Language Technologies Institute

Carnegie Mellon University

Algorithms for NLP

CS 11-711 · Fall 2020

Lecture 4: Vector semantics and word embeddings

Emma Strubell

Announcements

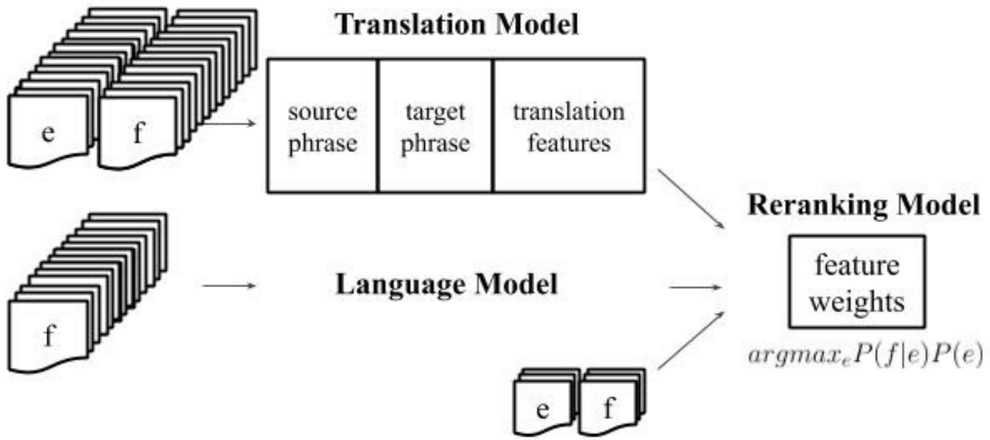
- Don’t forget we will hold recitations Friday to discuss P1.
- Working on getting lectures posted on YouTube (CMU-only) w/ closed captions.

Recap

Nonlinear classification & evaluating classifiers

Engineered features

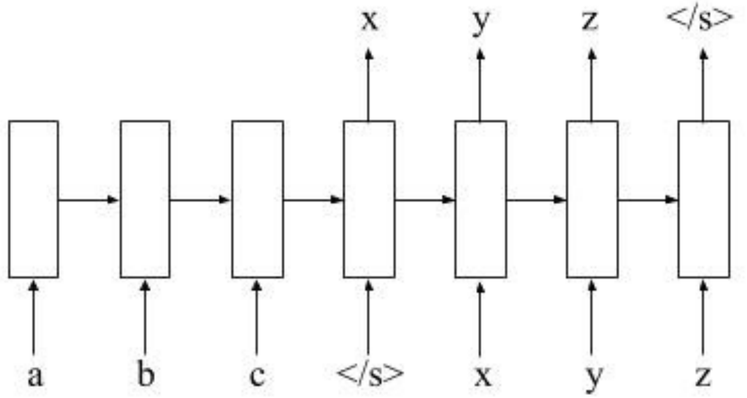
linear classification



~mid 2010s

Learned features

nonlinear classification



Recap

Another choice of $\mathcal{R}$: word embeddings

- Text is naturally viewed as a sequence of tokens w_1, w_2, …, w_T
- Context is lost when this sequence is converted to a bag-of-words.
- Instead, a **lookup layer** can compute **embeddings** (real-valued vectors) for each type, resulting in a matrix

$\boldsymbol{w}$ =

-1.36	0.09	0.71	-1.57	-0.72	-1.36	0.45	0.71	0.23
-0.23	-1.69	1.43	-0.42	-0.08	-0.23	-2.55	1.43	0.21
0.84	-0.16	0.11	0.54	1.56	0.84	-0.39	0.11	1.11
…	…	…	…	…	…	…	…	…
-0.067	0.71	-5.6	0.26	0.07	-0.067	-0.77	-5.6	0.55
the	drinks	were	strong	but	the	tacos	were	bland

How to represent a word?

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- Linguistic perspective: **lexical semantics**.

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pepper, *n.*

View as: Outline | Full entry

Pronunciation: Brit. /ˈpɛpə/, U.S. /ˈpɛpər/

Forms: OE **peopor** (*rare*), OE **pipcer** (transmission error), OE **pipor**, OE **pipur** (*rare*), OE–15 **piper**, ME **papeer**, ME **paupere**, ME **peopur**, ME **pepir**, ME **pepire**, ME **pepre**, ME **pepur**, ME **pepyr**, ME **pyper**, ME–15 **papur**, ME–17 **pep** error), 18 **pipper** (*Irish English*); *English regional* (*East Anglian*) 18– **pupper**; *Scottish* pre-17 **pepar**, pre-17 **peper**, pre-1 17 **pepyre**, pre-17 **piper**, pre-17 17– **pepper**. *N.E.D.* (1905) also records a form ME **pepyre**. (Show Less)

Frequency (in current use):

Origin: A borrowing from Latin. **Etymon:** Latin *piper*.

Etymology: < classical Latin *piper*, a loanword < Indo-Aryan (as is ancient Greek *πέπερι*); compare Sanskrit *pippalī* long p French, Middle French, French *poivre* (*c*1140 in Old French as *peivere* : see POIVRADE *n.*), Old Occitan, Occitan *pebre* (*a*1126),

I. The spice or the plant.

1.

a. A hot pungent spice derived from the prepared fruits (peppercorns) of the pepper plant, *Piper nigrum* (see sense 2a), used from early times to season food, either whole or ground to powder (often in association with salt). Also (locally, chiefly with distinguishing word): a similar spice derived from the fruits of certain other species of the genus *Piper*; the fruits themselves.

b. With distinguishing word: any of certain other pungent spices derived from plants of other families, *esp.* ones used as seasonings.

2.

a. The plant *Piper nigrum* (family Piperaceae), a climbing shrub indigenous to South Asia and also cultivated elsewhere in the tropics, which has alternate stalked entire leaves, with pendulous spikes of small green flowers opposite the leaves, succeeded by small berries turning red when ripe. Also more widely: any plant of the genus *Piper* or the family Piperaceae.

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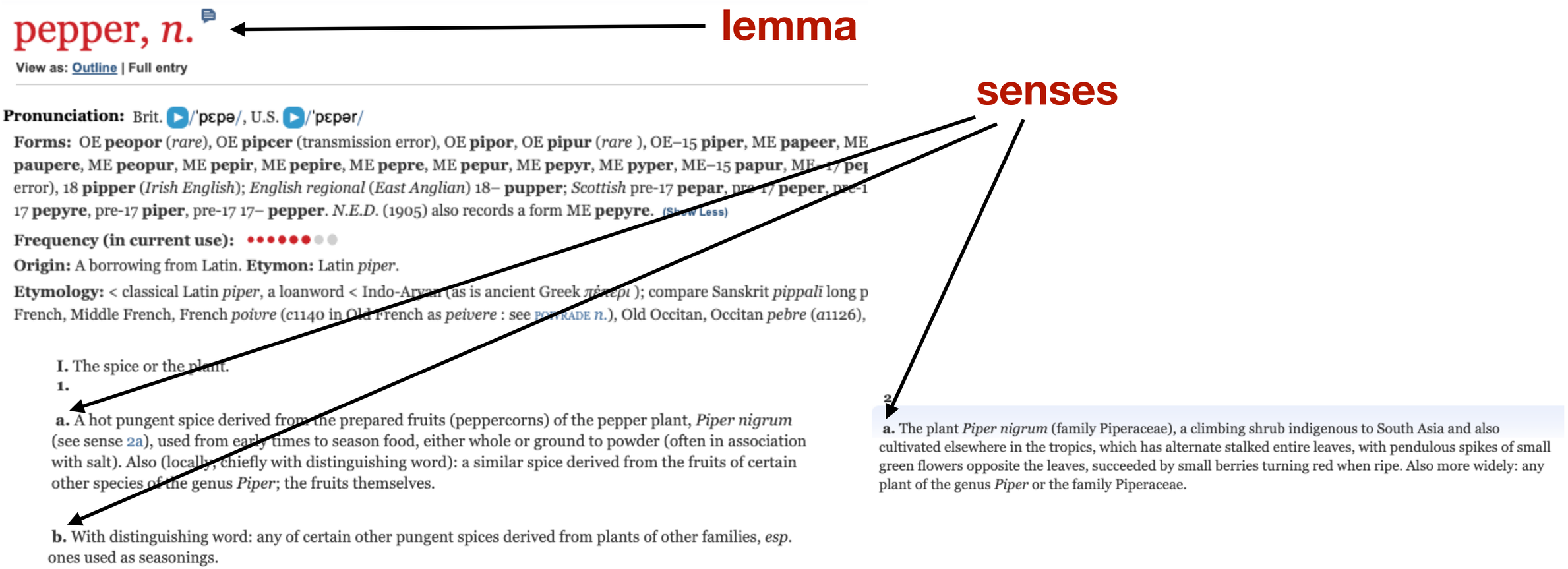

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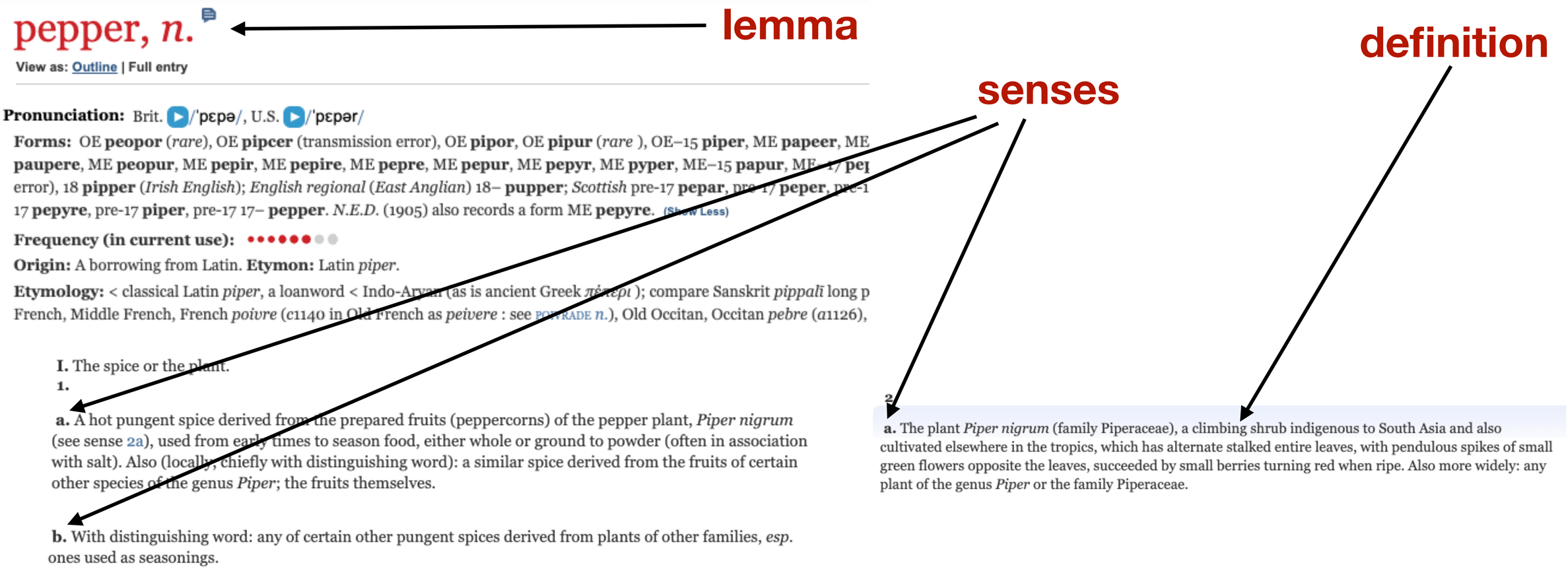

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Lexical semantics

A sense or “concept” is the meaning component of a word.

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    5. capsicum (i.e. chili, paprila, bell pepper, etc.)

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- Note that there are probably **no** examples of perfect synonymy
  - Even if many aspects of meaning are identical
  - Still may not preserve the acceptability based on notions of politeness, slang, register, genre, etc.

Relations between words

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word$_1$	**word$_2$**	**similarity**
vanish	disappear	9.8
behave	obey	7.3
belief	impression	5.95
muscle	bone	3.65
modest	flexible	0.98
hole	agreement	0.3

SimLex-999 dataset [Hill et al. 2015].

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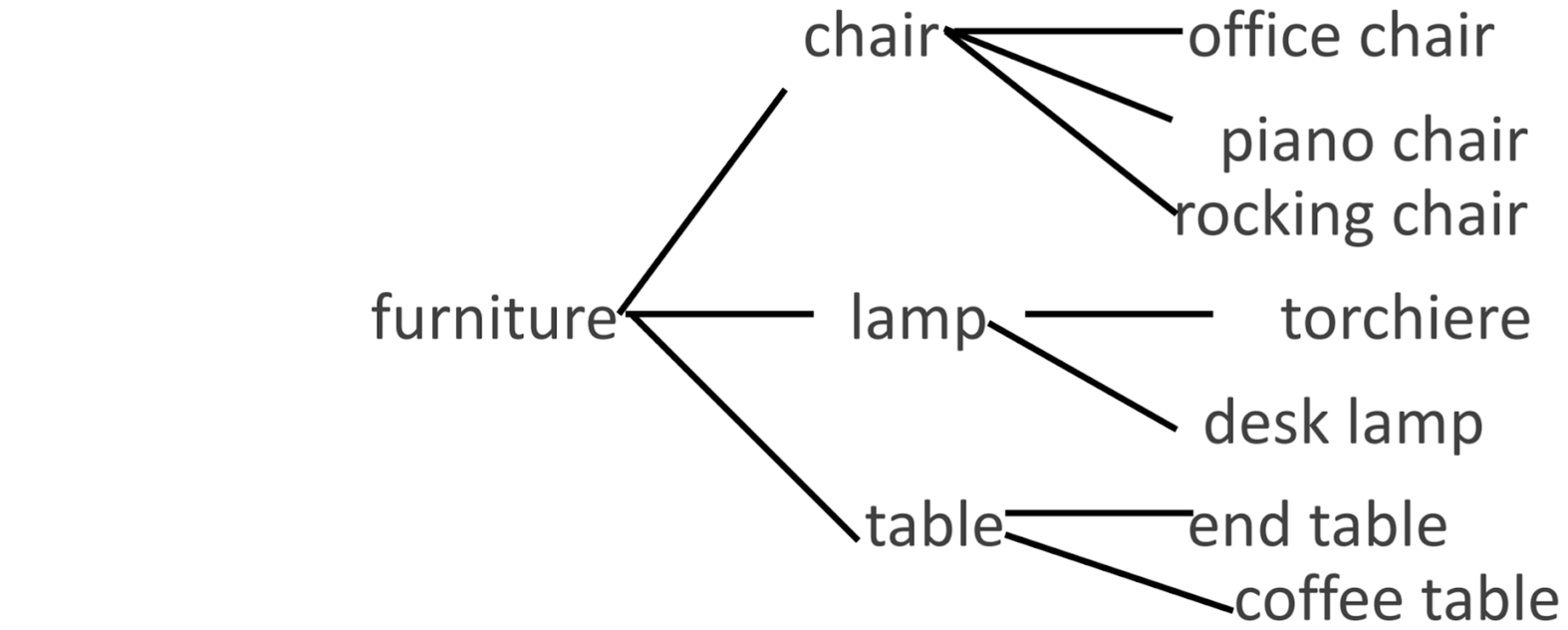
houses

door, roof, kitchen, family, bed

Relations between words

Hypernym / hyponym (superordinate / subordinate)



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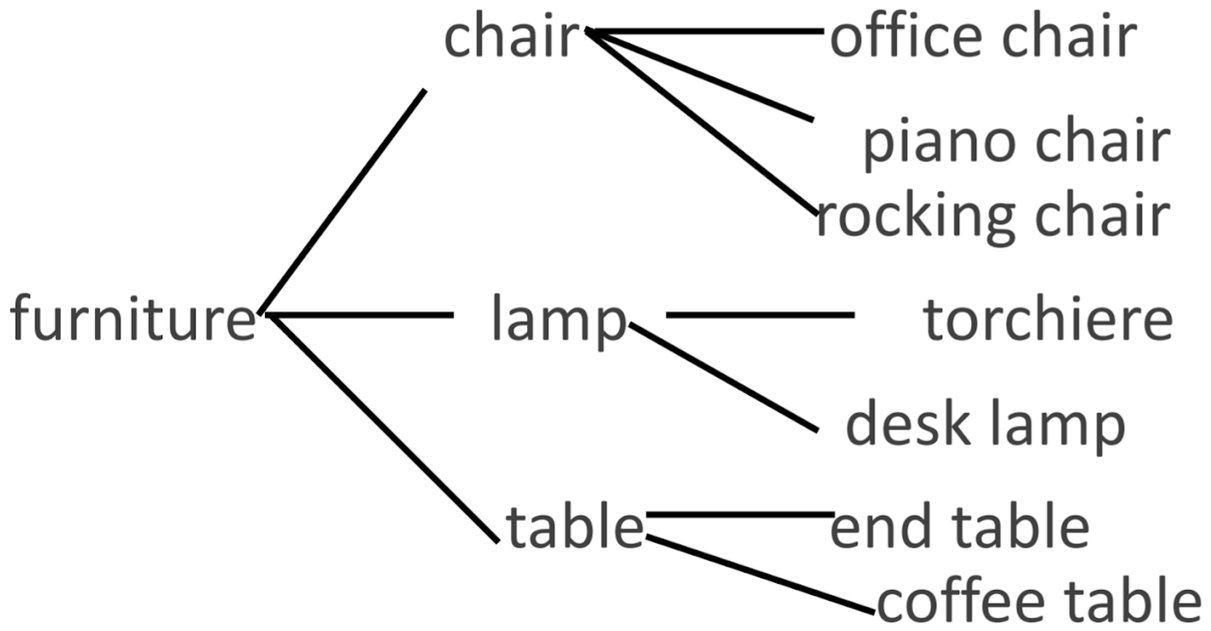
- One sense is a **hyponym** of another if the first sense is more specific, denoting a subclass of the other



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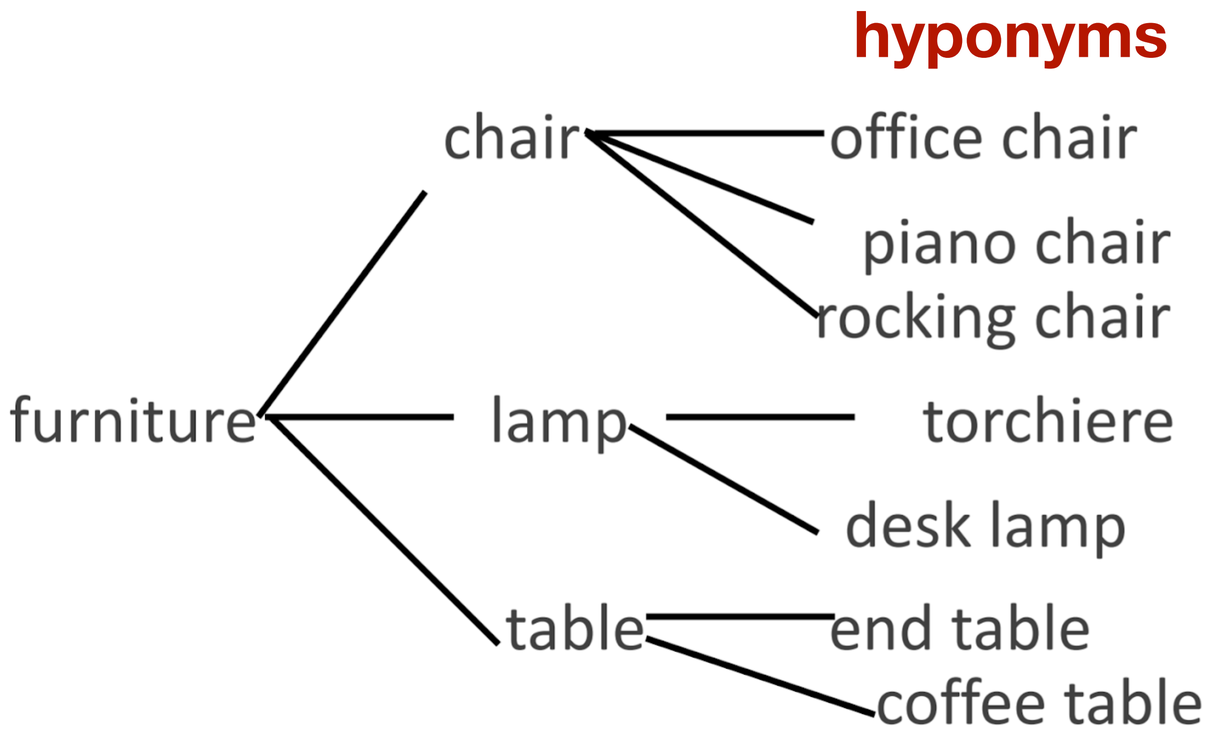

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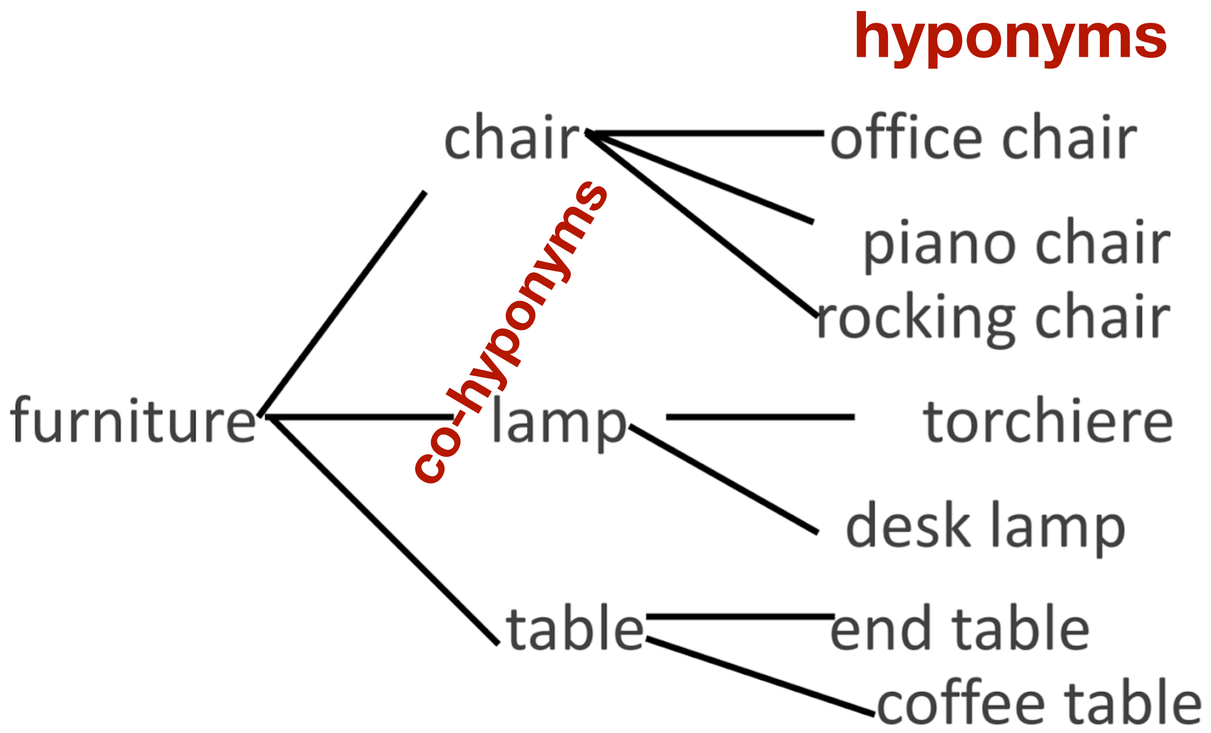

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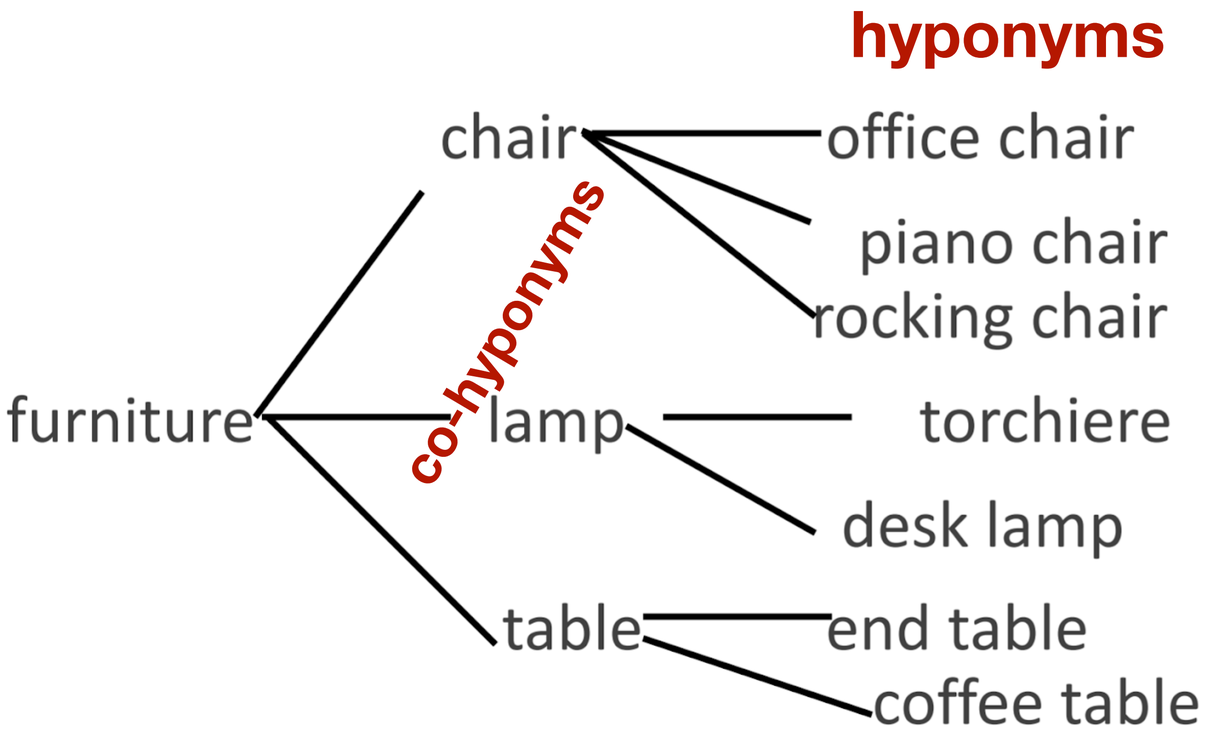

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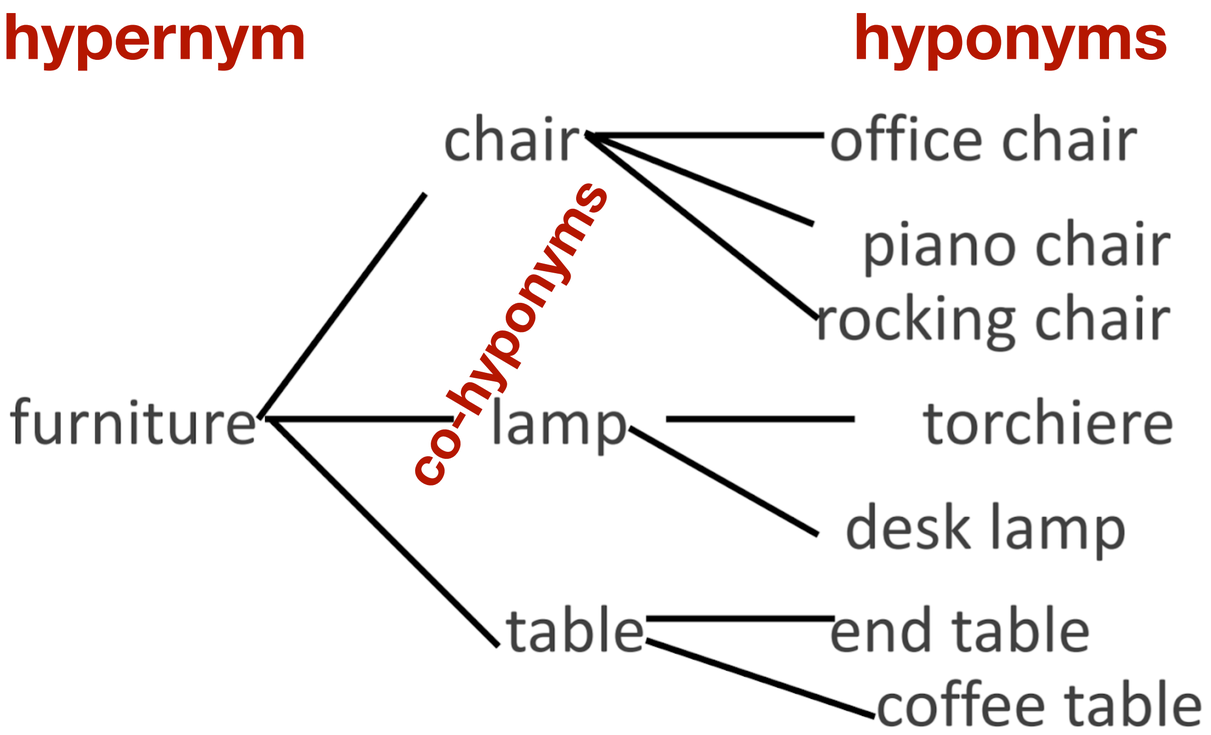

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Lexical semantics

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- Dictionary definition
- Lemma and word forms
- Senses
- Relationships between words or senses
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  Ling sold the book to Sam.

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pleasantness intensity degree of control

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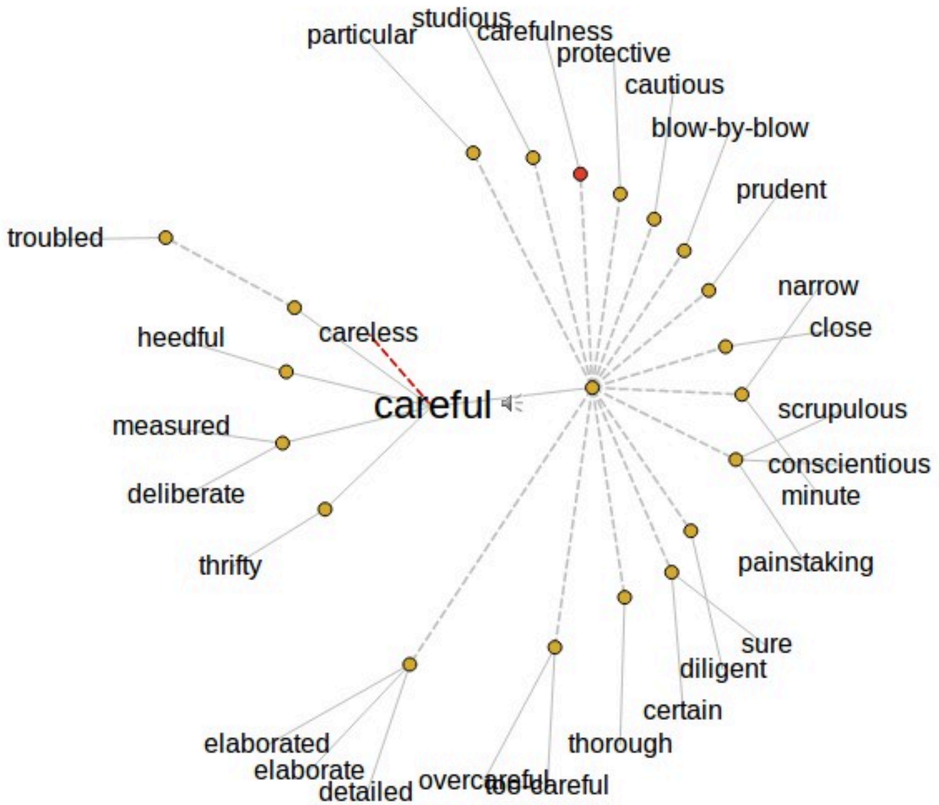

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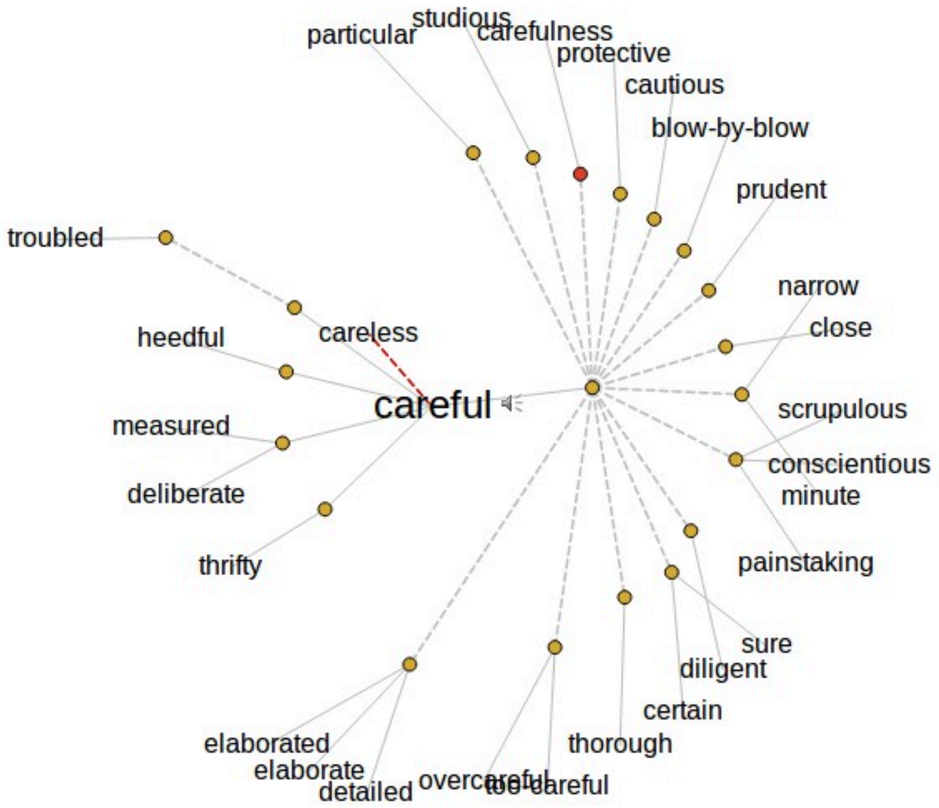

WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: bank Search WordNet

Display Options: (Select option to change) Change

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **bank** (sloping l *pulled the canoe up watched the currents*
- S: (n) depository fina company (a financial money into lending a *holds the mortgage*
- S: (n) **bank** (a long ri
- S: (n) **bank** (an arran *operated a bank of s*
- S: (n) **bank** (a supply emergencies))
- S: (n) **bank** (the fund gambling games) *"he*
- S: (n) **bank**, cant, car is higher than the ins
- S: (n) savings bank, slot in the top) for ke
- S: (n) **bank**, bank bui transacted) *"the bank*
- S: (n) **bank** (a flight axis (especially in tur

Verb

- S: (v) **bank** (tip latera
- S: (v) **bank** (enclose
- S: (v) **bank** (do busin *do you bank in this t*
- S: (v) **bank** (act as th
- S: (v) **bank** (be in the
- S: (v) deposit, **bank** (*every month"*
- S: (v) **bank** (cover wit
- S: (v) count, bet, dep faith or confidence ir *your friends for supp times of crisis"*

```
from nltk.corpus import wordnet as wn
panda = wn.synset('panda.n.01')
hyper = lambda s: s.hypernyms()
list(panda.closure(hyper))
```

```
[Synset('procyonid.n.01'),
Synset('carnivore.n.01'),
Synset('placental.n.01'),
Synset('mammal.n.01'),
Synset('vertebrate.n.01'),
Synset('chordate.n.01'),
Synset('animal.n.01'),
Synset('organism.n.01'),
Synset('living_thing.n.01'),
Synset('whole.n.02'),
Synset('object.n.01'),
Synset('physical_entity.n.01'),
Synset('entity.n.01')]
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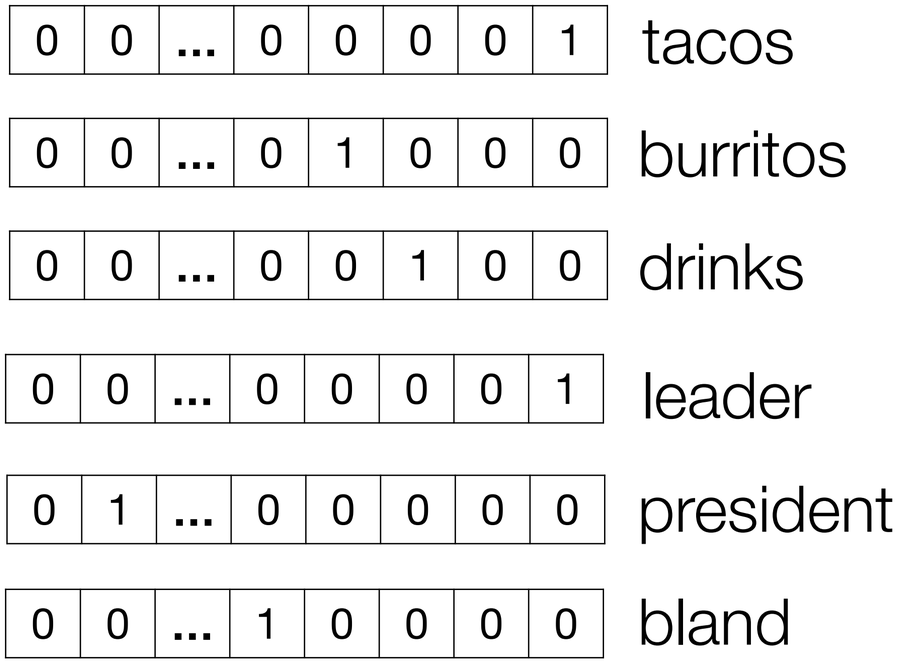

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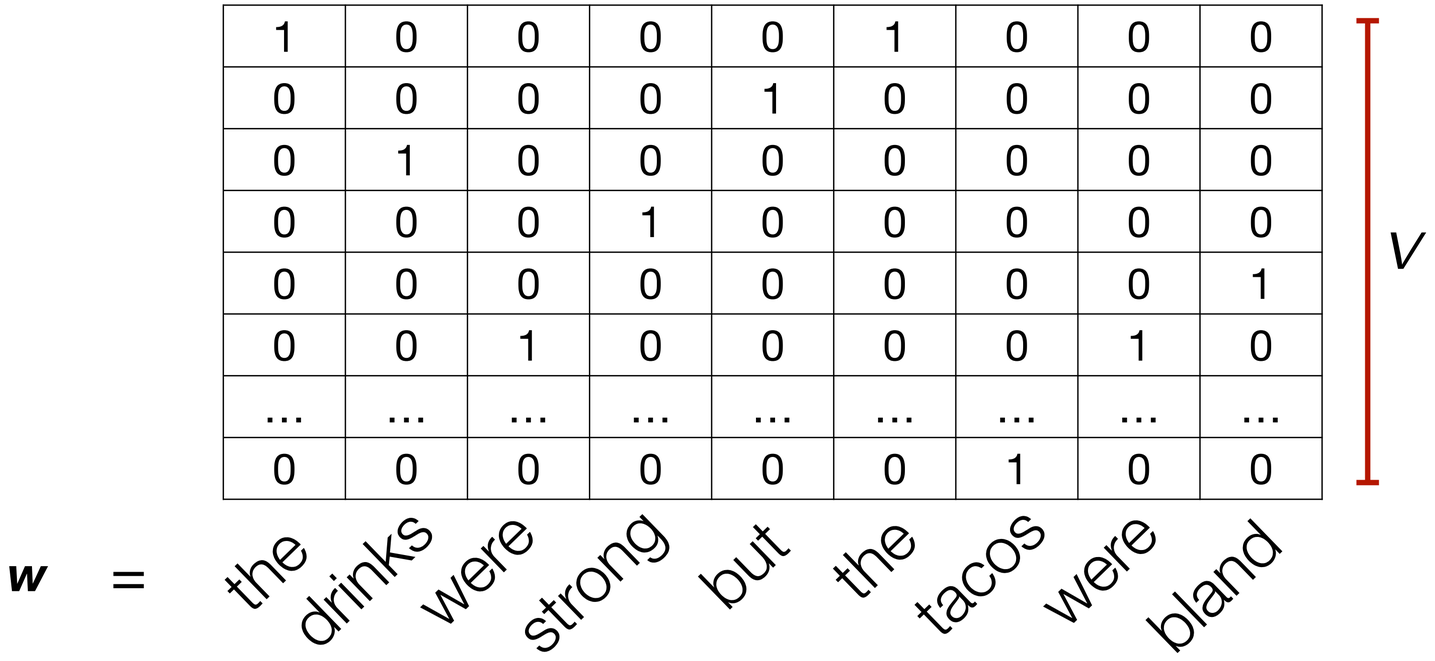
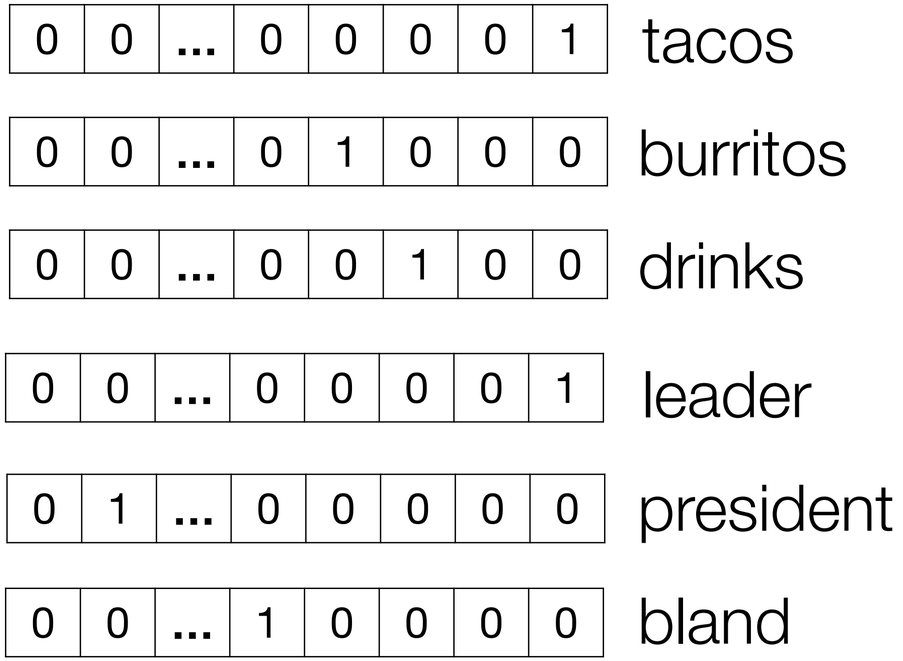
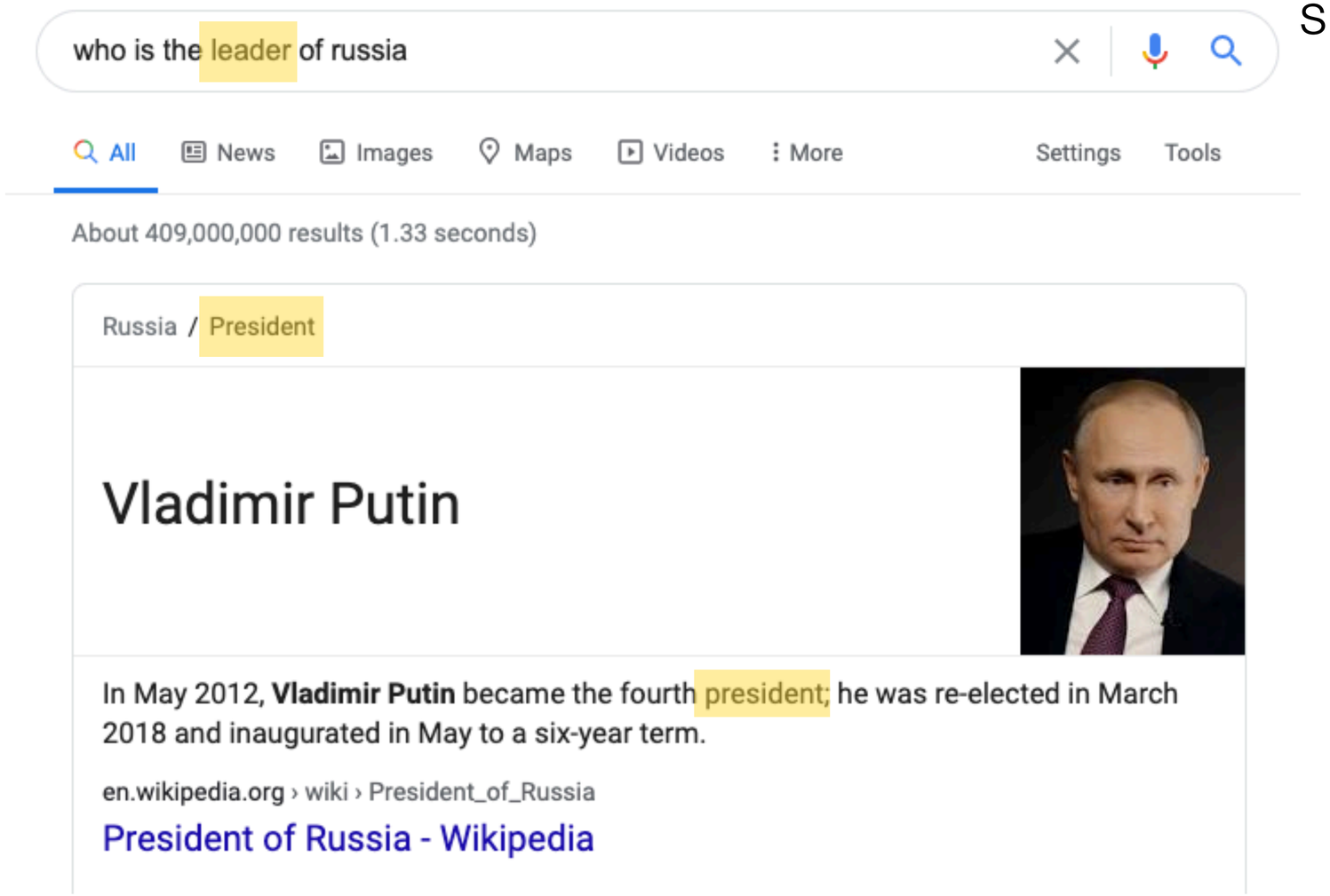




How to represent a word?

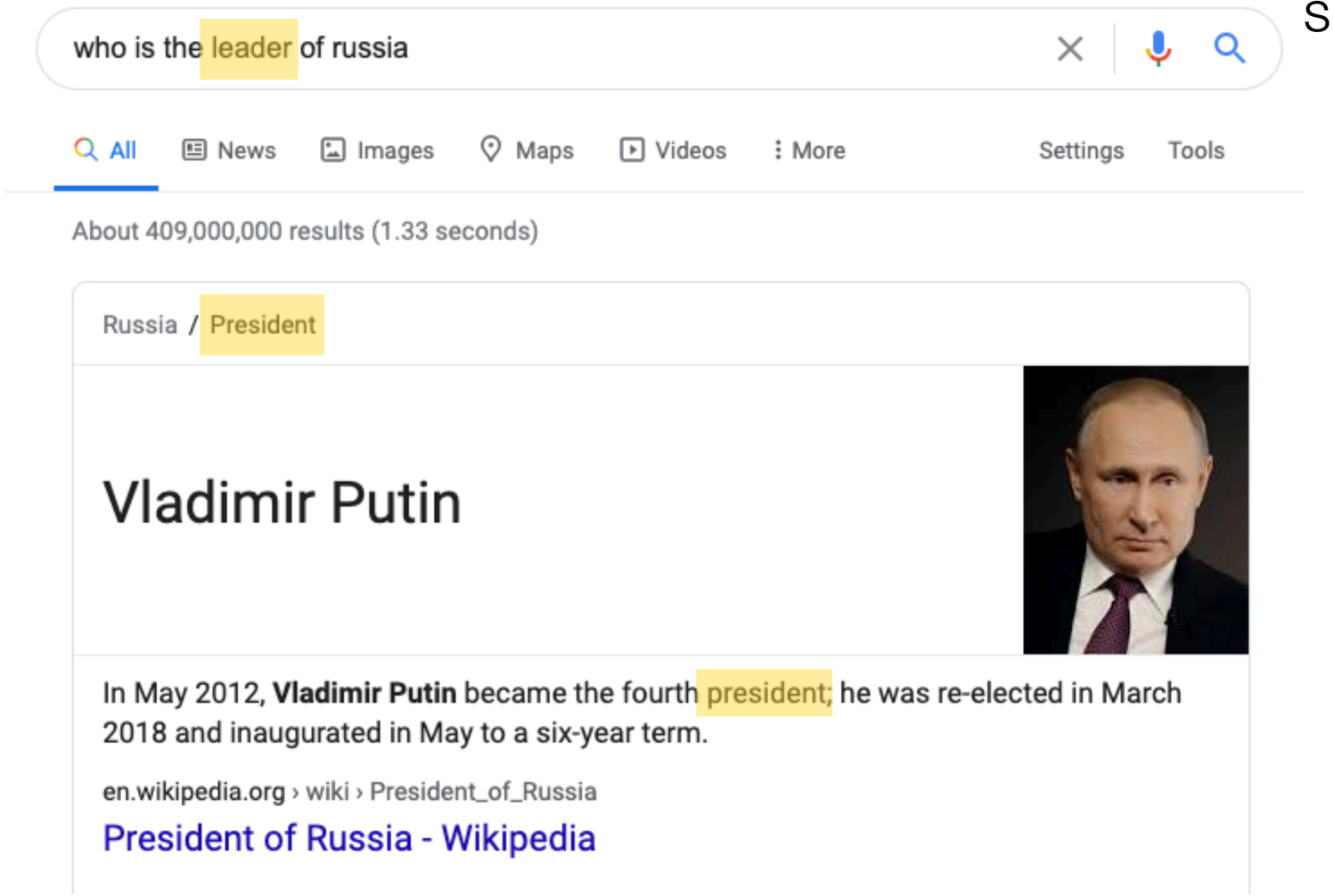


S

0	0	...	0	0	0	0	1	tacos
0	0	...	0	1	0	0	0	burritos
0	0	...	0	0	1	0	0	drinks
0	0	...	0	0	0	1	0	leader
0	1	...	0	0	0	0	0	president
0	0	...	1	0	0	0	0	bland

w

How to represent a word?



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0	0	...	0	0	0	0	1	tacos
0	0	...	0	1	0	0	0	burritos
0	0	...	0	0	1	0	0	drinks
0	0	...	0	0	0	1	0	leader
0	1	...	0	0	0	0	0	president
0	0	...	1	0	0	0	0	bland

w

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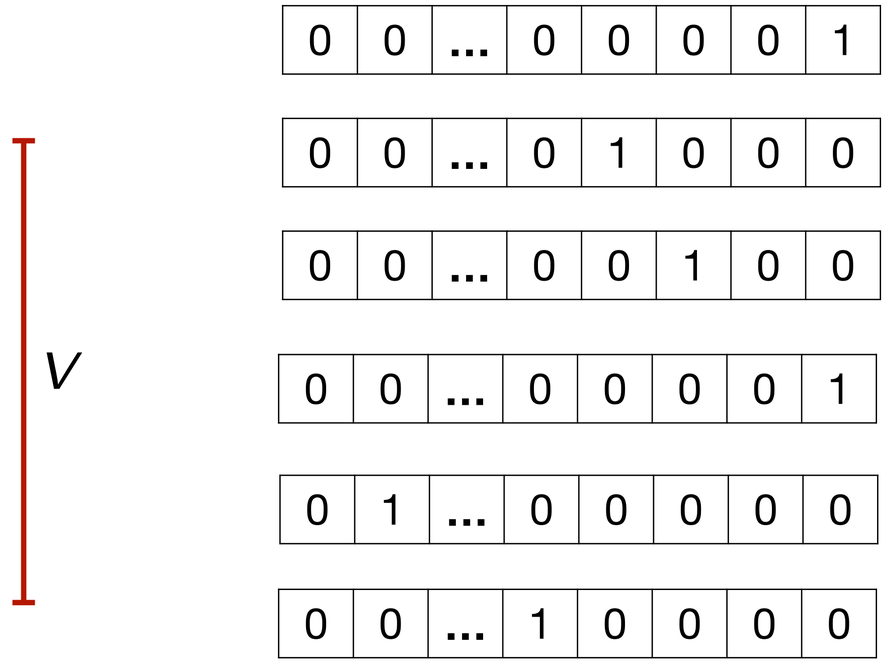

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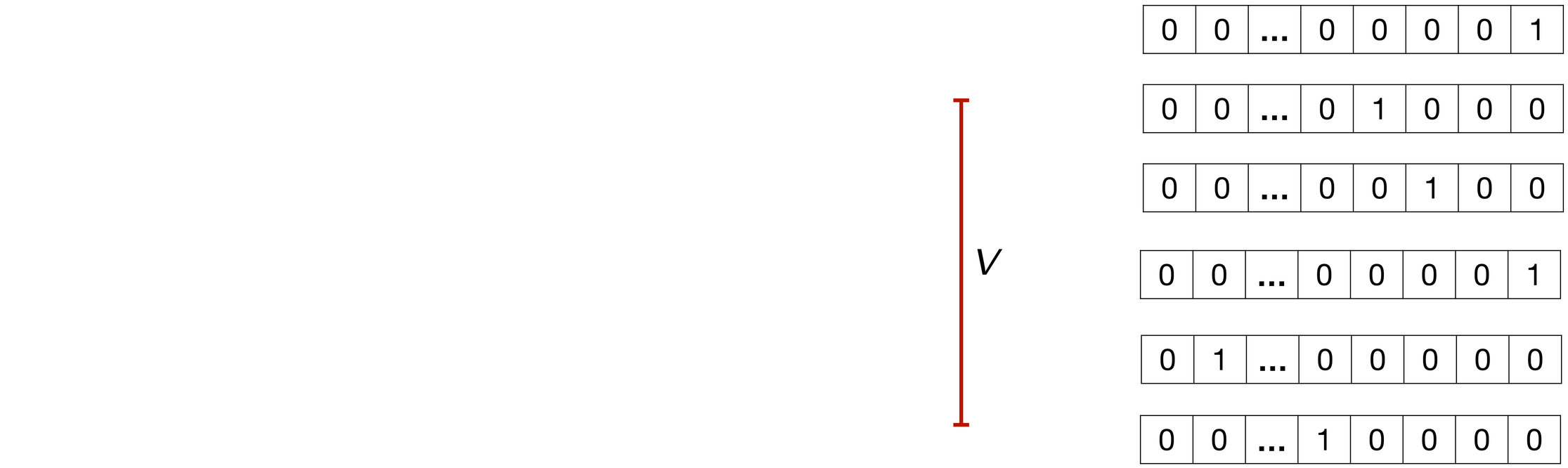

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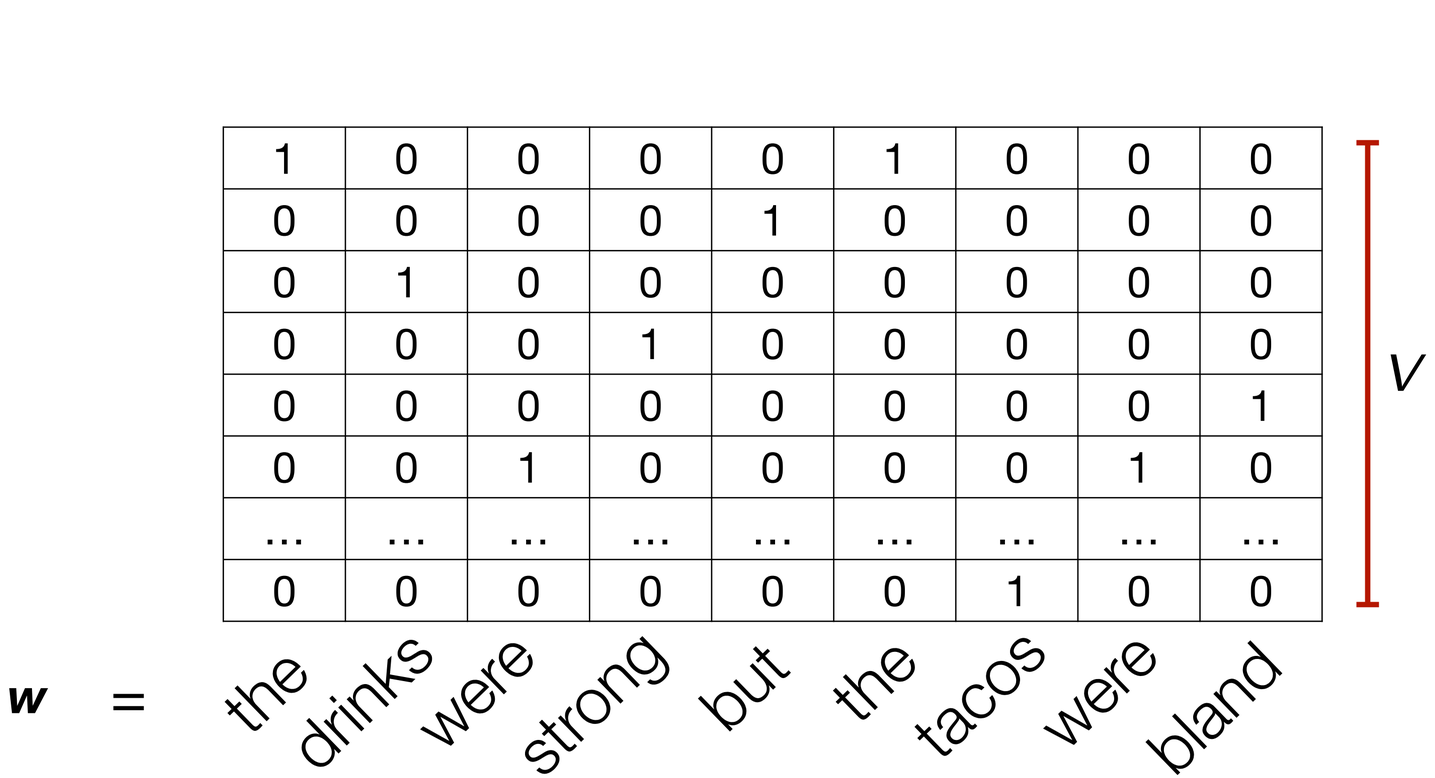
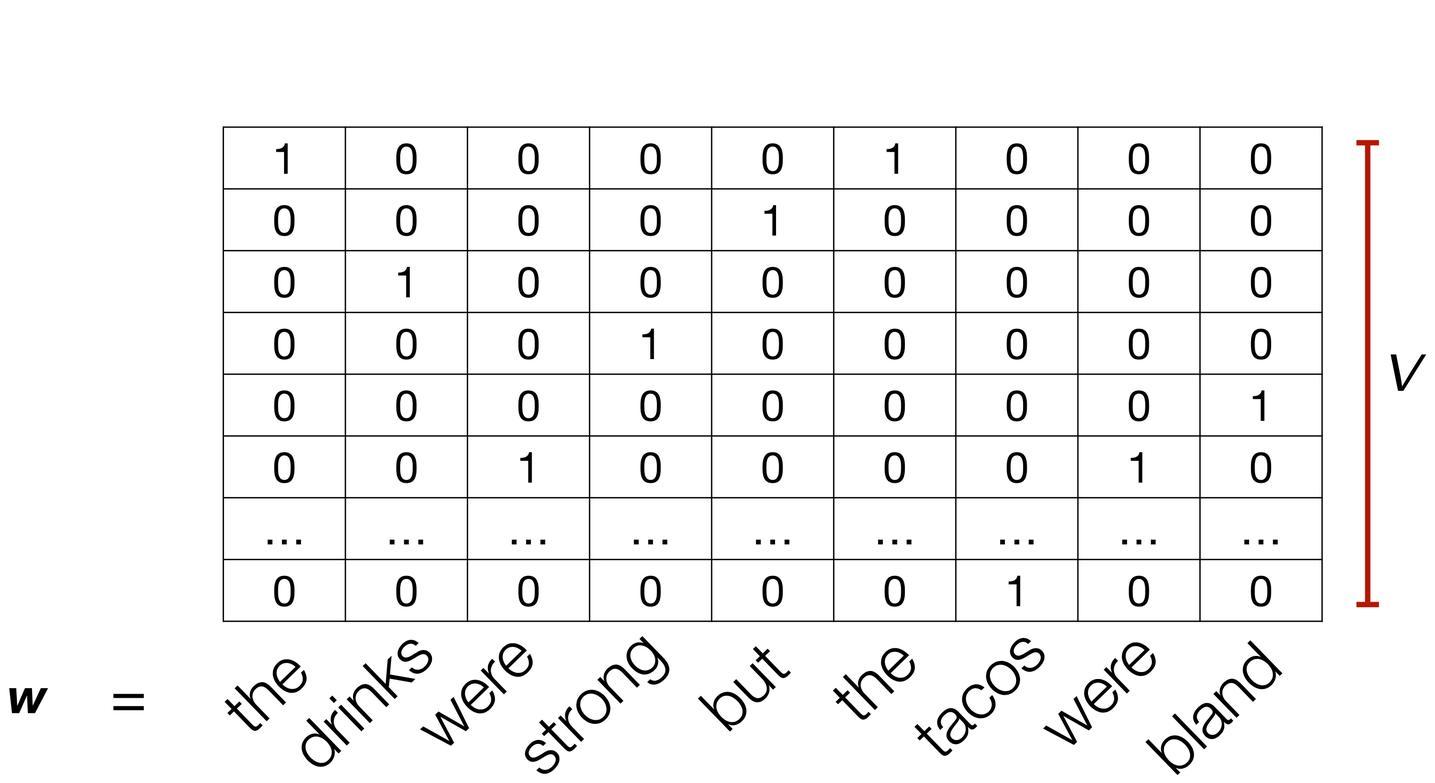


1	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0
0	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	1	0
…	…	…	…	…	…	…	…	…
0	0	0	0	0	0	1	0	0

0	0	…	0	0	0	0	1
0	0	…	0	1	0	0	0
0	0	…	0	0	1	0	0
0	0	…	0	0	0	0	1
0	1	…	0	0	0	0	0
0	0	…	1	0	0	0	0

How to represent a word?

- Until the ~2010s, in NLP words == atomic symbols.



1	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0
0	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	1	0
…	…	…	…	…	…	…	…	…
0	0	0	0	0	0	1	0	0

0	0	…	0	0	0	0	1
0	0	…	0	1	0	0	0
0	0	…	0	0	1	0	0
0	0	…	0	0	0	0	1
0	1	…	0	0	0	0	0
0	0	…	1	0	0	0	0

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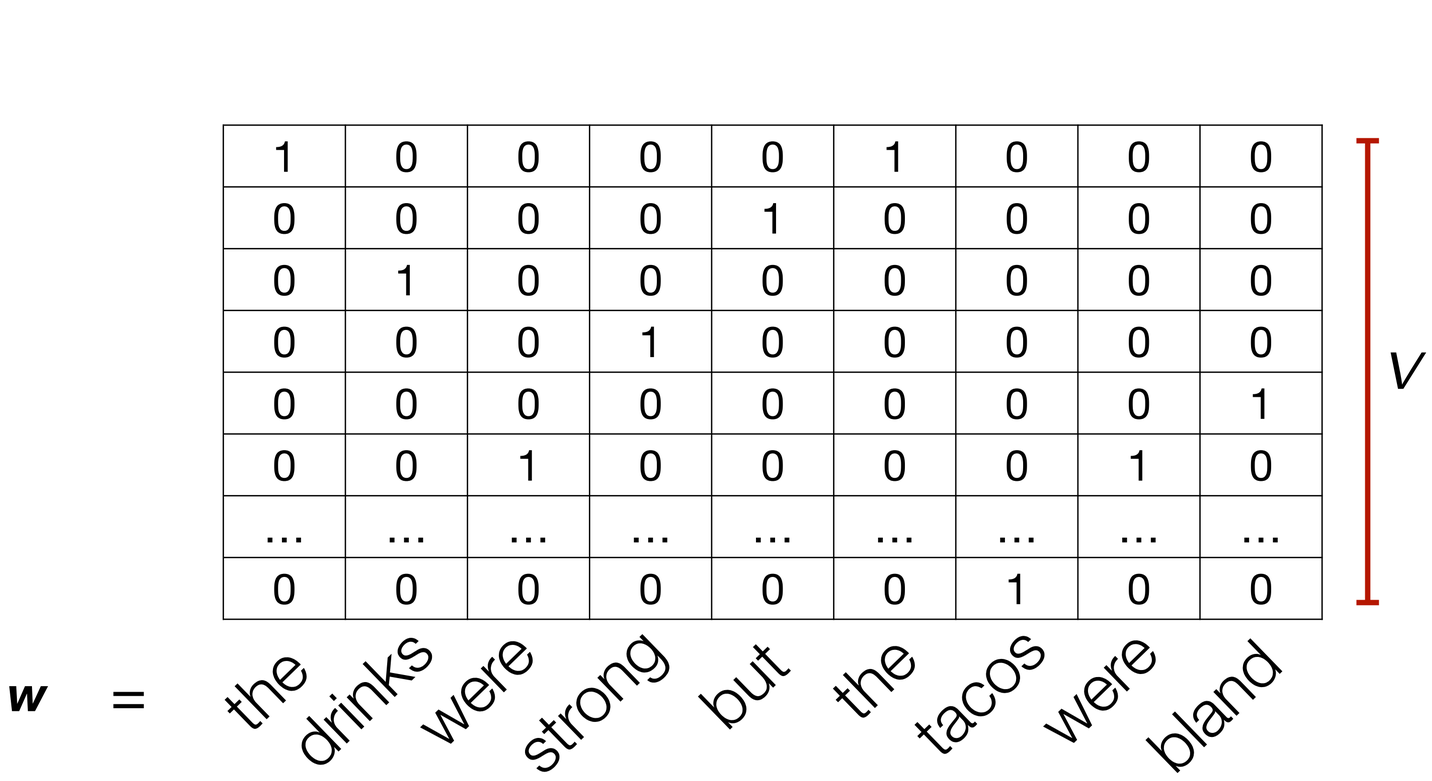

1	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0
0	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	1	0
...	...	...	...	...	...	...	...	...
0	0	0	0	0	0	1	0	0

0	0	...	0	0	0	0	1
0	0	...	0	1	0	0	0
0	0	...	0	0	1	0	0
0	0	...	0	0	0	0	1
0	1	...	0	0	0	0	0
0	0	...	1	0	0	0	0

How to represent a word?

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- **One-hot** representations in vector space.
- But *leader* and *president* are orthogonal!

	the	drinks	were	strong	but	the	tacos	were	bland
	1	0	0	0	0	1	0	0	0
	0	0	0	0	1	0	0	0	0
	0	1	0	0	0	0	0	0	0
	0	0	0	1	0	0	0	0	0
	0	0	0	0	0	0	0	0	1
	0	0	1	0	0	0	0	1	0
	...	...	...	...	...	...	...	...	...
	0	0	0	0	0	0	1	0	0

w =

V

0	0	...	0	0	0	0	1	tacos
0	0	...	0	1	0	0	0	burritos
0	0	...	0	0	1	0	0	drinks
0	0	...	0	0	0	0	1	leader
0	1	...	0	0	0	0	0	president
0	0	...	1	0	0	0	0	bland

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term	context 1	2	3	4
tezgüino	1	1	1	1
loud	0	0	0	0
motor oil	1	0	0	1
tortillas	0	1	0	1
choices	0	1	0	0
wine	1	1	1	0

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motor oil	1	0	0	1	2
tortillas	0	1	0	1	2
choices	0	1	0	0	1
wine	1	1	1	0	3

Distributional hypothesis

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really, really big

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sparse

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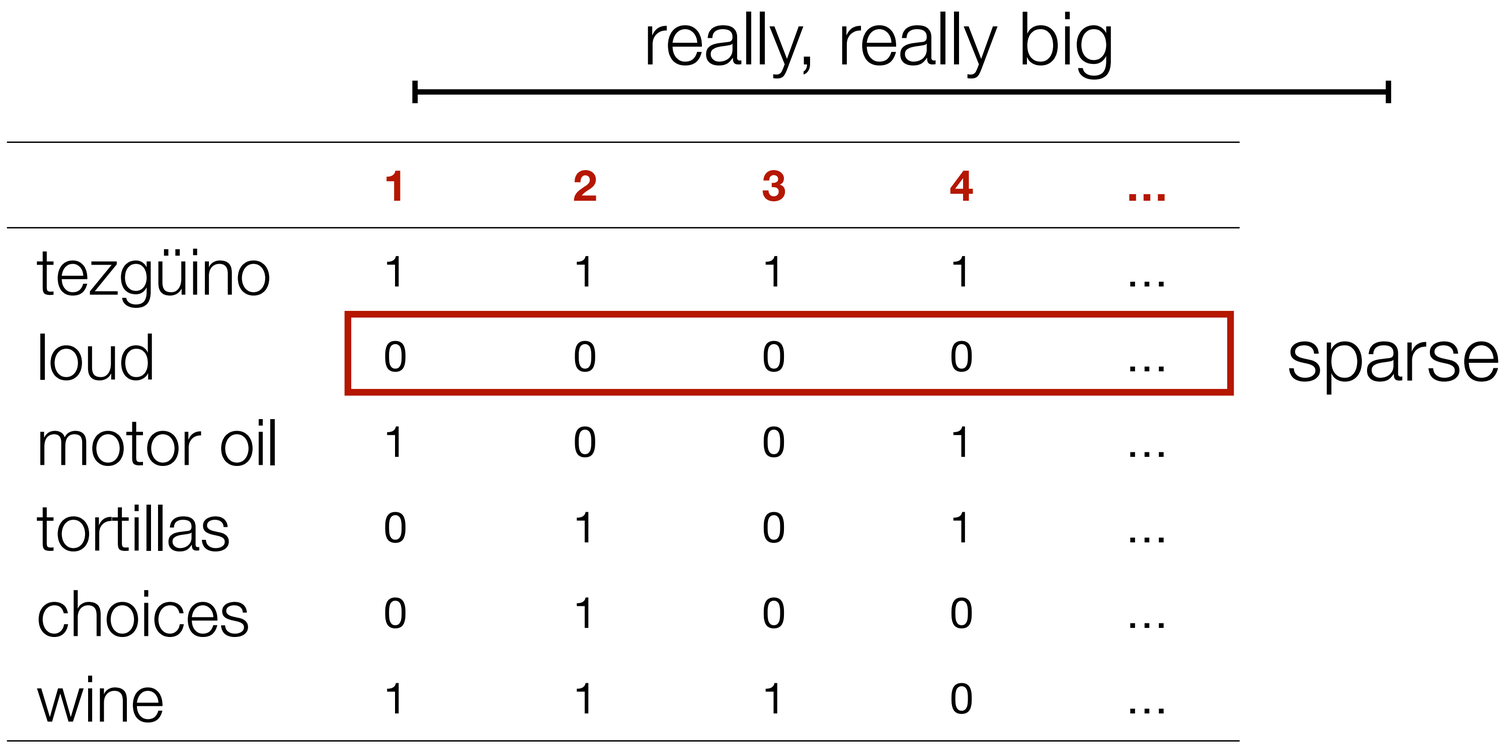

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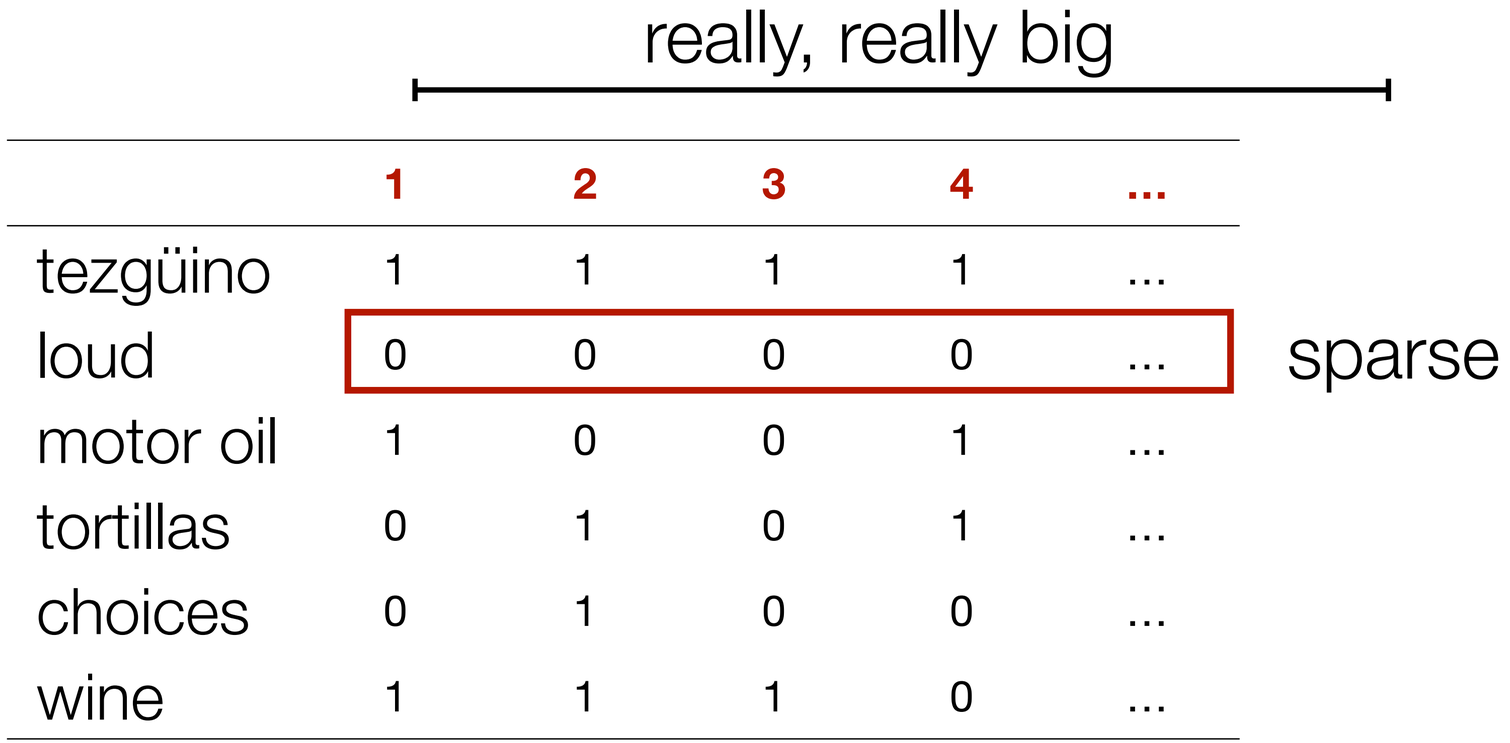

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- Same problem as term-context matrix: useless signal from *the*, *they*, *and*

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Encoding context with tf-idf

- **tf-idf** combines term frequency and inverse document frequency:

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fool	0.019	0.021	0.0036	0.0083
wit	0.049	0.044	0.018	0.022

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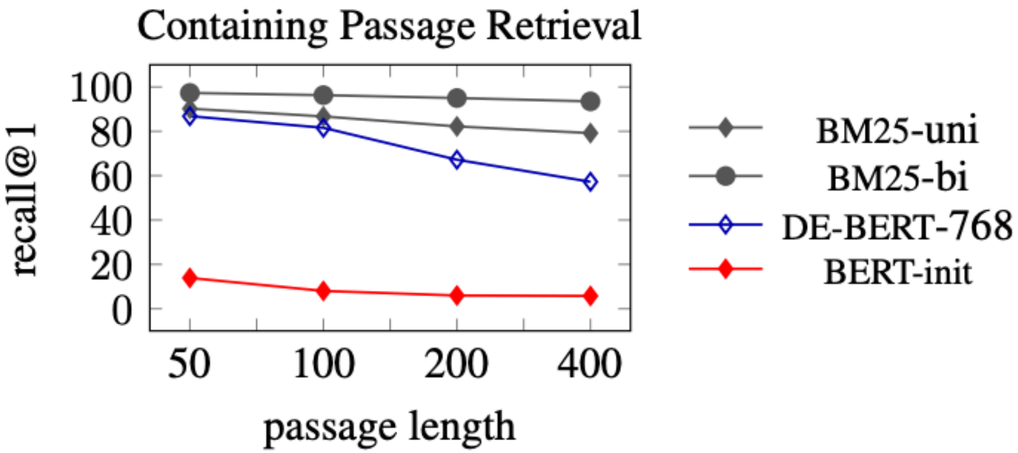
Recent history in NLP might suggest that learned dense representations should always outperform sparse features, but this is not necessarily true: as shown in Figure 1, the BM25 model (Robertson et al., 2009) can outperform a dual encoder based on BERT, particularly on longer documents (See § 7).



Yi Luan, Jacob Eisenstein, Kristina Toutanova, Michael Collins. Sparse, dense and attentional representations for text retreival. arXiv preprint 2005.00181, 2020.

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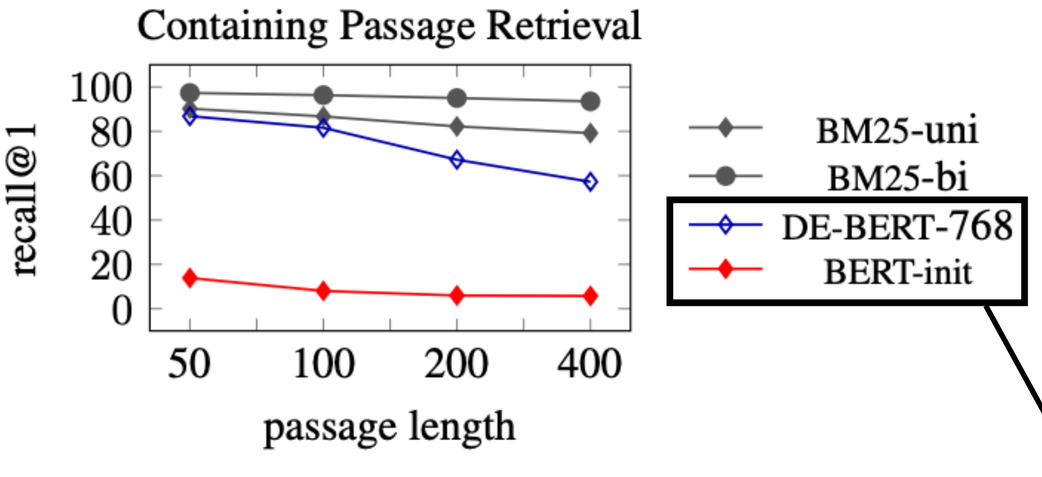

Fancy, computationally expensive neural network models!

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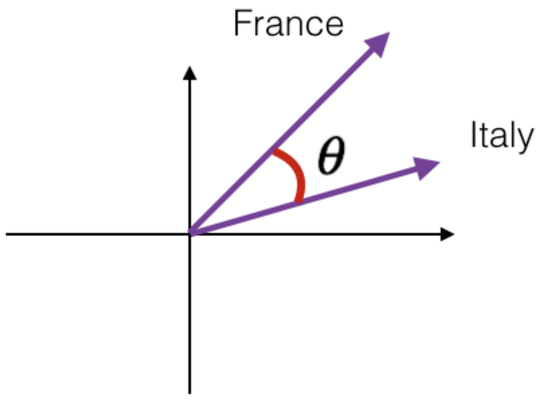

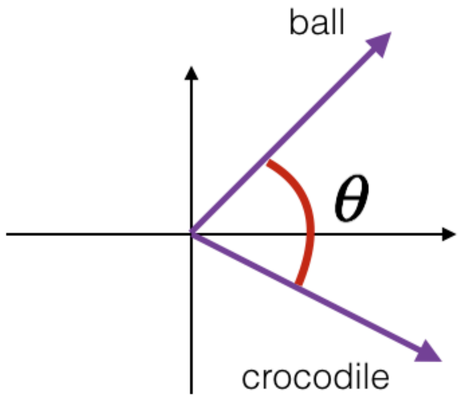

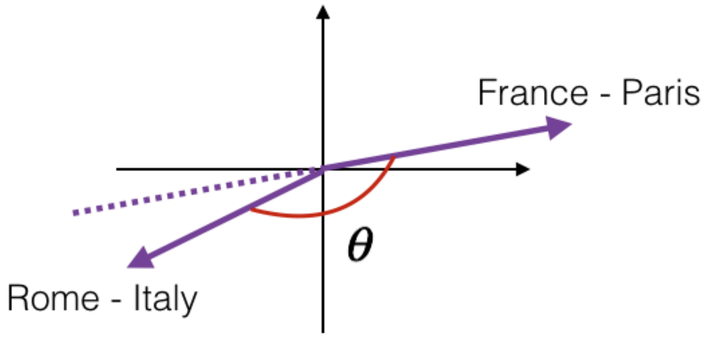

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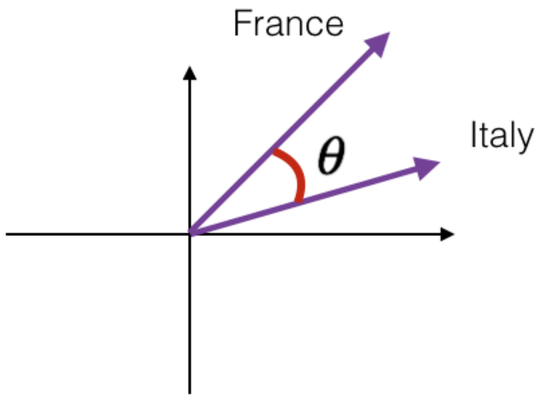

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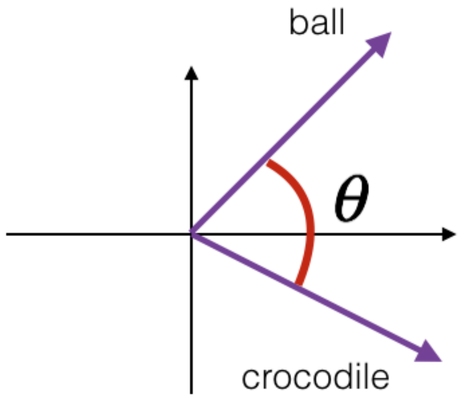

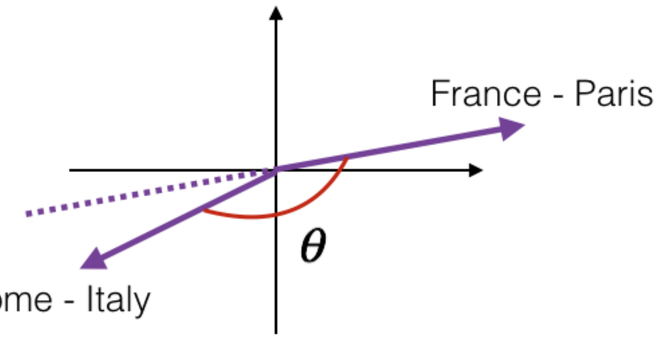

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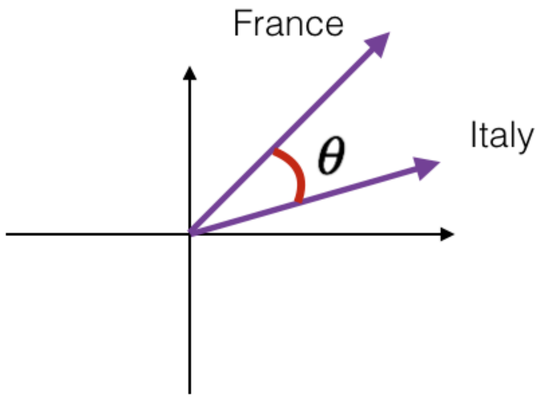

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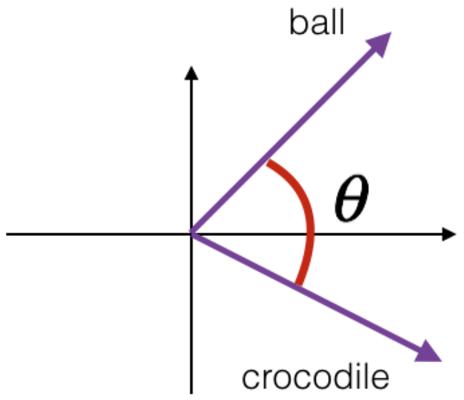

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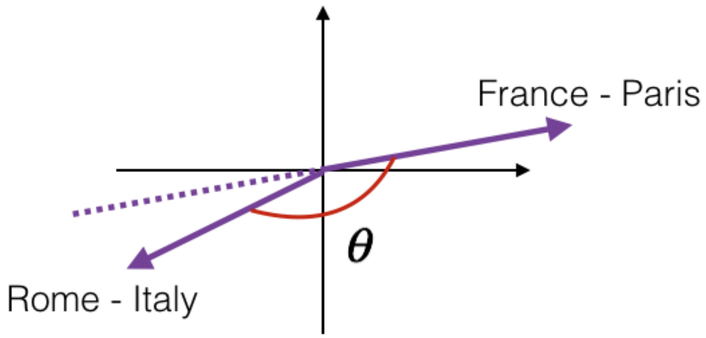

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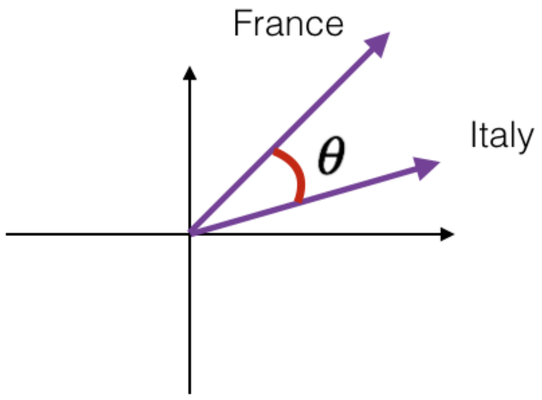

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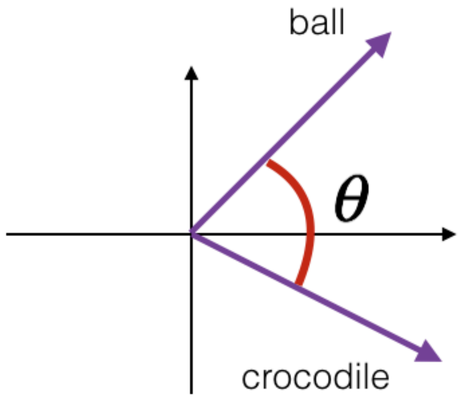

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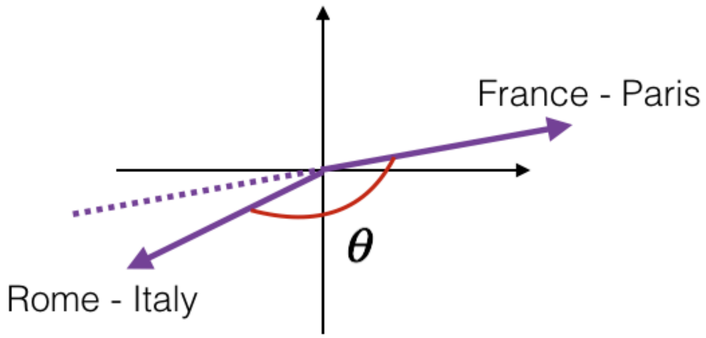

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How to encode context?

- This encoding could work, but it's not practical to enumerate all possible contexts.
- Also, many entries not very discriminative: *the*, *it*, *they*
- Approaches for encoding words as vectors:
  - Matrix factorization
  - Brown clusters
  - tf-idf
  - **word2vec**

$$\overrightarrow{king} - \overrightarrow{man} + \overrightarrow{woman} = \overrightarrow{queen}$$

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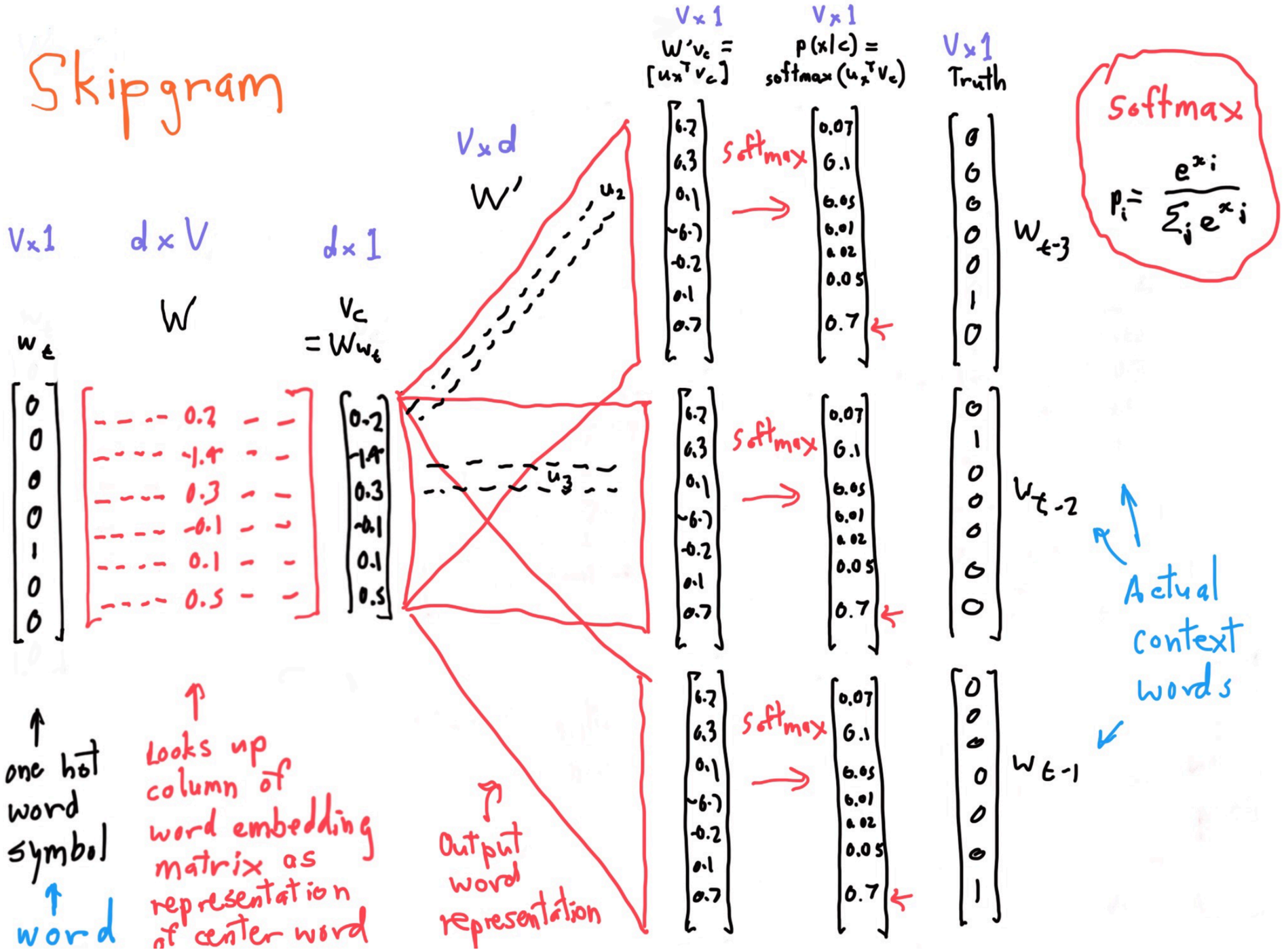

slide from: http://web.stanford.edu/class/cs224n/

skip gram w/ negative sampling

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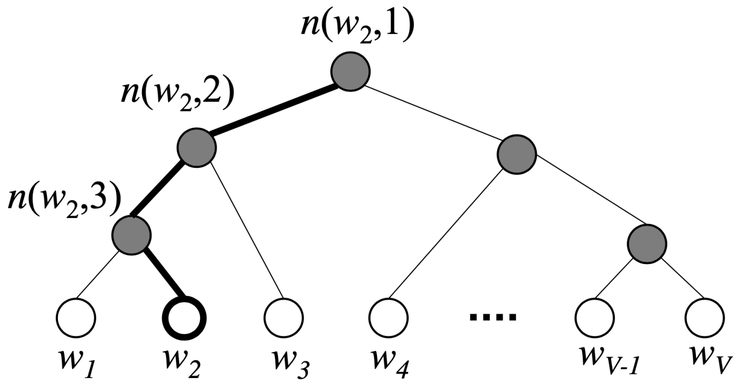

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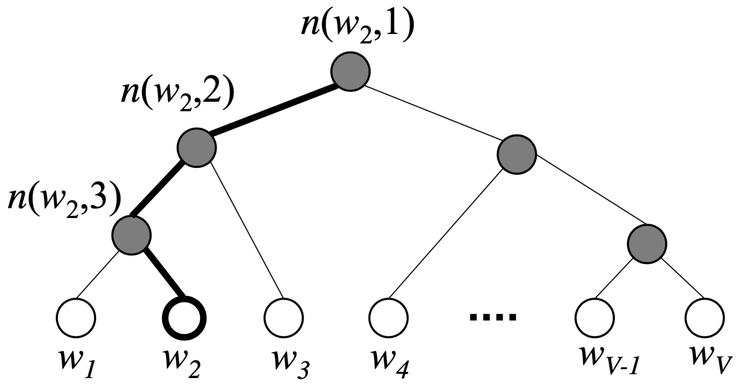

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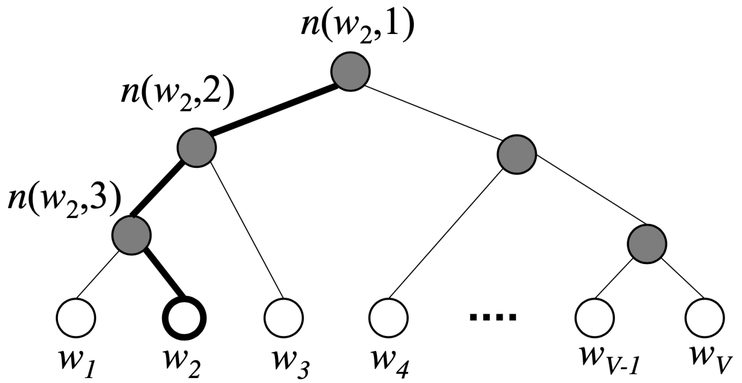

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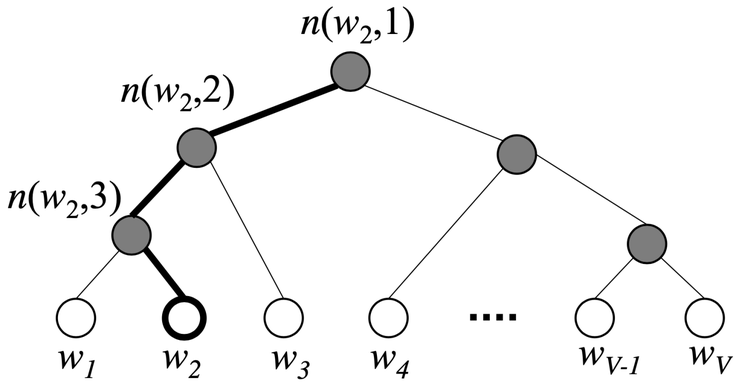

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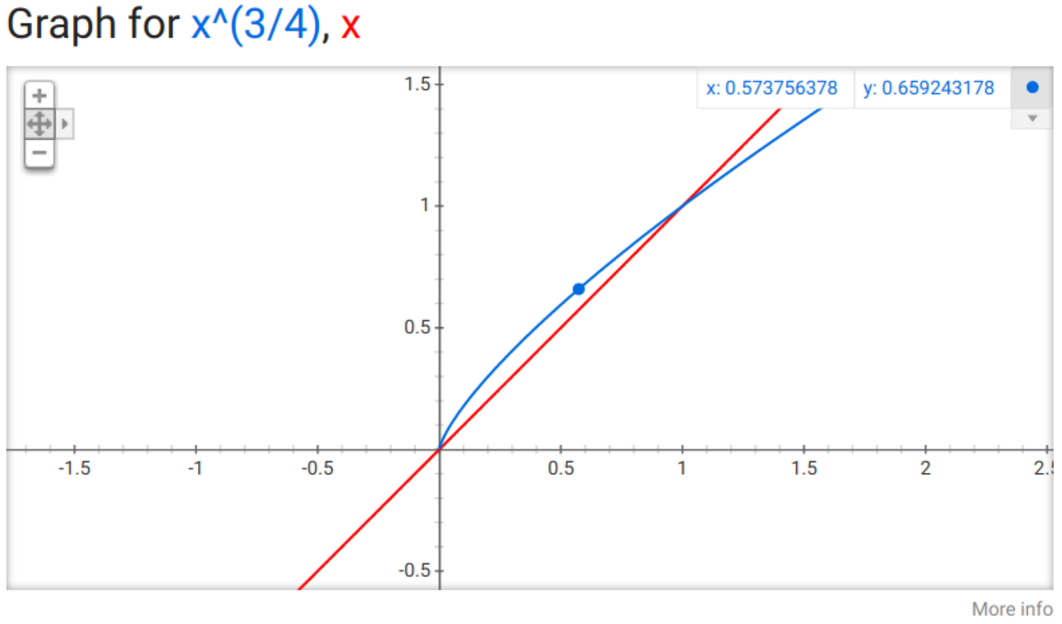

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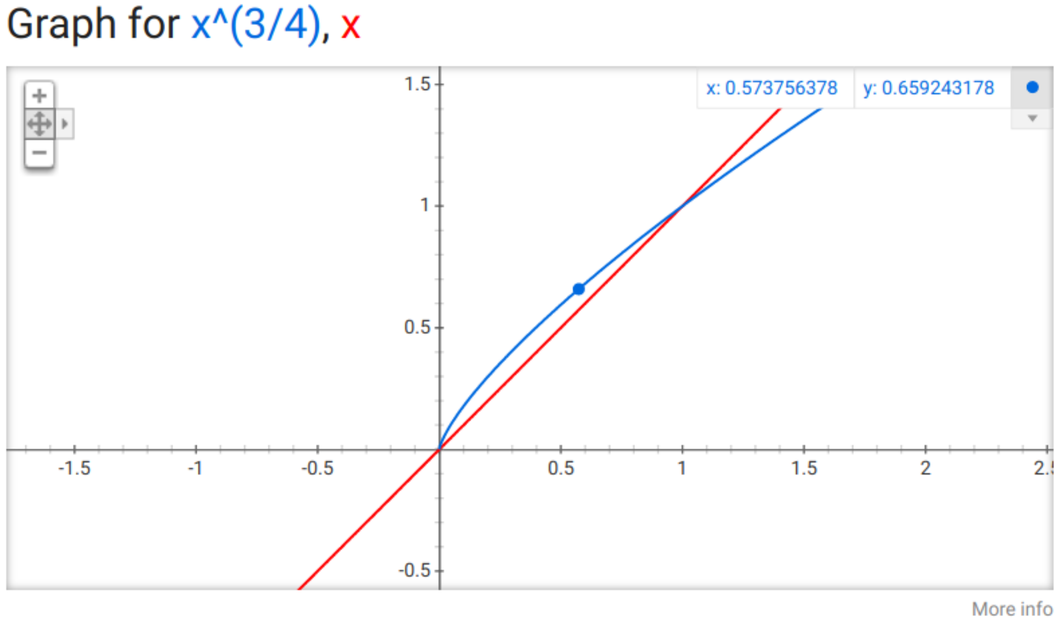

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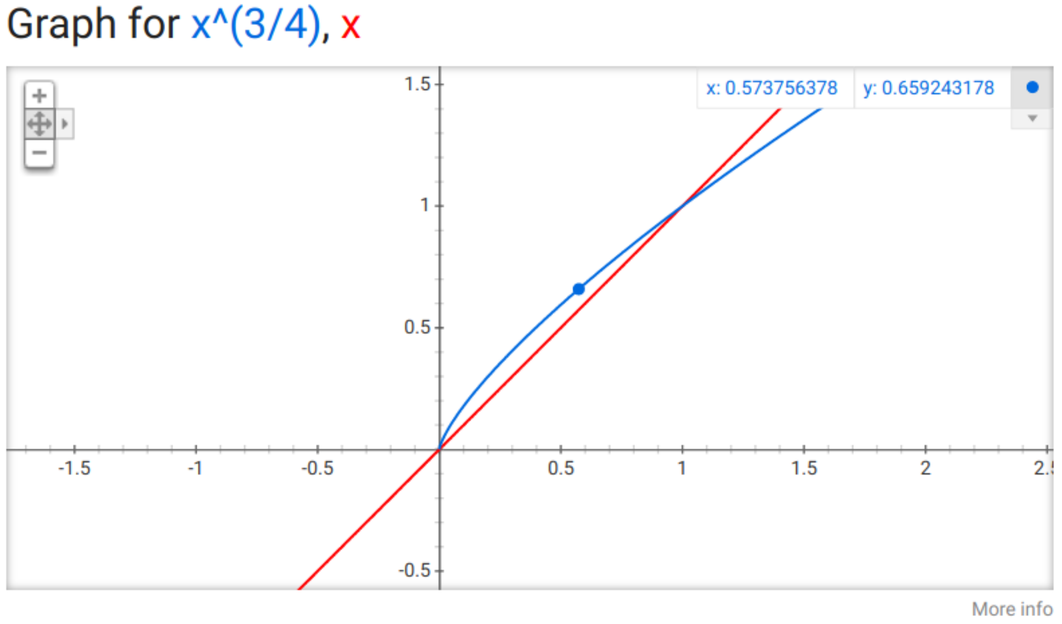

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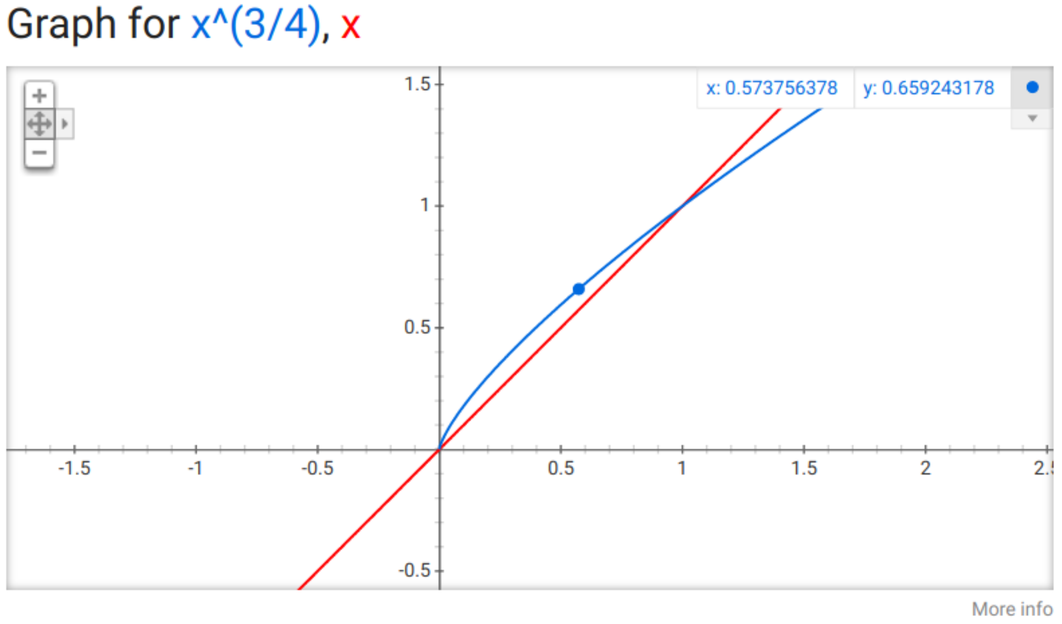

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	Singular+neut	Plural+neut	
Nominative	предложение	предложения	sentence (s)
Genitive	предложения	предложений	(of) sentence (s)
Dative	предложению	предложениям	(to) sentence (s)
Accusative	предложение	предложения	sentence (s)
Instrumental	предложением	предложениями	(by) sentence (s)
Prepositional	предложении	предложениях	(in/at) sentence (s)

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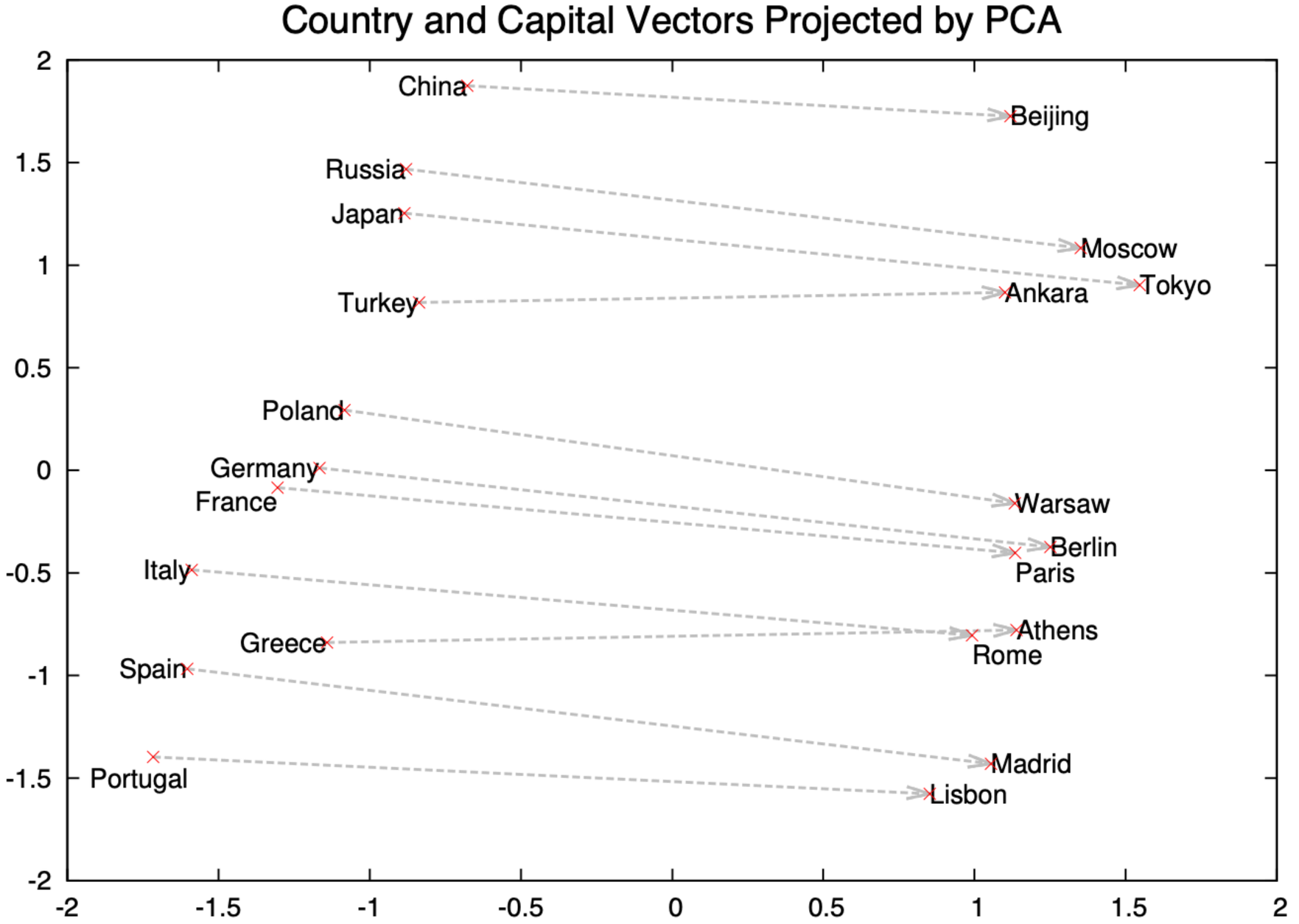

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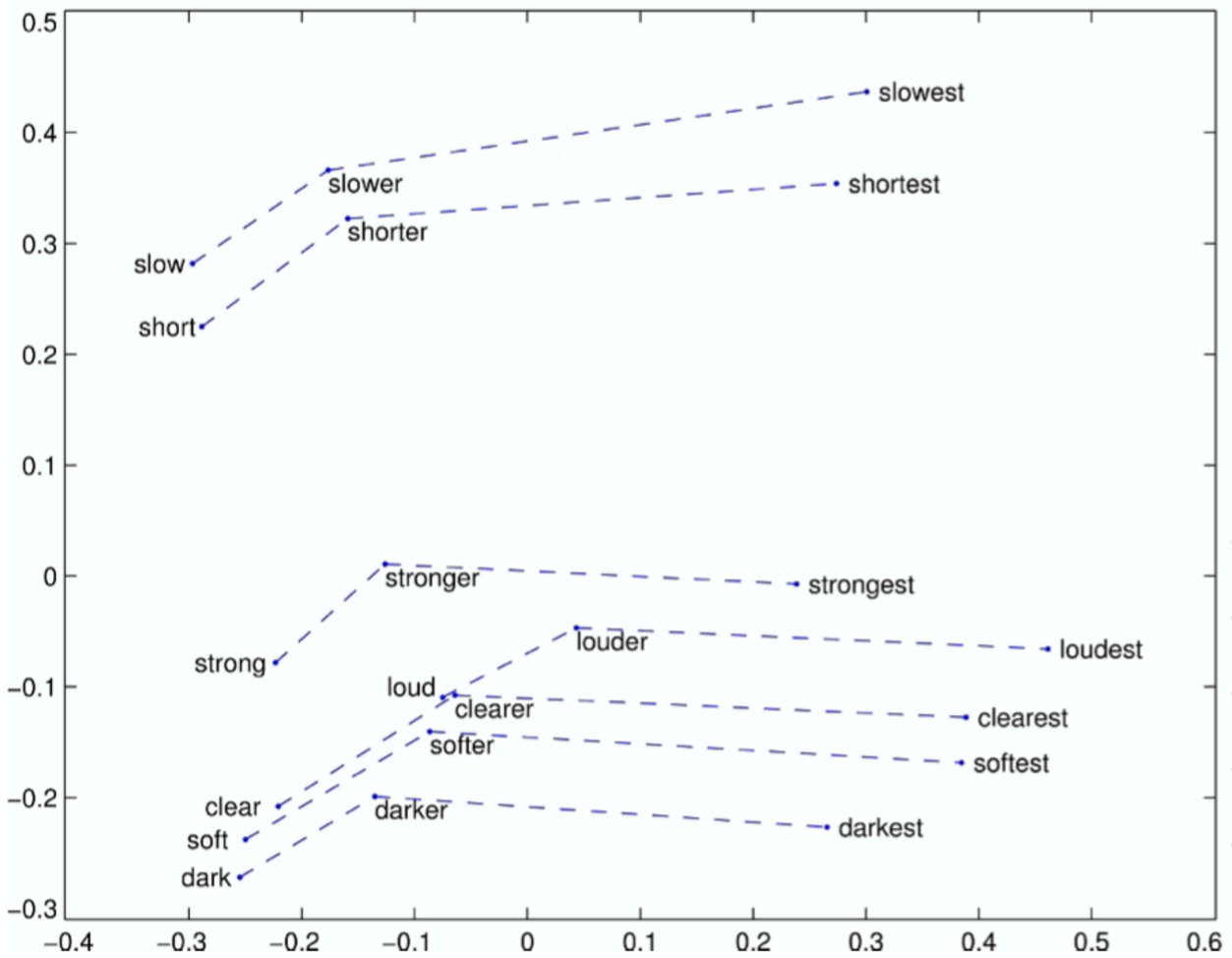


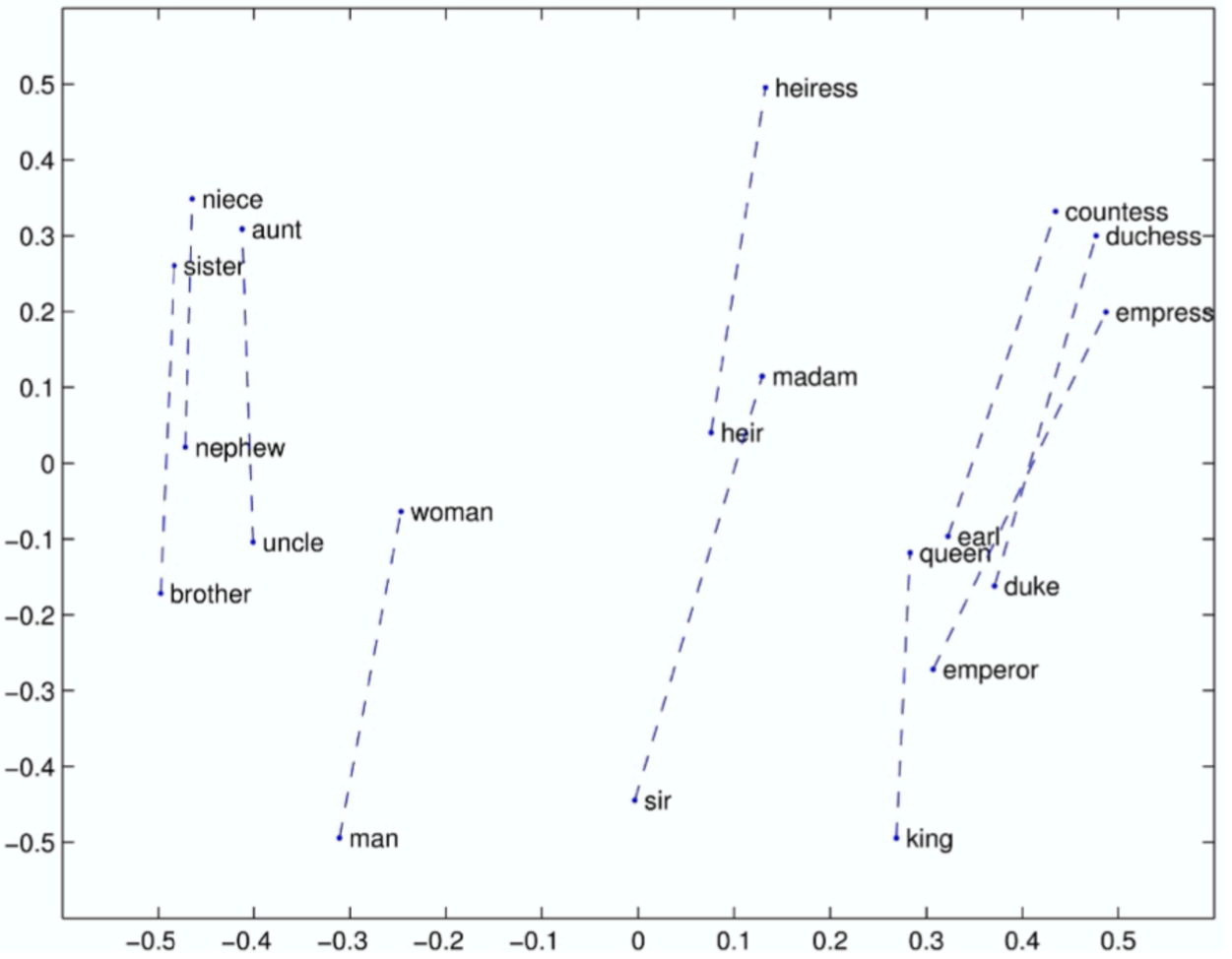
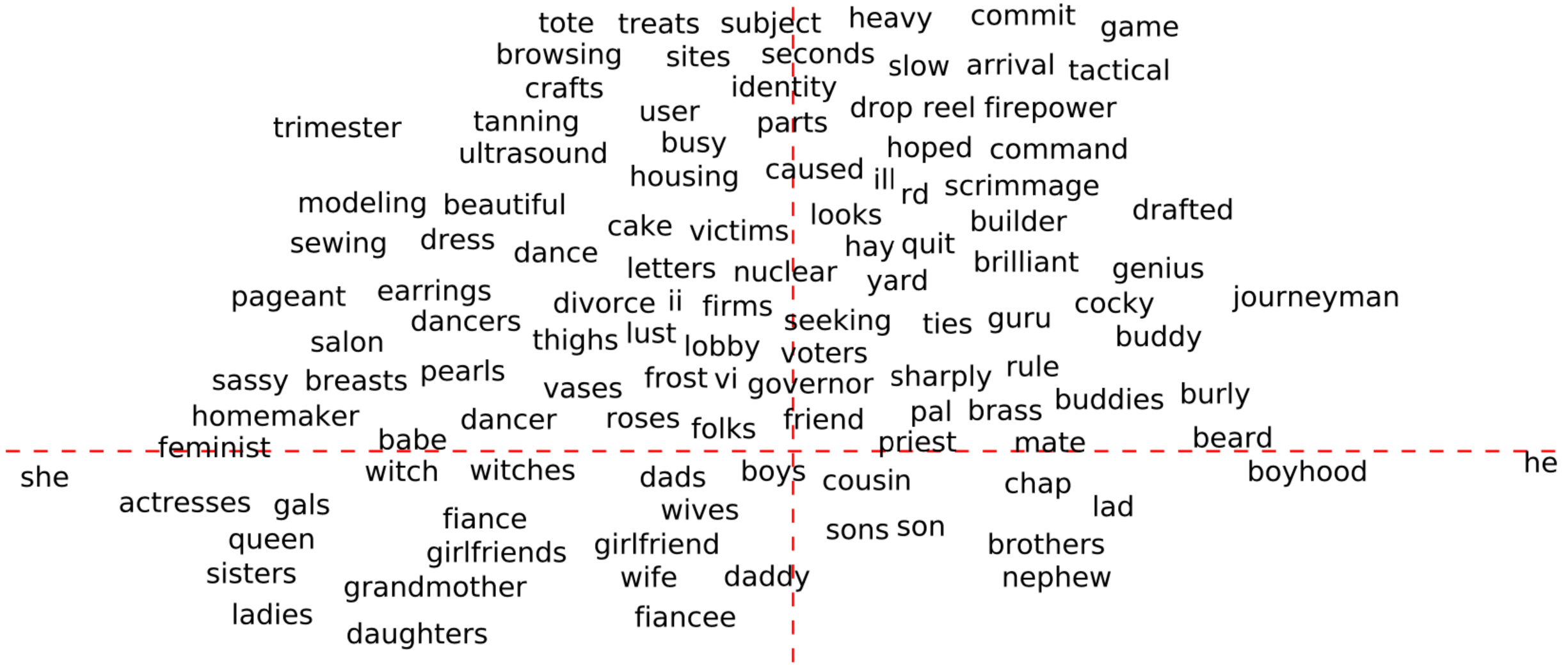


Image: http://ruder.io/secret-word2vec



$$\overrightarrow{computer\ programmer} - \overrightarrow{man} + \overrightarrow{woman} = \overrightarrow{homemaker}$$

[Bolukbasi et al. 2016]

Bias in word embeddings

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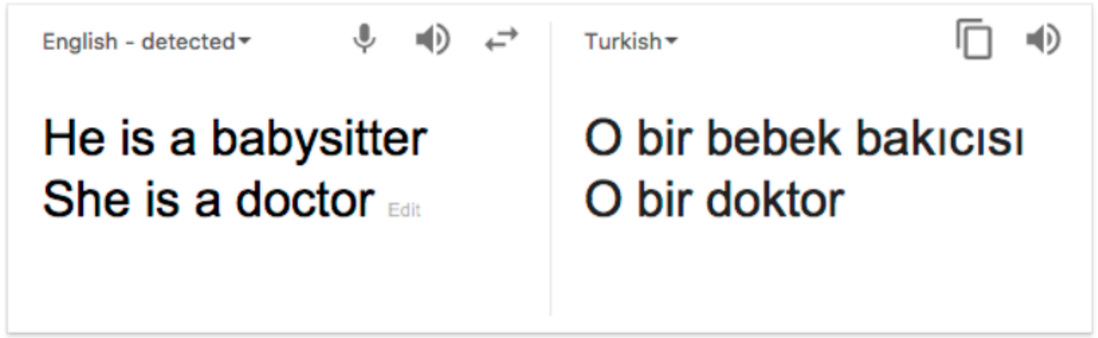

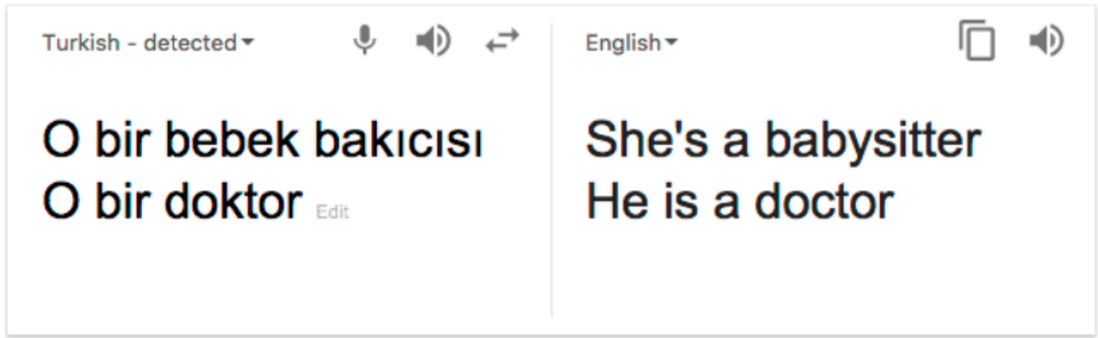

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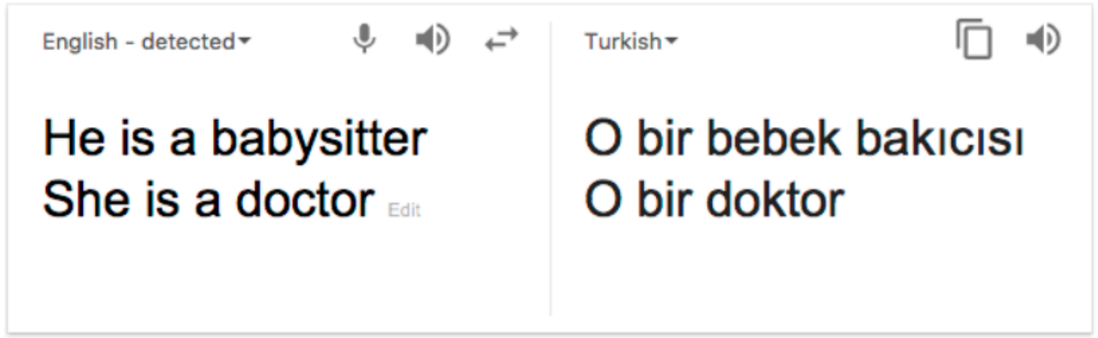

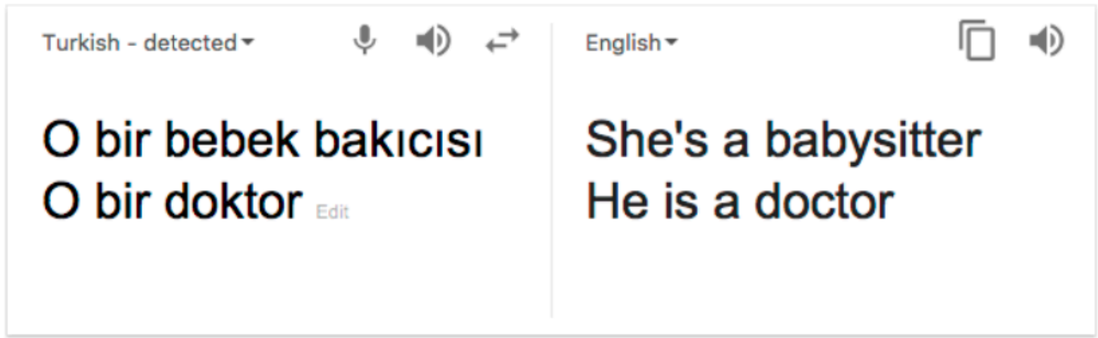

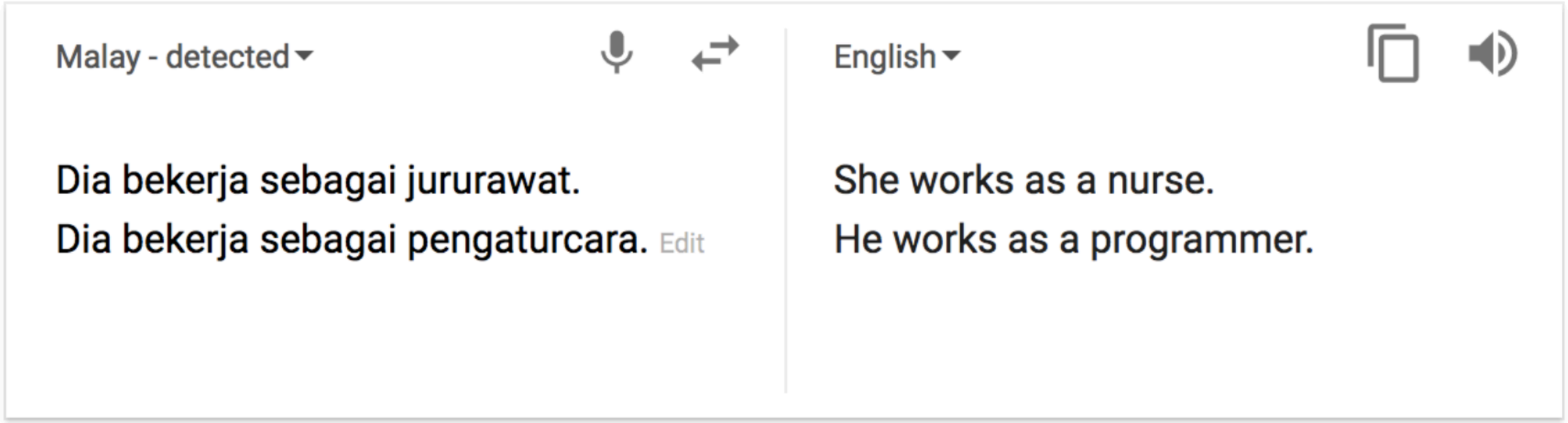

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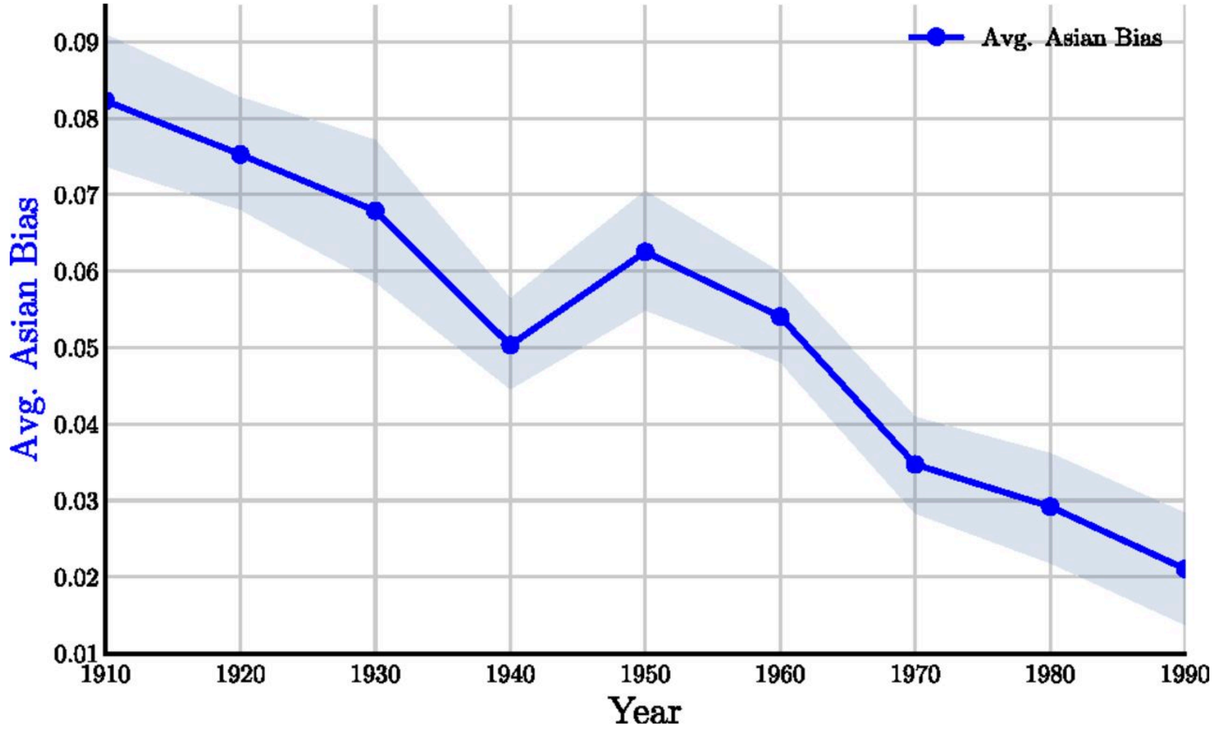
Change in linguistic framing 1910-1990



Change in association of Chinese names with adjectives framed as "othering" (barbaric, monstrous, bizarre)

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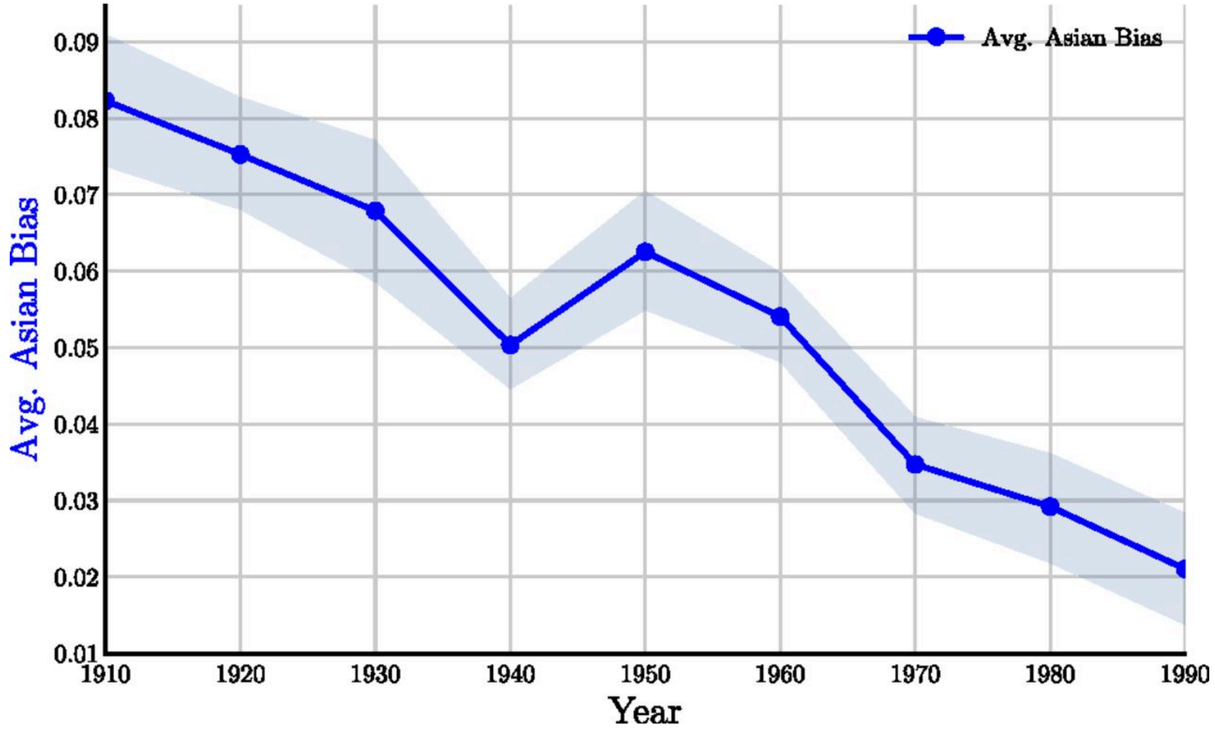

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ML algorithms shown to **amplify** bias in data! [Zhao et al. 2017]

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