Do multi-sense word embeddings learn more senses?

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math.bme, 2020. május 18.

Overview

Word embeddings
- Static
- Contextualized

Word senses
- Results

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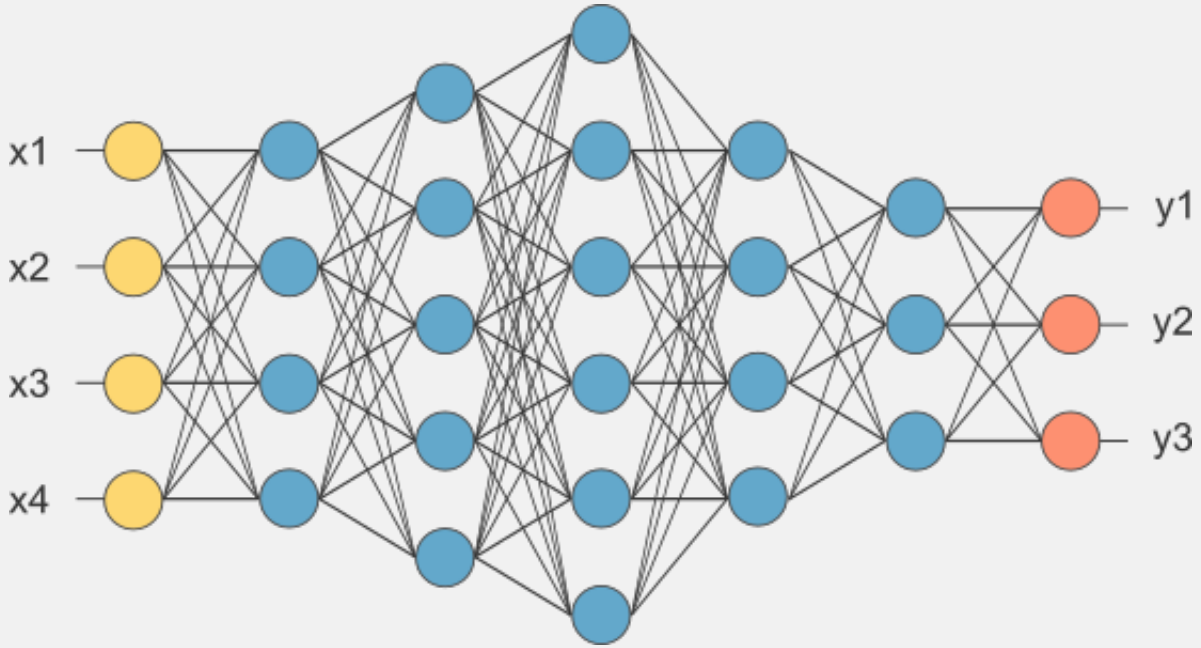
Artificial neural networks



- neural i.e. like the brain?
- cybernetics (1949), connectionism (1974), deep learning (2006)
- Learning features, more and more abstract layers
- - computer vision (Krizhevsky and Sutskever, 2012)
  - speech recognition (Hinton et al., 2012)
  - language (Peters et al., 2018a; Devlin et al., 2018)
- architectures + data + hardware + pretraining

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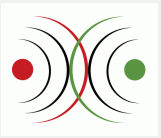
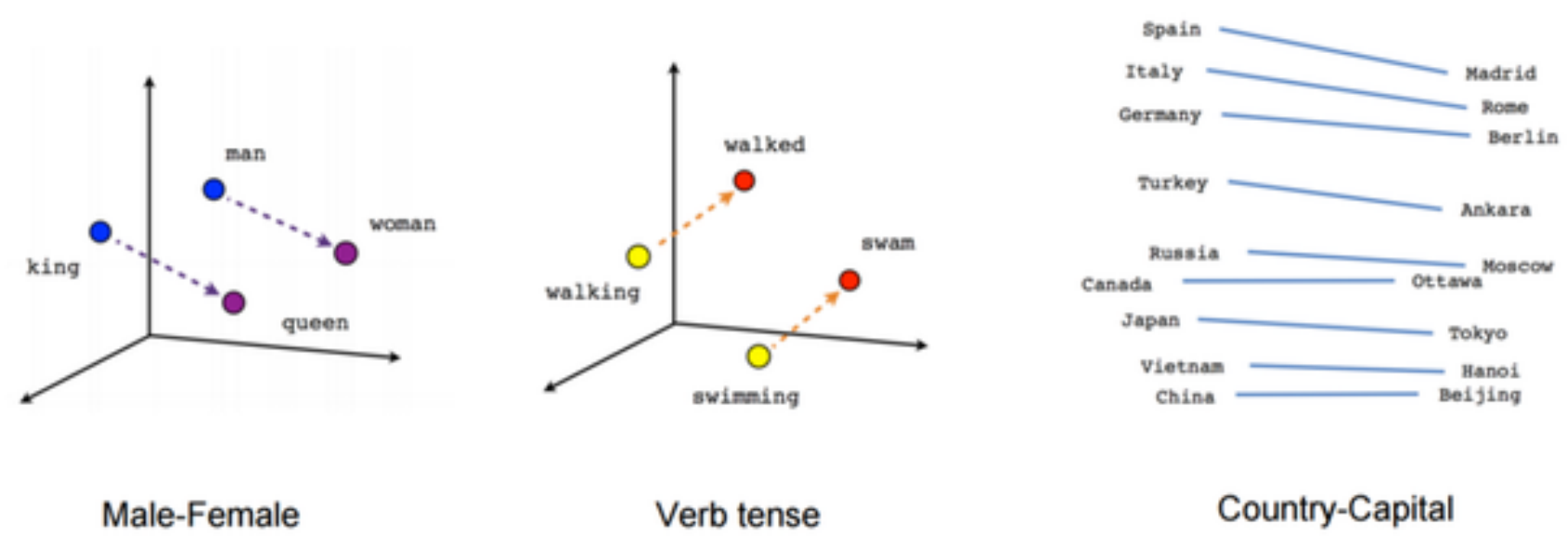
Word embeddings (static)

- before Peters et al., (2018a), in a galaxy...
- Representation of words in neural networks
- $\mathbf{w} \in \mathbb{R}^{300}$
- words with similar distribution $\rightsquigarrow$ similar points
- unsupervised training on giga-word corpora
- word2vec: skip-gram or continuous bag of words (Mikolov et al., 2013a)
- representation sharing (Collobert et al., 2011; Hashimoto et al., 2017)
- linguistic levels:
  character $<$ morph $<$ word $<$ query $<$ sentence $<$ rhetorics
  - morphs (Lazaridou et al., 2013)
  - bellow the word level: fastText
    - (Bojanowski, Joulin, and Mikolov, 2016)
  - thought vector (Vaswani et al., 2017)



Meaning decomposition with vectors

Katz and Fodor, 1963; Mikolov, Yih, and Zweig, 2013



$$\textbf{king} + \textbf{woman} - \textbf{man} \approx \textbf{queen}$$

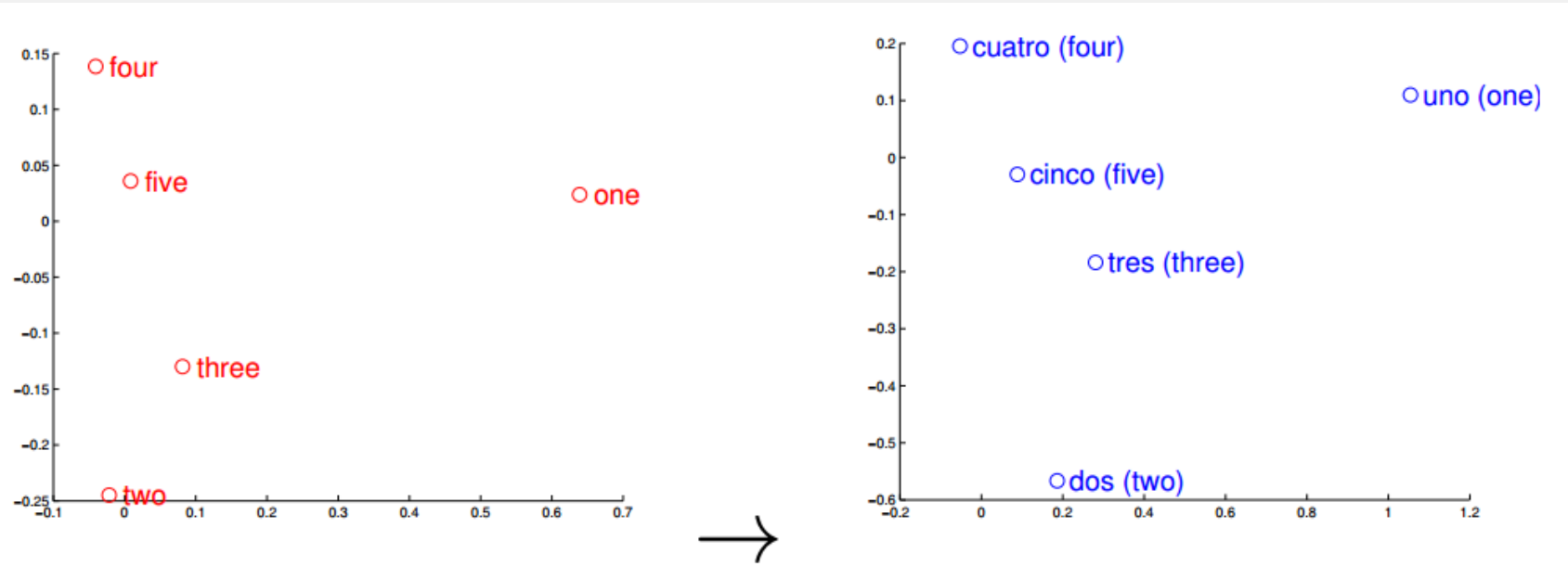
- nearest neighbors

Word translation (Mikolov et al., 2013)

- linear mapping between embeddings, 600 → 300 dim
- training on the 5 000 most frequent pairs
- test on the next 1 000

$$W : \mathbb{R}^{d_1} \rightarrow \mathbb{R}^{d_2} \quad z \approx Wx$$

$$\min_W \sum_i ||Wx_i - z_i||^2$$



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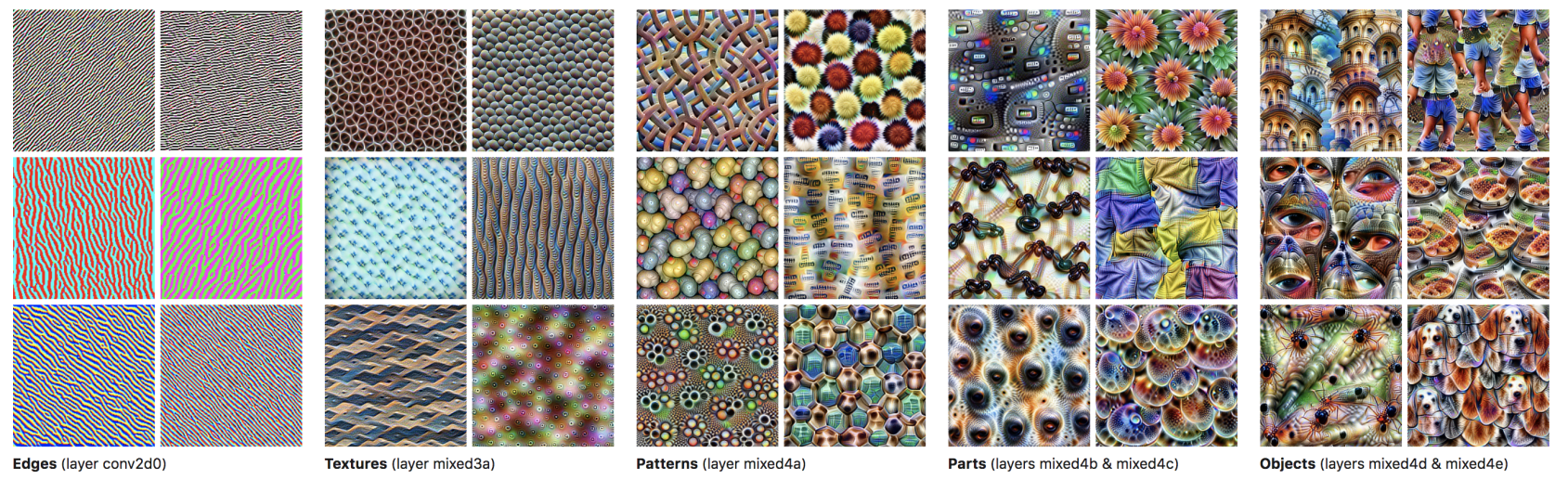
Pre-trained deep language models
aka. contextualized word representations

- Peters et al., 2018a; Devlin et al., 2018
- NLP's ImageNet moment, `https://ruder.io/nlp-imagenet/`
- vision: edges → textures → patterns → parts → objects
- language: morphology → syntax → semantics (and pragatics)



- multilingual transfer

Interpretability in deep language models I
Belinkov and Glass, 2019; Coenen et al., 2019

- accountability, trust, fairness, safety, and reliability
- earlier NLP work: feature-engineering
  - features: morphological properties, lexical classes, syntactic categories, semantic relations
  - one could observe the importance of each feature
    - at least in theory
- approaches to probing models (Conneau et al., 2018)
  - visualization
  - adversarial examples
- representations by layer (Peters et al., 2018b)
- individual neurons in a network may have meaning (Dalvi et al., 2019)
- syntax trees represented in a neural network's word representation space (Hewitt and Manning, 2019)

Interpretability in deep language models II
Belinkov and Glass, 2019; Coenen et al., 2019

- rich morphology (Şahin et al., 2019)
  - word-level probing tasks
    - case marking, possession, word length, morph tag count and pseudo-word identification, 24 languages
  - they relate the probing task performance to classic NLP tasks
    - POS-tagging, dep parsing, sem role labeling, NER, and nat lang infer
- finite or infinite number of context-specific representations/word-senses? (Ethayarajh, 2019)

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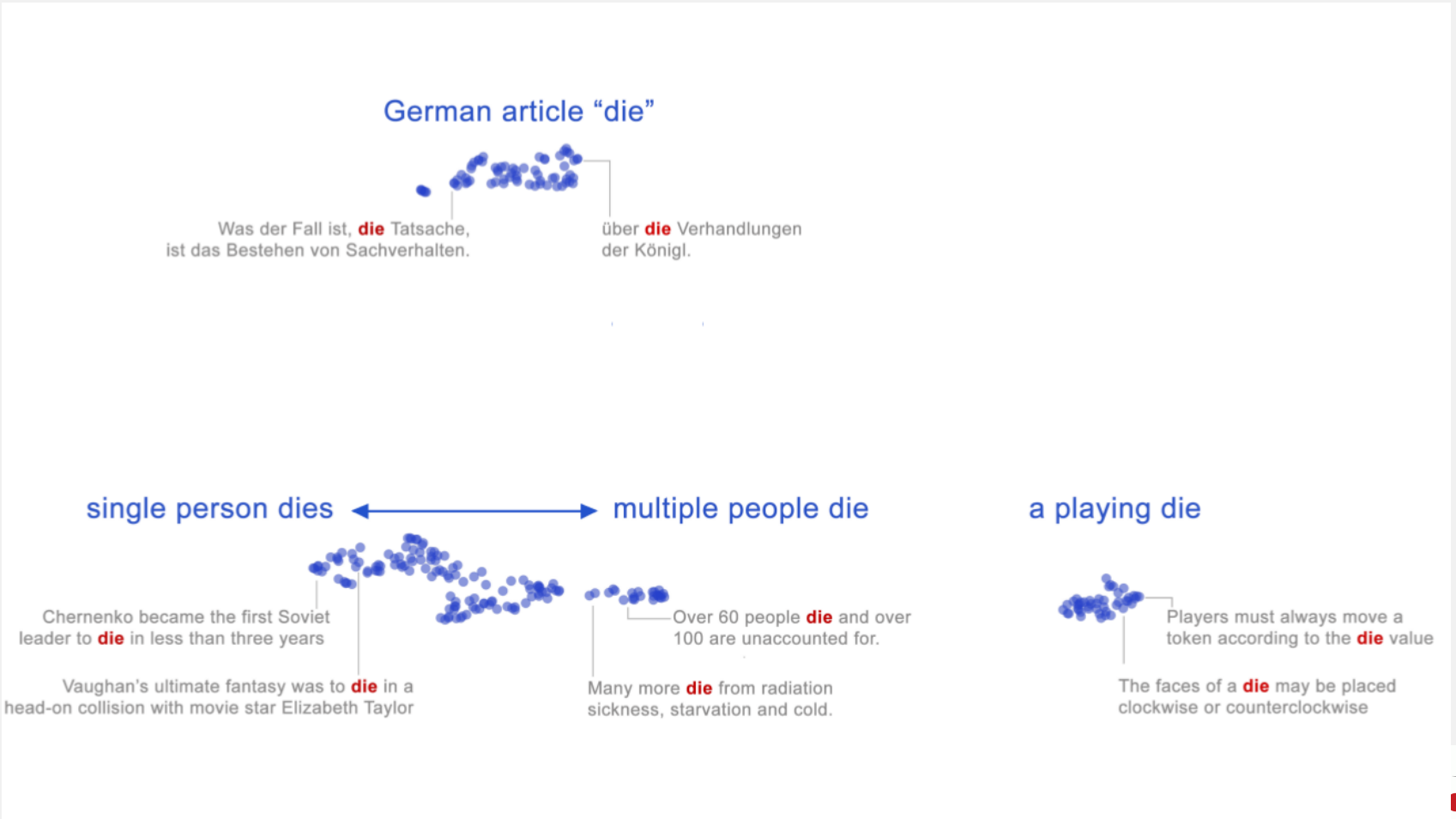
Homonymy and polysemy

- homonymy: Russian *mir* ‘world’; ‘peace’
- polysemy: Hungarian *nap* ‘Sun; day’
- evidence for differentiation
  - etymology: common origin
    - uncertain for many words
    - how far back?
  - relatedness of meanings (intuition. Agreement?)

disambiguation (WSD)	classification	supervised
induction (WSI) (Schütze, 1998)	clustering	unsupervised

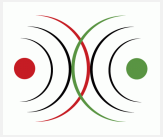
Polysemy in contextualized word embeddings

Coenen et al., (2019)



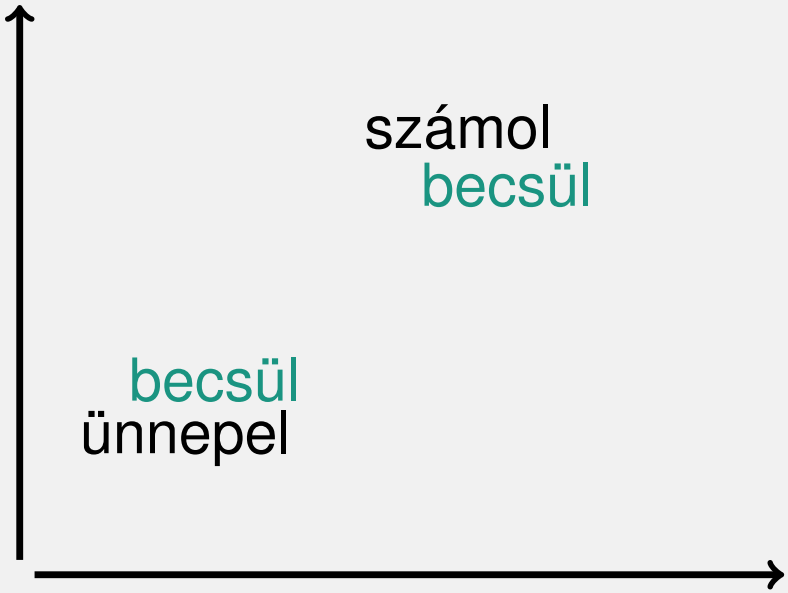
Multi-sense word embeddings (static)

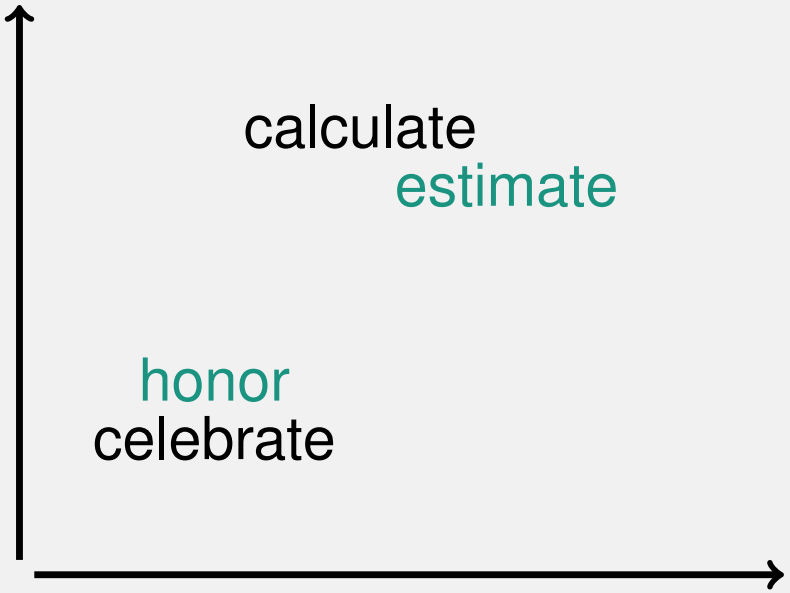
- before contextualized word representations, in a galaxy. . .
- multi-“prototype” embeddings (Reisinger and Mooney, 2010)
- with neural network (Huang et al., 2012)
- multi-sense skip gram, open-source tools
  - Neelakantan et al., 2014
  - as a Dirichlet Process
    - `AdaGram` (Bartunov et al., 2016)
    - `mutli` (Li and Jurafsky, 2015)
- if the number of parameters is controlled (Li and Jurafsky, 2015)
  - slight performance boost in
    - semantic similarity for words and sentences,
    - semantic relation identification,
    - part-of-speech tagging
  - no improvement in
    - sentiment analysis
    - named entity extraction
- sense resolution is too fine (duplicates and noise vectors)



Linear translation from multi-sense embedding

- Borbély, Makrai, Nemeskey, and Kornai 2016
- principle: homonymous senses $\rightsquigarrow$ different translations
- target embedding remains single-sense
  (Pennington, Socher, and Manning, 2014; Mikolov et al., 2013b)



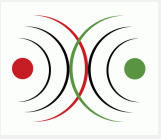


Data

- source corpus
  - de-glutinized version (Borbély et al., 2016a; Nemeskey, 2017) of the Hungarian National Corpus (Oravecz, Váradi, and Sass, 2014)

`jelmondatával`	→	`jelmondat <POSS> <CAS<INS»`	‘(with its) motto’
`akartak`	→	`akar <PAST> <PLUR>`	‘(they) want(ed)’

- target embedding: GloVe 840B 300d (Pennington, Socher, and Manning, 2014)
- seed dictionary: wikt2dict (Ács, Pajkossy, and Kornai, 2013)
- training on the first meaning



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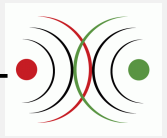
Examples

	sim			covg
S	0.0974	kapcsolat	affair, conjunction, linkage	0.33
S	0.136	futó	runner, bishop	1.0
I	0.1361	kocsi	coach, carriage	1.0
S	0.1626	fogad	bet, greet	1.0
S	0.1873	induló	march, candidate	1.0
S	0.2052	zavar	disturbance, annoy, disturb, turmoil	0.57
S	0.2206	bemutató	exhibition, presenter	0.67
I	0.2494	gazda	farmer, boss	0.67
I	0.2506	kapu	gate, portal	1.0
I	0.2515	előbbi	anterior, preceding	0.67
I	0.2558	kötelezettség	engagement, obligation	0.67
S	0.2807	sorozat	suite, serial, succession	1.0
S	0.2935	durva	coarse, gross	0.18
I	0.3097	megkülönböztetés	discrimination, differentiation	0.5
I	0.319	hirdet	advertise, proclaim	1.0
I	0.3299	aláírás	signing, signature	0.67



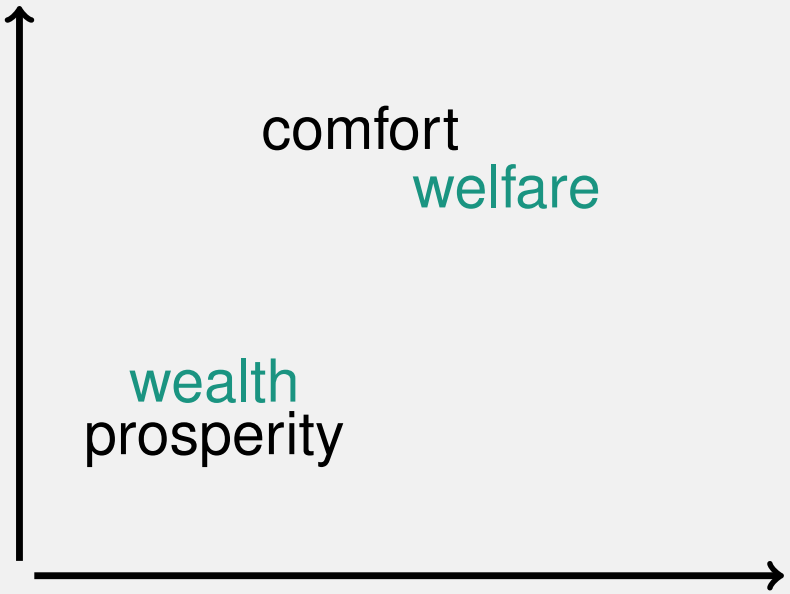
The resolution trade-off

- different vectors $\overset{?}{\Rightarrow}$ different meanings
- `lax`: selection of parameters and target embedding
  - at least one meaning vector should have a good translation
- `disamb`: different sense vectors should have a different set of good translations
  - ratio of such items among those predicted to be ambiguous

	`lax`	`disamb`
`AdaGram`	73.3%	18.53%
`mutli` "sense vectors" (u_i)	71.0%	19.46%
`mutli` "context vectors" (v_i)	69.9%	**20.76%**

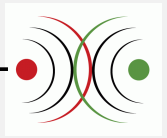
$$p(w_i \mid w_j) \propto \exp(u_i^\top v_j)$$

Problem: synonymous translations



Some of the most ambiguous 25 words

		sim		covg
mutli "context vs"	sokaság	0.07848	plurality crowd multitude	0.38
	kar	0.1008	arm choir	1.0
	alkalmazás	0.1087	adaptation hiring employ app	0.67
	bejelent	0.1119	announce lodge	1.0
	csomó	0.116	lump mat knot	1.0
	összeállítás	0.1247	binding compilation editing composition	0.8
	agy	0.1746	butt hub	1.0
	találkozó	0.1898	reunion appointment	1.0
AdaGram	fordítás	0.06056	turning compilation translation	0.75
	ruha	0.1154	dress costume rig clothes garment	0.62
	alkalmazás	0.1236	app employ	0.33
	törzs	0.1308	tribe stem trunk waist hull	0.62
	függő	0.145	dependent aerial addict	0.6
	hangsúlyoz	0.1595	stress accent	0.67
	nyom	0.2582	clue squeeze weigh hint push trace slot foil	0.62
	mag	0.2634	kernel seed	0.4



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