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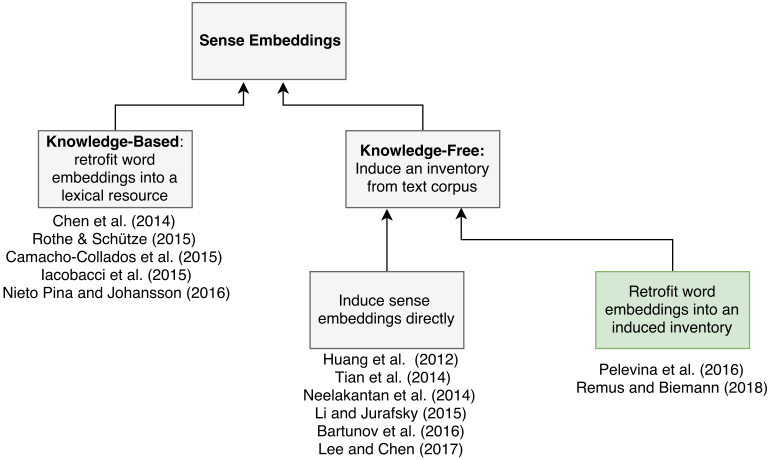
INDUCING INTERPRETABLE WORD SENSES FOR WSD AND ENRICHMENT OF LEXICAL RESOURCES

Inducing word sense representations

Word vs sense embeddings

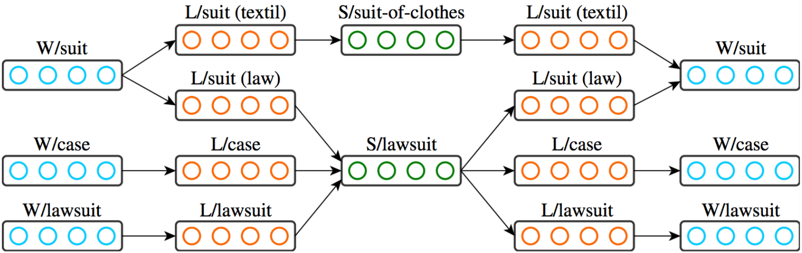
Word vs sense embeddings

Related work



Related work: knowledge-based

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



* image is reproduced from the original paper

Related work: knowledge-free

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- Multiple vector representations θ for each word:

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

  - z_i – a hidden variable: a sense index of word x_i in context C;
  - α – a meta-parameter controlling number of senses.

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  - z_i – a hidden variable: a sense index of word x_i in context C;
  - α – a meta-parameter controlling number of senses.
- **See also**: [Neelakantan et al., 2014] and [Li and Jurafsky, 2015]

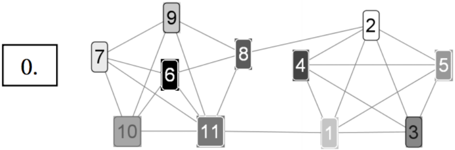
Related work: word sense induction

- 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]

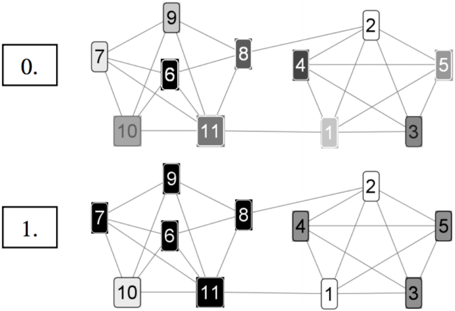
Related work: Chinese Whispers#1

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

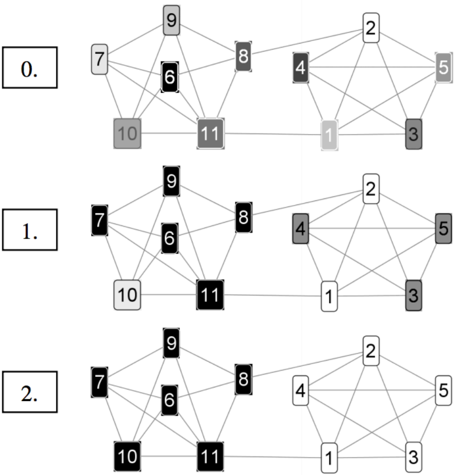
Related work: Chinese Whispers#2



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:

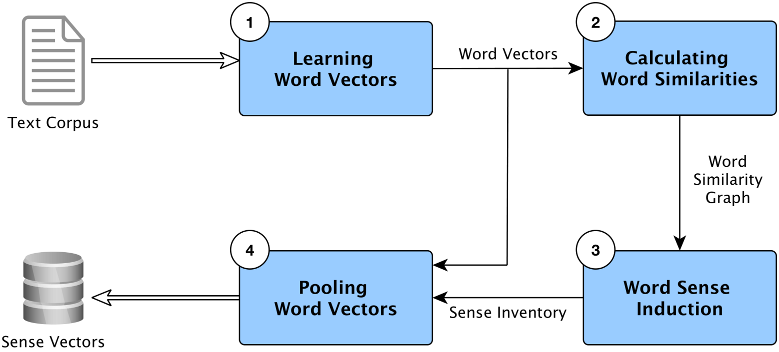
- Induce inventory by clustering of word instances
- Use existing sense inventories

Our method:

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

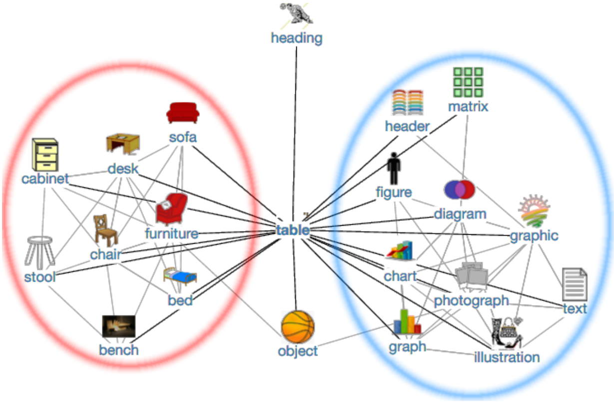
Sense embeddings using retrofitting

- 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, 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

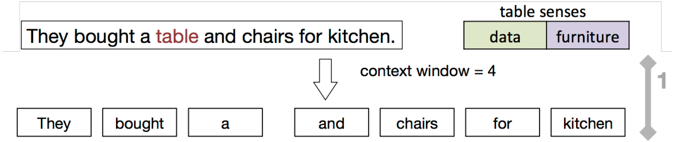
Sense embeddings using retrofitting

They bought a table and chairs for kitchen.

table senses

data	furniture

Sense embeddings using retrofitting



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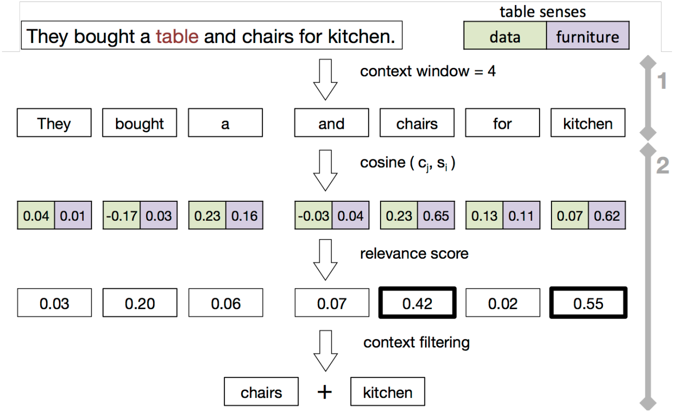
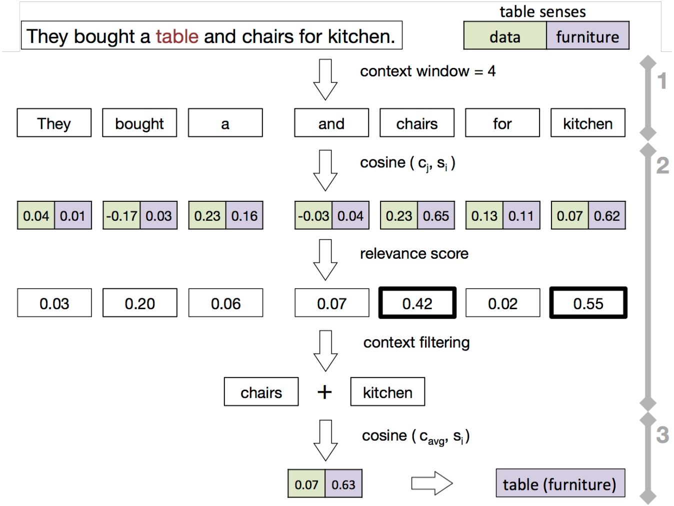


Sense embeddings using retrofitting



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

Sense embeddings using retrofitting

LREC'2018 [Remus and Biemann, 2018]

	AUTOEXTEND	ADAGRAM	SGNS	.	GLOVE	.	SYMPAT	.	LSABOW	.	LSAHAL	.	PARAGRAMSL	.
SIMLEX999	0.45	0.29	0.44		0.37		0.54		0.30		0.27		0.68	
MEN	0.72	0.67	0.77		0.73		0.53		0.67		0.71		0.77	
SIMVERB	0.43	0.27	0.36		0.23		0.37		0.15		0.19		0.53	
WORDSIM353	0.58	0.61	0.70		0.61		0.47		0.67		0.59		0.72	
SIMLEX999-N	0.44	0.33	0.45		0.39		0.48		0.32		0.34		0.68	
MEN-N	0.72	0.68	0.77	____	0.76	____	0.57	____	0.71	____	0.73	____	0.78	____

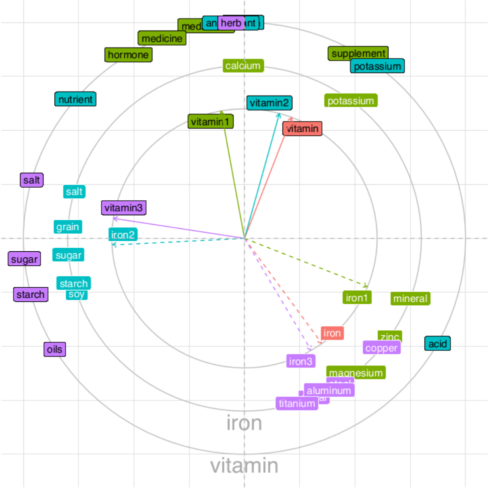
Sense embeddings using retrofitting

LREC'2018 [Remus and Biemann, 2018]

	AUTOEXTEND	ADAGRAM	SGNS	SGNS+SENSES	GLOVE	GLOVE+SENSES	SYMPAT	SYMPAT+SENSES	LSABOW	LSABOW+SENSES	LSAHAL	LSAHAL+SENSES	PARAGRAMSL	PARAGRAMSL+SENSES
SIMLEX999	0.45	0.29	0.44	**0.46**	0.37	**0.41**	0.54	**0.55**	0.30	**0.39**	0.27	**0.38**	**0.68**	0.64
MEN	0.72	0.67	0.77	**0.78**	0.73	**0.77**	0.53	**0.68**	0.67	**0.70**	0.71	**0.74**	0.77	**0.80**
SIMVERB	0.43	0.27	0.36	**0.39**	0.23	**0.30**	0.37	**0.45**	0.15	**0.22**	0.19	**0.28**	0.53	0.53
WORDSIM353	0.58	0.61	**0.70**	0.69	0.61	**0.65**	0.47	**0.62**	**0.67**	0.66	0.59	**0.63**	0.72	**0.73**
SIMLEX999-N	0.44	0.33	0.45	**0.50**	0.39	**0.47**	0.48	**0.55**	0.32	**0.46**	0.34	**0.44**	**0.68**	0.66
MEN-N	0.72	0.68	0.77	**0.79**	0.76	**0.80**	0.57	**0.74**	0.71	**0.73**	0.73	**0.76**	0.78	**0.81**

- Sense-aware similarities are marked with **+SENSES**.
- These results are using a sense inventory based on **sparse dependency features** (JoBimText).

Sense embeddings using retrofitting



- Word and sense embeddings of words **iron** and **vitamin**.

LREC'18 [Remus and Biemann, 2018]

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.

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