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Online

A View-Adversarial Framework for Multi-View Network Embedding





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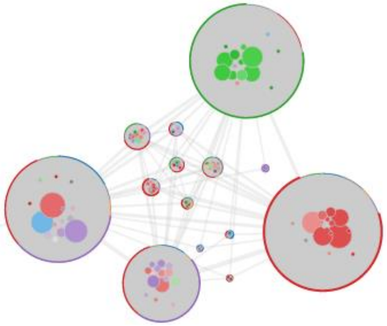
Roadmap

- Motivation
- Problem Definition
- Proposed VANE Framework
- Experiments
- Conclusion

Network Embedding

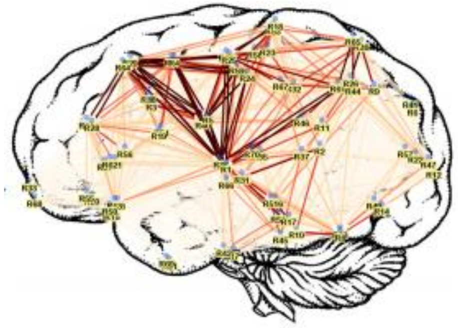
- Network embedding algorithms aim to embed nodes and graphs into low-dimensional representation vectors.

- Representation vectors have wide applications in real networks:
  - Clustering and Classification
  - Link Prediction
  - Anomaly Detection
  - ……



Collaboration Network

Traffic Network



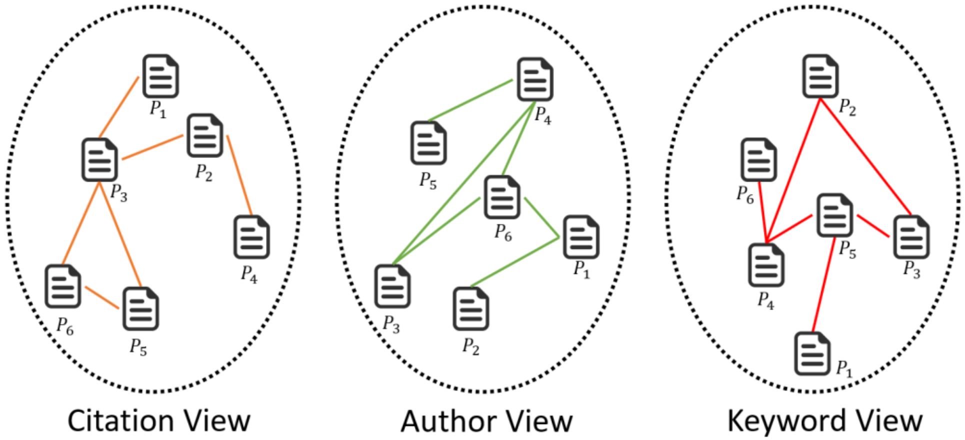
Brain Network

Existing Work

- Existing network embedding algorithms
  - Single-view embedding algorithms: DeepWalk [Perozzi et al., 2014], LINE [Tang et al., 2015], node2vec [Grover et al., 2016], GCN [Kipf and Welling, 2017], GraphSAGE [Hamilton et al., 2017] and GAT [Velickovic et al., 2018].
  - Multi-view embedding algorithms: MVE [Qu et al., 2017] and MNE [Zhang et al., 2018].
  - GAN-based embedding algorithms: GraphGAN [Wang et al., 2018] and ANE [Dai et al., 2018].

Challenges

- If we have the topology (i.e., structure) of a multi-view network
  - Challenge 1 (comprehensiveness): How can we learn comprehensive node representations which are consistent across different views?
  - Challenge 2 (robustness): How can we ensure the learned comprehensive node representations robust enough (i.e., hard to fit)?
- Multi-view network of academic literatures



A multi-view network of 3 views with 6 papers

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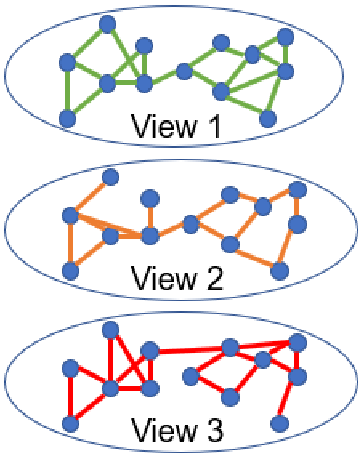
Multi-View Network Embedding

- Given:
  - A multi-view network with k views,
    $$G = \{V, E_1, E_2, \dots, E_k\}$$
    where E_i is the set of edges in the i-th view.



- Find:
  - Robust node representations,
    $$\{\boldsymbol{x}_v\}_{v \in V} \in \mathbb{R}^d, \text{ with } d \ll |V|$$
    which are consistent across k different views.

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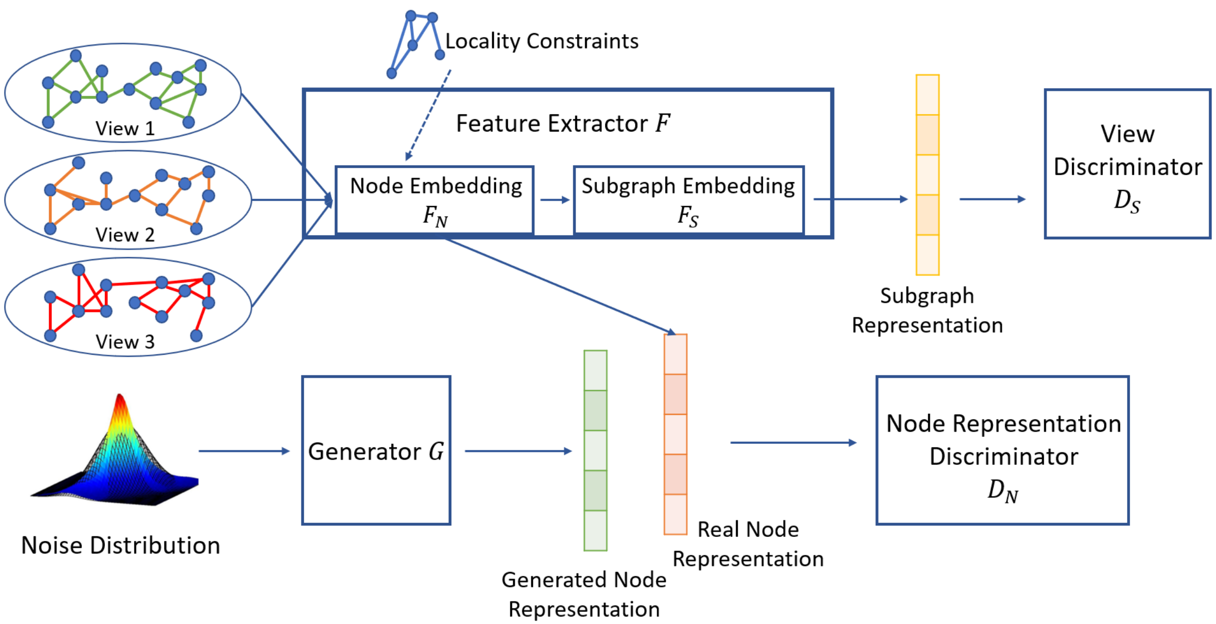
Overview of VANE

- VANE (**V**iew-**A**dversarial Multi-View **N**etwork **E**mbedding)
  - Extracts robust node representations that are consistent across all given views via two adversarial games for two mentioned challenges.



VANE Framework

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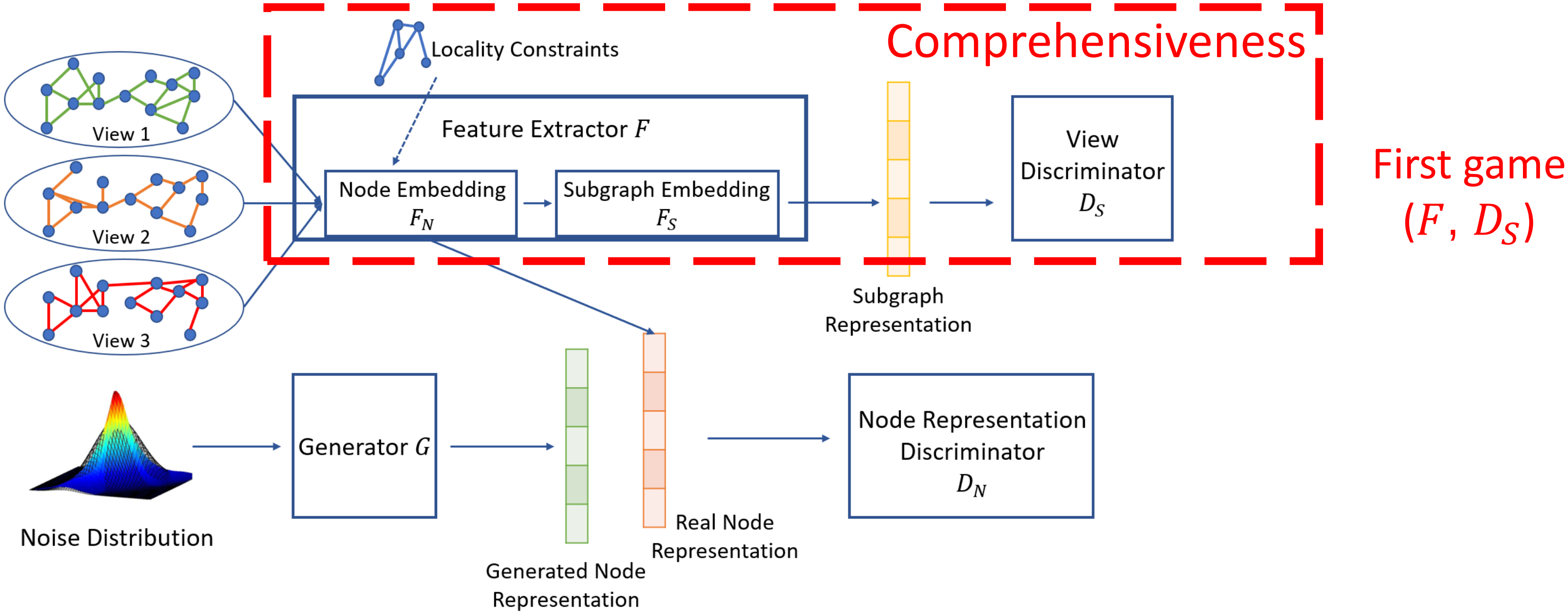

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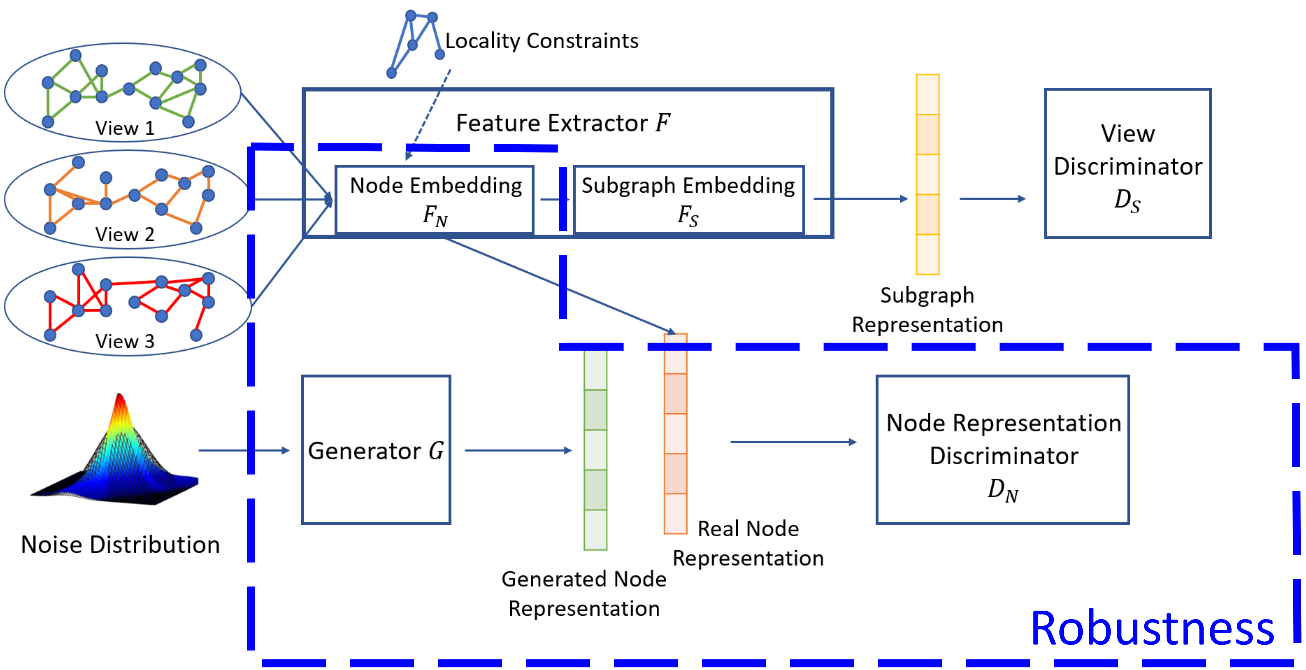

Second game (G, F_N, D_N)

VANE Framework

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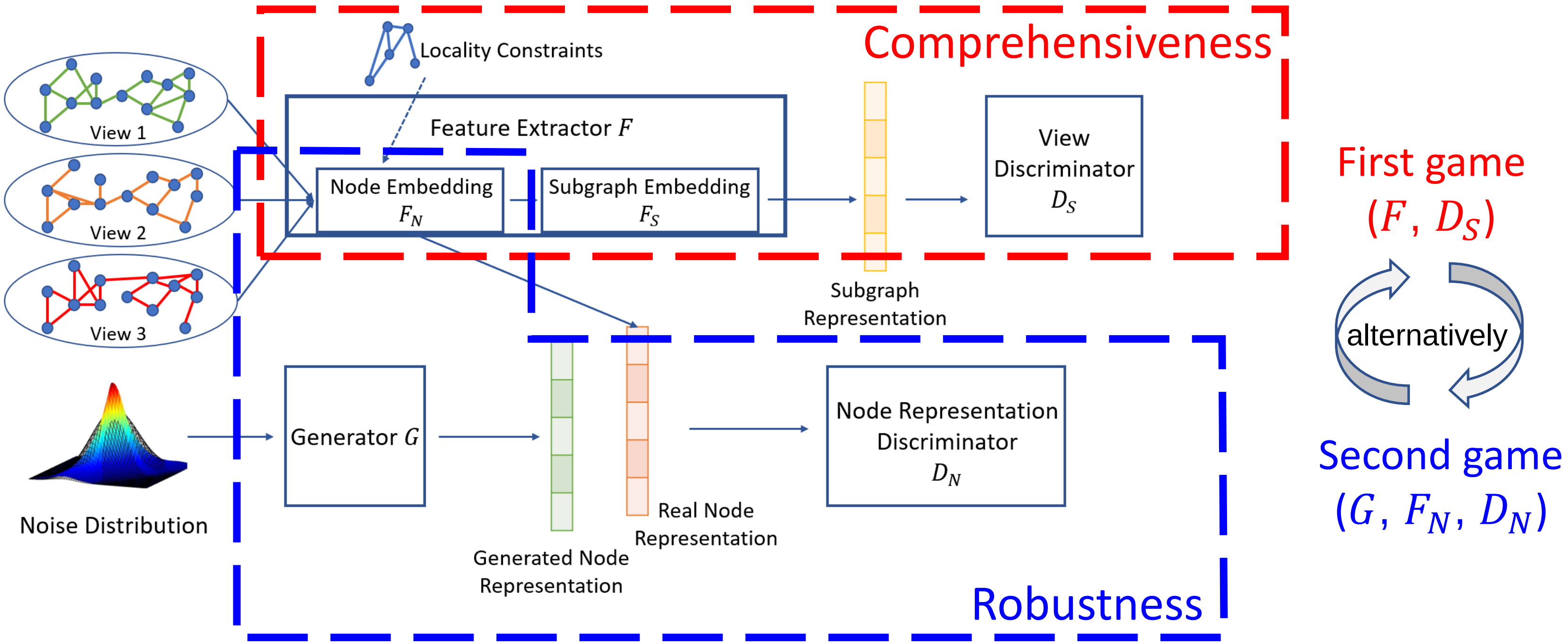
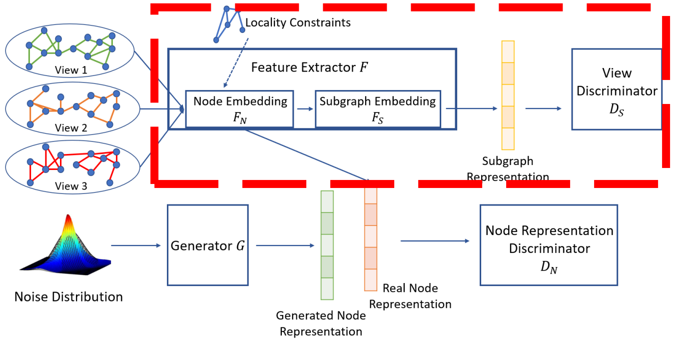


VANE Framework

VANE Framework



- First adversarial game (F, D_S)
  - Intuition: Feature extractor F tries to extract the **view-invariant** subgraph representations (aggregated by node representations) across different views, while the view discriminator D_S tries to discriminate which subgraph representation comes from which view.
  - Objective:

S: the node sequence (i.e., subgraph) sampled from one view by random walk

$$\min_F \max_{D_S} J_S(D_S, F) = \min_F \max_{D_S} \mathbb{E}_{F(S)\sim p_i(F(S))}[\log(D_S(F(S)))] + \mathbb{E}_{F(S)\sim \bar{p}_i(F(S))}[\log(1 - D_S(F(S)))]$$

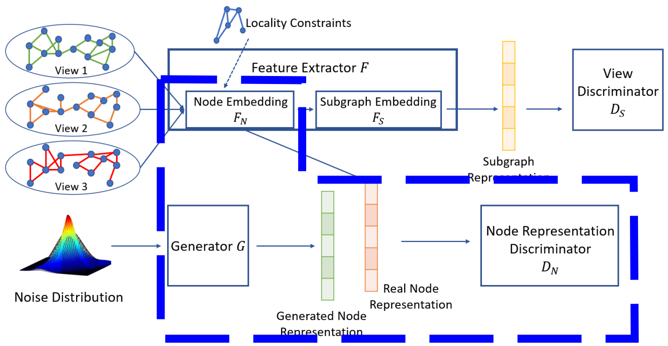
$F(S)$: the subgraph embedding vector, and F consists of F_N (node embedding model) and F_S (subgraph embedding model)

$F(S)\sim p_i(F(S))$: the distribution of subgraph representation $F(S)$ from the i-th view

locality constraints: $$\min_{F_N} J_{LC}(F_N(v_i), F_N(v_j)) = \min_{F_N} \mathbb{E}_{v_i, v_j \in S}[1 - \cos(F_N(v_i), F_N(v_j))]$$

$F_N(v)$: the node embedding vector

VANE Framework



- Second adversarial game (G, F_N, D_N)
  - Intuition: Generator G generates fake node representations to fit node representations produced by F_N, and F_N tries to provide robust representations that are hard to fit to help discriminator D_N tell fake vectors.
  - Objective:

$$\boxed{\begin{aligned} &\min_{G} \max_{D_N} \max_{F_N} J_N(D_N, G, F_N) \\ =&\min_{G} \max_{D_N} \max_{F_N} \mathbb{E}_{F_N(v)\sim p_{data}(F_N(v))}[\log(D_N(F_N(v)))] \\ &+\mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(1-D_N(G(\mathbf{z})))] \end{aligned}}$$

$F_N(v)$: the real node representation

$G(\boldsymbol{z})$: the generated node representation

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Experimental Setup

- Comparison methods
  - Single-view embedding algorithms: DeepWalk [Perozzi et al., 2014], node2vec [Grover et al., 2016].
  - GAN-based single-view embedding algorithm: GraphGAN [Wang et al., 2018].
  - Multi-view embedding algorithms: MVE [Qu et al., 2017], MNE [Zhang et al., 2018].
  - GAN-based multi-view embedding algorithms: Our VANE-RW (sampling with random walk), VANE-BRW (sampling with biased random walk).
- Dataset
  - **Aminer** academic literature dataset: 27,734 papers (nodes) in total, citation view (111,819 edges) and common-author view (525,623 edges).
  - **Twitter-Rugby** dataset: 850 users (nodes) in total, follow view (22,861 edges), mention view (21,660 edges), retweet view (9,627 edges).

Effectiveness Comparison

- VANE outperforms baseline methods

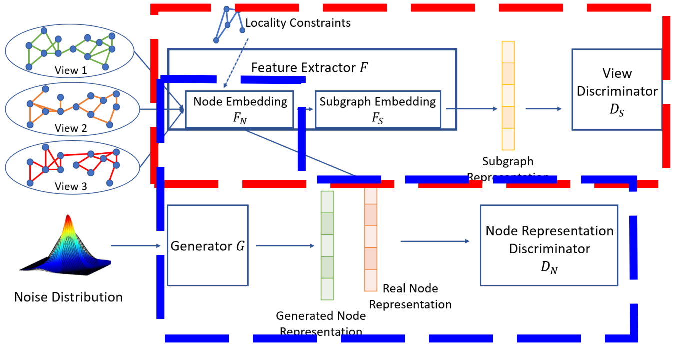
Methods	View	Accuracy (%)	
		Node Classification	Link Prediction
DeepWalk	Citation	78.03±0.72	95.99
	Common-Author	72.72±0.77	96.29
	Combined	74.94±0.54	97.28
node2vec	Citation	78.05±0.57	97.73
	Common-Author	73.69±0.68	95.58
	Combined	74.88±0.91	97.85
GraphGAN	Citation	74.29±1.20	88.93
	Common-Author	72.07±1.11	89.57
	Combined	71.69±1.06	90.21
MNE	Citation	N/A	54.25
	Common-Author	N/A	52.32
MVE	All	80.16±0.42	72.82
VANE-RW	All	78.84±0.63	97.62
VANE-BRW	All	**80.79±0.80**	**98.53**

Performance on Aminer Dataset

Methods	View	Accuracy (%)	
		Node Classification	Link Prediction
DeepWalk	Follow	70.95±2.56	50.30
	Mention	69.64±5.46	50.27
	Retweet	73.78±5.18	52.24
	Combined	66.47±2.85	50.03
node2vec	Follow	79.52±4.42	65.45
	Mention	79.64±3.47	62.94
	Retweet	81.83±4.31	52.18
	Combined	80.59±2.75	60.61
GraphGAN	Follow	76.15±1.92	53.97
	Mention	71.95±2.74	51.88
	Retweet	39.20±2.42	50.21
	Combined	72.44±1.69	55.41
MNE	Follow	85.66±2.87	56.37
	Mention	84.70±3.45	74.66
	Retweet	85.06±3.42	76.15
MVE	All	83.76±4.90	68.85
VANE-RW	All	82.89±2.38	69.40
VANE-BRW	All	**90.60±2.57**	**85.36**

Performance on Twitter-Rugby Dataset

Ablation Study



- Versatility of VANE
  - Comprehensive information from multiple views.
  - Robust information from the generator.

Model	Locality Constraints	Node Representation Generator	Accuracy (%)	
			Node Classification	Link Prediction
VANE-BRW	No	No	19.28±4.03	50.03
	No	Yes	17.59±3.33	60.49
	Yes	No	84.70±4.60	81.29
	Yes	Yes	**90.60±2.57**	**85.36**

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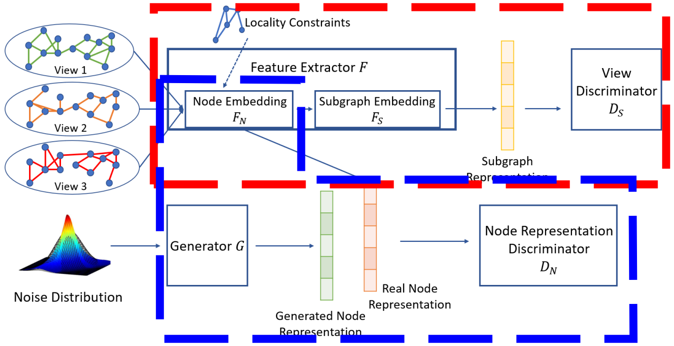
Conclusion

- VANE: View-Adversarial Multi-View Network Embedding
  - First adversarial game for comprehensive representations.
  - Second adversarial game for robust representations.



- Results
  - VANE extracts effective node representations for two down-stream graph mining tasks.

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Thanks !





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Please refer to our paper and code at
https://github.com/DongqiFu/VANE

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