Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Alexander Panchenko

INDUCING INTERPRETABLE WORD SENSES FOR WSD AND ENRICHMENT OF LEXICAL RESOURCES

Overview

Overview

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

Overview

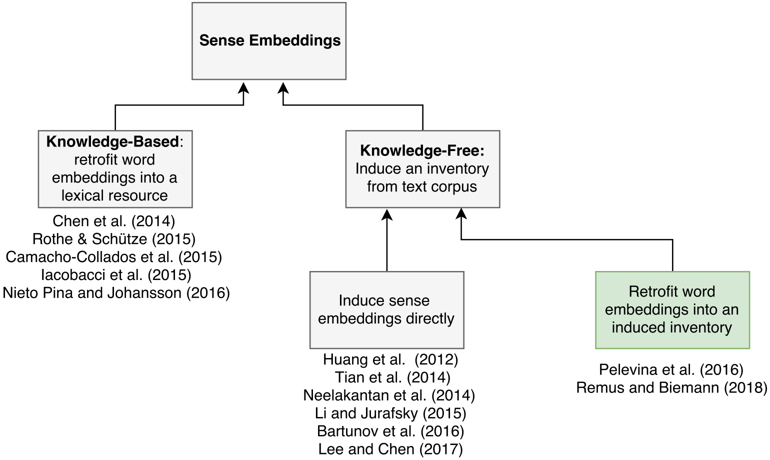
- **Inducing word sense representations**:
  - word sense embeddings via retrofitting [Pelevina et al., 2016, Remus and Biemann, 2018];
  - sparse sense representations [Panchenko et al., 2017c];
  - inducing synsets [Ustalov et al., 2017]
  - sense semantic classes [Panchenko et al., 2018]
- **Making induced senses interpretable** [Panchenko et al., 2017b, Panchenko et al., 2017c]

Overview

- **Inducing word sense representations**:
  - word sense embeddings via retrofitting [Pelevina et al., 2016, Remus and Biemann, 2018];
  - sparse sense representations [Panchenko et al., 2017c];
  - inducing synsets [Ustalov et al., 2017]
  - sense 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** [Faralli et al., 2016, Panchenko et al., 2017a, Biemann et al., 2018]

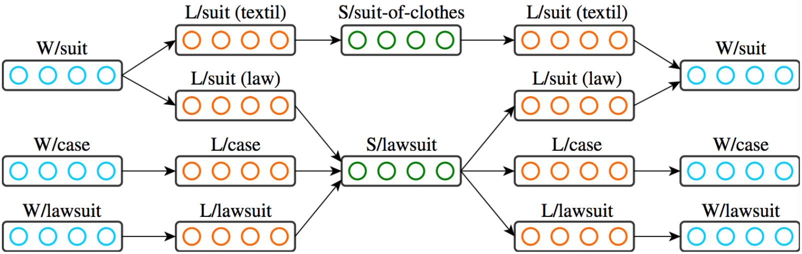
Inducing word sense representations

Related work



Related work: knowledge-based

- **AutoExtend** [Rothe and Schütze, 2015]



* image is reproduced from the original paper

Related work: knowledge-free

- **Adagram** [Bartunov et al., 2016]
- Multiple vector representations θ for each word:

$$p(Y, Z, \beta | X, \alpha, \theta) = \prod_{w=1}^{V} \prod_{k=1}^{\infty} p(\beta_{wk}|\alpha) \prod_{i=1}^{N} [p(z_i|x_i, \beta) \prod_{j=1}^{C} p(y_{ij}|z_i, x_i, \theta)],$$

Related work: knowledge-free

- **Adagram** [Bartunov et al., 2016]
- Multiple vector representations θ for each word:

$$p(Y, Z, \beta | X, \alpha, \theta) = \prod_{w=1}^{V} \prod_{k=1}^{\infty} p(\beta_{wk} | \alpha) \prod_{i=1}^{N} [p(z_i | x_i, \beta) \prod_{j=1}^{C} p(y_{ij} | z_i, x_i, \theta)],$$

  - α – a meta-parameter controlling number of senses;
  - z_i – a hidden variable: a sense index in context;
  - $p(\beta_{wk} | \alpha)$ – probability of the k-th sense of the word w;
  - $p(z_i | x_i, \beta)$ – probability of observing word x_i in the sense z_i;
  - $\prod_{j=1}^{C} p(y_{ij} | z_i, x_i, \theta)$ – probability of the context C.

Related work: knowledge-free

- **Adagram** [Bartunov et al., 2016]
- Multiple vector representations θ for each word:

$$p(Y, Z, \beta | X, \alpha, \theta) = \prod_{w=1}^{V} \prod_{k=1}^{\infty} p(\beta_{wk}|\alpha) \prod_{i=1}^{N} [p(z_i|x_i, \beta) \prod_{j=1}^{C} p(y_{ij}|z_i, x_i, \theta)],$$

  - α – a meta-parameter controlling number of senses;
  - z_i – a hidden variable: a sense index in context;
  - $p(\beta_{wk}|\alpha)$ – probability of the k-th sense of the word w;
  - $p(z_i|x_i, \beta)$ – probability of observing word x_i in the sense z_i;
  - $\prod_{j=1}^{C} p(y_{ij}|z_i, x_i, \theta)$ – probability of the context C.
- **See also**: [Neelakantan et al., 2014] and [Li and Jurafsky, 2015]

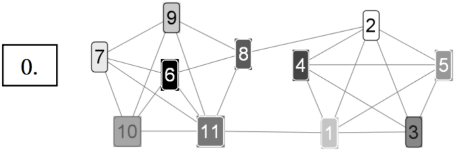
Related work: word sense induction

- Word sense induction (WSI) based on **graph clustering**:
  - [Lin, 1998]
  - [Pantel and Lin, 2002]
  - [Widdows and Dorow, 2002]
  - **Chinese Whispers [Biemann, 2006]**
  - [Hope and Keller, 2013]

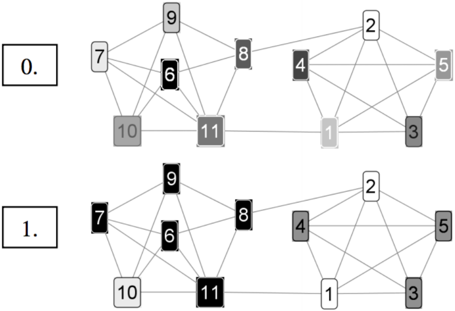
Related work: Chinese Whispers#1

* source of the image: `http://ic.pics.livejournal.com/blagin_anton/33716210/2701748/2701748_800.jpg`

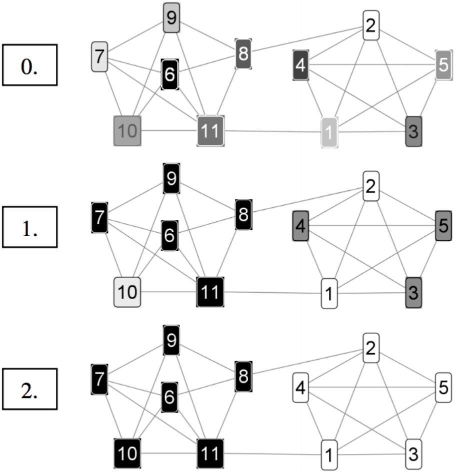
Related work: Chinese Whispers#2



Related work: Chinese Whispers#2



Related work: Chinese Whispers#2



Sense embeddings using retrofitting

RepL4NLP@ACL'16 [Pelevina et al., 2016], LREC'18 [Remus and Biemann, 2018]

Prior methods:

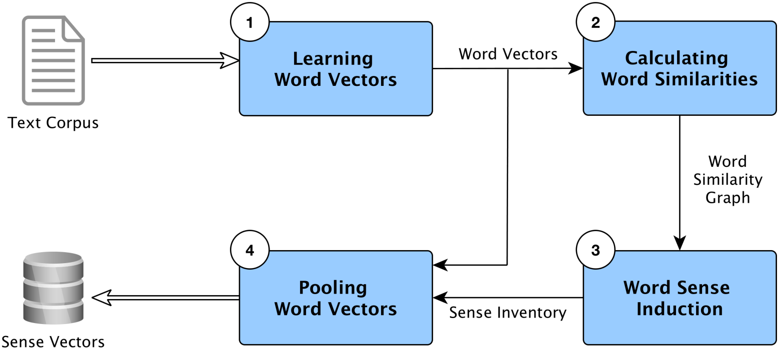
- Induce inventory by clustering of word instances
- Use existing sense inventories

Our method:

- **Input:** word embeddings
- **Output:** word sense embeddings
- **Word sense induction** by clustering of word ego-networks

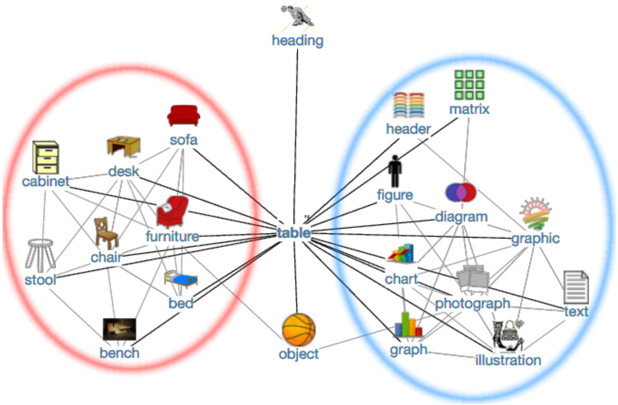
Sense embeddings using retrofitting

- From word embeddings to sense embeddings



Sense embeddings using retrofitting

- Word sense induction using ego-network clustering



Sense embeddings using retrofitting

- Neighbours of Word and Sense Vectors

Vector	**Nearest Neighbors**
table	tray, bottom, diagram, bucket, brackets, stack, basket, list, parenthesis, cup, trays, pile, playfield, bracket, pot, drop-down, cue, plate

Sense embeddings using retrofitting

- Neighbours of Word and Sense Vectors

Vector	**Nearest Neighbors**
table	tray, bottom, diagram, bucket, brackets, stack, basket, list, parenthesis, cup, trays, pile, playfield, bracket, pot, drop-down, cue, plate
table#0	leftmost#0, column#1, randomly#0, tableau#1, top-left#0, indent#1, bracket#3, pointer#0, footer#1, cursor#1, diagram#0, grid#0
table#1	pile#1, stool#1, tray#0, basket#0, bowl#1, bucket#0, box#0, cage#0, saucer#3, mirror#1, birdcage#0, hole#0, pan#1, lid#0

Sense embeddings using retrofitting

Word Sense Disambiguation

1. **Context extraction**: use context words around the target word
2. **Context filtering**: based on context word's relevance for disambiguation
3. **Sense choice in context**: maximise similarity between a context vector and a sense vector

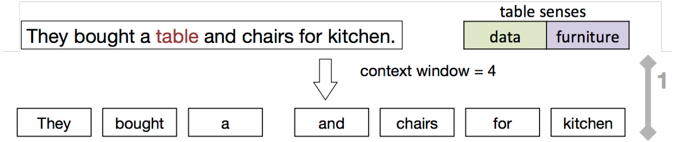
Sense embeddings using retrofitting

They bought a table and chairs for kitchen.

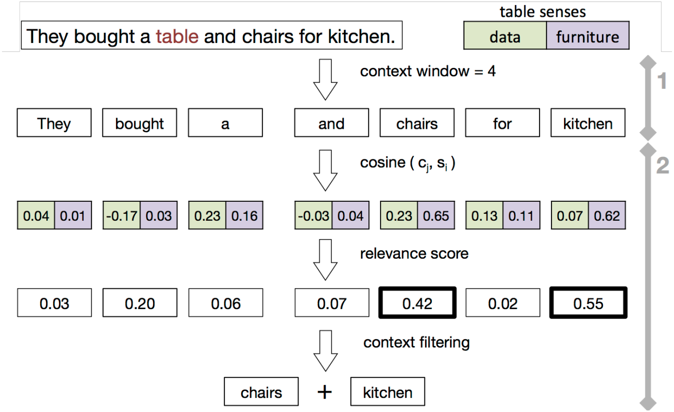
table senses

data	furniture

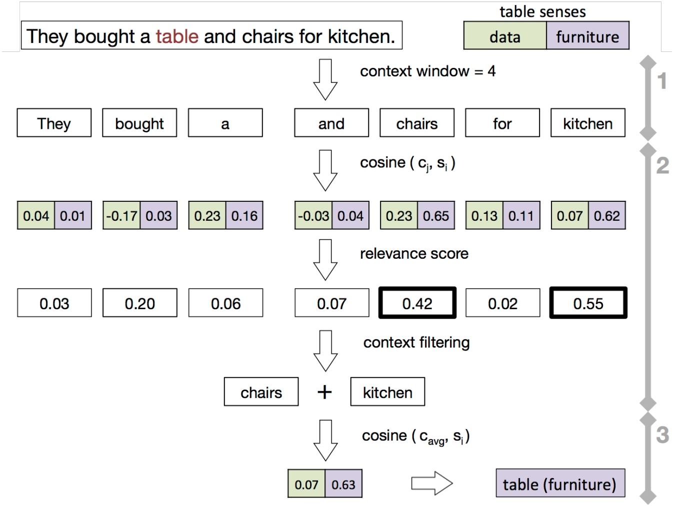
Sense embeddings using retrofitting



Sense embeddings using retrofitting



Sense embeddings using retrofitting



Sense embeddings using retrofitting

Evaluation on SemEval 2013 Task 13 dataset: comparison to the state-of-the-art

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, $\alpha = 0.05$, 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

Sense embeddings using retrofitting

Results of Steffen ... or summarize both SemEval'13

Sparse sense representations

Sparse sense representations

Watset: synset induction

Watset: synset induction

Watset: synset induction

Induction of sense semantic classes

Induction of sense semantic classes

Induction of sense semantic classes

Making induced senses interpretable

Conclusion

Summary

- How to **induce word senses**, **synsets** and **semantic classes** from text and synonyms.

Summary

- How to **induce word senses**, **synsets** and **semantic classes** from text and synonyms.
- **Interpretability can be added** on the top of induced word senses in a model agnostic way.

Summary

- How to **induce word senses**, **synsets** and **semantic classes** from text and synonyms.
- **Interpretability can be added** on the top of induced word senses in a model agnostic way.
- Hypernymy labels **improve hypernymy extraction**.

Summary

- How to **induce word senses**, **synsets** and **semantic classes** from text and synonyms.
- **Interpretability can be added** on the top of induced word senses in a model agnostic way.
- Hypernymy labels **improve hypernymy extraction**.
- Linking induced word senses to lexical resources:
  - improves **performance of WSD**;
  - can be used to **enrich lexical resources** with new senses.

A New Shared Task on WSI&D

- Participate in an ACL SIGSLAV sponsored shared task on **word sense induction and disambiguation** for Russian!

A lexical sample task evaluated using the ARI measure

- Target word, e.g. “bank” (in Russian).
- Contexts where the word occurs.
- You need to group the contexts by senses.

A New Shared Task on WSI&D

- Participate in an ACL SIGSLAV sponsored shared task on **word sense induction and disambiguation** for Russian!

A lexical sample task evaluated using the ARI measure

- Target word, e.g. “bank” (in Russian).
- Contexts where the word occurs.
- You need to group the contexts by senses.

- **More details**: `http://russe.nlpub.org/2018/wsi`
- You can participate by **31.01.2018**.

Thank you!

Bartunov, S., Kondrashkin, D., Osokin, A., and Vetrov, D. (2016).
Breaking sticks and ambiguities with adaptive skip-gram.
In *Artificial Intelligence and Statistics*, pages 130–138.

Biemann, C., Faralli, S., Panchenko, A., and Ponzetto, S. P. (2018).
A framework for enriching lexical semantic resources with distributional semantics.
In *Journal of Natural Language Engineering*, pages 56–64. Cambridge Press.

Faralli, S., Panchenko, A., Biemann, C., and Ponzetto, S. P. (2016).
Linked disambiguated distributional semantic networks.
In *International Semantic Web Conference*, pages 56–64. Springer.

Panchenko, A., Faralli, S., Ponzetto, S. P., and Biemann, C. (2017a).

Using linked disambiguated distributional networks for word sense disambiguation.
In *Proceedings of the 1st Workshop on Sense, Concept and Entity Representations and their Applications*, pages 72–78, Valencia, Spain. Association for Computational Linguistics.

Panchenko, A., Marten, F., Ruppert, E., Faralli, S., Ustalov, D., Ponzetto, S. P., and Biemann, C. (2017b).
Unsupervised, knowledge-free, and interpretable word sense disambiguation.
In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 91–96, Copenhagen, Denmark. Association for Computational Linguistics.

Panchenko, A., Ruppert, E., Faralli, S., Ponzetto, S. P., and Biemann, C. (2017c).
Unsupervised does not mean uninterpretable: The case for word sense induction and disambiguation.
In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1,*

Long Papers, pages 86–98, Valencia, Spain. Association for Computational Linguistics.

Panchenko, A., Ustalov, D., Faralli, S., Ponzetto, S. P., and Biemann, C. (2018).
Improving hypernymy extraction with distributional semantic classes.
In *Proceedings of the LREC 2018*, Miyazaki, Japan. European Language Resources Association.

Pelevina, M., Arefiev, N., Biemann, C., and Panchenko, A. (2016).
Making sense of word embeddings.
In *Proceedings of the 1st Workshop on Representation Learning for NLP*, pages 174–183, Berlin, Germany. Association for Computational Linguistics.

Remus, S. and Biemann, C. (2018).
Retrofittingword representations for unsupervised sense aware word similarities.

In *Proceedings of the LREC 2018*, Miyazaki, Japan. European Language Resources Association.

Rothe, S. and Schütze, H. (2015).
Autoextend: Extending word embeddings to embeddings for synsets and lexemes.
In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1793–1803, Beijing, China. Association for Computational Linguistics.

Ustalov, D., Panchenko, A., and Biemann, C. (2017).
Watset: Automatic induction of synsets from a graph of synonyms.
In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1579–1590, Vancouver, Canada. Association for Computational Linguistics.