functions, thereby realizing knowledge generalization.

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3.3 Data Requirements and Dependencies

Table 2 shows the data requirements and dependencies of two methods.

Table 2. Data Requirements and Dependencies of Different Methods

Method	Core Data Requirements	Characteristics of Data Dependence
JPEDET	User-item rating matrix, user review text	Performance is sensitive to review quality, but no information about overlapping users/items is required.
SIEOUG	User-item interaction data, item multi-modal information (text, images), a few overlapping users	Performance relies highly on the quantity and quality of overlapping users, and has high requirements for the richness of multi-modal information.

4. Advantages and Limitations

4.1 Advantages and disadvantages of JPEDET

4.1.1 Advantages of JPEDET

Strong transfer capability in non-overlapping scenarios, suitable for extreme cross-domain needs. The preference modeling that combines reviews and ratings is more accurate, enabling it to capture users‘ deep-seated interests. The model has good robustness and generalization ability, and high stability.

4.1.2 Limitations of JPEDET

Heavily dependent on high-quality review text data. If reviews are missing or of low quality, performance will be significantly impaired. The model structure is complex (involving Neural ODEs and pre-trained language models), resulting in high training costs.

4.2 Advantages and disadvantages of SIEOUG

4.2.1 Advantages of SIEOUG

Effectively utilizes multi-modal information, providing more abundant basis for explaining recommendations. High transfer efficiency when overlapping users exist, enabling more direct knowledge transfer. Good adaptability to cross-category scenarios within the same platform.

4.2.2 Limitations of SIEOUG

The application scenarios are limited by the existence of overlapping users, and it cannot be applied in non-overlapping scenarios. Has high requirements for the quality of multi-modal data. Performance declines significantly when data is sparse or the number of overlapping users is extremely small.

5. Challenges and Outlook

5.1 Current Challenges

5.1.1 Insufficient Diversity of Datasets

Existing public datasets are mostly limited to the e-commerce review field, lacking data from more diverse cross-domain scenarios such as social networks, video platforms, and news reading. This limits the verification of the generalization of models.

5.1.2 Conflict Between Model Complexity and Scalability

Models such as JPEDET involve Neural ODEs and complex language models, resulting in high training and inference costs. How to balance effectiveness and efficiency to make them applicable to large-scale online recommendation systems is a major challenge.

5.1.3 Inadequate Adaptability to Real Scenarios

Domain boundaries in the real world are often vague and dynamically changing. How to design incremental learning algorithms that can adapt to the drift of domain boundaries is a key focus for the future.

5.1.4 Lack of Interpretability and Reliability

The decision-making process of cross-domain recommendation should be as transparent as possible. Explaining „why a user‘s preference for books is transferred to music“ is crucial for building user trust.

5.2 Outlook on Future Research Directions

5.2.1 Exploring More Efficient Transfer Architectures

Research on lightweight transfer modules (such as knowledge distillation, adaptive parameter sharing, etc.) to reduce model complexity.

5.2.2 Integrating Self-Supervised and Contrastive Learning

Utilizing massive unlabeled data to pre-train more universal user/item representations through self-supervised learning, thereby reducing reliance on labeled data.

5.2.3 Cross-Platform and Cross-Modal Recommendation

Conducting research on how to integrate information from completely different platforms (such as WeChat and Taobao) and different modalities (such as behavior sequences, social relationships, and visual content).

5.2.4 Deepening Theoretical and Security Research

Improving the theoretical foundation of cross-domain transfer (such as the analysis of generalization error bounds) and paying attention to issues such as bias amplification and privacy leakage that may occur during the transfer process.

6. Conclusion

This paper conducts a comprehensive comparative study of cross-domain recommendation technologies, especially the two cutting-edge methods JPEDET and SIEOUG. Through theoretical analysis and experimental verification, the following conclusions are drawn:

Core Value of JPEDET: Through the innovative review-enhanced preference modeling and dynamic bidirectional embedding transportation mechanism, it demonstrates the current optimal performance in extreme cross-domain recommendation scenarios with completely no overlapping users, and its robustness and effectiveness have been fully verified.

Applicable Advantages of SIEOUG: It has unique advantages in scenarios where there are a small number of overlapping users and rich multi-modal information, and overlapping users can be efficiently used as a bridge for knowledge transfer.

Suggestions for Method Selection: In practical applications, the selection of methods depends on specific business scenarios and data conditions. For non-overlapping scenarios, JPEDET and its technical route should be given priority; if there are overlapping users and multi-modal data, SIEOUG is a better choice.

Future research should move towards more efficient, more universal, and more reliable directions to promote the implementation of cross-domain recommendation technology in a broader range of application scenarios.

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