Related work

1. Static Service recommendation

Most existing service recommendation approaches are designed for static mashup development scenario. They only generate one candidate service list for target mashup and can hardly update their recommendations given developers’ online selection behavior. These approaches mainly fall into three types: content-based approaches, collaborative filtering (CF)-based ones, and hybrid ones.

Content-based approaches predict the rating of a service over a mashup according to the similarity between service description and developer requirements. As a key-word-based framework, WS-Finder [1] applied the Earth Mover’s Distance (EMD) in multimedia databases to many-to-many partial matching between developer requirements and service attributes. Malak *et al.* [2] used domain ontologies to enrich semantics of the content information, and then applied logical reasoning to semantic similarity measurement. Shi *et al.* [3] first utilized service labels to retrieve and highlight the functional-related words in the service description based on the attention mechanism, and then proposed a deep structured semantic model to measure the matching degree between the functionality of a mashup and a service.

Based on historical information, CF-based approaches discover users’ implicit preference and generalize the pattern of similar users or items. Samanta *et al.* [4] applied matrix factorization (MF) to the invocation records between services and mashups and took the inner-product of their obtained latent factors as an important factor determining their interaction probability. Wu *et al.* [5] applied graph embedding techniques to user co-tag network and social network and got two representations containing user preference and social relations, and finally capitalize on them in user-based CF service recommendation. Zou *et al.* [6] incorporated user-based and service-based CF in a reinforced CF framework and removed the services (or users) dissimilar with the target service (or the target user) when predicting the quality of service (QoS).

Hybrid approaches integrated multiple models or various kinds of feature to make recommendations. Some approaches added side information into MF-based models to improve their performance. Convinced that some contextual factors, such as geographical location information and textual descriptions, have an underlying influence on developer’s selection behavior, Khavee *et al.* [8] derived two relevance scores from the two factors and leveraged them in MF-based service recommendation. Mo *et al.* [9] mined the relationship between services based on their functional similarities and used it to regularize the attentional Matrix Factorization. Inspired by some remarkable models in click through rate (CTR) prediction, some other approaches applied Factorization Machine (FM) [10] and deep neural network to service recommendation. Xiong *et al.* [11] blended collaborative filtering and content-based recommendation with a DNN. Chen *et al.* [12] presented a neural CF recommender model that learned user’s preference on a service in terms of their matching degree on explicitly declared attribute preference and on implicit preference exploited from historical invocation. Cao et al. [13] first extended the content information of a mashup and a service according to Wikipedia corpus and then got a representation of the extended information with Hierarchical Dirichlet Process (HDP). Finally, it integrated all available features, including the extracted content feature, similar services or mashups, popularity and the co-occurrence of services, into FM to capture their 2nd-order interaction. The authors in [14] pointed out FM neglected the fact that not all features were equally important for the final prediction. They introduced the attention mechanism into FM and discriminated each feature when learning their interactions.

1. Interactive service recommendation

Some researchers adopted the strategy of step-by-step recommendation according to the real demands when building their service discovery or composition platforms. Zhao *et al.* [15] designed a platform for service consuming and navigation named HyperService. For a non-technical user, HyperService searched and recommended a set of relevant services according to his or her input keywords and navigation context. Every time the user selected a service, another candidate service list was dynamically generated and recommended. Considering that social networks influenced and even could change developer’s selection, Maaradji *et al.* [16] proposed a framework that retrieved knowledge from social networks and incorporated it with user profile to make dynamic recommendations for service discovery and selection. Liu *et al.* [17] first applied Generalized Sequential Pattern algorithm to engaged mashups and discovered the frequent composition pattern of services. When recommending next sequence, they leveraged users’ current selection and considered both the frequency and the logic order of internal components to facilitate mashup development.

Considering user preference were evolving because of the changes in user’s needs and service functions or QoS, some studies improved service recommendation by tracking the dynamic preference sequence and predicting user’s future preference. Zhang *et al.* [18] extracted user’s dynamic preference from time slice data by time-series LDA and generated a new service list based on the latest user’s preference and QoS. Kwapong *et al.* [19] composed a user’s invocation preference at a timestamp as a combination of non-functional attribute (such as Qos when service invocation occurs) and the functional features extracted from WSDL of the invoked service. Then they applied a LSTM to model user preference sequence and predict his latest preference for the next step of recommendation.

User-based CF was able to re-calculate mashup similarity, find more accurate neighbor mashups and update their recommendations when developers selected new services. In [20] and [21], the authors first organized all entities in service recommendation, including mashups, services, their descriptions, tags and providers, with a heterogeneous information network (HIN), then measured an overall similarity between mashups based on the network, and finally leveraged the similarity in the user-based CF.

Some deep-learning-based models regarded user behavior sequence as a reflection of user interest and leveraged it as a supplement of user portrait, such as [22][23] in the domain of CTR prediction. Inspired by them, DINRec [24] employed the attention mechanism to distinguish different selected services according to their relevance to the next service selection. If newly selected services were available, the model could make use of the user feedback and learned the latest interaction between developers and candidate services.

Conclusion

In this study, we summarized an interactive mashup development scenario and presented a deep attention-based framework for it. We leveraged selected services into the framework and employed the attention mechanism to distinguish the effect of different services on the selection of next service. Our framework learned the interaction among a target mashup, its selected services and a candidate service, and finally predicted the probability of the mashup invoking the service in the next round. According to the framework, we proposed two models that learned the interaction from the content information and historical invocations, respectively. Then we integrated these two kinds of interactions in a hybrid model. Experiments on a real-world dataset indicated that our hybrid model outperformed various service recommendation approaches in several cases of the interactive developing scenario.

In the future, we are going to improve our approach from the following perspectives. Firstly, the services appeared in the recommendation list but not selected by developers indeed imply user preference from a negative aspect. We will study how to sufficiently make use of this kind of feedback. Secondly, there may exists some frequent local patterns in developer’s selection behavior, i.e., after developers invoke a service, they usually invoke another related service. We will explicitly introduce these patterns into our model.

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