DySR: A Dynamic Representation Learning and Aligning based Model for Service Bundle Recommendation

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An increasing number and diversity of services are available, which result in significant challenges to effective reuse service during requirement satisfaction. There have been many service bundle recommendation studies and achieved remarkable results. However, there is still plenty of room for improvement in the performance of these methods. The fundamental problem with these studies is that they ignore the evolution of services over time and the representation gap between services and requirements. In this paper, we propose a dynamic representation learning and aligning based model called DySR to tackle these issues. DySR eliminates the representation gap between services and requirements by learning a transformation function and obtains service representations in an evolving social environment through dynamic graph representation learning. Extensive experiments conducted on a real-world dataset from ProgrammableWeb show that DySR outperforms existing state-of-the-art methods in commonly used evaluation metrics, improving F@5 from 36.1% to 69.3%.

Index Terms—Service Bundle Recommendation, Evolving Service Social, Cold Start, Deep Learning, Dynamic Graph

I. INTRODUCTION

With the rapid development of new technologies such as cloud, edge, and mobile computing, the number and diversity of available services are dramatically exploding, and services have become increasingly important to people’s daily work and life. The increasing number and diversity of services bring significant challenges to effective service management and reuse. Consequently, recommending suitable services for developers based on requirements to help them reduce the burden of service selection in creating applications (mashups) becomes a non-trivial issue, and such task is often called service bundle recommendation in services computing.

Service bundle recommendation refers to recommending a set of services based on these services’ functions and history compositions to satisfy the user’s explicit and implicit requirements[1]. There have been many service recommendation studies from different perspectives. Existing approaches can be categorized into natural language processing (NLP) based approaches[2, 3, 4], graph-based approaches[5, 6, 7], and hybrid approaches[8, 9]. These approaches have achieved remarkable results. However, ignoring the following factors limits the performance of their approaches and the application scenarios in reality:

(1) Cold Start: Most existing approaches leverage the interaction history between mashups and services to recommend missing services. They work well in normal situations like user-item recommendations and user-movie recommendations. The co-occurrence between users(mashups) and items(movies/services) can be repeated. However, in the application scenario of mashup creation, each mashup only appears once and without any interaction with existing services. The lack of such information decreases the performance of existing approaches. This phenomenon is also known as the cold start of requirements, which has recently started to attract the attention of researchers[9, 10]. Additionally, existing approaches assume all services have enough description document and historical usage information (e.g., invocation history, co-invocation, and popularity). While, in the real world, services are created in temporal order, and newly created services often do not accumulate enough historical usage information or even no historical usage information. Or, due to unregulated development, some service providers do not provide a comprehensive service description. These services are usually ignored in existing approaches. We call this phenomenon the cold start of services, which has not received enough attention in service bundle recommendations.

(2) Evolving Service Social: Since, in most cases, services do not actively update their profile promptly[11]. existing approaches assume services’ function and quality are static. However, we argue that the quality of services evolves, and the functionality of services evolves in a latent way as their social environment changes. For example, a service that other applications have not invoked for a long time may indicate that the service quality has degraded or that an alternative service with better similar functionality is available and should be avoided when making service recommendations. Readmill is an example of service function evolving[12], which is designed for “Social” as its profile says “Readmill is an online and mobile platform for readers to share information about ..., allowing them to highlight and discuss sections of eBooks with other users. . .”. The mashups that invoke Readmill are gradually moving from the “Social” domain to the “Book” domain, indicating that the social environment of Readmill is gradually evolving from “Social” to “Books”.

(3) Representation Gaps between Services and Requirements: There is a large gap between services and requirements representation, often overlooked in existing approaches. The representation of requirements focuses on the functionality and value that the constructed mashup can provide to the

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1https://www.programmableweb.com/api/readmill
Three Challenges: Cold Start, Evolving Service Social, and Representation Gap

Innovations of DySR: Requirement-Service Matching Function, Evolving Representation of Service, Learnable Transformation Function, and Joint Learning & GAN-style Training

Fig. 1. The correspondence between the innovations of our proposed DySR model and the service bundle recommendation challenges

This paper proposes a dynamic representation learning and aligning based model called DySR to solve the three challenges mentioned above. Fig. 1 shows how the innovation modules in DySR address the challenges mentioned above, where Learnable Transformation Function, Evolving Representation of Service, and Requirement-Service Matching Function are used to address Representation Gaps, Evolving Service Social, and Cold Start, respectively. In addition, Joint Learning & GAN-style Training is used to combine the other three modules so that they can provide complementary information to each other:

1) Learnable Transformation Function: We propose a learnable transformation function that aligns the representation of requirements to the semantic space where the representation of services resides, thus eliminating the representation gap between requirements and services.

2) Evolving Representation of Service: We form a dynamically evolving graph of services based on co-invocation relations. Then we perform dynamic representation learning on this dynamic graph to obtain a dynamic representation of the services to solve evolving service social environment.

3) Requirement-Service Matching Function: We introduce a learnable function called the requirement-service matching function to evaluate the probability of an invocation between a given requirement and a service. This function works with only the aligned representation of the requirements and services and does not require other information (e.g., known component service, historical usage). Thus the cold start of mashups and the cold start of services are solved at the same time.

4) Joint Learning & GAN-style Training: DySR models the influence mechanism of service and requirement by jointly learning the dynamic representation learning task of services and service recommendation task. A Generative Adversarial Network (GAN) like training approach is also proposed to model the process of requirement-induced service evolution and service evolution reacting to requirement, unlike GAN, where the two tasks are not adversarial but cooperative.

Besides the proposed DySR model, the contributions of this paper also include: 1) We provide an in-depth analysis of the issues that have not been sufficiently discussed in real-world service recommendation scenarios; 2) We have conducted extensive experiments on the real-world dataset ProgrammableWeb, which shows that our proposed model significantly outperforms several state-of-the-art approaches in terms of recommendation performance; 3) We have also constructed additional experiments to discuss the effects of the different components of DySR.

The remainder of this paper is organized as follows: In Section II we introduce related work. In Section III we describe relevant details of the DySR model. In Section IV we give the details of the experiment settings. In Section V we present the experiment results and discuss how DySR works. In the final section, we present the conclusion.

II. RELATED WORK

The use of service bundle recommendations to satisfy the requirements of users creating new mashups has recently attracted a great deal of academic and industrial attention. Service recommendation approaches can be divided into the following categories based on the information used: NLP-based approaches, graph-based approaches, and hybrid approaches.

A. NLP-based Approaches

The main idea of NLP-based approaches is to make recommendations by measuring the similarity between the description of the candidate services and the requirement. Keywords[14], [15] and TF-IDF[16] are used to match services to satisfy mashup creation. However, these matching procedures cannot really understand semantic and suffer from poor performance.

Ontology-based approaches annotate requirements and services with domain ontologies and use these ontologies to match high-level concepts or calculate their semantic
similarities. However, the lack of suitable domain ontologies and the huge manual annotation cost of ontology construction make ontology-based approaches difficult to use in real-world scenarios. Some studies attempt to use latent semantics to denote text features. Currently, the most common technique used to solve this problem in the field of service computing is the topic model. For example, Li et al. use a topic model to explore the semantic relationships between mashups and services. Zhong et al. refactor descriptions by using Author-Topic Model to eliminate the gaps between mashups and services. However, small data volumes, high noise in data, and ignoring word orders make the performance of topic model-based methods unsatisfactory; for example, the recent SOTA method based on topic models has an F1@5 value of only about 30% on the ProgrammableWeb dataset. With the great success of pre-trained language models (PLMs) and deep learning models in the NLP, some researchers start using PLMs and deep learning to solve the service recommendation problem. For example, Bai et al. designed a stacked denoising autoencoder (SADE) to extract features for the recommendation. However, experimental results show that the simple introduction of PLMs and deep learning does not significantly improve recommendation performance, possibly due to the inability of existing models to directly adapt to service recommendation and negative transfer.

The major drawback of the NLP-based approaches is the inability to leverage the social information between services, leading to recommended service bundles with combinations of services that cannot co-occur due to real-world constraints, despite being functionally compatible.

B. Graph-based Approaches

Unlike NLP-based approaches, graph-based approaches make recommendations by mining information from historical interaction between services or requirements (users). For example, [25], [5], [26] design recommendation algorithms based on the feature learned on knowledge graph.

The graph-based approach usually works in conjunction with collaborative filtering (CF). For example, Chen et al. propose a neighborhood integrated matrix factorization approach to predict the quality of service (QoS) of candidate services. Chang et al. designed a graph-based matrix factorization approach to predict QoS, then use the QoS to select services. Besides predicting QoS, graph is also applied to find similar users or services. For example, Maardji et al. proposes a frequent pair mining method for mashup development. Qi et al. adopts a hybrid random walk to compute the similarities between users or services, and a CF model is designed for service recommendation. [31], [52] build a heterogeneous information network using various information of services and mashups to measure the similarity between mashups, and then use the user-based CF to ranking candidate services.

Graph-based approaches cannot solve the cold start problem, as new requirements do not have any historical information.

C. Hybrid Approaches

Considering the complementarity of textual and graph information, a number of hybrid service recommendation approaches combining the two types of data have been proposed in recent years.

Li et al. add the invocation relations between requirements and services to a latent Dirichlet allocation (LDA) model to enable the topic model learn the relationship between services and requirements. Incorporates data structure made up of service and their co-invocation records into LDA. Jain et al. and Samanta et al. use topic models and neighbor interaction probabilities to calculate similarity scores between services and requirements, then multiply these scores to rank candidate services.

Deep learning-based approaches are becoming the mainstream of hybrid methods. For example, Xiong et al. integrates the invocation relations between services and requirements as well as their description similarity into a deep neural network (DNN). Chen et al. propose a preference-based neural collaborative filtering recommendation model, which uses multi-layer perceptron to capture the non-linear user-item relationships and obtain abstract data representation from sparse vectors. Ma et al. utilize the powerful representation learning abilities provided by deep learning to extract textual features and features from various types of interactions between mashups and services. Wu et al. propose a neural framework based on multi-model fusion and multi-task learning, which exploits a semantic component to generate representations of requirements and introduces a feature interaction component to model the feature interaction between mashups and services.

Although the hybrid approach is a significant improvement over the NLP-based approaches and graph-based approaches, the current SOTA approach still has an F1@5 value below 40% on the ProgrammableWeb dataset. This is mainly caused by ignoring the difference in representation between services and requirements and the evolving service social environment. The DySR model proposed in this paper is a hybrid approach that achieves F1@5 values close to 70% on the ProgrammableWeb dataset by tackling the representation gap and service evolution.

III. DYNAMIC REPRESENTATION LEARNING AND ALIGNING BASED MODEL

In this section, we introduce the details of the DySR model. In Section II-A, we first explain the joint learning framework of DySR. Next, we detail two main subtasks in DySR, supervised service recommendation task and unsupervised evolving service representation task, in Section II-B and Section II-C respectively. Finally, in Section III-D, we describe the GAN-style training process. Table I list frequently-used notions in this section and their meanings.

A. Overall Framework

As shown in Fig. 2, the proposed DySR model consists of two subtasks: a supervised service bundle recommendation task and an unsupervised evolving service representation task.
The service recommendation subtask is used to satisfy our need to recommend suitable services for a new requirement, and this task is used in both the training and inference stage of the DySR model. The representation gaps between requirement and service are eliminated, and the requirement-service matching function is learned in this subtask. The evolving service representation subtask is used to solve the service evolving problem. It is a supplementary task to the service recommendation subtask and is used to provide a suitable service representation for service bundle recommendation, so it will only be used in the training stage of the DySR model.

During the training stage, the input of DySR model is a requirement \( r \) that is satisfied at historical time \( t \) by a set of component services \( C^+ = \{s_1, s_2, \ldots, s_n\} \), which is used in the supervised task as ground truth. And a set of co-invocation event \( O = \{(o = (s_u, s_v, t))|s_u, s_v \in C^+ \text{ and } s_u \neq s_v\} \) is generated from \( C^+ \) as the training samples of the unsupervised task. While in the inference stage, the input of DySR model is a requirement \( r \), and the output is a set of recommended component services \( \hat{C} = \{\hat{s}_1, \hat{s}_2, \ldots, \hat{s}_m\} \).

### B. Supervised Service Bundle Recommendation

For a requirement \( r \) at time \( t \), we denote the latent representation as \( v_r \in \mathbb{R}^d_r \), a dense vector obtained by a certain encoding method (e.g., text encoding using pre-trained language model), where \( d_r \) is the dimension of the requirement’s latent representation. We use \( z^t_s \in \mathbb{R}^d_z \) to denote the recently updated latent representation of candidate service \( s \) just before \( t \), where \( d_z \) is the dimension of each service’s latent representation. And \( Z^t \) is all candidate services latent representation. The obtaining of \( Z^t \) is discussed in detail in Section III-C.

#### 1) Transformation Function

As we state in Section III-A, a key problem in real-world service recommendation is to eliminate the gap between requirement representations and service representations. Transformation function \( \Psi \) can be learned to align the representation space to solve this problem, and the overall idea is illustrated in Fig. 2.

In this paper, we use affine transformation \( [39] \) to implement the transformation function \( \Psi \):

\[
\Psi(v_r) = W_\Psi \cdot v_r + b_\Psi
\]

where \( W_\Psi \in \mathbb{R}^{d_z \times d_r} \) is affine transformation matrix and \( b_\Psi \in \mathbb{R}^{d_z} \) is translation vector. The main advantage of affine transformation is preserves collinearity and ratios of distance.
which means that similar requirements remain similar after affine transformation.

2) Requirement-Service Matching Function

After transforming the requirement representation into the same semantic space of the service representations, we design a requirement-service matching function that first fuses the representations of requirement $r$ and candidate service $s$ under the same semantic space and then outputs the probability that $s$ is a component service of $r$ at time $t$:

$$
\Lambda(\Psi(v_r), z^t_s) = z^t_s \cdot W_\Lambda \cdot v_r^\top
$$

(2)

where $\tau$ is vector transpose operation and $W_\Lambda \in \mathbb{R}^{d_s \times d_s}$ is a trainable parameter. Since we want to know the probability, we adopt a sigmoid activation function in the output the requirement-service matching function:

$$
y^t_{r,s} = \sigma(\Lambda(\Psi(v_r), z^t_s))
$$

(3)

3) Loss Function

For a given requirement $r$ with component services $C^+ = \{s_1, s_2, \ldots, s_n\}$ at time $t$, we minimize the following loss function:

$$
L_1 = - \sum_{s \in C^+ \cup C^-} y^t_{r,s} \log y^t_{r,s} + (1 - y^t_{r,s}) \log(1 - y^t_{r,s})
$$

(4)

where $y^t_{r,s} \in \{0, 1\}$ denotes whether $s$ is a component service of $r$ at time $t$, and $C^-$ denotes a set of negative samples with services that are not component services of $r$ at time $t$. Usually, a requirement is satisfied using a limited number of services, but the number of candidate services is much larger than the number of services required. So it is not appropriate to use all unselected services as negative samples, and we select negative samples of number $|C^-| = 6|C^+|$ by random sampling.

C. Unsupervised Evolving Service Representation

Unlike existing approaches that maintain a requirement-service invocation graph, DySR only needs to maintain a dynamic service co-invocation graph, which is more practical:

- Compared to services, requirements are one-off and grows rapidly in volume, making the requirement-service invocation graph very large and sparse over time. On the one hand, this does not facilitate the extraction of information, and on the other hand, requires more expensive hardware resources.

- Requirements are usually created by users, which may involve privacy and security issues. For example, users may not want their requirements to be available to other users. Service co-invocation graph can solve this problem, as it only records co-invocations between services but not specific requirement content.

The service co-invocation graph can be represented as a dynamic adjacency matrix $A^t \in \mathbb{R}^{|C^+| \times |C^+|}$, where $C^+$ is the set of services at time $t$, and $A^t_{s_u, s_v}$ is the number of times service $s_u$ and $s_v$ have been co-invoked before time $t$. The phenomenon of service evolution can be reflected by the evolution of the service co-invocation graph, which can be seen as a co-invocation event-driven temporal point process. We use $o = (s_u, s_v, t)$ to represent a co-invocation event, which means $s_u$ and $s_v$ are co-invoked at time $t$.

We use a variant of the DyRep[40] model to learn the service representation on a dynamic service co-invocation graph. For a given co-invocation event $o = (s_u, s_v, t) \in \mathcal{O}$, the main training steps consist of the following:

1) Service Representation Update

When an co-invocation event occurs, the representation of participating service $s_u$ is updated based on the three terms of Self-propagation, Exogenous Drive and Attention-based Aggregation. Specially, for an event of service $s_u$ at time $t$, updating $z^t_{s_u}$ as:

$$
z^t_{s_u}(t) = \sigma(\underbrace{W_a h^t_{rec}(s_u) + W_{rec} z^t_{s_u}}_{\text{Aggregation}} + W_t (t - t^{s_u}))
$$

(5)

where $W_a \in \mathbb{R}^{d_s \times d_s}$, $W_{rec} \in \mathbb{R}^{d_s \times d_s}$ and $W_t \in \mathbb{R}^{d_s}$ are learned parameters used to control the effect of above-mentioned three terms on the computation of service representation, respectively. $\sigma(\cdot)$ is a nonlinear function. $z^{t^{s_u}}_{s_u}$ is the previous representation of service $s_u$. $t$ denotes the time point just before current event time $t$ and $t^{s_u}$ represent the time point of last co-invocation event involved $s_u$. $h^t_{rec}(s_u) \in \mathbb{R}^{d_s}$ is the output representation obtained from the aggregation of service $s_u$’s neighbors $N^t_{s_u} = \{s_v: A^t_{s_u, s_v} > 0\}$:

$$
h^t_{rec}(s_u) = \max(\text{softmax}(S^{t}_{s_u})_{s_v} W_{b} z^t_{s_v}, \forall s_r \in N^t_{s_u}))
$$

(6)

where $W_{b} \in \mathbb{R}^{d_s \times d_s}$ is learned parameters. Temporal attention $S^{t}_{s_u}$ is used to control the amount of information propagated from service $s_u$’s neighbors, which is updated by a hard-coded algorithm[1] adopted from DyRep[40].

Conditional intensity $\lambda^t_{s_u, s_v}$ models the occurrence of co-invocation between $s_u$ and $s_v$ at time $t$:

$$
\lambda^t_{s_u, s_v} = \psi \log(1 + \exp\{\omega^t \frac{z^t_{s_u} \cdot z^t_{s_v}}{\psi}\})
$$

(7)

where $\psi$ is trainable scalar parameter, which denotes the rate of events arising from a point process, and $\omega \in \mathbb{R}^{2d_s}$ is designed to learn time-scale specific compatibility. $\{\cdot\}$ denotes concatenation.
Algorithm 1: Update Algorithm for $S$ and $A$

**Input**: Co-invocation event record $o = (s_u, s_v, t)$; Co-invocation event intensity $\lambda_{s_u, s_v}^t$; Service representations of previous time $Z^t$; Most recently updated $A_t$ and $S_t$;

**Output**: Updated $A_t$ and $S_t$;

1. $S_t = S_t^t$
2. $A_t = A_t^t$
3. if $A_{s_u, s_v}^t = 0$ then
4.   $A_{s_u, s_v}^t = A_{s_u, s_v}^t = 1$
5. for each $j \in \{s_u, s_v\}$ do
6.   $b = \frac{1}{|\Omega|^t}$
7.   $y_t \leftarrow S_j^t$
8. if $A_{s_u, s_v}^t > 0$ then
9.   /* $i$ is the other service involved in the event. */
10.   $y_i = b + \lambda_{s_u, s_v}^t$
11. else
12.   $b' = \frac{1}{|\Omega|^t}$
13.   $x = b' - b$
14.   $y_i = b + \lambda_{s_u, s_v}^t$
15.   $y_w = y_w - x \quad \forall w \neq i, y_w \neq 0$
16. end
17. Normalize $y$ and set $S_j^t \leftarrow y$
18. end
19. return $A_t$ and $S_t$

2) Loss Function

For a given set $O$ of $P$ co-invocation events, we learn parameters $\Omega = \{W_a, W_{rec}, W_i, W_h, \psi, \omega\}$ by minimizing the following loss function:

$$L_2 = L_{\text{events}} + L_{\text{nonevents}}$$

where $L_{\text{events}} = -\sum_{r \in R} \log(\lambda_{0_n})$ is the total negative log of the intensity rate for all co-invocation events between service $s_u$ and service $s_v$; $L_{\text{nonevents}} = \int_0^T \Gamma(\tau)d\tau = \sum_m \log(\lambda_{0_n})$ represent total survival probability for co-invocation events that do not happen. It is intractable to compute all non-positive nonevent, we use Monte Carlo method to sample a subset to compute this term, with following [40] setting $M = 5P$.

D. GAN-style training step

To model the process that requirements trigger service evolution and that service evolution reacting the selection of services by requirements, we adopt a GAN-style training step. Specifically, we use two independent Adam optimizers [41] $\text{opt}_1$ and $\text{opt}_2$ to optimize the parameters $\{\Psi, \Lambda, \Omega\}$ in the supervised service recommendation task and parameters $\Omega$ in the unsupervised evolving service representation task. It is also important to note that we perform supervised task optimization for each batch of samples before unsupervised task optimization. The pseudo-code for the GAN-style training algorithm is given in Algorithm 2.

Algorithm 2: Training Algorithm for DySR

**Input**: Requirement sample set $Y$; Number of epochs $n$; Parameter sets $\{\Psi, \Lambda, \Omega\}$; Optimizers $\text{opt}_1$ and $\text{opt}_2$;

**Output**: Updated parameter sets $\{\Psi, \Lambda, \Omega\}$;

1. for epoch = 1, . . . , n do
2.   for each requirement $(v_r, C^+) \in Y$ do
3.     /* Optimize supervised service recommendation task related parameters */
4.     Do forward step described in Section III-B
5.     Update $\{\Psi, \Lambda\}$ to minimize $L_1$ in Eq. 4 with $\text{opt}_1$
6.     /* Optimize unsupervised unsupervised evolving service dynamic task related parameters */
7.     Generate co-invocation event set $O$ from $C^+$
8.     for each co-invocation event $(s_u, s_v, t) \in O$ do
9.        Do forward step described in Section III-C
10.       Update $\Omega$ to minimize $L_2$ in Eq. 8 with $\text{opt}_2$
11. end
12. end
13. end
14. return $\{\Psi, \Lambda, \Omega\}$

IV. EXPERIMENT SETTINGS

A. Dataset & Metrics

We evaluate the proposed DySR model on the real-world ProgrammableWeb dataset, which is also the dataset used in existing service recommendation studies.

ProgrammableWeb: The dataset is the largest online Web service registry. We collected a total of 23,520 APIs and 7,947 mashups on Oct 10, 2020. The mashups without functional description, the services that have not been invoked, and the mashups with fewer than two component services were removed. The experimental dataset contains 3,380 mashups, whose functional descriptions are used as requirements, and 720 APIs. We sorted the mashups by when they were created, and we initialize the adjacency matrix $A$ using the co-invocations from the earliest 300 mashups. The next 2,400 mashups are used as the training set, and the remaining 680 mashups are used as the test set.

We adopted the following evaluation metrics to measure the recommendation performance:

$$\text{Precision@N} = \frac{1}{|R|} \sum_{r \in R} \frac{|\hat{C}_r \cap C_r|}{|C_r|}$$

$$\text{Recall@N} = \frac{1}{|R|} \sum_{r \in R} \frac{|\hat{C}_r \cap C_r|}{|C_r|}$$

$$F1@N = \frac{1}{|R|} \sum_{r \in R} \frac{|\hat{C}_r \cap C_r|}{|C_r| + |\hat{C}_r|}$$
where $R$ is the set of requirements in the test set and $|R|$ denotes the size of $R$. For requirement $r$, $\hat{C}_r$ is the recommended services, while $C_r$ is its actual component services.

### B. Implementation Details

We use bert-base-uncased provided by Transformers\textsuperscript{42} to obtain requirement representation with the dimension $d_r$ set to 768, and it should be noted that we do not do fine-tune on bert-base-uncased. Service representations $Z^0$ are initialized by a 128d Word2Vec\textsuperscript{43} word embedding trained on text8.\textsuperscript{4} We use the two different pre-trained language models to reflect the representation gap between requirement and service. It should be noted that the initial representation of the service in the DySR model can theoretically be obtained using other information or in a random way. We implement a DySR variant called DySR-Rand, which does not need any prior knowledge of service and uses a randomly initialized representation of the service.

Gradient clipping is used in $opt_2$ to avoid gradient explosion, and the clipping value is set to 100. We do not use dropout, and batch size is set to 50. We conduct five independent experiments for each approach to preventing serendipity, and early-stop is applied to avoid over-fitting. All the results reported are average results.

### C. Baselines

To evaluate the effectiveness of model, we select five state-of-the-art service recommendation approaches:

1) AFUP\textsuperscript{33}: This approach first leverage probabilistic topic models to compute relevance between a service and a given requirement. description. And then use collaborative filtering to estimate the probability of a service being used by existing similar requirements. Finally, the multiplies these two term based on Baye’s theorem to rank candidates service.

2) SFTN\textsuperscript{32}: This approach extend AFUP by using hierarchical dirichlet process (HDP) and probabilistic matrix factorization (PMF) to tackle cold start issues and usage history.

3) PNCF\textsuperscript{36}: This approach use multi-layer perceptron to capture the non-linear user-item relationships and obtain abstract data representation from sparse vectors. However, text features were not considered in their original version, so we constructed two variants: PNCF-HDP using HDP adopted in SFTN to obtain text features, and PNCF-Deep using a pre-trained language model to obtain text features.

4) MISR\textsuperscript{9}: This approach propose a deep neural network that can captures multiplex interactions between services and requirements to extract hidden structures and features for better recommendation performance.

It should be noted that most baselines do not provide official code, and we can only reproduce it as described in their papers. In some cases, we were not able to reproduce the results they reported, possibly due to different ways of dividing the dataset and missing important parameter values. In these cases, we chose to directly compare the results reported in [9].

### V. Results & Discussion

#### A. Overview

In this section, we give an overview performance comparison between our proposed DySR and baseline approaches. Fig. 4 shows the performance comparison of different approaches, showing that the DySR and DySR-Rand outperform all the five baselines across all evaluation metrics.

The AFUP and PNCF-HDP performed the worst of all the baselines for the following two main reasons: 1) They use a topic model to extract service/requirement representation from the description text, which ignores the order of words and further leads to lost semantic information; 2) Rough handling of service historical usage information. The introduction of probabilistic matrix factorization allows SFTN to handle historical usage information somewhat better, but the poor service/requirement representations obtained by the topic model remain limiting to its performance. The PNCF-Deep and MISR perform better than the other baselines because they use a pre-trained language model to obtain better representations of the services/requirements. In addition, MISR performs the best of all the benchmark methods because it takes into account multiple types of interactions between services and requirements.

Although DySR-Rand does not require any a priori knowledge of the service, DySR-Rand obtains competitive results with DySR, which shows that our proposed model is well suited to eliminate the gap between requirements and services. DySR and DySR-Rand require less information than the baselines, while their performance is significantly better than all baselines. For example, all baselines need to maintain a requirement-service invocation matrix, while DySR only needs to maintain a small-scale service co-invocation matrix, and MISR additionally requires the tags of the service and historical requirements, which are not needed in DySR. Compared to the best performing baseline approach MISR, which requires the most information, DySR (DySR-Rand) improves the Precision@5, Recall@5 and F1@5 metrics by 28.4% (25.8%), 34.1% (30%) and 33.2% (30%), respectively. The performance improvements mainly benefit from evolving service representation and transformation function that allows the use of time information and the acquisition of better representation of services and requirements in same vector space.

#### B. Ablation Study & Qualitative Performance

DySR unifies several components that contribute to its effectiveness in service recommendation. In this section, we provide insights on evolving service representation component and transformation component and how they are indispensable to the service recommendation by performing an ablation study on various design choices of DySR. We designed the following variants of DySR for comparison:

\textsuperscript{4}http://mattmahoney.net/dc/text8.zip
Fig. 4. Performance comparison of different approaches.

Fig. 5. Performance comparison of different variants of DySR.
• DySR-Static: In this variant, we do not perform unsupervised evolving service task representations so that the service representation remains initialized, i.e., $Z' \equiv Z^0$.

• DySR-Space: In this variant, we turn off transformation function (Eq. 1) and directly use the original requirement representation and the dynamic service representation as inputs to the requirement-service matching function (Eq. 2). The dimension of the corresponding requirement-service matching matrix $W_A$ sets to $d_r \times d_s$.

• DySR-None: In this variant, we do not perform unsupervised evolving service representation task and turn off transformation function.

The comparison among the variants of our approach is shown in Fig. 5. Both DySR-Space and DySR-Static outperform DySR-None on Precision@N, Recall@N and F1@N, suggesting that evolving service representation and transformation function do contribute to the recommended performance. DySR outperforms DySR-Space and DySR-static indicating that evolving service representation and transformation function are complementary.

We conduct a series of qualitative analyses to understand how evolving service representation and transformation function contribute to recommendation performances. We first compare our evolving service representation against the static content-based service representation. Fig. 6 shows the UMAP embeddings leaned by DySR (right) and initialized by service function description. The visualization demonstrates the evolving service representation have more discriminative power as it can effective capture the distinctive and evolving patterns of service combinations (line clusters in Fig. 6(b)) as well as outdated sets of services (block clusters in Fig. 6(b)) with empirical evidence.

Fig. 7 explains how DySR eliminates the representation gap between service and requirement. Fig. 7(a) demonstrates the gap between the representation of requirements and the representation of service that we stated in Section II. Compared with Fig. 7(a) the requirement representation space is much closer to the space of service representation in Fig. 7(b) which shows that the transformation function in DySR does eliminate the difference between requirement and service representations to some extent. The same conclusion can be obtained by comparing Fig. 7(c) and Fig. 7(d). Fig. 7(c) and Fig. 7(d) can also illustrate that evolving service representations reduce the probability of selecting outdated services by moving them away from requirement representation space thereby improving recommendation performance.

VI. CONCLUSION

In this paper, we propose an end-to-end deep learning model called DySR for cold-start service recommendations. DySR solves the service evolution problem by introducing evolving service representation, eliminating the gap between services and requirements through transformation functions, and solving the cold start problem through a requirement-service matching function. Experiments on a real-world dataset demonstrated that the proposed approach significantly outperforms several state-of-the-art service recommendation methods regarding three evaluation metrics. In future work, we will try to show theoretically why evolving service representation and space alignment have an impact on service performance.

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Fig. 6. UMAP for static service representation and evolving service representation.

(a) Static Service Representation

(b) Evolving Service Representation

Fig. 7. UMAP for explaining how DySR eliminates the representation gap between service and requirement.

(a) Static Services & Origin Requirements (DySR-None)

(b) Static Services & Aligned Requirements (DySR-Static)

(c) Evolving Services & Origin Requirements (DySR-Space)

(d) Evolving Services & Aligned Requirements (DySR)

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