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 are evolving because of the changes in users’ needs and service functions or Qos (quality of service), some studies improved service recommendation by tracking the dynamic preference sequence and predicting the user’s future preference. Therefore, these models can respond to the newly selected services and update user preference to make next round recommendation. Zhang *et al.* [18] extracted the user dynamic preference from time slice data by time-series LDA to and generated the lasted service list based on the latest user preferences 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 functional features extracted from WSDL of the invoked service by HDP. Then they applied a LSTM to model user preference sequence and predict his preference of next step to generate a new recommendation list.

User-based CF methods could re-calculate mashup similarity, find more accurate mashup neighbors and update their recommendation result 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 a user-based CF way.

Some deep-learning-based models took user behavior sequence as a reflection of the user's interest and leverage it into the model as a supplement of the user's 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. When fed newly selected services, the model could make use of the user feedback and learned the latest interaction between developers and candidate services.

1. Jiangang Ma, Quan Z. Sheng, Kewen Liao, Yanchun Zhang, Anne H. H. Ngu: WS-Finder: A Framework for Similarity Search of Web Services. ICSOC 2012: 313-327
2. M. Al-Hassan, H. Lu, and J. Lu, “A semantic enhanced hybrid recommendation approach: A case study of e-Government tourism service recommendation system,” Decis. Support Syst., vol. 72, pp. 97–109, 2015, doi: 10.1016/j.dss.2015.02.001.
3. Min Shi, Yufei Tang, Jianxun Liu: TA-BLSTM: Tag Attention-based Bidirectional Long Short-Term Memory for Service Recommendation in Mashup Creation. IJCNN 2019: 1-8
4. P. Samanta and X. Liu, “Recommending Services for New Mashups through Service Factors and Top-K Neighbors,” in Proc. IEEE Int. Conf. Web Serv., 2017, pp. 381–388, doi: 10.1109/ICWS.2017.128.
5. Hao Wu, Hanyu Zhang, Peng He, Cheng Zeng, Yan Zhang: A Hybrid Approach to Service Recommendation Based on Network Representation Learning. IEEE Access 7: 60242-60254 (2019)
6. G. Zou, M. Jiang, S. Niu, H. Wu, S. Pang, and Y. Gan, “QoS-Aware Web Service Recommendation with Reinforced Collaborative Filtering,” in Proc. Int. Conf. Serv.-Oriented Comput., 2018, pp. 430–445, doi: 10.1007/978-3-030-03596-9\_31.
7. Yao L , Wang X , Sheng Q Z , et al. Mashup Recommendation by Regularizing Matrix Factorization with API Co-Invocations[J]. IEEE Transactions on Services Computing, 2018:1-1.
8. Khavee Agustus Botangen, Jian Yu, Sira Yongchareon, Liang Huai Yang, Quan Z. Sheng: Integrating Geographical and Functional Relevance to Implicit Data for Web Service Recommendation. ICSOC 2019: 53-57
9. Mo Nguyen, Jian Yu, Quan Bai, Sira Yongchareon, Yanbo Han: Attentional Matrix Factorization with Document-context awareness and Implicit API Relationship for Service Recommendation. ACSW 2020: 17:1-17:10
10. Steffen Rendle: Factorization Machines. ICDM 2010: 995-1000
11. R. Xiong, J. Wang, N. Zhang, and Y. Ma, “Deep Hybrid Collaborative Filtering for Web Service Recommendation,” Expert Syst. Appl., vol. 110, pp. 191–205, 2018, doi: 10.1016/j.eswa.2018.05.039.
12. L. Chen, A. Zheng, Y. Feng, F. Xie, and Z. Zheng, “Software Service Recommendation Base on Collaborative Filtering Neural Network Model,” in Proc. Int. Conf. Serv.-Oriented Comput., 2018, pp. 288–403, doi: 10.1007/978-3-030-03596-9\_28.
13. Buqing Cao, Bing Li, Jianxun Liu, Mingdong Tang, Yizhi Liu, Yanxinwen Li: Mobile Service Recommendation via Combining Enhanced Hierarchical Dirichlet Process and Factorization Machines. Mobile Information Systems 2019: 6423805:1-6423805:11 (2019)
14. Yingcheng Cao, Jianxun Liu, Min Shi, Buqing Cao, Ting Chen, Yiping Wen: Service Recommendation Based on Attentional Factorization Machine. SCC 2019: 189-196
15. Chenting Zhao, Chun'e Ma, Jing Zhang, Jun Zhang, Li Yi, Xinsheng Mao: HyperService: Linking and Exploring Services on the Web. ICWS 2010: 17-24
16. Abderrahmane Maaradji, Hakim Hacid, Johann Daigremont, Noël Crespi: Towards a Social Network Based Approach for Services Composition. ICC 2010: 1-5
17. Xinyi Liu, Hailong Sun, Hanxiong Wu, Richong Zhang, Xudong Liu: Using Sequential Pattern Mining and Interactive Recommendation to Assist Pipe-like Mashup Development. SOSE 2014: 173-180
18. Yanmei Zhang, Ya Qian, Yan Wang: A Recommendation Algorithm Based on Dynamic User Preference and Service Quality. ICWS 2018: 91-98
19. Benjamin A. Kwapong, Richard Anarfi, Kenneth K. Fletcher: Personalized Service Recommendation Based on User Dynamic Preferences. SCC 2019: 77-91
20. T. Liang, L. Chen, J. Wu, H. Dong, and A. Bouguettaya, “Meta-Path Based Service Recommendation in Heterogeneous Information Networks,” in *Proc. Int. Conf. Serv.-Oriented Comput.*, 2016, pp. 371–386, doi: 10.1007/978-3-319-46295-0\_23.
21. F. Xie, J. Wang, R. Xiong, N. Zhang, Y. Ma, and K. He, “An Integrated Service Recommendation Approach for Service-Based System Development,” *Expert Syst. Appl.*, vol. 123, pp. 178–194, 2019, doi: 10.1016/j.eswa.2019.01.025.
22. Guorui Zhou, Xiaoqiang Zhu, Chengru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, Kun Gai: Deep Interest Network for Click-Through Rate Prediction. KDD 2018: 1059-1068
23. Yufei Feng, Fuyu Lv, Weichen Shen, Menghan Wang, Fei Sun, Yu Zhu, Keping Yang: Deep Session Interest Network for Click-Through Rate Prediction. IJCAI 2019: 2301-2307
24. Yong Xiao, Jianxun Liu, Rong Hu, Buqing Cao, Yingcheng Cao: DINRec: Deep Interest Network Based API Recommendation Approach for Mashup Creation. WISE 2019: 179-193