Time-Series Snapshot Network as A New Model for Role Recommendation in OSS

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Abstract—The last decade has witnessed the rapid growth of open source software (OSS). Still, all contributors may find it difficult to assimilate into OSS community even they are enthusiastic to make contributions. We thus suggest that role recommendation may benefit both the users and developers, i.e., once we are able to make successful role recommendation for those in need, it may dramatically contribute to the productivity of developers and the enthusiasm of users, thus further boosting OSS projects' development. Motivated by this potential, we study the role recommendation from email data via network embedding methods. In this paper, we introduce time-series snapshot network (TSSN) which is a mixture network to model the interactions among users and developers. Based on the established TSSN, we perform temporal biased walk (TBW) to automatically capture both temporal and structural information of the email network, i.e., the behavioral similarity between individuals in the OSS email network. Experiments on ten Apache datasets demonstrate that the proposed TBW significantly outperforms a number of advanced random walk based embedding methods, leading to the state-of-the-art recommendation performance.

Index Terms—Social network, random walk, network embedding, temporal network, link prediction, open source software, role recommendation.

I. INTRODUCTION

The rapid growth of open source software (OSS) has risen to great prominence within the last several years. A large number of users are attracted to join the OSS community [1]. Developers and users’ active engagement is crucial to the success of OSS projects [2]. To promote OSS projects' sustainable development, it is necessary for developers to maintain projects’ code [3], [4], [5]. Similarly, it is essential to motivate, engage, and retain users and developers [6].

However, most of previous studies focused on the maintenance of project code, while ignoring the importance of users in OSS projects’ development. To maintain the quality of projects’ code, numerous approaches [7]–[9] are proposed to recommend a ranked list of developers based on software repositories to assist in performing software changes. Intuitively, recommending developers to review a patch could keep the projects’ code stable. While developers make contributions to projects’ sustainable development, it is also essential to pay attention to the users who use the software. Since they provide feedback to developers to maintain OSS projects’ development and they are potential developers who may contribute to the projects they interested in someday.

The participation of users and developers in OSS projects requires to overcome many obstacles, which discourages further contributions to OSS projects [10], [11]. As the mailing list is public communication channels in the OSS community, users and developers often use such means to start their interactions in the projects [12], i.e., those who lack understanding and guidance generally post their questions and request help or exploit existing information available in the mailing list. As an example, a user named Shaw solved the doubts about “Airflow” project by posting questions on the mailing list to ask for help and he received numerous replies to solve his doubts [13]: the question Global Custom Template Variables? Or is there another best practise here? and one of the replies Re: Global Custom Template Variables? Or is there another best practise here?. However, it’s not easy to access information due to the large volume and useless replies. The barriers that users and developers face will lead them to give up their further contributions to OSS. Given this scenario, it may be helpful to recommend experienced developers and users to those who need help so that they can send emails to specific individuals to avoid more frustration. However, it’s difficult to identify right and/or relevant people to help those in need. Identifying the right people is an important task and we often use a linguistic perspective to solve this challenge [14]. In this paper, we focus on the study of finding someone to be of general help in OSS projects and recommend them to those in need from network perspective. It could be useful to model the mailing list using a graph-based approach rather than a general method since the mailing list data is publicly available and universally applicable in social network analysis.

We construct the email network that relies on the network structure of the mail corpus composed of the OSS mailing list to gain better insight into the OSS mailing list, where users and developers are vertices in the email network and temporal edges capture email exchanges. To further retain the email’s temporal property, we define a mixture network namely time-series snapshot network (TSSN). Based on TSSN, we further introduce a temporal biased walk (TBW) to learn the representations of users and developers. We believe that, by comparison, the embeddedness of developers and users’ behavior on graph can capture more important interactions of individuals. For each user/developer, an unique searching strategy is adopted. The searching strategy depends on the number of email exchanges, structure-based transition probability, temporal transition probability, and role-based transition probability. Our approach efficiently learns individuals’
representations based on the proposed TBW and makes role recommendation via machine learning techniques. Also, we present some preliminary analysis of OSS email datasets which motivated the design of our method and verify the necessity to make role recommendation in OSS.

The main contributions of this paper are summarized as follows.

- We study the matter of recommending developers and users for individuals who need assistance in the OSS community from a network perspective. When individuals encounter difficulties, such recommendations can provide them with certain support, which is crucial for OSS projects’ sustainable development. In addition, the data used in this paper has been cleaned up and standardized and will be available online for future study.
- We construct time-series snapshot network (TSSN) for OSS mailing list to capture the evolution of the interactions among users and developers, and thus retain OSS email’s temporal property. Moreover, we propose a temporal biased walk (TBW) to effectively embed developers and users based on their interactions, which integrates temporal information, structural information, and individuals’ identities of the OSS email networks. Furthermore, our method is more applicable and can be modified for other datasets on their unique properties.
- We carry on several types of recommendation experiments on realistic OSS projects, and the results demonstrate that our proposed TBW significantly outperforms a number of random walk based embedding methods in role recommendations. More precisely, our method combined with OSS dataset’s properties can be more superior to other general machine learning methods.

The remainder of this paper is organized as follows. In Sec. II we review the related works in OSS email network analysis and random walk based embedding methods. Then, we present the data collection and preliminary analysis of OSS datasets in Sec. III. After that, in Sec. IV we give the basic definition and our proposed method, and in Sec. V we conduct extensive experiments with discussions. Finally, we conclude the paper and highlight future work in Sec. VI.

II. RELATED WORK

A. OSS Analysis

In OSS projects, the interaction between developers and users, as well as the code submission, is usually public and stored for future reference. Therefore, the project archive provides rich historical information resources that can be used to study many fascinating matters such as discovering potential cooperation between users and developers.

Most researchers usually use the OSS mailing list data for quantitative analysis to gain insight into the social aspects of software development and provide relevant insights [15], [16]. For example, Bird et al. proposed the technology of mining OSS email networks [17], and presented some preliminary results from email network analysis. In [18], they studied the social interaction in OSS projects and discovered the latent social structure. Xuan et al. [19] proposed a novel quantitative method to measure the impact of social communication on individual work rhythm by analyzing communication and code submission records in OSS projects. The results showed that mailing list activity is strongly related to source code activity.

Recently, they proposed another quantitative method [20] to identify synchronization activities in OSS projects and use them to connect developer synchronization with effective productivity and communication. Most of the aforementioned work is quantitative and based on the mailing list communication to study the relationship between users and developers. This is mainly because the interaction between developers and users is crucial to OSS projects’ development.

Maintaining projects’ code and retaining users to actively participate in the projects are equally essential for OSS projects’ sustainable development. However, most researchers focus on selecting excellent developers to maintain the stability of the projects’ code, while ignoring the importance of users in the projects. For instance, Lee et al. [8] proposed a graph-based method to automatically recommend experienced developers to review patches before applying or submitting them. Ouni et al. [9] introduced a search-based approach to find the most appropriate reviewers for submitted code changes for improving software quality and reducing defect proneness. Kagdi and Poshyvanyk recommended a ranked list of developers to assist in performing software changes [7]. Fu et al. designed a recommender system to recommend appropriate experts for developers to integrate new developers with team [21]. We argue that such preference may promote the short-term code contribution but may discourage the users and thus hurt the long-term development of the OSS community.

Therefore, in this paper, we address users and developers equally and try to support them in real time by proposing a TBW based role recommendation algorithm in TSSN, which considers users and developers as two kinds of roles.

B. Random Walk Based Network Embedding

Network embedding has received much attention over the past decades [22], [23]. Such methods intuitively focus on transforming each vertex into a low-dimensional vector based on its local structure in the network. Since vertices that share similar structural properties are closed to each other in the low-dimensional embedding space, one can easily use the learned embeddings for downstream tasks such as community detection [24], link prediction [25], and node classification [26].

One of the earliest efforts in network embedding is to combine random walk based methods with Skip-Gram [27] model to learn vertex representation, where Skip-Gram model was first introduced in the natural language processing (NLP) domain [28]. The theory underlying random walks and their connection to eigenvalues and other fundamental properties of graphs are well-understood [29], [30]. Thus, various random walk based embedding methods [31], [32], [33], combined with Skip-Gram model, have been vastly proposed.

Two of the most notable random walk based methods are DeepWalk [31] and Node2vec [33]. DeepWalk is one of the earliest work in network embedding, which uses the random walk to generate sequences for each vertex. The sequences
of vertices are treated as text in language models, based on which one can learn vertex representation by Skip-Gram model. Node2vec \cite{33} is a biased second-order random walk model that extends DeepWalk by employing biased random walks to learn vertex embedding, and it can capture both vertex homophily and structural equivalence. Tang et al. \cite{32} proposed another successful network embedding model LINE, which designs the objective function, optimizes the first-order and second-order proximity, and performs the optimizations by stochastic gradient descent with edge sampling. Biased-Walk \cite{34} overcomes the disadvantage that Node2vec needs to store the interactive information of vertices. It adopts simulation biased random walk to balance the breadth-first and depth-first graph traversal.

With the development of random walk based methods in network embedding, more and more researchers have tried to apply random walk on temporal networks \cite{35}. Dynode2vec \cite{36} modifies Node2vec by considering the previous embedding vectors as the initialization of Skip-Gram model, and employing random walks in network evolution to update Skip-Gram model based on previous timestamps. However, they didn’t consider the directly correlation between different snapshots, which may lead to extra loss. Nguyen et al. \cite{37}, \cite{38} proposed a general framework CTDNE. It’s a new class of embeddings learned directly from the temporal network (graph stream) without having to approximate the edge stream as a sequence of discrete static snapshot graphs. However, it does not consider the edge’s weight and may cause incomplete representations.

Considering the high expressiveness and learning ability of random walk based methods with different search strategies, we model general temporal networks as a spatial-temporal network, i.e., time-series snapshot network (TSSN). Furthermore, we implement a random walk using specific search strategies, namely temporal biased walk (TBW), on the proposed TSSN. In this algorithm, each vertex has its unique search strategy, reflecting its global and local structural properties in spatial and temporal domains simultaneously.

III. OSS DATASET

In this section, we first give a detailed description of the dataset and data preprocessing, and then conduct preliminary descriptive analyses that motivate our methodology in Sec. IV and indicate the reason to make role recommendation.

A. Data Description & Preprocessing

The Apache Software Foundation (ASF) is the largest open source foundation in the world and incubates hundreds of free enterprise projects, such as Hadoop and ApacheHTTP, which act as the backbone of some widely used applications. ASF opens not only source codes but also emails among individuals of all projects, making the ASF project archive a rare public data source for social and technical activity analysis. We gather email data by parsing the email activities on the Apache mailing list over a period starting from 1999 to Aug 2019. Besides, 10 projects which graduate from the incubator are selected as the representatives and we conduct further study according to the projects’ mailing list. Here, we focus on the projects graduated from the incubator. In particular, we first choose 20 projects with the maximum number of developers, among which we then select 10 most active ones, i.e., with most email communications.

We first extract recipient, sender, sending time, title and content of each email record contained in the mailing list before constructing network. To accurately scale an individual’s activity, we introduce identity matching to merge different aliases. In subsequent experiments, we retain only the date stamp of each email, anonymized sender and recipient IDs. Based on a number of projects’ emails extracted from the Apache mailing list, we construct several email networks. In every network, each vertex denotes either a user or a developer, and the weighted edge represents the email exchanges. Note that those with the same sender and recipient are removed for that such emails cannot be regarded as social interactions. The summary of the 10 projects and their descriptive statistics are provided in Table I.

| Project      | Users | Developers | Email exchanges | Timespan (month) |
|--------------|-------|------------|----------------|------------------|
| Airflow      | 411   | 95         | 4493           | 33               |
| Beam         | 159   | 61         | 3363           | 11               |
| CarbonData   | 123   | 53         | 1477           | 11               |
| Cordova      | 622   | 61         | 9832           | 14               |
| Geode        | 179   | 60         | 5860           | 21               |
| HAWQ         | 169   | 62         | 4015           | 36               |
| Impala       | 152   | 39         | 3511           | 25               |
| Metron       | 109   | 48         | 5445           | 17               |
| Spark        | 223   | 45         | 2707           | 10               |
| Zeppelin     | 379   | 67         | 5924           | 18               |

| Table I: Overview of Apache datasets. |

B. Preliminary Analysis

In each Apache project, we classify all projects’ participants into one of the following categories \cite{39}:

- **Users** are individuals who use the software. They provide feedback to developers in the form of bug reports and feature suggestions to contribute to the Apache projects, and help other users join the Apache community through mailing lists and support forums.
- **Developers** actively participate in the project and contribute to code and documentation. They are also active in the mailing list, participate in discussions, provide patches, documentation, suggestions, and criticism.

These roles can change over time, e.g., in July 2019, John may have been only reviewing patches or asking questions, but in August 2020, he may have submitted code changes/patches. In this paper, we suggest that if a user has submitted code, he will be a developer throughout the development of the project.

Before introducing our method, we first take a glance at Apache dataset. To study the different roles of users and developers, we count the emails received and sent by users and developers, respectively, and then carry out a simple T-test as shown in Table II. As we can see, there are statistically
Table II: T-test for the differences between users and developer in terms of emails received and sent.

|          | User  | Developer | T-value | Significance |
|----------|-------|-----------|---------|--------------|
| # Emails received | 10.9596 | 44.4396 | 8.6787 | p < 0.001 |
| # Emails sent     | 12.0478 | 54.0438 | 7.5854 | p < 0.001 |

significant structural differences between users and developers in the email network. Therefore, we should consider the differences in email behavior between users and developers in the design of role recommendation algorithm.

Fig. 1: The comparison of real proportion and random proportion demonstrates communication tendency.

We further study the communication tendency of users and developers to see whether they are more likely to contact the individuals of the same roles or not. Here, we compare the proportion of same and different type roles’ contact information with the random proportion of same and different information. If result > 1, it reflects roles’ real communication tendency. As shown in Fig. 1, we confirm that individuals tend to communicate with different ones. The results are not surprising because users are more likely to seek developer for help. Therefore, it’s reasonable to consider users and developers’ real identities in the design of role recommendation algorithm.

IV. THE PROPOSED METHOD

In this section, we give several basic definitions, and then present the search strategy based on the spatial and temporal features of each user (developer) in TSSN.

A. Basic Definition

In general, a project’s mailing list can be modeled as a graph $G = (V, E)$ comprised of a vertex set $V$ with two types of vertices (users and developers), and an edge set $E$ that represents the email exchanges with timestamps. On the basis of the given time interval $\epsilon$, we can divide the entire graph into several different snapshots. In order to capture the structural changing tendency of vertices in a temporal network, it is crucial to consider not only the snapshot at the current time, but also the nearby snapshots in time. Hence, we define TSSN, a spatial-temporal network shown in Fig. 2, to formulate our solution and further propose TBW to better capture the spatial and temporal properties of each vertex in TSSN, to facilitate the design of following role recommendation.

Definition 1 (Time-Series Snapshot Network (TSSN)). Given a graph $G = (V, E)$, which is divided into several snapshots $\{G_0, G_1, G_2, \cdots\}$ according to time span $\epsilon$, where $G_i = (V_i, E_i)$. Let $V_i$ and $E_i$ be sets of vertices and edges of snapshot $G_i$ respectively, in the timespan $[t\epsilon, (t+1)\epsilon)$, with time order $t \in \{0, 1, 2, \cdots\}$. All snapshots are sorted by time order $t$ (ascending). It’s worth noting that self-connections could be established when and only when a node existed in successive snapshots.

Self-connections in TSSN can make the random walk across successive snapshots, capturing the correlation between different snapshots, which may result in more appropriate embedding. For simplicity, we define a four-tuple $e = (u, v, w, t)$ in TSSN: for $\forall e \in E$, $Src(e) = u$, $Dst(e) = v$, $W(e) = w$, $T(e) = t$, where $u$ is the source vertex, $v$ is the target vertex, $w$ is the weight (number of emails) and $t$ is the time accessibility. Let $\eta_+: \mathbb{R} \rightarrow \mathbb{Z}^+$ be a function that maps each vertex to an index based on the time order, i.e., for a given vertex $u$ in snapshot $G_t$, we have $\eta_+(u) = i$. Therefore, we can design a sign function for each link in TSSN: $T(e) = \eta_+(v) - \eta_+(u) \in \{-1, 0, 1\}$, where $v$ is the target vertex and $u$ is the source vertex, to define the time accessibility of $v$ from $u$, i.e., $v$ is time accessible from $u$ if and only if the corresponding $T(e) \geq 0$. Now we can define the temporal walk as follows.

Definition 2 (Temporal Walk). In TSSN, a temporal walk from vertex $v_1$ to vertex $v_l$ is an $l$-length sequence of vertices together with a sequence of $(l - 1)$ edges $\{e_1, e_2, \cdots, e_{l-1}\}$, where $Src(e_i) = v_i$, $Dst(e_i) = v_{i+1}$, and $T(e_i) \geq 0$, for $1 \leq i \leq (l - 1)$.

In order to sample such temporal walks, we further define accessible edge in TSSN as follows.

Definition 3 (Accessible Edge). Given a TSSN $G = (V, E)$, the set of accessible edges for a vertex $v$ is defined as:

$$L_t(v) = \{e \mid Src(e) = v, T(e) \geq 0\}$$

An example of accessible edge and temporal walk is presented in Fig. 3. Next, we will introduce different sampling biases by formulating the selection probability for each accessible edge $e \in L_t(v)$, and present a sampling strategy by combining these biases.

B. Temporal Biased Walk

Based on the definitions in Sec. IV-A, we design a second-order neighborhood sampling strategy $s$ to choose accessible edges. The search strategy is the joint transition probability we proposed, which is composed of the static edge weight, the structural transition probability, the temporal transition probability, and the role-based transition probability.

Traditionally, for a given vertex $v$, we can perform a simple random walk. Let $Dst(e_i)$ denotes the $i$th vertex in the temporal walk sequence $N_s(v)$ and random walk resides at
Fig. 2: The detailed construction of time-series snapshot network (TSSN). Dashed lines represent the self-connections, and solid lines denote the connection of pairwise vertices in the same snapshot.

Fig. 3: The blue block represents a valid temporal walk path starting in vertex $u$ in $G_1$. Accessible edges of a vertex $z$ in snapshot $G_2$ denoted as $L_1(z)$. Note that $L_1(z)$ are orange lines where accessible edges only appear in the current and nearby following snapshots.

vertex $c$. Thus each accessible edge $e \in L_1(c)$ can be assigned the selection probability:

$$
P(e) = \frac{W(e)}{\sum_{e' \in L_1(c)} W(e')}$$  \hspace{1cm} (1)

where $W(e)$ is the weight between vertex $c$ and its temporal neighbor $x$, and $L_1(c)$ denotes the set of accessible edges of for vertex $c$. As illustrated in Sec. III, interactions (edge weights) exhibit some differences per role in the Apache email network. Thus we can use this simplest way to bias our temporal random walk, which is to sample the next vertex based on the static edge weight $W(e)$.

However, this simple way does not explain the network structure nor can it help us explore different types of neighbors in the whole network. When the links are relatively sparse in the network, this strategy may get affected easily. Therefore, we propose a second-order temporal random walk method. In the proposed method, we introduce a joint transfer probability, which is composed of the static edge weight, the structural transition probability, the temporal transition probability, and the role-based transition probability for each source vertex’s valid accessible edges. Suppose there is a random walk resides at vertex $c$, and the last traversed vertex is $t$. We calculate the latter three transition probabilities of the vertex $c$’s temporal accessible edges as follows.

**Structural Transition Probability:** We define the structural transition probability with return parameter $r$ and in-out parameter $q$ similar to [33]. For each valid accessible edge $e \in L_1(c)$, we set the unnormalized structural transition probability to $P_S(e) = \psi_S(e) \cdot W(e)$ with

$$
\psi_S(e) = \begin{cases} 
1/q, & d_{tx} = 2 \\
1 - r, & d_{tx} = 1 \\
1, & d_{tx} = 0 
\end{cases}
$$  \hspace{1cm} (2)

where $d_{tx} \in \{0, 1, 2\}$ denotes the shortest path distance between vertex $t$ and $x$.

It is worth noticing that the initial in-out parameter $q$ and return parameter $r$ jointly determine each vertex’s search direction. Our method, like [33], [40], uses the return parameter $r$ and in-out parameter $q$ to control how fast the walk explores and leaves the neighborhood of starting vertex.

**Temporal Transition Probability:** Apart from the structural features, the temporal information also counts for much in the vertex representation learning. When we divide the whole network into different snapshots based on time span, each snapshot represents a part of the network structure and the gradual change of time slice reflects the evolution process of network. Ignoring the correlation information that exists between two snapshots at consecutive time steps may cause the loss of temporal information. Hence, we propose temporal transition probability to capture vertex’s behavior changes in different snapshots. In this case, the probability of selecting each edge $e \in L_1(c)$ can be given as:

$$
P_T(e) = \frac{\psi_T(e)}{\sum_{e' \in L_1(c)} \psi_T(e')}$$  \hspace{1cm} (3)

where $\psi_T(e)$ is expressed as

$$
\psi_T(e) = \begin{cases} 
\alpha, & T(e) > 0 \\
1 - \alpha, & T(e) = 0 
\end{cases}
$$  \hspace{1cm} (4)

Here, the temporal bias $\alpha$ ($0.1 \le \alpha \le 0.9$) decides whether the temporal walk resides on the current snapshot or transfers to the next.

**Role-Based Transition Probability:** Every role has a different communication tendency as illustrated in Sec. III-B, which means that the individuals may be more inclined to communicate with those of the same role or the opposite. To explore more various temporal neighbors of a role via communication tendency, we consider both unbiased and biased sampling strategies as follows.

- **Role Unbiased Sampling (RUS).** It assumes that each accessible edge $e \in L_1(c)$ of vertex $c$ has the same
probability to be sampled:
\[ P_R(e) = \frac{1}{|L_t(c)|} \]  

- **Role Biased Sampling (RBS).** We have role bias parameter \( \beta \) (0.1 \leq \beta \leq 0.9) to control whether the temporal walk is toward the same type of vertices or different. The biased transition probability of each \( e \in L_t(c) \) is then defined as:
\[ P_R(e) = \frac{\psi_R(e)}{\sum_{e' \in L_t(c)} \psi_R(e')} \]

where \( \psi_R(e) \) is set to
\[ \psi_R(e) = \begin{cases} 
\beta, & \omega(t) = \omega(x) \\
1 - \beta, & \omega(t) \neq \omega(x) 
\end{cases} \]

with \( \omega(v) \) denoting vertex \( v \)'s real identity, i.e., user or developer, \( t \) being the last traversed vertex, and \( x = Dist(e) \).

**Joint Transition Probability:** Now, we normalize the aforementioned structural transition probability, temporal transition probability, and role-based transition probability, and then combine them as one. Finally, each edge \( e \in L_t(c) \) can be assigned the selection probability:
\[ P(e) = P_S(e) P_T(e) P_R(e). \]

Based on the joint transition probability, we propose a second-order neighborhood sampling strategy \( s \) which can help each vertex find a suitable search direction and get its optimal temporal accessible edges. In each vertex’s temporal walk, the in-out parameter \( q \), return parameter \( r \), temporal bias \( \alpha \) and role bias \( \beta \) jointly determine the search direction.

The return parameter \( r \) mainly controls the probability of the source vertex revisiting the last traversed vertex. When \( r \) is small, it would keep the walk close to the source vertex. On the other hand, setting it to a large value ensures that the walk is less likely to be the already visited vertices. The parameter \( q \) prefers to consider searching for different types of inward and outward vertices structurally. The definition of an inward (or outward) vertex is based on whether there is a link with the last traversed vertex. When \( q > 1 \), the next walk of the source vertex is more inclined to return to the source vertex, which is more like a local exploration like the BFS behavior. When \( q < 1 \), the next vertex is more likely to walk away from the source vertex. This method can make the source vertex explore a wider range of vertices, which is a kind of approximate DFS behavior. By adjusting the parameter \( q \), we allow our search direction to combine BFS with DFS. On the whole, the in-out parameter \( q \) and return parameter \( r \) control the search direction in spatial domain simultaneously.

Temporal bias \( \alpha \) decides the temporal search orientation: resides on current snapshot or move to next snapshot. If \( \alpha \) is small, the temporal walk is more inclined to stay in the current snapshot, otherwise the walk favors edges appearing in future snapshot. This helps to explore changes in vertices’ interaction during very different time periods as the network evolves. Role bias \( \beta \) control vertex’s communication tendency. If \( \beta \) is large, the temporal walk is more likely to traverse the same type of vertices as the source vertex, otherwise the walk encourages the exploration of vertices of different type.

### C. Learning Temporal Network Embeddings

Our goal is to obtain a mapping function \( f : V \rightarrow \mathbb{R}^d \), which maps a given vertex to a \( d \)-dimensional representation. For a vertex \( v \in V \), let \( N_s(v) \) denotes the set of temporal neighbors that are generated according to the search strategy \( s \), and \( f_t(v) \) is the representation of vertex \( v \) in snapshot \( G_t \). Our objective function maximizes the log-probability of observing \( N_s(v) \) and historical embedding \( f_t(v) \) for the vertex \( v \) conditioned on its representation:
\[ \max_f \sum_{v \in V} \log(Pr(N_s(v), f_t(v) | f(v))). \]

We assume that the temporal neighbors in \( N_s(v) \) and the vertex’s historical representations \( f_t(v) \) are independent of each other. Accordingly, we factorize the formula:
\[ \log(Pr(N_s(v), f_t(v) | f(v))) = \log(\prod_{u_i \in N_s(v)} Pr(u_i | f(v))) + \log(Pr(f_t(v) | f(v))). \]

Based on the network analysis, we can see that the likelihood of observing a source vertex is independent of observing any other and the definition of neighborhood vertices is symmetric [33]. Therefore, we factorize the likelihood of observing temporal neighbors and model the likelihood of every source-neighborhood vertex pair as a softmax unit that is parametrized by a dot product of their mapping features. Learning representations using random walk has proved to measure better graph proximity, and thereby improving the performance [23], [41]. Hence, we use random walk to learn the conditional probability of observing a vertex \( u_i \) given the learned representation \( f(v) \) as follows:
\[ Pr(u_i | f(v)) = \frac{\exp(f(u_i) f(v))}{\sum_{n \in V} \exp(f(n) f(v))}, \]

where \( u_i \in N_s(v) \) is the \( i \)th neighbor of vertex \( v \). With the above hypothesis, the objective function in Eq. [9] can be described as:
\[ \max_f \sum_{v \in V} \log(\prod_{u_i \in N_s(v)} \exp(f(u_i) f(v)) - \sum_{n \in V} \exp(f(n) f(v)))) + \log(Pr(f_t(v) | f(v))). \]

Considering the complexity of this objective function, we use negative sampling strategy to approximate it [42]. The stochastic gradient descent (SGD) [43] method is used to iteratively update the objective function.

Due to the nonlinear nature of real-world networks, we define a novel search strategy \( s \) that samples different temporal neighbors of a given source vertex \( v \). The temporal neighbors \( N_s(v) \) are not restricted to just nearest neighbors but also have vastly structural similarity with the source vertex in spatial and temporal domains simultaneously. While the above seems to just consider the process of network topological properties, it actually takes into account the role’s real identity to get more informative representations.

In Algorithm [1], we propose the framework to learn time-preserving embeddings in TSSN. Our procedure in Algorithm [II] generalizes the Skip-Gram architecture to learn time-series snapshot network embeddings. In this biased random
walk, every start vertex has a unique search strategy. The three phases of temporal biased walk (Algorithm 2), i.e., preprocessing to compute joint transition probability, random walk simulations, and optimization using SGD, are executed sequentially. Each phase is parallelizable and can be executed asynchronously, which contributes to the overall scalability of TBW. Furthermore, TBW can be easily used for other deep graph models since the temporal walks can serve as input vectors for neural networks. There are many random walk methods that can be adapted in TSSN because it is not tied to any particular approach.

V. EXPERIMENTS ON APACHE

A. Experiment Setup

We compare the performance of TBW with six random walk based network embedding methods. And the basic settings are described as follows:

- **LINE** [32] preserves both the local and global network structures through modeling vertex co-occurrence probability and conditional probability. The final representation for each vertex in this work is created by second-order representation.
- **BiasedWalk** [34] is a random walk based sampling method, which can behave as Breath-First-Search (BFS) and Depth-First-Search (DFS) sampling, in order to capture the homogeneity and role equivalence between vertices in the network. We set the parameters to the provided defaults.
- **DeepWalk** [31] is the first vertex embedding method that obtains vertices context via random walks, which uses Skip-Gram model and uniform random walks to learn the neighborhood structure of the graph.
- **Node2vec** [33] keeps the neighborhood of vertices to learn the vertex representation in the network, and it achieves a balance between homophily and structural equivalence. The ranges of its hyper parameters in this paper are set to \( p, q \in \{0.5, 1, 2\} \).
- **Dynnode2vec** [36] is an embedding method using temporal information based on [33] that can capture evolving patterns in temporal networks. It uses evolving random walks and initializes the current graph embedding with previous embedding vectors.
- **CTDNE** [37] is a general framework for incorporating temporal information into network embedding methods, which is based on random walk and stipulates that the timestamp of the next edge in the walk must be larger than that of the current edge.

We take one month as the time span to construct TSSN for each dataset and conduct our role recommendation experiments with TBW. For all random walk based embedding methods, including ours, we utilize the same hyper-parameter setting (the number of walks per vertex \( w = 10 \), the length of walk \( l = 80 \), and the size of context window \( k = 5 \)). To guarantee \( d \ll D \) (\( D \) is the number of network vertices), we set the dimension \( d = 128 \) for all datasets and methods. After the embeddings are learned for each vertex, we use average operation on the learned embedding vectors of pairwise vertices to compute the feature vector for the corresponding edge. For all baselines, we implement experiments by using a one-vs-rest logistic regression classifier with hold-out validation of 25% on Apache datasets. Experiments are repeated for 10 random seed initializations and the average performance (AUC) is reported. In the following experiments, our hyper-parameters set as follows: return parameter \( r \) and in-out parameter \( q \) are grid searched in \( \{0.5, 1, 2\} \), temporal bias \( \alpha \) and role bias \( \beta \) vary in \( [0.1, 0.9] \).

B. Role Recommendation

We treat the role recommendation problem as a link prediction task between two roles in the Apache community: users and developers. We adopt the following recommendation strategy to investigate the desirability for those in need, i.e., for a given user/developer, we make a random recommendation to the target without considering their roles. Before
the experiments, we hide a certain fraction of individuals’ connections in the email network for a given project, and our goal is to predict these missing connections so as to achieve the recommendation via link prediction.

We first randomly hide 25% of links in the original network as the ground truth and use the remaining to train all network embedding models. The test set consists of the hidden 25% links in the original network as positive samples, and the same number of disconnected vertex pairs are randomly selected as negative samples. Table III shows the performance of all the compared methods on role recommendation. We can observe that TBW achieves consistently and significantly better performance over static baselines, which is reasonable since these two methods totally ignore temporal information. Moreover, compared with those temporal embedding methods such as CTDNE and Dynnode2vec, TBW also has better performance, indicating that edge weight information and the correlation between each snapshot considered in our method also provide useful information for the link prediction.

To make the model more practical, we also use the historical data to predict future edges, i.e., we first sort the edges by time (ascending) and use the first 75% to create email network for the representation learning. The remaining 25% are considered as positive connections and an equal number of disconnected vertex pairs are randomly chosen as negative samples. The results are presented in Table IV, where we can see that TBW still outperforms the baselines in most cases.

| Project   | LINE  | BiasedWalk | DeepWalk | Node2vec | Dynnode2vec | CTDNE | TBW  |
|-----------|-------|------------|----------|----------|-------------|-------|------|
| Airflow   | 0.8214 | 0.8645     | 0.8631   | 0.8909   | 0.8671      | 0.8540 | 0.9211|
| Beam      | 0.9072 | 0.9243     | 0.9146   | 0.9197   | 0.9102      | 0.9420 | 0.9526|
| CarbonData| 0.8631 | 0.8613     | 0.8387   | 0.8669   | 0.8546      | 0.7668 | 0.9060|
| Cordova   | 0.8765 | 0.9308     | 0.9345   | 0.9371   | 0.9287      | 0.9267 | 0.9536|
| Geode     | 0.8316 | 0.8598     | 0.8551   | 0.8468   | 0.8657      | 0.8776 | 0.8947|
| HAWQ      | 0.8175 | 0.8125     | 0.7943   | 0.8029   | 0.8511      | 0.8681 | 0.8842|
| Impala    | 0.8512 | 0.8672     | 0.8479   | 0.8643   | 0.8626      | 0.8564 | 0.9041|
| Metron    | 0.8393 | 0.8072     | 0.8158   | 0.7828   | 0.8466      | 0.7849 | 0.8740|
| Spark     | 0.8000 | 0.8198     | 0.8167   | 0.8362   | 0.8305      | 0.8277 | 0.8670|
| Zeppelin  | 0.8379 | 0.8996     | 0.8935   | 0.8945   | 0.9042      | 0.9025 | 0.9365|

| Project   | LINE  | BiasedWalk | DeepWalk | Node2vec | Dynnode2vec | CTDNE | TBW  |
|-----------|-------|------------|----------|----------|-------------|-------|------|
| Airflow   | 0.8546 | 0.8882     | 0.9000   | 0.9189   | 0.9309      | 0.8513 | 0.9404|
| Beam      | 0.9319 | 0.8880     | 0.8497   | 0.8885   | 0.9420      | 0.8542 | 0.9513|
| CarbonData| 0.8354 | 0.8244     | 0.8085   | 0.8462   | 0.8751      | 0.8665 | 0.9040|
| Cordova   | 0.8952 | 0.9383     | 0.9423   | 0.9548   | 0.9632      | 0.9679 | 0.9577|
| Geode     | 0.8922 | 0.9125     | 0.8949   | 0.9119   | 0.9237      | 0.9378 | 0.9396|
| HAWQ      | 0.7616 | 0.7333     | 0.6945   | 0.7634   | 0.8071      | 0.8441 | 0.8607|
| Impala    | 0.8621 | 0.7506     | 0.5945   | 0.7267   | 0.8507      | 0.7885 | 0.8838|
| Metron    | 0.8947 | 0.8736     | 0.8367   | 0.8699   | 0.9265      | 0.8040 | 0.9400|
| Spark     | 0.7771 | 0.8415     | 0.8191   | 0.8449   | 0.8609      | 0.7248 | 0.8838|
| Zeppelin  | 0.8679 | 0.9152     | 0.8898   | 0.9138   | 0.9352      | 0.9551 | 0.9379|

The goal is to predict these missing connections so as to achieve the recommendation via link prediction.

We first randomly hide 25% of links in the original network as the ground truth and use the remaining to train all network embedding models. The test set consists of the hidden 25% links in the original network as positive samples, and the same number of disconnected vertex pairs are randomly selected as negative samples. Table III shows the performance of all the compared methods on role recommendation. We can observe that TBW achieves consistently and significantly better performance over static baselines, which is reasonable since these two methods totally ignore temporal information. Moreover, compared with those temporal embedding methods such as CTDNE and Dynnode2vec, TBW also has better performance, indicating that edge weight information and the correlation between each snapshot considered in our method also provide useful information for the link prediction.

To make the model more practical, we also use the historical data to predict future edges, i.e., we first sort the edges by time (ascending) and use the first 75% to create email network for the representation learning. The remaining 25% are considered as positive connections and an equal number of disconnected vertex pairs are randomly chosen as negative samples. The results are presented in Table IV, where we can see that TBW still outperforms the baselines in most cases. All of these results suggest that our TSSN could be more informative than the traditional temporal networks, and thus of importance for learning appropriate and meaningful network representations. It is worth noting that many other random walk based approaches can also be generalized by using our proposed TSSN [44], [45], [46].

C. Parameter Sensitivity

Here, we mainly focus on the effects of role bias $\beta$ and temporal bias $\alpha$ on the performance of TBW, since these two parameters are newly introduced in our method. The other parameters are set as follows: the in–out parameter $q$ and the return parameter $r$ are grid searched in $\{0.5, 1, 2\}$, the number of walks $w = 10$, the walk length $l = 80$.

As shown in Fig. If we find that individuals in most projects are more likely to contact those of different roles. Thus we first investigate the effect of role bias $\beta$ which varies in $[0.1, 0.9]$. The results of random recommendation are shown in Fig. 4 where we can see that, generally, the link prediction performance steadily improves as role bias $\beta$ decreases. Since smaller $\beta$ encourages exploration of multiple types of vertices, this result validates again that, in OSS projects, users always seek developers for help, while developers are inclined to share knowledge with users. Therefore, we need choose smaller role bias $\beta$ to address this tendency, so as to improve the recommendation performance. Besides, we further vary the temporal bias $\alpha$ in $[0.1, 0.9]$, to investigate how this parameter influences the recommendation performance. The results are shown in Fig. 5 where we can see that the link prediction performance decreases as the temporal bias $\alpha$ increases. This may be because a larger $\alpha$ usually causes a faster transfer.
to the next snapshot, resulting in incomplete sampling in the current snapshot. Therefore, in this work, a small temporal bias is preferred to capture enough structural information in different snapshots, so as to ensure an acceptable recommendation result.

VI. CONCLUSION

In this paper, we study role recommendation in OSS email networks. Particularly, we construct TSSN to retain both temporal and structural information of email network. And then, we propose a random walk embedding method namely TBW, to make recommendation by leveraging embeddings learned from structural properties, temporal information, and individual real identities. Furthermore, we adopt TBW for role recommendation on realistic OSS email networks, and compare our method with a number of random walk based embedding methods. Experimental results demonstrate the effectiveness of our method and indicate that TSSN can better capture the temporal information of email networks. For future work, we hope to apply deep learning methods to expand our methods, and utilize OSS unique code repositories to establish social-technical TSSN so as to further improve role recommendation.

REFERENCES

[1] F. Fronchetti, I. Wiese, G. Pinto, and I. Steinmacher, “What attracts newcomers to onboard on oss projects? tl; dr: Popularity,” in IFIP International Conference on Open Source Systems. Springer, 2019, pp. 91–103.
[2] I. Steinmacher, I. S. Wiese, T. Conte, M. A. Gerova, and D. Redmiles, “The hard life of open source software project newcomers,” in Proceedings of the 7th international workshop on cooperative and human aspects of software engineering, 2014, pp. 72–78.
[3] X. Xia, D. Lo, X. Wang, and X. Yang, “Who should review this change,” Proc. of ICSME, Bremen, Germany, 2015.
[4] Y. Yu, H. Wang, G. Yin, and C. X. Ling, “Who should review this pull-request: Reviewer recommendation to expedite crowd collaboration,” in 2014 21st Asia-Pacific Software Engineering Conference, vol. 1. IEEE, 2014, pp. 335–342.
[5] M. Feijer, P. Przymus, and K. Stencel, “Profile based recommendation of code reviewers,” Journal of Intelligent Information Systems, vol. 50, no. 3, pp. 597–619, 2018.

[6] I. Steinmacher, M. A. Gerosa, and D. Redmiles, “Attracting, onboarding, and retaining newcomer developers in open source software projects,” in Workshop on Global Software Development in a CSCW Perspective, 2014.

[7] H. Kajdi and D. Poshyvanyk, “Who can help me with this change request?” in 2009 IEEE 17th International Conference on Program Comprehension. IEEE, 2009, pp. 273–277.

[8] J. B. Lee, A. Ihara, A. Monden, and K.-i. Matsumoto, “Patch reviewer recommendation in oss projects.” in APSEC (2), 2013, pp. 1–6.

[9] A. Ouni, R. G. Kula, and K. Inoue, “Search-based peer reviewers recommendation in modern code review,” in 2016 IEEE International Conference on Software Maintenance and Evolution (ICSMSE). IEEE, 2016, pp. 367–377.

[10] I. Steinmacher, M. A. G. Silva, M. A. Gerosa, and D. F. Redmiles, “A systematic literature review on the barriers faced by newcomers to open source software projects,” Information and Software Technology, vol. 59, pp. 67–85, 2015.

[11] I. Steinmacher, A. P. Chaves, T. U. Conte, and M. A. Gerosa, “Preliminary empirical identification of barriers faced by newcomers to open source software projects,” in 2014 Brazilian Symposium on Software Engineering. IEEE, 2014, pp. 51–60.

[12] I. Steinmacher, I. Wiese, A. P. Chaves, and M. A. Gerosa, “Why do newcomers abandon open source software projects?” in 2013 6th International Workshop on Cooperative and Human Aspects of Software Engineering (CHASE). IEEE, 2013, pp. 25–32.

[13] A. S. Foundation, “Available mailing lists,” http://mail-archives.apache.org/mod_mbox/airflow-users/201905.mbox/browser/ 2019.

[14] L. Lü and T. Zhou, “Link prediction in complex networks: A survey,” Physics reports, vol. 501, no. 6, p. e215059, 2019.

[15] V. W. Zheng, H. Cai, K. C.-C. Chang, and E. Cambria, “Node2vec: Scalable feature learning on graphs,” in Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining, 2016, pp. 855–864.

[16] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” arXiv preprint arXiv:1301.3781, 2013.

[17] X. Rong, “word2vec parameter learning explained,” arXiv preprint arXiv:1411.2738, 2014.

[18] F. Chung, “Random walks and local cuts in graphs,” Linear Algebra and its applications, vol. 423, no. 1, pp. 22–32, 2007.

[19] D. Po, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” in Proceedings of the 23rd International Conference on Machine Learning, 2006, pp. 1137–1144.

[20] P. Drineas, and A. A. Abouzeid, “Random walks in time-graphs,” in Proceedings of the Second International Workshop on Mobile Opportunistic Networking, 2010, pp. 93–100.

[21] S. Mahdavi, S. Khoshkravar, and A. An, “Transdeep2vec: Scalable dynamic network embedding,” in 2018 IEEE International Conference on Big Data (Big Data). IEEE, 2018, pp. 3762–3765.

[22] J. B. Lee, G. Nguyen, R. A. Rossi, N. K. Ahmed, E. Koh, and S. Kim, “Continuous-time dynamic network embeddings,” in Companion Proceedings of The Web Conference 2018, 2018, pp. 969–976.

[23] J. B. Lee, G. Nguyen, R. A. Rossi, N. K. Ahmed, E. Koh, and S. Kim, “Temporal network representation learning,” arXiv preprint arXiv:1904.06449, 2019.

[24] Y. Kamei, S. Matsumoto, H. Maeshima, Y. Onishi, M. Ohira, and K.-i. Matsumoto, “Analysis of coordination between developers and users in the apache community,” in IFIP International Conference on Open Source Systems. Springer, 2008, pp. 81–92.

[25] J. Chen, Y. Wu, X. Xu, H. Zheng, Z. Ruan, and Q. Xuan, “Pso-ane: Adaptive network embedding with particle swarm optimization,” IEEE Transactions on Computational Social Systems, vol. 6, no. 4, pp. 649–659, 2019.

[26] P. Goyal and E. Ferrara, “Graph embedding techniques, applications, and performance: A survey,” Knowledge-Based Systems, vol. 151, pp. 78–94, 2018.

[27] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” in Advances in neural information processing systems, 2013, pp. 3111–3119.

[28] L. Bottou, “Large-scale machine learning with stochastic gradient descent,” in Proceedings of COMPSTAT’2010. Springer, 2010, pp. 177–186.

[29] S. Cavallari, W. Z. Zheng, H. Cai, K. C.-C. Chang, and E. Cambria, “Learning community embedding with community detection and node embedding on graphs,” in Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, 2017, pp. 377–386.

[30] Y. Dong, N. V. Chawla, and A. Swami, “metapath2vec: Scalable representation learning for heterogeneous networks,” in Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining, 2017, pp. 135–144.

[31] L. F. Ribeiro, P. H. Saverese, and D. R. Figueiredo, “struc2vec: Learning node representations from structural identity,” in Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining, 2017, pp. 385–394.