Persona2vec: A Flexible Multi-role Representations Learning Framework for Graphs

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Abstract

Graph embedding techniques, which learn low-dimensional representations of a graph, are achieving state-of-the-art performance in many graph mining tasks. Most existing embedding algorithms assign a single vector to each node, implicitly assuming that a single representation is enough to capture all characteristics of the node. However, across many domains, it is common to observe pervasively overlapping community structure, where most nodes belong to multiple communities, playing different roles depending on the contexts. Here, we propose persona2vec, a graph embedding framework that efficiently learns multiple representations of nodes based on their structural contexts. Using link prediction-based evaluation, we show that our framework is significantly faster than the existing state-of-the-art model while achieving better performance.

1 Introduction

Graph embedding maps the nodes in a graph to continuous and dense vectors that capture relations among the nodes [1–3]. Resulting node representations allow direct applications of algebraic operations and common algorithms, facilitating graph mining tasks such as node classification [4–1].
Yet, with the scarcity of embedding methods embracing this idea, the full potential of this approach is not realized. We adopt and refine the ego-splitting method \[17, 18\]. For each node in the original graph, we first transform the original graph into a persona graph. Every edge in the original graph is preserved in the persona graph, while new directed persona edges with weight $\lambda_k$ for each local community are added between the persona nodes. (d) Graph embedding is applied to the persona graph. (e) The final persona embedding where each persona node has its own vector representation.

Figure 1: Illustration of persona2vec framework. (a) A graph with an overlapping community structure. (b) Graph embedding of the original graph is obtained first to initialize the persona embeddings. (c) Transform the original graph into a persona graph. Every edge in the original graph is preserved in the persona graph, while new directed persona edges with weight $\lambda_k$ for each local community are added between the persona nodes. (d) Graph embedding is applied to the persona graph. (e) The final persona embedding where each persona node has its own vector representation.

community detection \[5, 6\], link prediction \[2\] and visualization \[3\]. Most methods map each node to a single vector, implicitly assuming that a single representation is sufficient to capture the full characteristics of a node.

However, nodes often play multiple roles. For instance, people have multiple roles, or “personas”, across contexts (e.g., professor, employee, and so on) \[7–10\]. Similarly, proteins and other biological elements play multiple functionalities \[11–13\]. Another example is the polysemy of words when their relations are modeled with graphs: many words possess multiple meanings differentiated by the contexts \[14–15\]. Explicit modeling of such multiplicity and overlapping clusters has been fruitful not only for community detection \[16–18\], but also for improving the quality of embedding \[14–18\]. Yet, with the scarcity of embedding methods embracing this idea, the full potential of this approach has not been properly explored.

In this paper, we propose persona2vec, a scalable framework that builds on the idea of ego-splitting \[17\], the process of identifying local structural contexts of a node via performing local community detection on the node’s ego-network. For each detected local community (role), we transform each node into multiple personas if there are multiple local communities to which the node belongs. After the split, the original node is replaced by the new persona nodes that inherit the connection from each local community, producing a new persona graph. Instead of separating a node’s persona nodes from each other completely, we add directed, weighted edges between personas to capture their origin. In doing so, we allow the direct application of the existing graph embedding methods. In addition, we take an approach of considering persona-based learning as fine-tuning of the base graph embedding, achieving both efficiency and balance between information from the original graph and the persona graph. Compared with the previous approach \[17\], our framework is conceptually simpler to understand and practically easier to implement. Furthermore, it achieves state-of-the-art performance in the link prediction tasks while being much faster. Our implementation of persona2vec is publicly available at https://github.com/jisungyoon/persona2vec

2 Proposed method: persona2vec

persona2vec creates a persona graph, where some nodes are split into multiple personas. We then apply a graph embedding algorithm to the persona graph to learn the embeddings of the personas (see Fig. 1). Let us explain the method formally. Let $G = (V, E)$ be a graph with a set of nodes $V$ and a set of edges $E$. $|V|$ and $|E|$ denote the number of nodes and edges respectively. Let $f: v \rightarrow \mathbb{R}^d$ be the embedding function that maps a node $v$ to a $d$-dimensional vector space ($d \ll |V|$).

2.1 Refined Ego-splitting

We adopt and refine the ego-splitting method \[17, 18\]. For each node in the original graph, we first extract its ego graph, remove the ego, and identify the local clusters. Every cluster in the ego graph leads to a new persona node in the persona graph (see Fig. 1, c). For example, if we consider each connected component as a local community with a connected component algorithm, node $C$ in the
Any graph clustering algorithm can be employed for splitting a node into personas. The simplest algorithm is considering each connected component in the ego-network (sans the ego) as a cluster.

Algorithm 1: Refined ego-splitting for generating the persona graph. Case of the undirected graph

\begin{algorithm}
\begin{algorithmic}
1: function \textsc{RefEgoSplit}(G) 
2: \hspace{1em} for each \(v_o \in V\) do
3: \hspace{2em} \(P_{v_o} \leftarrow C(v_o)\) \hspace{1em} \(\triangleright\) find local clusters of \(v_o\)
4: \hspace{2em} for each \(p \in P_{v_o}\) do
5: \hspace{3em} Create \(v_p\) \hspace{1em} \(\triangleright\) create persona nodes for local clusters
6: \hspace{2em} Add \(v_p\) to \(G_P, V2P(v_o)\)
7: \hspace{2em} \(P2C(v_p) \leftarrow p\)
8: \hspace{2em} for each edge \((v_i, v_j)\) in \(E\) do
9: \hspace{3em} \(w \leftarrow \text{weight of edge}\)
10: \hspace{2em} \hspace{3em} for each persona node \(v_p\) in \(V2P(v_i)\) do
11: \hspace{4em} \hspace{3em} for each persona node \(v_p'\) in \(V2P(v_j)\) do
12: \hspace{5em} \hspace{3em} \hspace{3em} if \(v_i \in P2C(v_p')\) and \(v_j \in P2C(v_p')\) then
13: \hspace{6em} \hspace{3em} \hspace{3em} Add original edges \((v_p, v_p', w), (v_p', v_p, w)\) to \(E_P\)
14: \hspace{2em} \hspace{3em} \hspace{3em} \(k_o^{\circ} \leftarrow \text{out-degree sequence after adding original edges}\)
15: \hspace{2em} \hspace{3em} for each \(v_o \in V\) do
16: \hspace{3em} \hspace{4em} \hspace{3em} for each pair \((v_i, v_j)\) in \(V2P(v_o)\) do
17: \hspace{4em} \hspace{5em} \hspace{3em} Add persona edges \((v_i, v_j, k_o^{\circ} \times \lambda), (v_j, v_i, k_o^{\circ} \times \lambda)\) to \(E_P\)
18: return \(G_P(V_P, E_P), V2P\)
\end{algorithmic}
\end{algorithm}

original graph belongs to two non-overlapping clusters \(\{A, B\}\) and \(\{D, E, F\}\) in its ego-network. Given these two clusters, in the persona graph, \(C\) is split into \(C_1\) and \(C_2\) to represent the two roles in respective clusters. \(C_1\) and \(C_2\) inherit the connections of \(C\) from both clusters separately (see Fig. [1]). On the other hand, node \(A\) only belongs to one ego cluster \(\{B, C\}\), so it does not split into multiple personas.

Any graph clustering algorithm can be employed for splitting a node into personas. The simplest algorithm is considering each connected component in the ego-network (sans the ego) as a cluster. This approach is fast and works well on sparse graphs. However, in dense graphs, ego-networks are more likely to form fewer connected component, thus other algorithms such as the Louvain method [19], Infomap [20], and label propagation [21] would be more appropriate.

In previous studies, the personas get disconnected without retaining the information about their origin, creating isolated components in the splitting process [17, 18]. Because of this disconnectedness, common embedding methods could not be directly applied to the ego-split graph. A previous study attempted to address this issue by imposing a regularization term in the cost function to penalize separation of persona nodes originating from the same node [18].

Here, instead of adopting the regularization strategy, we add weighted persona edges between the personas, maintaining the connectedness between them after the splitting (see Fig. [1]). Because the persona graph stays connected, classical graph algorithms and graph embedding methods can now be readily applied without any modification. As we will show later, our strategy achieves both better scalability and better performance.

In persona graph, we set the weights of the unweighted original edges as 1 and tune the strength of the connections among personas with \(\lambda\). Persona edges are directed and weighted, with weight \(\lambda k_o^p\), where \(k_o^p\) is the out-degree of the persona node after splitting (see Fig. [1]). Assigning weight proportional to \(k_o^p\) helps the random walker explore both the local neighbors and other parts of the graph connected to the other personas regardless of its out-degree \(k_i^o\).

Imagine node \(u\), which is split into \(n_p\) personas. Consider one of the personas \(i\) with out-degree \(k_i^o\) and persona edges with weight \(w_i\). Then the probability \(p_i\) that an unbiased random walker at \(i\) visits neighbors connected with the original edge at the next step is \(\frac{k_i^o}{k_i^o + n_p w_i}\). If we set constant weight \(w_i = \lambda\), then \(p_i = \frac{k_i^o}{k_i^o + n_p \lambda} = \frac{1}{1 + \frac{n_p \lambda}{k_i^o}}\), which depends on \(k_i^o\). A random-walker would not explore its
As explained above, any graph embedding algorithm that recognizes edge direction and weight can be extended to the ego graph. Algorithm 2 presents an algorithm for ego-splitting. Note that it can be generalized to the directed graphs.

### Algorithm 2: ego-splitting

**Input:** Original graph $G(V,E)$; embedding dimension $d$; number of walks per node for base embedding $\gamma_b$; random walk length for base embedding $t_b$; window size for base embedding $w_b$; number of walks per node for persona embedding $\gamma_p$; random walk length for persona embedding $t_p$; window size for persona embedding $w_p$; learning rate $\alpha$; refined ego-splitting method REEGOSPLIT; node to personas mapping $V2P$; a graph embedding method (e.g. DeepWalk, Node2vec) EMBEDDINGFUNC

**Output:** $\Phi_{G_P}$, A $N_p \times d$ matrix with $d$-dimensional vector representations for all $N_p$ persona nodes.

```plaintext
1: function persona2vec(G, EMBEDDINGFUNC)
2:     $G_P$, V2P ← REEGOSPLIT(G)
3:     $\Phi_G$ ← EMBEDDINGFUNC($G, d, w_b, \gamma_b, t_b, \alpha$)
4:     for each $v_o \in V$ do
5:         for each persona node $v_p$ in $V2P(v_o)$ do
6:             $\Phi_{G_P}(v_p) = \Phi_G(v_o)$
7:     return $\Phi_{G_P}$
```

local neighborhood if $n_p \gg k_o^3$, while the opposite happens when $n_p \ll k^3$. Instead, assigning the weight proportional to $k^2_o$, namely $w_i = \lambda k^2_o$, removes such bias because $p_i = \frac{k^2_o}{k^2_o + n_p \lambda k^3_o} = \frac{1}{1 + n_p \lambda}$, which is independent of $k^3_o$. Our experiments also show that using the out-degree yields better performance than assigning the identical weight to each persona edge. Our algorithm for refined ego-splitting is described in Algorithm 1. Note that it can be generalized to the directed graphs.

### 2.2 Persona graph embedding

As explained above, any graph embedding algorithm that recognizes edge direction and weight can be readily applied to the persona graph. Although we use node2vec as the embedding method here, other embedding methods can also be employed. We initialize the persona vectors with the vectors from the original graph before ego-splitting (see Fig. 1b) to leverage the information from the original graph structure. Persona nodes that belong to the same node in the original graph are thus initialized with the same vector. We then execute the embedding algorithm for a small number of epochs to fine-tune the embedding vectors with the information from the persona graph (see Fig. 1a). Experiments show that usually only one epoch of training is enough. Our full algorithm is described in Algorithm 2.

### 2.3 Complexity

The persona graph is usually larger than the original graph, but not too large. Node $u$ with degree $k_u$ may be split into at most $k_u$ personas. In the worst case, the number of nodes in the persona graph can reach $O(|E|)$. But, in practice, only a subset of nodes split into personas, and the number of personas rarely reaches the upper bound. If we look at the persona edges, for a node $u$ with degree $k_u$, at most $O(k^3_u)$ new persona edges may be added. Thus, the whole persona graph has at most $O(|V| \times k^3_{\max})$ or $O(|V|^3)$ (: $k_{\max} \leq |V|$) extra persona edges. If graph’s degree distribution follows a power-law distribution $P(k) \sim k^{-\gamma}$, then $k_{\max} \sim |V|^{1/\gamma-1}$. Hence, it could be $O(|V|^\gamma+1/\gamma-1)$ and it is between $O(|V|^2)$ and $O(|V|^3)$ (: $2 \leq \gamma \leq 3$ in general). However, real graph tends to be sparse and $k_i \ll |V|$. If we further assume $k_i < |E|$ holds for every node, then $\sum_{n=1}^{\sqrt{|V|}} k^2_n \leq \sum_{n=1}^{\sqrt{|E|}} k_n \sqrt{|E|} = 2|E| \sqrt{|E|}$. Under this assumption, the upper bound becomes $O(|E|^3/2)$. Similarly, with the scale-free condition, the upper bound could be $O(|E||V|^{1/\gamma-1})$, which is between $O(|E|^2)$ and $O(|E||V|)$. Again, in practice, the number of persona edges is much smaller than this upper bound. To illustrate, we list the number of nodes and persona edges in the persona graph for the graphs we use in this paper in Table 1. All considered, the extra nodes and edges do not bring too much space complexity burden in practice.

Assessing the time complexity requires consideration of the two steps: ego-splitting and embedding. The ego-splitting algorithm has complexity of $O(|E|^{3/2} + \sqrt{|E|T(|E|)})$ in the worst case, where $|E|$ is the number of edges in the original graph and $T(|E|)$ is the complexity of detecting the ego clusters...
Table 1: **Descriptive statistics in the graphs used in the evaluation.** We report the number of nodes $|V|$, number of edges $|E|$, number of nodes in the persona graph $|V_p|$, the ratio of $|V_p|$ over $|V|$, number of persona edges $|E_p|$ added in ego-splitting, and the ratio of $|E_p|$ over $|E|^{3/2}$ which is the upper bound of space complexity.

| Dataset  | Type     | $|V|$  | $|E|$       | $|V_p|$ | $|V_p|/|V|$ | $|E_p|$ | $|E_p|/|E|^{3/2}$ |
|----------|----------|-------|-------------|--------|------------|--------|-----------------|
| PPI      | Undirected | 3,863 | 38,705      | 16,734 | 4.34       | 132,932| 0.0175          |
| ca-HepTh | Undirected | 9,877 | 25,998      | 16,071 | 1.86       | 33,524 | 0.0800          |
| ca-AstroPh | Undirected | 17,903| 197,301     | 25,706 | 1.44       | 29,012 | 0.0003          |
| wiki-vote| Directed  | 7,066 | 103,633     | 21,476 | 3.04       | 118,020| 0.0035          |
| soc-epinions | Directed | 75,877| 508,836     | 220,332| 2.90       | 3,550,594| 0.0098 |

The final complexity is $O(|E|^{3/2} + \sqrt{|E|T(|E|)} + O(|V|\gamma t w d(1 + log(|V|)))$. Removing the constant factors and assuming close-to-linear local community detection algorithm, the whole process has time complexity of $O(|E|^{3/2})$ with space complexity of $O(|E|^{3/2})$ if $k_t < \sqrt{|E|}$ holds. Complexity can be increased depending on the clustering algorithms on the ego-network.

To test the validity of our assumptions, we sample 1,000 graphs from a public network repository [23]. We apply the refined ego-splitting with connected component algorithms on these samples and report the actual number of persona edges $|E_p|$ with respect to the practical upper bound $|E|^{3/2}$ in Fig. [2] which shown that the actual number of persona edges $|E_p|$ rarely exceeds the tighter upper bound that we proposed and is usually orders of the magnitude smaller.

### 3 Case Study

Before diving into systematic evaluations, we provide two illustrative examples: Zachary’s Karate club network and a word association network.

**Case Study: Zachary’s Karate club network** We use the Zachary’s Karate club network [24], a well-known example for the community detection. Nodes represent members of the Karate club, and
edges represent ties among the members (see Fig. 3a). Although it is often considered to have two large disjoint communities, smaller overlapping communities can also be seen, highlighted by nodes such as 1, 3, 28, and 32. In Fig. 3b, we present the persona graph of the network. \texttt{persona2vec} successfully recognizes these bridge nodes and place their personas in reasonable places. Take node 1 for example. It splits into four persona nodes, which then end up in two different communities. The orange and green communities are clearly separated as a result.

**Case Study: word association network** Word association network captures how people associate words together (free association task). The dataset was originally assembled from nearly 750,000 responses [28]. In Fig. 3c, we shows the \texttt{persona2vec} clusters around the word “Newton”. We use the Louvain method [19] to split the personas of each word. \texttt{persona2vec} successfully captures multiple contexts of the word “Newton”. For instance, the red persona is associated with “scientists” and “philosopher”, grey one is linked to the physics, and yellow one is associated with “apple” (note that there is a cookie called “(Fig) Newton” in the U.S.). Furthermore, \texttt{persona2vec} also captures different nuances of the word “law” that are related to the crime (brown cluster) and the legal concepts (orange cluster).

4 Numerical Experiment

4.1 Link Prediction Task

To systematically evaluate the performance and scalability of the \texttt{persona2vec} framework, we perform a link prediction task using real-world graphs [2, 29]. Link prediction aims to predict missing edges in a graph with partial information, which is useful for many tasks such as suggesting new friends on social networks or recommending products. It has been employed as a primary task to evaluate the performance of unsupervised graph embedding methods [29, 30].

We follow the task setup from the literature [2, 29]. First, the edge set of an input graph is divided equally and randomly into $E_{\text{train}}$ and $E_{\text{test}}$. We then refine $E_{\text{test}}$ using a rejection sampling based on the criterion that, even when we remove all edges in $E_{\text{test}}$, the graph should be connected as a single component. $E_{\text{train}}$ is used to train the models, and $E_{\text{test}}$ is used as positive examples for the prediction task. Second, a negative edge set $E_{\text{test}}^{-}$ of non-existent random edges with the same size of $E_{\text{test}}$ are generated as negative examples for testing. The performance of a model is measured by its ability to correctly distinguish $E_{\text{test}}$ and $E_{\text{test}}^{-}$ after being trained on $E_{\text{train}}$. We then report ROC-AUC.

4.2 Datasets

To facilitate the comparison with the state-of-the-art baseline, we use five graph datasets that are publicly available and previously used [18]. We summarize them as follows.

- **PPI** is a protein-protein interaction graph of \textit{Homo sapiens} [31]. Nodes represent proteins and edges represent physical interactions between the proteins. \textit{ca-HepTh} is a scientific collaboration graph. It represents the co-authorship among researchers from the Theoretical High Energy Physics field, derived from papers on arXiv. \textit{ca-AstropPh} is also scientific collaboration graph, but from Astrophysics. \textit{wiki-vote} is a voting network, each node is a Wikipedia user and a directed edge from node $i$ to node $j$ represents that user $i$ voted for user $j$ to become an administrator. \textit{soc-opinions} is a voting graph from a general consumer review site Epinions.com, each node is a member, and a directed edge from node $i$ to node $j$ means that member $i$ trusted member $j$.

For **PPI**, we use the prepossessed version from the node2vec project web page [2], while other graphs are downloaded from the SNAP library homepage [32]. We use the largest component of the undirected graphs and the largest weakly connected component of the directed ones. The statistics of all the graphs are reported in Table 1.

4.3 Methods

The state-of-the-art method in this link prediction task is \texttt{SPLITTER} [18], which also models multiple roles. As reported in the paper, it outperforms various exiting algorithms ranging across non-embedding methods like Jaccard Coefficient, Common Neighbors, and Adamic-Adar as well
Figure 4: **Performance of persona2vec in the link prediction task** The confidence intervals are all within the range of the markers. Given the same number of dimensions, persona2vec is always on par or better than SPLITTER as embedding methods like Laplacian EigenMaps [33], node2vec [2], DNGR [34], Asymmetric [29] and M-NMF [35].

Given the state-of-the-art performance of SPLITTER, for simplicity, we compare our framework with SPLITTER using the identical task setup and datasets. In addition, because our method can be considered as an augmentation of a single-role embedding method, and because we use Node2vec as the base embedding method, we also employ Node2vec. We run the link prediction task using the original authors’ implementation of Node2vec and SPLITTER. The parameters are also kept consistent with the original paper.

persona2vec and SPLITTER have multiple representations on each node, which leads to non-unique similarity estimations between two nodes. Hence, we define the similarity score of a pair of nodes on persona2vec as the maximum dot-product of embedding vectors between any pair of their personas. We found that, among experiment with three aggregation functions min, max, mean, the highest performance is achieved with max, same with SPLITTER [18]. For SPLITTER, we use maximum cosine similarity, following the author’s note in their implementation.

Node2vec (baseline method) For Node2vec, we set random walk length $t = 40$, the number of walks per node $\gamma = 10$, random walk parameters $p = q = 1$, the window size $w = 5$, and the initial learning rate $\alpha = 0.025$. In the original paper, they learn an additional logistic regression classifier over the Hadamard product of the embedding of two nodes for the link prediction. In general, the logistic regression classifier improves the performance. Here, we report results on Node2vec with both dot products and the logistic regression classifier.

SPLITTER (baseline method) For SPLITTER, we use the same parameters in their paper [18] and Node2vec baseline. We use node2vec with random walk parameters $p = q = 1$.

persona2vec (our proposed method) We set the hyper-parameters of the original graph embedding with $t_b = 40$, $\gamma_b = 10$, $w_b = 5$. For the persona embedding, we set $t_p = 80$, $\gamma_p = 5$, $w_p = 2$ to better capture the micro-structure of the persona graph. The size of the total trajectories is determined by random walk length $t_a$ times number of walks per node $\gamma_a$, and we keep $t_a\gamma_a$ constant to roughly preserve the amount of information used in the embedding. For both embedding stages, we use the $\alpha = 0.025$, and node2vec with the random walk parameters ($p = q = 1$) as the graph embedding function.

### 4.4 Experiment Results

Fig. 4 shows the link prediction performance of persona2vec in comparison with the baselines. Overall, persona2vec yields superior performance across graphs and across a range of hyperparameter choice. We show that augmenting Node2vec by considering personas significantly improves the link prediction performance, evinced by the significant performance gain (see Table 2).

As expected, larger dimensions lead to better performance, although persona2vec achieves reasonable results even with tiny embedding dimensions like 8 or 16. We also show how the performance of persona2vec varies with $\lambda$. For undirected graphs, larger $\lambda$ is beneficial but the trend saturates quickly. For directed graphs, however, optimal performance is achieved with smaller values of $\lambda$. In practice, we suggest starting with $\lambda = 0.5$ as a default parameter because the overall variation brought
Table 2: Performance of persona2vec with $\lambda = 0.5$. All methods use $d = 128$. Node2vec* refers to Node2vec with the logistic regression classifier, SPLITTER* refers to SPLITTER with one epoch, and persona2vec* refers to persona2vec with $\lambda = 0.5$, our suggested default. Performance gain is performance difference between Node2vec and persona2vec*. We omit the standard error which is smaller than $10^{-3}$.

| Method       | PPI  | ca-HepTh | ca-AstroPh | wiki-vote | soc-epinions |
|--------------|------|----------|------------|-----------|--------------|
| Node2vec     | 0.585| 0.825    | 0.901      | 0.694     | 0.547 ± 0.007|
| Node2vec*    | 0.662±0.001| 0.848    | 0.914      | 0.705 ± 0.001| 0.767 ± 0.002|
| SPLITTER     | 0.856| 0.903    | 0.982      | 0.931     | 0.961 ± 0.001|
| SPLITTER*    | 0.853| 0.898    | 0.984      | 0.931     | 0.954 ± 0.001|
| persona2vec* | 0.879| 0.897    | 0.985      | 0.936     | 0.936         |

Performance gain

|       | 0.294| 0.102 | 0.084      | 0.242     | 0.414±0.007  |

by $\lambda$ is not substantial and even when the performance increases with $\lambda$, near-optimal performance can be achieved at $\lambda = 0.5$. When compared with the SPLITTER baseline, persona2vec shows on par or better performances given the same embedding dimensions across a wide range of $\lambda$. We also report the performance summary for persona2vec with $\lambda = 0.5$ (our suggested default) compared with the best baselines in Table 2, which show that persona2vec outperforms the baseline consistently.

In addition to the performance of the link prediction task, we also report the execution time of persona2vec and SPLITTER to compare their scalabilities in practice (see Fig. 5). Note that the reported execution time is on the link-prediction task, with half of the edges removed from the original graph. SPLITTER runs the embedding procedures for 10 epochs by default in the original implementation, whereas persona2vec only runs for one epoch. For a fair comparison, we also report the results of SPLITTER with one epoch of training. When being limited to only one epoch, SPLITTER’s performance slightly suffers on three graphs while it goes up or stays stable for the other two.

Nevertheless, persona2vec is more efficient—39 to 58 times faster than SPLITTER with 10 epochs and five to eight times faster than SPLITTER with one epoch, while consistently outperforming both. The main reason behind the drastic difference is the overhead from the extra regularization term in the cost function of SPLITTER, which persona2vec gets rid of. In sum, persona2vec outperforms the previous state-of-the-art method both in terms of scalability and link prediction performance.

5 Related Work

In addition to graph embedding, our work is closely related to the research of identifying overlapping communities in graphs. Various non-embedding methods such as link clustering [7, 36], clique percolation [11], and mixed membership stochastic blockmodel [37] have been proposed. Another thread of works focuses on using local graph structure to extract community information [8, 38, 17]. Specifically, Epasto et al. introduce the persona graph method for detecting overlapping communities in graphs [17], leveraging ego-network partition. The combination of ego-network analysis and graph embedding methods is still rare. An example is SPLITTER [18], which we use as the baseline in this paper. Instead of constraining the relations between personas with a regularization term, we propose a simpler and more efficient way of adding persona edges to the graph.

Our work is also related to the word disambiguation problem in word embedding. Recently, word embedding techniques [39–41] have been extensively applied to various NLP tasks as the vectorized word representations can effectively capture syntactic and semantic information. Although some
words have multiple senses depending on the context, the original word embedding methods only assign one vector to each word. Li et al. shows that embedding that is aware of multiple word senses and provides vectors for each specific sense does improve the performance for some NLP tasks [14]. For this issue, some utilize the local context information and clustering for identifying word sense [42–44], some resort to external lexical database for disambiguation [45–47, 13, 48], while some combine topic modeling methods with embedding [49–52]. We adopt the idea of assigning multiple vectors to each node in the graph to represent different roles as well as exploiting local graph structure for the purpose.

6 Conclusions

We present persona2vec, a framework for learning multiple node representations based on the node’s local structural contexts. persona2vec first performs ego-splitting, where nodes with multiple non-overlapping local communities in their ego-networks are replaced with corresponding persona nodes. The persona nodes inherit the edges from the original graph and remain connected by newly added persona edges, forming the persona graph. Initialized by the embedding of the original graph, the embedding algorithm applied to the persona graph yields the final representations. Instead of assigning only one vector to every node with multiple roles, persona2vec learns vectors for each of the personas.

With extensive link prediction evaluations, we demonstrate that persona2vec achieves the state-of-the-art performance while being able to scale better. Moreover, our method is easy to comprehend and implement without losing any flexibility for incorporating other embedding algorithms, presenting great potential for applications. The possible combination with various algorithms provides vast space for further exploration.

Broader Impact

The graph (relational) structure is ubiquitous across many complex systems, including physical, social, economic, biological, neural, and information systems, and thus fundamental graph algorithms have far-reaching impacts across many areas of sciences. Graph embedding, in particular, removes the barrier of translating methods to the special graph data structure, opening up a powerful way to transfer existing algorithms to the graphs and relational data. Therefore, graph embedding methods are being actively adopted in many fields and may continue to have strong broader impacts across all areas of sciences that deal with graph structure. Furthermore, given that it is natural to assume overlapping clusters in most real networks, multi-role embedding methods may find numerous applications in physical, biological, and social sciences.

At the same time, the advancement of graph algorithms can adversely impact our society because more and more data about our everyday life is getting captured by smart devices and our online activities, and in turn harnessed by companies and governments. The ability to predict relationships between entities, people, and traits, as well as human behaviors, has been called out as a threat to personal privacy and even our social systems, sometimes referred to as “surveillance capitalism”. Therefore, we believe that it is also crucial to study the risk brought by strong prediction algorithms on social graphs and ways to protect privacy while providing utility.

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