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INDUCING INTERPRETABLE WORD SENSES FOR WSD AND ENRICHMENT OF LEXICAL RESOURCES

Overview

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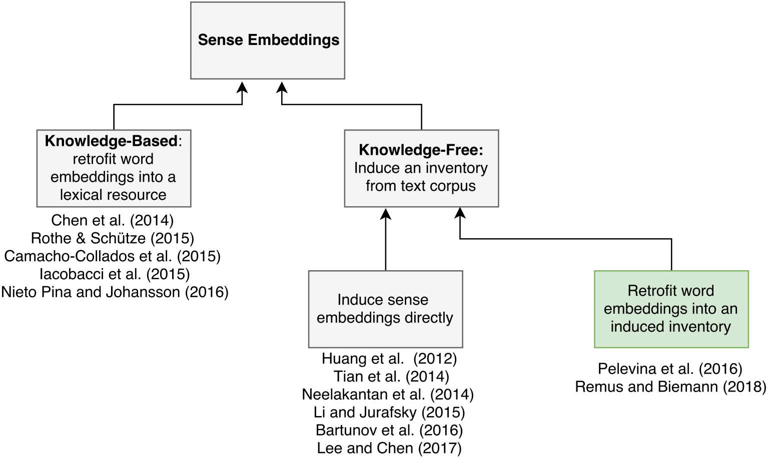
- **Making induced senses interpretable** [Panchenko et al., 2017b, Panchenko et al., 2017c]

- **Linking induced word senses to lexical resources** [Faralli et al., 2016, Panchenko et al., 2017a, Biemann et al., 2018]

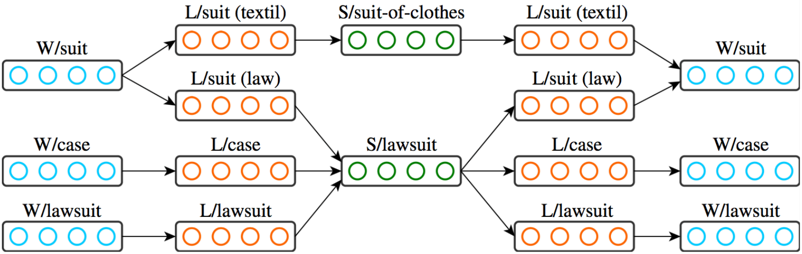
Inducing word sense representations

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 θ for each word:

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

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  - 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;
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  - $\prod_{j=1}^{C} p(y_{ij}|z_i, x_i, \theta)$ -- probability of the context C.
- **See also**: [Neelakantan et al., 2014] and [Li and Jurafsky, 2015]

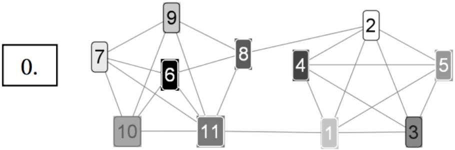
Related work: word sense induction

- 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]

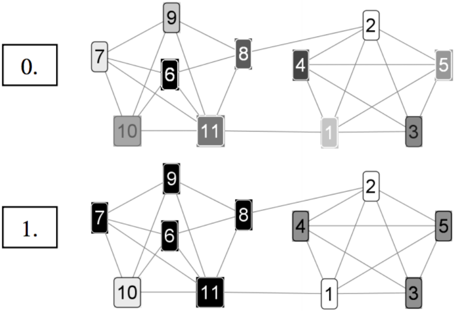
Related work: Chinese Whispers#1

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

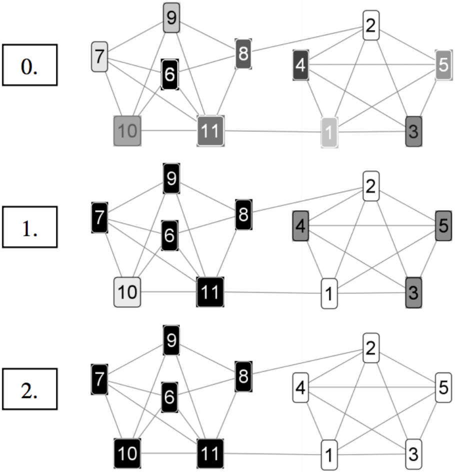
Related work: Chinese Whispers#2



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:

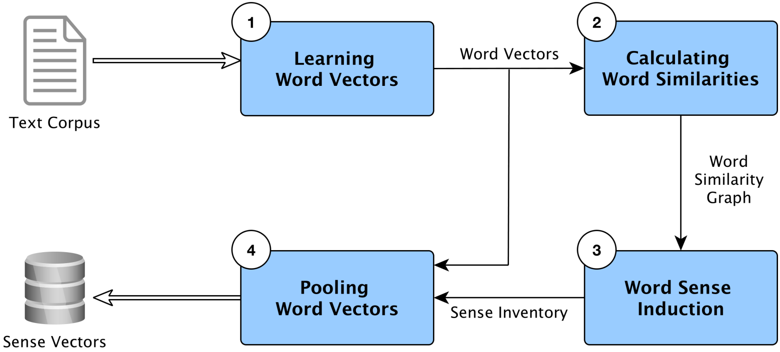
- Induce inventory by clustering of word instances
- Use existing sense inventories

Our method:

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

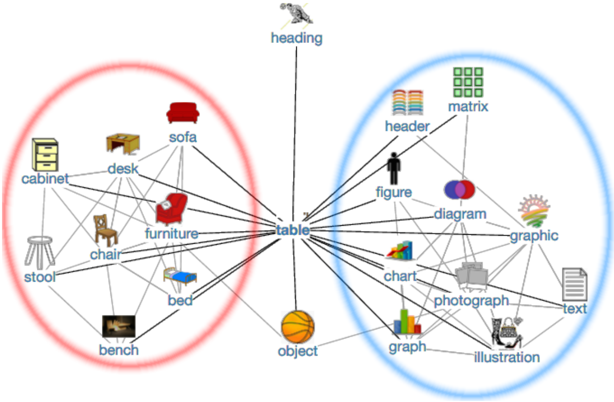
Sense embeddings using retrofitting

- 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

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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

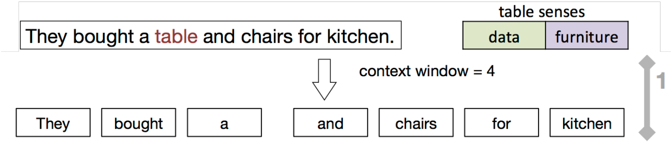
Sense embeddings using retrofitting

They bought a table and chairs for kitchen.

table senses

data	furniture

Sense embeddings using retrofitting



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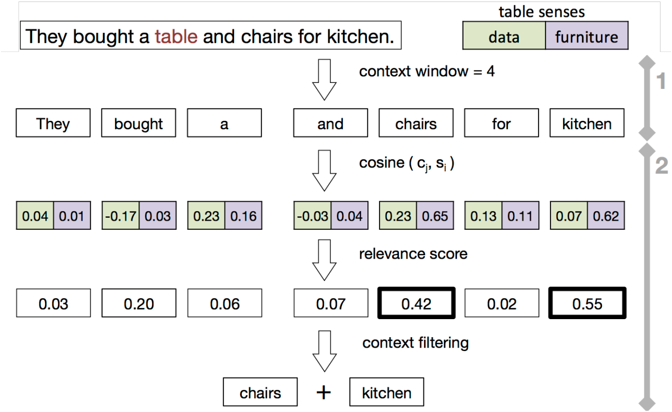

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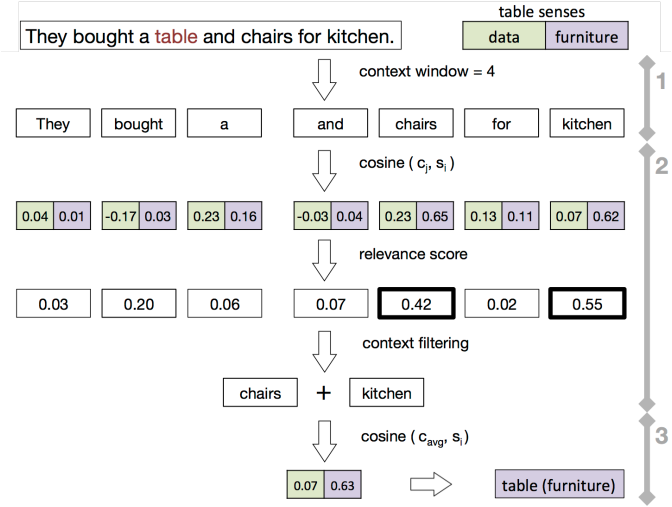

Sense embeddings using retrofitting

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, 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 ([illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

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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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...

EN **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, -0.0118133 ,  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)
```

Making induced senses interpretable

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Linking induced senses to resources

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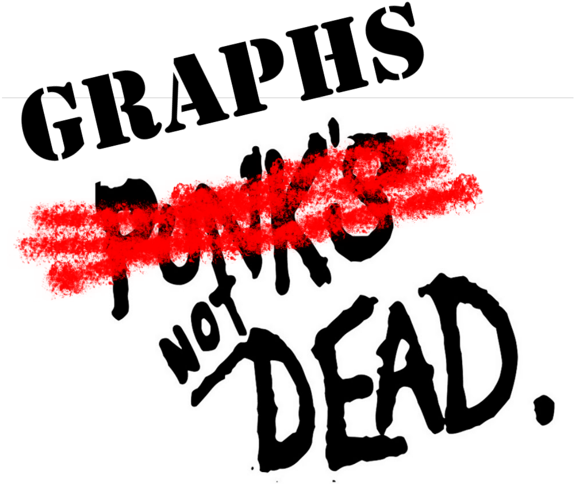
Conclusion

Vectors + Graphs = ♡



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- Hypernymy labels **improve hypernymy extraction**.

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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.
- 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.

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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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