Deep Learning Framework for Online Interactive Service Recommendation in Iterative Mashup Development

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Abstract—Recent years have witnessed the rapid development of service-oriented computing technologies. The boom of Web services increases the selection burden of software developers in developing service-based systems (such as mashups). How to recommend suitable follow-up component services to develop new mashups has become a fundamental problem in service-oriented software engineering. Most of the existing service recommendation approaches are designed for mashup development in the single-round recommendation scenario. It is hard for them to update recommendation results in time according to developers’ requirements and behaviors (e.g., instant service selection). To address this issue, we propose a deep-learning-based interactive service recommendation framework named DLISR, which aims to capture the interactions among the target mashup, selected services, and the next service to recommend. Moreover, an attention mechanism is employed in DLISR to weigh selected services when recommending the next service. We also design two separate models for learning interactions from the perspectives of content information and historical invocation information, respectively, as well as a hybrid model called HISR. Experiments on a real-world dataset indicate that HISR outperforms several state-of-the-art service recommendation methods in the online interactive scenario for developing new mashups iteratively.

Index Terms—Deep Learning, Service Recommendation, Mashup development, Attention, Session.

I. INTRODUCTION

With the maturity of the service-oriented computing paradigm, service-oriented software development has increasingly become popular. A large number of Web services have been released on the Internet. By integrating these existing Web services, software developers can build more efficiently their mashups (i.e., Web applications that can provide certain functionalities by composing one or more services). Until now, this methodology has shown ample ability to reduce the cost of system development and increase the quality of service-based software [1]. However, the rapid growth of the number of Web services available in Web application programming interface (API) directories such as ProgrammableWeb raises challenges in selecting suitable services for mashups. Service recommendation has emerged as a critical technology that recommends appropriate component services for developers in the development process of mashups.

Many service recommendation methods have been proposed in the past decade. They can be roughly classified into three main categories: content-based, collaborative filtering (CF)-based, and hybrid recommendations, according to the type of information used in the recommendation process. Given keyword-based developer requirements, content-based approaches [2]-[4] make recommendations according to the textual similarities between service descriptions and developer requirements. CF-based approaches [5]-[8] leverage the historical experience of similar mashups/services to generate a recommendation list. By integrating content-based and CF-based approaches, hybrid approaches [9]-[15] consider explicitly-specified requirements, implicit invocation preferences, and other information of service usages, such as co-invocation and popularity, to make recommendations.

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1 https://www.programmableweb.com/
Invocation indicates the call relationship between a mashup and its component service.

Generally speaking, these existing service recommendation approaches are mainly applicable to mashup development in a one-shot scenario. In other words, they recommend all candidate services for a new mashup each time, which is a type of single-round request-response recommendations. However, this single-round recommendation has some limitations. We use an example of developing a trip preparation mashup for illustration. Assume that a developer’s initial requirements are as follows: “a mashup can help tourists prepare for their trips. It can especially provide users with information about weather and tourist attractions, help them design travel routes, and book hotels online.” A service recommendation system (SRS) usually provides suggestions for component services in the development process. In a one-shot recommendation scenario shown in Fig. 1(a), the SRS generates a recommendation list that contains Google Maps, Microsoft Bing Maps, AccuWeather, and Airbnb. After the developer selects Google Maps, AccuWeather, and Airbnb from the list, the recommendation process ends. Since young users prefer to prepay online after booking a hotel, an electronic payment service would also be necessary for mashup development. However, according to the initial requirements, the SRS used in this scenario cannot return services related to payment requirements. In other words, the single-round recommendation cannot make changes to the refinement of requirements.

Fig. 1(b) illustrates how an interactive service recommendation approach addresses the above limitations. Suppose an interactive SRS generates the same list in the first stage as the single-round recommendation mentioned above. The developer has also selected Google Maps, AccuWeather, and Airbnb as component services. Unlike the single-round recommendation, the interactive recommendation steps into the second stage after receiving the developer’s feedback (i.e., the selection result), and the SRS generates a new recommendation list. As a result, those services related closely to the selected services will have a higher priority in the recommendation list. For example, the SRS is more likely to recommend an online payment service due to its high relevance with Airbnb, a hotel booking service. Moreover, since the developer has chosen Google Maps from the recommendation list, the SRS will respond to this feedback and most likely filter out Bing Maps and other map APIs in subsequent recommendations. In other words, due to the homogenization effect of services, the developer is reluctant to select another service with the same functionality. Therefore, in the second-round recommendation, the SRS may prioritize some payment services like ApplePay and Alipay. If necessary, the interactive recommendation process will repeat until the requirements are satisfied.

Hence, the interactive recommendation has more potentiality in recommending appropriate component services to meet developer requirements by interacting with developers. To this end, we need an online interactive recommendation process for the iterative service selection in mashup development. In the first stage of the process, the SRS analyzes keyword-based developer requirements. It returns a list of candidate services, from which the target developer selects one or more candidate services. If the recommendation result does not fully satisfy the requirements, the recommendation process will enter the second stage. The SRS continues to generate a new service list according to the requirements and existing component services that have been selected. This step will repeat until a new mashup’s development process ends. However, such an online interactive scenario presents some challenges for SRSs.

1. There exist multiple kinds of complex interactions among a mashup, selected services, and the next service to recommend in the mashup development process. Firstly, the next service needs to interact with the target mashup, i.e., the next service is supposed to meet some specific requirements for the mashup. For example, ApplePay satisfies the online payment requirement in the above case. Secondly, the next service needs to interact with all the selected services. From a functional point of view, their functionalities may be relevant or even wholly identical. For example, the Airbnb API and ApplePay complement each other, while Bing Maps competes with Google Maps. From the perspective of service interoperability and compatibility [16], the next service should be as much as possible both task interoperable and interface compatible. Thirdly, the interaction between the target mashup and its selected services also affects the next service’s selection. These interactions determine, to a great extent, developer selection behavior and mashup development process.

2. A new mashup’s development process is essentially a session, which is iterative and consists of two stages. When a developer initiates a session, the SRS will make the first-round recommendation according to the initial requirements. After the developer selects one or more services, the session enters the second stage. In this stage, the SRS needs to make a prompt response to user feedback each time. More specifically, the SRS should capture and analyze developer requirements for the next round more accurately and generate follow-up recommendations in time. How to support both two stages in a unified manner is another challenge for SRSs.

It is hard for most of the existing service recommendation approaches to address the above challenges. Model-based CF methods, such as matrix factorization (MF) [17] and neural CF [18], has a minimal ability to model new mashups without component services or make recommendations in the first stage. Even if developers have selected services in the second stage, it is hard to timely update recommendation models to obtain the latest representations of mashups. In other words, these methods cannot generate follow-up recommendations based on user feedback dynamically. User-based CF and content-based methods only consider the relationship between mashups and the next service to recommend while ignoring the critical role of selected services in the recommendation process. Therefore, it is hard for them to utilize developer feedback or update the recommendation list in the second stage. As a combination of content-based and CF-based methods, hybrid methods also face the same problems as these two types of methods.

From the viewpoint of model construction, the first stage in
the online interactive scenario could be deemed as a particular case of the second one. In this case, the number of selected services is zero. Without losing generality, the problem to be solved in this study is, given keyword-based developer requirements and some selected component services, how to recommend appropriate services for developers in the mashup development process? To address this issue, we propose a deep-learning-based framework that makes recommendations based on the interactions among the target mashup, existing services that have been selected, and the next service to recommend. In particular, since it is challenging to find mathematical functions to characterize these interactions, a multi-layer perceptron (MLP) is employed to learn such interactions in the proposed framework. In brief, the framework aims to learn how a mashup, selected component services, and a candidate service interact with each other and how the interactions affect a developer’s selection of candidate services. Considering that each selected service has a different impact on selecting the next service, the framework also adopts an attention mechanism to automatically weigh the impacts.

The framework can be easily applied to the first stage in the session-based interactive scenario by deactivating or masking its component designed for selected services. Besides, it can take various types of information as input, such as the content information and the historical invocation information. For each type of information, we obtain feature representations of a new mashup, selected services, and the next service to recommend, respectively, and then learn a specific interaction in the corresponding feature space to make a prediction. Note that the framework can take other types of information as input as long as the corresponding feature representation can be obtained. We finally integrate the interactions learned in different feature spaces to make a more accurate recommendation. It is also worth noting that the framework can make updated follow-up recommendations in case of newly-selected services.

In brief, the main contributions of this work are three-fold.

1. Unlike the traditional one-shot service recommendation scenario, we define and discuss an online interactive recommendation scenario for iterative and incremental mashup development during a session, which has not been sufficiently explored in the existing literature.

2. We propose an interaction-oriented recommendation framework for the session-based interactive scenario, called DLISR (short for deep-learning-based interactive service recommendation). With the help of MLPs and the attention mechanism, this framework can gradually recommend appropriate component services to satisfy developer requirements by leveraging selected services.

3. Following the DLISR framework, we implement two separate models, which learn specific interactions using the content information of mashups and services and the history of invocations between them, respectively, and a hybrid model. Moreover, experiments conducted on a real-world dataset indicate that the hybrid model outperforms other competitive baseline approaches.

The rest of this paper is organized as follows. Section II introduces the related work. In Section III, we present the definition of problems investigated in this study. Section IV details the proposed DLISR framework. Section V describes three implementation models by following the proposed framework, and Section VI presents the experimental results and analysis. Finally, Section VII summarizes this paper and puts forward our future work.

II. RELATED WORK

Web service recommendation has attracted much attention in the services computing field in the past decade. As mentioned above, existing service recommendation approaches are mainly applicable to one-shot mashup development in a request-response style. Although interactive service recommendation has not been investigated in existing approaches, interactive system development is not a new topic, and we will present the related work in this area.

A. Single-round service recommendation

In a one-shot recommendation scenario for mashup development, a service recommendation approach generates only a list of candidate services for the target mashup at a time. It is hard to update the recommendation result according to the target developer’s online service selection behavior. These existing approaches can be divided into three groups: content-based, CF-based, and hybrid approaches.

Content-based approaches predict a service’s rating over a mashup according to the similarity between service description and keyword-based developer requirements. As a keyword-based framework, WS-Finder [2] applied the Earth Mover’s Distance in multimedia databases to many-to-many partial matching between developer requirements and service attributes. Al-Hassan et al. [3] used domain ontologies to enrich the semantics of content information, and they measured the semantic similarity by logical reasoning. Shi et al. [4] utilized service labels to retrieve and highlight function-related words in service descriptions using the attention mechanism. They proposed a deep structured semantic model to measure the matching degree between a mashup’s function and a service’s function.

Generally speaking, CF-based approaches mine implicit user preferences and generalize patterns of similar users or items. For example, Samanta et al. [5] proposed an MF-based method that analyzes historical invocation records between services and mashups. They took the inner-product of latent factors as a critical factor in determining interaction probability. By applying the graph embedding technology to a user co-tag network and a social network, Wu et al. [6] obtained two different representations for user preference and social relationship. They integrated the two embeddings into a user-based CF recommendation model. Zhou et al. [7] incorporated user-based and service-based CF in a reinforced CF framework that can remove services/users dissimilar to the target service/user when predicting quality of service (QoS) values. Liang et al. [8] used a heterogeneous information network (HIN) to represent various entities, such as description and tag, and providers of mashups and services. They measured the similarity between mashups based on the HIN network and
leveraged the user-based CF approach to recommend services more relevant according to user requirements.

Nowadays, hybrid approaches integrating multiple models or various types of information to make recommendations have become popular. Some approaches add side information into MF-based models to improve their performance. For example, considering that some contextual factors have an underlying influence on developers’ selection behaviors, Botangen et al. [9] derived two relevance scores from two contextual factors, i.e., geographical location and textual description. They utilized the relevance scores in an MF-based recommendation model. Nguyen et al. [10] mined the relationship between services in terms of their functional similarities and leveraged this feature to regularize an MF-based model with an attention mechanism.

Inspired by some well-known models in click-through rate (CTR) prediction, a few hybrid approaches applied deep neural network (DNN) and factorization machine (FM) [11] to service recommendation. For example, Xiong et al. [12] combined CF and content-based recommendations with a DNN. Chen et al. [13] presented a neural CF recommender model that learns user preference on services in terms of their matching degree on explicitly-declared attribute preference and implicit preference mined from past invocations. By leveraging the Wikipedia corpus, Cao et al. [14] enriched mashups and services in content. They then obtained a representation of the extended information with the hierarchical Dirichlet process. Finally, all the features, including the extracted content feature, similar services or mashups, popularity, and the co-occurrence of services, were fused into an FM to capture their second-order interaction. However, Cao et al. [15] pointed out that FMs neglect that not all features were equally crucial to the final prediction. They introduced an attention mechanism into an FM and weighed each feature in question when learning their interactions.

B. Interactive system development

In the field of services computing, the concept of interactive design first appeared in service composition. Some researchers adopted the strategy of step-by-step recommendations in their service composition platforms. For example, Zhao et al. [19] designed a platform named HyperService, which can search and recommend a set of relevant services for end users according to input keywords and navigation contexts. In particular, service relations are detected and leveraged in the dynamical search process. Since social networks often affect developer selection, Maaradji et al. [20] proposed a framework that can acquire knowledge from a social network and incorporate the generated knowledge with user profiles to make recommendations for service discovery dynamically. Liu et al. [21] applied a generalized sequential pattern mining algorithm to discover frequent service composition patterns. When the proposed approach recommends the next sequence, it leverages current user selection and considers both the frequency and the logical order of internal components to facilitate mashup development.

These approaches extract service composition patterns from the history of service compositions or the neighborhood in social networks. They leverage such knowledge to calculate the probability of a service that will be selected next according to a user’s current selection. Due to the regularity of patterns, the recommendation result obtained after user selection is relatively fixed. Moreover, such a recommendation process often neglects the current requirements of target users.

Some studies make recommendations based on user behavior history. Due to the change in user needs and service functions or quality, user preference is evolving. A few studies then improved recommendation performance by tracking dynamic preference sequences and predicting user preference in the future. For example, Zhang et al. [22] extracted dynamic user preference from time slice data by the time-series latent Dirichlet allocation (LDA) model and generated a service list based on the latest user preference and QoS. Kwawong et al. [23] composed a user’s invocation preference at a timestamp as a combination of non-functional attributes such as QoS and functional features extracted from the Web services description language (WSDL) file of the invoked service. They modeled user preference sequences and predicted the target user’s latest preference for the next recommendation by a long short-term memory (LSTM) network.

However, these methods only focus on the evolution pattern of user selection behavior or preference while neglecting that the next service to recommend, together with selected services, should meet the target mashup’s requirements. In our previous work [24], we discussed a specific recommendation scenario with selected services in the mashup development process. When developers select one or more services, user-based CF is leveraged to re-calculate the mashup similarity, find more accurate neighbor mashups, and update their recommendations. Although the CF-based method leverages the interaction between the target mashup and candidate service, it does not explicitly characterize selected services’ critical impacts on developers’ service selection behaviors.

Inspired by the recent work on user interest representation in CTR prediction, e.g., [25], [26], DINRec [27] employs an attention mechanism to weigh different selected services according to their relevance to the next service to recommend. Unfortunately, DINRec is designed to develop mashups with some selected services. In other words, DINRec does not apply to build a new mashup in an online session. Besides, it has the following two drawbacks. First, DINRec’s prediction model needs to be retrained after a developer selects a component service. Second, the prediction model takes only discrete features, such as the tag attribute of mashups and services, as input. It does not consider the textual description of services and mashups. Therefore, DINRec cannot fully characterize the functional interactions (or called content interactions) between mashups and services.

To summarize, the above existing studies cannot work well in the online interactive recommendation scenario to support iterative service selection for mashup development. In other words, few of them can work in the cold-start scenario and also make online recommendations when a developer selects component services for the target mashup step by step. Therefore, our study aims to address the above issues.
III. PROBLEM STATEMENT

A service repository is a collection of mashups and services, represented as \( R = M \cup S \), where \( M \) is a set of mashups and \( S \) is a set of services. Mashups and services have their respective attributes. We leverage the content information (such as textual descriptions and tags) of mashups and services, as well as the provider information of services, to make recommendations in this study. Besides, the history of invocations between \( M \) and \( S \) is regarded as a special kind of implicit feedback. We represent the invocation history as an invocation matrix \( MS \), where the cell value in the \( m \)-th row and the \( s \)-th column is defined as

\[
\tau_{m,s} = \begin{cases} 
1, & \text{if } s \text{ is a component service of mashup } m \\
0, & \text{otherwise} 
\end{cases} \tag{1}
\]

Then, we present the problem to be solved in this study as follows. Suppose a developer plans to build a new mashup \( m \) and has provided his/her keyword-based requirements, referred to as \( MReq \). Given a set of selected component services \( SS \), how can the SRS recommend the next service to use to the developer accurately? Note that \( SS \) is empty when the developer starts building \( m \).

IV. AN INTERACTION-ORIENTED FRAMEWORK FOR INTERACTIVE SERVICE RECOMMENDATION

In the online interactive recommendation scenario, there exist multiple interactions among keyword-based developer requirements \( MReq \), selected services, and the next service to recommend. On the one hand, the next service to recommend and services that have been selected may be replaceable or complementary to each other. On the other hand, the next service and selected services need to work together to satisfy \( MReq \). Such interactions help developers determine whether they will select a candidate service as a component service of the target mashup. In this section, we first briefly introduce the DLISR framework and then detail it layer by layer.

A. Overview of DLISR

Fig. 2 shows the DLISR framework’s architecture. It consists of three layers, i.e., a feature extraction layer, an interaction layer, and an output layer.

According to the original input information, the feature extraction layer aims to obtain feature representations of a new mashup, each selected service, and the candidate service. The interaction layer learns the correlation weight between each selected service and the candidate service based on an attention block. After calculating all selected services’ compressed representations, it employs an MLP to learn interactions among the target mashup, candidate service, and all selected services. By leveraging the learned interactions, the output layer predicts the possibility that a developer will select the candidate service as a component service in the next round.

When training the DLISR framework offline, we need to construct a training dataset based on all existing mashups and services in a given repository. The training samples are built by simulating how developers gradually select component services for mashup construction. Therefore, the framework trained offline can make online recommendations for developing new mashups.

B. Details of Each Layer in DLISR

1) Feature extraction layer

This layer takes as input one type of information, such as the content information of a new mashup \( m \), a set of selected services \( SS \), and each candidate service \( s \) (or the history of invocations between mashups and services). It then outputs the corresponding feature representation of the same type to learn about interactions among \( m \), \( SS \), and \( s \). Note that what we obtain in this layer is a feature representation of a mashup or a single service. If developers need to implement the framework, we provide two different feature extractors for the content information and the invocation history. For more details, please refer to Section V.

2) Interaction layer

The goal of this layer is to learn about interactions among \( m \), \( SS \), and \( s \). Although there are a few ways to model such interactions, we employ MLPs in this study because they can, in theory, fit arbitrary functions well [28]. Usually, we can employ multiple MLPs to simultaneously learn the interactions among \( m \), \( s \), and each selected service, and then integrate them with another MLP. However, this straightforward way will consume too much computing resources. Alternatively, we first compress representations of all selected services into a fixed-dimensional vector by utilizing the attention mechanism. As a result, this layer takes only an MLP to learn about interactions among \( m \), \( s \), and \( SS \).

a) Attention-based feature integration

The simplest way to get a comprehensive representation of selected services is to concatenate their representations directly. However, this strategy does not fit our task here. On the one
hand, the concatenation will increase the final representation’s dimension and reduce the framework’s efficiency, especially when the size of selected services is large. On the other hand, either the number of selected services or the dimension of concatenation results is changeable in this scenario. Instead, the fully-connected networks used to learn about interactions in our framework can only handle fixed-length input.

Another possible solution is to perform average pooling or sum pooling on the representation of each selected service. The pooling method still has its disadvantages, despite generating a fixed-length representation. Let us continue to analyze the case mentioned above, where a developer is building a mashup to help tourists prepare for their trips. Suppose the developer has already selected several services, including a hotel reservation service, a weather forecast service, and an online map service. Considering that tourists usually prepay online after booking a hotel, the hotel reservation service will have a more significant impact than the other two services on selecting an electronic payment service as the next service to recommend. Therefore, each selected service has a different impact on selecting the next service to recommend, which suggests that we should assign a different weight to the representation of each service in question. However, the pooling method weights them equally.

According to the above analysis, we design an attention-based method to integrate each selected service’s representation in this layer. It pays attention to those selected services that are more relevant to the next service to recommend and filters out unnecessary services. Note that the relevance is measured by the similarity between functions or the complementarity (i.e., different functions complement each other).

We use the weighted sum of each selected service’s features to represent the set of all selected services.

\[ v_{SS} = \sum_{i \in SS} w_{is} v_i, \quad s.t. \sum_{i \in SS} w_{is} = 1, \]

where \( v_i \) is the vector representation of each selected service \( s_i \) and \( w_{is} \) is the weight of \( s_i \). The physical meaning of \( w_{is} \) is the correlation degree between \( s_i \) and \( s \), i.e., the contribution of \( s_i \) to the target developer’s selection on \( s \). So, \( w_{is} \) is jointly determined by features of \( s_i \) and \( s \).

In general, the similarity between two vectors can be measured by their element-wise multiplication or by their element-wise subtraction for the difference between them. Given vector representations \( v_i \) and \( v_s \) of \( s_i \) and \( s \), the results of these two operations can be used as prior knowledge to help model the correlation between \( s_i \) and \( s \). We concatenate them with features of \( s_i \) and \( s \) and input the concatenation result into an MLP to learn the correlation between \( s_i \) and \( s \) automatically. The MLP then outputs a scalar score. The above process can be described as

\[ a_{is} = \text{MLP}(v_i \oplus v_s \oplus (v_i \otimes v_s) \oplus (v_i \ominus v_s)), \]

where \( \oplus \) denotes the element-wise multiplication, \( \otimes \) denotes the element-wise subtraction, \( \ominus \) denotes the concatenation operation, and \text{MLP}(\cdot) represents all the default operations within an MLP.

We finally input the score into a softmax function to calculate the final weight \( w_{is} \), i.e., a scalar score.

\[ w_{is} = \frac{\exp(a_{is})}{\sum_{j \in SS} \exp(a_{js})}. \]

Unlike the average pooling operation, we calculate the vector representation of each selected service adaptively according to its correlation with the candidate service. In this layer, selected services contribute different weights to the overall representation \( v_{SS} \). Also, this representation varies with the candidate service. Compared with the average pooling operation, our attention-based method can obtain a more adaptable representation due to a better expression ability.

\[ \text{b) MLP-based interaction learning} \]

Up to now, we have obtained representations of \( m \), \( SS \), and \( s \), i.e., \( v_{MReq} \), \( v_{SS} \), and \( v_s \), respectively. Because there are no local or sequential patterns in the concatenated representations, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are not suitable for this interaction learning task [29]. We concatenate these representations and then utilize an MLP to capture interactions among \( m \), \( SS \), and \( s \). Moreover, we select the parametric rectified linear unit (ReLU) as the activation function since it can improve model fitting with nearly zero extra computational cost and little overfitting risk [30]. The learning process can be written as

\[ i_{MReq,SS,s} = \text{MLP}(v_{MReq} \oplus v_{SS} \oplus v_s), \]

where \( i_{MReq,SS,s} \) is the learned interaction vector.

\[ \text{3) Output layer} \]

We finally feed the learned interaction vector into a softmax function, whose output, \( \hat{r} \), represents the probability of \( m \) selecting \( s \) as the next service to recommend. The process can be written as

\[ \hat{r} = \text{softmax}(W^T i_{MReq,SS,s} + b), \]

where \( W \) is a weight matrix and \( b \) is the bias parameter.

V. IMPLEMENTATION MODELS

Given a new mashup \( m \), a set of all services that have been selected \( SS \), and the candidate service \( s \), the DLISR framework learns about their interactions and predicts the probability of \( m \) selecting \( s \) as the next service to recommend. We can construct various implementation models by extracting different types of features and learning their corresponding interactions. This section will introduce two implementation models: a function-interaction-based service recommendation (FISR) model and a neighbor-interaction-based service recommendation (NISR) model. The two models apply the DLISR framework to content information and the history of invocations between mashups and services. Also, we present a hybrid model named HISR (short for hybrid-interaction-based service recommendation) that integrates these two models.

A. FISR Model

When calculating the selection probability of a component
service, developers will first consider whether the service’s functionality, together with those of selected services, can satisfy their requirements for the target mashup. Therefore, we design a functional interaction model that captures their interactions from the perspective of functionality.

The functionality of a service, i.e., the service’s content information, generally fall into two forms: word sequence (such as service description) and separate words (such as tags). The same is true of developer requirements described in natural languages. To get the representation of a mashup or a service in functionality, we use two deep-learning-based techniques to process these two forms of content information, respectively, and then concatenate their extracted features.

To apply deep-learning-based feature extraction, we need to preprocess the content information of services and mashups with word embeddings. More specifically, we convert all terms into sparse binary vectors with one-hot encoding, input these vectors into an embedding layer, and map each term into a dense vector or an embedding. We then truncate or pad a piece of the content information if necessary. Finally, we stack the corresponding embeddings of its terms, transforming the content information into a matrix $E$ with a fixed size. The process can be written as

$$E = [e_{t_1}, e_{t_2}, ..., e_{t_p}, ..., e_{t_L}]^T,$$

where $L$ is the length of the content information, $t_i$ is the $i$-th term in the content information, and $e_{t_i}$ is the word embedding of $t_i$.

For the content information represented in a word sequence, we apply the text_inception network used in our previous work [31] to its feature extraction. This method first parallels stacked convolution layers to extract local patterns in a word sequence and then employs the global average pooling (GAP) operation to emphasize important features. Finally, an MLP is employed to perform a non-linear transformation on the extracted features. The process to get the representation of a word sequence, $v_{\text{seq}}$, can be simply written as

$$v_{\text{seq}} = \text{text_inception}(E).$$

There is no order between terms for the content information represented in the form of a separate word set, which makes text_inception inapplicable. Instead, we retrieve and average the embedding of each term to get a fixed-length representation of the separate word information, $v_{\text{set}}$, described as

$$v_{\text{set}} = \text{average}[e_{t_1}, ..., e_{t_i} ... e_{t_M}],$$

where $e_{t_i}$ is the embedding of the $i$-th term in the set and $M$ is the size of the set.

For each mashup or service, we concatenate the two features extracted from its content information, $v_{\text{seq}}$ and $v_{\text{set}}$, and obtain a representation that characterizes its functionality.

$$v = v_{\text{seq}} \oplus v_{\text{set}}.$$  

In this way, we can transform the content information of developer requirements, the next service to recommend, and each selected service into real-valued feature vectors. We then feed them into the DLISR framework’s interaction layer and obtain a vector, $ci_{\text{MReq<SS}}$, to model their functional interactions. Finally, we input this vector into the output layer to predict a score for the candidate service.

### B. NISR Model

Besides content information, the history of invocations between existing mashups and services is also beneficial to good recommendation results. Inspired by the user-based CF approach, we design a neighbor-interaction-based model for learning about interactions among $m$, $SS$, and $s$, according to the historical invocation information of mashups similar to the target mashup (i.e., neighbor mashups, denoted as $NM$). The challenge of applying the DLISR framework to such information is how to obtain the representations of $m$, $s$, and $SS$. To get the representations of existing mashups and services, we employ node2vec [32], a typical graph embedding method, to process the graph transformed from the historical invocation matrix $MS$. Compared with traditional MF-based approaches, such as probabilistic matrix factorization [17] and singular value decomposition, node2vec can capture a more non-linear relationship between a mashup and a service.

In the interactive scenario of this study, new mashups are built and completed online. The MF-based methods mentioned above cannot update their models with newly-selected services in time, nor can they get an adequate representation of the target mashup. Instead, we search out neighbor mashups for the target mashup and compute its representation using representations of neighbor mashups and the similarities between the target mashup and existing ones. Therefore, the key to this model lies in how to calculate the similarity between the target mashup $m$ and an existing neighbor mashup $nm_i$.

To this end, we adopt a similar method proposed in [23] to calculate the similarity. We first extract topics from the content information by the LDA model and use the top three topics to represent service functionality. Next, we construct a HIN network that contains mashups and services. Then, we use a meta-path-based method to calculate six types of similarities between two mashups: sharing the same topics, labeled by the same tags, invoking the same service, and invoking similar services that have the same topics, tags, or providers. Finally, the weighted sum of these six types of similarities is calculated as an overall similarity between two mashups. We detail the above method in the Appendix. Note that we set the similarity weights to the values pre-trained by [23]. The overall similarity $sim_{m,nm_i}$ between $m$ and $nm_i$ can be expressed as

$$sim_{m,nm_i} = \sum_{p=1}^{6} w_p * sim_p(m,nm_i),$$

where $sim_p(m,nm_i)$ is the $p$-th meta-path-based similarity and $w_p$ is its corresponding weight.

According to the similarities between the target mashup and existing mashups, we select $K$ mashups most similar to the target mashup as $NM$ and then obtain a weighted representation $v_m$ of $m$. 


where $\mathbf{v}_{nm}^{i}$ is the representation of $nm^{i}$ obtained by node2vec.

In addition to the content information of two mashups, this similarity calculation method also considers their component services’ information. After a developer selects a new service, the method will improve its similarity measurement and better represent the target mashup to build. Besides, the method that calculates mashup similarities based on meta-paths is efficient. We can also adopt some pruning strategies (e.g., reducing the number of candidate mashups) to further improve the efficiency of searching for neighbor mashups in a large-scale service repository.

Till now, we have obtained the representations of $m$, each service in $SS$, and $s$ in the same feature space based on the historical invocation information. Then, we can input them into the DLISR framework’s interaction layer and compress their interactions in this space into a dense vector, $\mathbf{h}_{MReq,SS}$. The vector is fed into the output layer to make a prediction.

C. HISR Model

The above two models learn two forms of interactions among $m$, $SS$, and $s$, according to content information and invocation history, respectively. This subsection proposes a hybrid model named HISR that integrates these two models to leverage multiple interactions.

The HISR model (see Fig. 3) consists of two underlying modules, an integration layer, and an output layer. A module takes as input a type of information and learns a unique type of interaction among $m$, $SS$, and $s$. More specifically, a module could be viewed as the result of removing the output layer from a separate implementation model (i.e., FISR and NISR) of the DLISR framework. That is to say, each of the two underlying modules has only a feature extraction layer and an interaction layer. Then, the integration layer incorporates all interactions learned from different underlying modules with an MLP. The process can be expressed as

$$i_{MReq,SS} = \text{MLP}(ci_{MReq,SS} \oplus hi_{MReq,SS}).$$

Finally, the HISR model’s output layer makes a prediction based on the learned interactions. It is also worth mentioning that this hybrid model is easily extensible. Suppose a new kind of information is available. In that case, we can add another underlying module to learn a new type of interaction and then integrate it into the original model to improve model performance further.

D. Offline Model Training

The proposed models predict the probability of mashup $m$ choosing service $s$ as the next service to invoke when it has selected a set of component services $SS$. A sample in our study is denoted as $(m, SS, s)$. The predicted value approximates one for a positive sample and zeroes for negative samples. So, the likelihood function of our models is

$$P(Y^{+}, Y^{-}|\Theta) = \prod_{(m, SS, s) \in Y^{+}} \hat{r}_{(m, SS, s)} \times \prod_{(m, SS, s) \in Y^{-}}(1 - \hat{r}_{(m, SS, s)}),$$

where $\Theta$ is the model parameter set, $\hat{r}_{(m, SS, s)}$ is the predicted probability for a sample $(m, SS, s)$, and $Y^{+}$ and $Y^{-}$ represents positive samples and negative samples, respectively.

The loss function to be minimized is defined as follows.

$$J = -\log P(Y^{+}, Y^{-}|\Theta) = -\sum_{(m, SS, s) \in (Y^{+} \cup Y^{-})} \log \hat{r}_{(m, SS, s)} + (1 - r_{(m, SS, s)}) \log(1 - \log \hat{r}_{(m, SS, s)}),$$

where $r_{(m, SS, s)}$ is the actual label of a sample $(m, SS, s)$.

**Algorithm 1.** Training algorithm of FISR or NISR

**Input:** number of epochs $p$ and sample set $Y$

**Output:** parameter set $\Theta$

1. for epoch = 1, ..., $p$
2. for each sample composed of mashup $m$, service $s$ and selected services $SS$ in $Y$
3. Compute $\mathbf{v}_{m}$ and $\mathbf{v}_{s}$
4. Compute $\mathbf{v}_{SS}$ using Eq. (2);
5. Compute $i_{MReq,SS}$ using Eq. (5);
6. Compute $\hat{r}$ using Eq. (6);
7. Update $\Theta$ to minimize $J$ in Eq. (15) with the Adam;
8. end for
9. end for
10. return $\Theta$;

**Algorithm 1** presents the model training process of the DLISR framework for the FISR and NISR models. Lines 3-6 show a forward-propagation process to make a prediction. In the third line, we obtain representations of $m$ and $s$ by a feature extraction layer. For the FISR model, we get the representations of mashups and services using Eq. (10). For the NISR model, we obtain the representations of existing mashups and services by node2vec and then calculate the representation of the target mashup $m$ using Eq. (12). In the fourth line, we adopt an attention-based method to get an overall representation of all selected services using Eq. (2). In the fifth line, we get the interactions among $m$, $SS$, and $s$, according to Eq. (5). In the
Case 3  

service 1 − × 2 SR . SS … , 1

Case 2  

∑ ve ∑ s

requirement Core 8 Xeon mashup. In online interactive scenario has two stages. Stage 4.

3  

Output fine the FISR and NISR models and then hybrid model, described in Algorithm 2. This algorithm trains the FISR and NISR models and then initializes each underlying module in the hybrid model according to the corresponding pre-trained parameters. Next, it freezes the two modules and trains only the integration layer and the output layer. Finally, HISR’s all learnable parameters are unfrozen, and the whole model is fine-tuned.

Algorithm 2. Training algorithm of HISR

Input: sample set Y and number of epochs p
Output: parameter set θ
1. Train FISR and NISR using Algorithm 1 and get their parameter sets, θFISR and θNISR;
2. Initialize HISR’s two underlying modules with θFISR and θNISR and then freeze them;
3. Train learnable parameters in the integration layer and the output layer with the input obtained by Eq. (13);
4. Update all the model parameters by fine-tuning the hybrid model;
5. return θ;

VI. EXPERIMENTAL SETUPS AND RESULT ANALYSIS

A. Experimental Setups

Fig. 4 illustrates the scenario setting of our experiments. The online interactive scenario has two stages. Stage 1 aims to deal with the cold-start problem when developers start to build a new mashup. In stage 2, we consider several typical cases where a developer has selected one or more component services. This study’s experiments were conducted on a workstation with Intel Core 8 Xeon @3.50 GHz, GeForce GTX 2080, and 32 GB memory. The source code implemented based on Keras2 is available on GitHub3.

1) Dataset and samples

We collected experimental data from ProgrammableWeb, the largest online Web service registry, on July 25, 2016. We removed all mashups and services without content information from the original dataset. Also, we filtered out any mashups that contain only one component service. The experimental dataset contains 1,979 mashups, 728 Web services, and 5,802 mashup-service invocations.

Each experiment sample designed for the online interactive scenario consists of a mashup to build, one or more selected services, and one Web service for testing. The sampling process is defined as follows. Suppose that a new mashup m consists of a few component services Sn = {s1, s2, ..., sn}, a sample can be described as (m, CS, si), where CS ∈ P(Sn − {si})|{Sm}, i.e., CS belongs to the power set of the difference between Sn and {si} excluding Sm. The difference between a positive sample and a negative one is whether si belongs to Sm or not. The size of negative samples is twelve times that of positive samples in our training sample set. Considering that the number of a mashup’s component services seldom exceeds four in our experimental dataset, we chose one, two, and three services as the selected services when building the sample set.

In this study, we evaluated the performance of models using five-fold cross-validation. Mashups in our experimental dataset were divided into five-folds, where one fold for testing and the others for training each time.

2) Evaluation Metrics

We used the following metrics to evaluate recommendation results and averaged the five-folds’ metric values as the final evaluation result.

Three commonly-used metrics, Precision, Recall, and F1-measure at the top N services in a ranking list, are defined as

\[ P@N = \frac{1}{|M|} \sum_{m \in M} \frac{|\text{rec}(m) \cap \text{act}(m)|}{|\text{rec}(m)|}, \]  

\[ R@N = \frac{1}{|M|} \sum_{m \in M} \frac{|\text{rec}(m) \cap \text{act}(m)|}{|\text{act}(m)|}, \]  

\[ F1@N = \frac{1}{|M|} \sum_{m \in M} \frac{2 |\text{rec}(m) \cap \text{act}(m)|}{|\text{rec}(m)| + |\text{act}(m)|}, \]  

where M is a set of mashups in the test set. For mashup m, rec(m) and act(m) represent a list of recommended services and a collection of actual component services, respectively.

Mean average precision (MAP) at the top N services in a ranking list is defined as

\[ \text{MAP@N} = \frac{1}{|M|} \sum_{m \in M} \frac{1}{N_m} \sum_{i=1}^{N} \frac{N_i}{i} \times I(i), \]  

where \( I(i) \) represents whether the i-th recommended service hits an actual component service of mashup m, \( N_i \) is the number of the hits in the top i positions of the ranking list, and \( N_m \) is the number of component services of m.

Normalized discounted cumulative gain (NDCG) at the top N services in a ranking list is defined as

2 https://keras.io

3 https://github.com/ssca-lab/DLISR
Table 1. Performance comparison of different approaches in two different stages.

| Method     | Stage1 | Stage2 | Stage1 | Stage2 | Stage1 | Stage2 | Stage1 | Stage2 | Stage1 | Stage2 |
|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| WVSM       | 0.0484 | 0.0306 | 0.1854 | 0.1750 | -      | -      | 0.0743 | 0.0484 | 0.1356 | 0.1097 |
| BPR-MF     | -      | 0.0426 | -      | 0.2438 | -      | 0.0675 | -      | 0.1567 | -      | 0.1114 |
| SFTN       | 0.1198 | 0.0754 | 0.4365 | 0.4135 | 0.1815 | 0.1187 | 0.3717 | 0.2895 | 0.2707 | 0.2193 |
| ISRec      | 0.1714 | 0.1004 | 0.6326 | 0.5238 | 0.2609 | 0.1558 | 0.5889 | 0.4099 | 0.4867 | 0.3359 |
| PaSRec     | 0.1666 | 0.1027 | 0.6205 | 0.5371 | 0.2545 | 0.1598 | 0.5909 | 0.4298 | 0.4949 | 0.3545 |
| DINRec     | 0.1638 | 0.1035 | 0.6025 | 0.5395 | 0.2492 | 0.1611 | 0.5540 | 0.4172 | 0.4941 | 0.3361 |
| FISR       | 0.1647 | 0.1022 | 0.6093 | 0.5291 | 0.2511 | 0.1584 | 0.5636 | 0.4128 | 0.4594 | 0.3335 |
| NISR       | 0.1670 | 0.1002 | 0.6132 | 0.5236 | 0.2528 | 0.1559 | 0.5827 | 0.4115 | 0.4816 | 0.3343 |
| HISR       | 0.1771 | 0.1072 | 0.6617 | 0.5572 | 0.2705 | 0.1665 | 0.6090 | 0.4391 | 0.5017 | 0.3583 |

\[ NDCG@N = \frac{1}{|M|} \sum_{m \in M} \frac{1}{Q_m} \sum_{i=1}^{N} \frac{2^{T(i)} - 1}{\log_2 (1 + i)} \]  

where \( Q_m \) denotes the ideal maximum DCG score of a recommendation result for mashup \( m \).

3) Baseline Approaches

As mentioned in Section II, existing service recommendation approaches can be classified into content-based, CF-based, and hybrid approaches. To demonstrate our model’s effectiveness in the online interactive scenario, we selected several competitive methods for comparison, covering the above three types of approaches.

- WVSM (short for weighted vector space model) [34]. This content-based method predicts the probability of a service over a mashup using the WVSM-based similarity between their content information.
- BPR-MF (short for Bayesian personalized ranking for matrix factorization) [35]. This method trains MF-based service recommendation models with a pairwise ranking loss of the Bayesian personalized ranking algorithm. Since BPR-MF is a model-based CF approach, it cannot work well in the online interactive scenario. In the first stage, it fails to work due to the lack of information about selected services. To enable BPR-MF to work in the second stage in the online interactive scenario, we update it manually whenever developers select a new service.
- SFTN (short for recommendation through service factors and top-K neighbors) [5]. This method first calculates two probabilities that a mashup invokes a service in the next round according to the content similarity and the historical interaction between neighbor mashups and the service. It then multiplies the probabilities as a final rating according to Bayes’ theorem.
- PaSRec [23]. PaSRec is a meta-path-based service recommendation approach. In the scenario of service recommendation, PaSRec constructs a HIN network and then measures an overall similarity between two mashups based on meta-paths between them. Finally, it adopts a user-based CF strategy to make a prediction based on the similarity. Besides, this approach designs a pairwise loss function and applies BPR to model optimization.
- ISRec [24]. ISRec is an integrated service recommendation approach. It improves PaSRec with the measure of content similarity using word embeddings. Moreover, it speeds up the search of neighbor mashups by clustering existing mashups offline and classifying a new mashup online.
- DINRec [25]. This method applies a deep interest network in CTR prediction to service recommendations. It exploits available features of the target mashup, selected services, and candidate services, and then learns their interaction in a well-designed network. Besides, a local activation unit is employed to activate those selected services related to the candidate service. We enabled DINRec to utilize the same information and feature extractors as our models for a fair comparison. For this model to work in the scenario studied in this study, we trained it in the same way as our model.

4) Parameter Settings

The parameters of text_inception designed for textual feature extraction in FISR were set as the same as those in [31]. For node2vec in NISR, the dimension of node embeddings, walk length, return probability \( p \), and the in-out probability \( q \) were set to 25, ten, 0.25, and four, respectively. The pre-trained weights of six meta-path-based similarities were set to 0.14, 0.14, 0.27, 0.15, 0.15, and 0.15. For the MLPs in the attention block, the unit numbers of two hidden layers were set to 80 and 40, respectively. For the MLPs in the interaction layer of FISR or NISR, the unit numbers of two hidden layers were set to 100 and 50, respectively. For the MLPs in the integration layer of HISR, the unit numbers of three hidden layers were set to 128, 64, and 32, respectively. The learning rate was set to 0.0003 for the Adam algorithm [33]. For all the baseline approaches, we retained the default parameter settings mentioned in the original references.

B. Performance of HISR

Table 1 presents the performance comparison of different approaches in the first and second stages. As mentioned above, we introduce selected services into samples to evaluate the model performance in the second stage. In our experiment, Stage2 has three cases where the numbers of selected services were set to one, two, and three. The average values of the three cases were taken as the metric values in this stage. Numbers shown in bold font indicate the best results.

FISR and WVSM are two approaches that use only content information. The former performed much better than the latter in terms of the five evaluation metrics. The reasons are two-fold.
On the one hand, FISR uses a CNN-based feature extractor and can obtain high-quality and task-specific features. On the other hand, FISR considers the functionality of selected services when it learns the interactions between mashups and services.

Both BPR-MF and NISR utilize only historical invocation information. The recommendation result of BPR-MF is much worse than that of NISR, suggesting that model-based CF does not work well in this online interactive scenario. To obtain the embedding of a mashup built online, BPR-MF needs to update its model according to the selected services of the target mashup. However, the number of selected services is usually too small for BPR-MF to obtain a high-quality embedding of the target mashup, which leads to poor recommendation results.

SFTN works like BPR-MF, and it is a hybrid approach that leverages content information and historical invocation information. As a result, SFTN improved the performance of BPR-MF (see Table 1). However, it performed worst among all the five hybrid approaches. DINRec, PaSRec, and ISRec have their respective advantages regarding the given indicators. For example, PaSRec outstripped DINRec and ISRec in terms of NDCG and MAP. Compared with them, HISR achieved better results across all the evaluation metrics in both the two stages, indicating its effectiveness over the baselines.

For hybrid approaches, we further compared HISR and the three competitive baselines mentioned above, namely DINRec, ISRec, and PaSRec. Table 2 presents their indicator values in all the three cases of Stage2. Note that the symbol “Gain” denotes the percentage of the performance improvement of HISR relative to the target baseline. A higher positive value of “Gain” indicates a significant improvement of our method in service recommendation.

When the developer selected only one component service, HISR did not perform better than ISRec and PaSRec regarding MAP, NDCG, and Recall. The reason is that the solely-selected service contributed little useful information or even noise to the interactive learning process. When the number of selected services increased to two, HISR achieved the best results across all the given indicators. Moreover, as the number of selected services increased to three, our hybrid approach got increasing advantages over the three baselines. The reasons are analyzed as follows.

DINRec was proposed based on a deep interest network designed by Zhou et al. [25] for e-commerce recommendation. Considering that each item’s features are usually sparse and homogeneous, the original deep interest network enforces all kinds of features of items to interact with each other sufficiently to learn latent interaction patterns. In the online interactive scenario, features of mashups and services are extracted from content information and historical invocations. DINRec shows a limited ability to learn the interactions between features from two independent and heterogeneous spaces. In contrast, HISR learns internal interactions in the two feature spaces and then fuses them with an MLP, thus increasing the performance of interactive learning.

PaSRec and ISRec estimate one service’s scalar score over a new mashup according to the history of invocations between neighbor mashups and the service. However, neither of the two baselines makes use of their interactions with selected services. Instead, HISR learns the interactions among the target mashup, selected services, and the next service to recommend by an elaborate interaction layer equipped with an MLP and an attention block.

C. Integration strategies of selected services

DLISR predicts the probability of a mashup with selected services invoking a service based on their interactions. To learn such interactions more efficiently, we need to integrate each selected service’s representation and obtain a comprehensive representation of all selected services. An attention mechanism is utilized in our framework to accomplish this task. To compare the impact of different integration strategies on recommendation performance, we replaced the attention mechanism with three other strategies and generated three framework variants.

- **DLISR-Average.** This framework performs the average pooling strategy on the representation of each selected service and assigns equal weight to them.
- **DLISR-Concatenation.** This framework directly concatenates the representation of each selected service. We truncate or pad the set of selected services to get a final representation with a fixed size.
- **DLISR-None.** This framework discards selected services during the interactive learning process.
We evaluated the performance of DLISR and its three different variants in all three cases of Stage 2. Table 3 shows the comparison result and highlights the “Gain” of our framework relative to the target baseline.

DLISR-None performed the worst in most cases, indicating that selected services did play an essential role in the online interactive recommendation. When developers selected only one service, there was no apparent difference in performance among DLISR, DLISR-Concatenation, and DLISR-Average. When developers selected two and more services, our attention-based framework performed better than DLISR-Average and DLISR-Concatenation. The above result indicates that DLISR can pay more attention to those selected services related closely to the current prediction and obtain adaptive representations specific to different services for testing. Our approach aims to help develop large-size mashups, but the number of selected component services in our experimental dataset is relatively small. Therefore, the performance improvement of adopting the attention mechanism is not as significant as expected. This assertion can be verified by the observation that the percentage of performance improvement gradually increases as the number of selected services increases in most cases.

### D. Impact of the Size of Neighbor Mashups

It is hard to directly model the interaction between a new mashup and an existing service due to the cold-start problem. In this study, we infer such an interaction using the interactions between the new mashup’s neighbor mashups and the service. Therefore, the number of neighbor mashups, $K$, is a critical factor for the DLISR framework. To study this parameter’s effect on recommendation performance, we adjusted $K$ from 10 to 50 with step 10.
As shown in Fig. 5, all the indicators increase as the value of $K$ increases from 10 to 20, which suggests that our approach can exploit more beneficial information from neighbor interactions. However, the opposite is true when $K$ exceeds 20. Perhaps the introduction of noisy data brings harmful interference to interaction learning at this stage. Therefore, we set $K$ to 20 in our experiments.

According to the experimental results mentioned above, we can draw the following conclusions:

- HISR outperforms other competitive baseline approaches in both the first and second stages of the session-based interactive recommendation scenario for iterative mashup development.
- Selected services do affect the selection of the next service. Furthermore, when integrating representations of selected services, the attention mechanism performs better than the commonly-used concatenation and average-pooling strategies in most cases.

VII. CONCLUSION

This study highlights an online interactive scenario of service recommendation for mashup development. We propose a deep-learning-based interactive service recommendation framework to address the problems of single-round (or one-shot request-response-style) recommendations. An attention mechanism is employed to weigh selected services when determining the next service to recommend. The framework can learn the interaction among the target mashup, selected services, and candidate service. Finally, it predicts the probability of the target mashup invoking the candidate service in the next round of recommendations. According to the framework, we design two separate models for learning such interactions from the perspectives of content information and historical invocations. Then, we integrate these two types of interactions in a hybrid model called HISR. Experiments conducted on a real-world dataset indicate that the hybrid model outperforms several state-of-the-art service recommendation approaches in different interactive development scenarios of mashups.

In the future, we plan to improve our approach from the following three aspects. Firstly, there may exist a few frequent local patterns in developers' selection behaviors [36]. For example, after a developer invokes a service, the developer has a high probability of invoking other services related closely to the selected service. We will explicitly introduce these patterns into our framework and implementation models. Secondly, the online interactive service recommendation is investigated only from the perspective of functionalities. Therefore, we plan to incorporate QoS properties into the interactive recommendation process. Thirdly, the proposed framework does not leverage developers' personalized preferences or long-term interests due to the lack of such experimental data. Suppose these related data of developers are available. In that case, we can compute an extra score concerning developers' long-term preferences and personal attributes and then integrate it with the selection probability computed by our interactive model to make a more accurate prediction.

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APPENDIX

CALCULATING SIMILARITY BETWEEN MASHUPS BASED ON A HETEROGENEOUS INFORMATION NETWORK

We build a heterogeneous information network (HIN) to organize existing entities in a service registry, e.g., mashups and services. Each mashup or service has its content information, which generally falls into two forms: word sequence (such as service description) and separate words (such as tags).

We first process the content information in the form of word sequence by the latent Dirichlet allocation (LDA) model and use the obtained top three latent topics as a straightforward and approximate representation of the information. In the HIN, we use the hasTopic edge to connect mashups or services and the corresponding latent topics. Meanwhile, we use the hasTag edge to connect mashups or services and the content information in the form of separate words. Considering each service has a provider, we use the hasProvider edge to connect services and their providers. Since invocations exist between mashups and services, we use the HasComponentService edge to connect mashups and their component services. Fig. A1 shows the structure of our HIN.

In the HIN, we find six types of meta-paths to establish connections between two mashups:

- MetaPath1: mashup1-topic-mashup2, which means that two mashups share the same latent topic.
- MetaPath2: mashup1-tag-mashup2, which means that two mashups have the same tag.
- MetaPath3: mashup1-service-mashup2, which means that two mashups invoke the same service.
- MetaPath4: mashup1-topic-service2-mashup2, which means that two mashups invoke similar services that share the same topic.
- MetaPath5: mashup1-tag-service2-mashup2, which means that two mashups invoke similar services that have the same tag.
- MetaPath6: mashup1-provider-service2-mashup2, which means that two mashups invoke similar services released by the same provider.

We employ the path-based method mentioned in [37] to calculate the similarity between mashups. Taking MetaPath1 between mashups $m_1$ and $m_2$ as an example. The similarity based on this path, $sim_p(m_1, m_2)$, can be calculated using the following formula:

$$
sim_p(m_1, m_2) = \frac{2 \times |topics(m_1) \cap topics(m_2)|}{|topics(m_1)| + |topics(m_2)|} \quad (A1)
$$

where $topics(m_1)$ and $topics(m_2)$ are the latent topic sets of $m_1$ and $m_2$, respectively.

In this way, we can obtain all the six types of similarities between two mashups based on the six meta-paths and calculate their weighted sum to get an overall similarity between the two mashups.