Mining relationships in Heterogeneous Academic Networks

Xiao Zeng 515030910531 Yinan He 515030910532

......

Outline for Section 1

1. Problem Description

2. Model

2.1 Path2vec Model
2.1.1 Model Description
2.1.2 Experiments & Results
2.2 Citation-based Model
2.2.1 Model Description
2.2.2 Experiments & Results

- 3. Future Work
- 4. Bibliography

Problem Description

Relationship identification

- Heterogeneous academic networks with papers, authors and venues
- Mining relationships by network structure & content information



Figure: Problem Description

Outline for Section 2

1. Problem Description

2. Model

2.1 Path2vec Model

2.1.1 Model Description

2.1.2 Experiments & Result

2.2 Citation-based Model

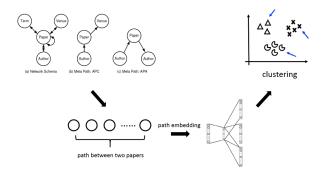
- 2.2.1 Model Description
- 2.2.2 Experiments & Results
- 3. Future Work

4. Bibliography

Path2vec Model

Graph Structure Model Framework

- Generating heterogeneous node sequence
- Embedding
- Adaptive clustering



Path2vec Model

Path Pattern

We use the following metapath pattern to guide random walkers.

Figure: Path Pattern

Path2vec Model Path Pattern

The transition probability is denoted as follows.

$$P(v^{i+1}|v_t^i, \mathcal{P}^1) = \begin{cases} \frac{1}{|N_{t+1}(v_t^i)|} & (v^{t+1}, v_t^i) \in E, \ \phi(v^{i+1} = t+1) \\ 0 & (v^{t+1}, v_t^i) \in E, \ \phi(v^{i+1} \neq t+1) & (1) \\ 0 & (v^{t+1}, v_t^i) \notin E \end{cases}$$

where $v_t^i \in V_t$ and $N_{t+1}(v_t^i)$ denote the V_{t+1} type neighborhood of node v_t^i .

Path2vec Model

Adaptive Clustering

- To classify the nodes into a rational number of categories
- Adjust the clustering number by setting a threshold δ

$$\delta = \beta \max_{v_i, v_j \in V} d(v_i, v_j)$$

• Get the least k that satisfy the threshold δ: optimal k



Figure: Adaptive Clustering

Experiments

Datasets

DBLP

Number of papers: 1.2M Number of authors: 710K Number of venues: 5K

DBIS

Number of papers: 10K Number of authors: 5K Number of venues: 424

AMiner

Number of papers: 30k Number of authors: 90K Number of venues: 3800+

Results Embedding Visualization

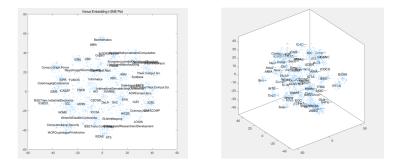


Figure: Venue Embedding Visualization

Results Embedding Visualization

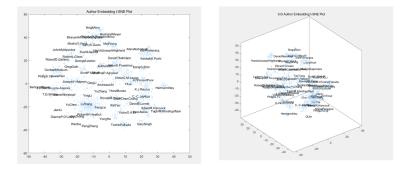


Figure: Author Embedding Visualization

Results Embedding Visualization

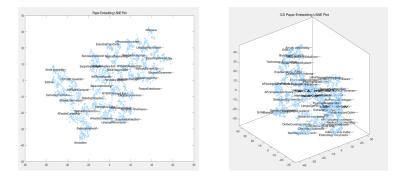


Figure: Paper Embedding Visualization

Results

Embedding Clustering Evaluation

- Compactness CP
- Davies-Bouldin Index DB(DBI)



Figure: Embedding Clustering Evaluation

Results Venue Embedding Clustering Visualization

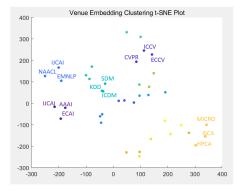


Figure: Venue Embedding Clustering Visualization

Case Study Venue Similarity Search

ACL		NIPS		INFOCOM	
ACL	1	NIPS	1	INFOCOM	1
EMNLP	0.966946	ICML	0.955095	IEEE/ACM TN	0.980632
CL	0.959138	AISTATS	0.945436	MobiHoc	0.939416
CoNLL	0.933703	NC	0.908183	MobiCom	0.91177
IJCNLP	0.922411	COLT	0.89621	SECON	0.905895
COLING-ACL	0.914321	UAI	0.873626	IWQoS	0.904628
NLE	0.913332	CVPR	0.842136	GLOBECOM	0.896472
LREC	0.902107	KDD	0.84182	WiOpt	0.896011
EACL	0.900098	ACML	0.832118	vCoNEXT	0.890572
ANLP	0.899777	ECCV	0.830614	SIGCOMM	0.888044
LREC	0.888303	AAAI	0.824888	VICC	0.885082

Table: Case study of Venue similarity search in AMiner Data

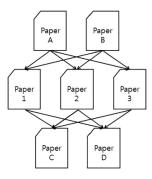
Case Study Author Similarity Search

Table: Case study of Author similarity search in AMiner Data

LuoyiFu		JohnE.Hopcroft		
LuoyiFu	1	JohnE.Hopcroft	1	
XinbingWang	0.887362	PrabhakarRaghavan	0.868889	
WenyeWang	0.873246	AllanBorodin	0.842907	
MichalisTitsias	0.864281	C.Seshadhri	0.829507	
BenLiang	0.857967	AndrewChi-ChihYao	0.828785	
KejieLu	0.857905	RudolphLanger	0.825836	
aShiwenMao	0.856818	RobertEndreTarjan	0.825729	
aShangqianHu	0.855743	RasmusPagh	0.82545	
aKiTaekLee	0.852274	JurisHartmanis	0.821832	
aMarcoFeletig	0.850694	JakubOcwieja	0.819203	
aUlasC.Kozat	0.84784	VikrantSinghal	0.818596	

Citation Network

- Directed graph G = (V, E)
- $V = \{v_i | i = 1, 2, ..., n\}$
- $E = \{e_{ij} | i = 1, 2, ..., n; j = 1, 2, ..., n; i \neq j\}$



Measure Relevance

Katz Graph Distance Measure The relevance between two nodes x and y in a graph can be defined as:

$$R(x, y) = \sum_{p_i \in P} \eta^{|p_i|}$$
(2)

Where $\eta \in [0, 1]$ is a decay parameter, P denote the set of all paths between x and y.

Measure Relevance

• Weighted Citation Link $e_{ij} = (v_i, v_j, \omega_{ij})$, where ω_{ij} reflects the citation type.

 $\omega_{ij} = \begin{cases} \omega_0, \text{ paper j is an important citation of paper i} \\ \omega_1, \text{ paper j is an unimportant citation of paper i} \end{cases}$

Weighted Katz Graph Distance Measure

$$R(x, y) = \sum_{p_i \in P} \eta^{|p_i|} \frac{\sum_{e_{jk} \in p_i} \omega_{jk}}{|p_i|}$$
(3)

Generating Weight

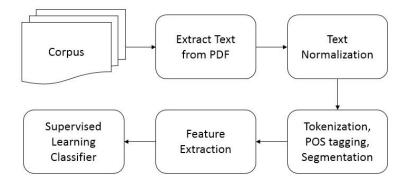


figure: model flowchart

Citation Classification Model *Features*

Number of direct citation	Cue words similarity for important class	
Number of direct citation/Number of all direct citation	Cue words similarity for unimportant class	
Number of direct citation per section	Abstract similarity	
Number of indirect citation	Number of paper that cited the citation per year	
Number of indirect citation/Number of all indirect citation	Citation appears in table or caption	
Number of indirect citation per section		

figure: List of Features

Dataset for Training

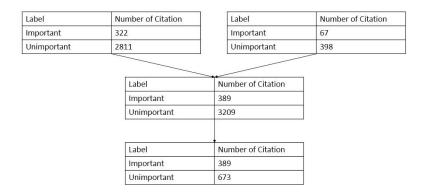


figure: Annotated Dataset

Training Result

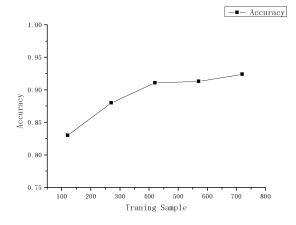


figure: Training Curve of SVM

Training Result

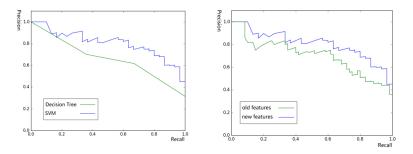


figure: Precision-Recall Curve Comparison

Experiment Result

Paper	Citation	Author	Venue
21290	12382	14981	341

figure: Dataset

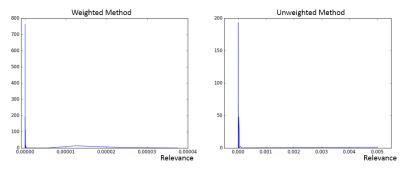


figure: Relevance Distribution

Outline for Section 3

- 1. Problem Description
- 2. Model
 - 2.1 Path2vec Model
 2.1.1 Model Description
 2.1.2 Experiments & Results
 2.2 Citation-based Model
 2.2.1 Model Description
 2.2.2 Experiments & Results

3. Future Work

4. Bibliography

Future work

- Integrate path2vec on heterogeneous academic networks and citation-based method on citation network
- Increase efficiency in classifying citations
- Incorporate path bias in applying path generation strategy

Outline for Section 4

- 1. Problem Description
- 2. Model
 - 2.1 Path2vec Model
 2.1.1 Model Description
 2.1.2 Experiments & Results
 2.2 Citation-based Model
 2.2.1 Model Description
 2.2.2 Experiments & Results
- 3. Future Work

4. Bibliography

Bibliography

- 1. Yuxiao Dong, Nitesh V. Chawla, Ananthram Swami: metapath2vec: Scalable Representation Learning for Heterogeneous Networks. KDD 2017: 135-144
- 2. Yizhou Sun, Jiawei Han, Xifeng Yan, Philip S. Yu, Tianyi Wu: PathSim: Meta Path-Based Top-K Similarity Search in Heterogeneous Information Networks. PVLDB 4(11): 992-1003 (2011)
- Liben-Nowell, D., Kleinberg, J.: The Link-prediction Problem for Social Networks. Journal of the American Society for Information Science and Technology 58(7), 1019–1031 (2007)
- Ienzuela M, Ha V, Etzioni O.Identifying Meaningful Citations AAAIWorkshop: Scholarly Big Data.2015.
- Zhu, X.; Turney, P.; Lemire, D.; and Vellino, A. 2013. Measuring academic influence: Not all citations are equal. submitted to Journal of the Association for Information Science and Technology (JASIST).

THANK YOU!