修　士　論　文

A Research on Cross-Domain Recommendation under Non-Overlapping Settings by Integrating Gaussian Mixture User Preference Distributions and Optimal Transport

非重複設定下におけるガウス混合モデルユーザ嗜好分布と最適輸送を統合したクロスドメイン推薦に関する研究

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Abstract

Recommendation systems are essential tools for helping users discover items of interest in various domains, such as e-commerce, streaming services, and social media. With the rapid growth of online platforms, the need for effective recommendation systems has become increasingly important.

However, traditional recommendation systems often face challenges such as data sparsity and cold-start problems, which can limit their effectiveness. Cross-domain recommendation has emerged as a promising approach to address these challenges by leveraging information from multiple domains to improve recommendation accuracy. Nevertheless, existing cross-domain recommendation methods often assume overlapping users or items between domains, which may not hold in many real-world scenarios. Also, they usually represent user preferences as point estimates, which may not capture the full complexity of user behavior.

To address these limitations, in this thesis, we propose a novel framework that models user preferences as Gaussian Mixture Models (GMMs) and integrates optimal transport techniques for cross-domain recommendation under non-overlapping settings. By representing user preferences as distributions, our approach can capture the uncertainty and diversity of user behavior more effectively and fine-grainedly. The use of optimal transport allows us to align user preference distributions across domains, facilitating knowledge transfer even in the absence of overlapping users or items.

We evaluate our proposed method on Amazon datasets across multiple domains, comparing its performance against state-of-the-art cross-domain recommendation techniques and traditional single-domain methods. We also conduct ablation studies to assess the effectiveness of representing user preferences as distributions and the impact of boosting target domain recommendation performance using source domain information. The experimental results demonstrate that our approach significantly outperforms existing methods in terms of recommendation accuracy, highlighting the effectiveness of modeling user preferences as distributions and leveraging optimal transport for cross-domain knowledge transfer.

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Chapter 1

Introduction

1.1 Background

These days, information overload has become a significant challenge for users in various online platforms, such as e-commerce websites, streaming services, and social media[1, 2, 3]. Recommender systems play a crucial role in addressing this challenge by providing personalized guidance to users by selecting items with the highest predicted utility from a large space of options.[4, 5, 6] By analyzing user-item interactions, recommender systems can help users discover relevant content, products, or services, thereby enhancing user satisfaction and engagement. Besides improving user experience, recommender systems also benefit businesses by increasing sales, customer retention, and overall platform activity[7]. As the volume of online content continues to grow, the importance of effective recommender systems becomes even more pronounced. Despite their significance, recommender systems face several challenges that can hinder their performance. One of the primary challenges is data sparsity, where users interact with only a small fraction of the available items, making it difficult to accurately model user preferences. This issue is particularly prevalent in new or niche platforms with limited user interactions. Another challenge is the cold-start problem, which occurs when new users or items are introduced to the system. In such cases, there is insufficient data to make reliable recommendations, leading to suboptimal user experiences. Both data sparsity and cold-start problems are caused by the limited availability of user-item interaction data, which can significantly impact the effectiveness of recommender systems. To address these challendges, cross-domain recommendation has emerged as a promising approach that leverages information from multiple domains to improve recommendation accuracy. Cross-domain recommendation aims to enhance the performance of recommender systems by transferring knowledge from a source domain to a target domain. This approach is particularly useful in scenarios where the target domain suffers from data sparsity or cold-start issues. By utilizing user-item interactions from a related source domain, cross-domain recommendation can help alleviate these challenges and provide more accurate recommendations. However, existing cross-domain recommendation methods often assume overlapping users or items between the source and target domains, and rely on these overlaps to build connections between the two domains in the training stage. However, in many real-world scenarios, such overlaps may not exist, limiting the applicability of these methods. Additionally, traditional recommender systems typically represent user preferences as point estimates, which may not capture the full complexity and uncertainty of user behavior. To overcome these limitations, there is a need for novel approaches that can effectively model user preferences and facilitate knowledge transfer between non-overlapping domains during the training process. In this thesis, we propose a novel framework that models user preferences as Gaussian Mixture Models (GMMs) and integrates optimal transport techniques for cross-domain recommendation under non-overlapping settings. By representing user preferences as distributions, our approach can capture the uncertainty and diversity of user behavior more effectively. The use of optimal transport allows us to align user preference distributions across domains, facilitating knowledge transfer even in the absence of overlapping users or items. The proposed framework consists of two main components: (1) modeling user preferences as GMMs to capture the complexity of user behavior, and (2) employing optimal transport to align these distributions between the source and target domains. This combination enables our method to leverage information from the source domain to enhance recommendation accuracy in the target domain, even when there are no overlapping users or items.

1.2 Contributions

The main contributions of this thesis are as follows:

- We introduce a novel framework for cross-domain recommendation under non-overlapping settings by modeling
- We propose representing user preferences as Gaussian Mixture Models (GMMs) to capture the uncertainty and diversity of user behavior more effectively.
- We integrate optimal transport techniques to align user preference distributions across domains, enabling knowledge transfer
- We conduct extensive experiments on Amazon datasets across multiple domains to evaluate the performance of our proposed method. The results demonstrate that our approach significantly outperforms existing cross-domain recommendation techniques and traditional single-domain methods in terms of recommendation accuracy.
- We perform ablation studies to assess the effectiveness of representing user preferences as distributions and the impact of boosting target domain recommendation performance using source domain information.
- We provide insights into the benefits of modeling user preferences as distributions and leveraging optimal transport for cross-domain knowledge transfer, highlighting the potential of our approach for addressing challenges in recommender systems.

1.3 Thesis Organization

The remainder of this thesis is organized as follows:

- In Chapter 2, we provide an overview of the fundamental concepts and techniques relevant to this research, including recommender systems, cross-domain recommendation, Gaussian Mixture Models, and optimal transport.
- In Chapter 3, we review related work on recommender systems, cross-domain recommendation, and optimal transport techniques.
- In Chapter 4, we present our proposed framework for cross-domain recommendation under non-over
- In Chapter 5, we describe the experimental setup, datasets, and evaluation metrics used to assess the performance of our proposed method.
- In Chapter 6, we present and discuss the experimental results, including comparisons with existing methods and ablation studies.
- Finally, in Chapter 7, we summarize the main findings of this thesis and discuss potential directions for future research.

Chapter 2

Preliminaries

2.1 Recommender Systems

Recommender systems can be mathmatically modeled as a function $R : U \times I \to S$, where U is the set of users, I is the set of items, and S is the set of possible scores or ratings. The goal of a recommender system is to predict the score $s \in S$ that a user $u \in U$ would give to an item $i \in I$. This prediction can be represented as $\hat{s} = R(u, i)$. The final task of recommender systems is to generate a ranked list of items for each user based on the predicted scores.

2.2 Cross-Domain Recommendation

Cross-domain recommendation aims to leverage user preferences and behaviors from one or more source domains to improve recommendation performance in a target domain. Formally, let D_s be the source domain with user set U_s and item set I_s, and D_t be the target domain with user set U_t and item set I_t. The objective is to learn a recommendation function $R_t : U_t \times I_t \to S$ for the target domain by utilizing information from the source domain(s) D_s. The infromation that can be transferred from the source domain to the target domain includes user-item interactions, user profiles, item attributes, and latent factors learned from the source domain. The challenge in cross-domain recommendation lies in effectively transferring knowledge while addressing issues such as domain heterogeneity, data sparsity, and cold-start problems.

2.3 Gaussian Mixture Models

A Gaussian Mixture Model (GMM) is a probabilistic model that assumes data is generated from a mixture of several Gaussian distributions. Formally, a GMM can be represented as:

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k) \tag{2.1}$$

where K is the number of Gaussian components, π_k are the mixture weights satisfying $\sum_{k=1}^{K} \pi_k = 1$, and $\mathcal{N}(x|\mu_k, \Sigma_k)$ is the Gaussian distribution with mean μ_k and covariance matrix Σ_k.

2.4 Optimal Transport

Optimal transport is a mathematical framework for comparing and transforming probability distributions. Given two probability distributions μ and ν defined on spaces X and Y, respectively, the optimal transport problem seeks to find a mapping $T : X \to Y$ that minimizes the cost of transporting mass from μ to ν. The cost function $c(x, y)$ quantifies the expense of moving mass from point $x \in X$ to point $y \in Y$. The optimal transport problem can be formulated as:

$$\min_T \int_X c(x, T(x)) d\mu(x) \tag{2.2}$$

subject to the constraint that the pushforward measure $T_{\#}\mu = \nu$. Optimal transport has been widely used in various applications, including image processing, machine learning, and economics, due to its ability to capture the geometric structure of probability distributions. In our proposed method, we are not using optimal transport in the standard sense above, but using a related concept called Wasserstein distance to measure the distance between two probability distributions. The Wasserstein distance is defined as:

$$W_p(\mu, \nu) = \left(\inf_{\gamma \in \Pi(\mu,\nu)} \int_{X \times Y} c(x, y)^p d\gamma(x, y) \right)^{1/p} \tag{2.3}$$

where $\Pi(\mu, \nu)$ is the set of all joint distributions (couplings) with marginals μ and ν, and $c(x, y)$ is the cost function. The Wasserstein distance provides a meaningful way to compare probability distributions, taking into account the underlying geometry of the data. With the distance between two probability distributions defined, we can replace the conventional pointwise distance (e.g., Euclidean distance) between vectors with the Wasserstein distance between the corresponding distributions in our proposed method.

Chapter 3

Related Work

3.1 Recommender Systems

3.1.1 Divide by Technique

3.1.1.1 Traditional Recommender Systems

Collaborative filtering (CF) is one of the foundational approaches in recommender systems, operating on the principle that users with similar preferences will like similar items[8]. User-based CF finds neighbors with comparable rating patterns, while item-based CF identifies items that are similar based on user interactions. Content-based filtering recommends items by matching item features with user preferences learned from historical data. Hybrid methods combine multiple approaches to leverage their complementary strengths, addressing individual limitations such as sparsity and cold-start problems.

These traditional methods have proven effective for many applications but face challenges including data sparsity, scalability issues, and difficulty in capturing complex non-linear patterns in user behavior.

3.1.1.2 Machine Learning-based Recommender Systems

Machine learning techniques have been widely adopted in recommender systems to enhance prediction accuracy and address limitations of traditional methods. Matrix factorization (MF) techniques, such as Singular Value Decomposition (SVD), decompose the user-item interaction matrix into latent factors, enabling the capture of underlying user preferences and item characteristics. Neighborhood-based methods have also been extended using machine learning algorithms to improve similarity measures and prediction models.

3.1.1.3 Deep Learning-based Recommender Systems

Deep learning has revolutionized recommender systems by enabling the modeling of complex user-item interactions and capturing non-linear relationships. Neural Collaborative Filtering (NCF) employs multi-layer perceptrons to learn user-item interaction functions, outperforming traditional MF methods. Convolutional Neural Networks (CNNs) have been utilized to extract features from item content, such as images and text, enhancing recommendation quality. Recurrent Neural Networks (RNNs) have been applied to model sequential user behavior, capturing temporal dynamics in user preferences.

3.1.2 Divide by Application Domain

3.1.2.1 Sequential Recommender Systems

3.1.2.2 Graph-based Recommender Systems

3.1.2.3 Cross-Domain Recommender Systems

3.1.2.4 Generative Recommender Systems

Chapter 4

Distributional User Preferences for Cross-Domain Recommendation via Optimal Transport

Chapter 5

Experiments

Chapter 6

Results

Chapter 7

Conclusion

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Appendix

A Graph-Enhanced EEG Foundation Models

Publications

- 王 力敏, 脇 聡志 and 鈴村 豊太郎. 大規模マルチモーダルモデルを用いたグラフィックレイアウトの自動生成に向けて. 2024 年度人工知能学会全国大会. 2024.
- Limin Wang, Toyotaro Suzumura, and Hiroki Kanezashi. Graph-Enhanced EEG Foundation Model. AAAI-25 Workshop on Large Language Models and Generative AI for Health. 2025.

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