Discretized Word Representations Meet Knowledge Graphs

Gábor Berend

09/11/2017
GraphNLP meetup

Semantics

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Computational Semantics

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Rehabilitation of Count-based Models for Word Vector Representations

Rémi Lebret[1,2] and Ronan Collobert[1]

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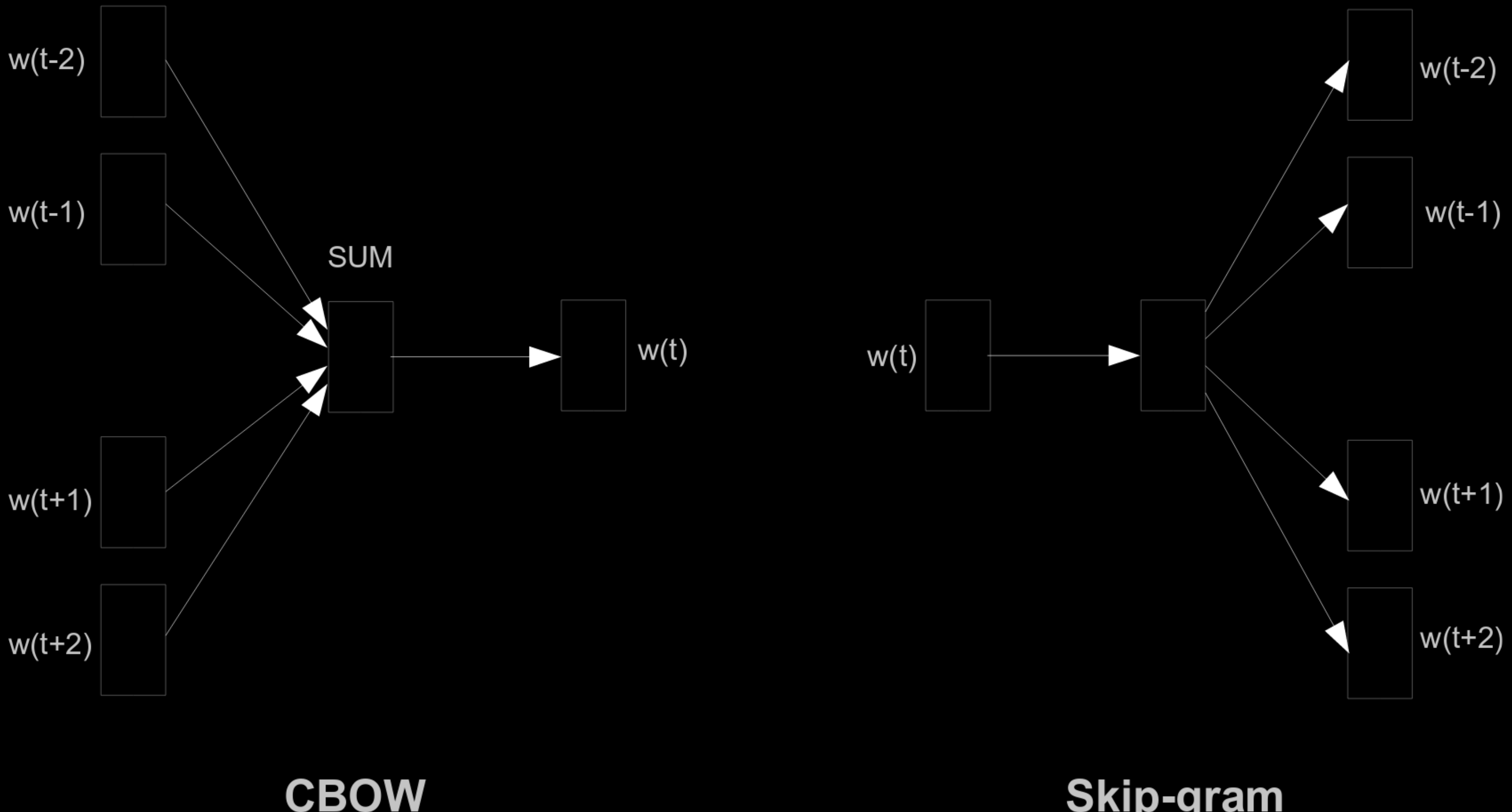
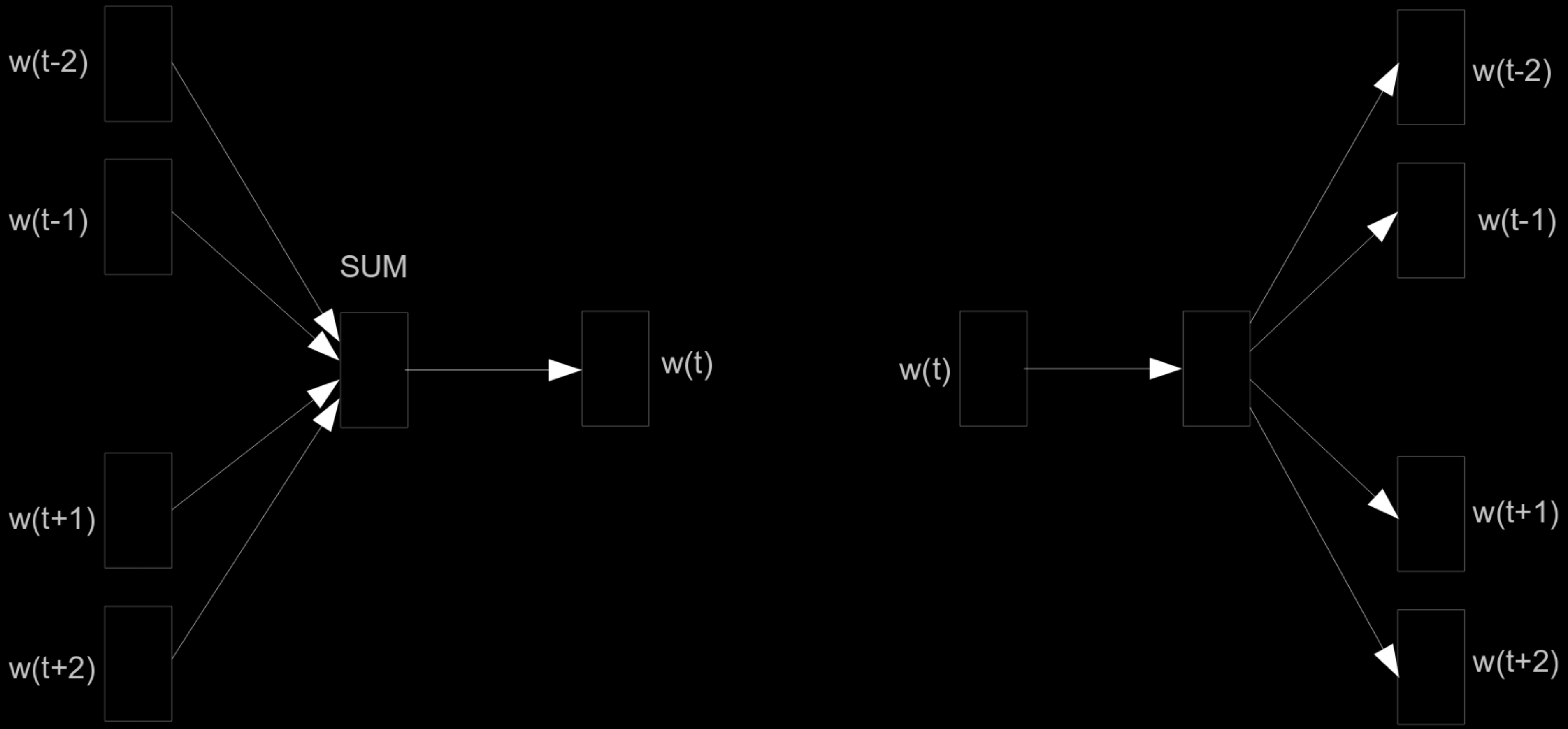
$$\overrightarrow{dog}^T \overrightarrow{cat} \gg \overrightarrow{dog}^T \overrightarrow{train}$$

word2vec variants



word2vec variants

quick brown X jumps over

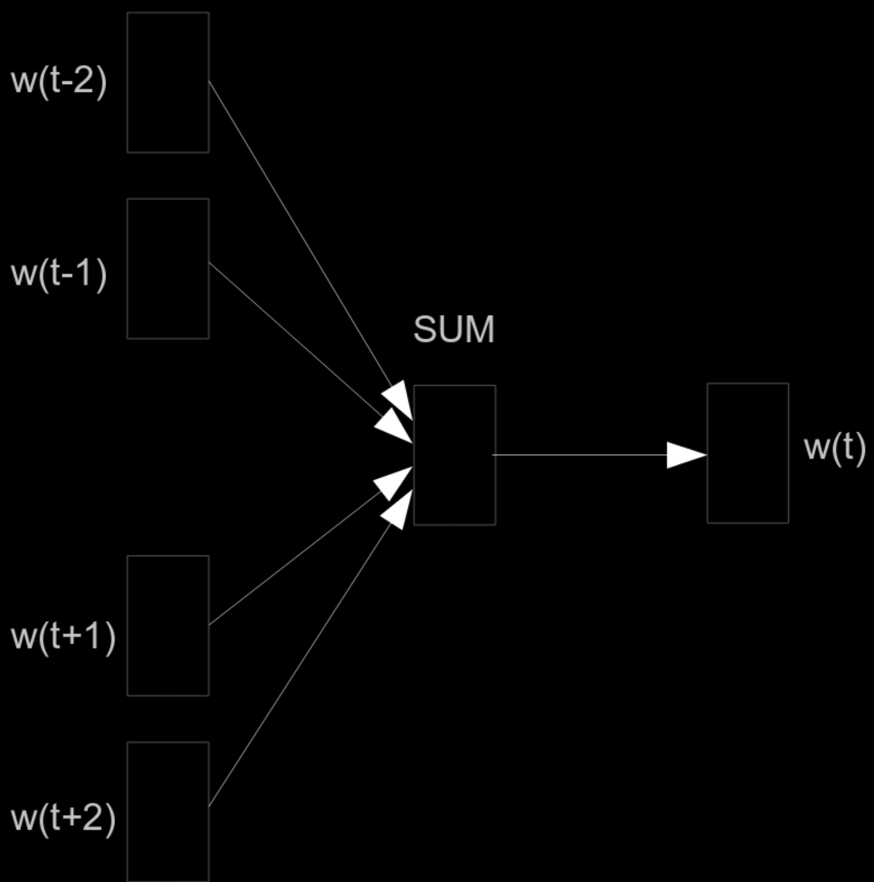


CBOW **Skip-gram**

word2vec variants

quick brown X jumps over

U V fox Y Z



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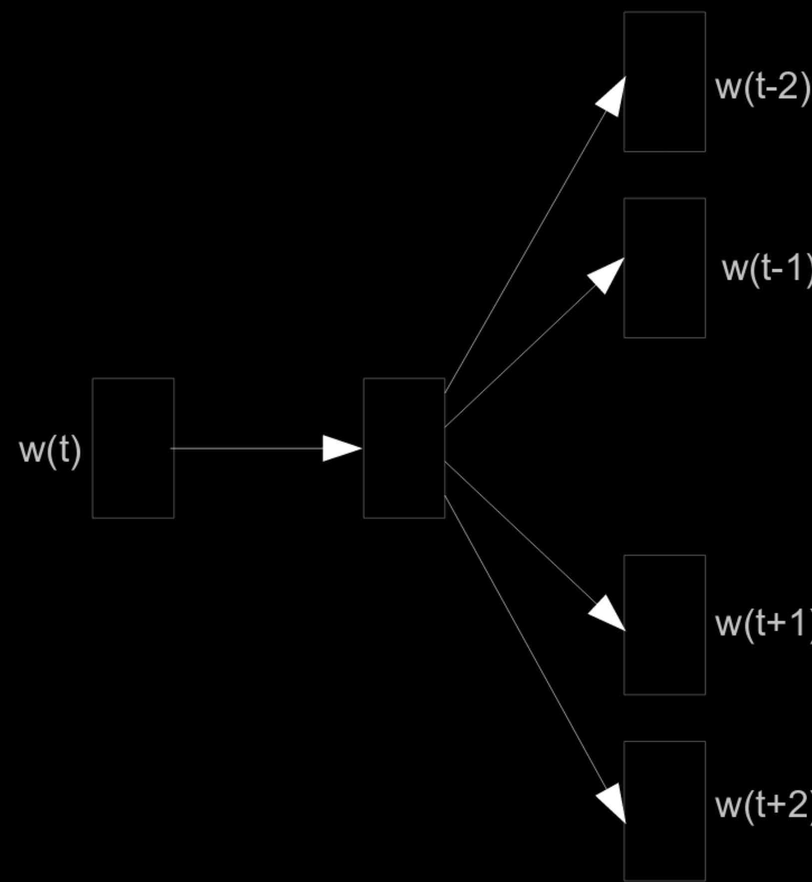


Skip-gram

The goal of word2vec

- The NN view: given an input word **x** ‘predict’ an output word which fits in its context

$$y(x) = softmax(V(W 1_x))$$

  - The more similar two input vectors, the more similar their predictions tend to be

Continuous word representations

apple [1 0 0 0 … 0 0 0 0 0 … 0] → [3.2 -1.5]

...

banana [0 0 0 0 … 1 0 0 0 0 … 0] → [2.8 -1.6]

...

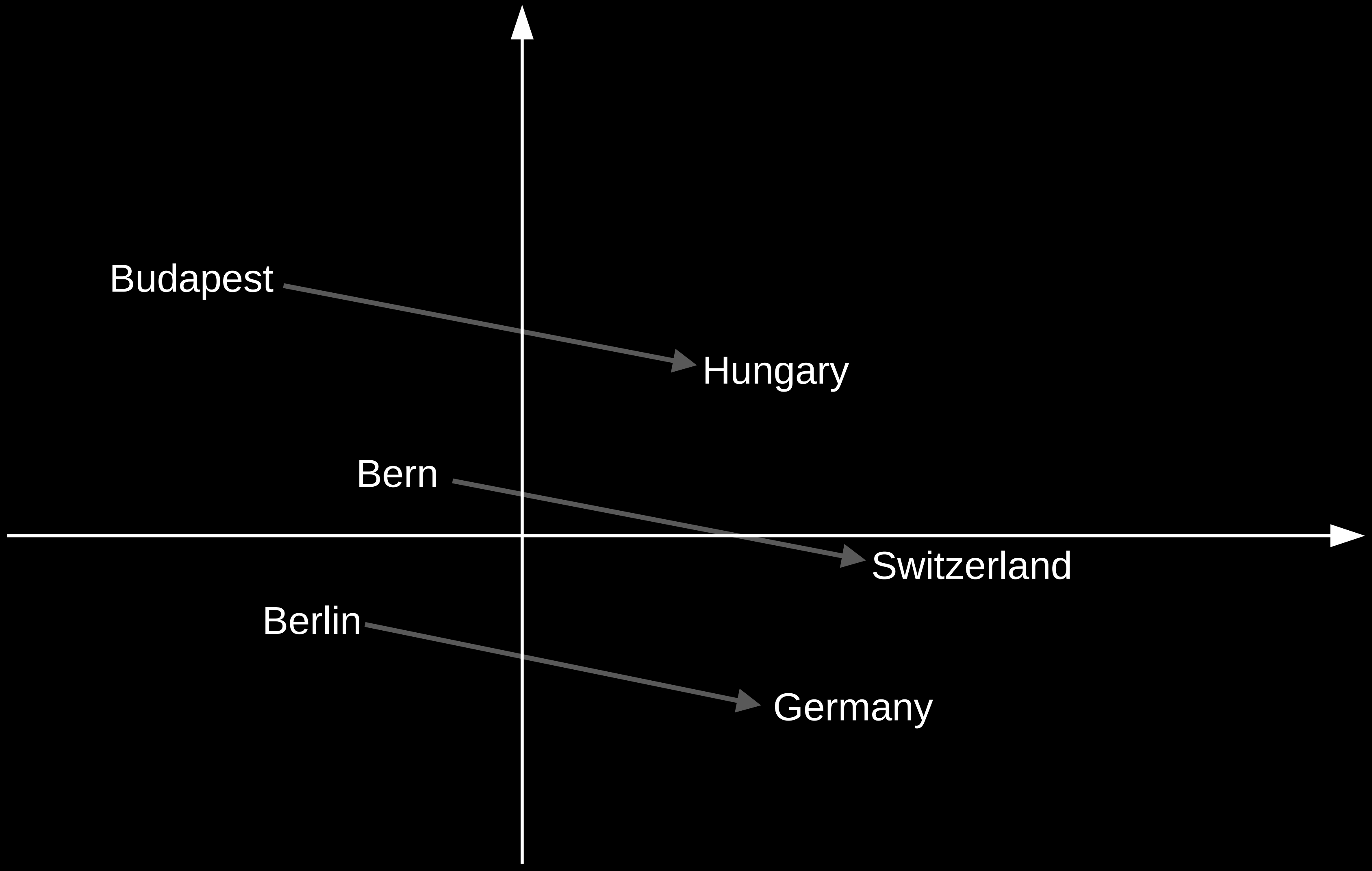
door [0 0 0 0 … 0 0 1 0 0 … 0] → [-1.1 12.6]

…

zebra [0 0 0 0 … 0 0 0 0 0 … 1] → [0.8 0.5]

Word analogies

- a:b::c:?



RepEval 2016

Analysis Track

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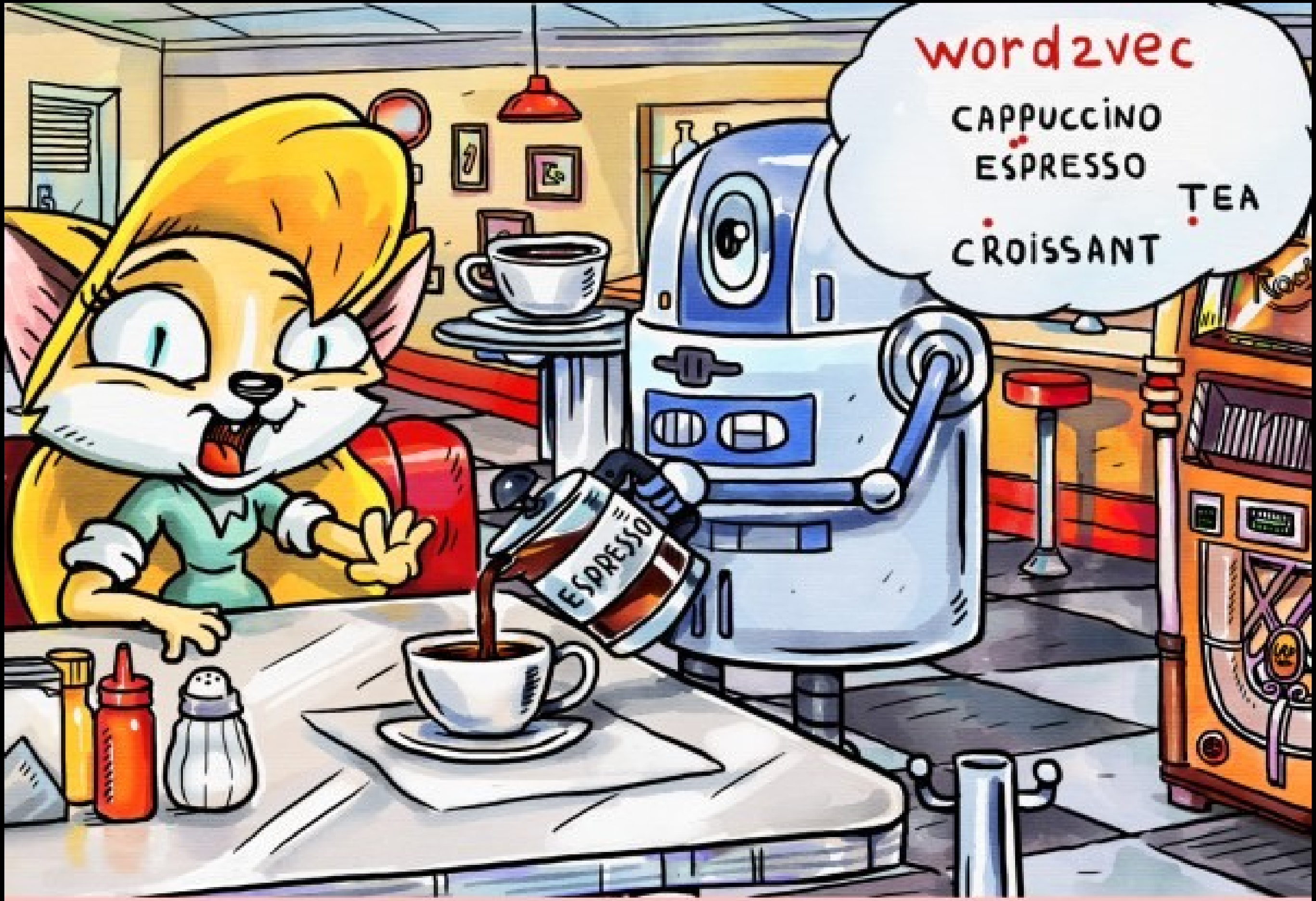
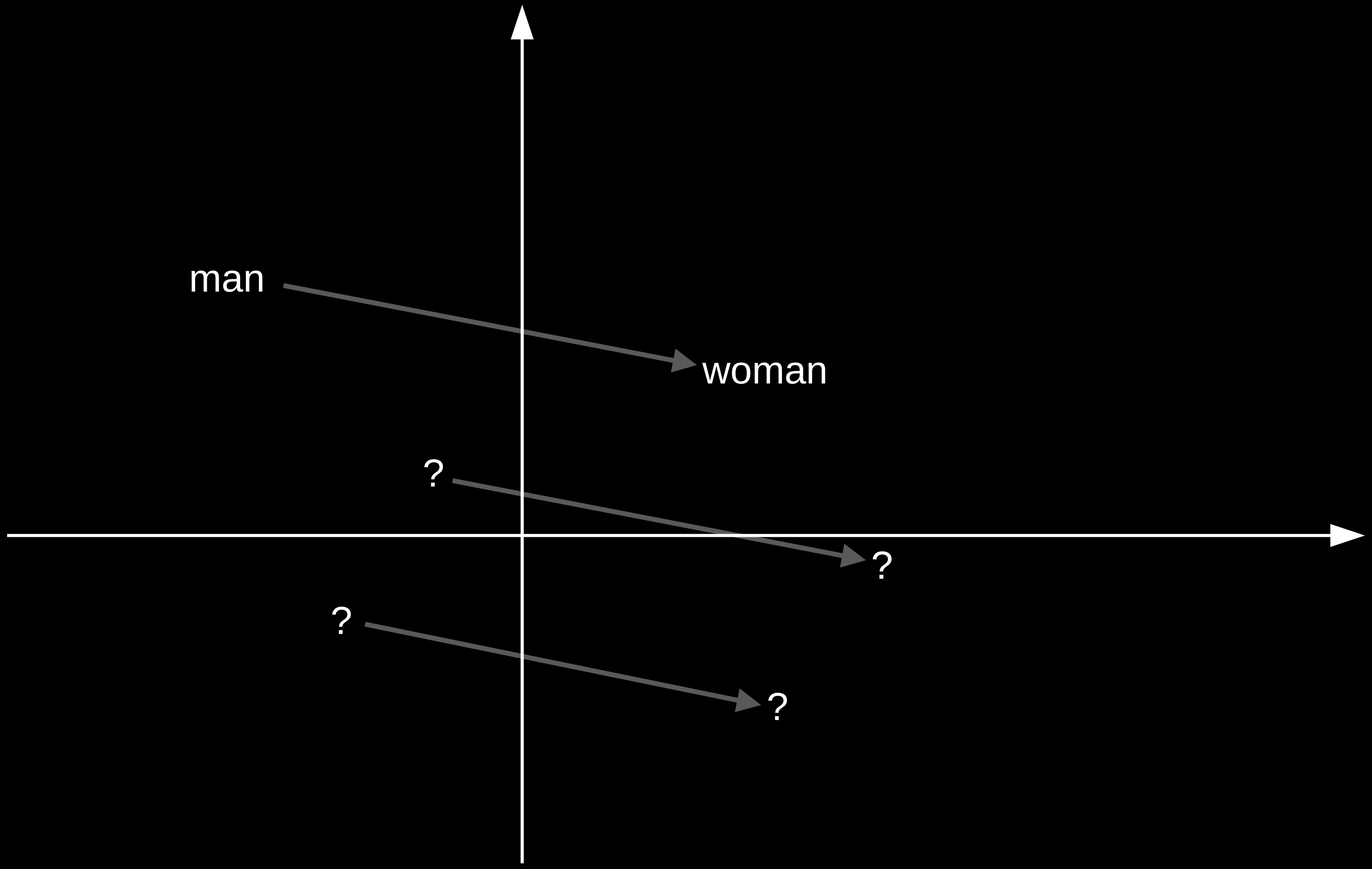


- Espresso? But I ordered a cappuccino!
- Don't worry, the cosine distance between them is so small that they are almost the same thing.

Word analogies revisited

- a:b:?:?



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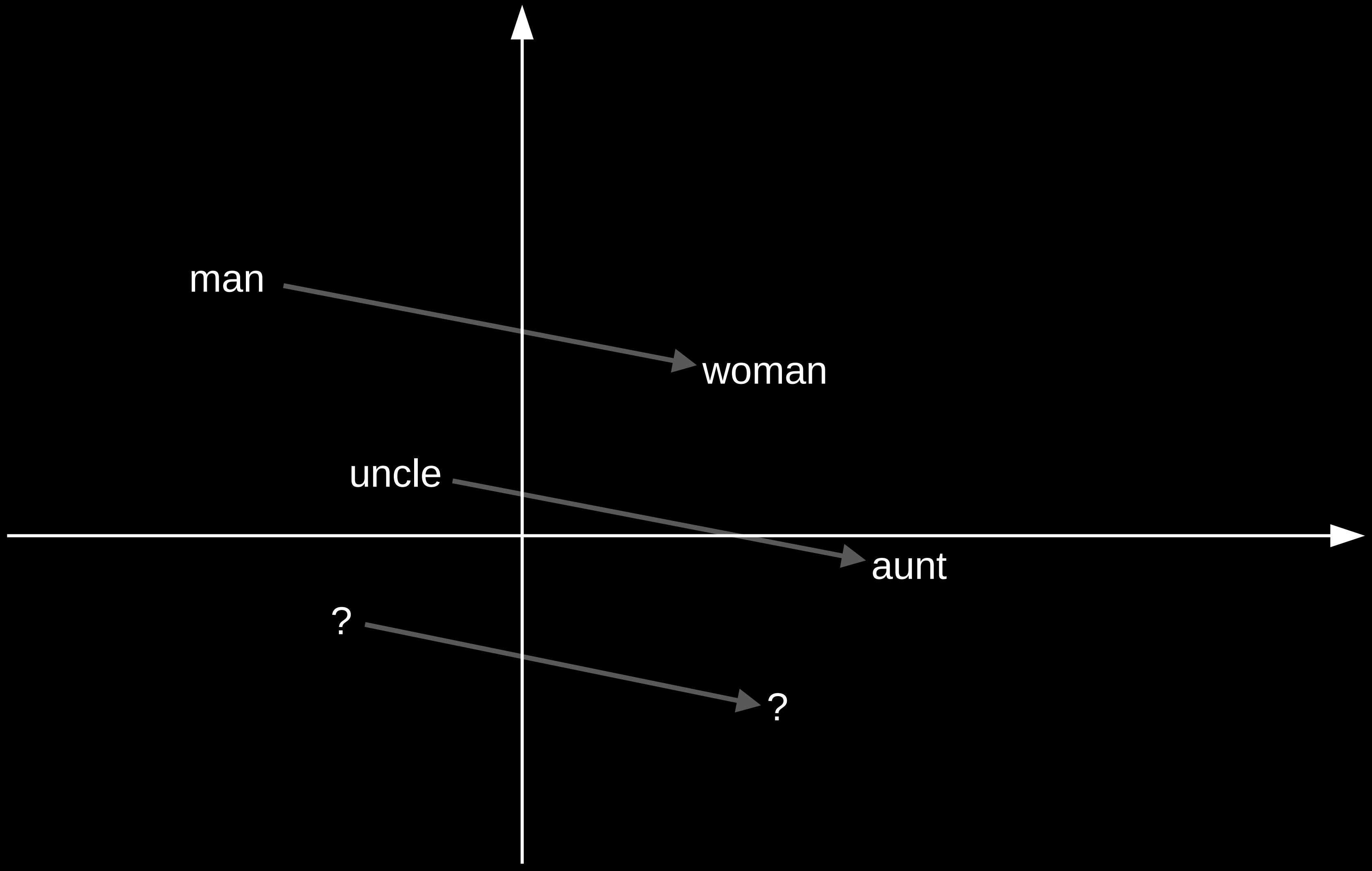

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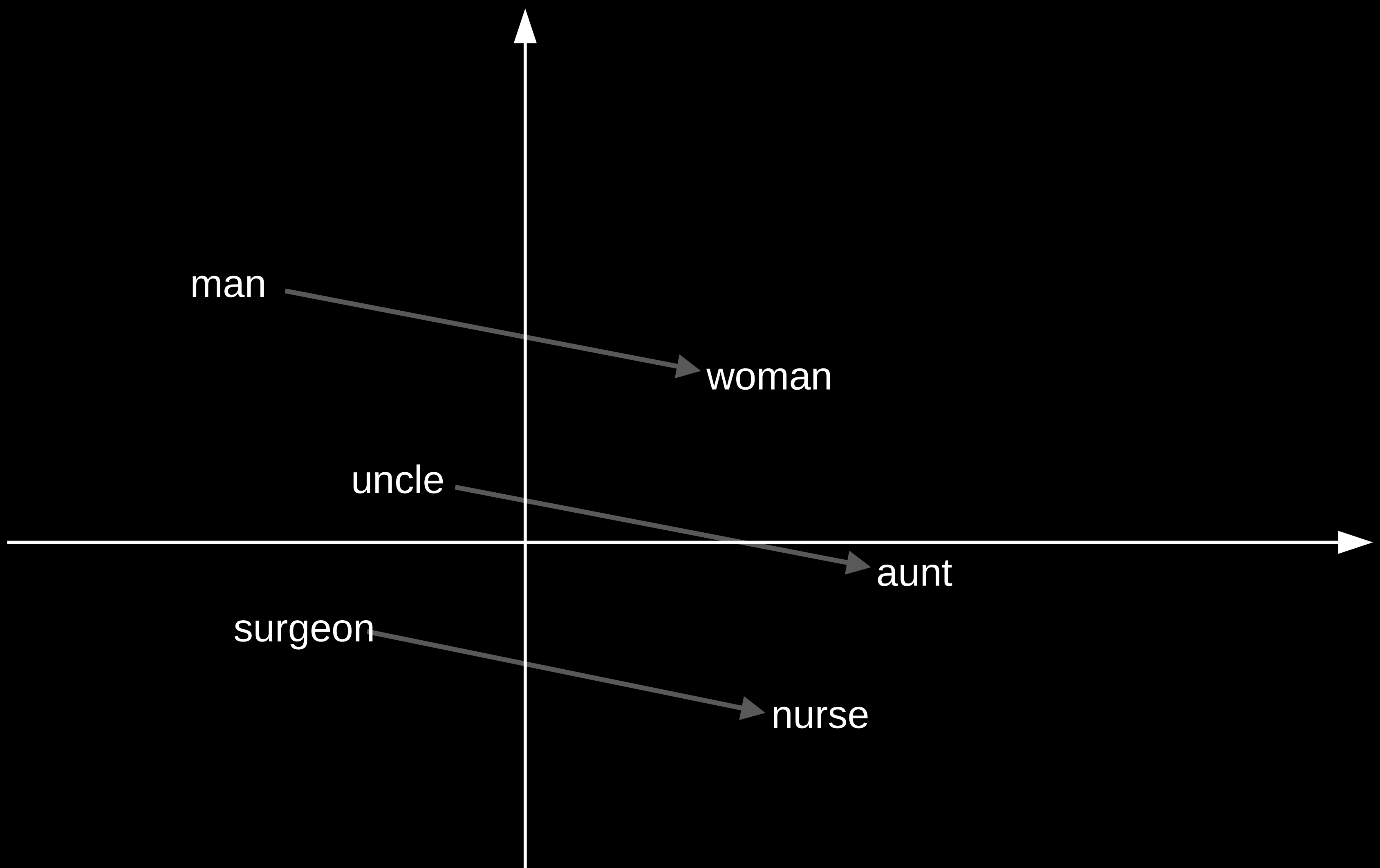

Limitations of word embeddings

- The quality of the embedding is determined by the corpus it is trained on

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  - Potential recall issues (esp. for agglutinative languages)
    - Character level models
  - Polisemy (e.g. bank)
  - Multilinguality
  - Difficulties of evaluation
  - PCness (e.g. man : programmer :: women : X)
  - **Limited interpretability**

Sparse & continuous representations

apple [3.2 -1.5] → [0 1.7 0 0 -0.2 0]

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banana [2.8 -1.6] → [0 1.1 0 0 -0.4 0]

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door [-1.1 12.6] → [1.7 0 -2.1 0 0 -0.8]

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zebra [0.8 0.5] → [0 0 1.3 0 -1.2 0]

Creating sparse word representations

- Assuming trained word embeddings w_i (i=1,…,|V|)

$$\min_{D \in C, A} \sum_{i=1}^{|V|} \| x_i - D a_i \|_2^2$$

Embedding vector ($\in \mathbb{R}^L$)

Dictionary ($\in \mathbb{R}^{LxK}$)

coefficients

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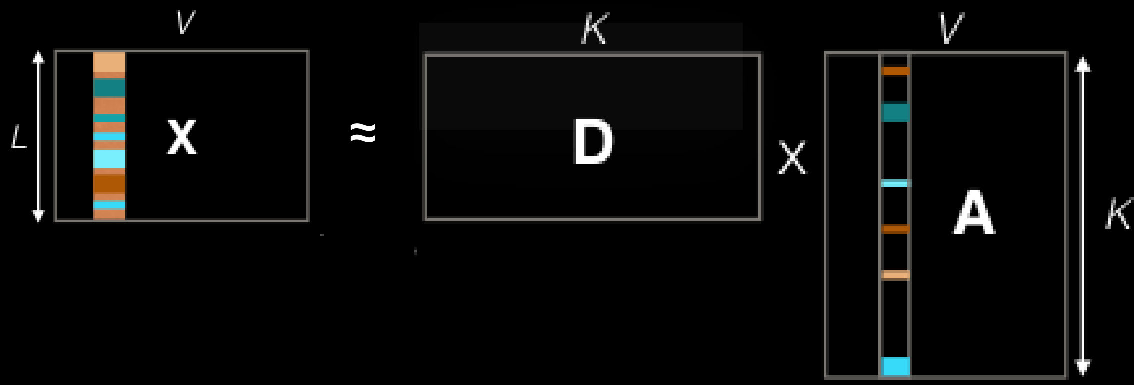

“Classical” sequence labeling

- Calculate a set of (surface form) features using feature functions φ_j
  - φ_j could check for capitalization, suffixes, prefixes, neighboring words, etc.

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Y:	NN	NN	VB	DT	NN	PUNCT
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φ:	P28 N171	P77 P88 ...	N11 N62 ...	N88 N40 ...	P28 N210 ...	N21 P67 ...

Experimental setup

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- Part of Speech tagging
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- Hyperparameter settings
  - polyglot/w2v/Glove
  - m=64
  - k=1024
  - Varying λs

$$\min_{D \in C, \alpha} \sum_{i=1}^{|V|} \|w_i - D\alpha_i\|_2^2 + \lambda \|\alpha_i\|_1$$

Embedding vector ($\in \mathbb{R}^m$)

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Baselines

- Feature rich baseline (FR)
  - Standard feature set borrowed from CRFsuite
    - Previous, next word, word combinations, …
  - 2 variants:
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$FR_{w+c} \supset FR_{w}$

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- Features from **dense** embeddings
  - $\phi(w_i) = \{ j : \alpha_i[j] \mid \forall j \in 1, \ldots, 64 \}$

Continuous vs. sparse embeddings

- Results averaged over 12 languages

	Dense	Sparse	
CBOW	88.30%	93.74%	
SG	86.89%	93.63%	

- Key inspections
  - polyglot > CBOW > SG > Glove

Continuous vs. sparse embeddings

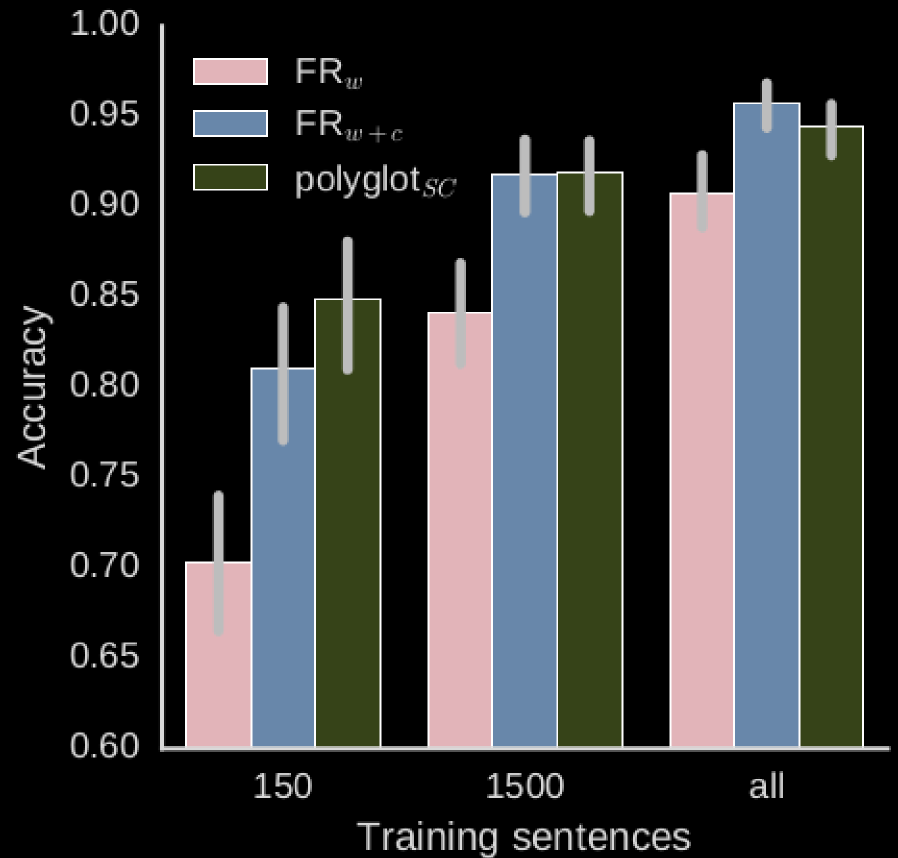
- Results averaged over 12 languages

	Dense	Sparse	Improvement
CBOW	88.30%	93.74%	+5.4
SG	86.89%	93.63%	+6.7

- Key inspections
  - polyglot > CBOW > SG > Glove
  - Sparse embeddings >> dense embeddings

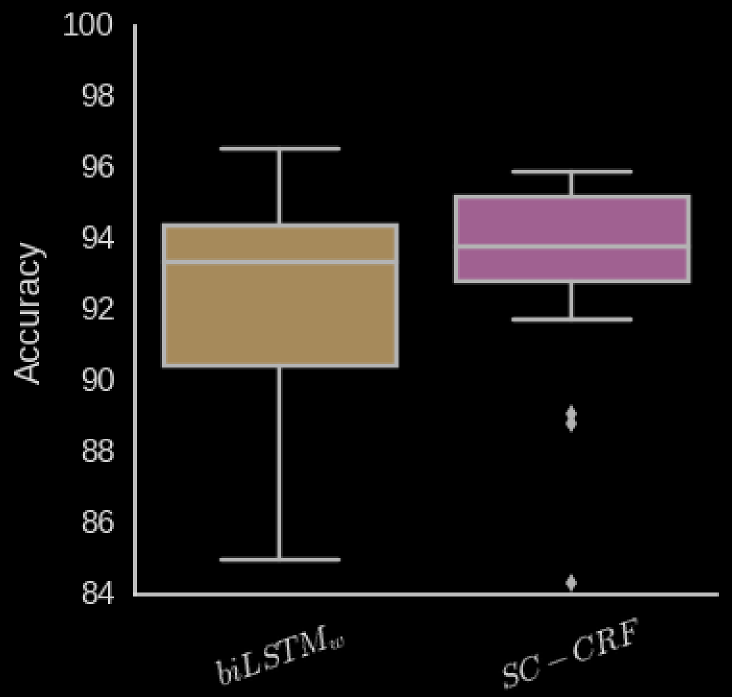
Experiments on generalization

- Training data artificially decreased
  - First 150 and 1500 sentences



Comparison with biLSTMs

- POS tagging experiments on UD v1.2 treebanks
- Same settings as before (k=1024, λ=0.1)
- biLSTM results from *Plank et al. (2016)*



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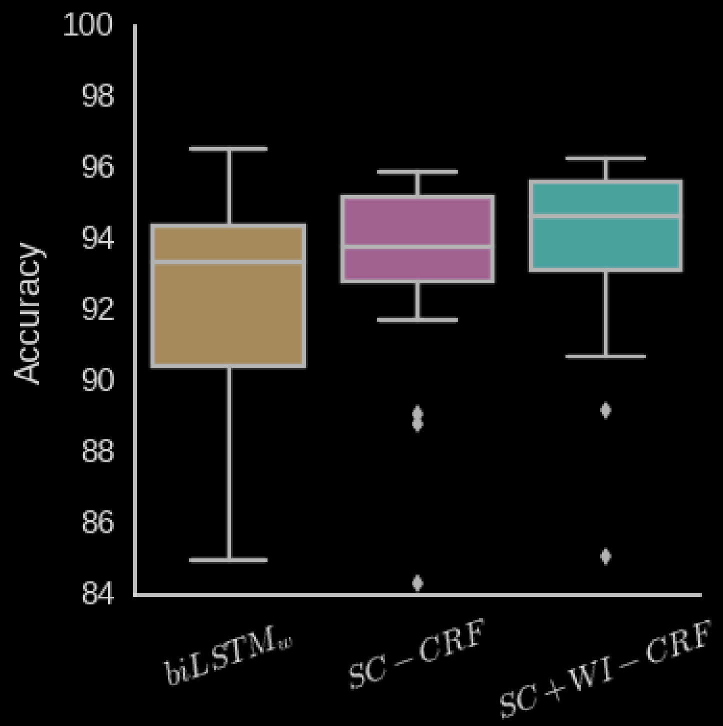

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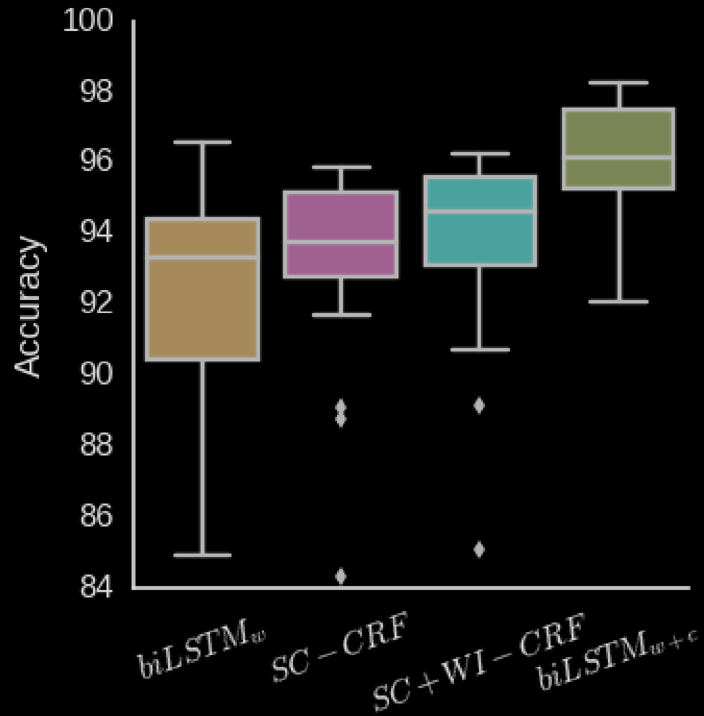

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biLSTM_{w+c}	95.99%

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  - E.g. house → {4, **<u>31</u>**, **<u>91</u>**} and IsA('house', 'shelter') and hut → {7, **<u>31</u>**, 52, **<u>91</u>**} and IsA('hut', 'shelter')

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  - E.g. house → {4, **31**, **91**} and IsA('house', 'shelter') and hut → {7, **31**, 52, **91**} and IsA('hut', 'shelter')
    - The presence of base 31 and/or 91 seems to be a good indicator that something can be used as a shelter

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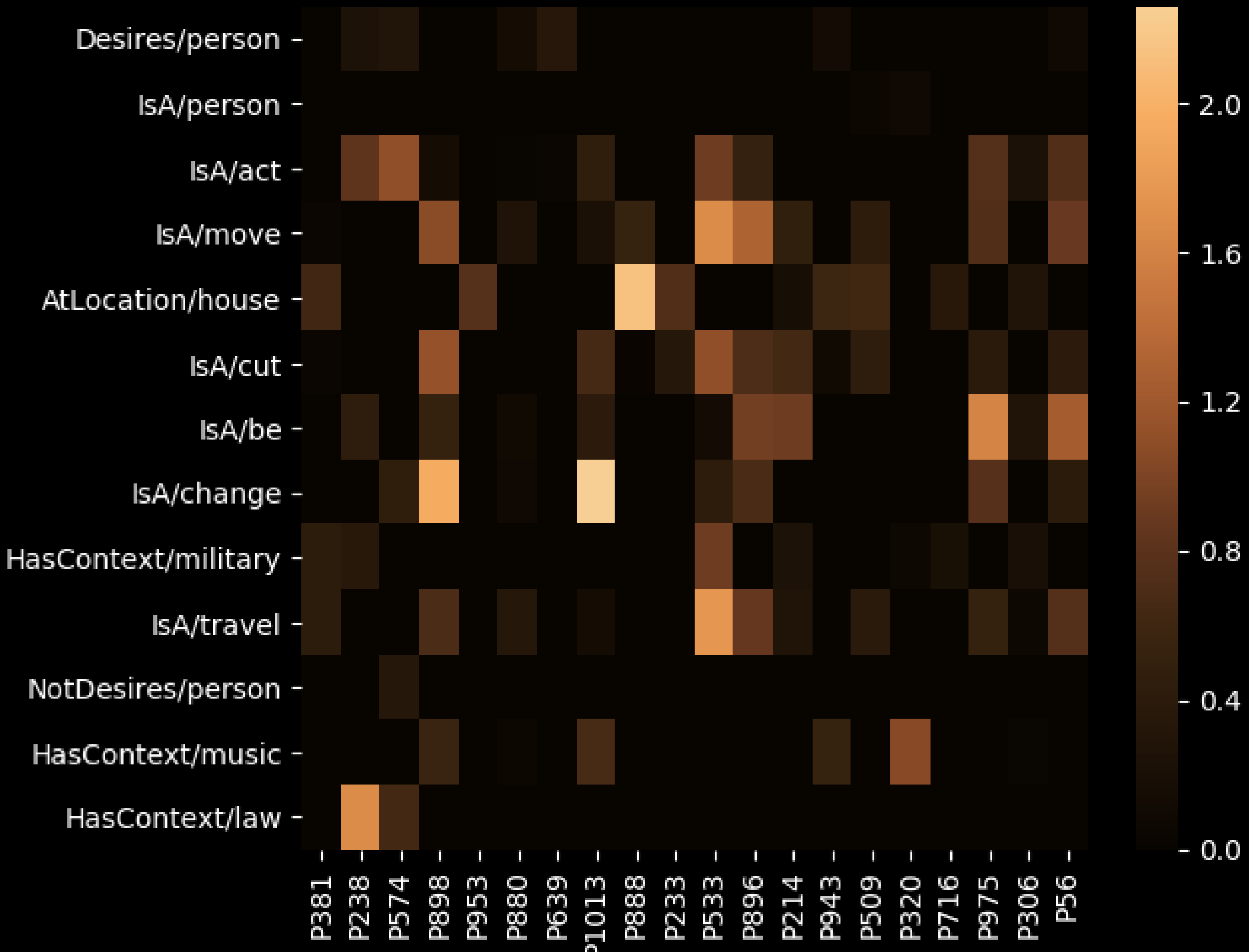

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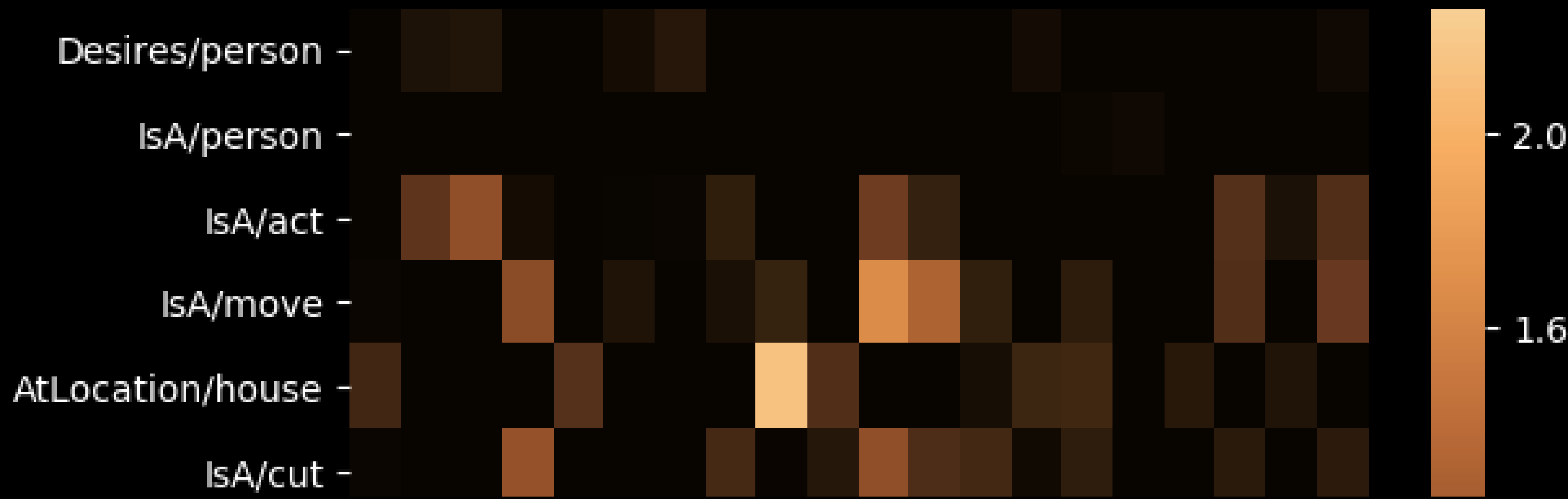

Basis	Top-1	Top-2	Top-3	Top-4	Top-5	Most associated ConcepNet relation
P381	village	neighbourhood	neighborhood	fort	township	AtLocation/house
P238	amendment	decision	inquiry	obligation	petition	HasContext/law
P574	stability	coherence	sensitivity	separation	efficiency	IsA/act
P898	harden	darken	pierce	flatten	loosen	IsA/change
P953	coal	oil	food	cotton	grain	AtLocation/house

Conclusion

- Simple to implement, yet accurate analyzers
- Robustness across many languages (and tasks)
- Good generalization properties
- Encouraging results towards interpretability

Thank you for your attention!

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