Dual Preference Distribution Learning for Explainable Item Recommendation

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Recommender systems can automatically recommend users with items that they probably like. The goal of them is to represent the user and item and model their interaction. Existing methods have primarily learned the user’s preferences and item’s features with vectorized representations, and modeled the user-item interaction by the similarity of them. In fact, the user’s preferences to items can be traced to his/her preferences to item attributes, and the user’s different preferences are also related. Thus, exploring such fine-grained preferences and modeling their relationships could help better understand the user’s preferences. Toward this end, we propose a dual preference distribution learning framework, which jointly captures the user’s preferences to both the items and attributes by a Gaussian distribution, termed the general and specific preference distributions, respectively. In this manner, the mean vector of the Gaussian distribution can capture the user’s preferences, while its covariance matrix can learn their relationships. The proposed DUPLE is a generative method that can produce the preference distribution for a given user. Thus, by tracking the user’s specific preference distribution, we can summarize a preferred attribute profile for each user, depicting his/her preferred item attributes. Based on that, we can provide the explanation of recommending an item with the overlap between the item attributes of the user prefers and the item has. Extensive quantitative and qualitative experiments on six public datasets demonstrate the effectiveness and explainability of the DUPLE method.

CCS Concepts: • Information systems → Retrieval models and ranking; Recommender systems; • Mathematics of computing → Distribution functions; Computing most probable explanation.

Additional Key Words and Phrases: Recommender System, Preference Distribution Learning, Explainable Recommendation.

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INTRODUCTION

Recommender systems, which aim to recommend users items that they probably like, have been attracting increasing research attention [30, 32, 46, 49]. Mainstream approaches target at learning the vector-based user and item embedding (used as an identifier without any semantic meaning) based on users' historical ratings to items, respectively, and then predicting a user’s preference to an item according to certain interaction between their embeddings [17, 22, 44, 48]. Different from these methods that directly learn the user’s general preferences to items, several recent research attempts [31, 59] further explored the user’s specific preferences to items (i.e., the user’s preference to the item’s side information, e.g., attributes) to improve the recommendation performance and explainability. They typically involve the extra attribute embedding to enrich each item’s embedding, and use the attention mechanism to discriminate the user’s preference to different attributes of this item. Despite of their compelling success, existing approaches overlook the relationships among the user’s multiple preferences. In fact, a user could have multiple related preferences. For example, if a user prefers action movies, it would be more likely that he/she is interested in movies played by the actor Jackie Chan. Thus, we argue that it is necessary to model the relationships among the user’s preferences to better understand the user’s preferences.

Towards this end, we propose a dual preference distribution learning framework for the explainable item recommendation, termed DUPLE. It engages a Gaussian distribution to characterize the user’s general preferences to items and specific preferences to item attributes, termed the general and specific preference distributions, respectively. In this manner, the user’s preferences can be modeled by the mean vector of the Gaussian distribution, while their relationships can be captured by the covariance matrix. Specifically, as illustrated in Fig. 1, DUPLE consists of three key components: the general preference learning, specific preference learning, and explanation production. In the first component, we introduce a parameter construction module to learn the essential parameters (i.e., the mean vector and covariance matrix) of the user’s general preference distribution based on the user embedding. In the second component, we design a general-specific transformation module to infer the user’s specific preference distribution from the user’s general preference distribution. To be more specific, the transformation bridges the gap between the general and specific preferences with the help of predict the item attributes from the item embedding based on its ground truth attribute label. We then can derive the the user’s specific preference distribution by transforming the parameters of the general preference distribution into their specific counterparts. Next, we predict the user rating to an item by the probability densities of the item in both the user’s general and specific preference distributions. Ultimately, once the specific preference distribution has been learned, in the third component, we summarize a preferred attribute profile to store the user’s inherent preferences to item attributes, and the explanation of recommending the item to the user can be derived by the overlap between the attributes that the user prefers and an item has. Extensive experiments on six version datasets derived from the Amazon Product [30] and MovieLens [14] demonstrate the superiority of our proposed DUPLE over state-of-the-art methods.

We summarize our main contributions as follows:

- We propose a dual preference distribution learning framework (DUPLE) that captures the user’s preferences to both the general item and specific attributes with Gaussian distributions. Benefited from the covariance matrix of the Gaussian distribution, we can capture the relationships between the user’s different preferences for the better recommendation.
- Different from existing explainable recommender systems that focus on determining which attributes of an item the user likes, the proposed DUPLE can summarize the preferred attributes of the user. Accordingly, we can provide the explanation for an recommended item by the overlap between the attributes that the user prefers and an item has.
Fig. 1. Illustration of the proposed dual preference distribution learning framework (DUPLE) for the explainable item recommendation, which jointly learns the user’s preferences to general item (blue flow) and specific attribute (green flow) for the better recommendation.

- Extensive qualitative and quantitative experiments conducted on six real-world datasets have proven the both the effectiveness and explainability of the proposed DUPLE method. We will release our codes to facilitate other researchers.

2 RELATED WORK

In this section, we briefly introduce traditional recommender systems in Subsection 2.1 and explainable recommender systems in Subsection 2.2.

2.1 Recommender Systems

Initial researches utilize the Collaborative Filtering techniques [39] to capture the user’s preferences from the interacted relationships between users and items. Matrix Factorization (MF) is the most popular method [22, 23, 34]. It focuses on factorizing the user rating matrix into the user matrix and item matrix and predicting the user-item interaction by the similarity of their representations. Considering that different users may have different rating habits, Koren et al. [22] introduced the user and item biases into the matrix factorization, achieving a better performance. Several other researchers argued different users may have similar preferences to items. Consequently, Yang et al. [55] and Chen et al. [5] clustered the users into several groups according to their historical item interactions and separately captured the common preferences of users in each group. Recently, due to the great performance of graph convolutional networks, many approaches have resorted to constructing a graph of users and items according to their historical interactions, and exploring the high-order connectivity from user-item interaction [13, 43, 46, 48–50]. For example, Wang et al. [48] served users and items as nodes and their interaction histories as edges between nodes. And then, they proposed a three-layer embedding propagation to propagate messages from items to user and then back to items. Wang et al. [49] designed the intent-aware interaction graph that disentangles the item representation into several factors to capture user’s different intents.

Beyond directly learning the user’s preferences from the historically user-item interactions, other researchers began to leverage the item’s rich context information to capture the user’s detailed preferences to items. Several of them incorporated the visual information of items to improve the recommendation performance [16, 30, 57]. For example, He et al. [16] enriched the
item’s representation by extracting the item’s visual feature by a CNN-based network from its image and added it into the matrix factorization. Yang et al. [57] further highlighted the region of the item image that the user is probably interested in. Some other researches explore the item attributes [2, 31, 59] or user reviews [6, 41, 54] to learn the user’s preferences to the item’s specific aspects. For example, Pan et al. [31] utilized the attribute representations as the regularization of learning the item’s representation during modeling the user-item interaction. In this manner, the user’s preferences to attributes can be tracked by the path of the user to item and then to attributes. And Chen et al. [6] proposed a co-attentive multi-task learning model for recommending user items and generating the user’s reviews to items. Besides, the multi-modal data has been proven to be important for the recommendation [10, 24, 51]. For example, Wei et al. [51] constructed a user-item graph on each modality to learn the user’s modal-specific preferences and incorporated all the preferences to predict the user-item interaction.

Although these above approaches are able to capture the user’s preferences to items or specific contents of the item (e.g., attributes), they fail to model the relationships among the user’s different preferences, which is beneficial for the better recommendation. In this work, we proposed to capture the user’s preferences with the multi-variant Gaussian distribution, and model the user-item interaction with the probability density of the item in the user’s preference distribution. In this manner, the relationships among the user’s preferences can be captured by the covariance matrix of the distribution.

### 2.2 Explainable Recommender Systems

The recommender systems trained by deep neural networks are perceived as a black box only able to predict a recommendation. Thus, to make the recommendation more transparent and trustworthy, interpretable recommender systems [4, 59] are therefore gaining popularity, which focus on what and why to recommend an item. Initial approaches can provide rough reasons of recommending an item based on the similar items or users [35, 37]. Thereafter, researchers attempt to seek more explicit reasons provided to users, e.g., explain recommendations with item attributes, reviews, and reasoning paths.

**Interpretation with Item Attributes.** This group of interpretable recommender systems consider that the user likes an item may be caused by its certain attributes, e.g., “you may like Harry Potter because it is an adventure movie”. Thus, mainstream approaches in this research line have been dedicated to bridging the gap between users and attributes [4, 18, 31, 56]. In particular, Wang et al. [47] employed a tree-based model to learn explicit decision rules from item attributes, and designed an embedding model to generalize to unseen decision rules on users and items. Benefited from the attention mechanism, several researchers [4, 31] learned the item embedding with the fusion of its attribute embeddings. By checking the attention weights, these methods can infer how does each attribute cause the high/low rating score.

**Interpretation with Reviews.** These methods leverage the review as the extra information to the user-item interaction, which can infer the user’s altitude towards one item [8, 9, 28, 36, 52]. In particular, several approaches aggregated review texts of users/items and adopted the attention mechanism to learn the users/items embeddings [12, 28, 36, 52]. Based on the attention weights, the model can highlight the high words in reviews as explanations. Different from highlighting the review words as explanations, other researches attempt to automatically generate reviews for a user-item pair [6, 9, 25, 29]. Specifically, Costa et al.[9] designed a character-level recurrent neural network, which generates review explanations for user-item pair using long-short term memories. Li et al.[25] proposed a more comprehensive model to generate tips in review systems. Inspired by human information processing model in cognitive psychology, Chen et al. [6] developed an
encoder-selector-decoder architecture, which exploits the correlations between recommendation and explanation through co-attentive multi-task learning.

**Interpretation with Reasoning Paths.** This kind of approaches construct a user-item interaction graph and aim to find a explicitly path on the graph that traces the decision-making process [1, 15, 19, 46, 53, 54]. In particular, Ai et al. [1] constructed a user-item knowledge graph of users, items, and multi-type relations (e.g., purchase and belong), and generated explanations by finding the shortest path from the user to the item. Wang et al. [46] proposed a Knowledge Graph Attention Network (KGAT) that explicitly models the high-order relations in the knowledge graph in an end-to-end manner. Xian et al. [53] proposed a reinforcement reasoning approach over knowledge graphs for interpretable recommendation, where agent starts from a user and is trained to reach the correct items with high rewards. Further, considering that users and items have different intrinsic characteristics, He et al. [15] designed a two-stage representation learning algorithm for learning better representations of heterogeneous nodes. Yang et al. [58] proposed a Hierarchical Attention Graph Convolutional Network (HAGERec) that involves the hierarchical attention mechanism to exploit and adjust the contributions of each neighbor to one node in the knowledge graph.

Despite of their achievements in the explainable recommendation, existing approaches mainly a discriminative method to provide an explanation, i.e., they provide an explanation for a given user-item pair. However, in fact, users select items according to their inherent preferences. Therefore, we argue that it is important to first summarize the user’s preferences and then the explanation can be easily derived from the overlap between the user’s preferences and item properties.

### 3 THE PROPOSED DUPLE MODEL

To improve the readability, we declare the notations used in this paper. We use the squiggled letters (e.g., $X$) to represent sets. The bold capital letters (e.g., $X$) and bold lowercase letters (e.g., $x$) to represent matrices and vectors, respectively. Let the non-bold letters (e.g., $x$) denote scalars. The notations used in this paper are summarized in Table 1.

We now present our proposed dual preference distribution learning framework (DUPLE) for the explainable recommendation, which is illustrated in Fig. 1. It is composed of three key modules: 1) the general preference learning, where a parameter construction module is proposed to construct the essential parameters of the user’s general preference distribution; 2) the specific preference learning, where we propose a general-specific transformation module to learn the user’s specific preference distribution by transforming the parameters of the user’s general preference distribution into their specific counterparts; and 3) the explanation production that explains why recommending an item for a user from the item attribute perspective. In the rest of this section, we first briefly define our explainable recommendation problem in Subsection 3.1. Then, we detail the three key modules in Subsections 3.2, 3.3, and 3.4, respectively. Finally, we illustrate the model optimization in Subsection 3.5.

#### 3.1 Problem Definition

Without losing generality, suppose that we have a set of users $U$, a set of items $I$, and a set of item attributes $A$ that can be applied to describe all the items in $I$. Each user $u ∈ U$ is associated with a set of items $I_u$ that the user historically likes. Each item $i ∈ I$ is annotated by a set of attributes $A_i$. Following mainstream recommender models [17, 23, 49], we describe a user $u$ (an item $i$) with an embedding vector $f_u ∈ \mathbb{R}^D (f_i ∈ \mathbb{R}^D)$, where $D$ denotes the embedding dimension. Besides, to describe the item with its attributes, we represent the item $i$ by a bag-of-words embedding of its attributes $t_i ∈ \mathbb{R}^{|A|}$, where the $j$-th elements $t_i^j = 1$ refers to the item has the $j$-th attribute in $A$. 

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Table 1. Summary of the Main Notations.

| Notation | Explanation |
|----------|-------------|
| $\mathbf{U}$, $\mathbf{I}$, $\mathbf{A}$ | The sets of users, items, and attributes, respectively. |
| $\mathbf{I}_u$ | The set of historical interacted items of the user $u \in \mathbf{U}$. |
| $\mathbf{A}_i$ | The set of attributes of the item $i \in \mathbf{I}$. |
| $\mathbf{A}_u$ | The summarized preferred attribute profile of the user $u$. |
| $\mathbf{D}$ | The training set of triplet $(u, i, k), u \in \mathbf{U}, i \in \mathbf{I}_u, k \notin \mathbf{I}_u$. |
| $\mathbf{f}_u, \mathbf{f}_i$ | Embeddings of the user $u$ and item $i$, respectively. |
| $\mathbf{t}_i$ | Bag-of-words attribute embedding of the item $i$. |
| $\mathbf{\mu}_u^g, \mathbf{\Sigma}_u^g$ | Mean vector and covariance matrix of the user $u$’s general preference distribution. |
| $\mathbf{\mu}_u^s, \mathbf{\Sigma}_u^s$ | Mean vector and covariance matrix of the user $u$’s specific preference distribution. |
| $\mathbf{p}_u^g, \mathbf{p}_u^s$ | The general and specific preferences of the user $u$ to the item $i$, respectively. |
| $\mathbf{p}_{ui}$ | The final preference of the user $u$ to the item $i$. |
| $\mathbf{\Theta}$ | To-be-learned set of parameters. |

**Inputs:** The inputs of the dual preference distribution learning framework (DUPLE) consist of 3 parts: the set of users $\mathbf{U}$, set of items $\mathbf{I}$, and the set of attributes $\mathbf{A}_i$ of the item $i \in \mathbf{I}$.

**Outputs:** Given a user $u$ and item $i$ with its attributes $\mathbf{A}_i$, DUPLE predicts the user-item interaction $\mathbf{p}_{ui}$ from both the general item and specific attribute perspectives as follows,

$$
\mathbf{p}_{ui} = \lambda \mathbf{p}_{ui}^g + (1 - \lambda) \mathbf{p}_{ui}^s,
$$

where $\mathbf{p}_{ui}^g$ and $\mathbf{p}_{ui}^s$ are the general and specific preferences of the user $u$ to the item $i$ (will be introduced in Subsection 3.2 and 3.3), respectively. $\lambda \in [0, 1]$ is a hyper-parameter for adjusting the trade-off between the two terms. Besides, DUPLE can summarize a preferred attribute profile $\mathbf{A}_u$ for the user $u$ and provide the explanation for recommending an item $i$ with the form of “you may like $\mathbf{A}_u \cap \mathbf{I}_i$ of the item”.

### 3.2 General Preference Learning

We utilize a general preference distribution $\mathcal{G}(\mathbf{\mu}_u^g, \mathbf{\Sigma}_u^g)$ for the user $u$ to capture his/her preferences to the general items. More specifically, the mean vector $\mathbf{\mu}_u^g$ refers to the center of the user $u$’s general preference, while the covariance matrix $\mathbf{\Sigma}_u^g$ stands for the relationships among the latent variables affecting the user’s preferences to items.

Thus, the key to learn the user’s general preference distribution is to construct the mean vector and covariance matrix. We design a parameter construction module to separately construct the mean vector and covariance matrix, as they are different in the form and mathematical properties. In particular, the mean vector is a $D$-dimensional vector indicating the center of the user’s general preference. Therefore, we simply adopt one fully connected layer to map the user embedding $\mathbf{f}_u$ to the mean vector of the general preference distribution $\mathbf{\mu}_u^g \in \mathbb{R}^D$ as follows,

$$
\mathbf{\mu}_u^g = \mathbf{W}_\mu \mathbf{f}_u + \mathbf{b}_\mu,
$$

where $\mathbf{W}_\mu \in \mathbb{R}^{D \times D}$ and $\mathbf{b}_\mu \in \mathbb{R}^D$ are the non-zero parameters to map the user embedding.

As the covariance matrix is a symmetric and positive semi-definite matrix according to its mathematical properties, it is difficult to construct it directly based on the user embedding. Instead, we propose to first derive a low-rank matrix $\mathbf{V}_u \in \mathbb{R}^{D \times D'}$, $D' < D$, from the user embedding as a
bridge, and then construct the covariance matrix through the following equation,
\[
\Sigma_u^g = V_u V_u^T,
\] (3)
where \(V_u = [\nu_u^1; \nu_u^2; \cdots; \nu_u^{D'}]\) arranged by \(D'\) column vectors, which can be derived by the column-specific transformation as follows,
\[
\nu_u^j = W^j \xi_u + b^j, \quad j = 1, 2, \cdots, D',
\] (4)
where \(W^j \xi_u \in \mathbb{R}^{D \times D'}\) and \(b^j \in \mathbb{R}^D\) are the non-zero parameters to derive the \(j\)-th column of \(V_u\). These parameters and the user embedding \(f^g_u\) (i.e., non-zero vector) guarantee that the \(\nu_u^j\) is a non-zero vector. With the simple algebra derivation, the covariance matrix \(\Sigma_u^g\) derived according to Eqn. (3) is symmetric as \(\Sigma_u^g = (V_u V_u^T)^T = V_u V_u^T = \Sigma_u^g\), and positive semi-definite as \(x \Sigma_u^g x^T = x V_u V_u^T x^T = ||x V_u||^2 \geq 0, \forall x \neq 0, x \in \mathbb{R}^D\).

In the user \(u\)’s general preference distribution, we adopt the probability density of the embedding \(f_i\) of the item \(i\) as the proxy of the general preference \(p^g_{u,i}\) of the user \(u\) toward the item \(i\). Formally, we define \(p^g_{u,i}\) as follows,
\[
p^g_{u,i} = P(f_i | \mu_u^g, \Sigma_u^g) = \frac{1}{\sqrt{2\pi|\Sigma_u^g|}} \exp \left( -\frac{1}{2} (f_i - \mu_u^g)^T (\Sigma_u^g)^{-1} (f_i - \mu_u^g) \right),
\] (5)
where \(|\Sigma_u^g|\) and \((\Sigma_u^g)^{-1}\) are the determinant and inverse matrix of the covariance matrix \(\Sigma_u^g\) of the user’s general preference distribution defined in Eqn. (3), respectively.

### 3.3 Specific Preference Learning

We learn the user’s specific preference to item attributes from his/her general preference to items, with the help of bridging the gap between the items and their attributes. Specifically, we design a general-specific transformation that predicts the item’s attribute representation from the item embedding. Thus, we can learn the user’s specific preference distribution from the general preference distribution by transforming its mean vector and covariance matrix to their specific counterparts. Instead of introducing another branch to construct the specific preference distribution anew, i.e., learning its parameters \(\mu_u^s\) and \(\Sigma_u^s\) through the user embedding as the similar with the parameter construction module, this has the following benefits. (1) The user’s general preference toward an item often comes from his/her specific judgments toward the item’s attributes. In light of this, it is promising to derive the specific preference distribution by referring the general preference distribution. (2) Learning the general and specific preferences of the user with one branch allows the knowledge learned by each other to be mutually referred. And 3) this would facilitate the specific preference modeling directly from the pure general preference, enables the testing cases that lack item attribute details.

In particular, following the approach [31], we adopt the linear mapping as the general-specific transformation to predict the item \(i\)’s attribute representation \(\hat{t}_i\) from the item embedding \(f_i\) as follows,
\[
\hat{t}_i = W_t f_i,
\] (6)
where \(W_t \in \mathbb{R}^{|A| \times D}\) is the parameter of the general-specific transformation.

We adopt the ground-truth attribute label \(t_i\) of the item \(i\) to supervise the general-specific transformation learning. Specifically, we enforce the predicted item \(i\)’s attribute representation \(\hat{t}_i\) to be as close as to its ground truth attribute label vector \(t_i\) by the following objective function,
\[
\mathcal{L}_t = \sum_{i,k \in T, i \neq k} -\log(\sigma(\cos(\hat{t}_i, t_i) - \cos(\hat{t}_i, t_k)) ),
\] (7)
where \( t_k \) is the ground-truth attribute label vector of another item \( k \). We estimate the similarity between item \( i \)'s attribute representation and the ground-truth attribute label vector with their cosine similarity as: \( \cos(t_i, \hat{t}_i) = \frac{t_i^T \hat{t}_i}{|t_i||\hat{t}_i|} \). By minimizing this objective function, the item \( i \)'s attribute representation \( \hat{t}_i \) is able to indicate what attributes the item \( i \) has.

We then introduce how to construct the user \( u \)'s specific preference distribution \( \mathcal{G}(\mu_u^g, \Sigma_u^g) \) from the general one based on the general-specific transformation. Differently from the general preference distribution, each dimension in the specific preference distribution refers to a specific item’s attribute. Therefore, the mean vector \( \mu_u^g \in \mathbb{R}^{|A|} \), i.e., the center of the user’s specific preference, indicates what attributes that the user prefers. The covariance matrix \( \Sigma_u^g \in \mathbb{R}^{[|A|] \times [|A|]} \) stands for the relationships of these preferences.

Technically, we project the parameters of the general preference distribution, i.e., \( \mu_u^g \) and \( \Sigma_u^g \), into their specific counterparts as follows,

\[
\begin{align*}
\mu_u &= W_t \mu_u^g, \\
\Sigma_u &= W_t \Sigma_u^g W_t^T.
\end{align*}
\] (8)

In this manner, the transformed parameters, i.e., \( \hat{\mu}_u \) and \( \hat{\Sigma}_u \), are the mean vector and covariance matrix of the specific preference distribution, respectively, i.e., \( \hat{\mu}_u = \mu_u^s, \hat{\Sigma}_u = \Sigma_u^s \). The rationality proof is given as follows,

- **Argument 1.** \( \hat{\mu}_u \) is the mean vector of the user \( u \)'s specific preference distribution, i.e., \( \hat{\mu}_u = \mu_u^s \).
- **Proof 1.** Referring to the mathematical definition of the mean vector, and the additivity and homogeneity of the linear mapping, we have,

\[
\begin{align*}
\hat{\mu}_u &= W_t \mu_u^g = W_t \left( \frac{1}{|I_u|} \sum_{i \in I_u} f_i \right) \\
&= \frac{1}{|I_u|} W_t \sum_{i \in I_u} f_i = \frac{1}{|I_u|} \sum_{i \in I_u} W_t f_i \\
&= \frac{1}{|I_u|} \sum_{i \in I_u} \hat{t}_i := \mu_u^s.
\end{align*}
\]

- **Argument 2.** \( \hat{\Sigma}_u \) is the covariance matrix of the user \( u \)'s specific preference distribution, i.e., \( \hat{\Sigma}_u = \Sigma_u^s \).
- **Proof 2.** Referring to the mathematical definition of the covariance matrix, and the additivity and homogeneity of the linear mapping, we have,

\[
\begin{align*}
\hat{\Sigma}_u &= W_t \Sigma_u^g W_t^T \\
&= W_t \left( \frac{1}{|I_u|} \sum_{i \in I_u} (f_i - \mu_u^g)(f_i - \mu_u^g)^T \right) W_t^T \\
&= \frac{1}{|I_u|} \sum_{i \in I_u} W_t (f_i - \mu_u^g)(f_i - \mu_u^g)^T W_t^T \\
&= \frac{1}{|I_u|} \sum_{i \in I_u} (W_t (f_i - \mu_u^g))(W_t (f_i - \mu_u^g))^T \\
&= \frac{1}{|I_u|} \sum_{i \in I_u} (W_t f_i - W_t \mu_u^g)(W_t f_i - W_t \mu_u^g)^T \\
&= \frac{1}{|I_u|} \sum_{i \in I_u} (\hat{t}_i - \hat{\mu}_u)(\hat{t}_i - \hat{\mu}_u)^T
\end{align*}
\]
Fig. 2. Illustration of the explanation production of the proposed DUPLE. We first derive the user’s preferred attribute profile with the mean vector of the learned user specific distribution. We then use the overlapped attributes between the learned attribute profile and the recommended item’s attributes as the explanation.

\[
\frac{1}{|I_u|} \sum_{i \in I_u} (\hat{t}_i - \mu_u^s)(\hat{t}_i - \mu_u^s)^T := \Sigma_u^s.
\]

After constructing the user’s specific preference distribution, we define the specific preference \( p_{u_i}^s \) of the user \( u \) toward the item \( i \) as the probability density of the item \( i \)’s attribute representation \( \hat{t}_i \) in the similar form as follows,

\[
p_{u_i}^s = P(\hat{t}_i | \mu_u^s, \Sigma_u^s) = \frac{1}{\sqrt{2\pi|\Sigma_u^s|}} \exp \left( -\frac{1}{2} (\hat{t}_i - \mu_u^s)^T (\Sigma_u^s)^{-1} (\hat{t}_i - \mu_u^s) \right).
\]

### 3.4 Explanation Production

In addition to the item recommendation, DUPLE can also explain why to recommend an item to a user as a byproduct, as shown in Fig. 2. In particular, in the specific preference distribution, each dimension refers to a specific attribute and the mean vector indicates the center of the user’s specific preference. Accordingly, we can infer what attributes the user likes and summarize a preferred attribute profile for the user. Technically, suppose that the user \( u \) prefers \( r \) attributes totally, then we can define the preferred attribute profile \( \mathcal{A}_u \) as follows,

\[
\begin{align*}
\{ u_1, u_2, \ldots, u_r & = \arg \max_r(\mu_u^s), \mu_u^s \in \mathbb{R}^{|\mathcal{A}|}, \\
\mathcal{A}_u & = \{ a_{u_1}, a_{u_2}, \ldots, a_{u_r} \},
\end{align*}
\]

where \( \arg \max_r(\cdot) \) is the function returning the indices of the \( r \) largest elements in the vector. \( a_{u_j} \) is the \( u_j \)-th attribute in \( \mathcal{A} \). After building the preferred attribute profile of the user \( u \), for a given recommended item \( i \) associated with its attributes \( \mathcal{A}_i \), we can derive the reason why the user likes the item by checking the overlap between \( \mathcal{A}_u \) and \( \mathcal{A}_i \). Suppose that \( \mathcal{A}_u \cap \mathcal{A}_i = \{ a_{u_j}, a_{u_k} \} \). Then we can provide the explanation for user \( u \) as “you may like the item \( i \) for its attributes \( a_{u_j} \) and \( a_{u_k} \).”

Besides, it is worth mentioning that the diagonal elements of the covariance matrix \( \Sigma_u^s \) in the specific preference distribution can capture the significances of user’s different preferences to attributes. Specifically, if the value of the diagonal element in one dimension is small, its tiny change will sharply affect the prediction of the user-item interaction, and we can infer that the user’s preference to the attribute in the corresponding dimension is “strict”, i.e., significant.
Algorithm 1 Dual Preference Distribution Learning Framework (DUPLE).

**Input:** The sets of users \( \mathcal{U} \) and items \( \mathcal{I} \). The set of attributes \( \mathcal{A}_i \) of each \( i \in \mathcal{I} \). The training set \( \mathcal{D} \). The number of the optimization step \( N \).

**Output:** The parameters \( \Theta \) of DUPLE.

1. Initialize the user embedding \( f_u, u \in \mathcal{U} \), and item embedding \( f_i, i \in \mathcal{I} \).
2. Initialize the model parameters \( \Theta \).
3. for \( n \) in \([1, \cdots, N]\) do
   4. Randomly draw a mini-batch of training triplets \((u, i, k)\) from \( \mathcal{D} \).
   5. Calculate the mean vector \( \mu^g_u \) and covariance matrix \( \Sigma^g_u \) of the general preference distribution through Eqn. (2) and (3), respectively.
   6. Calculate the mean vector \( \mu^s_u \) and covariance matrix \( \Sigma^s_u \) of the specific preference distribution through Eqn. (8).
   7. Predict the user-item interaction \( p_{ui} \) through Eqn. (1).
   8. Update the parameters through Eqn. (12):
      \[ \Theta \leftarrow \Theta - \eta \frac{\partial L}{\partial \Theta} \]
4. end for

3.5 **Optimization**

The learned general and specific preference distributions are expected to assign a higher probability for the items that the user historically interacted item, and vice versa. Thus, regarding the optimization of the proposed DUPLE method, we build the following training set according to the Bayesian personalized ranking mechanism [33],

\[
\mathcal{D} = \{(u, i, j)|u \in \mathcal{U}, i \in \mathcal{I}_u, j \in \mathcal{I} \setminus \mathcal{I}_u\},
\]

where the training triplet \((u, i, j)\) indicates that the user \( u \) prefers item \( i \) to the item \( j \).

Ultimately, based on our constructed training set in Eqn. (11), we define the objective function for the DUPLE model as follows,

\[
\mathcal{L} = \min_\Theta (L_t + \sum_{(u, i, k) \in \mathcal{D}} - \log(\frac{p_{ui}}{p_{ui} + p_{uk}}) ),
\]

where \( p_{ui} \) (\( p_{uk} \)) is the user-item interactions between the user \( u \) and item \( i \) (\( k \)) defined in Eqn. (1). \( L_t \) is the loss function of the general-specific transformation defined in Eqn. (7). \( \Theta \) refers to the set of to-be-learned parameters of the proposed framework. The detailed training process of DUPLE is summarized in Algorithm 1.

4 **EXPERIMENTS**

In this section, we first introduce the dataset details and experimental settings in Subsections 4.1 and 4.2, respectively. And then, we conduct extensive experiments by answering the following research questions:

1. Does DUPLE outperform the state-of-the-art methods?
2. How do the different variants of the Gaussian distribution perform?
3. What are the learned relations of the user’s preferences?
4. How is the explainable ability of DUPLE for the item recommendation?
Table 2. Statistics of the six public datasets (after preprocessing), including the numbers of users (#user), items (#item), their interactions (#rating), and attributes (#attri.), as well as the density of the dataset

| Dataset                        | #user | #item | #rating | #attri. | density |
|-------------------------------|-------|-------|---------|---------|---------|
| **Amazon Product Dataset**    |       |       |         |         |         |
| Women’s Clothing              | 19,972| 285,508| 326,968 | 1,095   | 0.01%   |
| Men’s Clothing                | 4,807 | 43,832| 70,723  | 985     | 0.03%   |
| Cell Phone & Accessories      | 9,103 | 51,497| 132,422 | 1,103   | 0.03%   |
| **MovieLens Dataset**         |       |       |         |         |         |
| MovieLens-small               | 579   | 6,296 | 48,395  | 698     | 1.33%   |
| MovieLens-1M                  | 5,950 | 3,532 | 574,619 | 543     | 2.73%   |
| MovieLens-10M                 | 66,028| 10,254| 4,980,475| 446     | 0.74%   |

### 4.1 Dataset and Pre-processing

To verify the effectiveness of DUPLE, we adopted six public datasets with various sizes and densities: the Women’s Clothing, Men’s Clothing, Cell Phones & Accessories, MovieLens-small, MovieLens-1M, and MovieLens-10M. The former three datasets are derived from Amazon Product dataset [30], where each item is associated with a product image and a textual description. The latter three datasets are released by MovieLens dataset [14], where each movie has the title, published year, and genre information. User ratings of all the six datasets range from 1 to 5. To gain the reliable preferred items of each user, following the studies [26, 27], we only kept the user’s ratings that are larger than 3. Meanwhile, similar to the studies [11, 20], for each dataset, we filtered out users and items that have less than 10 interactions to ensure the dataset quality.

Since there is no attribute annotation in all the datasets above, following the studies [45, 52], we adopted the high-frequency words in the item’s textual information as the ground truth attributes of items. Specifically, for each dataset, we regarded the words that appear in the textual description of more than 0.1% of items in the dataset as the high-frequency words. Notably, the stopwords (like “the”) and noisy characters (like “/”) are not considered. The final statistics of the datasets are listed in Table 2, including the numbers of users (#user), items (#item), their interactions (#rating), and attributes (#attri.), as well as the density of the dataset. Similar to the study [49], we calculated the dataset density by the formula

\[
\frac{\text{#rating}}{\text{#user} \times \text{#item}}.
\]

### 4.2 Experimental Settings

**Data Split.** We adopted the widely used leave-one-out evaluation [7, 11, 17] to split the training, validation, and testing sets. In particular, for each user, we randomly selected an item from his/her historical interacted items for validation and testing, respectively, and lefted the rest for training. In the validation and testing, in order to avoid the heavy computation on all user-item pairs, following the studies [11, 17], we composed the candidate item set by one ground-truth item and 100 randomly selected negative items that have not been interacted by the user.

**Evaluation Metrics.** We adopted the Area Under Curve (AUC), Mean Reciprocal Rank (MRR), Hit Rate (HR@10) and Normalized Discounted Cumulative Gain (NDCG@10) truncated the ranking list at 10 to comprehensively evaluate the performance. In particular, AUC indicates the classification ability of the model in terms of distinguishing the user’s likes and dislikes. MRR, HR@10, and NDCG@10 reflect the ranking ability of the model in terms of the top-N recommendation.

**Implementation Details.** Following the study [11], we unified the dimension \(D\) of the item and user embedding as 64. Besides, to gain the powerful representation of the user and item, we added a two-layer perceptron to transform the raw embeddings before feeding them into the
network. We used the random normal initialization for the parameters and trained them by Adam optimizer \[10^{-4}\] and batch size of 256. For different dataset, the number of the optimization steps \(N\) is different. This is because a large dataset needs more steps to converge. We showed the curves of the training loss in Eqn. (12) and metrics (i.e., MRR and NDCG@10) on the validation set on the six datasets in Fig. 3. For our method, we tuned the trade-off parameter \(\lambda\) in Eqn.(1) from 0 to 1 with the stride of 0.1 for each dataset, and the dimension \(D'\) in Eqn.(3) from [2, 4, 8, 16, 32].

### 4.3 Comparison of Baselines (RQ1)

**Baselines.** We compared the proposed DUPLE method with the following baselines.

- **BPR** [33]. Bayesian personalized ranking (BPR) is one of the most widely used methods for the top-N recommendation. It represents the users and items with feature vectors and introduces a personalized ranking criterion for the optimization, which aims to yield a larger similarity for a user and a positive item as compared to a user and a negative item.

  - **AMR** [42]. To enhance the recommending robustness, this approach involves the adversarial learning onto the BPR model. Specifically, it trains the network to defend an adversary by adding perturbations to the item image.

  - **DVMF** [38]. This model is a distribution-based method for the click prediction task, which represents users and items with Gaussian distributions, respectively. DVMF designs a densely-connect multi-Layer perceptron (D-MLP) to produce the parameters of the Gaussian distribution based on the randomly initialized embedding, and utilizes the variational inference to measure the user-item rating. We replaced its objective function of the classification with the ranking loss as the same as our work. It is worth noting that this modification boosts the performance of DVNE in the context of top-N recommendation.
- **ex-DVMF.** This method is a extension of DVMF, which involves the item attribute representation to enrich the item embedding. Specifically, the BOWs attribute embedding of the item is first mapped into the same dimension of the item embedding, and then, the summation of the two embeddings is adopted as the enriched item embedding.

- **NARRE [3].** This method is designed for the click prediction. It adds the item’s attributes into the matrix factorization. It enriches the item representation with the attribute representation, which is the weighted-summation of all the word-embedding of the item’s attributes. Ultimately, based on the learned weights for the attribute representations, NARRE can capture the user’s specific preferences to attributes. We also replaced its objective function with the ranking loss to boost its performance in the top-N recommendation.

- **AMCF [40].** This method adds the item’s attributes into the matrix factorization by enriching the item representation with the attribute representation. AMCF considers that there exist a projection between the item representation and attribute representation, and utilizes the weighted-summation of attribute representations as a regularization for the item representation learning. According to the weights, AMCF can determine the user’s specific preferences to different attributes.

It is worth noting that the first three baselines, i.e., BPR, AMR, and DVMF, only focus on the user’s general preference, termed as single-preference-based (SP-based) method. The rest methods, i.e., ex-DVMF, NARRE, AMCF, and our proposed DUPLE consider both the general and specific preferences during recommending items, termed as dual-preference-based (DP-based) method. For each method, we reported its average results of three runs with different random initialization of model parameters. Table 3 shows the performance of baselines and our proposed DUPLE method on the six datasets. The best and second-best results are in bold and underlined, respectively. The row “%improv” indicates the relative improvement of DUPLE over the best results of baselines. From Table 3, we have the following observations:

1. DUPLE outperforms all the baselines in terms of almost metrics across different datasets, which demonstrates the superiority of our proposed framework over existing methods. This may be due to the fact that by learning the user’s dual preferences (i.e., general and specific preferences) with the probabilistic distributions, DUPLE is capable of exploring the relationships of the user’s difference preferences, whereby gains the better performance.

2. The DP-based methods (i.e., ex-DVMF, NARRE, AMCF, and DUPLE) gain the better performance than the SP-based methods (i.e., BPR, AMR, and DVMF) on average. It proves that jointly learning the user’s general and specific preferences helps to better understand the user overall preferences and gains a better recommendation performance. Besides, we found that in datasets from Amazon, the improvements of the DP-based methods over SP-based methods are larger than improvements in datasets from MovieLens. This may be because that datasets from Amazon are sparse so that the user and item embeddings cannot be learned well with the limited user-item interacted data. In this cases, engaging the information of the item attribute helps more to understand the item properties and better learn the user’s preferences.

3. Among SP-based method, AMR outperforms BPR on all the datasets. This indicates that adding perturbations enables the network to be robust and has a better generalization ability. Besides, DVMF that utilizes the distribution to represent user’s preferences outperforms other SP-based methods, i.e., BPR and AMR. This proves that a distribution has more descriptive power to represent the user’s preferences than a vector.

4. AMCF is an extension of the BPR method, which utilize the item attributes as the supervision to learn the item embedding. It outperforms BPR with a large margin in all datasets,
Table 3. Comparison results on the six datasets. The best and second-best results are in bold and underlined, respectively. %impro is the relative improvement of the proposed DUPLE compared to the strongest baseline.

| Method | Women’s Clothing | MovieLens-Small | MovieLens-1M | Men’s Clothing | MovieLens-10M | MovieLens-10M |
|--------|------------------|-----------------|-------------|---------------|---------------|---------------|
|        | Metrics          | Metrics         |             | Metrics       | Metrics       | Metrics       |
|        | AUC MRR HR@10    | AUC MRR HR@10   |             | AUC MRR HR@10 | AUC MRR HR@10 | AUC MRR HR@10 |
| BPR    | 54.01 6.73 13.43 | 72.04 12.12 29.36 |             | 73.95 15.26 33.83 | 76.19 15.17 34.97 |             |
| AMR    | 55.94 7.79 16.73 | 74.66 12.66 32.70 |             | 74.73 15.37 34.21 | 78.12 16.15 38.18 |             |
| DVMF   | 58.45 8.32 19.80 | 73.48 13.07 33.16 |             | 77.91 17.15 39.00 | 80.50 16.68 40.91 |             |
| ex-DVMF| 70.09 11.72 27.33 | 77.54 15.30 37.01 |             | 79.20 18.59 40.97 | 84.04 22.31 49.07 |             |
| AMCF   | 62.18 9.85 22.14 | 76.06 11.91 35.15 |             | 77.90 15.42 38.18 | 84.70 23.74 51.67 |             |
| NARRE  | 74.93 17.95 39.12 | 76.30 13.23 36.84 |             | 79.06 17.45 40.23 |             |             |
| DUPLE  | 77.48 20.35 42.43 | 79.07 16.43 38.86 |             | 80.65 20.38 45.47 |             |             |
| %impro | +3.40 +13.37 +8.46 | +1.97 +7.38 +4.99 |             | +4.84 +5.73 +7.76 |             | +4.02 +8.98 +10.49 |

| Method | Cell Phone & Accessories | MovieLens-1M | MovieLens-1M |
|--------|--------------------------|-------------|-------------|
|        | Metrics                  |             |             |
|        | AUC MRR HR@10            |             |             |
| BPR    | 66.97 13.06 28.75        | 76.19 15.17 34.97 |             |
| AMR    | 67.12 13.60 30.02        | 78.12 16.15 38.47 |             |
| DVMF   | 68.71 15.55 30.10        | 84.04 22.31 49.07 |             |
| ex-DVMF| 75.88 15.29 36.59        | 84.74 23.34 50.97 |             |
| AMCF   | 69.61 13.45 30.85        | 80.50 16.68 40.91 |             |
| NARRE  | 77.53 18.70 41.15        | 83.90 22.22 49.29 |             |
| DUPLE  | 80.65 20.38 45.47        | 84.70 23.74 51.67 |             |
| %impro | +4.02 +8.98 +10.49       | -0.04 +1.71 +1.37 | +0.7 |

demonstrating the necessity of modeling the user’s specific preference to attributes. However, AMCF performs worst among all DP-based method. This may be because that this method only utilize the item attributes as the supervision, while failing to directly calculate the user’s specific preferences.

4.4 Comparison of Variants (RQ2)

In order to verify that the user’s different preferences are related, i.e., each dimension of the user’s two preference distributions are dependent, we introduced the variant of our model, termed as DUPLE-diag, whose covariance matrices of the two distributions (i.e., $\Sigma_u^g$ and $\Sigma_u^s$) are set to be diagonal matrices, i.e., the off-diagonal elements of the covariance matrix are all zeros. Besides, to further demonstrate that the user’s different preferences contribute differently to predict the user-item interaction, we designed DUPLE-iden method that $\Sigma_u^g = \Sigma_u^s = E$, where $E$ is an identity matrix. Formally, according to Eqn.(5) and Eqn.(9), by omitting constant terms, the user’s general and specific preferences can be simplified as $p_{ui}^g \propto e^{-\frac{1}{2}||f_i-\mu_{ui}^g||^2}$ and $p_{ui}^s \propto e^{-\frac{1}{2}||f_i-\mu_{ui}^s||^2}$, respectively.

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Table 4. The results of the comparison of different variants of DUPLE. DUPLE-iden and DUPLE-diag set the covariance matrix of the preference distributions are identity and diagonal matrices, respectively. The best results are highlighted in bold.

|                      | Method       | Metrics       |   |   |   |
|----------------------|--------------|---------------|---|---|---|
|                      |              | AUC | MRR | HR@10 | NDCG@10 |
| Women’s Clothing     | DUPLE-iden   | 72.23 | 18.48 | 37.14 | 21.09 |
|                      | DUPLE-diag   | 75.19 | 18.43 | 40.14 | 21.22 |
|                      | DUPLE        | **77.48** | **20.35** | **42.43** | **23.60** |
| Men’s Clothing       | DUPLE-iden   | 72.80 | 19.27 | 38.86 | 20.38 |
|                      | DUPLE-diag   | 75.76 | 18.16 | 41.26 | 22.16 |
|                      | DUPLE        | **76.00** | **19.35** | **40.95** | **23.62** |
| Cell Phone & Accessories | DUPLE-iden  | 77.84 | 19.49 | 41.10 | 24.00 |
|                      | DUPLE-diag   | 80.64 | **20.99** | **46.64** | **25.65** |
|                      | DUPLE        | **80.65** | 20.38 | 45.47 | **25.14** |
| MovieLens-Small      | DUPLE-iden   | 77.26 | 14.89 | 36.26 | 19.32 |
|                      | DUPLE-diag   | 78.33 | 15.13 | 36.09 | 18.11 |
|                      | DUPLE        | **79.07** | **16.43** | **38.86** | **20.80** |
| MovieLens-1M         | DUPLE-iden   | 76.38 | 16.56 | 37.65 | 19.57 |
|                      | DUPLE-diag   | 76.53 | 15.66 | 36.87 | 17.57 |
|                      | DUPLE        | **79.52** | **18.80** | **42.85** | **22.28** |
| MovieLens-10M        | DUPLE-iden   | 79.16 | 17.57 | 40.32 | 20.93 |
|                      | DUPLE-diag   | 80.07 | 18.48 | 41.84 | 21.74 |
|                      | DUPLE        | **84.70** | **23.74** | **51.67** | **28.10** |

Intuitively, the variant DUPLE-diag leverages Euclidean distance to measure the user preference, whose philosophy is as similar as the baselines we used.

Under the aforementioned settings, the learned distribution of DUPLE-iden can be regarded as a circular in the high-dimensional space, while it of DUPLE-diag is a ellipse that allows the radius of each dimension to stretch. Moreover, the learned distribution of DUPLE is more flexible that allows the arbitrary rotation of the ellipse. For each method, we reported the average result of three runs with different random initialization of the model parameters. The results are shown in Table 4 and the detailed analysis is given as follows.

1. DUPLE outperforms the two variant methods with respect to almost all datasets, which demonstrates that it is necessary to learn the relationships and different contributions among the user’s preferences to predict the user rating.

2. DUPLE-iden, whose covariance matrix is set to identify matrix, performs worst in this comparison. Besides, the results of DUPLE-iden are comparably with the existing baselines on average. The reason behind may be that with the identity covariance matrix setting, DUPLE-iden represents user’s preferences by only a mean vector, which is as the same as existing approaches using vectorized embedding, it thus achieves the similar performance. This proves that it is better to capture the user’s preferences with probabilistic distribution compared to the vectorized embedding of the existing approaches.

3. DUPLE-diag performs worse than DUPLE. The reason behind may be that, equipped with the diagonal covariance matrix, DUPLE-diag cannot capture the relationships among the user’s preferences.
different preferences. Differently, DUPLE can explore such relationships by the off-diagonal elements of the covariance matrix to better understand the user preferences and gain a better performance.

(4) In Cell Phone & Accessories dataset, it is unexpected that DUPLE performs worse than DUPLE-diag on average. This may be attributed to that the user’s different preferences to items in this category rarely interact with each other. For example, whether a user prefers black phone will not be influenced by whether he/she prefers its LCD-screen. Therefore, leveraging more parameters to capture these relations of user’s preferences only decreases the performance of DUPLE.

4.5 Visualization of User’s Preferences Relationships (RQ3)

In order to further gain a deeper insight of the relationships of the user’s preferences, we visualized the learned covariance matrix of the specific preference distribution of a randomly selected user in the Women’s Clothing and MovieLens-1M datasets, respectively. For clarity, instead of visualizing the relationships of the user’s preferences to all the attributes, we randomly picked up 20 attributes and visualized their corresponding correlation coefficients in the covariance matrix of the specific preference distribution in each dataset by heat maps in Fig. 4. The darker blue color indicates that the user’s preferences to the two attributes are higher related. We circled the four most prominent preference pairs, where two pairs with the highest relationship are surrounded by the yellow boxes, and two pairs with the lowest relationship by the red boxes.

From Fig. 4, we can see that in the dataset Women’s Clothing, this user’s preferences to attributes black and sexy, as well as attributes silk and sexy, are highly relevant, while those to attributes casual and sexy, as well as attributes sweatshirt and sexy are less relevant. This is reasonable as one user that prefers the sexy garments are more probably to like garments in black color, but hardly like casual garments. As for the MovieLens-1M dataset, the user’s preference to attribute Princess has the high relevance with the preferences to attributes Friends and Women, while the
### Historical Items
| Recommended Item | Explanation |
|------------------|-------------|
| Men's New Balance MX608V3 Cross-Training Men's Shoes | We recommend you try this. |
| New Balance MX623 Cross-Training Men's Shoes | New Balance Men's Sneaker |
| Men's New Balance MX623v2 Cross-Training Men's Shoes | Because that you may like its attributes Balance, Men, and Shoes. |
| New Balance Men's Sneaker | New Balance Men's Sneaker |

### Recommended Item
| Preferred Attribute Profile | Historical Items | Recommended Item | Explanation |
|-----------------------------|------------------|------------------|-------------|
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |

### Historical Items
| Preferred Attribute Profile | Historical Items | Recommended Item | Explanation |
|-----------------------------|------------------|------------------|-------------|
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |

### Historical Items
| Preferred Attribute Profile | Historical Items | Recommended Item | Explanation |
|-----------------------------|------------------|------------------|-------------|
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |

### Historical Items
| Preferred Attribute Profile | Historical Items | Recommended Item | Explanation |
|-----------------------------|------------------|------------------|-------------|
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |
| balance, running, shoes, corduory, half, skeskers, river, heuer, jacket, jeans, pendleton, asics, designer, ultra, long, armour, puma, ray, tissot, tough, lap, columba, sleeve, american, fila, originals, cut, weather, lite, men, athletic. | Dickies Men's Duck-Sanded Carpenter Jeans | We recommend you try this. |

Fig. 5. Examples of the explainable recommendation of the proposed DUPLE method. Each example displays a user’s historical preferred items, the preferred attribute profile summarized by DUPLE (the frontier position of the attribute means a bigger preference degree), and a recommended item with its explanations.

user’s preferences to the attribute Sci-fi are mutually exclusive with those to attributes Animation and Princess. These relationships uncovered by DUPLE also make sense. Overall, these observations demonstrate that the covariance matrix of one’s specific preference distribution is able to capture the relationships of the his/her preferences.

### 4.6 Explainable Recommendation (RQ4)
To evaluate the explainable ability of our proposed DUPLE, we first provided examples of our explainable recommendation in Subsection 4.6.1. And then, we conducted a subjective psycho-visual test to judge the explainability of the proposed DUPLE in Subsection 4.6.2.

#### 4.6.1 Explainable Recommendation Examples
Fig. 5 shows four examples of our explainable recommendation. Each example lists the user’s historical preferred items (we provide both images and
textual descriptions of items to facilitate readers to learn the user’s preferences), the summarized user’s preferred attribute profile by our proposed DUPLE, and a recommended item with the explanation. The users from the top to bottom in Fig. 5 are from the datasets Men’s Clothing, Women’s Clothing, Cell Phone & Accessories, and MovieLens-1M, respectively. The reason why we only provided the example in the dataset MovieLens-1M rather than all the three datasets MovieLens-small, MovieLens-1M, and MovieLens-10M, lies in that items in these three datasets are all movies. From Fig. 5, we have the following observations.

(1) The summarized users’ preferred attribute profiles in the center column are in line with the users’ historical preferences. For example, as for the first user, he has bought many sporty shoes and upper clothes, based on which we can infer that he likes sports and prefers the sporty style. These inferences are consistent with the preferred attributes DUPLE summarizes, e.g., DUPLE summarizes many brand of sports (skechers, asics, and columbia). In addition, as for the 4-th user, he/she has watched several animations like Iran Giant and Fairy Tales. DUPLE correctly captures the user’s preferences and summarizes his/her preferred attributes, including children’s, animation, and comedy.

(2) DUPLE is able to recommend the correct item and attach the reasonable explanations for the user. For example, the first user in Fig. 5 has bought many New Balance (i.e., a sports brand) shoes historically. DUPLE has recommended the similar shoes of this brand and attached the explanation of “The user like its attribute(s) Balance, Men, and Shoe”.

(3) It is worth noting that when the recommended item’s attributes have no overlap with the user’s preferred attribute profile, DUPLE cannot provide the explanation. For example, for the second user in Fig. 5, DUPLE recommends the “Crocs Women’s Sexi Flip Sandal” with no explanation. However, we found this recommended sandal is highly compatible with the dresses in the user’s historical interacted items, so that we can infer the user may also like this sandal, which is in a same style. Thus, the failure case of providing explanations may be because that this item is not recommended for the user according to his/her specific preference to item attributes, according to the general preference.

4.6.2 Subjective Psycho-visual Test. For the subjective psycho-visual test on judging the quality of the provided explanations of our DUPLE, we first designed a survey consisting of 12 questions (two questions from six dataset, respectively). Fig. 6 shows two question examples. As can be seen, each question consists of three parts: 6 items that a user historically likes, a new recommended item with explanations, and a judgment of the explanations. For each question, volunteers first learned the user’s preferences from the user’s historical items and then made their judgment on rationality of explanations (choose from “Reasonable”, “Not Sure”, or “Unreasonable”). Meanwhile, if volunteers chose “Not Sure”, or “Unreasonable”, we required them to write down their decision reasons in the blank behind the option.

In total, we invited 126 volunteers to finish the above subjective psycho-visual test. The statistical information of the invited volunteers is listed in Fig. 7 (a). The collected results of the psycho-visual test, shown in Fig. 7 (b), is representative for the public, as male and female volunteers distributed homogeneously and their age ranged widely. Besides, we provided two examples of the volunteer’s answers in Fig. 6 below the questions. Combining analyzing the survey results and answer examples, we have the following observations.

(1) Most volunteers (88%) thought the explanations produced by DUPLE are reasonable. This demonstrates that our proposed DUPLE method can correctly provide the explanation for recommending an item to a user.
The user historically likes these items.
We recommend this, because the user like its attributes Infinity, Multicolor, and Scarf.

Is the explanation reasonable?
- Reasonable
- Not Sure
- Unreasonable

Answer examples:
1. No. x volunteer (Male, 25~30)
   - Not Sure. Not sure about the multicolor.
2. No. x volunteer (Male, 25~30)
   - Reasonable.

We recommend this item, because the user like its attributes 1997, Action, Crime, and Thriller.

Is the explanation reasonable?
- Reasonable
- Not Sure
- Unreasonable

Answer examples:
1. No. x volunteer (Male, 18~24)
   - Not Sure. what is 1997 ?
2. No. x volunteer (Female, 18~24)
   - Unreasonable. 1997 shouldn’t be as explanation.

Fig. 6. Two example questions in the subjective psycho-visual survey, each of which consists of the user’s historical interacted items, a recommended item and explanation provided by DUPLE, and a judgment of the explanations. Two answers collected from volunteers are below the corresponding question, respectively.

(2) A few volunteers (5%) are not sure about the explanations. This may be because that sometimes volunteers can not derive the explicit cues in the user’s historical preferred items for the certain attribute in the explanations. For example, as for the top question in Fig. 6, some volunteers are not sure about explaining the recommended scarf with multicolor. This may be because multicolor has not explicitly appeared in the attributes of the user’s historical preferred items, while the user’s most historical preferred items are multi-color.

(3) 7% volunteers thought the explanations are unreasonable. A part of volunteers thought it is unreasonable to explain recommending a movie with its published year. For example, as for the (a) question in Fig. 6, DUPLE recommends the movie “Face Off” and explains that the user likes its attributes 1997. Besides, some volunteers thought certain attributes should be treated as a whole as the recommended reason. For example, as for the first example in Fig. 5, DUPLE explains the recommended shoes with its attribute Balance, while New Balance (a sports brand) should be treated as a whole.

5 CONCLUSION AND FUTURE WORK

We propose a dual preference distribution learning framework (DUPLE), which captures the user’s preferences from both the general item and specific attribute perspectives for a better recommendation. Different from existing approaches that represent the user and item as vectorized representations, DUPLE attempts to represent the user’s preferences with the Gaussian distribution and then predict the user-item interaction by calculating the probability density at the item in the...
user’s preference distribution. In this manner, DUPLE is able to explicitly model the relationships of the user’s different preferences by the covariance matrix of the Gaussian distribution. Besides, the proposed DUPLE method can summarize a preferred attribute profile, depicting the item attributes that the user likes, based on which we can provide the explanation for a recommendation. Quantitative and qualitative experiments have been conducted on six real-world datasets and the promising empirical results demonstrate the effectiveness and explainability of the proposed DUPLE.

Limitations of DUPLE include the two followings. 1) It is time-consuming that DUPLE learns a preference distribution to capture the user’s general and specific preferences, respectively, and we need to test the best trade-off parameter to combine the user’s general and specific preferences for different dataset. In the future, we plan to leverage a robust preference distribution that captures all user’s preferences to simplify the model. 2) The item attributes that collected from the high-frequency words of the text descriptions are still faulty, leading to adding noises into the specific preference learning of our proposed DUPLE. Thus, we plan to devise a attribute predictor that can automatically produce the attribute of an item from its text descriptions.

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