Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Alexander Panchenko

FROM UNSUPERVISED INDUCTION OF LINGUISTIC STRUCTURES FROM TEXT TOWARDS APPLICATIONS IN DEEP LEARNING

Graph embeddings

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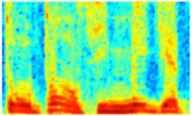
Text: sparse symbolic representation

AUDIO



Audio Spectrogram

DENSE

IMAGES

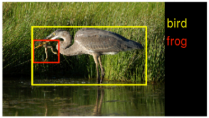


Image pixels

DENSE

TEXT

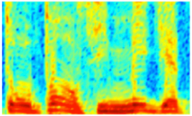
0	0	0	0.2	0	0.7	0	0	0	...	...

Word, context, or document vectors

SPARSE

Text: sparse symbolic representation

AUDIO



Audio Spectrogram

DENSE

IMAGES

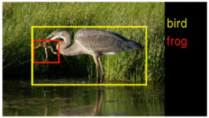
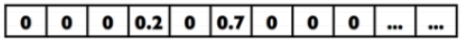


Image pixels

DENSE

TEXT



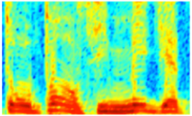
Word, context, or document vectors

SPARSE

Image source:
`https://www.tensorflow.org/tutorials/word2vec`

Graph: sparse symbolic representation

AUDIO



Audio Spectrogram

DENSE

IMAGES

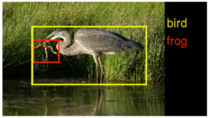
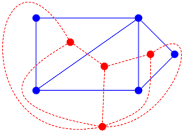


Image pixels

DENSE

GRAPH

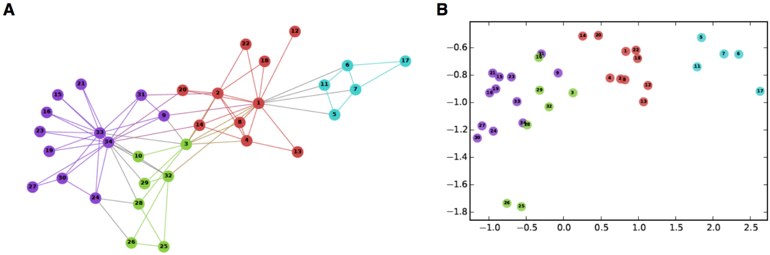


Nodes, edges, weights

SPARSE

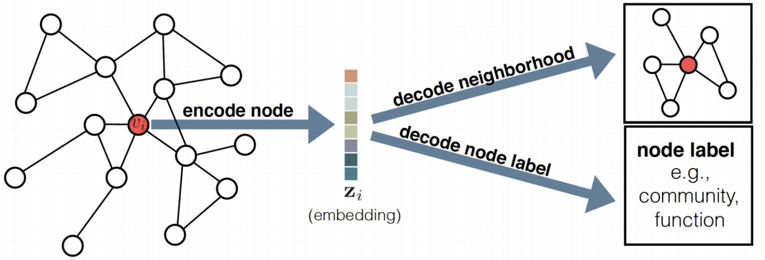
Embedding graph into a vector space

From a **survey on graph embeddings** [Hamilton et al., 2017]:



Learning with an “autoencoder”

From a **survey on graph embeddings** [Hamilton et al., 2017]:



Some established approaches

From a **survey on graph embeddings** [Hamilton et al., 2017]:

Type	Method	Decoder	Similarity measure	Loss function (ℓ)
Matrix factorization	Laplacian Eigenmaps [4]	$\|\mathbf{z}_i - \mathbf{z}_j\|_2^2$	general	$\mathrm{DEC}(\mathbf{z}_i, \mathbf{z}_j) \cdot s_{\mathcal{G}}(v_i, v_j)$
	Graph Factorization [1]	$\mathbf{z}_i^\top \mathbf{z}_j$	$\mathbf{A}_{i,j}$	$\|\mathrm{DEC}(\mathbf{z}_i, \mathbf{z}_j) - s_{\mathcal{G}}(v_i, v_j)\|_2^2$
	GraRep [9]	$\mathbf{z}_i^\top \mathbf{z}_j$	$\mathbf{A}_{i,j}, \mathbf{A}_{i,j}^2, ..., \mathbf{A}_{i,j}^k$	$\|\mathrm{DEC}(\mathbf{z}_i, \mathbf{z}_j) - s_{\mathcal{G}}(v_i, v_j)\|_2^2$
	HOPE [45]	$\mathbf{z}_i^\top \mathbf{z}_j$	general	$\|\mathrm{DEC}(\mathbf{z}_i, \mathbf{z}_j) - s_{\mathcal{G}}(v_i, v_j)\|_2^2$
Random walk	DeepWalk [47]	$\frac{e^{\mathbf{z}_i^\top \mathbf{z}_j}}{\sum_{k \in \mathcal{V}} e^{\mathbf{z}_i^\top \mathbf{z}_k}}$	$p_{\mathcal{G}}(v_j \mid v_i)$	$-s_{\mathcal{G}}(v_i, v_j) \log(\mathrm{DEC}(\mathbf{z}_i, \mathbf{z}_j))$
	node2vec [28]	$\frac{e^{\mathbf{z}_i^\top \mathbf{z}_j}}{\sum_{k \in \mathcal{V}} e^{\mathbf{z}_i^\top \mathbf{z}_k}}$	$p_{\mathcal{G}}(v_j \mid v_i)$ (biased)	$-s_{\mathcal{G}}(v_i, v_j) \log(\mathrm{DEC}(\mathbf{z}_i, \mathbf{z}_j))$

Hamilton, W. L., Ying, R., & Leskovec, J. (2017).
Representation learning on graphs: Methods and applications.
arXiv preprint arXiv:1709.05584.