
Inductive Learning of Concept Representations from Library-Scale Bibliographic Corpora

Lukas Galke^{1,2} & Tetyana Melnychuk² & Eva Seidlmayer³ & Steffen Trog¹ &
Konrad U. Förstner³ & Carsten Schultz² & Klaus Tochtermann¹

¹ ZBW, ² Kiel University, ³ ZB MED

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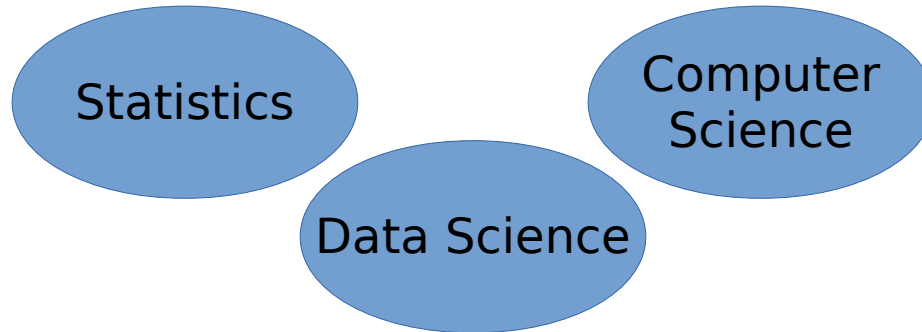
Outline

- 1) Motivation: **analyses of research dynamics**
- 2) Problem statement: **learning concept similarity from graph data**
- 3) Approach: **unsupervised training objective for graph neural nets**
- 4) Quantitative and (small-scale) qualitative evaluation

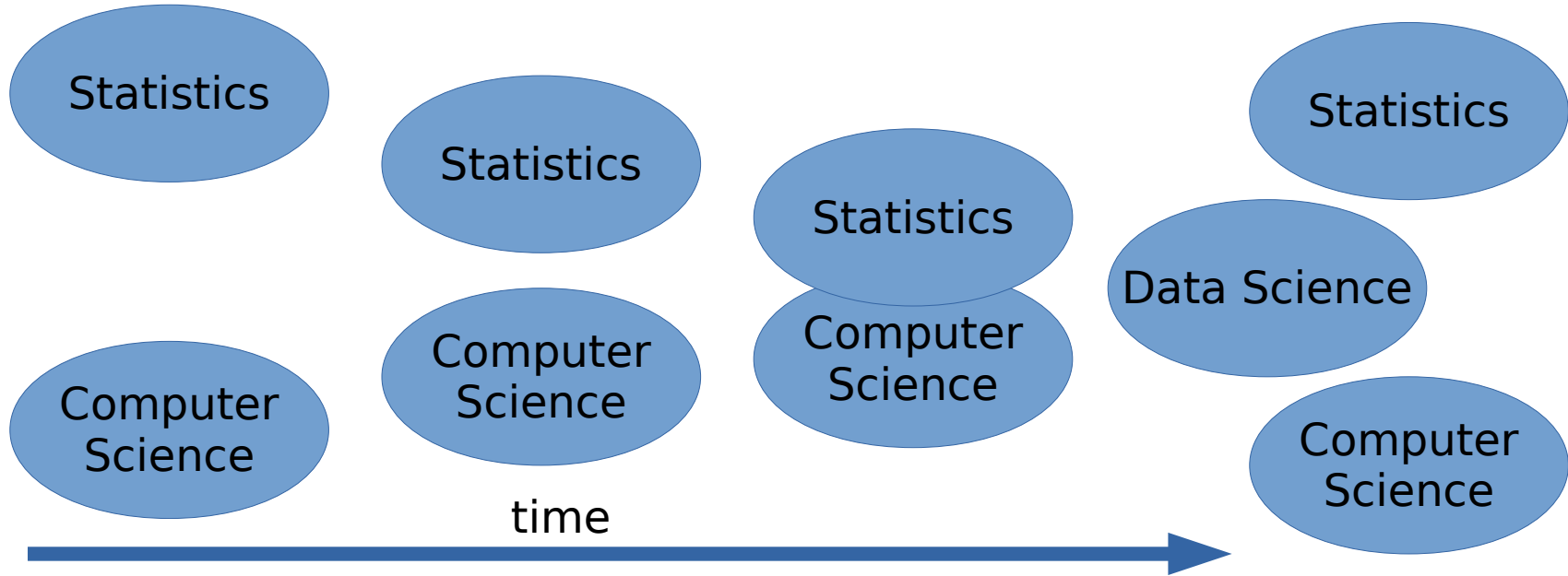
Motivation

- Digital libraries accumulate a large amount of bibliographic data
- Include valuable annotations with controlled vocabularies (concept hierarchies)
- Used for multi-label classification
- Used for information retrieval
- Used for recommender systems
- What about analyses of research dynamics?

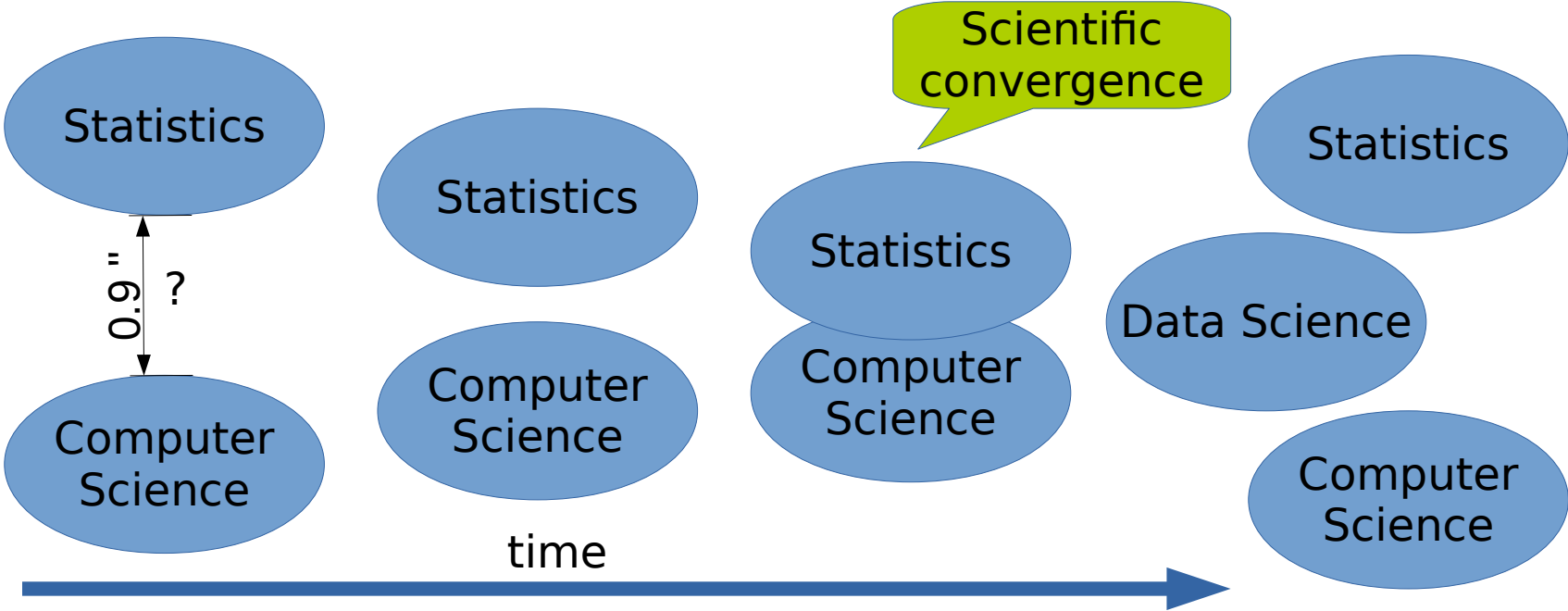
Motivation



Motivation: Research Dynamics



Motivation: Research Dynamics



How to identify scientific convergence?

- Decreasing distance over time
- $\frac{d_{t+1}(a,b)}{d_t(a,b)} < 1$ for t in $[t_{\text{start}}, \dots, t_{\text{end}}]$, distance metric d , arbitrary concepts a, b
- Metric learning in pairwise concept space
- Replace $d(a, b)$ by $d^{\text{euclidean}}(f(a), f(b))$, where f maps concept to vectors
- **This paper:** *We can learn function f from data*

Bibliographic Data

Authors



authorship



Papers with textual features



annotation

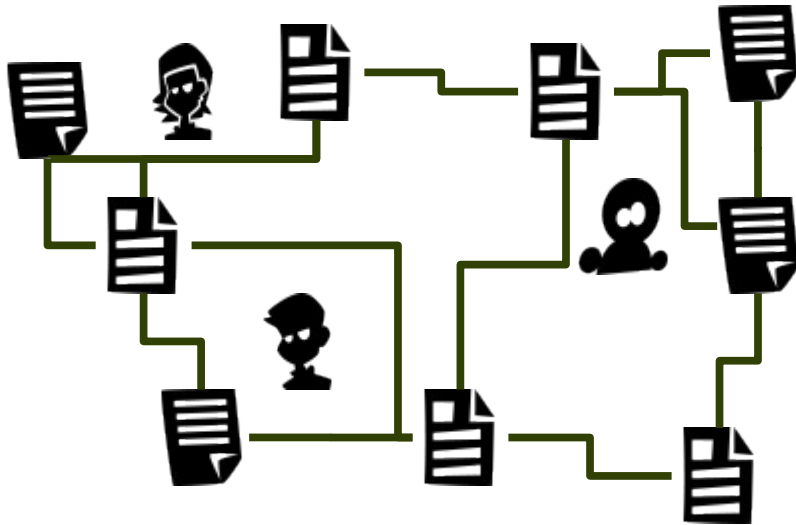


Concepts



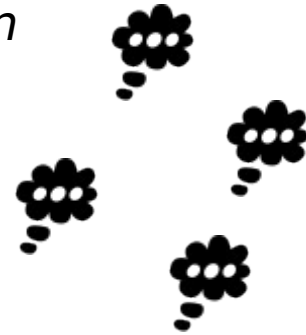
Bibliographic Data

Coauthorship edges between Papers



Concepts

annotation



Problem Statement

Learning Concept Representations

Given:

- a graph (V, E)
- V consists of paper nodes P and concept nodes C
- E consists of co-authorship and annotation edges
- Papers P have textual features (e.g. their title)
- Concepts C have no features

Desired output: *Meaningful* and *useful* vector representations for concepts C

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Induced similarity
corresponds to human judgments

useful for downstream tasks

Transductive vs Inductive Learning

Transductive Learning

- Look-up table for node representations
- Need further training whenever new nodes/edges appear
- Approaches: DeepWalk (Perozzi et al., KDD 2014), node2vec (Grover & Leskovec, SIGKDD 2016), TransE, (Bordes et al., NeurIPS 2013), ... (many more)

Inductive Learning

- Node representations solely induced by node features
- *Capable of dealing with unseen nodes/edges without retraining*
- Approaches: GCN (Kipf & Welling, ICLR 2017), GraphSAGE (Hamilton et al., NeurIPS 2017), ... (many more)

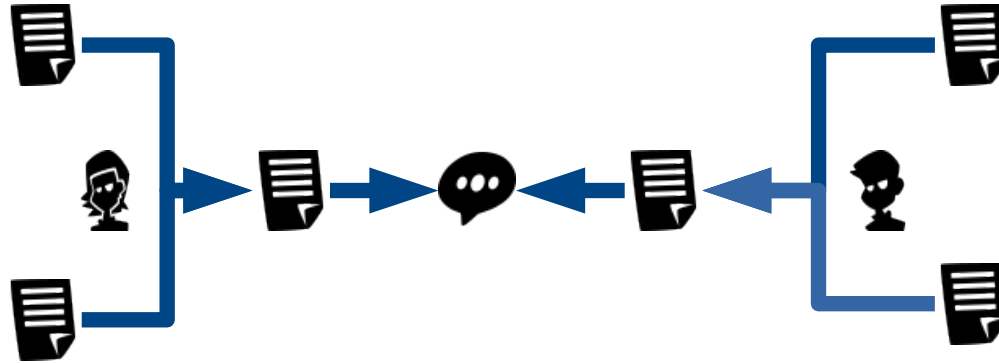
Valuable for dynamic graphs

Graph Convolution (Kipf & Welling 2017)

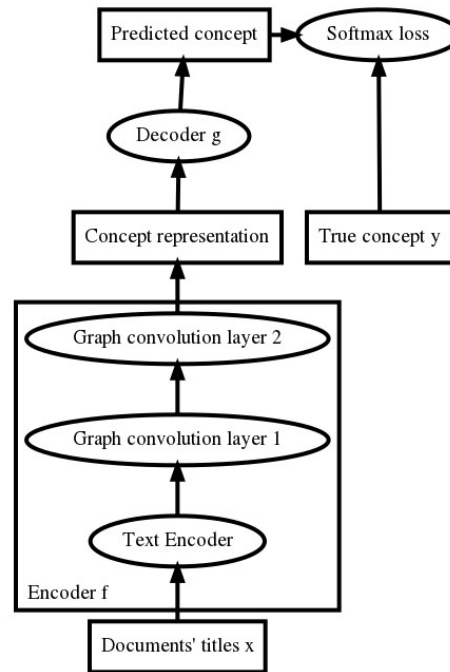
$$h_i^{(l+1)} = \sigma \left(\sum_{j \in \mathcal{N}(i)} \frac{1}{c_{ij}} W^{(l)} h_j^{(l)} + b^{(l)} \right)$$

From layer l to $l+1$

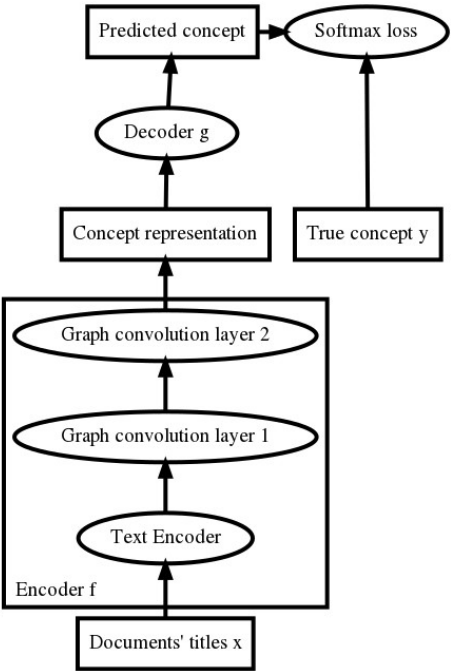
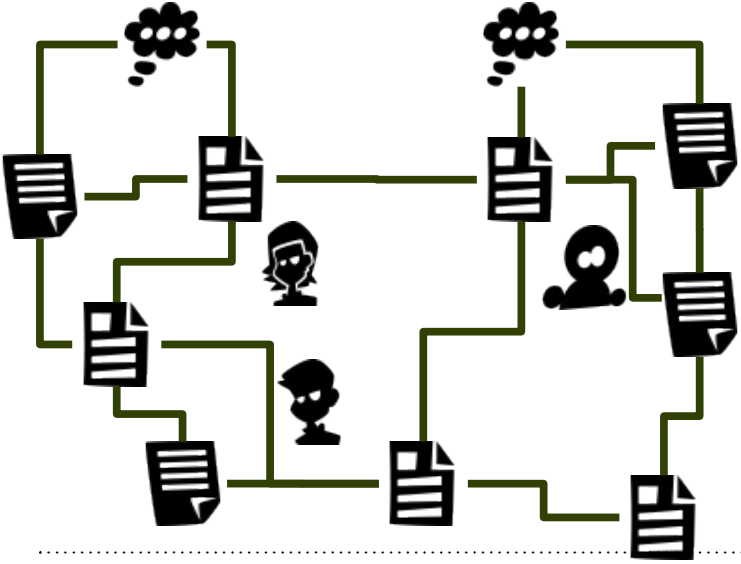
- 1) Transform via parameters W , b
- 2) Aggregate neighbor representations
- 3) Nonlinear activation



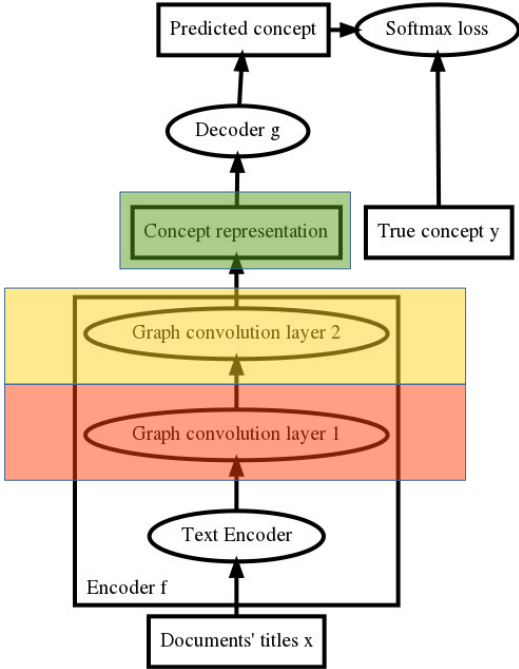
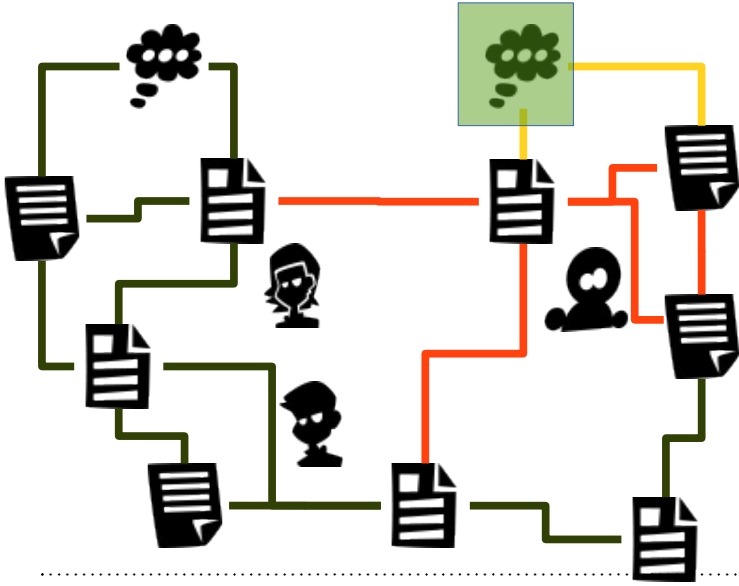
Reconstruction-based Training



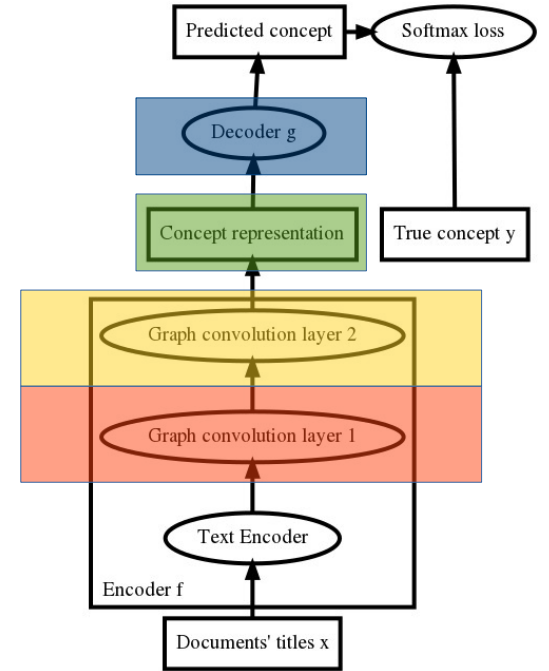
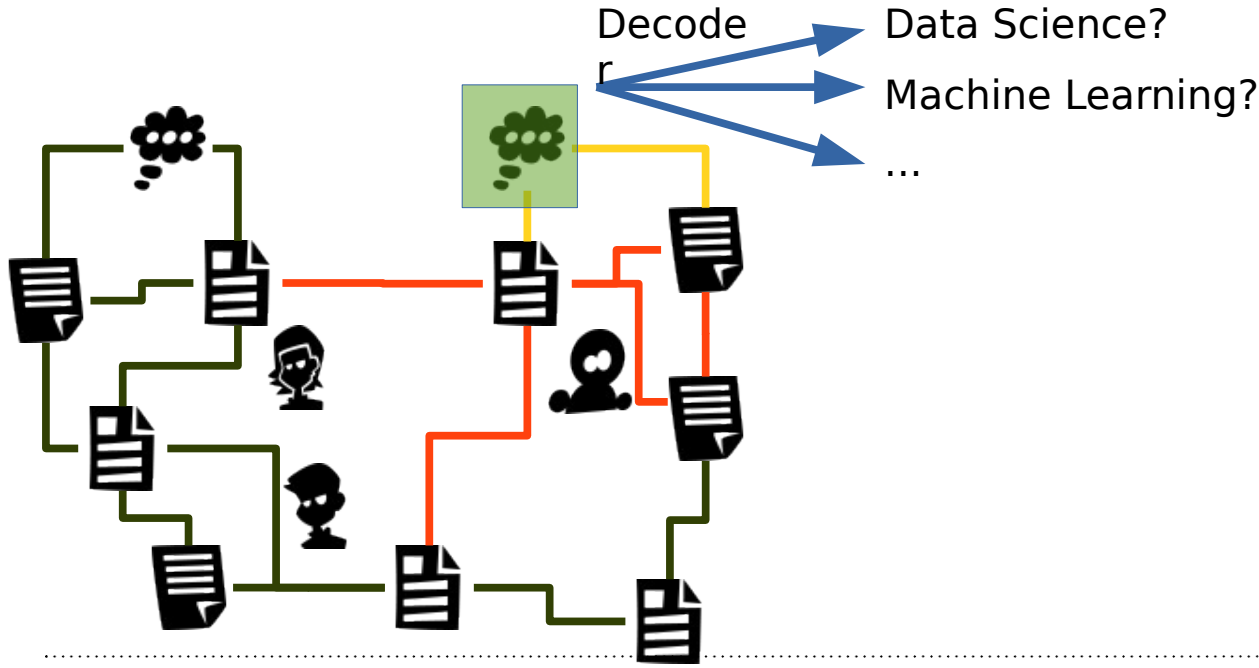
Reconstruction-based Training



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Reconstruction-based Training



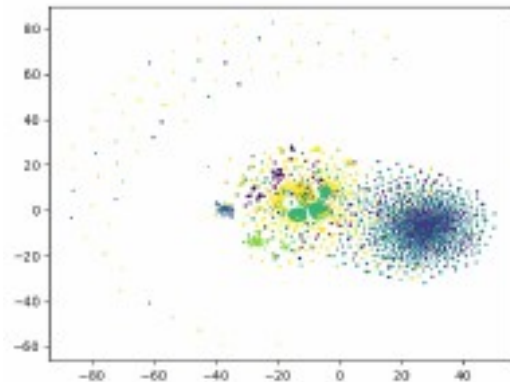
Experiments

- 2.1M English research papers from economics and business economics domain
- 5,688 concepts from Standardthesaurus Wirtschaft (<http://zbw.eu/stw>)
- Quantitative Evaluation
 - Subset of 3,113 concepts, which belong to only one of 7 subthesauri
 - Downstream tasks: clustering and classification
- Qualitative Evaluation:
 - Nearest concept queries
 - Linear operations in latent space

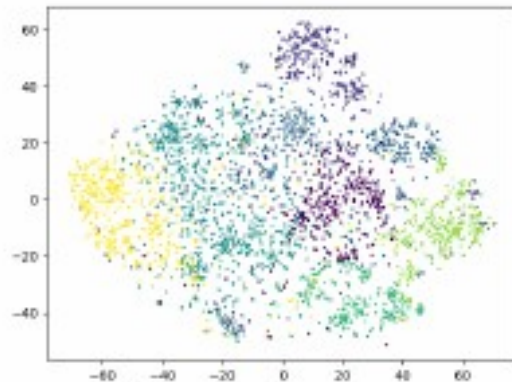
Results: Clustering with k-Means

Model	S	CH	H	C	V	ARI
Random	0.0062	13.83	0.0032	0.0030	0.0031	0.0000
Random (L2)	0.0062	13.92	0.0033	0.0031	0.0032	0.0001
LSA	-0.0207	53.45	0.0030	0.0071	0.0042	-0.0041
LSA (L2)	0.1284	96.44	0.0022	0.0025	0.0023	-0.0009
DeepWalk	0.0194	124.80	0.2165	0.2496	0.2318	0.1852
DeepWalk (L2)	0.0670	131.18	0.2930	0.2810	0.2869	0.1981
GCN	0.0667	171.13	0.1845	0.1761	0.1802	0.1178
GCN (L2)	0.0823	193.64	0.1992	0.1891	0.1940	0.1423

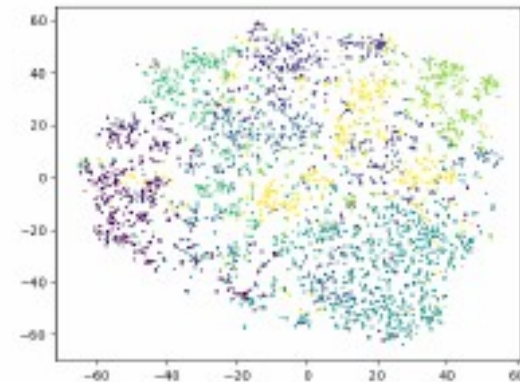
t-SNE Visualization



LSA



DeepWalk



GCN

Results: Classification with linear SVMs

Model	Norm	Accuracy
LSA	None	0.2345 (SD: 0.00)
LSA	Unit L2	0.2181 (SD: 0.02)
DeepWalk	None	0.6625 (SD: 0.04)
DeepWalk	Unit L2	0.6708 (SD: 0.03)
GCN	None	0.6813 (SD: 0.03)
GCN	Unit L2	0.6496 (SD: 0.03)

Nearest Concept Queries 1/4

Query: *Economic growth*

Textual descriptions are never shown to the models

LSA	DeepWalk	GCN
Management information system	Economic adjustment	Stages of growth model
Tobacco	Economic policy	Growth policy
Internet Usage	Growth policy	Resource wealth
Eurobond	Economic development	Kuznets curve
Automobile engine	Economic reform	Export-led growth

Nearest Concept Queries 2/4

Query: *Tax*

LSA	DeepWalk	GCN
Rehabilitation hospital	Fiscal administration	Tax policy
Abortion	Tax system	Tax system
Biodiversity	Tax policy	Tax reform
Financial statement analysis	Sales tax	Taxation procedure
Association agreement	Tax reform	Tax burden

Nearest Concept Queries 3/4

Query: *Germany*

LSA	DeepWalk	GCN
Debt crisis	Italy	East Germany
Mesoeconomics	France	Austria
Population policy	Comparison	West Germany
Complaint management	Netherlands	Lower Saxony
Unemployment theory	Austria	Western Europe

Nearest Concept Queries 4/4

Query: *Vehicle*

LSA	DeepWalk	GCN
Pigouvian tax	Transport research	Sustainable mobility
Cargo shipping	Transport economics	Passenger transport
Cyclical unemployment	Waste treatment	Freight transport
Wage subsidy	Battery	Major electrical appliances
Financial Statement analysis	Microsystems	Traffic

Linear relationship queries 1/2

Query: *Tax + Theory*

LSA	DeepWalk	GCN
Tax Theory	Tax Theory of taxation	Theory of taxation Theory
Financial statement analysis	Tax system	Second best
Nursing profession	Capital income	Optimal taxation
Rehabilitation hospital	Public economics	Welfare economics

Linear relationship queries 2/2

Query: *Economic growth + Theory*

LSA	DeepWalk	GCN
Economic growth	Economic growth	Growth theory
Banking services	Growth theory	Neoclassical growth model
Producer cooperative	Economic model	Unbalanced growth
Licence	Theory	Balanced growth
Laboratory	Endogenous growth model	Functional income distribution

Conclusion & Limitations

- DeepWalk works well despite using only structural features (confirms orig. paper)
- GCNs can be used for **inductive** representation learning
- Learned GCN representations are comparably meaningful & useful as DeepWalk's
- **Limitations:**
 - No ground truth for pairwise concept similarity
 - Only one dataset, but large-scale!

Next steps

- Add more structure (concept hierarchy, journals, institutions, ...)
- Use publication years for truly dynamic research analyses
- Create a ground truth for pairwise concept similarity



GitHub: lgalke/INFORMATIK2019-concept-representation-learning



Twitter: _lpag



E-mail: l.galke@zbw.eu

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