

# Graph Embedding with Self-Clustering

Eya CHERIF  
N.Sabri OZTURK  
Jamil SYED RAWSHON  
Seda TOPLAR  
Özer YENIHAYAT

Data Science Lab  
University of Passau

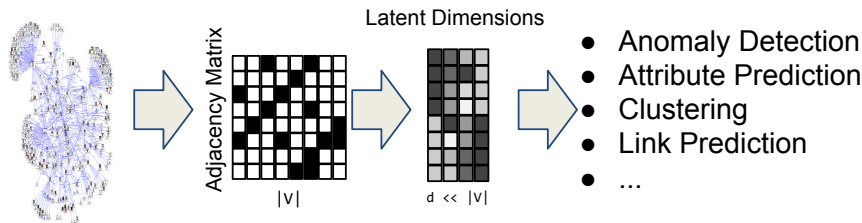
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# Outline

- 1 Introduction
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# Graph Embedding



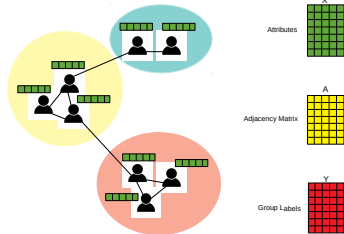
$$\Theta : V \mapsto \mathbb{R}^d$$

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# GEMSEC

use textblock to locate images in the frame

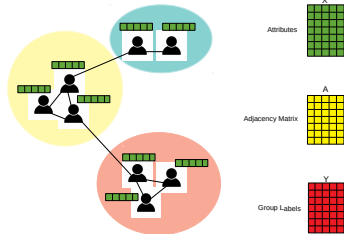
you can use pause



# GEMSEC

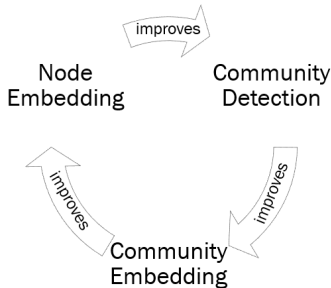
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you can use pause



# ComE

- Community embedding improves node embedding
  - Preserve high order proximity



**Figure:** Circular relation between node embeddding, community detection, community embedding



# ComE (Objective function)

## ■ First order proximity

- Two neighbor has similar embedding
- Objective function  $O_1 = -\sum_{(v_i, v_j) \in E} \log \sigma(\phi_j^T \phi_i)$

## ■ Second order proximity

- Both nodes share many context
- We adopt negative sampling
- Objective function  $O_2 = -\alpha \sum_{v_i \in V} \sum_{v_j \in C_i} \Delta_{ij}$ , where  $\Delta_{ij}$  define how well  $v_i$  generate it's context

## ■ Community detection and embedding

- Single objective function
- Objective function  $O_3 = -\frac{\beta}{K} \sum_{i=1}^{|V|} \log \sum_{k=1}^K \pi_{ik} \mathcal{N}(\phi_i | \psi_k, \Sigma_k)$

## ■ Final objective function

- $O = O_1 + O_2 + O_3$

# DANMF

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# Datasets

Table: Statistics of datasets.

Dataset	Nodes	Edges	Attributes	Labels
Cora	2,708	5,429	1,433	7
Citeseer	3,312	4,660	3,703	6

- Cora [1] and Citeseer [1]:

- The labels indicate publications topics.
- Attributes are binary representations of words in the corresponding publications.

# Node Classification

explain about node classification and compare the baselines  
use textblock to adjust images or tables in the frame

example for textblock:  $k$

# Node Classification

**Table:** Node classification performance (Macro-F1 score) of different methods on different datasets.

Dataset	Method	Macro-F1								
		10%	20%	30%	40%	50%	60%	70%	80%	90%
Cora	baseline	<b>0.828</b>	<b>0.841</b>	<b>0.854</b>	<b>0.869</b>	<b>0.883</b>	<b>0.901</b>	<b>0.909</b>	<b>0.916</b>	<b>0.921</b>
	baseline	0.663	0.673	0.684	0.691	0.726	0.754	0.769	0.788	0.808
	baseline	0.733	0.752	0.768	0.773	0.788	0.794	0.806	0.814	0.822
	baseline	0.778	0.795	0.812	0.822	0.837	0.854	0.861	0.869	0.877
	baseline	0.695	0.713	0.729	0.732	0.746	0.767	0.788	0.792	0.806
Citeseer	baseline	<b>0.731</b>	<b>0.739</b>	<b>0.755</b>	<b>0.778</b>	<b>0.786</b>	<b>0.790</b>	<b>0.796</b>	<b>0.804</b>	<b>0.812</b>
	baseline	0.538	0.588	0.607	0.610	0.616	0.621	0.635	0.656	0.677
	baseline	0.577	0.606	0.613	0.619	0.628	0.632	0.638	0.641	0.642
	baseline	0.604	0.633	0.671	0.678	0.696	0.705	0.723	0.735	0.745
	baseline	0.556	0.571	0.614	0.650	0.656	0.662	0.670	0.666	0.682

# Cora Visualization

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example for textblock:  $k$

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# Conclusion

- Community detection is useful for ...
- We learned ...

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# References



Prithviraj Sen, Galileo Namata, Mustafa Bilgic, Lise Getoor, Brian Gallagher, and Tina Eliassi-Rad, "Collective classification in network data", *AI magazine*, 29(3), 93-93, (2008).



Jure Leskovec and Julian J Mcauley, "Learning to discover social circles in ego networks", in *Advances in neural information processing systems*, pp. 539-547, (2012).

Thanks for your attention!