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Personalized Service Recommendation With Mashup Group Preference in Heterogeneous Information Network

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ABSTRACT In the service network, there exist various objects and rich relations among them. These various objects and rich relations naturally form a heterogeneous information network. Service recommendations can help users to locate their desired services. Previous service recommendation studies mainly aim at homogeneous networks or consider few kinds of relations rather than using the rich heterogeneous information. In this paper, we propose a mashup group preference-based service recommendation method in the heterogeneous information network for mashup creation. First of all, we analyze the historical invocation records between mashups and services and exploit the heterogeneous information to construct diverse meta paths with different semantic meanings. Then, we measure the similarity between the starting object and the ending object from different perspectives and integrate different similarity measures to obtain the hybrid similarity. Next, we introduce group preference to capture the rich interactions among mashups and apply a group preference-based Bayesian personalized ranking algorithm to learn the model. Finally, we recommend a list of personalized ranking services for mashup developers. A series of experiments conducted on a real-world dataset demonstrate the superiority of our proposed approach over other baseline approaches.

INDEX TERMS Heterogeneous information network, meta path, service recommendation, group preference.

I. INTRODUCTION

Mashups are a new type of Web applications that leverage contents coming from different data sources to create completely new and innovative services [1]. Mashups can accelerate the development process and reinforce scalability, since mashup can integrate existing services to generate novel or additional value-added services. Inspired by the economic benefits of mashups, a number of so-called mashup tools or mashup platforms, such as WireCloud,[1] Linked Widgets Platform,[2] and ProgrammableWeb,[3] have emerged on the Internet. These tools or platforms have significantly lowered the barriers to mashup development, and helped inexperienced service users easily assemble their own applications [2]. There have already been more than 20,000 services and more than 7,900 mashups on ProgrammableWeb until January 2019, and the number continues to grow. The exponential growth in the number of services results in an unparalleled large scope of choices on selecting services. Thus, it has become more difficult than ever to create novel mashup applications. In order to shorten the mashup development period, it becomes a significant challenge to effectively recommend mashup developers with appropriate services from the plenitude of services.

Some existing service recommendation investigations concentrate on social network based service recommendation [3]–[6]. They pay attention to recommending services

[1]https://wirecloud.readthedocs.io/en/latest/
[2]http://linkedwidgets.org/
[3]As the world's leading source of news and information about Internet-based application programming interfaces, ProgrammableWeb.com is known as the Web's defacto journal of the service economy. It publishes a repository of web services, mashups, and applications. Website: https://www.programmableweb.com/

to users via link prediction techniques from the perspective of complex social networks. However, the approaches based on social networks cannot always be applied to service recommendation in a very appropriate manner due to the limited field of application. Other research work focuses on Quality of Service (QoS) based service recommendation [7]–[10]. They first employ traditional collaborative filtering or matrix factorization methods to predict QoS values for services, and then recommend a high-quality service to users. However, the weakness of QoS based service recommendation approaches exists in two aspects: the QoS information is difficult to collect, and the QoS of services change over time and is subject to network environment. Apart from the two approaches mentioned above, semantics based service recommendation [11]–[14] is also a commonly adopted technique. Semantics based approaches tend to calculate the semantic similarity of two arbitrary services' description texts and recommend the service with higher semantic similarity. However, the shortcoming of the semantics based service recommendation approaches is the lack of variety in the type of exploitable data. Recently, most studies have transferred their attention to employ the information networks for service recommendation [15]–[17]. However, existing information network based approaches only utilize one or two related attributes of mashups/services and relationships between mashups/services. They do not consider the interactions among mashups and services, which highly limits the effect of these information networks based approaches.

Based on the above analysis, in this paper, we propose a novel model to recommend services to mashup developers by considering the mashup group preference and abundant semantic information. We first utilize the mashup information, the service information and the historical mashup-service invocation experience to build the heterogeneous information network. Then, we sample different semantic meanings of meta paths from the heterogeneous information network. Next, we exploit a hybrid similarity measurement to capture the rich interactions among mashups. In addition, we learn the model by leveraging the mashup group preference based Bayesian personalized ranking method. Finally, we employ the model to make personalized service recommendation for different mashup developers. Large amounts of experiments are carried out on a real-world dataset. The experimental results demonstrate that the model outperforms some other state-of-the-art approaches in terms of different kinds of evaluation metrics.

This paper is extended from its conference version [18]. The conference version is a two-page poster (extended abstract), which outlines the proposed approach, the framework of the GPSRec model and a part of experimental results. This paper expands contents and experiments. The main contributions of this paper are summarized as three folds:

- We propose the first mashup group preference based service recommendation approach for mashup creation by exploiting heterogeneous information network built with mashups, services and their related attributes.
- We specifically explore the historical invocation experience, the different semantic meanings of meta paths, the hybrid similarity measurement and the rich interactions among mashups. Further, we adopt a group preference based Bayesian personalized ranking algorithm to learn the recommendation model with implicit feedback data.
- We conduct various experiments on a real-world dataset crawled from ProgrammableWeb.com to validate the proposed approach. The experimental results demonstrate the effectiveness of the approach we propose and the significance of the factors we consider.

The rest of this paper is organized as follows. Section II presents background and preliminaries. Section III introduces the mashup group preference based service recommendation model. Section IV describes the experimental settings and empirical studies on the proposed approach. Related work is listed in Section V and a conclusion of the paper is drawn in Section VI.

II. BACKGROUND AND PRELIMINARIES

In this section, we introduce the background and preliminaries of this paper. First of all, the binary representation of mashup and service implicit feedback is introduced in Section II-A. Then, the definition of heterogeneous information network between mashups, services and their related attributes, and their network schema are presented in Section II-B. Finally, the meta path based hybrid similarity measurement is depicted in Section II-C and the problem description is given in Section II-D.

A. MASHUP-SERVICE IMPLICIT FEEDBACK

Let M and S be the set of mashups and services, respectively. With $|M|$ mashups and $|S|$ services, we define the mashup-service implicit feedback matrix $\mathcal{I} \in \mathbb{R}^{|M|\times|S|}$ as follows:

$$\mathcal{I}_{mi} = \begin{cases} 1, & \textit{if } (m, i) \textit{ interaction is observed}; \\ 0, & \textit{otherwise}. \end{cases} \tag{1}$$

We mainly take advantage of real historical invocation records between mashups and services to get feedback. The historical invocation records between mashups and services are crawled from ProgrammableWeb. Notice that the value 1 in the implicit feedback matrix $\mathcal{I}$ represents a positive feedback (mashups have been composed by services), while the value 0 represents a mixture of negative feedback (services are inappropriate for the composition of mashups) and unobserved potential interactions (mashups are unaware of such services).

B. HETEROGENEOUS INFORMATION NETWORK

A heterogeneous information network is a logical network comprising various kinds of objects and links denoting different relations among the objects [19]. The following definitions of the heterogeneous information network, the network schema and the meta path are from [19].

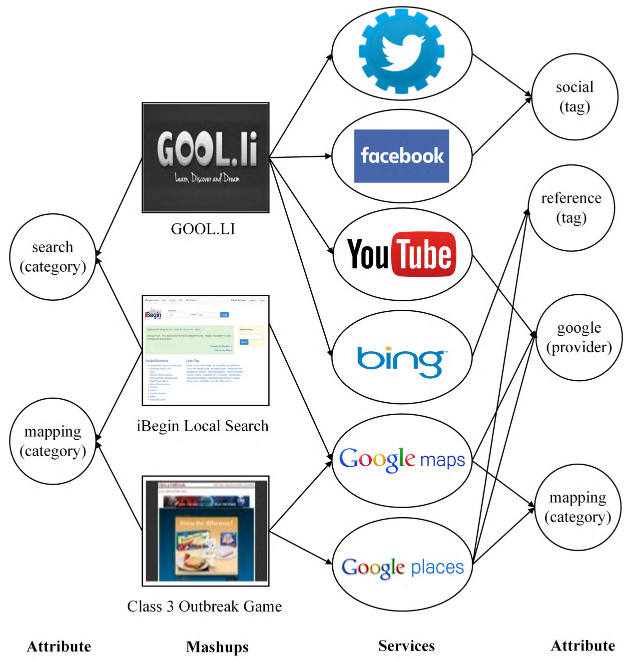

FIGURE 1. A toy example of heterogeneous information network in the scenario of service recommendation.

Definition 1 (Heterogeneous Information Network): An information network is denoted as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. It has two functions, i.e. $\Phi : \mathcal{V} \rightarrow \mathcal{A}$ and $\Psi : \mathcal{E} \rightarrow \mathcal{R}$, that perform object to object type mapping and link to relation type mapping, respectively. Unlike the traditional definition of network, we differentiate object categories and link categories in a heterogeneous network. While the objects categories $|\mathcal{A}| > 1$ or the links categories $|\mathcal{R}| > 1$, the network is called a *heterogeneous information network*.

An illustration of a small heterogeneous information network in the scenario of service recommendation is shown in Fig.1. It can be seen from Fig.1, there are various objects (e.g., search, mapping, Class 3 Outbreak Game, facebook, reference, google) and plenty of relations among these objects. For example, *Class 3 Outbreak Game*[4] and *iBegin Local Search*[5] are connected because they belong to the same category (*mapping*). *Twitter* and *facebook* are connected due to being labeled by the same tag (*social*). In addition, different meta paths between objects have diverse semantic meanings, which can be employed to measure the similarity between the objects. For instance, *google maps* and *google places* can be considered similar because they are provided by the same service provider (*google*). From another point of view, they are similar as they belong to the same category (*mapping*).

Definition 2 (Network Schema): The network schema $\mathcal{T}_{\mathcal{G}} = (\mathcal{A}, \mathcal{R})$ is a directed graph defined on object types $\mathcal{A}$, and relation types $\mathcal{R}$. Network schema identifies the number of object types in the network and where the links between these object types are located.

[4]http://www.class3outbreak.com/zombie-games/c3o/
[5]http://www.ibegin.com/

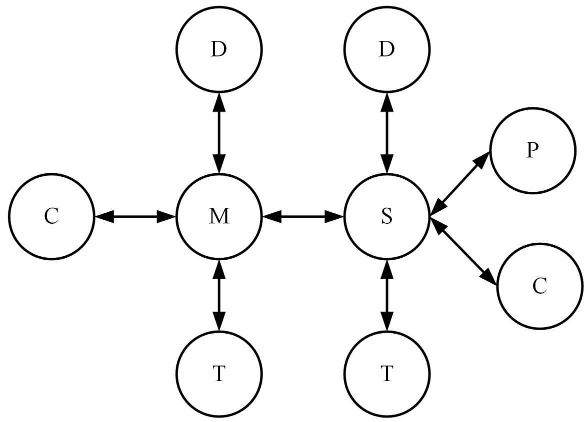

FIGURE 2. Network Schema of Service Network. M: mashup; S: service; D: description; T: tag; P: provider; C: category.

The network schema of our service network is shown in Fig.2. There are multiple types of objects, such as mashup, service, tag, category, description and provider. There are also multiple types of links, such as the compose and composed-by relation between services and mashups, describe and described-by relation between descriptions and mashups/services, label and labeled-by relation between tags and mashups/services, provide and provided-by relation between providers and services.

C. META PATH BASED SIMILARITY MEASUREMENT

Similarity measurement is the basis of our GPSRec model. Two objects can be connected via different meta paths representing diverse semantic meanings. The meta path is defined as follows.

Definition 3 (Meta Path): A meta path $\mathcal{P}$ is defined on the network schema $\mathcal{T}_{\mathcal{G}} = (\mathcal{A}, \mathcal{R})$, where nodes are objects types $\mathcal{A}$ and edges are links $\mathcal{R}$ between object types. It is represented following the template of $\mathcal{A}_1 \xrightarrow{\mathcal{R}_1} \mathcal{A}_2 \xrightarrow{\mathcal{R}_2} \cdots \xrightarrow{\mathcal{R}_l} \mathcal{A}_{l+1}$. The form is denoted as a composite relation $\mathcal{R} = \mathcal{R}_1 \bowtie \mathcal{R}_2 \bowtie \cdots \bowtie \mathcal{R}_l$ between type $\mathcal{A}_1$ and $\mathcal{A}_{l+1}$, where $\bowtie$ represents the composite operator on relations.

In service network, two objects associate with each other via paths of diverse semantic meanings. We use eight meaningful meta paths whose length are not longer than four, since the longer meta paths are not meaningful and they cannot bring about good similarity measure [19]. The eight kinds of meta paths in our service network are presented in Fig.3. Each meta path has a distinct semantic meaning. For instance, "M-C-M" (Mashup-Category-Mashup) means that the starting mashup belongs to the same category with the ending mashup. "M-S-P-S-M" (Mashup-Service-Provider-Service-Mashup) means that the starting mashup is composed by the services offered by the same providers with that of the ending mashup. "M-S-T-S-M" (Mashup-Service-Tag-Service-Mashup) represents that the starting mashup is composed by the services which are labeled by the same tags with that of the ending mashup. It is worth noting that the

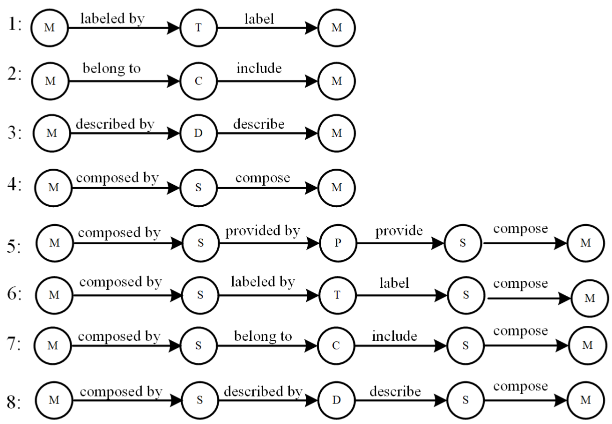

FIGURE 3. Diverse meta paths.

topics are extracted from descriptions by exploiting Latent Dirichlet Allocation [20]. Two services or mashups are connected through these topics.

We focus on measuring the similarity between two objects x and y following a given meta path from different aspects. In the following, we will introduce these similarity measures in detail.

- **Path Count (PC)**. Given a meta path $\mathcal{P}$, path count calculates the similarity between any two objects by considering the amount of path instances p between them, which is denoted as:
$$S_{PC}(x, y) = |p : p \in \mathcal{P}|, \tag{2}$$
- **Normalized Path Count (NPC)**. Normalized path count rebates the amount of path instances between two objects by their entire connectivity, and is defined as:
$$S_{NPC}(x, y) = \frac{S_{PC}(x, y) + S_{PC}(y, x)}{S_{PC}(x, \cdot) + S_{PC}(\cdot, y)}, \tag{3}$$
where $S_{PC}(x, \cdot)$ is the total number of path instances following $\mathcal{P}$ starting with x, and $S_{PC}(\cdot, y)$ is the total number of path instances following $\mathcal{P}$ ending with y.
- **Random Walk (RW)**. Random walk measures the probability that starts from x and ends with y along a given meta path $\mathcal{P}$. It is defined as:
$$S_{RW}(x, y) = \frac{S_{PC}(x, y)}{S_{PC}(x, \cdot)}, \tag{4}$$
- **Symmetric Random Walk (SRW)**. Symmetric random walk takes into account the random walk from the forward and reverse directions along a given meta path $\mathcal{P}$, and is defined as:
$$S_{SRW}(x, y) = S_{RW}(x, y) + S_{RW}(y, x), \tag{5}$$

After obtaining the four kinds of similarities, the hybrid similarity s_{mn}^l of mashup m and n under a meta path $\mathcal{P}_l$ can be calculated as follows:

$$s_{mn}^l = \alpha \cdot S_{PC}^l(m, n) + \beta \cdot S_{NPC}^l(m, n) + \gamma \cdot S_{RW}^l(m, n) + \delta \cdot S_{SRW}^l(m, n) \tag{6}$$

where $\alpha, \beta, \gamma, \delta$ are the weights for different kinds of similarity measurement, and $\alpha + \beta + \gamma + \delta = 1$.

D. PROBLEM DESCRIPTION

Given a heterogeneous information network $\mathcal{G}$ with mashup-service implicit feedback matrix $\mathcal{I}$, for a mashup m, we aim to build a personalized recommendation model for m, and recommend a ranked list of services that are of interest to m.

III. GROUP PREFERENCE BASED SERVICE RECOMMENDATION MODEL

In this section, we will describe our mashup group preference based service recommendation model in detail. First of all, we introduce two kinds of mashup preferences in Section III-A. Then, we describe the framework of the GPSRec model in Section III-B. Finally, we present the model learning algorithm in Section III-C.

A. MASHUP PREFERENCE

We describe the representation of two types of preference in the following, namely, a mashup's relative preference on a service and a group of mashups' relative preference on a service.

Definition 4 (Mashup Individual Preference): The mashup individual preference is represented as a mashup's preference score on a service. For example, the individual preference of mashup m on service i is denoted as r_{mi}.

By integrating the four aforementioned similarity measures (e.g., path count, normalized path count, random walk, symmetric random walk), we can obtain the hybrid similarity between mashups under a given meta path. Referring to the idea of collaborative filtering, the preference score of the target mashup on a service can be inferred from the preference scores of its similar mashups on the service. Given a meta path $\mathcal{P}_l$, the individual preference score of a mashup m on a service i, denoted as r_{mi}^l can be calculated as follows,

$$r_{mi}^l = \sum_{n \in T_m(k) \cap C(i)} s_{mn}^l \cdot r_{ni}, \tag{7}$$

where $T_m(k)$ is a set of k mashups that are most similar with mashup m, $C(i)$ denotes a set of mashups invoking service i, s_{mn}^l is the hybrid similarity of mashup m and n under the meta path $\mathcal{P}_l$, and r_{ni} denotes the preference score of mashup n on service i, $r_{ni} = 1$. It is worth noting that we aim to recommend the services that mashup n invokes to mashup m. Therefore, mashup n must invoke service i so that the feedback between mashup n and service i is 1. By applying Equation (7) to all kinds of L meta paths, we can obtain the overall individual preference score of a mashup m on a service i. Note that different meta paths have diverse semantic meanings, thus weights of these meta paths may be different. For instance, mashup developers may prefer certain services due to their providers rather than their tags. Based on the above analysis, the final individual preference score of mashup m on service

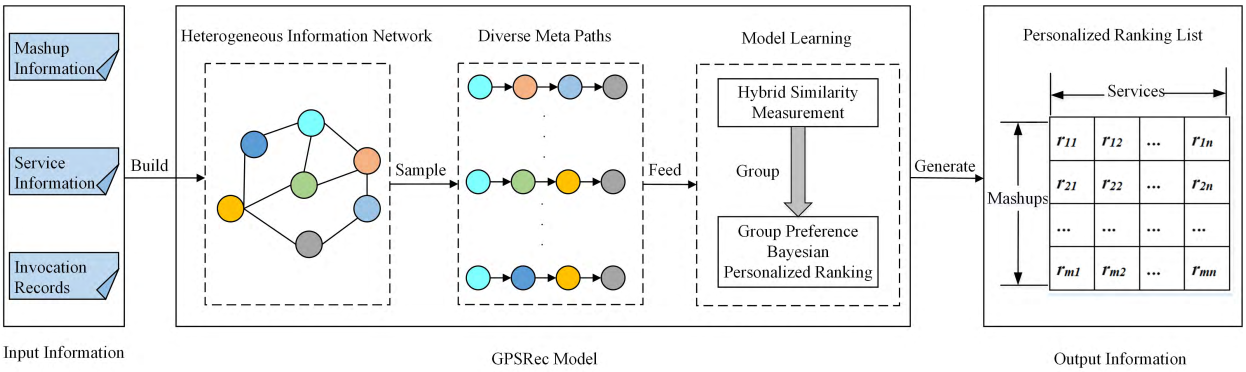

FIGURE 4. **Architecture of GPSRec.**

i under all meta paths can be calculated as follows,

$$r_{mi} = \sum_{l=1}^{L} \theta^l \cdot r_{mi}^l, \tag{8}$$

where θ^l denotes the weight for the individual preference score of a mashup m on a service i under a given meta path $\mathcal{P}_l$.

The drawback of mashup individual preference is its assumption that mashups are independent of each other. In reality, however, interactions and collaborations among mashup developers who are all with positive feedback on a specific service also contain useful information, implying common interests of them. Thus, the mashup group preference is used to obtain the rich interactions among mashup developers.

Definition 5 (Mashup Group Preference): The mashup group preference is represented as a group of mashups' preference score on a service. For example, the group preference of mashups from group G on service i is denoted as r_{Gi}. The mashup group preference can be estimated from mashup individual preference,

$$r_{Gi} = \frac{1}{|G|} \sum_{m \in G} r_{mi}, \tag{9}$$

To better comprehend our GPSRec model, we introduce the framework of our service recommendation model in the next subsection.

B. FRAMEWORK OF OUR SERVICE RECOMMENDATION MODEL

In this section, we give an overview of our GPSRec framework. As can be seen in Fig.4, our framework consists of three parts: Input Information, GPSRec Model, Output Information. Each part is elaborated as follows:

- Input Information. Mashup information (e.g., name, tag, category, description), service information (e.g., name, tag, category, description, provider) and historical interaction logs between mashups and services are treated as input parameters for the GPSRec model.
- GPSRec Model. After a range of input data preprocessing, mashups, services and their related attributes are first to compose a heterogeneous information network. Then, different types of meta paths are sampled from the heterogeneous information network. Mashups connect with each other through the eight types of meta paths representing various semantic meanings. Next, the diverse meaningful meta paths between mashups are fed to the part of model learning. A hybrid similarity measurement is leveraged to measure the similarity between mashups by combining four kinds of similarity measurement methods. Finally, a group preference based Baysesian personalized ranking algorithm [21] is employed to rank pairwise mashup-service.
- Output Information. After the procedure of GPSRec model learning and solving, a personalized ranked list of services are recommended to users.

C. MODEL LEARNING

In this section, we apply the group preference based Bayesian personalized ranking algorithm to learn our model.

In probability theory, Bernoulli distribution is usually used to calculate the probability of binary random variable. In our mashup-service implicit feedback matrix, $\mathcal{I}_{mi}$ is either 1 or 0 depending on whether or not an interaction is observed between mashup m and service i. Therefore, we assume that the pairwise preferences obey Bernoulli distribution. Then, for a service i, the overall likelihood (OL) of pairwise preferences among all mashups is,

$$\begin{aligned} OL(i) &= \prod_{m,n \in M} Pr(r_{mi} > r_{ni})^{\delta((m,i) \succ (n,i))} \\ &\quad \times [1 - Pr(r_{mi} > r_{ni})]^{[1-\delta((m,i) \succ (n,i))]} \\ &= \prod_{(m,i) \succ (n,i)} Pr(r_{mi} > r_{ni}) \prod_{(m,i) \preceq (n,i)} [1 - Pr(r_{mi} > r_{ni})] \\ &\approx \prod_{(m,i) \succ (n,i)} Pr(r_{mi} > r_{ni}) \prod_{(m,i) \prec (n,i)} [1 - Pr(r_{mi} > r_{ni})] \\ &= \prod_{(m,i) \succ (n,i)} Pr(r_{mi} > r_{ni})[1 - Pr(r_{ni} > r_{mi})], \end{aligned} \tag{10}$$

where $(m, i) \succ (n, i)$ and $(m, i) \prec (n, i)$ denote that service i is more and less appropriate to compose mashup m than mashup n, respectively. $\delta(x)$ denotes an indicator function,

$$\delta(x) = \{ \begin{matrix} 1 & if\ x\ is\ true, \\ 0 & otherwise \end{matrix} \tag{11}$$

Base on the above overall likelihood of pairwise preferences, the Bayesian personalized ranking (BPR) formulation [22] of mashup individual preference for a service i is:

$$BPR(i) = \prod_{m \in M_+} \prod_{n \in M_-} Pr(r_{mi} > r_{ni}) \times [1 - Pr(r_{ni} > r_{mi})], \tag{12}$$

where M_+ is the set of mashups that have positive feedback on service i, $M_- = M \setminus M_+$ is the set of mashups that have not observed service i.

We assume that the mashup group preference G on a service i is more likely to be stronger than the mashup individual preference m on service i, which can be written as $(G, i) \succ (m, i)$. To investigate the impact of mashup group preference and mashup individual preference in a unifying manner, we integrate them linearly,

$$r_{Gmi} = \rho r_{Gi} + (1 - \rho) r_{mi}, \tag{13}$$

where, r_{Gmi} is the combined preference of mashup group preference r_{Gi} and mashup individual preference r_{mi}. Note that $0 \leq \rho \leq 1$ is a tradeoff parameter to combine the two kinds of preferences. The combined preference is stronger than the individual preference, namely, $(G, i) + (m, i) \succ (n, i)$ or $r_{Gmi} > r_{ni}$.

With the above assumptions and the mashup group preference based Bayesian personalized ranking, the formulation of our GPSRec model for a service i is as follows:

$$GPSRec(i) = \prod_{m \in M_+} \prod_{n \in M_-} Pr(r_{Gmi} > r_{ni}) \times [1 - Pr(r_{ni} > r_{Gmi})], \tag{14}$$

where $G \in M_i$, M_i represents the set of mashups sharing the same feedback on service i.

For any two services, i and j, the joint likelihood can then be approximated via multiplication,

$$GPSRec(i, j) \approx GPSRec(i) GPSRec(j), \tag{15}$$

Then, we can obtain the following overall likelihood for all services,

$$GPSRec = \prod_{i \in S} \prod_{m \in M_+} \prod_{n \in M_-} Pr(r_{Gmi} > r_{ni}) \times [1 - Pr(r_{ni} > r_{Gmi})], \tag{16}$$

Following [22], we introduce the sigmoid function σ to formulate $Pr(.)$,

$$\begin{aligned} Pr(r_{Gmi} > r_{ni}) &= \sigma(r_{Gmi} - r_{ni}), \\ Pr(r_{ni} > r_{Gmi}) &= \sigma(r_{ni} - r_{Gmi}), \end{aligned} \tag{17}$$

where the sigmoid function σ is in the form of:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{18}$$

Next, Equation (16) can be represented as:

$$\begin{aligned} GPSRec &= \prod_{i \in S} \prod_{m \in M_+} \prod_{n \in M_-} \sigma(r_{Gmi} - r_{ni}) \\ &\quad [1 - \sigma(r_{ni} - r_{Gmi})] \\ &= \prod_{i \in S} \prod_{m \in M_+} \prod_{n \in M_-} \sigma^2(r_{Gmi} - r_{ni}), \end{aligned} \tag{19}$$

Furthermore, we add an L2 regularization term to the objective function to avoid overfitting. Therefore, the final objective function of our GPSRec model is as follows,

$$\begin{aligned} L(\theta) &= -\frac{1}{2} \ln GPSRec + \frac{1}{2} \lambda \|\theta\|_2^2 \\ &= -\sum_{i \in S} \sum_{m \in M_+} \sum_{n \in M_-} \ln \sigma(r_{Gmi} - r_{ni}) + \frac{1}{2} \lambda \|\theta\|_2^2, \end{aligned} \tag{20}$$

where $\theta = \{\theta^1, \cdots, \theta^L\}$ is a set of model parameters to be learned, i.e., the weight of L meta paths. λ is a model specific regularization parameter. The model parameters can be learned from implicit feedback data by minimizing the objective function.

As Equation (20) is differentiable, stochastic gradient descent (SGD) [23] is a good choice to learn the parameters for evaluation. SGD is a widely used optimal method in machine learning and deep learning. It adopts an iterative strategy to update model parameters until convergence. It starts from the initial point and moves one distance at a time along the current point's negative gradient direction of the objective function. The gradient of Equation (20) with respect to θ is:

$$\begin{aligned} \frac{\partial L(\theta)}{\partial \theta} &= -\sum_{i \in S} \sum_{m \in M_+} \sum_{n \in M_-} \frac{\partial}{\partial \theta} \ln \sigma(r_{Gmni}) + \frac{1}{2} \lambda \frac{\partial}{\partial \theta} \|\theta\|_2^2 \\ &= -\sum_{i \in S} \sum_{m \in M_+} \sum_{n \in M_-} \frac{e^{-r_{Gmni}}}{1 + e^{-r_{Gmni}}} \frac{\partial}{\partial \theta} r_{Gmni} + \lambda \theta, \end{aligned} \tag{21}$$

where $r_{G_{mni}} = r_{Gmi} - r_{ni}$.

After obtaining the gradient, the model parameters can be updated as:

$$\theta = \theta - \eta \frac{\partial L(\theta)}{\partial \theta}, \tag{22}$$

where η is the learning rate.

Notice that the calculation and combination of similarity measurement for the GPSRec model can be done offline. The major time consumption lies in the process of model learning. Therefore, the time complexity of the proposed approach is $O(|M|^2|S||L||G|)$, where $|M|$ is the number of mashups, $|S|$ is the number of services, $|L|$ is the number of built meta paths, and $|G|$ is the size of mashup group which is usually small (e.g., $|G| = 3$ in our experiments).

TABLE 1. Statistics of service dataset.

Statistics	Values
Number of Mashups	6958
Number of Mashup Categories	373
Number of Mashup Tags	2089
Number of Services	1272
Number of Service Categories	60
Number of Service Tags	975
Number of Service Providers	970

IV. EMPIRICAL EVALUATION

In this section, we carry out a series of experiments to answer the following research questions:

- **RQ1.** Is the hybrid similarity measurement really useful to enhance the recommendation results ?
- **RQ2.** Is adding more related attributes and considering the rich interactions among mashups helpful in improving the recommendation performance ?
- **RQ3.** How efficient is GPSRec ?
- **RQ4.** How large should the group size be ?
- **RQ5.** How to choose a learning rate ?
- **RQ6.** Is mashup group preference more effective than mashup individual preference ?

All experiments are conducted on a computer with 32GB memory running on Windows 10 64 bit.

A. DATASET DESCRIPTION

In our experiments, the real-world dataset is crawled from ProgrammableWeb in the range from June 2005 to December 2013. There are a total of 6958 mashups, 1272 services and 14731 interactions between mashups and services in our dataset. The density of the dataset is $\frac{\#interactions}{\#mashups \times \#services} = 0.167\%$. The detailed statistics of the dataset are shown in Table 1. If a mashup invokes a service, which means we observed the mashup-service interaction, we set this feedback as 1; otherwise, we set it as 0.

B. EVALUATION METRICS

Herein, we use four metrics (e.g., Recall, Precision, Mean Reciprocal Rank (MRR) [24], Normalized Discounted Cumulative Gain (NDCG) [25]) to evaluate the performance of our approach. The detailed formulas of these metrics are as follows:

$$Recall = \frac{1}{|M|}\sum_{m\in M}\frac{|\Gamma(m)\cap\Phi(m)|}{|\Phi(m)|}, \tag{23}$$

$$Precision = \frac{1}{|M|}\sum_{m\in M}\frac{|\Gamma(m)\cap\Phi(m)|}{|\Gamma(m)|}, \tag{24}$$

$$MRR = \frac{1}{|M|}\sum_{m\in M}(\sum_{i\in\Phi(m)}\frac{1}{\Psi(m,i)}), \tag{25}$$

$$DCG_m = p_m(1) + \sum_{k=2}^{N_m}\frac{p_m(k)}{\log_2 k}, \tag{26}$$

$$NDCG = \frac{1}{|M|}\sum_{m\in M}\frac{DCG_m}{1+\sum_{k=2}^{N_m^+}\frac{1}{\log_2 k}} \tag{27}$$

where $\Gamma(m)$ is the services' recommendation result list, $\Phi(m)$ is a list of services that have been invoked by mashup m in the testing set, $\Psi(m, i)$ represents the position of service i in the recommended list for mashup m. DCG_m is the DCG value for mashup m. $p_m(k)$ is the score of the service in the kth ranking position rated by mashup m. N_m is the number of services in the testing set, and N_m^+ is the number of services in the testing set that mashup m has positive feedback.

In the following subsections, we aim to answer the 6 research questions. For each question, 50% of the historical invocation records are set as training data, and the rest are used as testing data. In addition, we vary the training data density from 10% to 90% to adapt the GPSRec model for different data sparsity. The settings of other parameters will be elaborated in each subsection.

C. RQ1: IS THE HYBRID SIMILARITY MEASUREMENT REALLY USEFUL TO ENHANCE THE RECOMMENDATION RESULTS ?

1) STUDY SETUP

To address this research question, we compare the performance of hybrid similarity measurement with other four similarity measurements (i.e., PC, NPC, RW and SRW). The hybrid similarity computation between mashups is based on the weighted summation of the four different similarity measurement methods. Weights can be determined via empirically testing a validation set. The weights of PC, NPC, RW, SRW are set to 0.4, 0.3, 0.2, 0.1, respectively. In this experiment, the training data density is set as 50%. The learning rate, group size and weight of mashup group preference are set as 0.0001, 3 and 0.7, respectively.

2) RESULTS

The comparison between all similarity measurement methods is shown in Table 2. It could be found that the hybrid similarity measurement outperforms the other four similarity measurement methods steadily in all top recommendation results and evaluation metrics. This observation shows that measuring similarity from different aspects is indeed helpful in improving the recommendation results.

D. RQ2: IS ADDING MORE RELATED ATTRIBUTES AND CONSIDERING THE RICH INTERACTIONS AMONG MASHUPS HELPFUL IN IMPROVING THE RECOMMENDATION PERFORMANCE ?

1) STUDY SETUP

To tackle this research question, we compare the performance of GPSRec with other three approaches (i.e., NPC (6 meta paths), NPC (8 meta paths) and Hybrid (8 meta paths)). Types of 6 meta paths and 8 meta paths are presented in Table 3. The details of the other three approaches are as follows:

- NPC (6 meta paths): It uses NPC to measure the similarity between any two mashups, and considers 6 kinds

TABLE 2. Comparison between all similarity methods.

Top-N	Methods	Recall	Precision	MRR	NDCG
Top-3	PC	0.4892	0.2543	0.5197	0.5074
	NPC	0.5709	0.2956	0.6346	0.6106
	RW	0.3963	0.2067	0.4634	0.4605
	SRW	0.5197	0.2706	0.6097	0.5879
	Hybrid	**0.6072**	**0.3208**	**0.6722**	**0.6387**
Top-5	PC	0.6000	0.1966	0.5700	0.5521
	NPC	0.6362	0.2061	0.6681	0.6286
	RW	0.4759	0.1536	0.4966	0.4921
	SRW	0.5855	0.1900	0.6413	0.6095
	Hybrid	**0.6935**	**0.2338**	**0.7195**	**0.6590**
Top-10	PC	0.7233	0.1245	0.6058	0.5822
	NPC	0.7076	0.1204	0.6913	0.6388
	RW	0.6120	0.1025	0.5312	0.5284
	SRW	0.6840	0.1167	0.6700	0.6241
	Hybrid	**0.7668**	**0.1354**	**0.7449**	**0.6701**

TABLE 3. Types of meta paths.

Number of meta paths	Types of meta paths
6 meta paths	M-S-M, M-T-M, M-D-M, M-S-C-S-M, M-S-D-S-M, M-S-P-S-M
8 meta paths	M-S-M, M-T-M, M-D-M, M-S-C-S-M, M-S-D-S-M, M-S-P-S-M, M-C-M, M-S-T-S-M

of meta paths. Then, it uses a Bayesian personalized ranking algorithm to learn the weights of every meta path. Finally, it recommends the ranked list of services for mashup creation.

- NPC (8 meta paths): It also applies NPC to measure the similarity between mashups, and builds 8 kinds of meta paths. Then, it utilizes a Bayesian personalized ranking algorithm to learn the weights of every meta path. Further, the personalized ranking services are recommended to mashup developers.
- Hybrid (8 meta paths): It exploits the hybrid similarity measurement method and designs 8 types of meta paths. Then, it employs a Bayesian personalized ranking algorithm to learn model parameters. Lastly, a set of ranked services are provided to mashup developers for service selection.

2) RESULTS

The performance comparison between the number of meta paths, hybrid similarity and mashups' interactions are shown in Fig.5. It can be seen that when the number of meta paths is larger, we can obtain higher Recall, Precision, MRR, and NDCG values. That is to say, the performance of NPC (8 meta paths) is better than NPC (6 meta paths). The observation indicates that adding more related attributes of mashup/service is good to enhance the recommendation performance. Moreover, the performance of Hybrid (8 meta paths) is better than NPC (8 meta paths), and this further demonstrates that measuring the similarity between mashups from different aspects is useful to make better recommendations. Further, the performance of GPSRec is also better than that of Hybrid (8 meta paths), implying the consideration

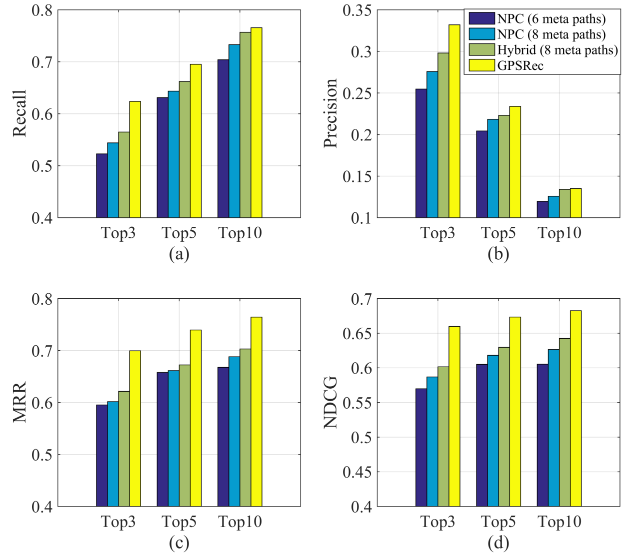

FIGURE 5. The performance comparison between number of meta paths, hybrid similarity and mashups' interactions.

of the rich interactions among mashups is indeed helpful in improving the recommendation performance.

E. RQ3: HOW EFFICIENT IS GPSREC ?

1) STUDY SETUP

To answer this research question, we compare our approach with the following approaches:

- POPRank. This approach employs the popularity of services in mashups' invoking list to rank services for mashups [26].
- SVD (singular value decomposition). This approach is a traditional matrix factorization technique in recommender systems [27].
- BPRKNN. This approach employs K-Nearest Neighbor (KNN) to measure the similarity and uses a Bayesian personalized ranking algorithm to learn the model with implicit feedback data.
- BPRSVD. This approach employs SVD and uses a Bayesian personalized ranking algorithm to learn the model with implicit feedback data, which is proposed in [22].
- PaSRec. This approach employs different types of meta paths in service related heterogeneous information network. It uses a Bayesian personalized ranking algorithm to learn the weights of meta paths, and recommends a set of services for mashup creation [17].

Moreover, the training data density is an important factor to impact the performance of service recommendation. It represents how much mashups information, services information, and their invocation information is utilized. In order to study the impact of training data density, we vary the training data density from 10% to 90% and randomly select 10% of the remaining data to test the performance. Furthermore, the weight of the regularization term λ and the learning rate

TABLE 4. Recommendation performance comparison.

Top-N	Methods	Recall	Precision	MRR	NDCG
Top-3	BPRKNN	0.1348	0.0706	0.1174	0.1360
	SVD	0.1499	0.0951	0.1699	0.1800
	BPRSVD	0.2394	0.1301	0.2687	0.2820
	PoPRank	0.2398	0.1306	0.2724	0.2852
	PaSRec	0.5648	0.2981	0.6214	0.6015
	GPSRec	**0.6072**	**0.3208**	**0.6722**	**0.6387**
	Improvement	7.51%	7.63%	8.18%	6.18%
Top-5	BPRKNN	0.1882	0.0641	0.1422	0.1683
	SVD	0.2888	0.1009	0.2188	0.2496
	BPRSVD	0.3119	0.1074	0.3014	0.3195
	PoPRank	0.3100	0.1048	0.3029	0.3213
	PaSRec	0.6621	0.2231	0.6723	0.6296
	GPSRec	**0.6935**	**0.2338**	**0.7195**	**0.6590**
	Improvement	4.75%	4.81%	7.03%	4.67%
Top-10	BPRKNN	0.2514	0.0467	0.1618	0.1942
	SVD	0.4200	0.0711	0.2470	0.2957
	BPRSVD	0.4118	0.0701	0.3234	0.3543
	PoPRank	0.4169	0.0714	0.3289	0.3590
	PaSRec	0.7567	0.1341	0.7030	0.6424
	GPSRec	**0.7668**	**0.1354**	**0.7449**	**0.6701**
	Improvement	1.33%	1.00%	5.96%	4.31%

η are set as 0.001 and 0.0001 for the best performance. The parameters of other state-of-the-art baseline methods are set with the best performance.

2) RESULTS

In order to demonstrate the experimental results explicitly, we present the comparison results between all methods in Table 4. In addition, the training data density and testing data density are set as 50%. It could be found in Table 4, our GPSRec model outperforms the other five baseline methods in terms of four metrics (e.g., Recall, Precision, MRR and NDCG). Compared with PaSRec, the GPSRec model can obtain 6.18% to 8.18% improvement of Top-3 recommendation, 4.67% to 7.03% improvement of Top-5 recommendation and 1.00% to 5.96% improvement of Top-10 recommendation.

The overall performance comparison results under all training data densities are presented in Fig.6, Fig.7 and Fig.8. It can be seen from the three figures, our GPSRec model always achieves the best performance under all percentages of training data. Concretely, BPRKNN presents the worst performance among all the approaches, because it simply ignores useful information such as network information and description information. Next, the performances of SVD and BPRSVD are better than BPRKNN due to the consideration of the latent factors of mashups and services. Moreover, BPRSVD achieves better performance than SVD, since BPRSVD introduces the concept of pairwise ranking and utilizes BPR to learn the model with implicit feedback data. POPRank outperforms BPRSVD for the reason that mashup developers tend to use prevalent services. PaSRec attains better performance than the aforementioned four baseline approaches owing to leveraging the heterogeneous information to obtain rich semantics. By considering more properties of the service network, measuring the similarities between

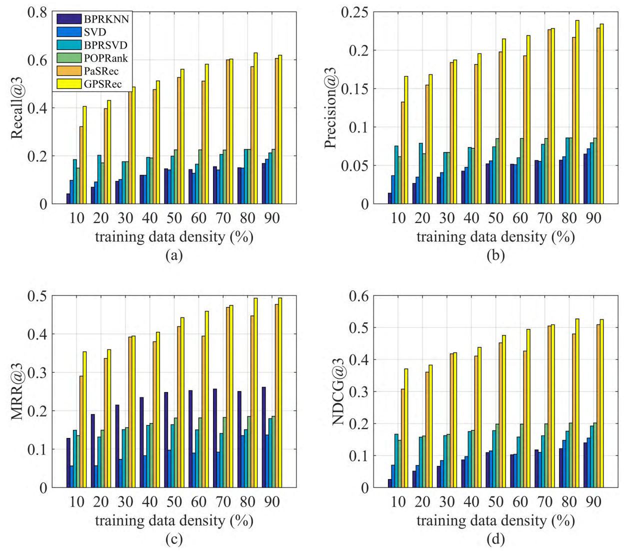

FIGURE 6. Impact of density (Top-3).

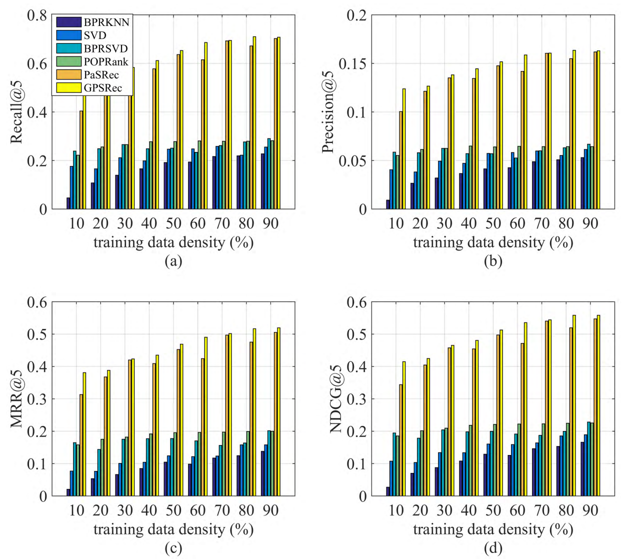

FIGURE 7. Impact of density (Top-5).

mashups from different perspectives, and introducing the rich interactions among mashups, the performance of our GPSRec model is better than PaSRec.

F. RQ4: HOW LARGE SHOULD THE GROUP SIZE BE ?

As mentioned before, the mashup group preference is used to capture rich interactions between mashups. The group size affects the intensity of mashup interactions in our GPSRec model. Therefore, the question (i.e., how large should the group size be) needs to be studied.

1) STUDY SETUP

To answer this research question, we conduct an experiment on determining the optimal size of mashup group $|G|$. We vary the size of mashup group from 2 to 10 with a

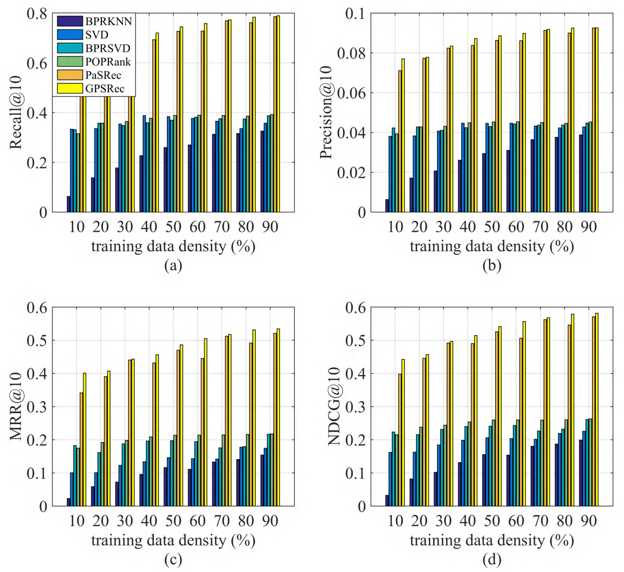

FIGURE 8. Impact of density (Top-10).

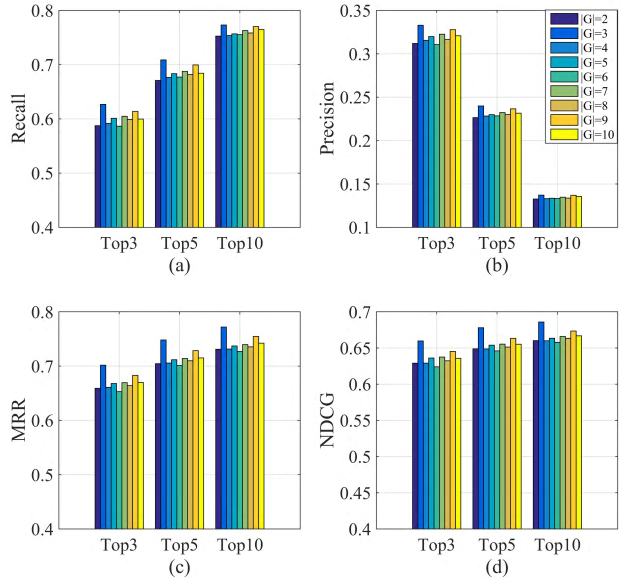

FIGURE 9. Impact of group size.

step value of 1. In addition, the training data density and the weight of mashup group preference are set as 50% and 0.7 respectively in this experiment.

2) RESULTS

Figure 9 presents the results of group size determination. When changing $|G|$ from 2 to 10, the Recall, Precision, MRR and NDCG values are first increasing and then decreasing. We can obtain the best performance at $|G| = 3$. The reason for this phenomenon is that when the group size is too small, GPSRec could not distinguish mashup preference very well. While an oversized mashup group could lead to training data deficiency, and thus lead to performance decreasing. That means using a relatively small mashup group improves the recommendation performance.

G. RQ5: HOW TO CHOOSE A LEARNING RATE ?

The learning rate determines the speed of updating the weights. If it is set too large, the training may make the result exceed the optimal value and not converge. If it is set too small, the optimization process will take a long time due to the too slow descent rate. Therefore, choosing an appropriate learning rate is pivotal.

1) STUDY SETUP

To tackle this research question, we vary the learning rate from 0.000001 to 1.0. In addition, the training data density, the group size and the weight of mashup group preference are set as 50%, 3 and 0.7 respectively in this experiment.

2) RESULTS

Figure 10 shows the effects of learning rate on performance. When varying η from 0.000001 to 1.0, the Recall, Precision, MRR and NDCG values increase at the beginning, and start to decrease thereafter. The best performance under all

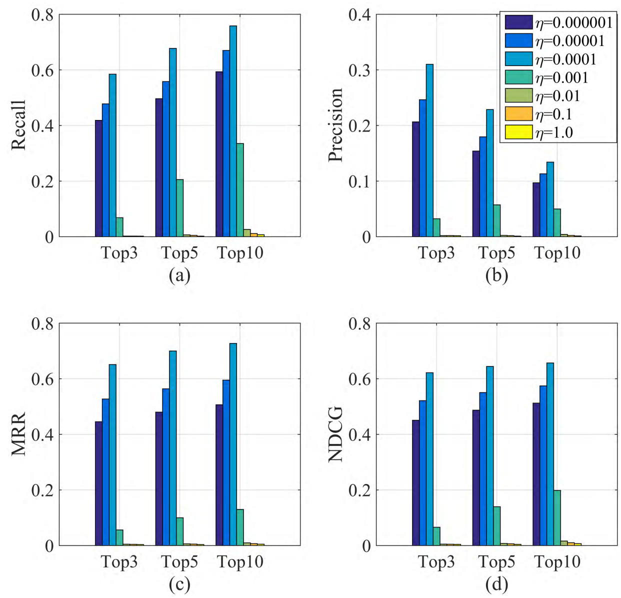

FIGURE 10. Impact of learning rate.

evaluation metrics is achieved at $\eta = 0.0001$. The observation indicates that a relatively small learning rate is good for enhancing the recommendation results.

H. RQ6: IS MASHUP GROUP PREFERENCE MORE EFFECTIVE THAN MASHUP INDIVIDUAL PREFERENCE ?

1) STUDY SETUP

To address this research question, we treat ρ as a parameter to study the effectiveness of mashup group preference and mashup individual preference. ρ determines the weight of two preferences. In order to study the impact of ρ, we vary the weight of mashup group preference from 0.1 to 1.0 with a step value of 0.1. In addition, the learning rate, the size of mashup

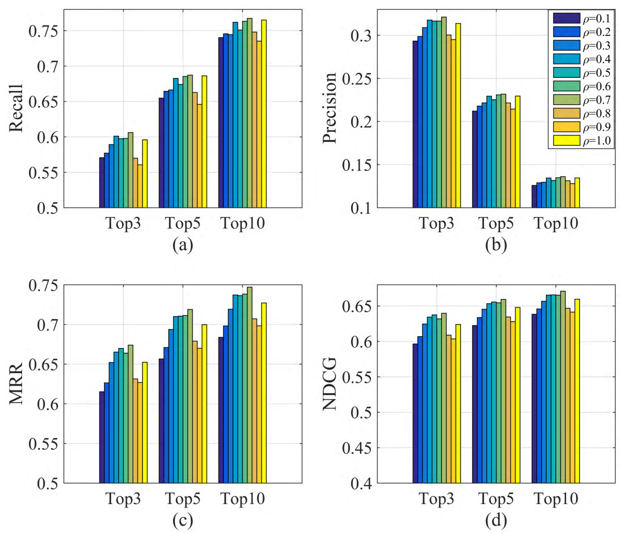

FIGURE 11. Impact of the weight of mashup group preference.

group and the training data density are correspondingly set as 0.0001, 3 and 50% in this experiment.

2) RESULTS

As presented in Fig.11, GPSRec performs differently with different weights of mashup group preference and mashup individual preference. When increasing ρ from 0.1 to 1.0, it exhibits an upward trend followed by a downward trend. We can obtain the highest Recall, Precision, MRR and NDCG value at $\rho = 0.7$, which demonstrates the weight of mashup group preference is larger than that of mashup individual preference. This signifies that mashup group preference is indeed more effective than mashup individual preference.

V. RELATED WORK

Currently, most of the research work in service recommendation has focused on semantics based service recommendation, QoS based service recommendation, social network based service recommendation and information network based service recommendation. In the following, we will discuss them separately and present some of the representative work.

The semantics based service recommendation approaches tend to calculate the semantic similarity of services' description texts and recommend services with higher semantic similarity to users. Yao *et al.* [11] proposed a novel approach that unified collaborative filtering and content-based recommendations. Naïm *et al.* [12] proposed a new content-based recommendation system by combining probabilistic topic models and pattern mining to capture the maximal common semantics of sets of services. Bassiliades *et al.* [13] introduced a recommendation method developed on the ontology to match and rank the best cloud service for the application developers. Hu *et al.* [14] designed a dynamic programming and variable length genetic algorithm to recommend more suitable services for users.

The QoS based service recommendation approaches focus on employing traditional collaborative filtering or matrix factorization methods to predict QoS values for the service, and then select a high-quality service to recommend to the user. Wu *et al.* [7] proposed a missing QoS prediction approach by exploiting the embedding techniques and factorization machine. Xu *et al.* [8] proposed two novel prediction models by employing the geographical information of users and the affiliation information of services. Su *et al.* [9] proposed a trust-aware approach for reliable personalized QoS prediction by clustering the users and services, calculating the reputation of users, and combining the QoS data of the trustworthy similar users and similar services. Li *et al.* [10] proposed a new QoS-aware Web service recommendation system by considering the contextual feature similarities of different services and using an enhanced matrix factorization method.

The social network based service recommendation approaches pay attention to recommending service to users via link prediction techniques from the perspective of complex social networks. Kalaï *et al.* [3] proposed a trusted friend detection mechanism and a Web service social recommendation mechanism in a social network by considering the dynamic of the users' interactions, the similarity of their interests and the expertise of the trusted friends. Wang *et al.* [4] presented a contextual social network model that considered both participants' personal characteristics and mutual relations. Further, they proposed an innovative probabilistic approach that considered cycles and information updates to social context-aware trust inference in social networks. Ren *et al.* [5] put forward a service combination and selection method by using service interaction and collaborative data on cloud platform. Yu *et al.* [6] proposed a personalized Markov chain based approach by considering the potential product bundling relationship and the related semantic features.

Recently, the attention of most studies are transferred to recommending services via employing information networks. Wan *et al.* [15] built a heterogeneous network consisting of mashups, services and their attributes, and proposed a novel framework to improve mashup discovery. Yu *et al.* [16] studied the entity recommendation problem in heterogeneous information networks, and proposed to combine various relationship information from the network with user feedback to provide high quality recommendation results. Liang *et al.* [17] proposed a Bayesian personalized ranking based approach to recommend services to mashup developers by using various types of relationships between mashups and services.

However, the shortcoming of the semantics based service recommendation approaches is the lack of variety in the type of exploitable data. The weakness of QoS based service recommendation approaches lies in that the QoS information is difficult to collect, and the QoS of services change over time and is subject to network environment. The drawback of social network based service recommendation approaches is the limitation of applications in the scenario of service recommendation. Most of the information networks based approaches mainly consider one or two related attributes of mashups/services and relationships between mashups/services, and lack of considering the interactions among mashups and services. Our approach considers the heterogeneous information, the diverse meta paths with different semantic meanings, the hybrid similarity, and the rich interactions among mashups to recommend a list of personalized ranking services for mashup creation.

VI. CONCLUSION

In this paper, we propose a service recommendation method for mashup creation with mashup group preference. The historical invocation experience is firstly exploited to build the implicit feedback matrix between mashups and services. Then, mashups, services and their related attributes are applied to constitute the heterogeneous information network and the diverse meta paths with different semantic meanings. Moreover, a hybrid similarity measurement is used to measure the similarity between two arbitrary mashups. Furthermore, a mashup group preference is utilized to capture the rich interactions among mashups. Finally, a mashup group preference based Baysesian personalized ranking algorithm is used to learn the model and make personalized service recommendation for different mashup developers. Comprehensive experiments are carried out on a real-world dataset, which demonstrates the factors we consider are indeed helpful for improving the recommendation performance. The effectiveness of our GPSRec model is further validated by comparing with other state-of-the-art baseline approaches. The impact of group size, learning rate and the effectiveness of mashup group preference are also studied in the empirical evaluation section.

For future work, we will attempt to combine heterogeneous information between mashups, services and their related attributes with neural network techniques (e.g., network embedding and attention) to further improve the performance of service recommendation. In addition, the popularity of services can also be taken into account for ranking.

REFERENCES

[1] D. Merrill, "Mashups: The new breed of Web app," *IBM Web Archit. Tech. Library*, pp. 1–13, 2006. [Online]. Available: http://public.dhe.ibm.com/software/dw/xml/x-mashups-pdf.pdf
[2] C. Cappiello, F. Daniel, M. Matera, and C. Pautasso, "Information quality in mashups," *IEEE Internet Comput.*, vol. 14, no. 4, pp. 14–22, Jul. 2010.
[3] A. Kalaï, C. A. Zayani, I. Amous, and F. Sedès, "Expertise and trust–aware social Web service recommendation," in *Proc. Int. Conf. Service-Oriented Comput.* Cham, Switzerland: Springer, 2016, pp. 517–533.
[4] Y. Wang, L. Li, and G. Liu, "Social context-aware trust inference for trust enhancement in social network based recommendations on service providers," in *Proc. Int. Conf. World Wide Web*, 2015, vol. 18, no. 1, pp. 159–184.
[5] M. Ren, L. Ren, and H. Jain, "Manufacturing service composition model based on synergy effect: A social network analysis approach," *Appl. Soft Comput.*, vol. 70, pp. 288–300, Sep. 2018.
[6] W. Yu, L. Li, X. Xu, D. Wang, J. Wang, and S. Chen, "Productrec: Product bundle recommendation based on user's sequential patterns in social networking service environment," in *Proc. IEEE Int. Conf. Web Services (ICWS)*, Jun. 2017, pp. 301–308.
[7] Y. Wu, F. Xie, L. Chen, C. Chen, and Z. Zheng, "An embedding based factorization machine approach for Web service QoS prediction," in *Proc. Int. Conf. Service-Oriented Comput.* Cham, Switzerland: Springer, 2017, pp. 272–286.
[8] Y. Xu, J. Yin, S. Deng, N. N. Xiong, and J. Huang, "Context-aware QoS prediction for Web service recommendation and selection," *Expert Syst. Appl.*, vol. 53, pp. 75–86, Jul. 2016.
[9] K. Su, B. Xiao, B. Liu, H. Zhang, and Z. Zhang, "TAP: A personalized trust-aware QoS prediction approach for Web service recommendation," *Knowl.-Based Syst.*, vol. 115, pp. 55–65, Jan. 2017.
[10] S. Li, J. Wen, F. Luo, M. Gao, J. Zeng, and Z. Y. Dong, "A new QoS-aware Web service recommendation system based on contextual feature recognition at server-side," *IEEE Trans. Netw. Service Manage.*, vol. 14, no. 2, pp. 332–342, Jun. 2017.
[11] L. Yao, Q. Z. Sheng, A. H. Ngu, J. Yu, and A. Segev, "Unified collaborative and content-based Web service recommendation," *IEEE Trans. Services Comput.*, vol. 8, no. 3, pp. 453–466, May 2015.
[12] H. Naïm, M. Aznag, N. Durand, and M. Quafafou, "Semantic pattern mining based Web service recommendation," in *Proc. Int. Conf. Service-Oriented Comput.* Cham, Switzerland: Springer, 2016, pp. 417–432.
[13] N. Bassiliades, M. Symeonidis, G. Meditskos, E. Kontopoulos, P. Gouvas, and I. Vlahavas, "A semantic recommendation algorithm for the paasport platform-as-a-service marketplace," *Expert Syst. Appl.*, vol. 67, pp. 203–227, Jan. 2017.
[14] B. Hu, Z. Cheng, and Z. Zhou, "Web services recommendation leveraging semantic similarity computing," *Math. Found. Comput.*, vol. 1, no. 2, pp. 101–119, 2018.
[15] Y. Wan, L. Chen, Q. Yu, T. Liang, and J. Wu, "Incorporating heterogeneous information for mashup discovery with consistent regularization," in *Pacific–Asia Conf. Knowl. Discovery Data Mining*. Cham, Switzerland: Springer, 2016, pp. 436–448.
[16] X. Yu *et al.*, "Recommendation in heterogeneous information networks with implicit user feedback," in *Proc. 7th ACM Conf. Recommender Syst.*, 2013, pp. 347–350.
[17] T. Liang, L. Chen, J. Wu, H. Dong, and A. Bouguettaya, "Meta-path based service recommendation in heterogeneous information networks," in *Proc. Int. Conf. Service-Oriented Comput.* Cham, Switzerland: Springer, 2016, pp. 371–386.
[18] F. Xie, L. Chen, D. Lin, C. Chen, Z. Zheng, and X. Lin, "Group preference based API recommendation via heterogeneous information network," in *Proc. 40th Int. Conf. Softw. Eng., Companion*, 2018, pp. 362–363.
[19] Y. Sun, J. Han, X. Yan, P. S. Yu, and T. Wu, "Pathsim: Meta path-based top-k similarity search in heterogeneous information networks," *Proc. VLDB Endowment*, vol. 4, no. 11, pp. 992–1003, 2011.
[20] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Mar. 2003.
[21] W. Pan and L. Chen, "GBPR: Group preference based Bayesian personalized ranking for one-class collaborative filtering," in *Proc. Int. Joint Conf. Artif. Intell.*, vol. 13, 2013, pp. 2691–2697.
[22] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "BPR: Bayesian personalized ranking from implicit feedback," in *Proc. 25th Conf. Uncertainty Artif. Intell.*, 2009, pp. 452–461.
[23] L. Bottou, "Large-scale machine learning with stochastic gradient descent," in *Proc. Int. Conf. Comput. Statist.* Berlin, Germany: Physica-Verlag HD, 2010, pp. 177–186.
[24] N. Craswell, "Mean reciprocal rank," in *Encyclopedia of Database Systems*. Boston, MA, USA: Springer, 2009, p. 1703.
[25] D. K. Agarwal and B.-C. Chen, *Statistical Methods for Recommender Systems*. Cambridge, U.K.: Cambridge Univ. Press, 2016.
[26] K. Huang, Y. Fan, and W. Tan, "Recommendation in an evolving service ecosystem based on network prediction," *IEEE Trans. Autom. Sci. Eng.*, vol. 11, no. 3, pp. 906–920, Jul. 2014.
[27] A. Paterek, "Improving regularized singular value decomposition for collaborative filtering," in *Proc. ACM SIGKDD Conf. Knowl. Discovery Data Mining Cup Workshop*, 2007, pp. 5–8.

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