



Adversarial Learning on Heterogeneous Information Networks

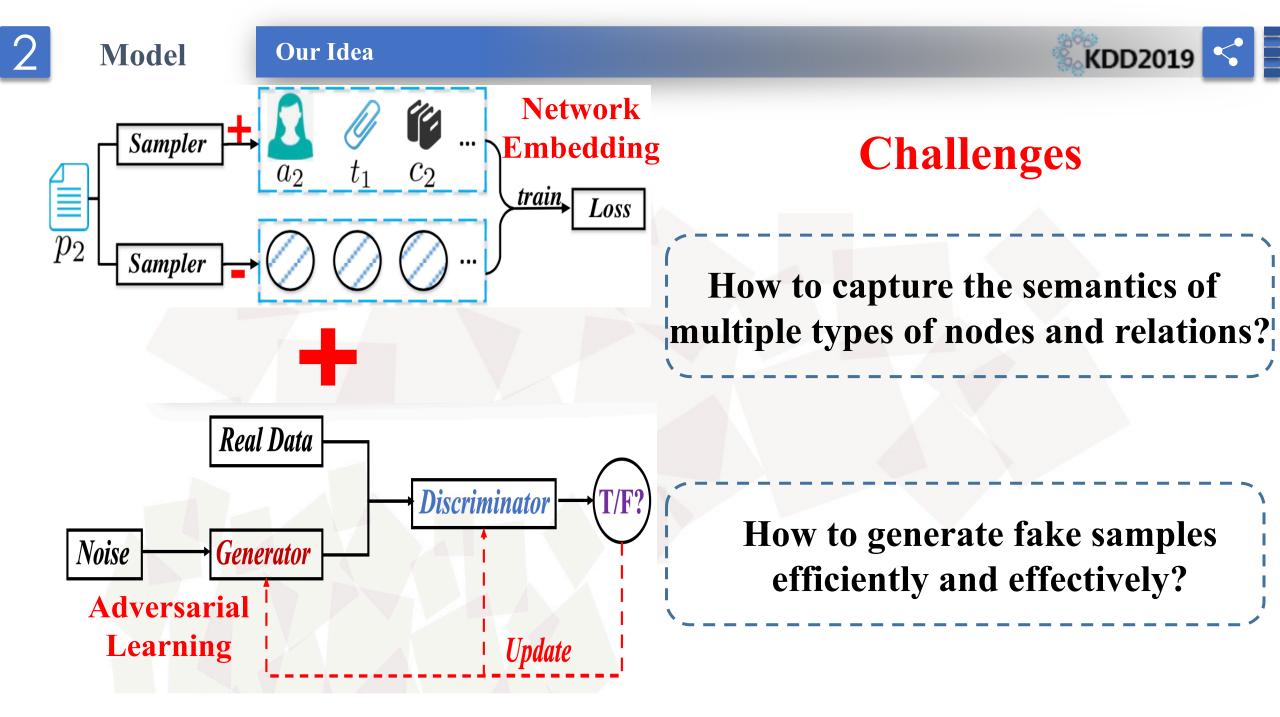
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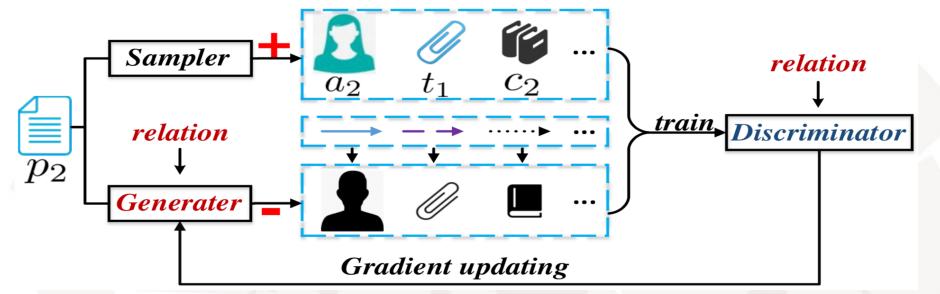


Background **Heterogeneous Information Network Embedding KDD2019** Sampler a_2 C_2 <u>train</u> Loss p_2 Sampler ... Limitations Randomly select existing nodes in Arbitrary and confined to the the network as negative samples universe of the original network Heed to the latent distribution of Focus on capturing the rich semantics on HINs the nodes so that lack robustness Require domain knowledge that is Rely on appropriate meta-paths to often expensive to obtain match the desired semantics





HIN Embedding with GAN based Adversarial Learning(HeGAN)



Relation-aware Generator and Discriminator > Challenge 1

(i) Discriminator can tell whether a node pair is real or fake w.r.t relation(ii) Generator can produce fake node pairs that mimic real pairs w.r.t relation

Generalized Generator

Model

HeGAN

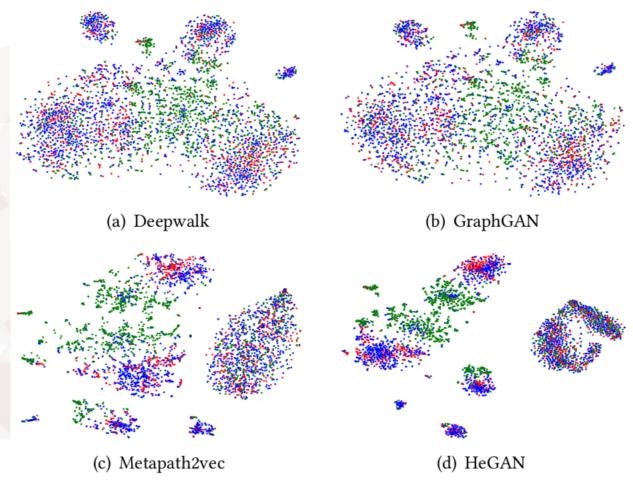


(i) Sample latent nodes from a continuous distribution(ii) no softmax computation and fake samples are not restricted to the existing nodes



Methods	DBLP	Yelp	AMiner
Deepwalk	0.7398	0.3306	0.4773
LINE-1st	0.7412	0.3556	0.3518
LINE-2nd	0.7336	0.3560	0.2144
GraphGAN	0.7409	0.3413	-
ANE	0.7138	0.3145	0.4483
HERec-HNE	0.7274	0.3476	0.4635
HIN2vec	0.7204	0.3185	0.2812
Metapath2vec	<u>0.7675</u>	<u>0.3672</u>	0.4726
HeGAN	0.7920**	0.4037**	0.5052**

HeGAN learn semantic-preserving representations in a robust manner through the adversarial principle



HeGAN has a more crisp boundary and denser clusters





More details will be published in our poster

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