AAANE: Attention-Based Adversarial Autoencoder for Multi-scale Network Embedding

Lei Sang[1,2], Min Xu[2(✉)], Shengsheng Qian[3], and Xindong Wu[1]

[1] School of Computer Science and Information Technology, Hefei University of Technology, Hefei, China
lei.sang@student.uts.edu.au, xwu@hfut.edu.cn

[2] Faculty of Engineering and IT, University of Technology Sydney, Ultimo, Australia
Min.Xu@uts.edu.au

[3] Institute of Automation, Chinese Academy of Sciences, Beijing, China
shengsheng.qian@nlpr.ia.ac.cn

Abstract. Network embedding represents nodes in a continuous vector space and preserves structure information from a network. Existing methods usually adopt a "one-size-fits-all" approach when concerning multi-scale structure information, such as first- and second-order proximity of nodes, ignoring the fact that different scales play different roles in embedding learning. In this paper, we propose an Attention-based Adversarial Autoencoder Network Embedding (AAANE) framework, which promotes the collaboration of different scales and lets them vote for robust representations. The proposed AAANE consists of two components: (1) an attention-based autoencoder that effectively capture the highly non-linear network structure, which can de-emphasize irrelevant scales during training, and (2) an adversarial regularization guides the autoencoder in learning robust representations by matching the posterior distribution of the latent embeddings to a given prior distribution. Experimental results on real-world networks show that the proposed approach outperforms strong baselines.

Keywords: Network embedding · Multi-scale · Attention · Adversarial autoencoder

1 Introduction

Network embedding (NE) methods have shown outstanding performance on many tasks including node classification [1], community detection [2,3] and link prediction [4]. These methods aim to learn latent, low-dimensional representations for network nodes while preserving network topology structure information. Networks' structures are inherently hierarchical [5]. As shown in Fig. 1, each individual is a member of several communities and can be modeled by his/her neighborhoods' structure information with different scales around him/her, which

Q. Yang et al. (Eds.): PAKDD 2019, LNAI 11441, pp. 3–14, 2019.
https://doi.org/10.1007/978-3-030-16142-2_1

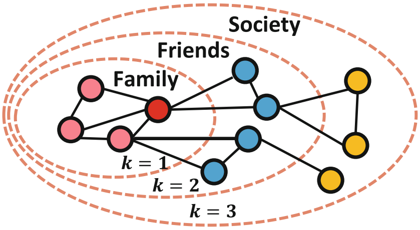


Fig. 1. Illustration of the multi-scale network with three scales.

range from short scales structure (e.g. families, friends), to long-distance scales structure (e.g. society, nation states). Every single scale is usually sparse and biased, and thus the node embedding learned by existing approaches may not be so robust. To obtain a comprehensive representation of a network node, multi-scale structure information should be considered collaboratively.

Recently, a number of methods have been proposed for learning data representations from multiple scales. For example, DeepWalk [1] models multi-scale indirectly from a random walk. Line [6] proposes primarily a breadth-first strategy, sampling nodes and optimizing the likelihood independently over short scales structure information such as 1-order and 2-order neighbors. GraRep [7] generalizes LINE to incorporate information from network neighborhoods beyond 2-order, which can embed long distance scales structure information to the node representation. More recently, some autoencoder based methods, For example, DNGR [8] learns the node embedding through stacked denoising autoencoder from the multi-scale PPMI matrix. Similarly, SDNE [9] is realized by a semi-supervised deep autoencoder model. Besides, MVE [10] aims to learn embedding from several multi-viewed networks with the same nodes but different edges, which is different from our single network setting.

Despite their strong task performance, existing methods have the following limitations: (1) *Lack of weight learning.* To learn robust and stable node embeddings, the information from multiple scales needs to be integrated. During integration, as the importance of different scales can be quite different, their weights need to be carefully decided. For example, if we consider very young kids on a social network, and they may be very tightly tied to their family and loosely tied to the society members. However, for university students, they may have relatively more ties to their friends and the society than very young kids. Existing approaches usually assign equal weights to all scales. In other words, different scales are equally treated, which is not reasonable for most multi-scale networks. (2) *Insufficient constrain for embedding distribution.* Take the autoencoder based method for example, an autoencoder is a neural network trained to attempt to copy its input to its output, which has a typical pipeline like ($x \rightarrow E \rightarrow z \rightarrow D \rightarrow x'$). Autoencoder only requires x to approach $x' = D(E(x))$, and for that purpose the decoder may simply learn to reconstruct x regardless of the distribution obtained from E. This means that $p(z)$ can be very irregular, which sometimes makes the generation of new samples difficult or even infeasible.

In this paper, we focus on the multi-scale network embedding problem and propose a novel Attention-based Adversarial Autoencoder Network Embedding (AAANE) method to jointly capture the weighted scale structure information and learn robust representation with adversarial regularization. We first introduce a set of scale-specific node vectors to preserve the proximities of nodes in different scales. The scales-specific node embeddings are then combined for voting the robust node representations. Specifically, our work has two major contributions. (1) To deal with the weights learning, we propose an attention-based autoencoder to infer the weights of scales for different nodes, and then capture the highly non-linear network structure, which is inspired by the recent progress of the attention mechanism for neural machine translation [11]. (2) To implement regularisation of the distribution for encoded data, we introduce adversarial training component [12] to the attention-based autoencoder, which can discriminatively predict whether a sample arises from the low-dimensional representations of the network or from a sampled distribution. Adversarial regularisation reduces the amount of information that may be held in the encoding, forcing the model to learn an efficient representation of the data. Through the attention-based weight learning together with the adversarial regularization, the proposed AAANE model can effectively combine the virtues of multiple scale information to complement and enhance each other.

2 Preliminaries

Network Embedding(NE): An information network is represented as $G = (V, E)$, where $V = \{v_i\}_{i=1,\cdots,N}$ consist a set of nodes, $e_{i,j} = (v_i, v_j) \in E$ is an edge indicating the relationship between two nodes. The task of NE aims to build a low-dimensional representation $x_i \in \mathbb{R}^d$ for each node $i \in V$, where d is the dimension of embedding space and expected much smaller than node number $|V|$.

We define *adjacency matrix* $\widetilde{A} \in \mathbb{R}^{|V|\times|V|}$ for a network and D is a diagonal degree matrix. To capture the transitions from one node to another, we can define the (first-order) probability transition matrix $A = D^{-1}\widetilde{A}$, where $A_{i,j}$ is the probability of a transition from node v_i to node v_j within one step. It can be observed that the matrix A is a normalized adjacency matrix where the summation of each row equals to 1.

In this paper, multi-scale structural information serves two functions: (1) the capture of long-distance relationship between two different vertices and (2) the consideration of distinct connections in terms of different transitional orders.

The (normalized) adjacency matrix A characterizes the first-order proximity which models the local pairwise proximity between vertices. As discussed earlier, we believe that the k-order (with varying k) long scale relational information from the network needs to be captured when constructing such multi-scale network embedding [7]. To compute the various scale transition probabilities, we introduce the following k-order probability proximity matrix:

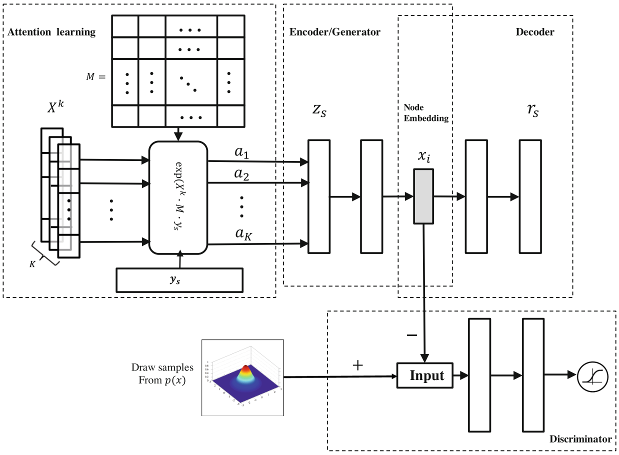


Fig. 2. The architecture of AAANE. The top row is an attention-based autoencoder that infers the weights of scales for different nodes, and then captures the highly non-linear network structure. The bottom row diagrams a discriminator trained to discriminatively predict whether a sample arises from the hidden code of the autoencoder or from a prior distribution specified by the user.

$$A^k = \underbrace{A \cdot A \cdots A}_{k} \tag{1}$$

where the entry $A^k_{i,j}$ refers to the k-order proximity between node v_i and v_j.

Multi-scale Network Embedding: Given a network $G = (V, E)$, the robust node representation $\{x_i\}_{v_i \in V} \subseteq R^d$ can be collaboratively learned from k successively network structural information representation, $A, A^2, \ldots, A^k$, where A^k captures the view of the network at scale k. Intuitively, each member of the family encodes a different view of social similarity, corresponding to shared membership in latent communities at different scales.

3 The Framework

In this section, we first give a brief overview of the proposed AAANE, and then formulate our method of multi-scale network embedding from attention based adversarial autoencoder.

3.1 An Overview of the Framework

In this work, we leverage attention-based adversarial autoencoder to help learn stable and robust node embedding. Figure 2 shows the proposed framework of Attention-based Adversarial Autoencoder for Network Embedding (**AAANE**), which mainly consists of two components, i.e., an attention-based autoencoder and an adversarial learning component.

We introduce an attention mechanism to the autoencoder for learning the weights of structure information with different scales. A standard autoencoder consists of an encoder network and a decoder network. The encoder maps the network structure information z_s into a latent code x_i, and the decoder reconstructs the input data as r_s. Then, the adversarial learning component acts as regularization for the autoencoder, by matching the aggregated posterior, which helps enhance the robustness of the representation x_i. The generator of the adversarial network is also the encoder of the autoencoder. The adversarial network and the autoencoder are trained jointly in two phases: the reconstruction phase and the regularization phase. In the reconstruction phase, the autoencoder updates the encoder and the decoder to minimize the reconstruction error of the inputs. In the regularization phase, the adversarial network first updates its discriminative network to tell apart the true samples (generated using the prior) from the generated samples (the hidden node embedding x_i computed by the autoencoder). As a result, the proposed AAANE can jointly capture the weighted scale structure information and learn robust representations.

3.2 Attention-Based Autoencoder

The Attention-based Autoencoder for network embedding (**AANE**) model uses a stacked neural network to preserve the structure information. As we discussed in Sect. 2, different k-order proximity matrices preserve network structure information in different scales. Scale vector X^k is column in each A^k, for $k = 1, 2 \dots K$, which denotes the k-th scale structure information for the node. The length of each scale vector X^k is the same as the node size. The autoencoder component tries to capture the full range of structure information. We construct a vector representation z_s for each node as the input of the autoencoder in the first step. In general, we expect this vector representation to capture the most relevant information with regards to different scales of a node. z_s is defined as the weighted summation of every scale vector $X^k, k = 1, 2, \dots K$, corresponding to the scale index for each node.

$$z_s = \sum_{k=1}^{K} a_k X^k \tag{2}$$

For each scale vector X^k of one node, we compute a positive weight a_k which can be interpreted as the probability that X_k is assigned by one node. Intuitively, by learning proper weights a_k for each node, our approach can obtain most informative scale information. Following the recent attention based models for neural machine translation, we define the weight of scales k for a node using a softmax unit as follows:

$$\begin{aligned} a_k &= \frac{\exp(d_k)}{\sum_{j=1}^{n} \exp(d_k)} \\ d_k &= {X^k}^\top \cdot M \cdot y_s \qquad y_s = \frac{1}{K} \sum_{k=1}^{K} X^k \end{aligned} \tag{3}$$

where y_s is the average of different scale vector, which can capture the global context of the structure information. M is a matrix mapping between the global context embedding y_s and each structure scale vector X^k, which is learned as part of the training process. By introducing an attentive matrix M, we compute the relevance of each scale vector to the node. If X^k and y_s have a large dot product, this node believes that scale k is an informative scale, i.e., the weight of scale k for this node will be largely based on the definition.

Once we obtain the weighted node vector representation $z_s \in \mathbb{R}^{|V|}$, a stacked autoencoder is used to learn a low-dimensional node embedding. An autoencoder performs two actions, an encoding step, followed by a decoding step. In the encoding step, a function $f()$ is applied to the original vector representation z_s in the input space and send it to a new feature space. An activation function is typically involved in this process to model the non-linearities between the two vector spaces. At the decoding step, a reconstruction function $g()$is used to reconstruct the original input vectors back from the latent representation space. The r_s is the reconstructed vector representation. After training, the bottleneck layer representations x_i can be viewed as the low dimension embedding for the input node v_i.

This attention-based autoencoder is trained to minimize the reconstruction error. We adopt the contrastive max-margin objective function, similar to previous work [13–15]. For each input node, we randomly sample m nodes from our training data as negative samples. We represent each negative sample as n_s, which is computed by averaging its scale vectors as y_s. Our objective is to make the reconstructed embedding r_s similar to the target node embedding z_s while different from those negative samples n_s. Therefore, the unregularized objective J is formulated as a hinge loss that maximizes the inner product between r_s and z_s, and minimizes the inner product between r_s and the negative samples simultaneously:

$$J(\theta) = \sum_{s \in D} \sum_{i=1}^{m} max(0, 1 - r_s z_s + r_s n_i) \tag{4}$$

where D represents the training dataset.

3.3 Adversarial Learning

We hope to learn vector representations of the most representative scale for each node. An autoencoder consists of two models, an encoder and a decoder, each of which has its own set of learnable parameters. The encoder is used to get a latent code x_i from the input with the constraint. The dimension of the latent code should be less than the input dimension. The decoder takes in this latent code and tries to reconstruct the original input. However, we argue that training an autoencoder with contrastive max-margin objective function gives us latent codes with similar nodes being far from each other in the Euclidean space, especially when processing noisy network data. The main reason is the insufficient constrain for embedding distribution. Adversarial autoencoder (AAE) addresses these issues by imposing an Adversarial regularization to the bottleneck layer representation of autoencoder, and then the distribution of latent code may be shaped to match a desired prior distribution. Adversarial regularisation can reduce the amount of information that may be held in the encoding process, forcing the model to learn an efficient representation for the network data.

AAE typically consists of a generator $G()$ and a discriminator $D()$. Our main goal is to force output of the encoder to follow a given prior distribution $p(x)$(this can be normal, gamma .. distributions). We use the encoder as our generator, and the discriminator to tell if the samples are from a prior distribution or from the output of the encoder x_i. D and G play the following two-player minimax game with the value function V (G, D):

$$\min_G \max_D V(D, G) = \mathbb{E}_{p(x)}[\log D(x_i)] + \mathbb{E}_{q(x)}[\log(1 - D(x_i))] \tag{5}$$

where $q(x)$ is the distributions of encoded data samples.

3.4 Training Procedure

The whole training process is done in three sequential steps: (1) The encoder and decoder are trained simultaneously to minimize the reconstruction loss of the decoder as Eq. 4. (2) The discriminator D is then trained to correctly distinguish the true input signals x from the false signals x_i, where the x is generated from target distribution, and x_i is generated by the encoder by minimizing the loss function 5. (3) The next step will be to force the encoder to fool the discriminator by minimizing another loss function: $L = -\log(D(x_i))$. More specifically, we connect the encoder output as the input to the discriminator. Then, we fix the discriminator weights and fix the target to 1 at the discriminator output. Later, we pass in a node to the encoder and find the discriminator output which is then used to find the loss.

4 Experiments

In this section, we conduct node classification on sparsely labeled networks to evaluate the performance of our proposed model.

4.1 Datasets

We employ the following three widely used datasets for node classification.

Cora. Cora is a research paper set constructed, which contains 2, 708 machine learning papers which are categorized into seven classes. The citation relationships among them are crawled form a popular social network.

Citeseer. Citeseer is another research paper set constructed, which contains 3, 312 publications and 4, 732 links among them. These papers are from 6 classes.

Wiki. Wiki contains 2, 405 web pages from 19 categories and 17, 981 links among them. Wiki is much denser than Cora and Citeseer.

4.2 Baselines and Experimental Settings

We consider a number of baselines to demonstrate the effectiveness and robustness of the proposed AAANE algorithm. For all methods and datasets, we set the embedding dimension $d = 128$.

DeepWalk [1]**:** DeepWalk first transforms the network into node sequences by truncated random walk, and then uses it as input to the Skip-gram model to learn representations.

LINE [6]**:** LINE can preserve both first-order and second-order proximities for the undirected network through modeling node co-occurrence probability and node conditional probability.

GraRep [7]**:** GraRep preserves node proximities by constructing different k-order transition matrices.

node2vec [16]**:** node2vec develops a biased random walk procedure to explore the neighborhood of a node, which can strike a balance between local properties and global properties of a network.

AIDW [17]**:** Adversarial Inductive DeepWalk (AIDW) is an Adversarial Network Embedding (ANE) framework, which leverages random walk to sample node sequences as the structure-preserving component.

Parameter Setting: In our experimental settings, we vary the percentage of labeled nodes from 10% to 90% by an increment of 10% for each dataset. We treat network embeddings as vertex features and feed them into a one-vs-rest logistic regression classifier implemented by LibLinear [18]. For DeepWalk, LINE, GraRep, node2vec, we directly use the implementations provided by OpenNE[1]. For our methods AAANE, the maximum matrix transition scale is set to 8, and the number of negative samples per input sample m is set to 7. For attention-based autoencoder, it has three hidden layers, with the layer structure as $512-128-512$. For the discriminator of AAANE, it is a three-layer neural network, with the layer structure as $512-512-1$. And the prior distributions are Gaussian Distribution following the original paper [19].

4.3 Multi-label Classification

Tables 1, 2 and 3 show classification accuracies with different training ratios on different datasets, where the best results are **bold-faced**. In these tables, AANE denotes our model AAANE without Adversarial component. From these tables, we have the following observations:

(1) The proposed framework, without leveraging the adversarial regularization version AANE, achieving average 2% gains over AIDW on cora and wiki when varying the training ratio from 10% to 90% in most cases, and slightly better result on Citeseer, which suggests that assigning different weights to different scales of a node may be beneficial.

[1] https://github.com/thunlp/OpenNE.

Table 1. Accuracy (%) of node classification on Wiki.

% Labeled nodes	10%	20%	30%	40%	50%	60%	70%	80%	90%
DeepWalk	57.2	62.98	64.03	65.78	66.74	68.69	68.36	67.85	67.22
LINE	57.09	59.98	62.47	64.38	66.5	65.8	67.31	67.15	65.15
GraRep	59.55	60.76	62.23	62.3	62.76	63.72	63.02	62.79	60.17
node2vec	58.47	61.38	63.9	63.96	66.08	66.74	67.73	67.57	66.8
AIDW	57.29	61.89	63.77	64.26	66.85	67.23	69.04	70.13	71.33
AANE	59.95	64.14	66.15	68.40	68.66	69.34	69.25	70.89	69.71
AAANE	**60.36**	**64.98**	**67.21**	**68.79**	**69.07**	**70.32**	**70.85**	**72.03**	**72.45**

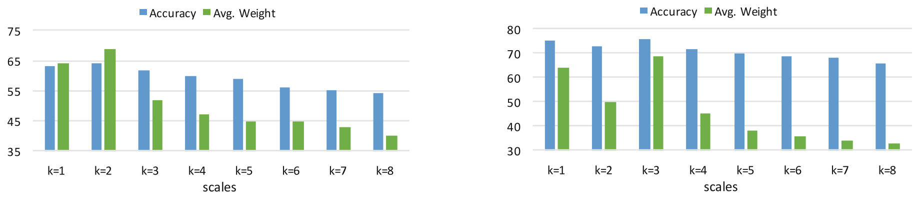
Table 2. Accuracy (%) of node classification on Cora.

% Labeled nodes	10%	20%	30%	40%	50%	60%	70%	80%	90%
DeepWalk	76.37	79.6	80.85	81.42	82.35	82.1	82.9	84.32	83.39
LINE	71.08	76.19	77.32	78.4	79.25	79.06	79.95	81.92	82.29
GraRep	77.02	77.95	78.53	79.75	79.61	78.78	78.6	78.23	78.23
node2vec	75.84	78.77	79.54	80.86	80.43	80.9	80.44	79.7	77.86
AIDW	76.21	78.93	80.21	81.45	82.03	82.74	82.81	83.69	83.92
AANE	77.65	81.50	82.49	84.43	84.71	84.69	84.75	85.98	86.03
AAANE	**78.23**	**82.14**	**82.76**	**85.31**	**85.69**	**86.12**	**86.02**	**86.74**	**87.21**

Table 3. Accuracy (%) of node classification on Citeser.

% Labeled nodes	10%	20%	30%	40%	50%	60%	70%	80%	90%
DeepWalk	53.47	54.19	54.6	57.55	57	59.02	58.95	58.22	55.72
LINE	48.74	50.87	52.82	52.72	52	52.3	53.12	53.54	52.41
GraRep	53.23	54.34	53.77	54.43	54.05	54.57	54.83	55.35	55.12
node2vec	53.94	54.08	56.23	57.34	57.55	60.3	61.17	61.24	59.33
AIDW	52.17	56.23	56.87	58.26	58.45	59.27	59.34	60.38	61.3
AANE	55.02	56.15	58.65	58.76	58.52	59.93	60.97	61.39	61.23
AAANE	**55.45**	**56.73**	**59.37**	**59.81**	**60.12**	**60.58**	**61.43**	**61.72**	**62.38**

(2) After introducing Adversarial component into AANE, our Method AAANE can achieve further improvements over all baselines. It demonstrates that adversarial learning regularization can improve the robustness and discrimination of the learned representations.
(3) AAANE consistently outperforms all the other baselines on all three datasets with different training ratios. It demonstrates that attention-based weight learning together with the adversarial regularization can significantly improve the robustness and discrimination of the learned embeddings.



(a) wiki. (b) cora.

Fig. 3. Comparison of performances on each individual scale and the average weights of scales. Scales with better performances usually attract more attentions from nodes.

(a) #Dimension. (b) #Scales.

Fig. 4. Parameter sensitivity of dimension d and scale size k.

4.4 Detailed Analysis of the Proposed Model

Analysis of the Learned Attentions over Scales: In our proposed AAANE model, we adopt an attention based approach to learn the weights of scales during voting, so that different nodes can focus most of their attentions on the most informative scales. The quantitative results have shown that AAANE achieves better results by learning attention over scales. In this part, we will examine the learned attention to understand why it can help improve the performances (Fig. 3).

We study which scale turn to attract more attentions from nodes. We take the Cora and Wiki datasets as examples. For each scale, we report the results of the scale-specific embedding corresponded to this scale, which achieves by taking only one scale vector A^k as an input of autoencoder. Then, we compare this scale-specific embedding with the average attention values learned by AAANE. The results are presented in Fig. 4. Overall, the performances of single scale and the average attention received by these scales are positively correlated. In other words, our approach can allow different nodes to focus on the scales with the best performances, which is quite reasonable.

Parameter Sensitivity: We discuss the parameter sensitivity in this section. Specifically, we assess how the different choices of the maximal scale size K, dimension d can affect node classification with the training ratio as 50%. Figure 4(a) shows the accuracy of AAANE over different settings of the dimension d. The accuracy shows an apparent increase at first. This is intuitive as more bits can encode more useful information in the increasing bits. However, when the number of dimensions continuously increases, the performance starts to drop slowly. The reason is that too large number of dimensions may introduce noises which will deteriorate the performance. Figure 4(b) shows the accuracy scores over different choices of K. We can observe that the setting $K = 2$ has a significant improvement over the setting $K = 1$, and $K = 3$ further outperforms $K = 2$. This confirms that different k-order can learn complementary local information. When K is large enough, learned k-order relational information becomes weak and shifts towards a steady distribution.

5 Related Work

To preserve multi-scale structure information, some random walk and matrix factorization methods [1,7] have been proposed. GraRep [7] accurately calculates k-order proximity matrix, and computes specific representation for each k using SVD based dimension reduction method, and then concatenates these embeddings. Another line of the related work is deep learning based methods. SDNE [9], DNGR [8] utilize this ability of deep autoencoder to generate an embedding model that can capture non-linearity in graphs. AIDW [17] proposes an adversarial network embedding framework, which leverages the adversarial learning principle to regularize the representation learning. However, existing approaches usually lack weight learning for different scales.

Our work is also related to the attention-based models. Rather than using all available information, attention mechanism aims to focus on the most pertinent information for a task and has been applied to various tasks, including machine translation and sentence summarization [11]. MVE [10] proposes a multi-view network embedding, which aims to infer robust node representations across different networks.

6 Conclusion

In this paper, we study learning node embedding for networks with multiple scales. We propose an effective framework to let different scales collaborate with each other and vote for the robust node representations. During voting, we propose an attention-based autoencoder to automatically learn the voting weights of scales while preserving the network structure information in a non-linear way. Besides, an Adversarial regularization is introduced to learn more stable and robust network embedding. Experiments on node classification demonstrate the superior performance of our proposed method.

References

1. Perozzi, B., Al-Rfou, R., Skiena, S.: DeepWalk: online learning of social representations. In: Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (2014)

2. Wang, X., Cui, P., Wang, J., Pei, J., Zhu, W., Yang, S.: Community preserving network embedding. In: AAAI, pp. 203–209 (2017)
3. Sang, L., Xu, M., Qian, S., Wu, X.: Multi-modal multi-view Bayesian semantic embedding for community question answering. Neurocomputing (2018)
4. Lü, L., Zhou, T.: Link prediction in complex networks: a survey. Phys. A: Stat. Mech. Appl. **390**(6), 1150–1170 (2011)
5. Perozzi, B., Kulkarni, V., Chen, H., Skiena, S.: Don't walk, skip!: online learning of multi-scale network embeddings. In: Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, pp. 258–265. ACM (2017)
6. Tang, J., Qu, M., Wang, M., Zhang, M., Yan, J., Mei, Q.: Line: large-scale information network embedding. In: Proceedings of the 24th International Conference on World Wide Web, pp. 1067–1077. International World Wide Web Conferences Steering Committee (2015)
7. Cao, S., Lu, W., Xu, Q.: Grarep: learning graph representations with global structural information. In: Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, pp. 891–900. ACM (2015)
8. Cao, S., Lu, W., Xu, Q.: Deep neural networks for learning graph representations. In: AAAI, pp. 1145–1152 (2016)
9. Wang, D., Cui, P., Zhu, W.: Structural deep network embedding. In: Proceedings of the 20th ACM SIGKDD (2016)
10. Qu, M., Tang, J., Shang, J., Ren, X., Zhang, M., Han, J.: An attention-based collaboration framework for multi-view network representation learning. In: Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, pp. 1767–1776. ACM (2017)
11. Luong, M.-T., Pham, H., Manning, C.D.: Effective approaches to attention-based neural machine translation. arXiv preprint arXiv:1508.04025 (2015)
12. Goodfellow, I., et al.: Generative adversarial nets. In: Advances in Neural Information Processing Systems, pp. 2672–2680 (2014)
13. Weston, J., Bengio, S., Usunier, N.: WSABIE: scaling up to large vocabulary image annotation. In: IJCAI, vol. 11, pp. 2764–2770 (2011)
14. Iyyer, M., Guha, A., Chaturvedi, S., Boyd-Graber, J., Daumé III, H.: Feuding families and former friends: unsupervised learning for dynamic fictional relationships. In: Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pp. 1534–1544 (2016)
15. He, R., Lee, W.S., Ng, H.T., Dahlmeier, D.: An unsupervised neural attention model for aspect extraction. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), vol. 1, pp. 388–397 (2017)
16. Grover, A., Leskovec, J.: node2vec: Scalable feature learning for networks. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 855–864. ACM (2016)
17. Dai, Q., Li, Q., Tang, J., Wang, D.: Adversarial network embedding. In: Proceedings of AAAI (2018)
18. Fan, R.-E., Chang, K.-W., Hsieh, C.-J., Wang, X.-R., Lin, C.-J.: Liblinear: a library for large linear classification. J. Mach. Learn. Res. **9**(Aug), 1871–1874 (2008)
19. Makhzani, A., Shlens, J., Jaitly, N., Goodfellow, I., Frey, B.: Adversarial autoencoders. arXiv preprint arXiv:1511.05644 (2015)