



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 [Plevina 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]

■ Inducing word sense representations:

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■ Making induced senses interpretable

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

■ Linking induced word senses to lexical

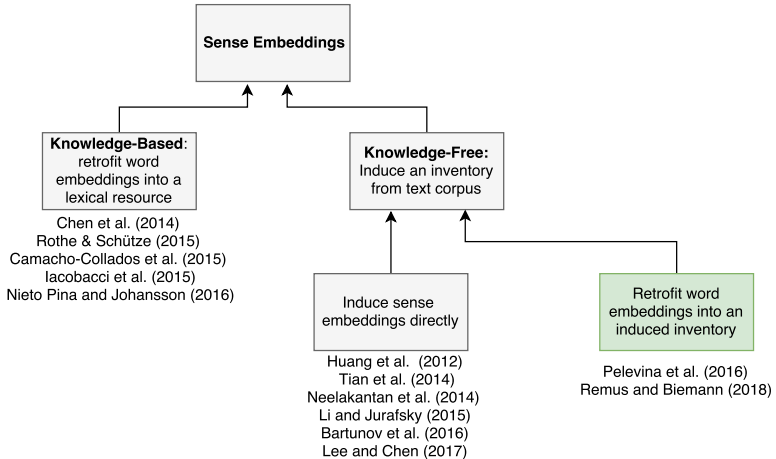
resources [Faralli et al., 2016, Panchenko et al., 2017a, Biemann et al., 2018]

Inducing word sense representations

Word VS sense embeddings

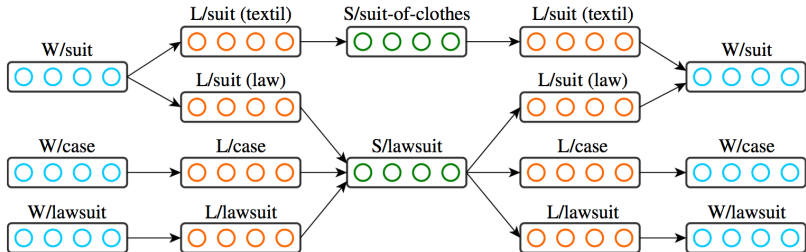
...

Related work



Related work: knowledge-based

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



* image is reproduced from the original paper

Related work: knowledge-free

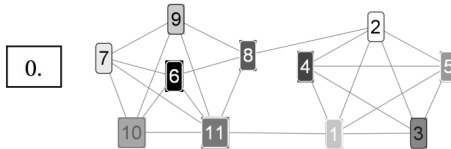
- **Adagram** [Bartunov et al., 2016]
- Multiple vector representations θ for each word:

Related work: Chinese Whispers#1

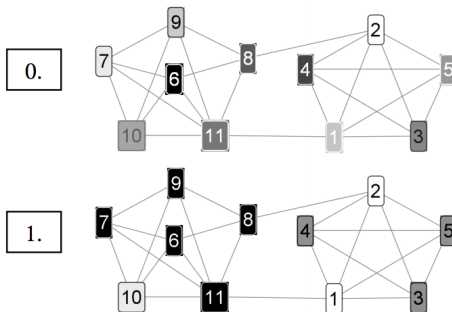


* source of the image: http://ic.pics.livejournal.com/blagin_anton/33716210/2701748/2701748_800.jpg

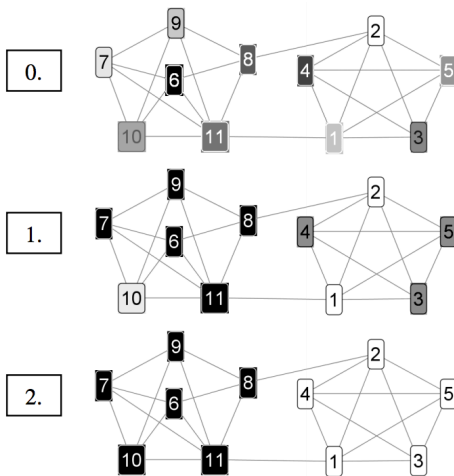
Related work: Chinese Whispers#2



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:

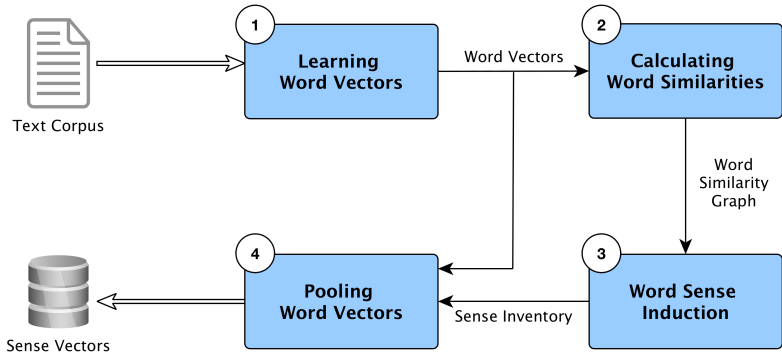
- Induce inventory by **clustering of word instances**
- Use **existing** sense inventories

Our method:

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

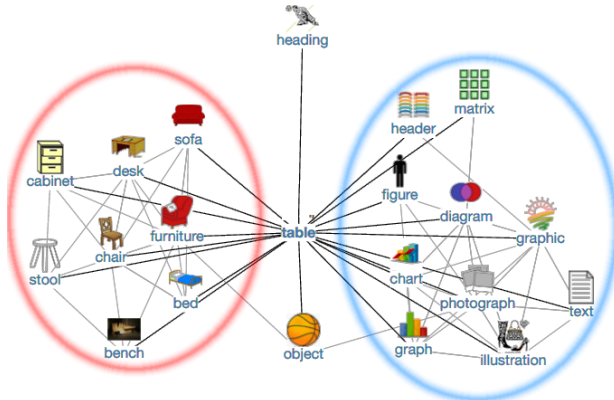
Sense embeddings using retrofitting

■ 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, saucer, 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, saucer, pile, playfield, bracket, pot, drop-down, cue, plate
table#0	leftmost#0, column#1, tableau#1, 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, 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

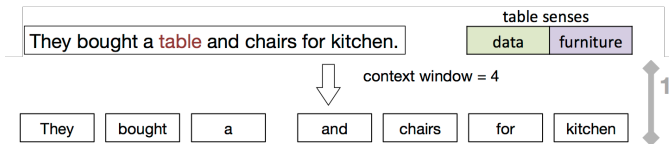
They bought a **table** and chairs for kitchen.

table senses

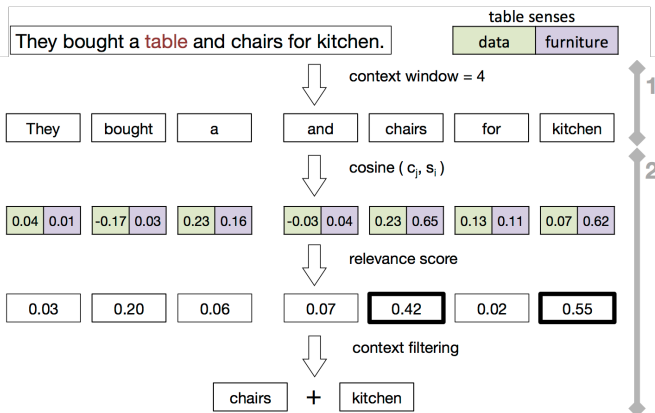
data

furniture

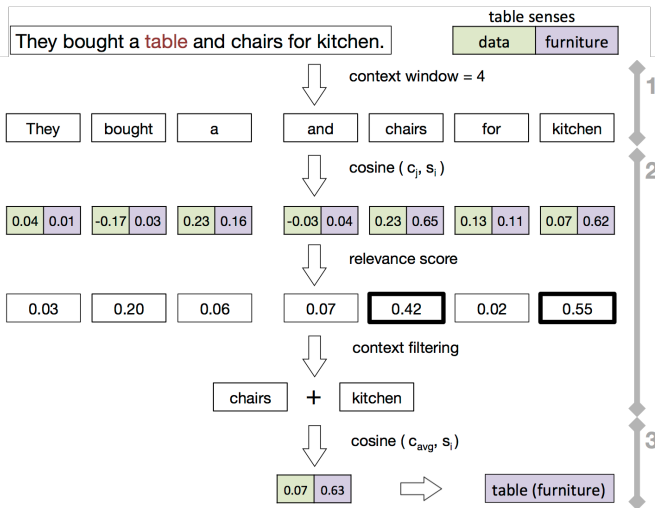
Sense embeddings using retrofitting



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
10T	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



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Inducing word sense representations

oooooooooooooooooooooooo●ooooo

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

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



Making induced senses interpretable



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Making induced senses interpretable



Making induced senses interpretable

Linking induced senses to resources

Linking induced senses to resources



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Linking induced senses to resources



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Linking induced senses to resources



Linking induced senses to resources

Linking induced senses to resources

Conclusion

Vectors + Graphs = ♥

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

Take home messages

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

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**.

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.

An ongoing shared task on WSI&D

- Participate in an **ACL SIGSLAV** sponsored shared task on **word sense induction and disambiguation** for Russian!
- **More details:** <http://russe.nlpub.org/2018/wsi>



Acknowledgments

Thank you! Questions?

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