GraphGAN: Generating Graphs via Random Walks

Aleksandar Bojchevski, Oleksandr Shchur, Daniel Zügner, Stephan Günnemann

16 Feb 2018 (modified: 16 Feb 2018) ICLR 2018 Conference Blind Submission Readers: Everyone Show Bibtex Show Revisions

Abstract: We propose GraphGAN - the first implicit generative model for graphs that enables to mimic real-world networks.
We pose the problem of graph generation as learning the distribution of biased random walks over a single input graph.
Our model is based on a stochastic neural network that generates discrete output samples, and is trained using the Wasserstein GAN objective. GraphGAN enables us to generate sibling graphs, which have similar properties yet are not exact replicas of the original graph. Moreover, GraphGAN learns a semantic mapping from the latent input space to the generated graph's properties. We discover that sampling from certain regions of the latent space leads to varying properties of the output graphs, with smooth transitions between them. Strong generalization properties of GraphGAN are highlighted by its competitive performance in link prediction as well as promising results on node classification, even though not specifically trained for these tasks.

TL;DR: Using GANs to generate graphs via random walks.

Keywords: GAN, graphs, random walks, implicit generative models

Summary

[–] ICLR 2018 Conference Acceptance Decision

ICLR 2018 Conference Program Chairs

30 Jan 2018 (modified: 30 Jan 2018) ICLR 2018 Conference Acceptance Decision Readers: Everyone

Decision: Reject

Comment: This paper proposes an implicit model of graphs, trained adversarially using the Gumbel-softmax trick. The main idea of feeding random walks to the discriminator is interesting and novel. However,
1) The task of generating 'sibling graphs', for some sort of bootstrap analysis, isn't well-motivated.
2) The method is complicated and presumably hard to tune, with two separate early-stopping thresholds that need to be tuned
3) There is not even a mention of a large existing literature on generative models of graphs using variational autoencoders.

Response

[–] Revision summary

ICLR 2018 Conference Paper876 Authors

05 Jan 2018 ICLR 2018 Conference Paper876 Official Comment Readers: Everyone

Comment: Based on the reviewers' comments we have made the following improvements to our paper:
* Added more details on the experimental setup (Section 4.4).

Review

[–] Claims and evaluation need some work

ICLR 2018 Conference Paper876 AnonReviewer1

03 Dec 2017 (modified: 11 Jan 2018) ICLR 2018 Conference Paper876 Official Review Readers: Everyone

Review: This paper proposes a WGAN formulation for generating graphs based on random walks. The proposed generator model combines node embeddings, with an LSTM architecture for modeling the sequence of nodes visited in a random walk; the discriminator distinguishes real from fake walks.

Rating: 4: Ok but not good enough - rejection

Confidence: 5: The reviewer is absolutely certain that the evaluation is correct and very familiar with the relevant literature

Response

[–] Authors' answer pt. 1

ICLR 2018 Conference Paper876 Authors

08 Dec 2017 ICLR 2018 Conference Paper876 Official Comment Readers: Everyone

Comment: Thank you for your review.

In the following comment we address your other concerns.

Response

[–] Authors' answer pt. 2

ICLR 2018 Conference Paper876 Authors

08 Dec 2017 ICLR 2018 Conference Paper876 Official Comment Readers: Everyone

Comment: 1) Generalization
The problem of detecting (near-)isomorphism between two graphs is extremely challenging in general (when the nodes may be permuted). In our case, since the ordering in both the original and sibling graphs is identical, having low edge overlap directly implies that they are not (nearly) isomorphic, (note that the model is still invariant to node permutations). Additionally, given the strong link prediction performance, we can surely claim that the model does not simply "memorize" the original graph, and that the "sibling" graphs contain edges that are plausible but not present in the input graph.

Comment

[–] The constructed matrix S while training with EO early stop strategy

Junliang Guo

27 Nov 2017 ICLR 2018 Conference Paper876 Public Comment Readers: Everyone

Comment: It's a very interesting work! There are two parts that I'm confused after reading the paper:

Response

[–] Re: The constructed matrix S while training with EO early stop strategy

ICLR 2018 Conference Paper876 Authors

28 Nov 2017 ICLR 2018 Conference Paper876 Official Comment Readers: Everyone

Comment: Thank you for your comment and interest in our work!

Response

[–] one more question

Junliang Guo

28 Nov 2017 (modified: 29 Nov 2017) ICLR 2018 Conference Paper876 Public Comment Readers: Everyone

Comment: Thanks for your clear reply! And one more question:

In Section 3.1, the next sample is generated as v_{t} = onehot(argmax v_{t}^{*}). How is this step differentiable? As argmax is a hard assignment, the gradients cannot be passed to v_{t}^{*} during backward as you claimed. Maybe I misunderstand somewhere?

Response

[–] Re: one more question

ICLR 2018 Conference Paper876 Authors

28 Nov 2017 ICLR 2018 Conference Paper876 Official Comment Readers: Everyone

Comment: We use the Straight-Through Gumbel-Softmax estimator that is described in [1]. In a nutshell, this allows us to approximate sampling from a categorical distribution in a differentiable way.

[1] Jang, Eric, Shixiang Gu, and Ben Poole. "Categorical reparameterization with Gumbel-softmax." ICLR 2017