Universität Hamburg
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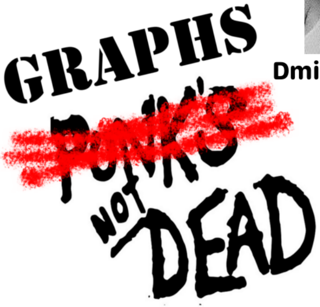
Alexander Panchenko

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

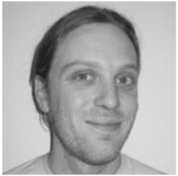
In close collaboration with ...

Chris Biemann



Dmitry 'Tsar' Ustalov

Stefano Faralli



Simone P. Ponzetto

In collaboration with ...

- **Andrei Kutuzov**
- **Eugen Ruppert**
- **Fide Marten**
- **Nikolay Arefyev**
- **Steffen Remus**
- **Martin Riedl**
- **Hubert Naets**
- **Maria Pelevina**

Overview

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- **Inducing word sense representations**:
  - **word sense embeddings via retrofitting** [Pelevina et al., 2016, Remus & Biemann, 2018];
  - **inducing synsets** [Ustalov et al., 2017b, Ustalov et al., 2017a, Ustalov et al., 2018b]
  - **inducing semantic classes** [Panchenko et al., 2018]

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  - **inducing semantic classes** [Panchenko et al., 2018]
- **Making induced senses interpretable** [Panchenko et al., 2017b, Panchenko et al., 2017c]

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  - **inducing semantic classes** [Panchenko et al., 2018]
- **Making induced senses interpretable** [Panchenko et al., 2017b, Panchenko et al., 2017c]
- **Linking induced word senses to lexical resources** [Panchenko, 2016, Faralli et al., 2016, Panchenko et al., 2017a, Biemann et al., 2018]

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- **Inducing semantic frames** [Ustalov et al., 2018a]
  - Inducing **FrameNet**-like structures;
  - ...using **multi-way clustering**.

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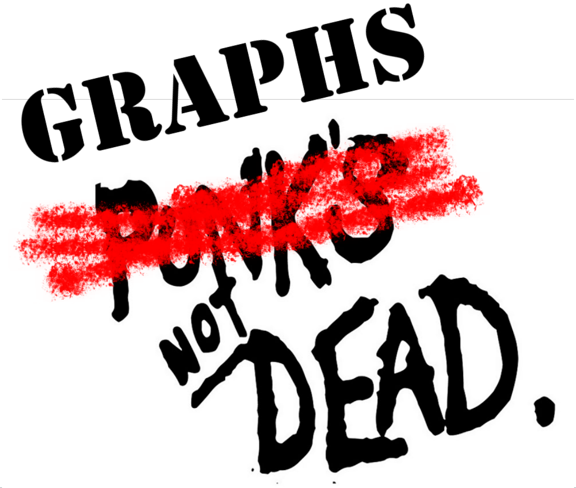
- **Inducing semantic frames** [Ustalov et al., 2018a]
  - Inducing **FrameNet**-like structures;
  - ...using **multi-way clustering**.
- **Learning graph/network embeddings** [ongoing joint work with Andrei Kutuzov]
  - How to **represent induced networks/graphs**?
  - ... so that they can be used in **deep learning architectures**.
  - ...**effectively** and **efficiently**.

Conclusion

Vectors + Graphs = ♡



Take home messages

- We can **induce word senses**, **synsets** and **semantic classes** in a knowledge-free way using **graph clustering** and **distributional models**.

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Take home messages

- We can **induce word senses**, **synsets** and **semantic classes** in a knowledge-free way using **graph clustering** and **distributional models**.
- We can make the **induced word senses interpretable** in a knowledge-free way with **hypernyms**, **images**, **definitions**.
- We can **link induced senses to lexical resources** to
  - improve **performance of WSD**;
  - **enrich lexical resources** with emerging senses.

A shared task on WSI

- An **ACL SIGSLAV** sponsored shared task on **word sense induction** (WSI) for the Russian language.
- **More details**: `http://russe.nlpub.org/2018/wsi`





Acknowledgments

Thank you! Questions?

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Sense embeddings using retrofitting

Evaluation on SemEval 2013 Task 13 WSI&D:

Model	**Jacc.**	**Tau**	**WNDCG**	**F.NMI**	**F.B-Cubed**
AI-KU (add1000)	0.176	0.609	0.205	0.033	0.317
AI-KU	0.176	0.619	0.393	0.066	0.382
AI-KU (remove5-add1000)	0.228	0.654	0.330	0.040	0.463
Unimelb (5p)	0.198	0.623	0.374	0.056	0.475
Unimelb (50k)	0.198	0.633	0.384	0.060	0.494
UoS (#WN senses)	0.171	0.600	0.298	0.046	0.186
UoS (top-3)	0.220	0.637	0.370	0.044	0.451
La Sapienza (1)	0.131	0.544	0.332	–	–
La Sapienza (2)	0.131	0.535	0.394	–	–
AdaGram, α = 0.05, 100 dim	0.274	0.644	0.318	0.058	0.470
w2v	0.197	0.615	0.291	0.011	0.615
w2v (nouns)	0.179	0.626	0.304	0.011	0.623
JBT	0.205	0.624	0.291	0.017	0.598
JBT (nouns)	0.198	0.643	0.310	0.031	0.595
TWSI (nouns)	0.215	0.651	0.318	0.030	0.573

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