Dynamics On and Of Complex Networks 2020

Recent advances in document network embedding @ERIC

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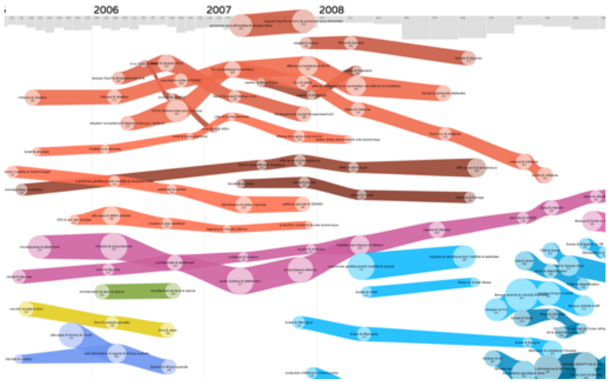
Context

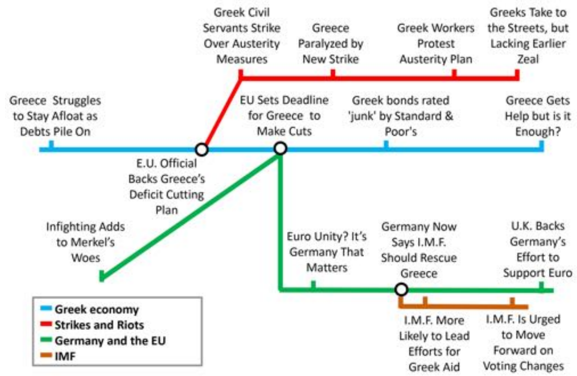
Informational landscape



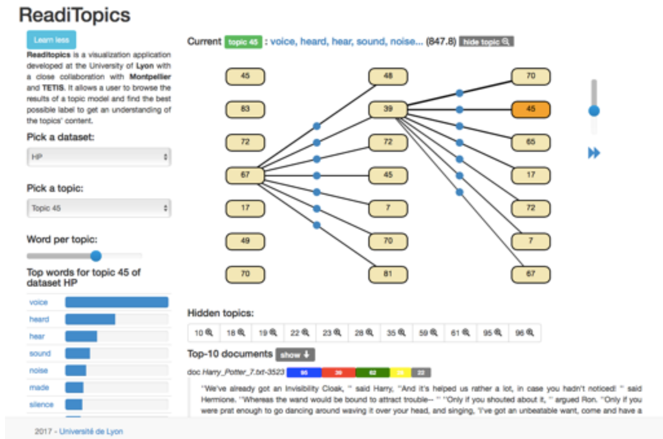
Projet Pulseweb
(Cointet, Chavalarias…)

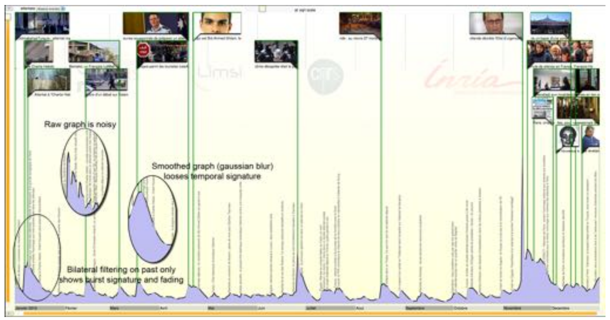
http://pulseweb.cortext.net

Metromaps
(Shahaf et al., 2015)



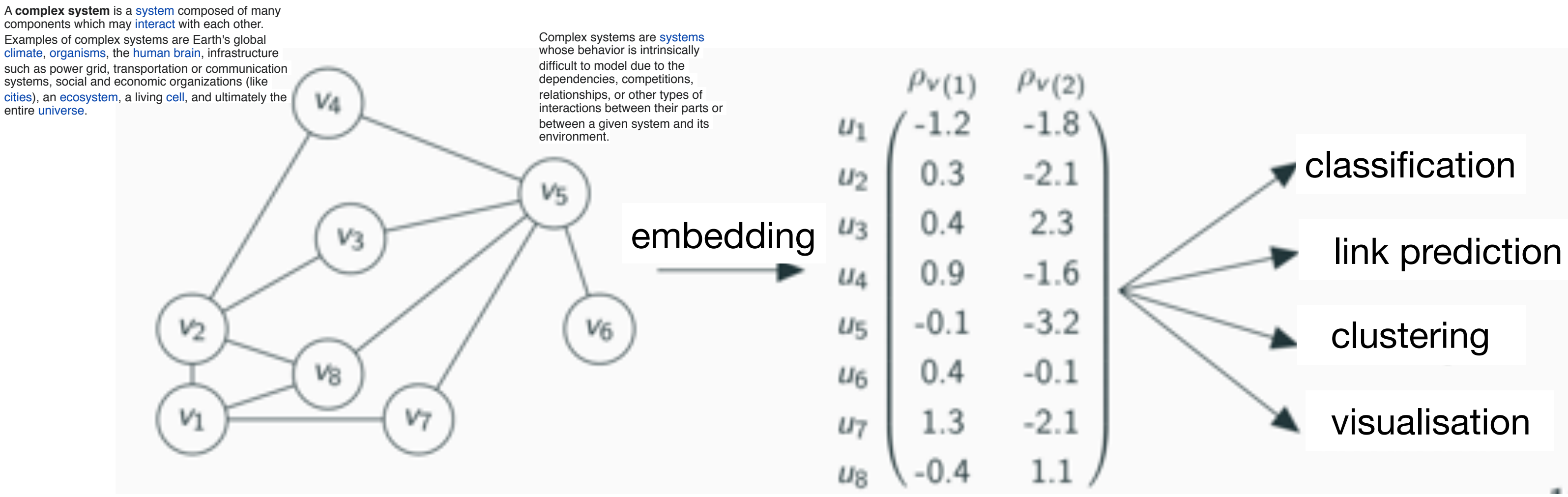
Readitopics
(Velcin et al., 2018)





Chronolines
(Nguyen et al., 2014)

Document network embedding



- **Document network**: “graph of vertices, where each vertex is associated with a text document” (Tuan et al., 2014)
  e.g.: scientific articles, newspapers, social media…

- Embedding for building a **joint** space for solving downstream tasks (e.g., link prediction, node classification, community detection)

Quick survey

- **Graph/Node embedding**
  - Laplacian Eigenmaps (Belkin and Niyogi, 2002)
  - DeepWalk (Perozzi et al., 2014), Node2vec (Grover and Leskovec, 2016)
  - Graph Neural Networks (Scarselli et al., 2009)
- **Document network embedding**
  - TADW (Yang et al., 2015)
  - Attention models and CANE (Tu et al., 2017)

Collaborators of the DMD team

Robin Brochier
Phd student
(now graduated!)

Antoine Gourru
Phd student

Adrien Guille
Associate
Professor

Julien Jacques
Professor

Contributions

Regularized Linear Embedding (RLE)

Gourru A., J. Velcin, J. Jacques and A. Guille
Document Network Projection in Pretrained Word Embedding Space. **ECIR** 2020.

Given:

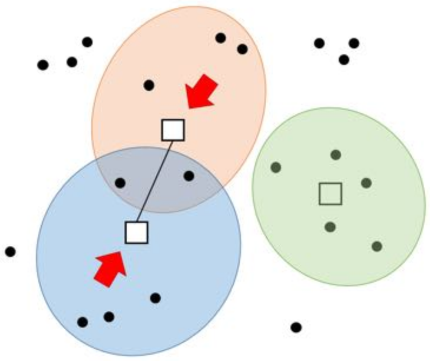
- $U \in \mathbb{R}^{v \times k}$ matrix of pretrained word embeddings
- $T \in \mathbb{R}^{n \times v}$ Document x Word matrix (*textual information*)
- $A \in \mathbb{R}^{[0,1] \times [0,1]}$ the transition matrix (*graph information*)

- **Goal:** learn the weights $p_i \in \mathbb{R}^{v}$ for the words composing d_i

$$d_i = p_i U$$

parameter to learn

The vector for d_i is just a weighted sum over pretrained WE



RLE (con't)

$$P = (1 - \lambda)T + \lambda B$$

with $\lambda \in [0,1]$ a tradeoff b/w textual and structural information

$$b_i = \frac{1}{\sum_j S_{i,j}} \sum_j S_{i,j} t_j$$

with $S \in \mathbb{R}^{n \times n}$ a squared matrix that reflects the pairwise similarity between nodes in the graph

(here, we use $S = \frac{A + A^2}{2}$)

Evaluation

Datasets:

- Cora (2,211 docs; 7 labels=topic; 5,001 citation links)
- DBLP (60,744 docs; 4 labels=topic; 52,914 links)
- New York Times (5,135 docs; 4 labels=article section; 3,050,513 links=common tag)

https://github.com/AntoineGourru/DNEmbedding

- **Task 1:** node classification
- **Task 2:** link prediction

Table 1. Comparison of Micro-F1 results on a classification task for different train/test ratios. The best score is in bold, second best is underlined. Execution time order is presented in seconds (Time).

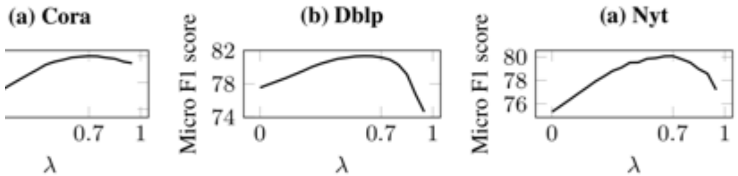
	Cora				Dblp			
train/test ratio	10%	30%	50%	Time	10%	30%	50%	Time
DeepWalk	70.6 (2.0)	77.2 (0.9)	81.0 (0.7)	10^1	52.3 (0.4)	53.4 (0.1)	53.5 (0.2)	10^2
LSA	72.3 (1.9)	79.0 (0.7)	80.6 (0.7)	10^{-2}	73.5 (0.2)	74.1 (0.1)	74.2 (0.2)	10^1
Concatenation	71.4 (2.1)	80.5 (1.0)	84.0 (1.1)	10^1	77.5 (0.2)	78.0 (0.1)	78.2 (0.2)	10^2
TADW	81.9 (0.8)	86.3 (0.8)	87.4 (0.8)	10^{-1}	74.8 (0.1)	75.3 (0.2)	75.5 (0.1)	10^1
AANE	79.8 (0.9)	83.3 (1.1)	84.4 (0.7)	10^{-1}	73.3 (0.1)	73.9 (0.1)	74.2 (0.2)	10^2
GVNR-t	83.7 (1.2)	86.4 (0.7)	87.0 (0.8)	10^1	69.6 (0.1)	70.1 (0.1)	70.2 (0.2)	10^2
VGAE	72.3 (1.7)	79.2 (0.9)	81.1 (0.7)	10^1	Memory overflow			–
G2G	79.0 (1.5)	83.7 (0.8)	84.8 (0.7)	10^1	70.8 (0.1)	71.3 (0.2)	71.5 (0.2)	10^2
STNE	79.4 (1.0)	84.7 (0.7)	86.7 (0.8)	10^2	73.8 (0.2)	74.4 (0.1)	74.5 (0.1)	10^4
RLE	**84.0** (1.3)	**86.9** (0.5)	**87.7** (0.6)	10^1	**79.8** (0.2)	**80.9** (0.2)	**81.2** (0.1)	10^1

	Nyt			
train/test ratio	10%	30%	50%	Time
DeepWalk	66.9 (0.7)	68.2 (0.3)	68.7 (0.9)	10^2
LSA	71.6 (1.0)	75.7 (0.7)	76.7 (0.7)	10^{-2}
Concatenation	**77.9** (0.3)	**80.0** (0.5)	**81.1** (0.7)	10^2
TADW	75.8 (0.5)	78.4 (0.5)	79.4 (0.4)	10^1
AANE	71.7 (0.5)	75.6 (0.8)	76.9 (1.1)	10^1
GVNR-t	74.3 (0.4)	76.0 (0.6)	76.7 (0.6)	10^2
VGAE	68.1 (0.8)	69.3 (0.9)	70.1 (0.6)	10^2
G2G	69.0 (0.5)	70.5 (0.7)	71.5 (0.8)	10^2
STNE	75.1 (0.7)	77.3 (0.5)	78.1 (0.6)	10^2
RLE	77.7 (0.7)	79.3 (0.5)	80.0 (0.6)	10^1

Table 2. Comparison of AUC results on a link prediction task for different perce hidden. The best score is in bold, second best is underlined.

	Cora		Dblp	
% edges hidden	50%	25%	50%	25%
DeepWalk	73.2 (0.6)	80.9 (1.0)	**89.7** (0.0)	**93.2** (0.2)
LSA	87.4 (0.6)	87.2 (0.8)	54.2 (0.1)	54.8 (0.0)
Concatenation	77.9 (0.3)	83.7 (0.8)	88.8 (0.0)	92.6 (0.3)
TADW	90.1 (0.4)	93.3 (0.4)	61.2 (0.1)	65.0 (0.5)
AANE	83.1 (0.8)	86.6 (0.8)	67.4 (0.1)	66.5 (0.1)
GVNR-t	83.9 (0.9)	91.5 (1.1)	88.1 (0.3)	91.4 (0.1)
VGAE	87.1 (0.4)	88.2 (0.7)	Does not scale	
Graph2Gauss	92.0 (0.3)	93.8 (1.0)	88.0 (0.1)	92.1 (0.5)
STNE	83.1 (0.5)	90.0 (1.0)	45.6 (0.0)	53.4 (0.1)
RLE	**94.3** (0.2)	**94.8** (0.2)	89.3 (0.1)	91.2 (0.2)

sensitivity to λ

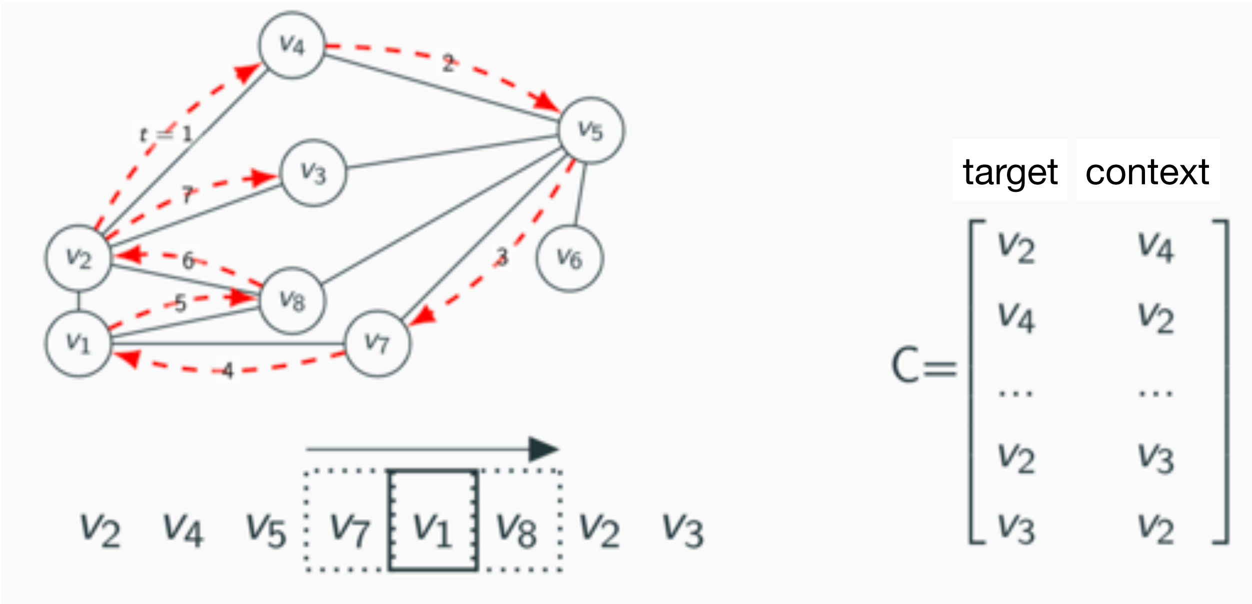


of λ on RLE in terms of document classification for $d = 160$. Optimum is achieved each dataset (Cora, Nyt: 0.7, Dblp: 0.65).

GVNR and GVNR-t

Brochier, A., Guille and J. Velcin. Global Vectors for Node Representation. The Web Conference (**WWW**) 2019.

- Quick reminder of DeepWalk (Perozzi et al., 2014):
  - goal: learn vector representation of nodes
  - approach: a) make multiple random walks
    b) paths views as documents
    c) use Skip-Gram to build vectors (Mikolov et al., 2013)



GVNR and GVNR-t

Brochier, A., Guille and J. Velcin. Global Vectors for Node Representation.
The Web Conference (**WWW**) 2019.

- Following GloVe (Pennington et al., 2014, GVNR solves **regression** task on the weighted cooccurrence matrix X where cells with small values are set to 0 (> threshold x_{min})

- We're looking for (U, b^U) and (V, b^V) s.t.:

$$\arg \min_{U,V,b^U,b^V} \sum_{i}^{n} \sum_{j}^{n} s(x_{ij})(u_i \, . \, v_j + b_i^U + b_j^V - log(1 + x_{ij}))^2$$

with $s(x_{ij}) = 1$ if $x_{ij} > 0$ and $m_i \sim B(\alpha)$ else

where α is chosen s.t. $m = k$ in average

$$X = \begin{pmatrix} 0 & 4 & 8 & 0 & 0 & 0 \\ 4 & 0 & 0 & 3 & 0 & 0 \\ 8 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 6 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 6 & 1 & 0 \end{pmatrix}$$

cooccurrence b/w x_i and x_j

- GVNR-t integrates textual information by modifying v_j:

$$\arg \min_{\mathrm{U,W}\,,b^U,b^V} \sum_{i}^{n} \sum_{j}^{n} s(x_{ij})(u_i \, . \, \boxed{\frac{\delta_j \, . \, W}{|\delta_j|_1}} + b_i^U + b_j^V - log(c + x_{ij}))^2$$

Results for GVNR-t

- Classification on two citation networks (Cora with 2,708 nodes and Citeseer with 3,312 nodes)
- Keyword recommendation on DBLP (1,397,240 documents and 3,021,489 citation relationships)

Table 8: Accuracy on the citation (1) network, considering the text features.

	% of training data				
	10%	20%	30%	40%	50%
LSA	54.7	61.0	62.4	63.0	62.8
DeepWalk+LSA	73.8	77.9	78.4	78.1	78.1
TADW	77.1	78.8	78.2	78.8	78.6
GVNR-t	**79.3**	**80.7**	**80.8**	**81.4**	**81.1**

Table 9: Accuracy on the citation (2) network, considering the text features.

	% of training data				
	10%	20%	30%	40%	50%
LSA	52.0	54.7	54.7	58.4	65.7
DeepWalk+LSA	58.3	60.7	61.1	60.0	61.2
TADW	60.6	60.1	60.1	66.2	69.3
GVNR-t	**63.3**	**62.5**	**64.9**	**68.6**	**70.4**

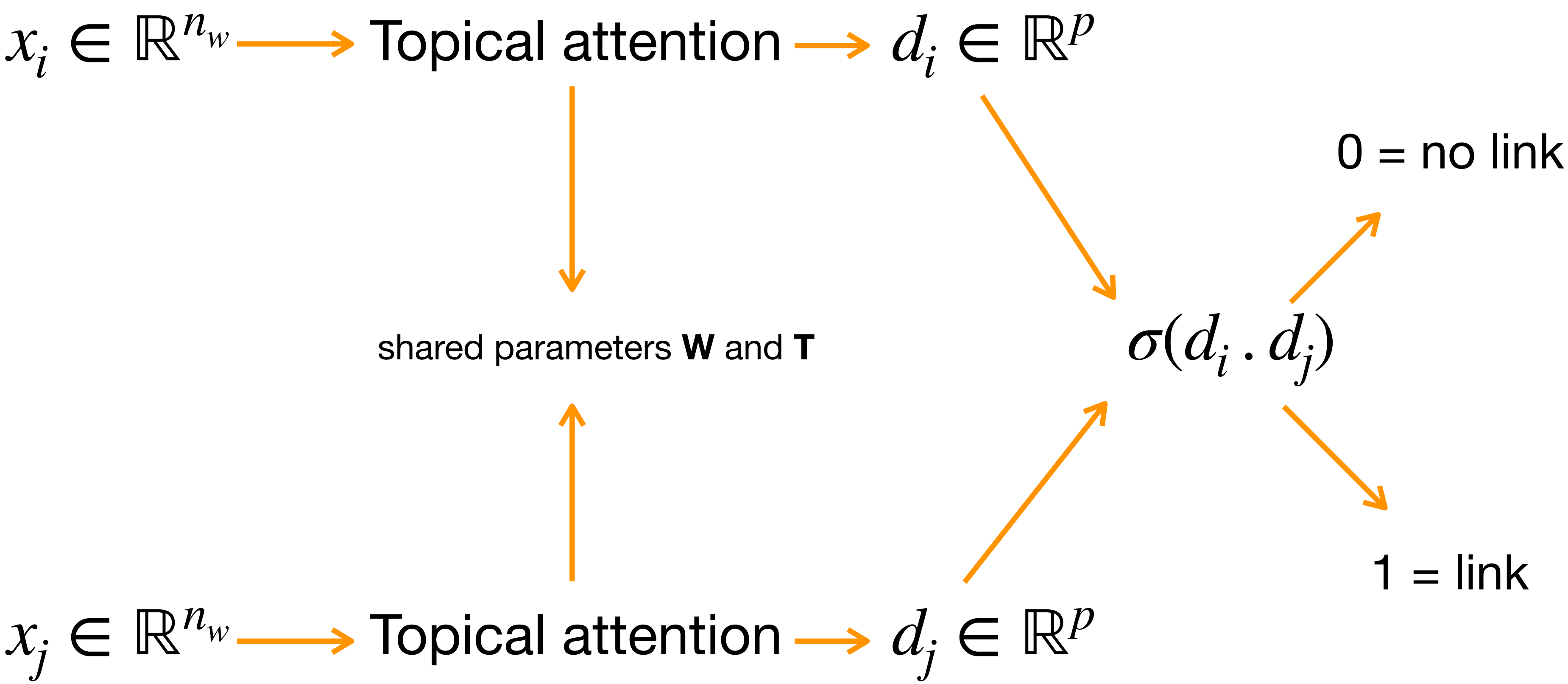
Table 10: Keyword recommendation by selecting the closest word embeddings w_k to both embeddings u (node) and v (content) of an input document (1).

Document	**A brief survey of computational approaches in social computing** Web 2.0 technologies have brought new ways of connecting people in social networks for collaboration in various on-line communities. Social Computing is a novel and emerging computing paradigm...
Closest words to u (node)	*cold start problem, storylines, document titles, movielens data, computational humor*
Closest words to v (content)	*social, social network, enron email corpus, social networks, extremely large datasets, sites blogs*

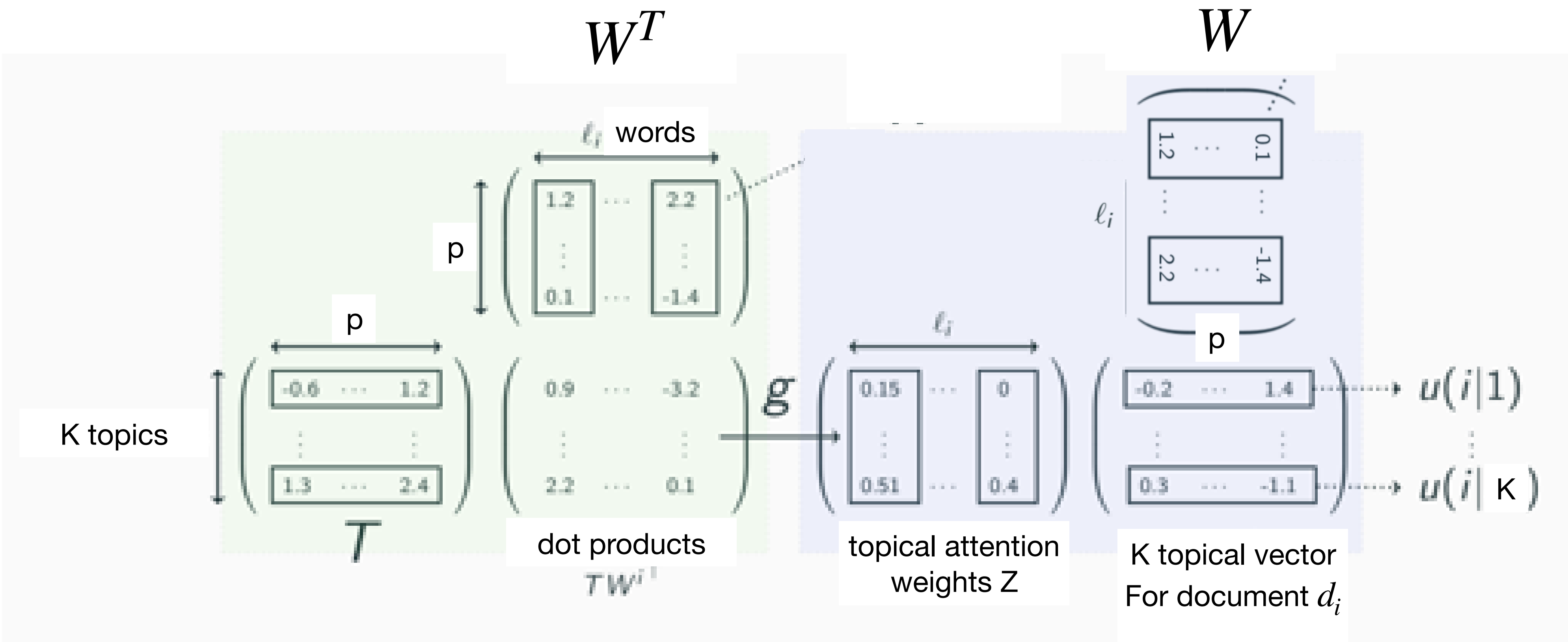
https://github.com/brochier/gvnr

Inductive Document Network Embedding (IDNE)

Brochier R., A. Guille and J. Velcin.
Inductive Document Network Embedding with Topic-Word Attention. **ECIR** 2020 (virtual).



Topical attention



Document representation d_i is the normalized sum over the K topics: $\sum_{k=1}^{K} \frac{u(i\,|\,k)}{|x_i|_1}$

Learning IDNE

Minimize

$L(W, T) = \sum_{i=1}^{n_d} \sum_{j=1}^{n_d} s_{ij} \log \sigma(u_i \,.\, u_j) + (1 - s_{ij}) \log \sigma(-u_i \,.\, u_j)$

so that:

- S is a binary similarity matrix based on A, for instance: $s_{ij} = 1$ if $(A + A^2)_{ij} > 0$ else $s_{ij} = 0$

Results of IDNE on Cora

	TC										IC		TP	IP
	F1					AUC					F1	AUC	AUC	AUC
	10%	20%	30%	40%	50%	10%	20%	30%	40%	50%	90%	90%	50%	90%
Aléatoire	13.85	13.70	12.66	12.83	12.53	51.51	51.96	51.60	51.22	51.22	11.80	48.84	49.87	50.27
TF	68.84	74.69	77.20	78.90	80.05	92.13	94.63	95.64	96.06	96.55	81.98	97.16	83.44	84.88
TF-IDF	72.56	76.99	80.13	80.66	81.84	93.11	95.24	96.38	96.74	97.20	**83.24**	**97.59**	85.17	85.02
LSA	72.46	77.22	79.92	80.56	81.16	93.65	95.47	96.63	96.95	97.17	81.26	97.35	87.17	88.63
DW+LSA	77.52	80.70	83.40	83.12	85.21	95.31	96.47	97.24	97.23	97.79	-	-	82.67	-
TADW	61.77	67.02	70.84	71.62	73.13	89.01	91.25	93.22	93.37	94.20	79.55	96.35	81.59	84.71
G2G	79.38	82.19	83.57	84.08	85.03	96.14	97.39	97.65	97.89	98.13	71.98	94.57	86.36	74.72
MATAN	75.48	76.65	77.58	79.20	78.30	95.19	95.79	96.23	96.41	96.69	76.13	94.91	82.72	71.47
GVNR-t	**82.20**	83.49	**85.26**	**85.82**	**86.67**	97.10	97.53	98.00	98.08	**98.48**	79.91	97.21	**94.31**	**92.44**
IDNE	80.41	**83.83**	84.79	84.67	86.06	**97.27**	**97.79**	**98.28**	**98.23**	98.45	82.25	97.57	92.90	88.56

T for Transductive
I for Inductive

C = classification
P = link prediction

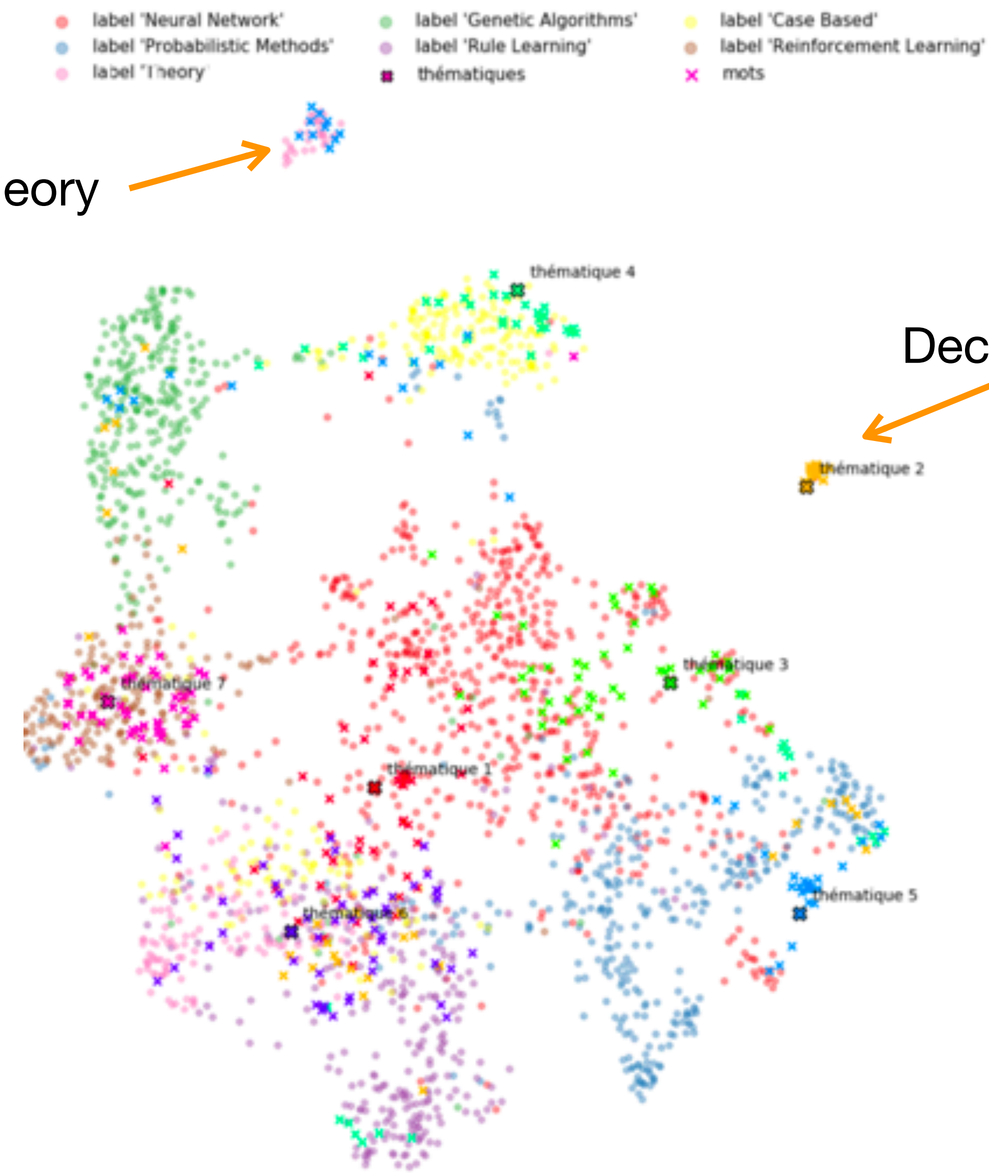
Observations

Thématique	Mots les plus proches
1	pattern, features, classification, regulate, machine, limitations, domains, datasets, methods, patterndirected, dataset, connectionist, backpropagation, pythia, accuracy, classifier, realworld, exemplar, symbolic, links
2	tree, decision, selection, trees, markov, radar, subsurface, moisture, cband, ers, cedar, sar, lband, polarized, minnesota, lter, ersjers, creek, raco, seasonality
3	saturation, separation, stabilization, gradient, blind, asymptotic, universal, matrix, square, signals, necessarily, sign, projection, approximated, bandpass, descent, norm, cubic, subproblems, speakers
4	design, casebased, pac, sme, analogical, mcmc, structuremapping, planning, wellunderstood, retrieval, reasoning, mistakes, case, reuse, retrieving, instance, chain, analogy, convolution, solving
5	mcmc, execution, speculation, ga, parallelism, genetic, instruction, aimed, dirichlet, instructions, chain, consensus, substantive, sequences, macroscopic, issue, processor, recipient, analogy, nerve
6	accuracy, learning, experiments, machine, ilp, datasets, comprehensibility, sufficed, sbc, inductive, accurate, decompose, warehouses, mining, induction, dataset, gratefully, attribute, assign, challenges
7	reinforcement, mdp, mdps, qlearning, policy, crosses, actions, value, reward, policies, brigade, rl, macros, relax, hinders, dynamic, satisficingoptimizing, action, functionings, barto

Observations (con’t)

MCMC + theory

Decision trees



Conclusion and future works

Conclusion

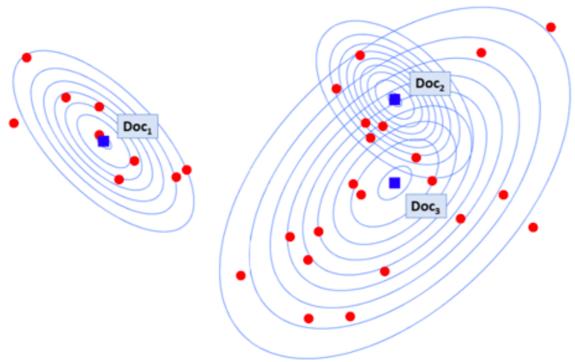
- Several contributions on the embedding of documents augmented with network information:
  RLE, **GVNR-t**, MATAN, **IDNE**, GELD

- Use of “absolute” WE leads to good results. Can they be improved using **contextualized WE** (Devlin et al., 2018)

- Recent advances in **GNN** should be considered in the future, e.g. GAT (Velikcovik et al., 2018)

Future works

- Integrating **uncertainty** in the modelling (Gourru et al., 2020)



- Moving to author embedding (Ganesh et al., 2016) and modeling **dynamics** following (Balmer et al., 2017)

- Information diffusion in information networks (work in progress with G. Poux and S. Loudcher)

References

- Brochier R., A. Guille and J. Velcin. Inductive Document Network Embedding with Topic-Word Attention. **ECIR** 2020 (virtual).
- Brochier R., A. Guille and J. Velcin. Link Prediction with Mutual Attention for Text-Attributed Networks. **Workshop on Deep Learning for Graphs and Structured Data Embedding**, colocated with WWW (Companion Volume), May 13–17, 2019, San Francisco, CA, USA.
- Brochier R., A. Guille and J. Velcin. Global Vectors for Node Representation. The Web Conference (**WWW**), May 13–17, 2019, San Francisco, CA, USA.
- Gourru A., J. Velcin, J. Jacques and A. Guille Document Network Projection in Pretrained Word Embedding Space. **ECIR** 2020 (virtual).
- Gourru A., J. Velcin and J. Jacques. Gaussian Embedding of Linked Documents from a Pretrained Semantic Space. **IJCAI** 2020.

➡ Code for GVNR and GVNR-t: https://github.com/brochier/gvnr

➡ Code for IDNE: https://github.com/brochier/idne

➡ Code for RLE and GELD: https://github.com/AntoineGourru/DNEmbedding