

Global and Local Feature Learning for Ego-Network Analysis

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Abstract—An ego-network organizes the social relationships between an individual (ego) and others (alters) into different groups (social circles). This social network can be efficiently analyzed after learning representations of egos and alters in a low-dimensional, continuous vector space. Such vectors are then easily exploited via statistical models for tasks such as social circle detection and prediction. Recent advancements in language modeling and deep learning have inspired new methods for learning network representations. These methods can capture the global structure of networks. In this paper, we evolve these techniques to also encode the local structure of neighborhoods. Therefore, our local representations reveal interesting network features that are hidden in the global representation of large ego-networks. We show that the task of social circle prediction benefits from a combination of global and local features generated by our technique.

Index Terms—Ego-Networks, Global Representations, Local Representations, Deep Learning, Graph Embeddings, Social Network Analysis

I. INTRODUCTION

There are numerous ways to represent the topological structure of a social network. However, with the exponential growth of today social networks, finding the appropriate representation to convey the desired network information is a challenging task. Due to computational difficulties, large network analysis becomes increasingly impractical for the full network. One effective way to help succinctly describe certain aspects of the networks is breaking up the network into smaller sub-networks[1]. This is accomplished by considering certain node or subgraph level locality statistics specified on local regions of a network. These local regions are defined as the neighborhoods around a focal node or ego-networks. Ego-networks have been studied to understand the role an ego plays and how he interacts with his alters [1]. Usually egos categorize their alters into different social circles such as family members, friends, colleagues, etc. Figure 1 shows an ego-network with his social circles.

The main critical challenge for ego-network analysis is how to represent the social graph properly so that advanced analytic tasks, such as pattern discovery, and prediction, can be conducted efficiently in both time and space. The most effective method is to learn low-dimensional representations of egos and alters in a contin-

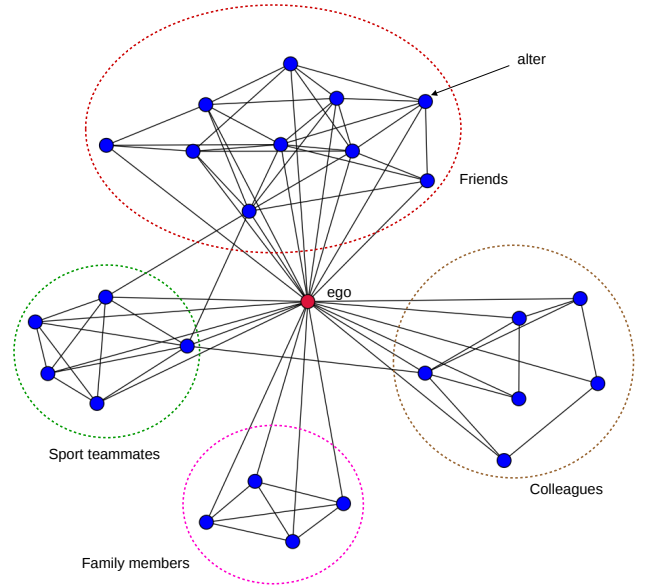


Figure 1: An ego-network with labeled circles

uous vector space. These vector representations can easily be exploited by statistical models for tasks such as social circle detection and prediction. In this paper, we aim to learn meaningful representations for ego-networks which consider the neighborhood structure of egos. The local neighborhood analysis of nodes can reveal patterns and features of the network which are concealed when only the global analysis is considered [24]. For example, nodes in the family circle are normally more densely connected compared to nodes in the colleague circle.

There has been many studies on global properties of social networks such as density, centrality measures, and vector representations. For instance, DeepWalk [9] learns latent representations for nodes in the social graph utilizing deep learning techniques. Similarly, node2vec [25] learns a mapping of nodes to a low-dimensional space of features that preserves the flexible notion of nodes' neighborhoods. However, there is not a systematic study on finding a low-dimensional representation for ego-networks considering the structure of the neighboring network around an ego.

Recent advances in deep neural networks have shown

powerful representations abilities [6] to generate practical representations for many types of data. Specifically, the Skip-gram model [7] aims to learn feature representations for words by optimizing a neighborhood preserving likelihood objective. Similarly, Paragraph Vector [10] is an unsupervised framework which learns continuous distributed vector representations for pieces of texts. Inspired by the Skip-gram model, a network can be represented as a document. The same way as a document is an ordered sequence of words, nodes can be sampled from the underlying network and turn a network into a ordered sequence of nodes [20]. This approach is useful to learn global representations for nodes in the social graph [9]. In this paper, we exploit the Paragraph Vector to learn neighborhood structures of egos in the social graph. Therefore, we investigate the interplay of global and local representations and make the following contributions:

- We introduce local vector representations for nodes in ego-networks to complement the global representations for capturing the neighborhood structure; learning relations in a small neighborhood instead of relations in the entire graph. (section II)
- We apply global and local feature learning to the circle prediction problem. (section III)
- We replace global representations by local representations to improve the performance. (section III)

The remainder of the paper is organized as follows. First, we elaborate on global and local feature learning of nodes in ego-networks in section II. Second, we describe the problem of circle prediction and our approach in section III. Third, we evaluate our approach on three datasets from large social networks in section IV. We conclude in section V.

II. GLOBAL AND LOCAL FEATURE LEARNING

We consider an undirected social graph $G = (V, E)$, where V is a set of n nodes and $E \subseteq V \times V$ is a set of edges. Furthermore, let G contain ego-networks with egos $\{u_1, u_2, \dots, u_m\} \in U \subseteq V$. For every ego u_i , we denote the set of his alters as A_{u_i} and his subgraph as $G(u_i)$. In this section, we apply the techniques which have been used to model sentences and paragraphs of natural languages to model community structure in networks. Therefore, we are able to capture information on the global and local network topology as follows:

A. glo: Learning global representation for each node

According to the DeepWalk, global feature learning consists of two main components; first a random walk generator and second an update procedure. Assume $\{v_1, v_2, \dots, v_n\} \in V$ are all nodes in the graph G , the idea is doing random walks started from every single node. Then, having sequences of nodes such as $v_1, v_2, \dots, v_{t-1}, v_t, \dots, v_n$ with a context length c , we up-

date the representations to maximize the average log probability:

$$\sum_{t=1}^n \log P(v_t | v_{t+c}, \dots, v_{t-c}). \quad (1)$$

Therefore, we have a mapping function $\text{glo} : v \in V \mapsto \mathbb{R}^{|V| \times d}$, where d is the embedding size.

B. loc: Learning local representation for each ego

Inspired by Paragraph Vector, we learn a vector representation for every ego $u_i \in U$. Given ego u_i , first, we do random walks on $G(u_i)$ to compose an artificial paragraph which is called an ego-walk. This means an ego-walk is a stream of short random walks started at every $v_i \in A_{u_i} \cup \{u_i\}$. Then, having the ego-walk $v_1, v_2, v_3, \dots, v_t, \dots, v_l$ for ego u_i , we aim to update the representations in order to maximize the average log probability:

$$\sum_{t=1}^l \log P(v_t | u_i, v_{t+c}, \dots, v_{t-c}) \quad (2)$$

Where l is the length of the ego-walk with $l < n$, and c is the context length. Therefore, we introduce a mapping function $\text{loc} : u \in U \mapsto \mathbb{R}^{|U| \times d}$, where d is the embedding size.

In our technique (see Figure 2), every ego is mapped to a unique vector, represented by a column in matrix D and every alter is also mapped to a unique vector, represented by a column in matrix W. The ego vector and alter vectors are concatenated to predict the next alter in a context.

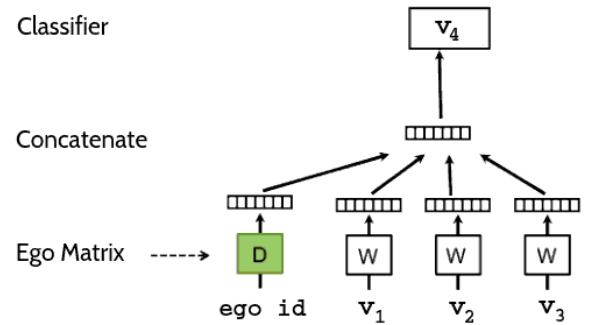


Figure 2: A technique for learning ego vector. The concatenation of ego vector with a context of three alters is used to predict the fourth alter.

III. CIRCLE PREDICTION

In online social networks, users need to organize their personal social networks to cope with the information overload generated by their friends [1]. However, this manual process is laborious, error-prone and inadaptible to changes. It is meaningful and essential to study how

to automatically organize user's friends into social circles when they are added to the network. These organized social circles could help solve many practical problems. For example, it can preserve user's privacy by showing updates and information only to some friends belong to the specific circles allowed by the user. It also can help a user who wants to read the latest news from his colleagues instead of scrolling through all the news from other users.

However, most of current social circle identification methods [1]–[5][11][12][13] are unsupervised learning methods which lacks emphasis on dataset quality and they could not predict well when there is a missing value in the query. The main supervised approach is proposed by McAuley & Leskovec [1] which trained a binary classifier for each circle. Their probabilistic model discriminates members from nonmembers based on node features. Node features are the information from both network topological structure and users' profiles. Although their model deals with weak supervision to predict the circle for a new alter, it fails to refit the model for every new alter that is added to the network. In this section, we study the problem of social circle prediction exploiting the global and local neighborhood structures.

A. Approach

We formulate the problem of circle prediction as a classification task on a new added alter into the graph. We thus leverage the topological structure of the alter and also his profile information. Indeed, Alters' and egos' profile information help with the circle prediction task. For example, if the ego and the alter both go to the same university, probably this alter belongs to the university friends circle. Therefore, we add the common profile features vector between an ego and its alter to the topological representations to perform a more accurate circle prediction. More formally, we denote i^{th} profile feature of the alter v as $v.\text{feat}_i$, and the ego u as $u.\text{feat}_i$. Given ego $u \in U$, and alter $v \in V$, we formulate the ego and alter profile similarity as $\text{sim}(u, v) = (b_1, \dots, b_f)$, where

$$b_i = \begin{cases} 1 & \text{if } u.\text{feat}_i = v.\text{feat}_i, \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

Therefore, for each pair of ego and alter, we have the binary vector $\text{sim}(u, v) \in \mathbb{R}^f$ where f is the number of profile features.

B. Classifier

Since some alters are the member of several circles, we need to use a multi-label classifier. Neural network classifiers have the ability to detect all possible interactions between predictor variables. Furthermore, they need less formal statistical training to develop [14]. In particular, feed-forward neural networks are appropriate for modeling relationships between a set of input variables and one or more output variables. In fact, they are suitable for any functional mapping problem where we want to know how

a number of input variables affect the output variable [18]. We thus define our classifier as a multi-layer feed-forward neural network with the following possible input layers:

- Where the input layer is the concatenation (\oplus) of the global and local representations:
 - **glo**: $\text{glo}(u) \oplus \text{glo}(v)$
 - **loc**: $\text{loc}(u) \oplus \text{glo}(v)$
 - **locglo**: $\text{loc}(u) \oplus \text{glo}(u) \oplus \text{glo}(v)$
- Where the input layer is the the concatenation of global representation, local representation and the profile similarity vector:
 - **glosim**: $\text{glo}(u) \oplus \text{glo}(v) \oplus \text{sim}(u, v)$
 - **locsim**: $\text{loc}(u) \oplus \text{glo}(v) \oplus \text{sim}(u, v)$
 - **locglosim**: $\text{loc}(u) \oplus \text{glo}(u) \oplus \text{glo}(v) \oplus \text{sim}(u, v)$

Overall, the architecture of our classifier is described as follows:

- **Input layer**: It can be one of six possible inputs which were described above.
- **Hidden layer**: We have a hidden layer with ReLU activation unit. [21].
- **Output layer**: The output layer has \mathcal{Y} units the same as the number of social circles in the graph with softmax activation function [22].
- **Optimizer**: we used RMSprop which is an adaptive learning rate method that has found much success in practice [19]. RMSprop divides the learning rate for a weight by a running average of the magnitudes of recent gradients for that weight.

IV. EXPERIMENTS

In this section, we first provide an overview of the datasets that we used in the experiments. We then present an experimental analysis of the proposed approach.

A. Datasets

Since our approach is supervised, we require labeled ground-truth data in order to evaluate its performance. We obtained ego-networks and ground-truth from three major social networking sites: Facebook, Google+, and Twitter available from the University of Stanford [1]. Table I describes the details of the datasets we used in our experiments.

Table I: Statistics of Social Network Datasets

		Facebook	Twitter	Google+
Number of nodes	$ V $	4,039	81,306	107,614
Number of egos	$ U $	10	973	132
Number of edges	$ E $	8,8234	1,768,149	13,673,453
Number of circles	\mathcal{Y}	46	100	468
Number of features	f	576	2271	4122

The number of circles refers to the number of different social circles such as family members, highschool, sport, colleagues, etc. For example, the Facebook dataset has 46 different social circles.

B. Experimental setup

In order to learn global representations for nodes in Facebook, Google+, and Twitter graphs, we first do random walks to compose three artificial corpus. We then apply word2vec of gensim [23] which is an implementation for the Skip-gram model on our artificial corpuses. We set the embedding size $d = 300$ [26], and the context length $c = 2$. Therefore, word2vec scans over the nodes, and for each node it tries to embed it such that the node's features can predict nearby nodes. The node feature representations are learned by optimizing the likelihood objective using SGD with negative sampling [8].

Similarly, we set the embedding size $d = 300$ and $c = 2$ to learn local representations for egos in these social graphs. First, we generate ego-walks doing random walks on each ego-network separately. For example, for the Facebook graph with 10 egos, we have a corpus with 10 ego-walks. Then, we apply doc2vec of gensim [23] which modifies the word2vec algorithm to learn continuous representations for paragraphs on our artificial corpuses. Therefore, every ego is represented by a vector which holds the semantics of his neighborhood structure.

To obtain common features for each pair of ego and alter, we select the first 500 features of their profiles include birthday, education, gender, hometown, languages, location, work along with their sub-branches. We then compare the ego's features to his alters' features one by one to generate a binary feature vector. This vector will be concatenated to the topological structure vectors as input of the classifier.

We create feature matrices $X_{loc} \in \mathbb{R}^{2d}$ and $X_{glo} \in \mathbb{R}^{2d}$ by concatenation of local and global vectors where $d = 300$. We also create two other feature matrices $X_{locsim} \in \mathbb{R}^{2d+f}$ and $X_{glosim} \in \mathbb{R}^{2d+f}$ considering common profile feature vectors where $f = 500$. The same manner we have $X_{locglo} \in \mathbb{R}^{3d}$ and $X_{locglosim} \in \mathbb{R}^{3d+f}$.

Regarding to the ground-truth matrix, we have circle labels for each alter available in the dataset. We need to convert the multi-label ground-truth to the binary form which is more suitable for the classification algorithm.

We finally perform the classification task considering different inputs X_{loc} , X_{glo} , X_{locsim} , X_{glosim} , X_{locglo} and $X_{locglosim}$ to compare the prediction results. In the multi-label classification setting, every alter is assigned one or more labels from a finite set \mathcal{Y} . During the training phase, we observe a 70% of alters and all their labels. The task is to predict the labels for the remaining 30% alters. The batch size of the stochastic gradient descent is set to 32 for Facebook and 64 for both Google+ and Twitter since they have bigger graphs. We consider the learning rate $\epsilon = 0.001$ for RMSprop optimizer over 50 iterations. We use K -fold cross-validation approach for estimating test error. The idea is to randomly divide the data into K equal-sized. We leave out part k , fit the model to the other $K - 1$ parts (combined), and then obtain predictions for

the left-out k^{th} part. This is done in turn for each part $k = 1, 2, \dots, K$, and then the results are combined. We set $K = 10$ in our experiments.

C. Results

We classify the alters of Facebook, Google+, and Twitter graphs into respective social circles and report the average performance in terms of F_1 score. To compute the F_1 score we follow evaluation metrics was described as [1] with 10-fold cross validation. Table II shows the average performance of the classifier along with the standard deviation (std). As can be seen, replacing global representation with local improved the performance of the circle prediction. Moreover, considering the profile similarity between ego and alter affected on the performance of the classifier. However, adding the global representations of egos to the input did not improve the performance.

Table II: Performance (F_1 score) of different embeddings for circle prediction on three ego-networks

Classifier Input	Facebook	Twitter	Google+	std
glo	0.37	0.46	0.49	0.02
loc	0.42	0.50	0.52	0.01
locglo	0.37	0.44	0.48	0.01
glosim	0.40	0.49	0.51	0.02
locsim	0.45	0.53	0.55	0.01
locglosim	0.38	0.46	0.47	0.01
McAuley & Leskovec [1]	0.38	0.56	0.59	

V. CONCLUSION

We described a technique for ego-network analysis based on the concept of local network neighborhoods. We applied new advancements of language modeling to learn latent social representations for egos. This allows analysis on large social networks and can reveal aspects of neighborhood structure that cannot be ascertained in a global network analysis. We provided an example of social circle prediction on different social graphs displaying the ability of our approach to capture local neighborhood structure. As a future work, we tend to study how the local representations can improve the other graph analysis tasks (e.g. link prediction, shortest path, etc).

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