



Universität Hamburg  
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**INDUCING INTERPRETABLE WORD  
SENSES FOR WSD AND ENRICHMENT OF  
LEXICAL RESOURCES**

# Overview

## ■ Inducing word sense representations:

- word sense embeddings via retrofitting [Peleвина 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]

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## ■ Making induced senses interpretable

[Panchenko et al., 2017b, Panchenko et al., 2017c]

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## ■ Making induced senses interpretable

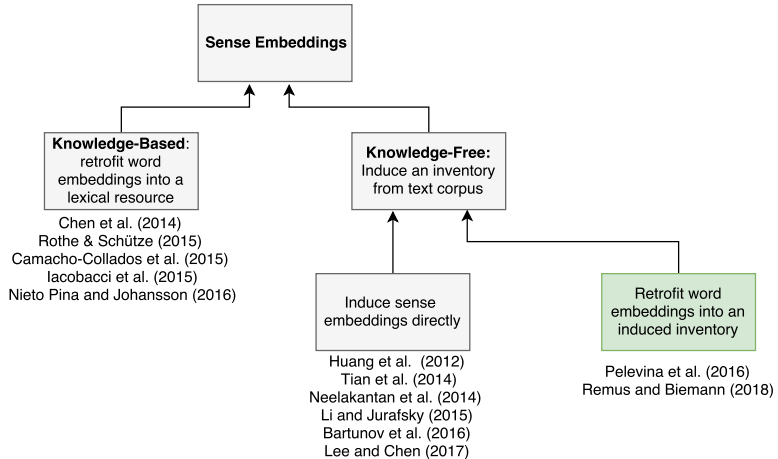
[Panchenko et al., 2017b, Panchenko et al., 2017c]

## ■ Linking induced word senses to lexical

**resources** [Faralli et al., 2016, Panchenko et al., 2017a, Biemann et al., 2018]

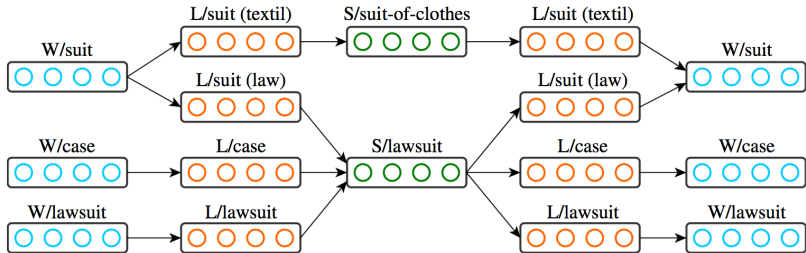
Inducing word sense representations

## 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  $\theta$  for each word:

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

- $\alpha$  -- 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]

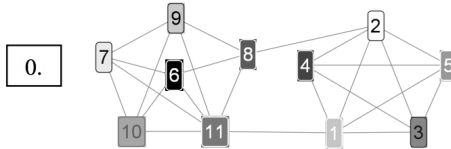


# Related work: Chinese Whispers#1

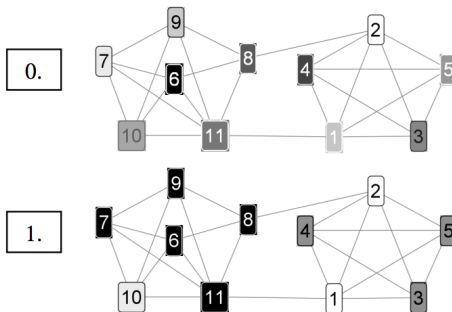


\* source of the image: [http://ic.pics.livejournal.com/blagin\\_anton/33716210/2701748/2701748\\_800.jpg](http://ic.pics.livejournal.com/blagin_anton/33716210/2701748/2701748_800.jpg)

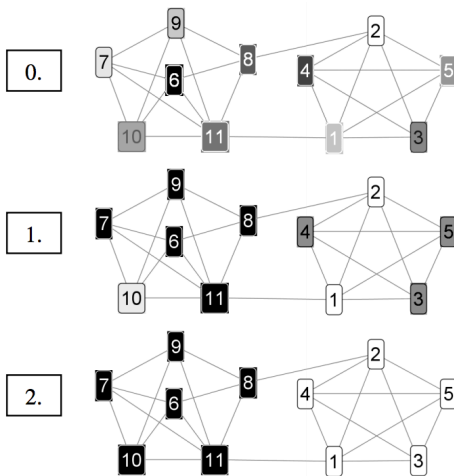
## Related work: Chinese Whispers#2



# 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:

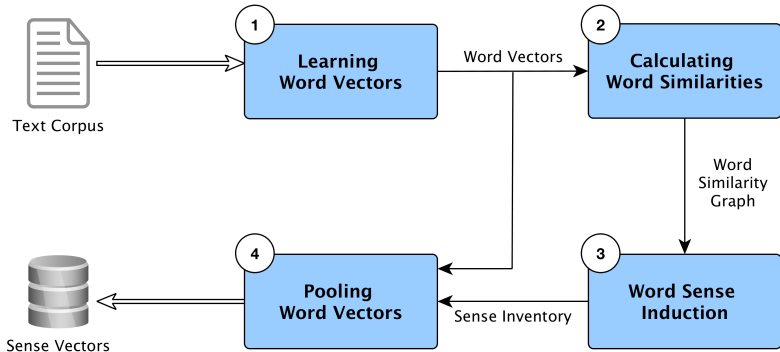
- Induce inventory by **clustering of word instances**
- Use **existing** sense inventories

## Our method:

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

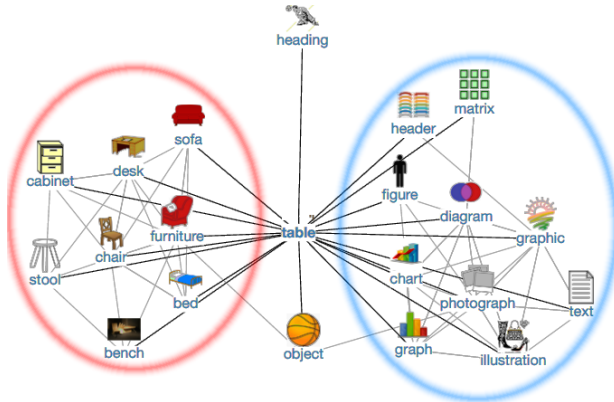
# Sense embeddings using retrofitting

## ■ 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

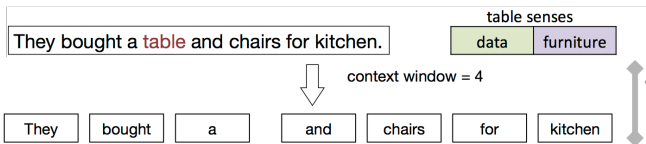
They bought a **table** and chairs for kitchen.

table senses

data

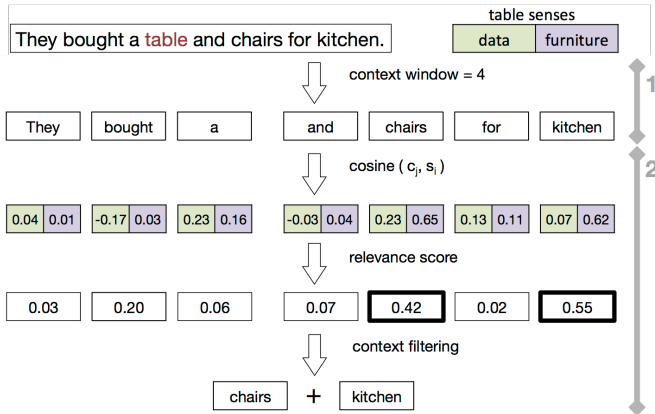
furniture

# Sense embeddings using retrofitting

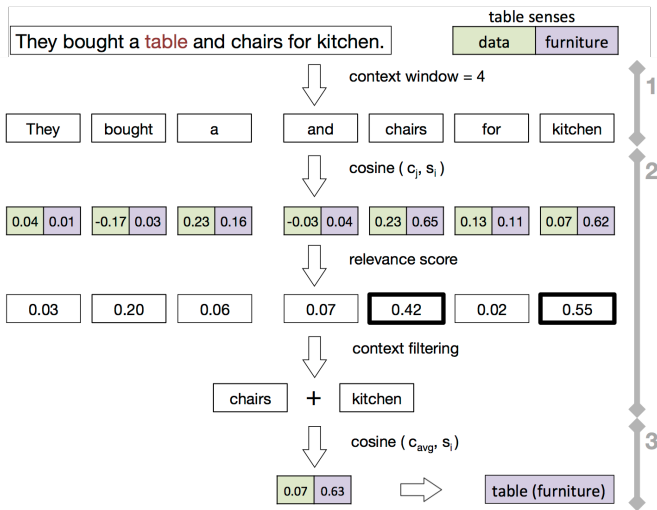




# Sense embeddings using retrofitting



# 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

# Sense embeddings using retrofitting

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



# Sparse sense representations



# Sparse sense representations



# Watset: synset induction



# Watset: synset induction

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# Watset: synset induction



# Induction of sense semantic classes



# Induction of sense semantic classes



# Induction of sense semantic classes

Making induced senses interpretable

# Making induced senses interpretable

## Knowledge-based sense representations are **interpretable**

bn:01713224n • NOUN • Named Entity • Categories: High-level programming languages, Dutch inventions, Class-based programming languages, Cross platform free software...

**Python (programming language)** • /usr/bin/python • /usr/local/bin/python • Python language • Python programming language

Python is a widely used general-purpose, high-level programming language. Wikipedia

More definitions

IS A	programming language • free software • scripting language
HAS PART	pandas
HAS KIND	Stackless Python
DESIGNER	Guido van Rossum
DEVELOPER	Python Software Foundation • Guido van Rossum
DIALECTS	Cython • Stackless Python
INFLUENCED BY	ALGOL 68 • alphabet • ruby
LICENSE	Python Software Foundation License

More relations

EXPLORE NETWORK



# Making induced senses interpretable

Knowledge-free sense representations are **uninterpretable**

```
In [11]: sv.syn0[sv.vocab["python#2"].index]
```

```
Out[11]:
```

```
array([-0.0493343 , -0.02244579,  0.02296794,  0.03484775,  0.0404554 ,
        0.04304857, -0.02211852, -0.02118347, -0.03212074, -0.01202453,
        0.01206081,  0.05609602, -0.05950832,  0.00859888, -0.01051112,
        0.03177784, -0.06489294,  0.03833736,  0.05437034, -0.01451268,
       -0.02419239, -0.03195219,  0.0620546 ,  0.10284331,  0.07430374,
       -0.04109243, -0.01181133 ,  0.05401124,  0.05283536,  0.00873093,
        0.03662092,  0.03762468,  0.02368712, -0.03980339,  0.02791001,
        0.02529952, -0.02255581, -0.00925604, -0.03940469, -0.02855149,
        ...,
       -0.08179335,  0.02319797, -0.0167018 ,  0.04818865, -0.06946786,
       -0.06530198,  0.00522405, -0.0336296 , -0.05401101,  0.01190361], dtype=float32)
```



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Making induced senses interpretable



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Making induced senses interpretable



# Making induced senses interpretable

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Linking induced senses to resources



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Linking induced senses to resources



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## Conclusion

Vectors + Graphs = ♥

**GRAPHS**  
~~**POINIS**~~  
**NOT DEAD.**

# Summary

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

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- 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.
- 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.

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  - Contexts where the word occurs.
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- 
- **More details:** <http://russe.nlpub.org/2018/wsi>
  - You can participate by **31.01.2018**.



# Thank you! Questions?

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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).

Retrofitting word 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.