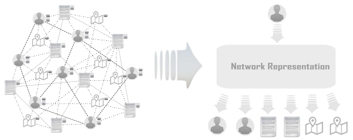


Universal Graph Embedding for Heterogeneous Study-trajectory Graph

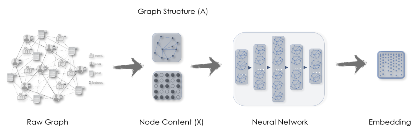
Authors: Ruiqi Hu, Qian Zhang, Yu Zheng

1 Introduction

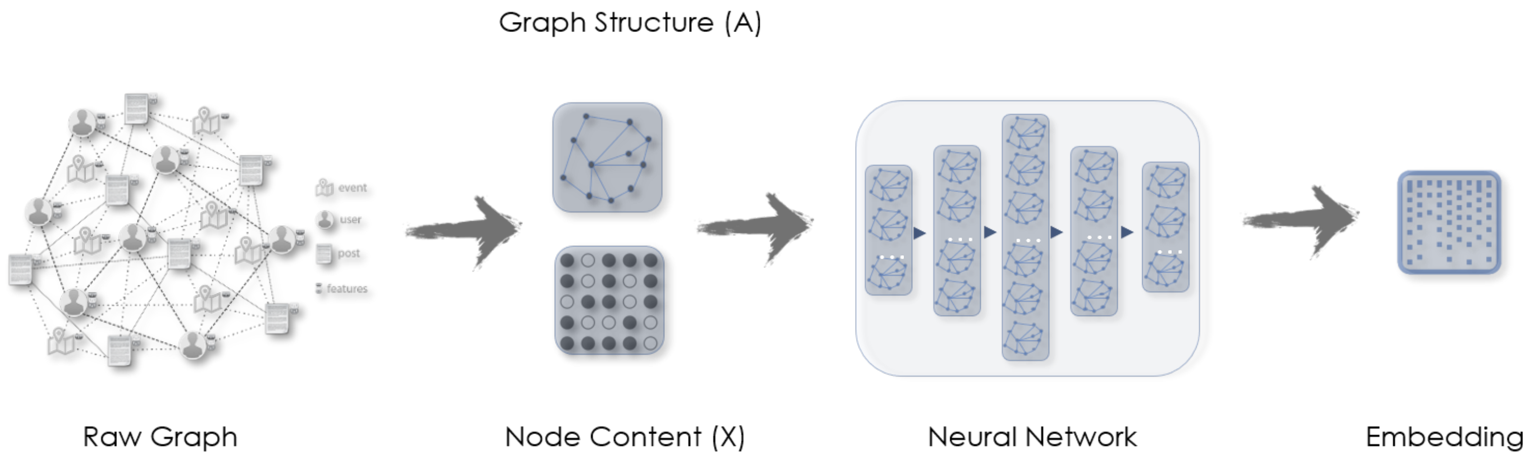
2 Problem Definition

3 Universal Graph Embedding

4 Experimental Study



Introduction

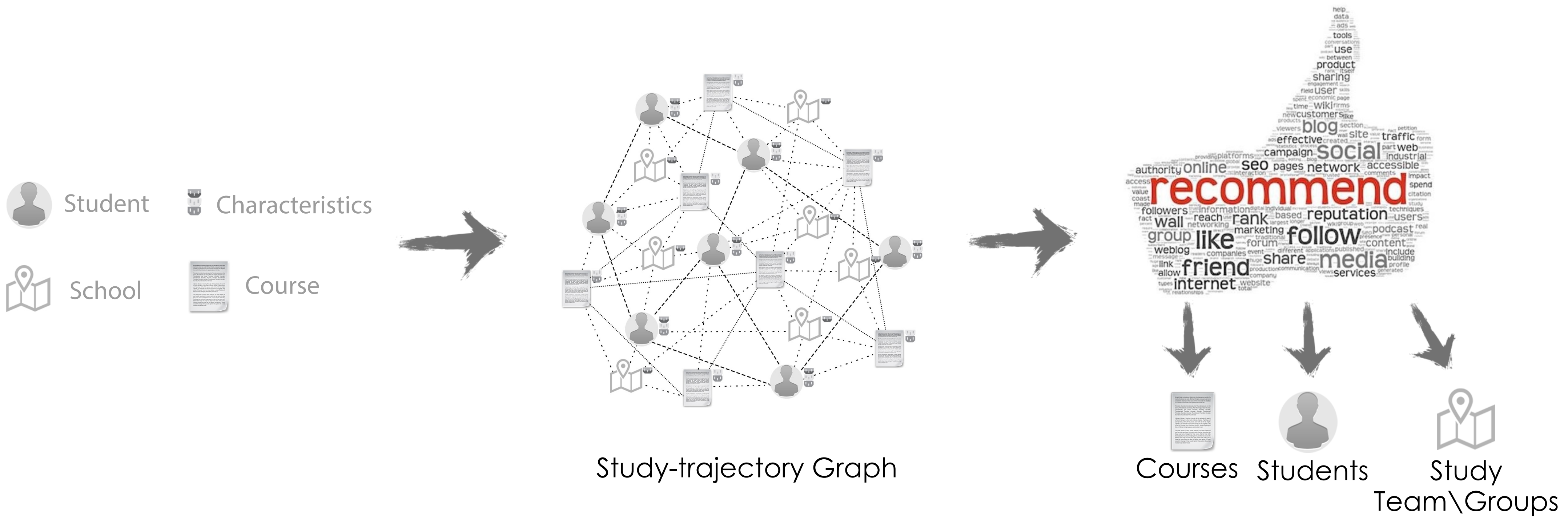


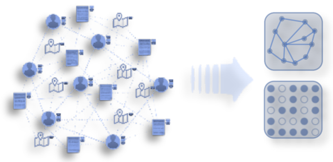
Graph Data

are ubiquitous in many areas: Biology, Social media and academic engine;

Graph Embedding

embeds homogeneous nodes with low-dimensional and unified vectors, while preserving the contextual information between nodes


Student
Characteristics
School
Course
Study-trajectory Graph
recommend
Courses
Students
Study
Team\Groups



Problem Definition

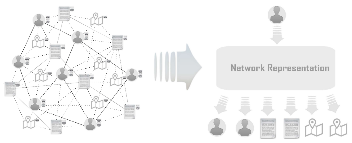
Graph: $G = \{V, E, X\}$, where V= $\{v_i\}_{i=1,\cdots,n}$ consists of a set of nodes in a graph;

Edge: $e_{i,j} = < v_i, v_j > \in E$;

A: is an adjacency matrix to present graph G where $A_{i,j} = 1\ if\ e_{i,j} \in E, otherwise\ A_{i,j} = 0.$

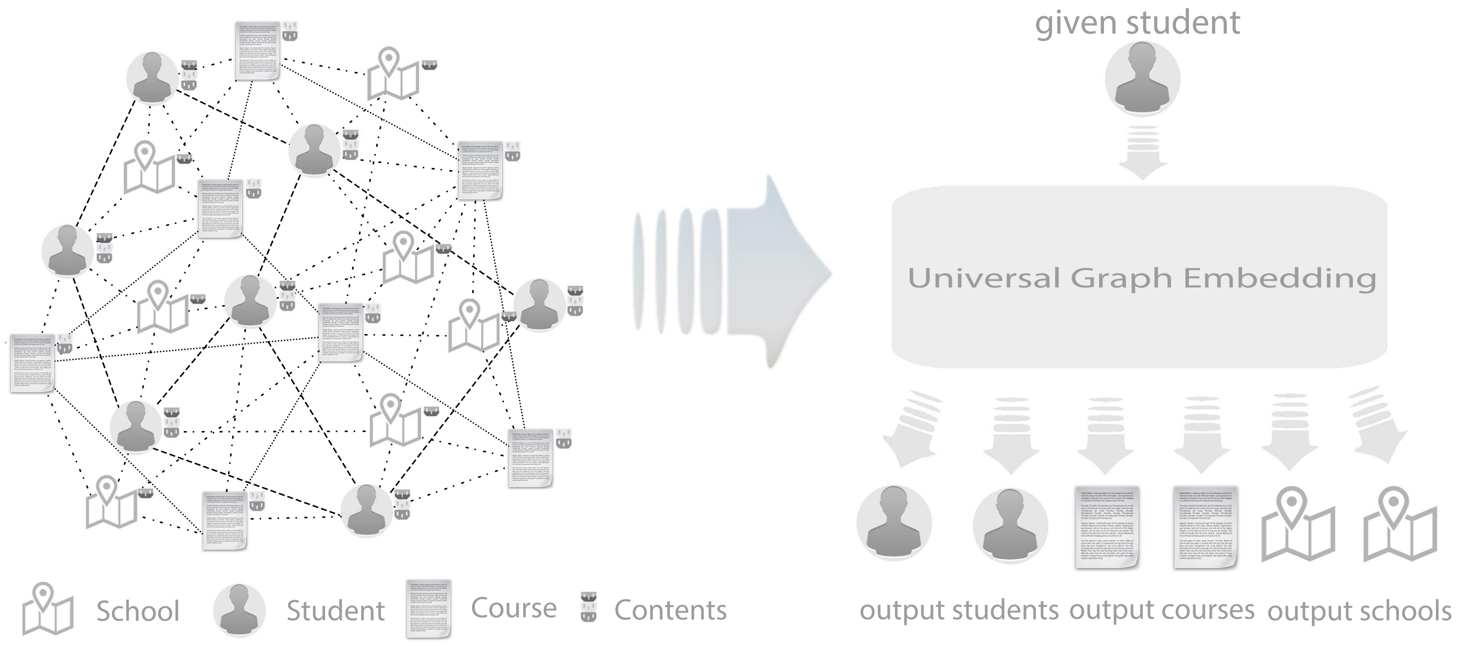
X: $x_i \in X$ indicates the content information associated with each node v_i

Given a graph **G**, our purpose is to map the **nodes** $\boldsymbol{v_i} \in \boldsymbol{V}$ to vectors $v_i \in \mathbb{R}^d$ with the formal format as follows: f : (A;X) ↣ Z, z_i^{T} is the i_{th} row of the matrix Z ∈ $\mathbb{R}^{d \times n}$.
n is the number of nodes
d is the dimension of embedding.
Z is the **embedding** matrix



Universal Graph Embedding (UGE)

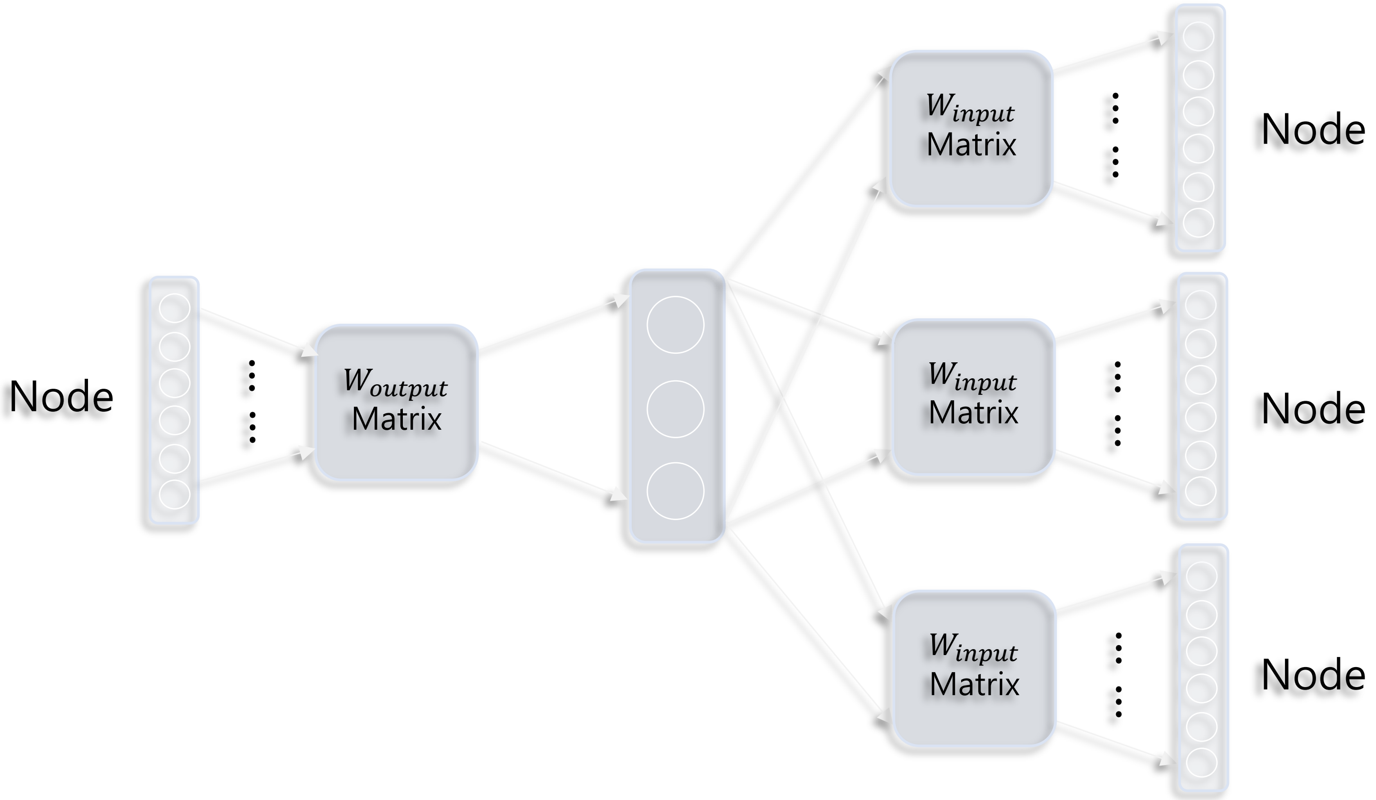
Motivations behind UGE



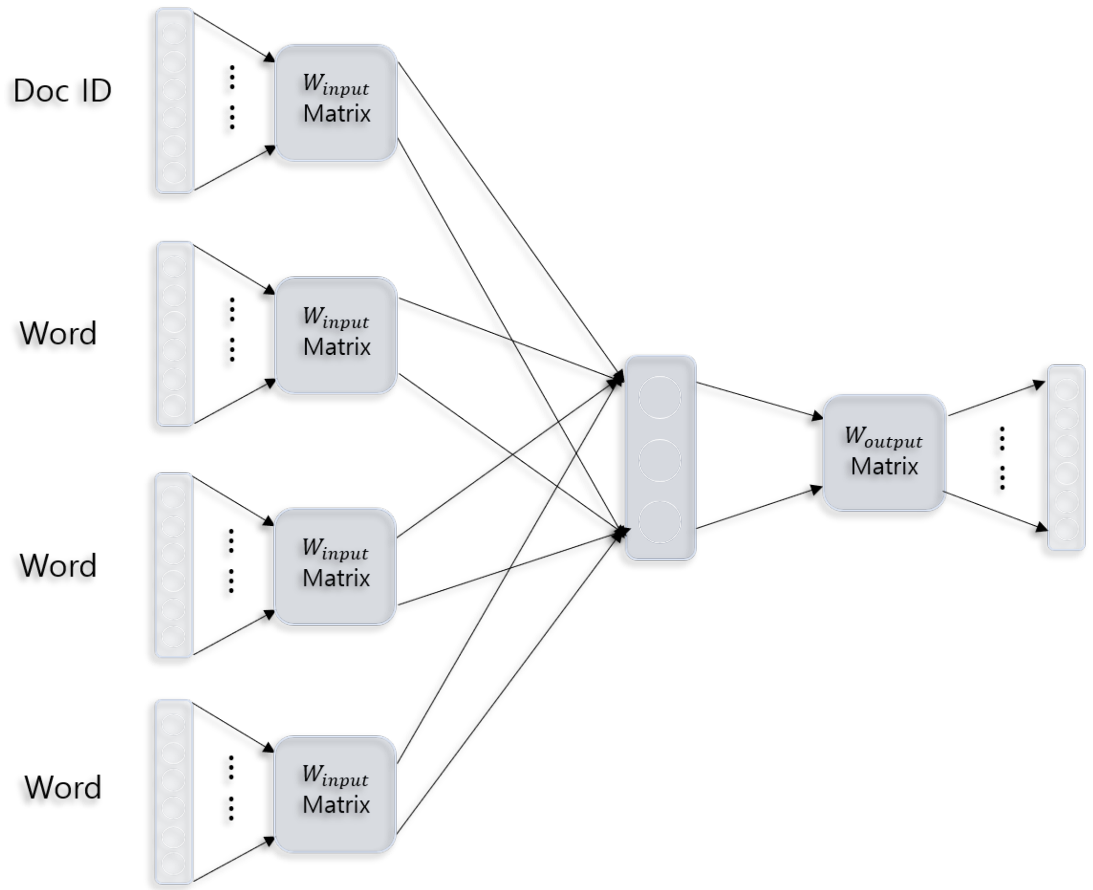
Existing algorithms are commonly designed for homogeneous information networks where all nodes of a network are of the same type.

To our best knowledge, there is no effective graph embedding algorithms have been leveraged in the graph domain.

Skip-gram / DeepWalk

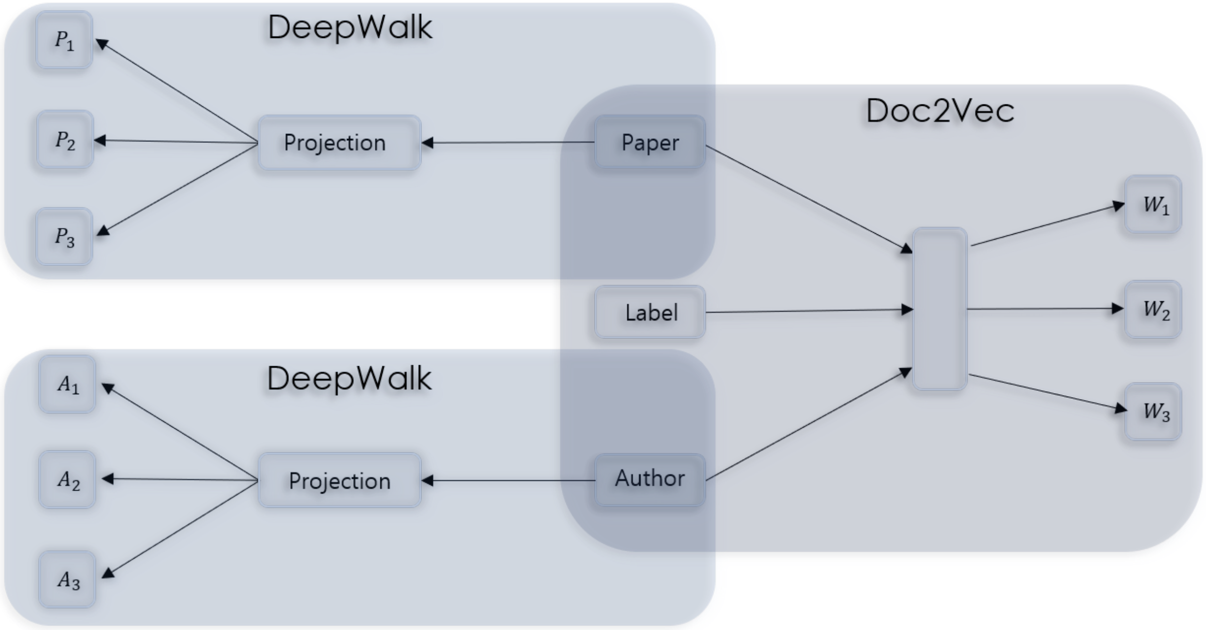


Doc2Vec



Doc ID
Word
Word
Word
W_{input} Matrix
W_{input} Matrix
W_{input} Matrix
W_{input} Matrix
W_{output} Matrix

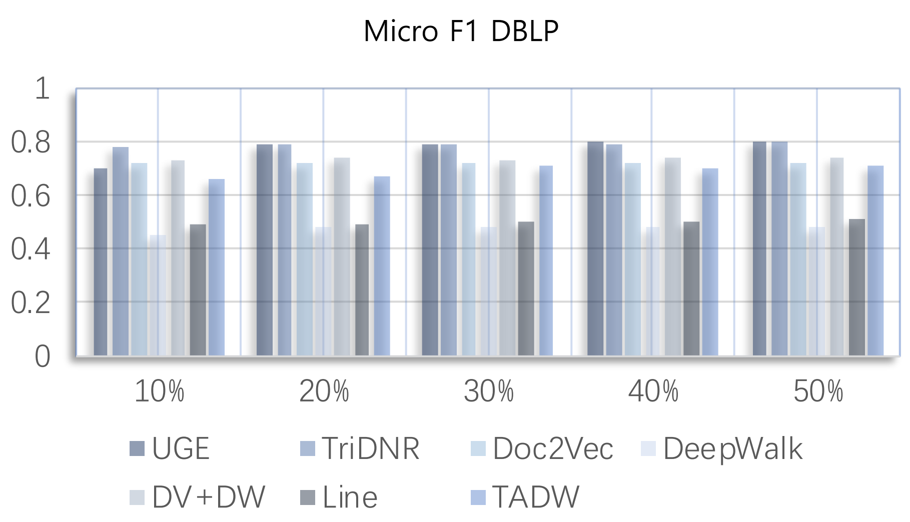
Universal Graph Embedding Framework



UGE Experiments

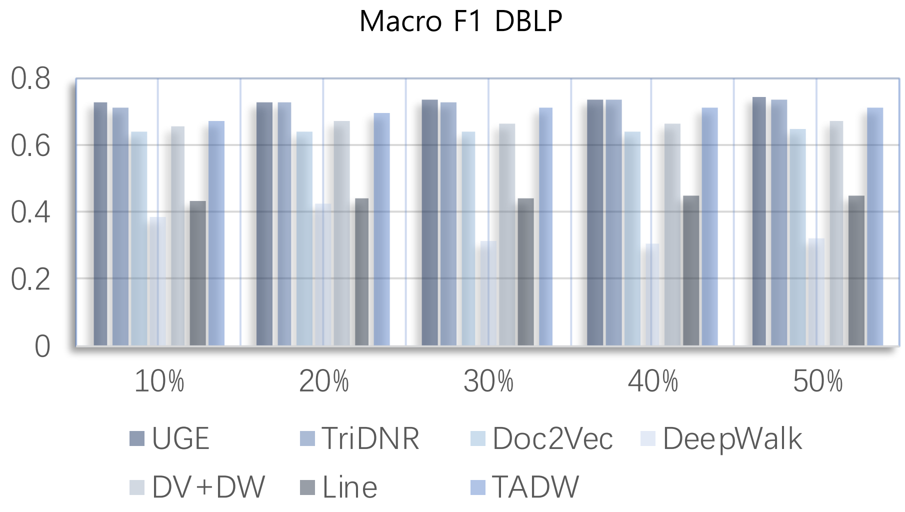
Computer science bibliography dataset

Data set	#paper nodes	#author nodes	#paper edges	#author edges	#content words	#labels
DBLP	56,503	58,279	106,752	142,581	3,262,885	4
CiteSeerX-Avs	18,720	40,139	54,601	41,458	2,649,720	5
CiteSeerX-M10	10,310	21,289	77,218	21,966	1,516,893	10



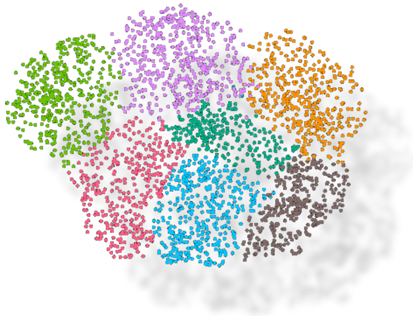
Micro F1 DBLP

Training size	UGE	TriDNR	Doc2Vec (DV)	DeepWalk (DW)	DV+DW	Line	TADW
10%	0.701	0.777	0.717	0.455	0.728	0.488	0.662
20%	0.792	0.787	0.722	0.478	0.737	0.494	0.67
30%	0.795	0.788	0.722	0.479	0.736	0.498	0.711
40%	0.797	0.793	0.722	0.48	0.739	0.499	0.705
50%	0.798	0.798	0.724	0.482	0.74	0.511	0.716



Macro F1 DBLP

Training size	UGE	TriDNR	Doc2Vec (DV)	DeepWalk (DW)	DV+DW	Line	TADW
10%	**0.732**	0.715	0.638	0.385	0.659	0.431	0.67
20%	**0.732**	0.727	0.644	0.43	0.669	0.439	0.698
30%	**0.736**	0.73	0.643	0.317	0.668	0.445	0.709
40%	**0.739**	0.736	0.643	0.308	0.668	0.446	0.711
50%	**0.742**	0.738	0.65	0.32	0.675	0.446	0.712



UGE

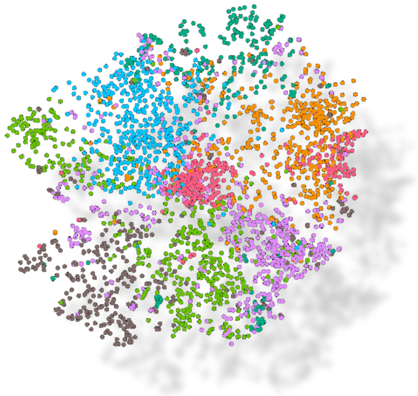
Dataset: Avs

TriDNR

Dataset: Avs

DeepWalk

Dataset: Avs



TADW

Dataset: Avs

Cases Study

OUTPUTS FROM REPRESENTATIONS. THE MATCHED IS MARKED WITH ⊙

Input: Learning in Neural Networks

UGE:
1. Adjoint-Functions and Temporal Learning Algorithms in Neural Networks ⊙
2. Bit-Serial Neural Networks ⊙
3. An Information-theoretic Learning Algorithm for Neural Network Classification ⊙
4. Polynomial Time Algorithms for Learning Neural Nets ⊙
5. Training of Large-Scale Feed-Forward Neural Networks ⊙

Doc2Vec:
1. Non-Cumulative Learning in METAXA.3
2. Learning Filaments
3. Learning of Kernel Functions in Support Vector Machines
4. Incremental Learning in SwiftFile
5. Learning While Searching in Constraint-Satisfaction-Problems

DeepWalk:
1. Estimating image motion from smear: a sensor system and extensions 2. Inferring 3D Volumetric Shape of Both Moving Objects and Static Background Observed by a Moving Camera
3. Secure face biometric verification in the randomized Radon space
4. An Ensemble Prior of Image Structure for Cross-Modal Inference
5. Closed Non-derivable Item sets

Thanks

Questions

Discussion