Community Aware Random Walk for Network Embedding

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Abstract:

Social network analysis provides meaningful information about behavior of network members that can be used in diverse applications such as classification, link prediction, etc. However, network analysis is computationally expensive because of feature learning for different applications. In recent years, many researches have focused on feature learning methods in social networks. Network embedding represents the network in a lower dimensional representation space with the same properties which presents a compressed representation of the input network. In this paper, we introduce a novel algorithm named “CARE” for network embedding that can be used for different types of networks including weighted, directed and complex. While current methods try to preserve local neighborhood information of nodes, we utilize local neighborhood and community information of network nodes to cover both local and global structure of social networks. CARE builds customized paths, which are consisted of local and global structure of network nodes, as a basis for network embedding and uses skip-gram model to learn representation vector of nodes. Then, stochastic gradient descent is used to optimize our objective function and learn the final representation of nodes. Our method can be scalable when new nodes are appended to network without information loss. Parallelize generation of customized random walks is also used for speeding up CARE.

We evaluate the performance of CARE on multi label classification and link prediction tasks. Experimental results on different networks indicate that the proposed method outperforms others in both Micro-f1 and Macro-f1 measures for different size of training data.

Keywords:

\textit{Representation learning, Network embedding, Community detection, Skip-gram model, Link prediction.}

1. Introduction:

There has been a noticeable growth in online social networks and the number of their users. There is many valuable information that can be extracted from social networks by analyzing both their structure and content. Machine learning techniques are used as a way to extract valuable features from social

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networks for different analysis tasks such as classification [1, 2, 3], recommendation [4, 5] and link prediction [6, 7, 8, 9]. These learning methods can be both supervised and unsupervised. Supervised learning algorithms are able to better extract features for a specific task on social networks but their scalability would be challenging for large networks. Unsupervised methods can handle scalability of feature learning methods; however, the extracted features show low accuracy in different network analysis tasks. Because they are so general and unable to obtain valuable information for a specific task [10, 11, 12, 13, 14, 15, 16].

Network embedding, as an unsupervised representation learning task, tries to learn informative lower dimensional representation of network nodes. These representation vectors can be used in different social network analysis tasks such as classification [17], recommendation [18] and link prediction [6]. Some of classic network embedding methods use eigenvectors of affinity graph as feature vectors [10, 15, 19, 20]. Graph factorization is another technique which is used for network embedding [21]. The aforementioned approaches suffer from scalability for large social networks.

In recent years, deep learning as an unsupervised method, is widely used in natural language processing which A detailed description of these researches can be found in [11]. There are also many researches that have used deep learning for social network embedding [22, 23, 24, 25]. Network embedding methods try to represent graph nodes with some informative feature vectors. DeepWalk was the first method that used deep Learning for social network embedding [22]. This method generates some random walks for each node and uses them as contextual information to learn representation of the node. LINE defines two loss function to extract first and second order proximity separately. Then uses them as surrounding context of network nodes [23]. Node2Vec generates second order random walks based on BFS\(^3\) and DFS\(^4\) strategies [24]. All the mentioned methods attempt to extract local structure information for each node, then apply them to learn final representation of the node. However, communities are one of the most structural information of a network that is not considered by these methods [26].

Community structure imposes constraints in a higher structural level on the node representations. The representations of nodes within a community should be more similar than those belonging to different communities. Also, for two nodes within a community, even if they only have weak relationship in local structure due to the data sparsity issue, their similarities will also be strengthened by the community structure constraint. Thus, the incorporation of community structure in network embedding can provide effective and rich information to solve data sparsity issues in global structures and also make the learned node representations more discriminative [25].

In this paper, we propose a new network embedding method called “CARE”, which utilize community information of network nodes to capture more structural information of networks. Some previous researches tried to embed community information on nodes’ representation. For instance, [24] only considers the community members that their distance to the source nodes is less than 2. However, in real world networks which communities have thousands of members, Node2vec would not be able to consider information about nodes that their distance is more than two from the source of random walk because Node2vec creates second order random walks. CARE can also produce representation vector of nodes for arbitrary type of networks such as weighted, complex and directed.

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\(^3\) Breadth first search  
\(^4\) Depth first search
CARE firstly extracts communities of the input network. We obtain this information with the Louvain method [27] which has effective performance on different social networks. To learn final representations, we generate some community aware random walks that considers both first and higher order proximities as well as community membership information for each node. Finally, the customized random walks are used as contextual information to learn final representation of nodes in skip-gram learning model.

CARE is evaluated with two social network analysis tasks: multi label classification and link prediction. The experimental results show that CARE outperforms over Node2vec with a gain of 50% on multi label classification with BlogCatalog dataset and 3% on link prediction task for PPI dataset.

To summarize, we make the following contributions:

- We present a novel network embedding algorithm named CARE that learn representation of nodes for different types of networks such as weighted and directed and complex networks.
- Our method can preserve community information of the input network in the learned representation vectors while the previous researches are not able to define an optimization function that consider this information explicitly.
- We empirically evaluate the algorithm on different multi label classification and link prediction with different real world social networks. The experimental results indicate the efficiency of CARE in contrast to other network embedding methods.

The rest of paper is organized as follows: In section 2, we summarize related works to network embedding. We explain details of CARE in section 3. Section 4 outlines the experimental results on two network analysis tasks. And finally, Section 5 presents conclusion and future works.

### 2. Related Works:

In this section, we review recent researches related to unsupervised representation learning of network nodes. Some feature learning approaches use adjacency matrix of the network and try to preserve first order proximity of nodes. These researches act as dimensionality reduction methods and find best eigenvectors of network matrices [10, 15, 16, 19, 20, 21, 28]. Then use them as feature vector of networks. Eigenvector decomposition is usually computationally expensive. Also, they just consider immediate neighborhood of nodes and do not use higher order proximities and community information. So they are unable to preserve global structure of networks. As a result, the learned representations would not provide an appropriate performance on diverse network analysis tasks.

In recent years, deep learning is used as a way to learn feature vector of network nodes. These methods have utilized deep learning to learn representation vectors, generate random walks with different graph exploration strategies and have used them as contextual information in skip-gram model. DeepWalk was the first method that used skip-gram model [22]. It uses DFS like search strategy to generate random walk. Despite the good performance on multi label classification, this method failed to preserve global network structure because it does not consider community information of network nodes. LINE uses first and second order proximities to learn nodes’ representation but it also preserves local information of the networks [23]. They define two independent function for first and second order proximities but they ignore community information. LINE and DeepWalk also fail to learn representation vector for network edges.
Node2Vec generates random walks based on DFS and BFS like strategies [24]. While they use two controlled parameters to consider both homophily [29] and structural equivalences [30] of input networks, they don’t guarantee to reach different nodes of a community. The main reason for this problem is that these algorithms only consider second order proximities and are unable to reach the nodes that their distance is more than 2 from the start node of random walk. Because in real networks, there are many nodes in a community and obviously their distance is more than two so Node2vec would not consider all the community members during creation of random walks for a node. SDNE proposes a semi-supervised deep model, which has multiple layers of non-linear functions, thereby being able to capture the highly non-linear network structure [31]. It exploits the first-order and second-order proximity jointly to preserve the network structure but it doesn’t use community information.

The proposed method in [25] uses modularized non negative matrix factorization to preserve both microscopic and mesoscopic information of networks. They define two independent model to embed local and community information independently and then optimize the joint function to learn representation of nodes. Their final representation is not so general to be used for different network analysis tasks because they learn local and community structure separately, then combine final representations. Their method also suffers from scalability when the networks are large because they should learn many parameters to preserve local and global structures, so it is not applicable on real social networks.

Unlike previous researches, we utilized BFS like strategy alongside community information of network nodes. We preserve both local and global information because we use first and higher order proximities as well as community information of nodes to learn nodes’ representations.

3. CARE: Community Aware Random Walk for Network Embedding

Community information is one of the key features of social networks which preserves global structure of the network [26]. However, it is ignored by the most previous researches in the field of network embedding when they want to gather information about network nodes. We present a new algorithm to embed graph structure alongside community information into learned representation vectors of network nodes. Therefore, we redefine network embedding as a maximum likelihood problem which is gained by global network structures. Suppose \( G = (V, E) \) is an (un)directed graph which \( V \) and \( E \) are set of graph nodes and edges. We are going to find a mapping function \( f: V \rightarrow \mathbb{R}^d \) which \( d \) is representation size of each graph node. To obtain best mapping function \( f \), skip-gram model is used [32, 33].

In CARE, first neighborhood structure for each node is extracted from the given network using community aware random walk strategy. Then by using skip-gram model, representation vector of the node is learned from these generated random walks. The most previous approaches for modeling neighborhood structure of a node, only used first and second order proximities. In contrast to them, we use the nodes that may not have an immediate connection or second order proximity with the source node. However, they have a homophily relationship which is not presented by first and second order proximities.
Once different neighborhood structure is extracted for each node, we use skip-gram model similar to [24] to maximize $N(u)$ which $N(u)$ keeps neighborhood structure of a node $u$. Skip-gram learns the best representation vector for node $u$ using $N(u)$. In the following, we explain how we create neighborhood structure and how they are used to learn social representations of a node in the given network. Algorithm 1 illustrates the steps of CARE algorithm.

Algorithm 1: CARE (G, $w$, $d$, $\mu$, $l$)

Input:
- Graph G (V, E)
- Window length $w$
- Representation size $d$
- Number of random walks per node $\mu$
- Random walk max length $l$

Output:
- Matrix of node representations $f \in \mathbb{R}^{|V| \times d}$

1: Com = CommunityDetection (G)
2: sample $f$ from $U^{|V| \times d}$
3: while (i < $\mu$)
4:     $\varsigma = \text{shuffle} (V)$
5:     for each $v_i \in \varsigma$ do
6:         $\mathcal{W}_{v_i} = \text{CommunityAwareRW}(G, v_i, \text{Com}, l)$
7:         SkipGram ($f$, $\mathcal{W}_{v_i}$, $w$)
8:     end for
9: end while

In algorithm 1, Line 1 detects the communities of the given graph G. The Louvain method is used for detecting communities which is explained in details in section 3.1. Before we learn the optimal representation vectors for graph nodes, we generate matrix U randomly to initialize representation vector of nodes in line 2. Now we are able to learn final representation vectors in lines 3-9 of algorithm 1. For each node in V, it is generated $\mu$ different customized random walks to better capture global and local structure of the node in line 4. Before iterating over $V$, it is shuffled to avoid the effect of nodes visiting order in the final representations. The core of the presented method for network embedding is line 7 where we generate customized random walks for the chosen node which would clarified in section 3.2. Finally, the generated paths are used to update node representation in line 8. In the next sections, different functions of the algorithm 1 is explained in details.

3.1. Community Detection:

We have used the Louvain method to maximize modularity in input network to detect communities [27]. Modularity is a metric to compare density of edges that are inside a community to the edges between communities. It is an optimization problem that first assigns
all nodes to whole groups and then assign the node to the group, in which the modularity is maximum. Modularity in the network is calculated using the following formula:

\[
Q = \frac{1}{2m} \sum_{ij} (A_{ij} - \frac{k_i k_j}{2m}) \delta(c_i, c_j)
\]

(1)

In Eq. 1, \(m\) stands for sum of all edge weights in the graph. \(A_{ij}\) denotes the edge weight between nodes \(i\) and \(j\). sum of edge weights of \(i\) and \(j\) are represented by \(k_i \cdot k_j\). The communities of \(i\) and \(j\) are shown by \(c_i\) and \(c_j\). Finally \(\delta\) is a delta function that returned 1 when communities are equal.

As modularity maximization problem is intractable, we have first used a heuristic version of the Louvain method to find communities, then each small community is considered as a node in a new network and we try to maximize the modularity with the new network [27].

3.2. Generation of neighborhood structure:

To extract neighborhood structure of a node, we build \(\mu\) customized random walks. A customized random walk that starts from node \(v\) is shown by \(W_v\). Since a random walk is a path in the given network, we can denote a customized random walk for node \(v\) with some random variables \(W^1_v, W^2_v, \ldots, W^L_v\) such that \(W^{k+1}_v\) is a node selected at random from immediate neighbors or the nodes that are in a same community with \(k\)-th node of the path.

To create a customized random walk started from node \(v\), we first extract all of its immediate neighbors. Then a random variable \(r\) between 0 and 1 is generated. if \(r\) is less than \(\alpha\), we pick a node at random from the immediate neighbors; else, we choose a node from the nodes that are in the same community with \(k\)-th node of \(W_v\) as it is shown in Eq.2.

\[
W^{k+1}_v = \begin{cases} 
\text{immediate neighbors} & 0 < r < \alpha \\
\text{nodes in community of } k\text{-th node} & \alpha < r < 1 
\end{cases}
\]

(2)

If \(k\)-th node of \(W_v\) be a member of several communities, we first extract all the members of these communities. Then we choose one of them, randomly.

This process is continued until it reaches a predefined length \(l\) for the path. Furthermore, if a node in the path has no new neighbor, we stop the expansion of the path. Algorithm 2 illustrates the details of generating customized random walks in CARE.

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**Algorithm 2: CommunityawareRW (G, vi, Comvi, l, α)**

**Input:**
- Graph G (V, E)
- Source node of RW \(v_i\)
- Nodes belong to the same community with \(v_i\) \(\text{Com}_v_i\)
- Random walk max length \(l\)
- Random variable to select from neighbors or same community members \(\alpha\)

**Output:**
- A path with max length \(l\)
1: initialize RW with $v_i$
2: while length(path) < $l$
3:     if current node has neighbors
4:         if (random (0, 1) > $\alpha$)
5:             select $v_j$ at random from $v_i$’s neighbors
6:         else
7:             select $v_j$ at random from members of $v_i$’s community
8:     else
9:         backtrack in the path and select the last node which has neighbors that are not in the path
10: end while

The proposed random walk generator extracts local and global information from the given network. In addition, we can parallelize the process to speed up network embedding algorithm because customized random walks are generated independently from others and we are able to consider both local and global structure of the network simultaneously. Also, if some new nodes are added to (removed from) the network, their biased random walks are generated without the need to obtain new customized random walks for previous nodes.

3.3. Skip-Gram:

According to Algorithm 1, after generation of random walks, we use skip-gram model to learn representation of graph nodes [32, 33]. Skip-gram is a language model that maximizes conditional probability of words’ co-occurrence in a predefined window $w$ as it is shown in Eq.3:

$$Pr(w \mid f(u)) = \max_f \prod_{j=i-w}^{i+w} Pr(v_j \mid f(u)) \quad w = \{v_{i-w}, \ldots, v_{i+w}\} \setminus u$$

(3)

For each node in the given network, we iterate over all its customized paths. We define a window $w$ to slide over a path. Similar to the previous approaches, the independence assumption of conditional probabilities is considered in Eq. 3. Also, Softmax function is used to approximate the probability distribution of Eq. 3 as the following in Eq. 4:

$$Pr(v_j \mid f(u)) = \frac{1}{1 + e^{-f(u) \cdot f(v_j)}}$$

(4)

Stochastic gradient descent (SGD) is used to optimize the parameters similar to the proposed method in [34].

For complex networks, we consider different edges of two nodes independently. If there are more edges between nodes in the given network, it is more probable to choose these nodes in the path. If the given network is weighted, we consider weights of edges as a probability to pick the edges when generating customized random walks.
Our algorithm is also scalable when some new nodes are appended to (removed from) the network. Customized random walks are only generated for new nodes and their representation vectors are calculated as stated above. We are able to parallelize the generation of customized random walks to increase the speed of CARE.

4. Experiments:

In this section, we evaluate CARE with two supervised learning tasks: multi label classification and link prediction. We also analyze the effect of different parameters. We compare our results on the aforementioned tasks with the best representation learning methods which are explained in section 4.1.

4.1. Baseline Algorithms:

To evaluate the performance of the proposed algorithm, we compare it with the following representation learning algorithms that have the best results on multi label classification and link prediction tasks:

Spectral clustering [28]:

This algorithm attempts to find graph cuts that lead to better classification of the graph. Therefore, it first calculates the normalized Laplacian matrix of graph G. Then, it considers the d-smallest eigenvectors of the matrix as the best feature vector to represent graph nodes.

DeepWalk [22]:

DeepWalk is the first algorithm that uses deep learning for social network embedding. It generates random walks for each node and use them as contextual information to learn representation vector of the nodes. DeepWalk could be considered as a variant of CARE with $\alpha = 0$ in algorithm 2.

LINE [23]:

LINE uses local information including first and second order proximities of nodes instead of generating random walks. It firstly defines two separate function to preserve immediate relations and second order proximities in a social network. In the second stage, two functions are combined linearly to calculate final representation of each node.

Node2vec [24]:

Node2vec is a semi supervised algorithm that generates a second order random walk to capture network neighborhood information of nodes. It uses two parameters to simulate BFS and DFS search strategies.
To compare our results with the above algorithms, we have used the same parameter settings that are reported in [24] for all the algorithms. We set \( w = 10, d = 128, \mu = 10, l = 80 \). The optimal value for \( \alpha \) is 0.2. We also use the same datasets and experimental procedure as [24].

### 4.2. Multi label classification:

In multi label classification task, we predict one or more label for each network node. To compare our algorithm with baseline algorithms, we evaluate the methods with the following datasets:

BlogCatalog [35]: This is a social network of bloggers in which, node labels are topic categories that each blogger generates. It has 10312 nodes and 333983 edges and 39 different topic label.

Protein-Protein Interactions (PPI) [36]. This is subgraph of Homo Sapiens PPI network which is preprocessed in [24] that has 3890 nodes, 76584 edges and 50 labels which are extracted from gene sets.

Wikipedia [37]: It is a co-occurrence word network of Wikipedia articles that has 4777 nodes, 184812 edges and 40 different labels. The labels of nodes are part of speech (POS) tags of network nodes.

Table 1 summarizes statistics of datasets that are used in multi label classification task.

| Dataset                                  | \(|V|\)   | \(|E|\)   | Labels |
|------------------------------------------|----------|----------|--------|
| BlogCatalog                              | 10312    | 333983   | 39     |
| Protein-Protein Interactions (PPI)       | 3890     | 76584    | 50     |
| Wikipedia                                | 4777     | 184812   | 40     |

*Table 1 datasets that used in multi label classification*

### 4.2.1. Experimental Results:

In the experiments, the training size of input datasets is increased from 10% to 90% and Micro-f1 and Macro-f1 measures are used to evaluate performance of different algorithms [31]. Micro-f1 is a metric which gives equal weight to each instance while Macro-f1 is a metric which gives equal weight to each class. They are defined as follows:

\[
\text{Precision} = \frac{\sum_{A \in C} TP (A)}{\sum_{A \in C} (TP(A) + FP(A))}
\]

\[
\text{Recall} = \frac{\sum_{A \in C} TP (A)}{\sum_{A \in C} (TP(A) + FN(A))}
\]

\[
\text{Micro - f1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

\[
\text{Macro - f1} = \frac{\sum_{A \in C} F1 (A)}{|C|}
\]
In the above formulas, TP(A), FP(A) and FN(A) are the number of true positives, false positives and false negatives in the instances which are predicted as A, respectively. Suppose C is the overall label set. F1(A) is the F1-measure for the label A.

Figure 1 shows the performance of CARE in comparison to the other methods for multi label classification task over different networks. In the following, we discuss the experimental results for each dataset.

**BlogCatalog:**

For BlogCatalog dataset, our method shows significant improvements over both Micro-f1 and Macro-f1. When there are only 10% training data, CARE achieves a gain of 50% over Node2vec. In this condition, both LINE and Spectral clustering show poor performance. This property would be useful especially in sparse networks. The most important difference between CARE and the other algorithms is the usage of community information during path generation. As a result, we will be able to maintain both local and global structural information of the network when learning the representation vector of each node.

**PPI:**

As the results shows in figure 1, both evaluation metrics have less value than BlogCatalog network because PPI network has lower density in comparison to BlogCatalog. CARE has significant improvements over Node2vec and DeepWalk. When training data is 50%, our method outperforms about 50 % over Node2vec because we utilize community membership information during nodes’ representation learning.

**Wikipedia:**

As another evaluation, we test CARE on co-occurrence word network of Wikipedia articles. The results of experiments show CARE outperformed baseline algorithms, considering both Micro-f1 and Macro-f1. When training data size reaches to 80%, our method achieved to highest improvements over Node2vec of 7%.
4.2.2. Parameter sensitivity:

In this experiment, the best parameter values for CARE is found on BlogCatalog in Multi label classification task. In each experiment, we consider default values for all the parameters and change just one parameter. We also pick 50% of input network as training set. One of the most important parameters of our method is $\alpha$. Figure 2(a) shows the best value of $\alpha$ while other parameters set to default values. The effect of different size of representation vector is illustrated in figure 2(b). When Micro-f1 reaches to 128, the curve is saturated. Of course, as it stated in [22], $\mu$ and $w$ can also effect on representation size.

We have shown the optimal value of $\mu$ in figure 2(c). When the number of walks for a node is increased, we are able to gather more information about that node. This would lead to more coverage of node’s neighborhood. Although, after number of walks reach 40, the curve is saturated for BlogCatalog and there is no difference in Micro-f1 when we increase $\mu$ more than 40.

Skip-gram model uses a window to extract relationship of words that are close to each other in a document. We use the same window to relate the node that are located in a path. As figure 2(d)
indicates, by increasing $w$, less local information about the nodes in $w$ would be embedded into representation vector. Therefore, the performance of CARE is decreased.

![Graphs](image)

(a) Effect of parameter $\alpha$ on CARE  
(b) Effect of different dimensions on CARE  
(c) Effect of $\mu$ on CARE  
(d) Effect of window size on CARE

**Figure 2** Effect of different parameters on CARE performance

### 4.3. Link Prediction:

Link prediction task is a supervised learning problem that attempts to detect some future edges of the given network. We removed 50% of network edges at random to evaluate performance of CARE in link prediction. In contrast to Node2vec, we don’t consider connectivity of the remained network after each edge removal. Node2vec dependsents to connectivity of networks, so it fails to detect edges of leaf nodes in the given network. While CARE be able to detect leaf nodes neighborhood structures using community information of them that are embed in their representation vector though their edge was removed.

Since representation learning algorithms only generate feature vector for each node separately, similar to [24], we also extend our algorithm by Hadamard operator to produce an edge representation for edge $(u, v)$ such that the learned representation has the same size with the representation vectors of source and destination nodes of the edge. Eq. 5 denotes how the edge representation are generated by Hadamard operator.

$$g(e) = f(u) * f(v)$$  

(5)
Where $g: V \times V \rightarrow \mathbb{R}^d$, $e$ denotes the edge between node $u$ and $v$. $f(u), f(v)$ are representation vectors which are learned by the learning representation methods. Although, some other binary operators such as average or weighted can be used but as stated in [24], Hadamard operator showed the best performance to generate edge representation vectors.

We validate performance of our method in comparison to other algorithms on the datasets which their statistics are presented in Table 2.

|       | $|V|$   | $|E|$  |
|-------|--------|--------|
| PPI [37] | 19706  | 390633 |
| arXiv ASTRO-PH [38] | 18772  | 198110 |

*Table 2 datasets that used for link prediction*

### 4.3.1. Experimental results:

The AUC score of our algorithm is reported in Table 3. For link prediction task, the best value for $\alpha$ is 0.15. We have compared CARE with previous heuristic methods for link prediction task [24]. These scores consider the number of shared immediate neighbors of nodes in different conditions as the score for each edge. Comparing the performance of CARE with heuristic methods showed about 14 % improvement on arXiv dataset.

We also compare the performance of our algorithm with some representation learning algorithms which are introduced in 4.1. Our method shows 3% gains over Node2vec algorithm on PPI dataset.

| Algorithm          | arXiv       | PPI        |
|--------------------|-------------|------------|
| Pref. attachments  | 0.6996      | 0.6670     |
| Jaccard’s Coefficient | 0.8067    | 0.7018     |
| Common neighbors   | 0.8153      | 0.7142     |
| Adamic-Adar        | 0.8315      | 0.7126     |
| Spectral Clustering| 0.5470      | 0.4920     |
| LINE               | 0.8902      | 0.7249     |
| DeepWalk           | 0.9340      | 0.7441     |
| Node2vec           | 0.9366      | 0.7719     |
| CARE               | **0.9473**  | **0.7966** |

*Table 3 AUC score for different methods on link prediction ( All values except for CARE come from [24] )

Our method shows improvements on both datasets in comparison to Node2vec and DeepWalk that have the best results in representation learning algorithms. DeepWalk and Node2vec generate walks randomly and there is no information about community of nodes. Although, Node2vec attempts to consider homophily property using two controlled parameters, but these parameters unable to guarantee to preserve community information of nodes in a biased random walk. In contrast to Node2vec, CARE embeds this information into a customized random walk...
while we jump with probability of $\alpha$ to the nodes that are in the same community with the last node of the path.

5. Conclusion:

In this paper, we have presented a novel algorithm for network embedding called CARE. To learn the representation vector of nodes, we generate some customized random walks as contextual information. In contrast to previous researches on network embedding methods, we consider both global and local neighborhood of nodes while creating paths. Skip-gram model is used in CARE to learn the final representations of nodes. Our algorithm can embed different types of networks. The proposed method is robust to nodes addition and removal. It is scalable because it is able to generate and process customized random walks for different nodes in parallel. We have evaluated CARE on multi label classification and link prediction tasks. Experimental results on different networks show significant improvements compared to the state of the art methods on network embedding.

As a part of future works, we plan to create customized random walks while we compute communities of input network to speed up CARE. We would also like to extend the proposed method to heterogeneous networks with different types of nodes and relations. In real world networks, nodes might be in multiple communities and as another research direction, we would like to investigate the effect of overlapping community detection algorithms on real world social networks using CARE. We also plan to investigate the effect of community aware random walks on Node2vec and LINE algorithms.

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