Yandex

UNIVERSITEIT VAN AMSTERDAM

Word Embeddings

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Plan

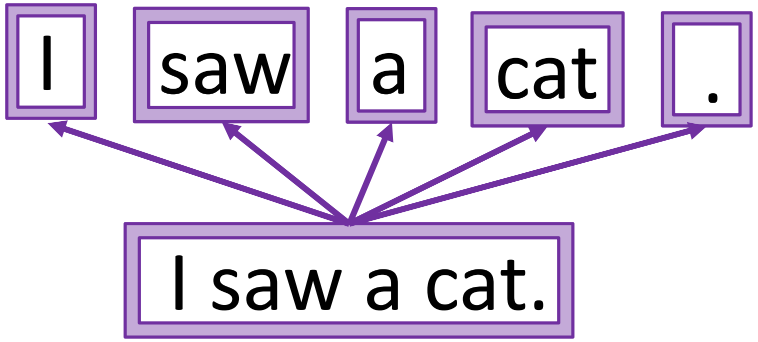
- Why do we need word representations?
- Distributional semantics
- Word2Vec in detail
- Glove overview
- Let’s take a walk!
- Further directions: subword information
- Further directions: abstract the ideas to sentence-level
- Further directions: exploiting the structure of semantic spaces
- Hack of the day!

Why do we need word representation?

I saw a cat.

Text

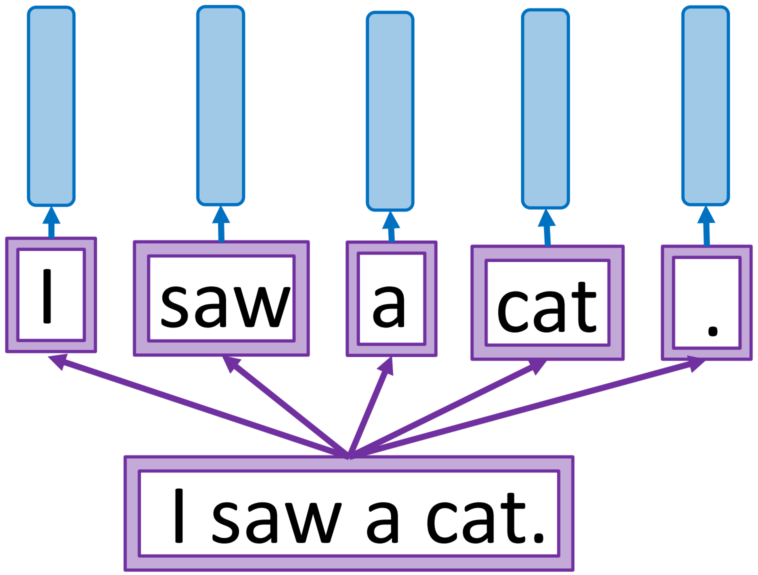
Why do we need word representation?



Sequence of tokens

Text

Why do we need word representation?



Word representation - vector (word embedding)

Sequence of tokens

Text

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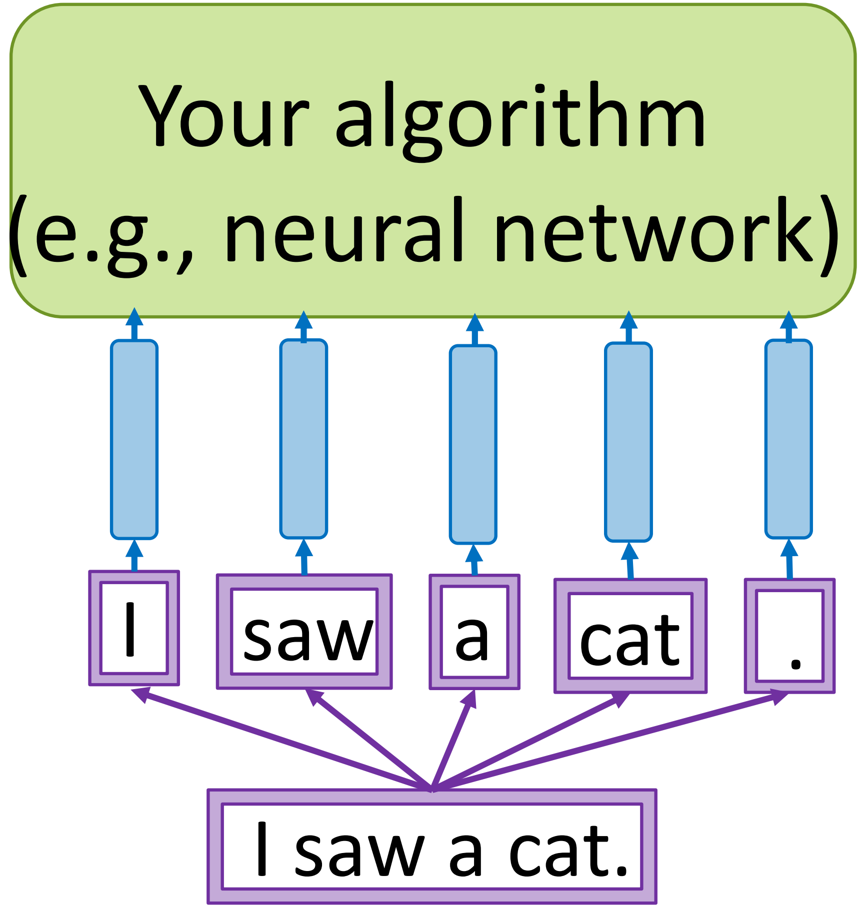


Any algorithm for solving any task

Word representation - vector
(word embedding)

Sequence of tokens

Text

Representing words as discrete symbols

In traditional NLP, we regard words as discrete symbols: **hotel, conference, motel**

Means one 1, the rest 0s

Words can be represented by **one-hot** vectors:

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]

Vector dimension = number of words in vocabulary (e.g. 500,000)

Problem with words as discrete symbols

Example: in web search, if user searches for "**Seattle motel**", we would like to match documents containing "**Seattle hotel**".

But:

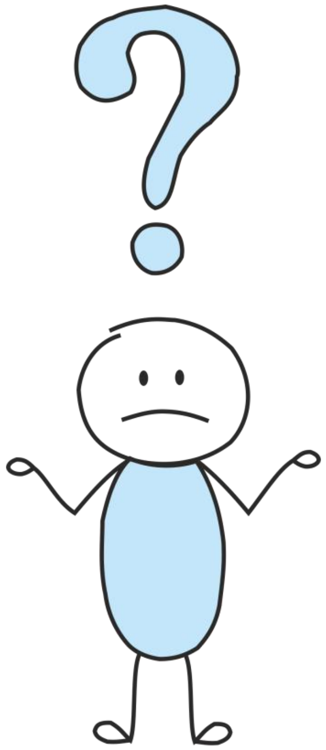
motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]

These two vectors are orthogonal.

There is no natural notion of **similarity** for one-hot vectors!

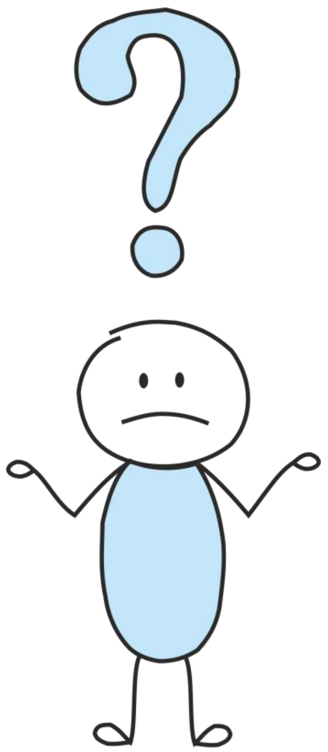
These vectors do not contain information about a **meaning** of a word.

But what is meaning?



But what is meaning?

What is bardiwac?



But what is meaning?

What is bardiwac?

- He handed her a glass of bardiwac.
- Beef dishes are made to complement the bardiwac.
- Nigel staggered to his feet, face flushed from too much bardiwac.
- Malbec, one of the lesser-known bardiwac grapes, responds well to Australia’s sunshine.
- I dined off bread and cheese and this excellent bardiwac.
- The drinks were delicious: blood-red bardiwac as well as light, sweet Rhenish.

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Bardiwac is a red alcoholic beverage made from grapes

Distributional semantics

- A bottle of _bardiwac_ is on the table.
- Everybody likes _bardiwac_.
- Don’t have _bardiwac_ before you drive.
- We make _bardiwac_ out of corn.

Distributional semantics

- A bottle of __________ is on the table.
- Everybody likes __________.
- Don’t have __________ before you drive.
- We make __________ out of corn.

What other words fit into these contexts?

Distributional semantics

- A bottle of __________ is on the table. (1)
- Everybody likes __________. (2)
- Don't have __________ before you drive. (3)
- We make __________ out of corn. (4)

What other words fit into these contexts?

	(1)	(2)	(3)	(4)	…
bardiwac	1	1	1	1	
loud	0	0	0	0	
motor oil	1	0	0	1	
tortillas	0	1	0	1	
wine	1	1	1	0	
choices	0	1	0	0	

Distributional semantics

- A bottle of __________ is on the table. (1)
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Distributional semantics

Does vector similarity imply semantic similarity?

Distributional semantics

Does vector similarity imply semantic similarity?

The **distributional hypothesis**, stated by Firth (1957):

"You shall know a word by the company it keeps."

Idea: co-occurrence counts

Corpus sentences

He also found five fish swimming in murky water in an old **bathtub**.
We do abhor dust and dirt, and stains on the **bathtub**, and any kind of filth.
Above At the far end of the garden room a **bathtub** has been planted with herbs for the winter.
They had been drinking Cisco, a fruity, wine-based fluid that smells and tastes like a mixture of cough syrup and **bathtub** gin.
Science finds that a surface tension on the water can draw the boats together, like toy boats in a **bathtub**.
In fact, the godfather of gloom comes up with a plot that takes in Windsor Davies (the ghost of sitcoms past), a **bathtub** and a big box of concentrated jelly.
'I'll tell him,' said the Dean from the bathroom above the sound of bathwater falling from a great height into the ample Edwardian **bathtub**.

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Co-occurrence counts

the	12
a	9
of	7
and	6
in	5
…	…
like	2
water	2
boat	2
from	2
stain	1
toy	1
god-father	1
Cisco	1
…	…

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vector

$$\begin{pmatrix} 12 \\ 9 \\ 7 \\ 6 \\ 5 \\ \vdots \\ 2 \\ 2 \\ 2 \\ 2 \\ 1 \\ 1 \\ 1 \\ 1 \\ \vdots \end{pmatrix}$$

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vector

$$\begin{pmatrix} 12 \\ 9 \\ 7 \\ 6 \\ 5 \\ \vdots \\ 2 \\ 2 \\ 2 \\ 2 \\ 1 \\ 1 \\ 1 \\ 1 \\ \vdots \end{pmatrix}$$

Dimensionality reduction

small vector

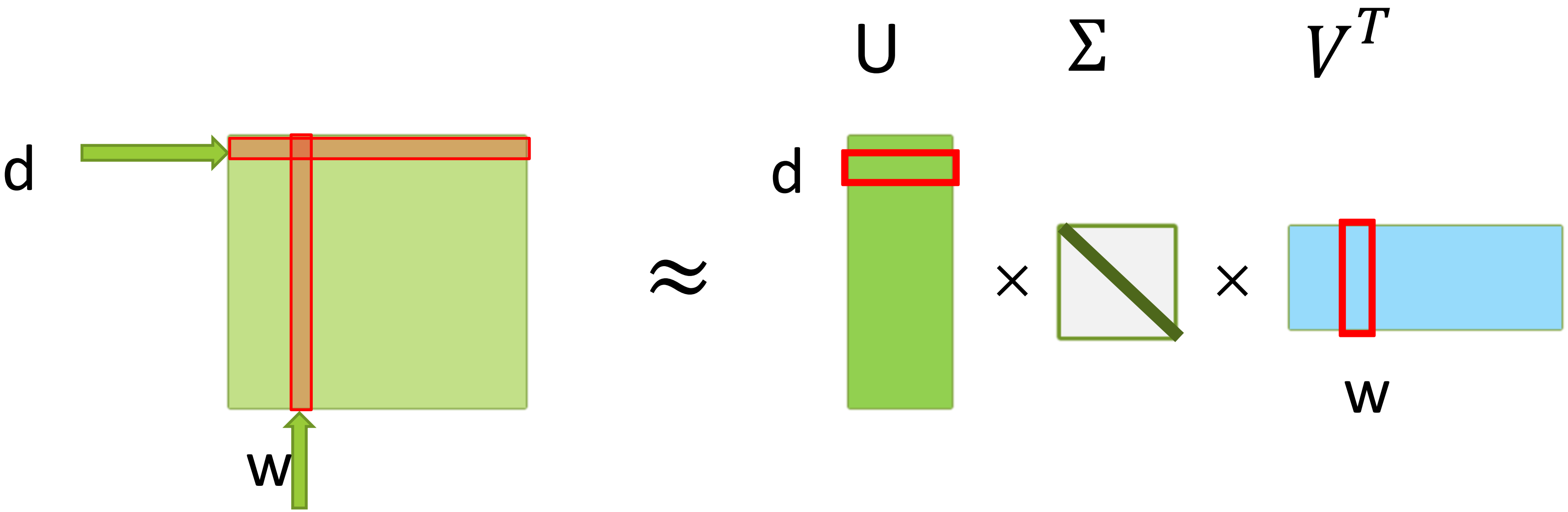
$$\begin{pmatrix} \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{pmatrix}$$

Latent semantic analysis (LSA)

X - document-term co-occurrence matrix

$$X \approx \hat{X} = U \, \Sigma \, V^T$$

- co-occurrence counts
- tf-idf
- filter stop-words
- lemmatize
- …



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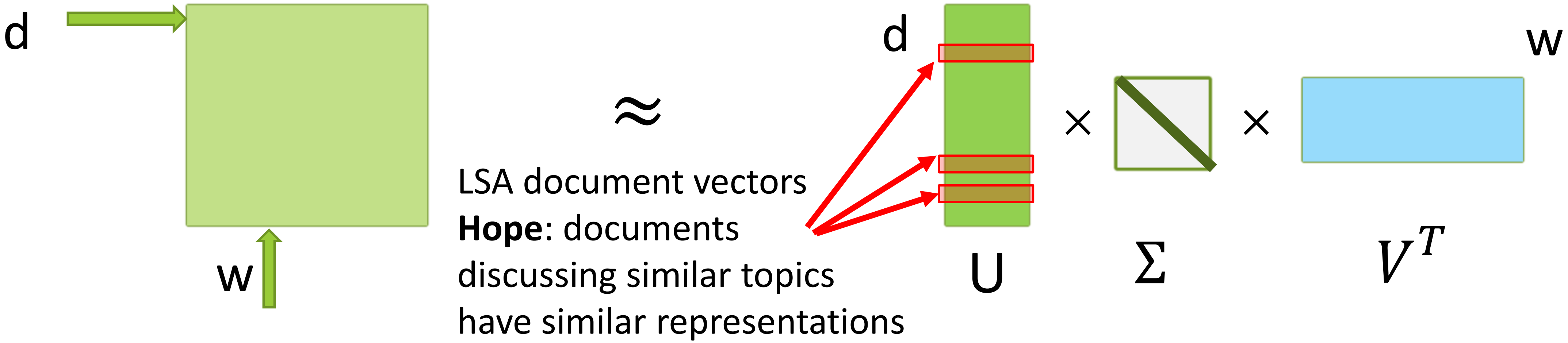

Latent semantic analysis (LSA)

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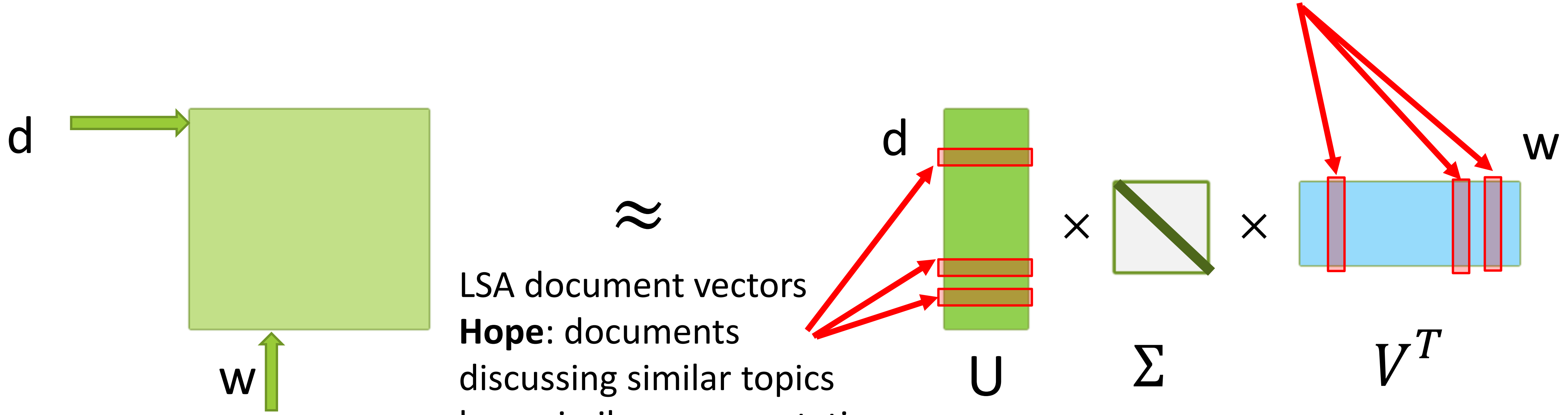
LSA term vectors
Hope: term having common meaning are mapped to the same direction



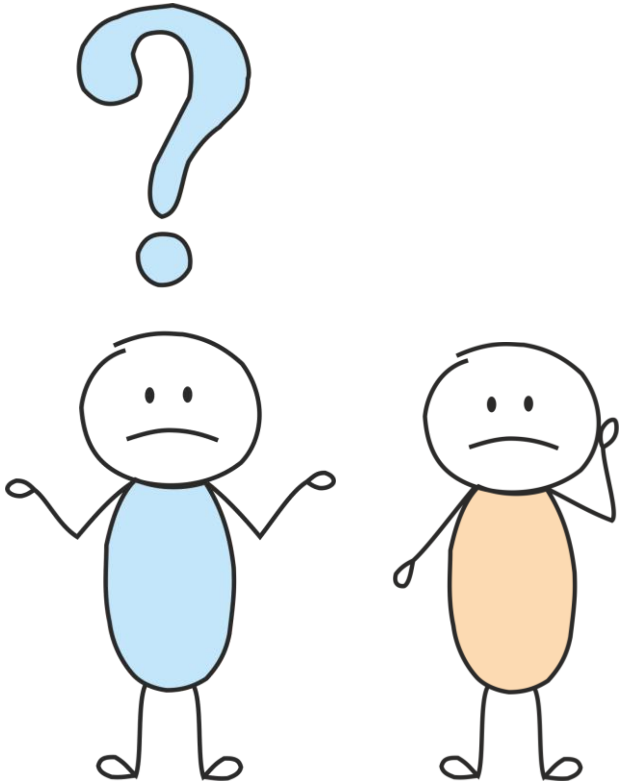
LSA document vectors
Hope: documents discussing similar topics have similar representations

Count-based methods

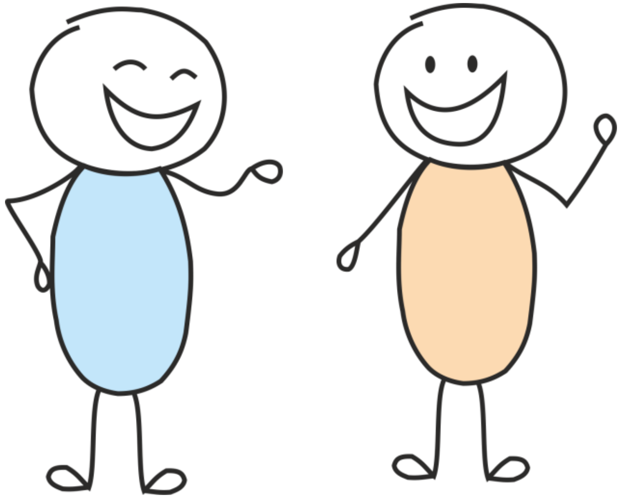
However, this is not the only way to induce
distributional representations

(and not the best one)

Why not to learn distributed representations?



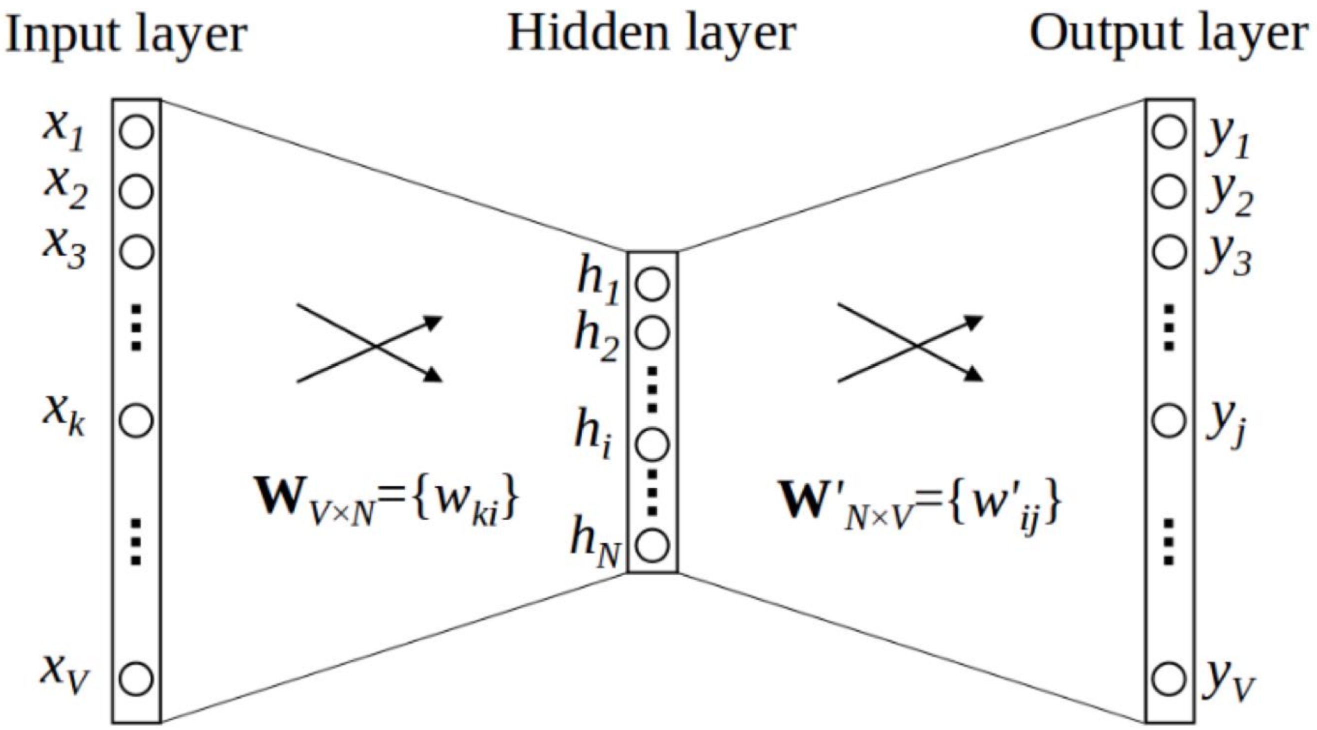
I mean, really, why?



We will learn a dense vector for each word, chosen so that it is similar to vectors of words that appear in similar contexts.

This **word vectors** are called **word embeddings** or word representations

Word2Vec

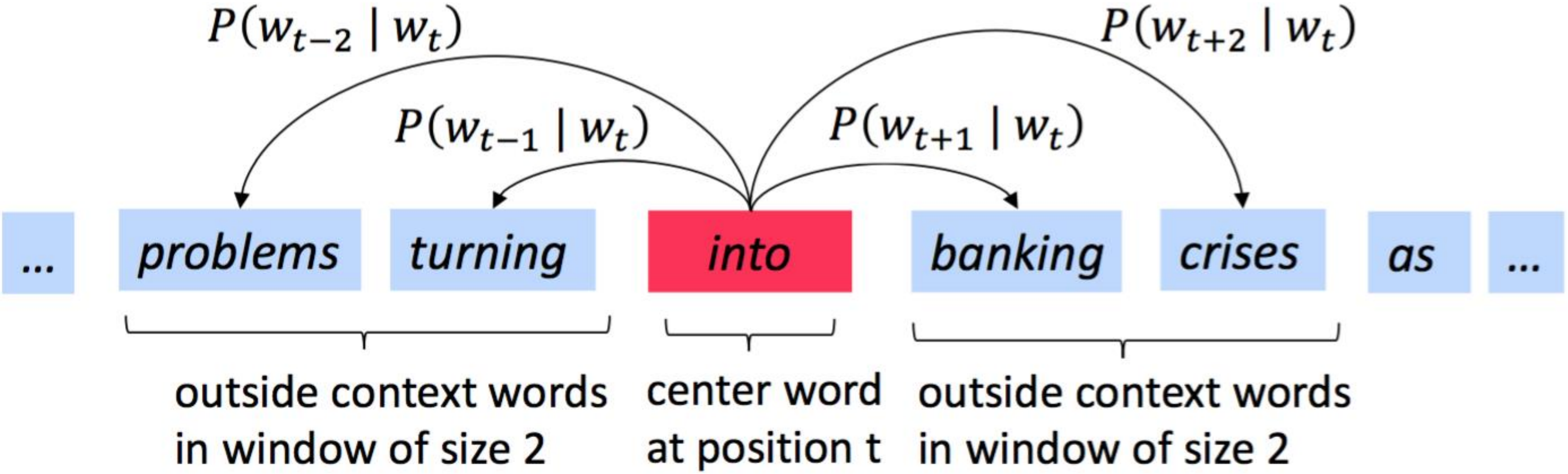


- a large corpus of text
- Every word in a fixed vocabulary is represented by a vector
- Go through each position t in the text, which has a center word c and context ("outside") words o
- Use the similarity of the word vectors for *c* and *o* to calculate the probability of *o* given *c* (or vice versa)
- Keep adjusting the word vectors to maximize this probability

Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

Word2Vec

- Examples windows and and process for computing $P(w_{t+j}|w_j)$



http://web.stanford.edu/class/cs224n/syllabus.html

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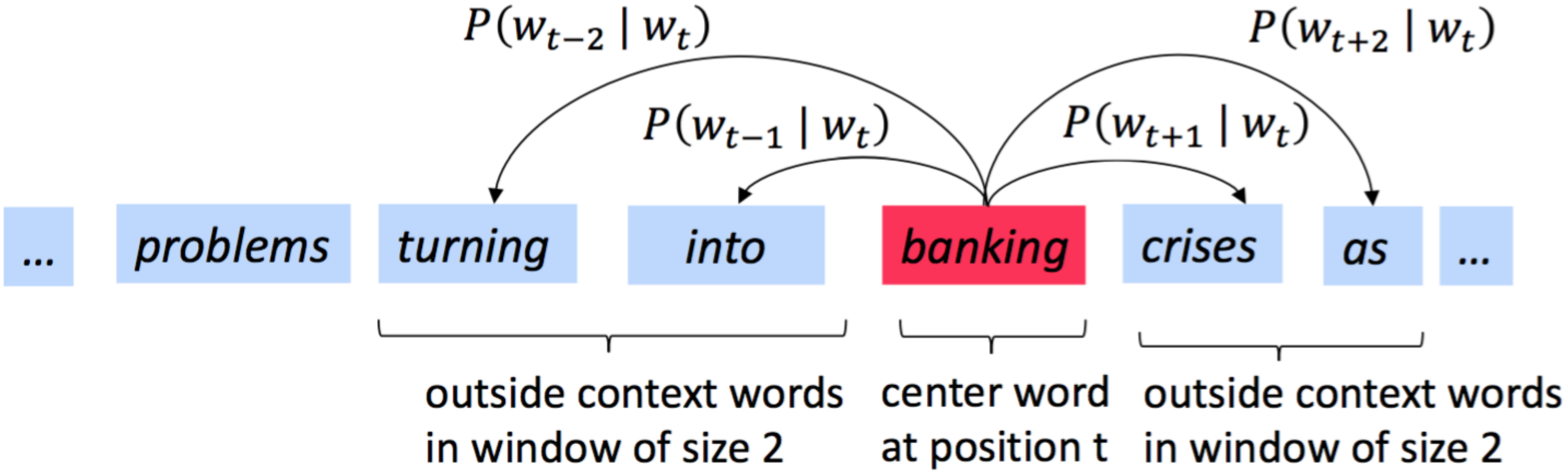

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Word2Vec: objective function

For each position $t = 1, \dots, T$, predict context words within a window of fixed size m, given center word w_t.

$$L(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \le j \le m \\ j \ne 0}} P(w_{t+j} \mid w_t; \theta)$$

Word2Vec: objective function

For each position $t = 1, \ldots, T$, predict context words within a window of fixed size m, given center word w_t.

Likelihood = $$L(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \leq j \leq m \\ j \neq 0}} P(w_{t+j} \mid w_t; \theta)$$

θ *is all variables to be optimized*

Word2Vec: objective function

The **objective function (or loss, or cost function)** $J(\theta)$ is the (average) negative log likelihood

$$J(\theta) = -\frac{1}{T}\log L(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\le j\le m\\ j\ne 0}}\log P\left(w_{t+j}\mid w_t;\theta\right)$$

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Minimizing objective function $\Longleftrightarrow$ Maximizing predictive accuracy

Word2Vec: objective function

- We want to minimize objective function $$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\leq j\leq m\\ j\neq 0}} \log P\left(w_{t+j} \mid w_t;\theta\right)$$

Word2Vec: objective function

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- Question: **How to calculate** $\boldsymbol{P}\left(\boldsymbol{w}_{t+j}\middle|\boldsymbol{w}_{j},\boldsymbol{\theta}\right)$?

Word2Vec: objective function

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- Question: **How to calculate $\boldsymbol{P\left(w_{t+j} \middle| w_j, \theta\right)}$?**
- Answer: We will use two vectors per word w
  - v_w is a center word
  - u_w is a context word

Word2Vec: objective function

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- Question: **How to calculate $\boldsymbol{P(w_{t+j}|w_j, \theta)}$?**

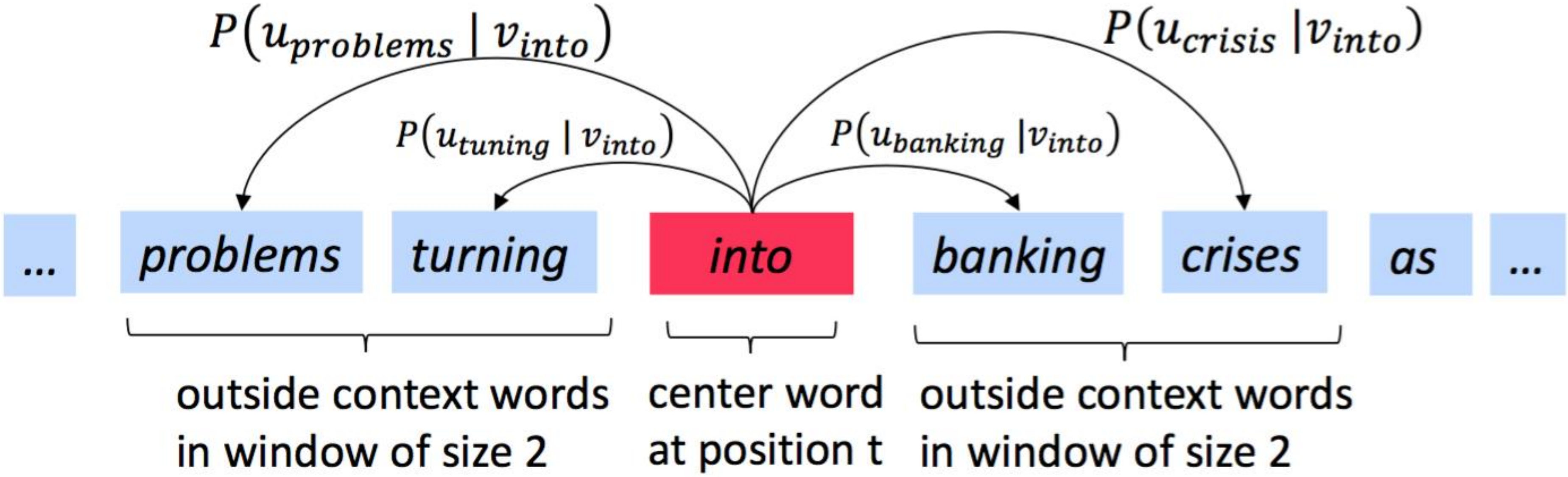
- Answer: We will use two vectors per word w
  - v_w is a center word
  - u_w is a context word

- Then for a center word **c** and a context word **o**:

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w\in V}\exp(u_w^T v_c)}$$

Word2Vec

- Examples windows and and process for computing $P(w_{t+j}|w_j)$
- $P(u_{problems}|v_{into})$ is short for $P(problems|into;\ u_{problems}, v_{into}, \theta)$



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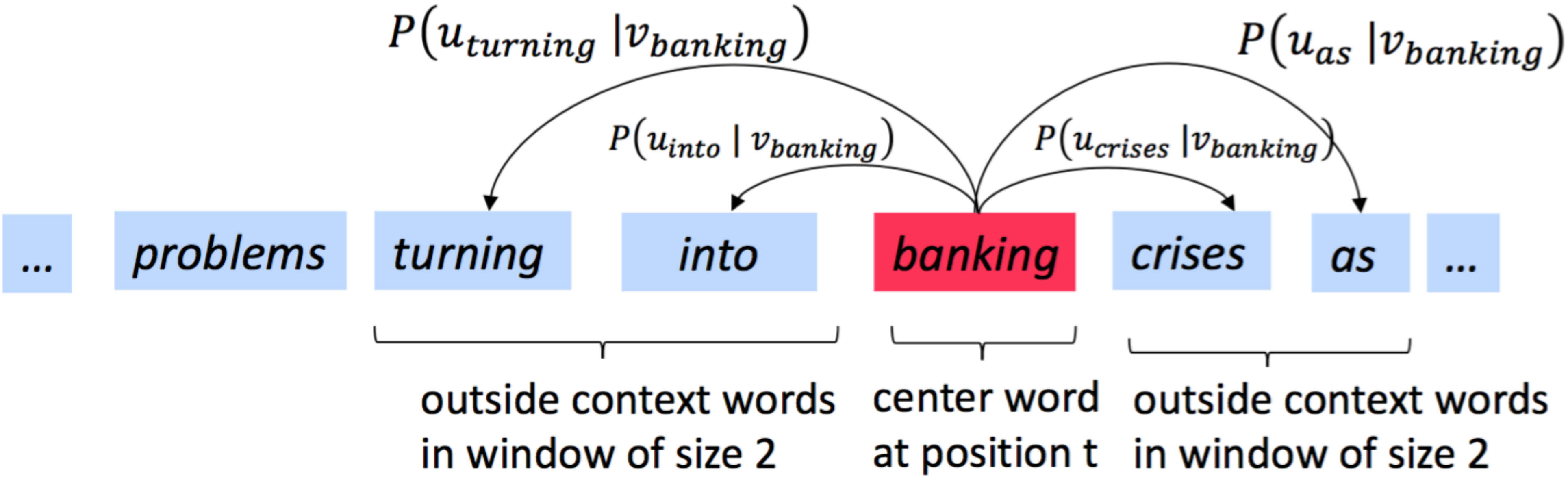

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Word2Vec: prediction function

$$P(o|c) = \frac{\exp(u_o^T\, v_c)}{\sum_{w \in V} \exp(u_w^T\, v_c)}$$

Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

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Dot product measures similarity of ***o*** and ***c***
Larger dot product = larger probability

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After taking exponent, normalize
over entire vocabulary

Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

This is softmax!

Softmax function $\mathbb{R}^n \rightarrow \mathbb{R}^n$:

$$softmax(\boldsymbol{x})_i = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} = p_i$$

- maps arbitrary values x_i to a probability distribution p_i
- ”max” because amplifies probability of largest x_i
- “soft” because still assigns some probability to smaller x_i
- **often used in Deep Learning!**

Where is $\boldsymbol{\theta}$?

$$\theta = \begin{bmatrix} v_{aardvark} \\ v_a \\ \vdots \\ v_{zebra} \\ u_{aardvark} \\ u_a \\ \vdots \\ u_{zebra} \end{bmatrix} \in \mathbb{R}^{2dV}$$

- θ - d-dimensional vectors for V words
- every word has two vectors!
- we optimize these parameters

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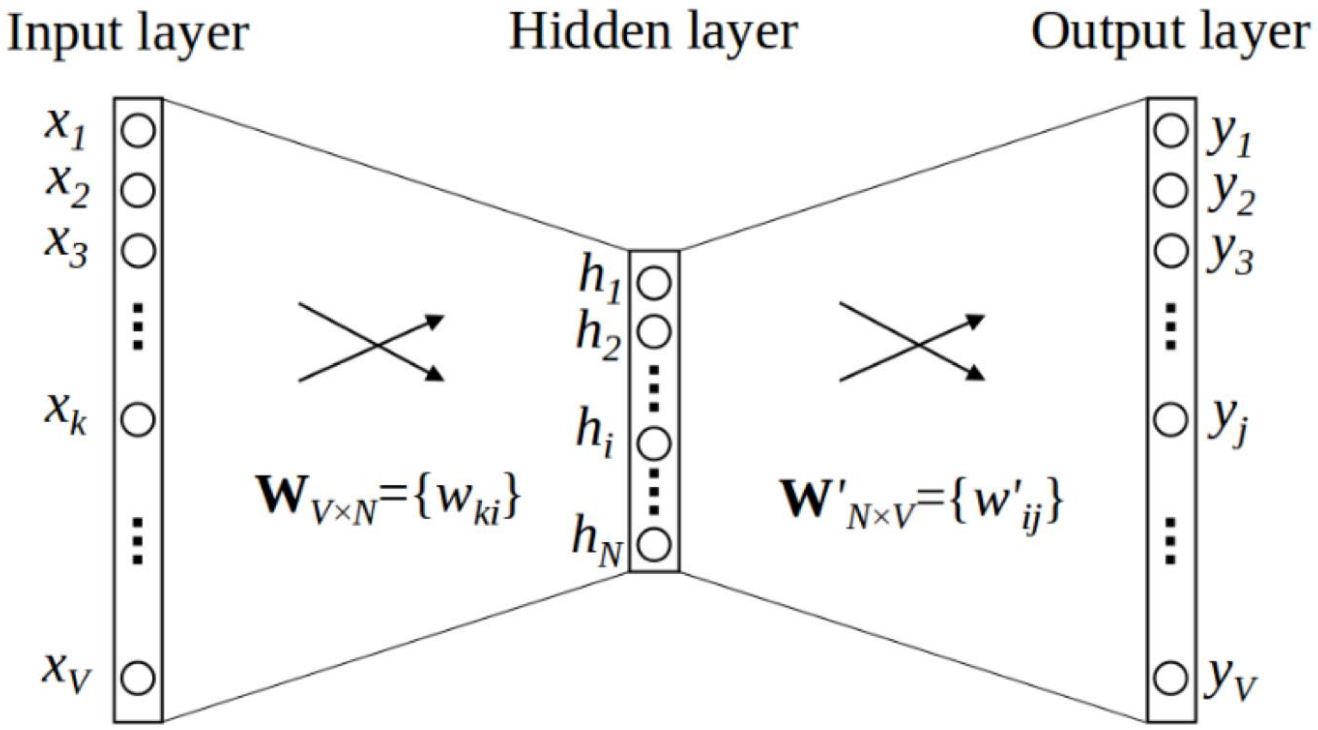
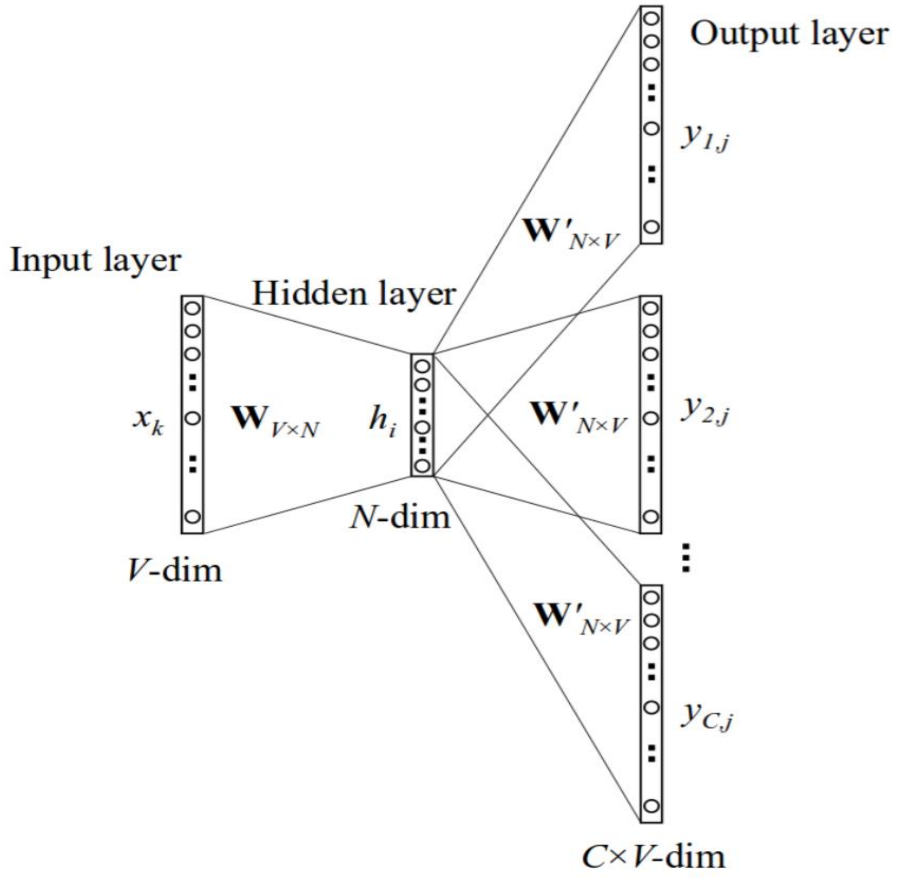


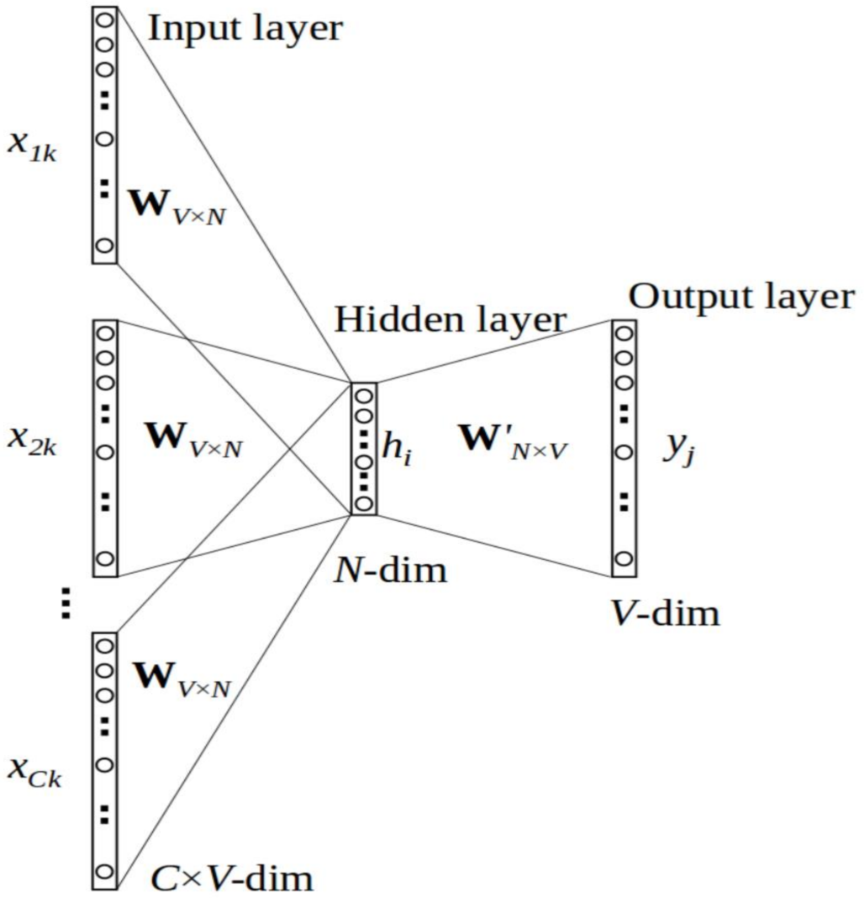
Word2Vec: Skip-gram (SG)

- Predict context (”outside”) words (position independent) given center word



Word2Vec: Continuous Bag of Words (CBOW)

- Predict center word from (bag of) context words



Word2Vec: Additional efficiency in training

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\boxed{\sum_{w \in V} \exp(u_w^T v_c)}}$$

Huge sum! Time for calculating gradients is proportional to |V|

Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

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Possible solutions:

- Hierarchical softmax
- Negative sampling

Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

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Huge sum! Time for calculating gradients is proportional to |V|

Possible solutions:

- Hierarchical softmax
- Negative sampling

$$\sum_{w \in V} \exp(u_w^T v_c) \Longrightarrow \sum_{w \in \{o\} \cup S\_k} \exp(u_w^T v_c)$$

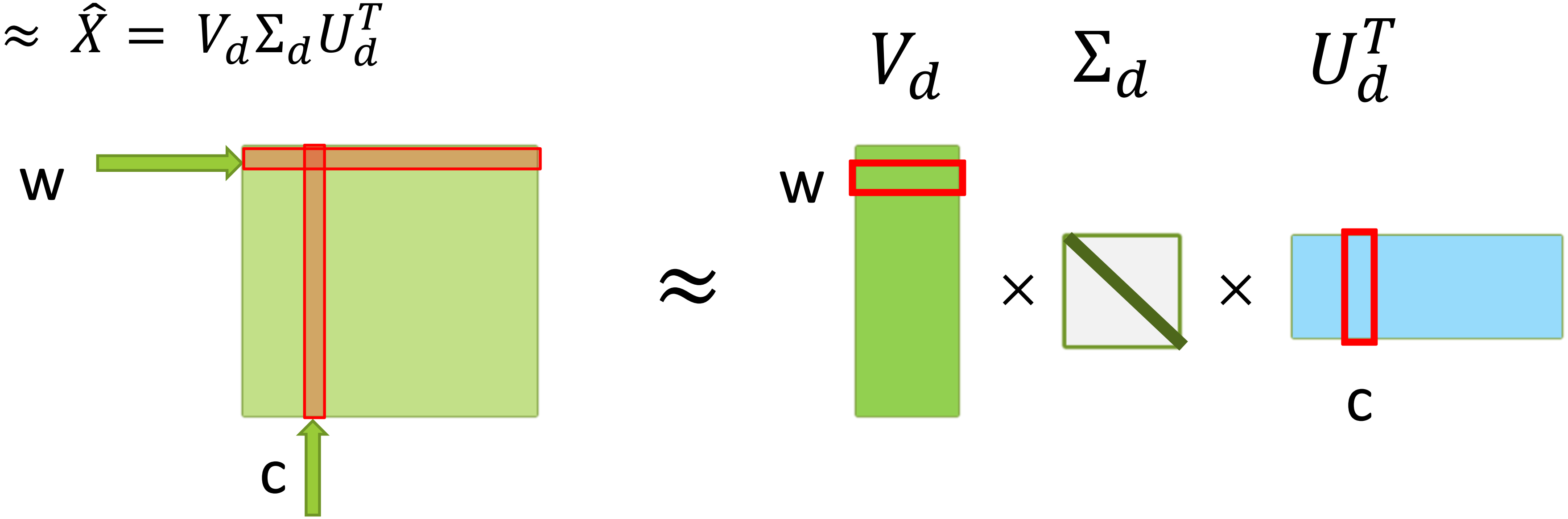
Sum over a small subset: *negative sample,* $|S_k|=k$

Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

Word2Vec:
(Near) equivalence to matrix factorization

$$PMI(w,c) = \log \frac{N(w,c) \times |V|}{N(w)N(c)}$$

$$PMI = X \approx \hat{X} = V_d \Sigma_d U_d^T$$



Levy et al, TACL 2015 http://www.aclweb.org/anthology/Q15-1016

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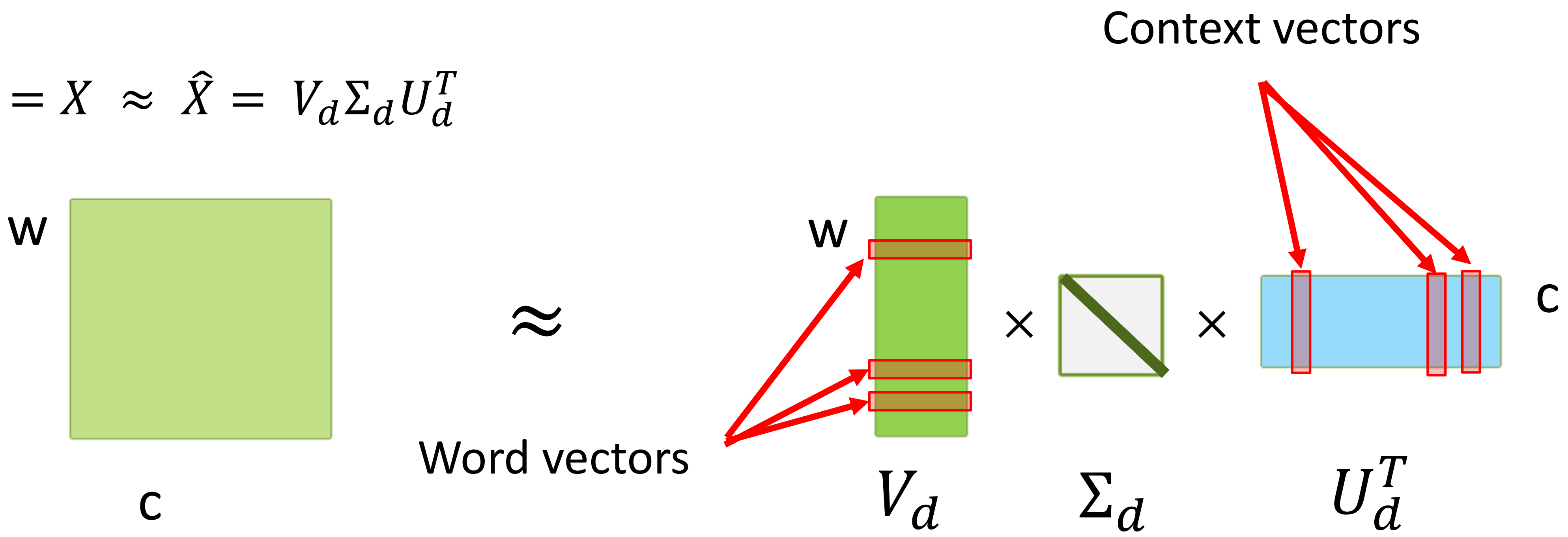

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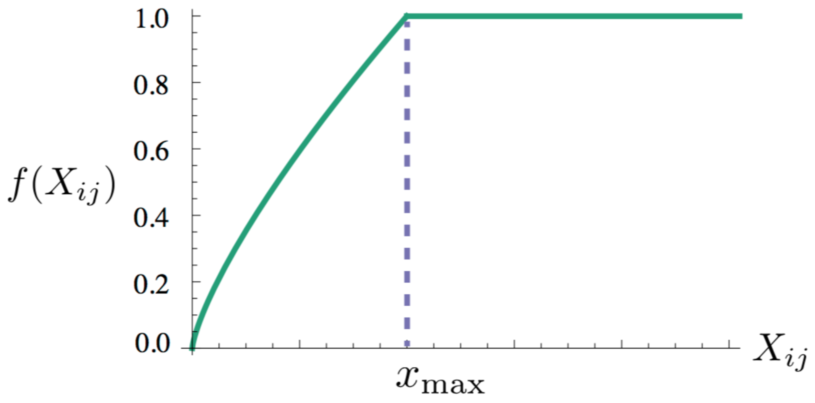
GloVe: combine count-based and direct prediction methods

$$J(\theta) = \frac{1}{2} \sum_{i,j=1}^{W} f(P_{ij})(u_i^T v_j - \log P_{ij})^2$$

$$X_{final} = U + V$$



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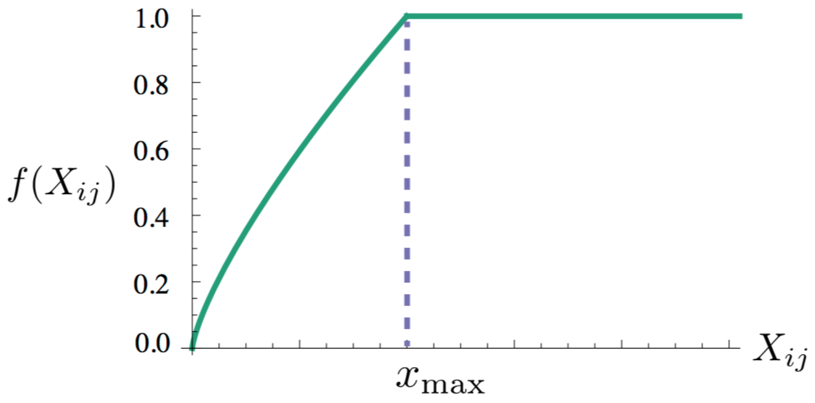
probability that word *j* appear in the context of word *i*



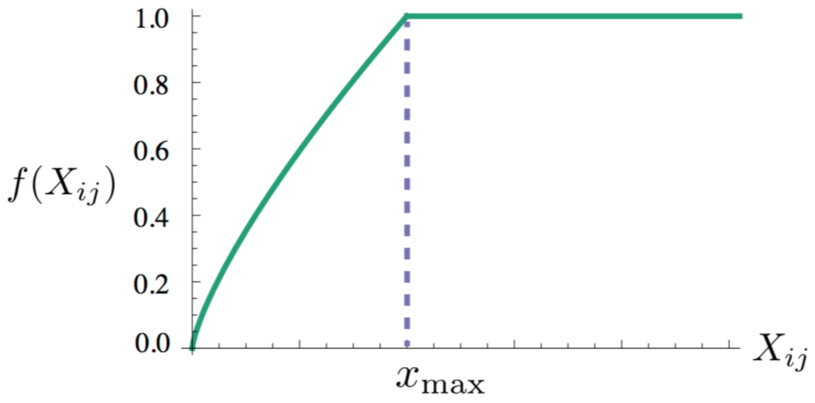
Pennington et al., EMNLP 2014, https://www.aclweb.org/anthology/D14-1162

GloVe: combine count-based and direct prediction methods

$$J(\theta) = \frac{1}{2}\sum_{i,j=1}^{W} f(P_{ij})\boxed{(u_i^T v_j - \log P_{ij})^2}$$

$$X_{final} = U + V$$

the idea is close to factorizing the log of the co-occurrence matrix (closely related to LSA)



Pennington et al., EMNLP 2014, https://www.aclweb.org/anthology/D14-1162

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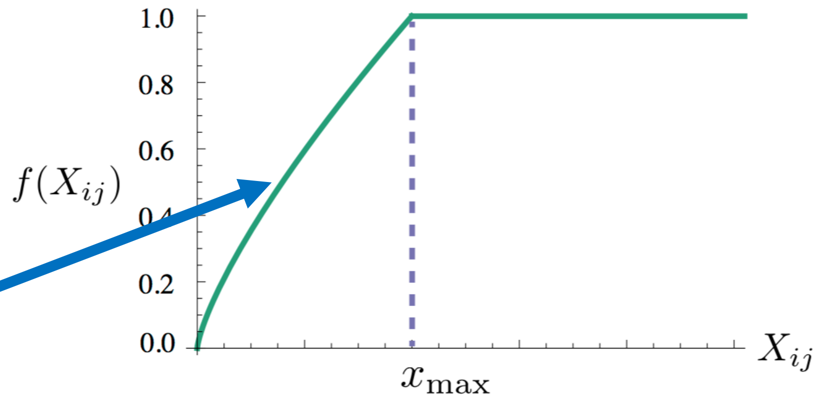
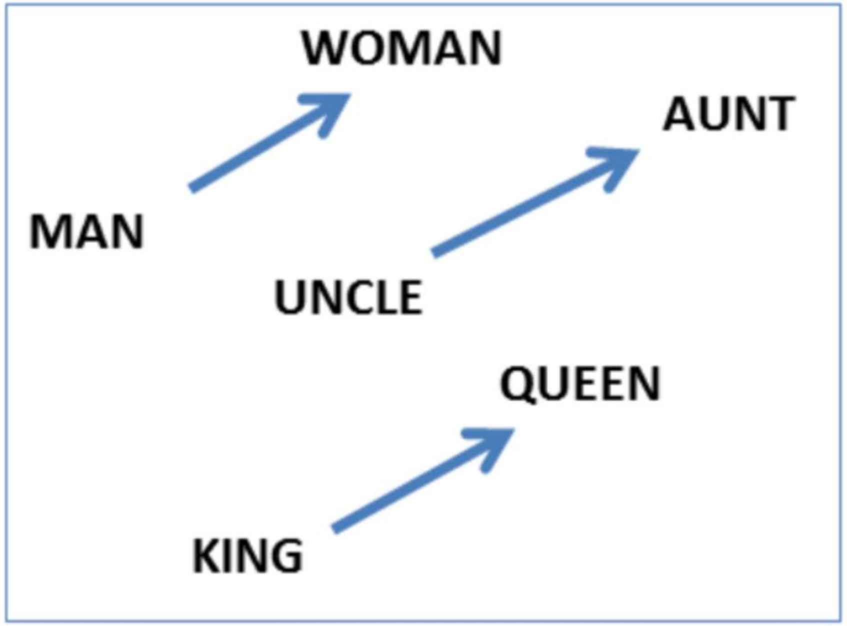


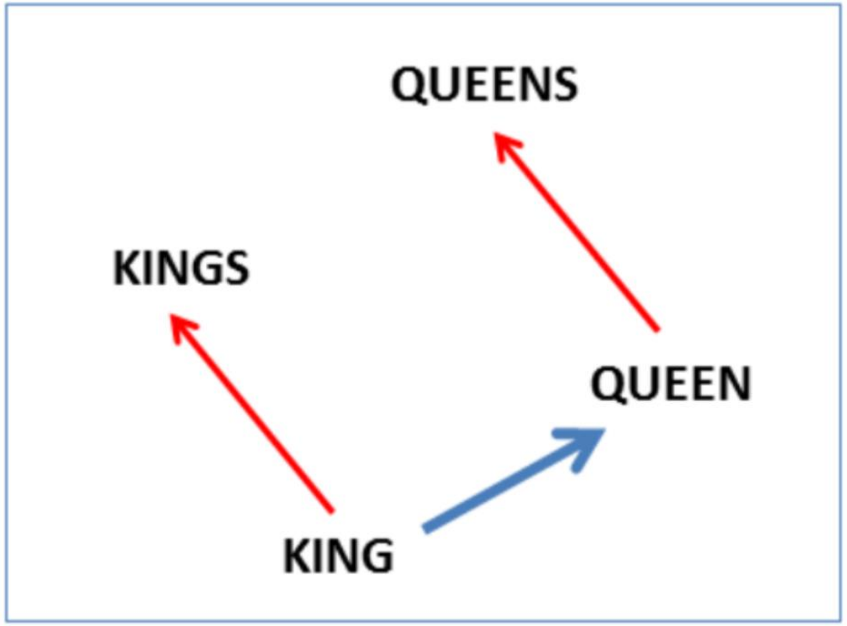
discard rare noisy co-occurrences

Pennington et al., EMNLP 2014, https://www.aclweb.org/anthology/D14-1162

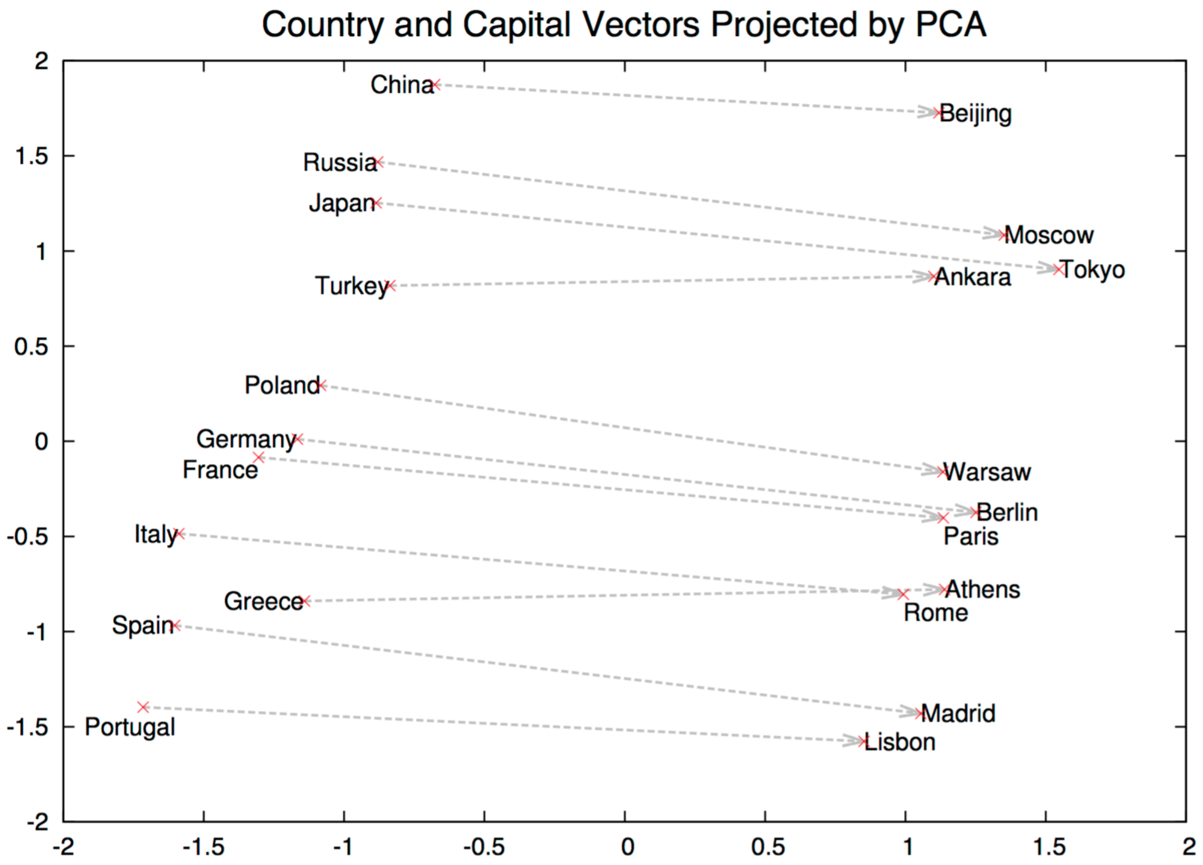
Word2Vec:
what are relations between vectors?

$$v(\text{king}) - v(\text{man}) + v(\text{woman}) \approx v(\text{queen})$$





What are relations between vectors?



Mikolov et al, 2013, https://arxiv.org/pdf/1310.4546.pdf

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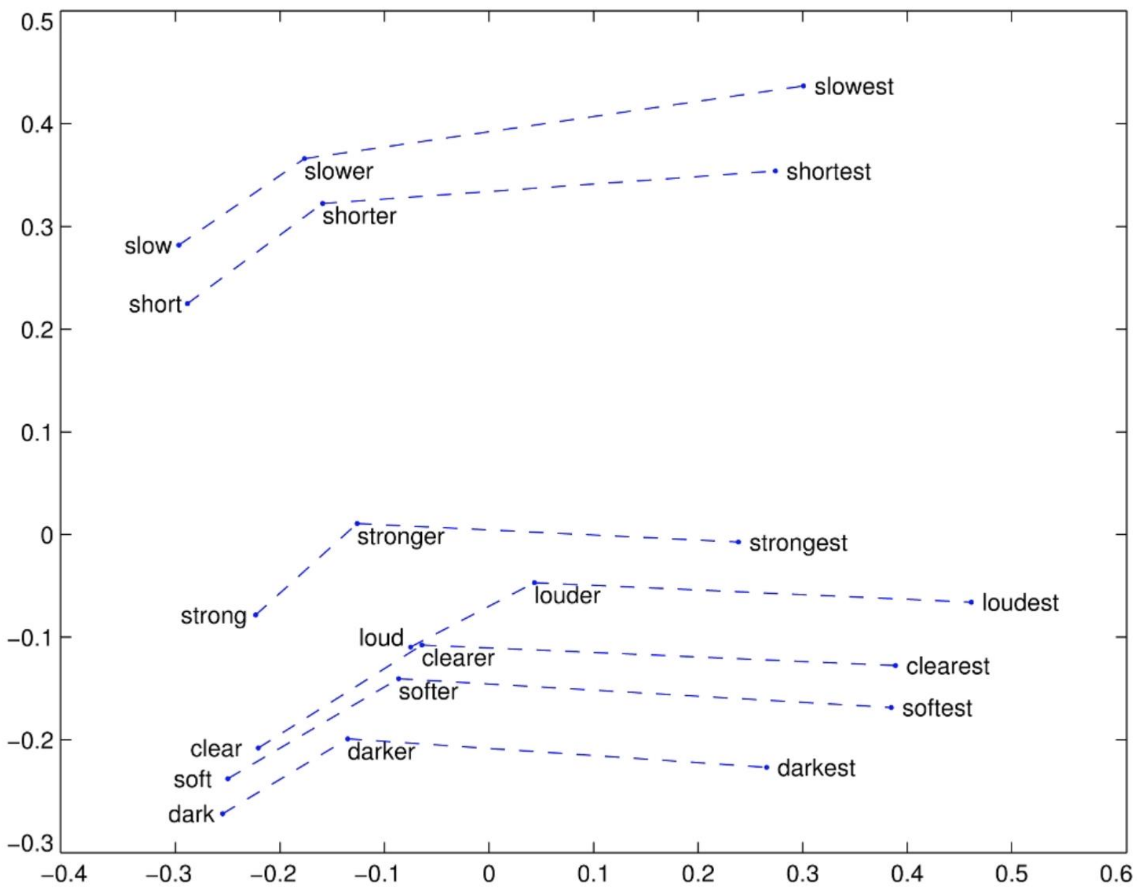


(http://nlp.stanford.edu/projects/glove/)

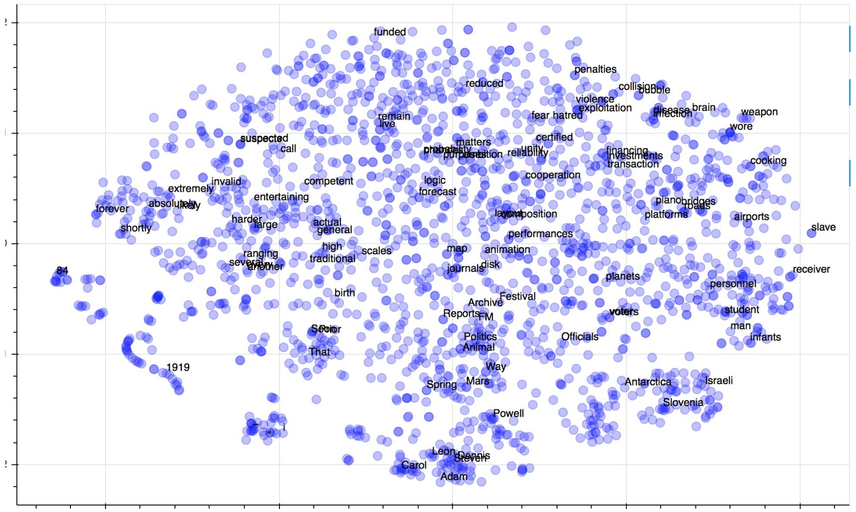
What are relations between vectors?

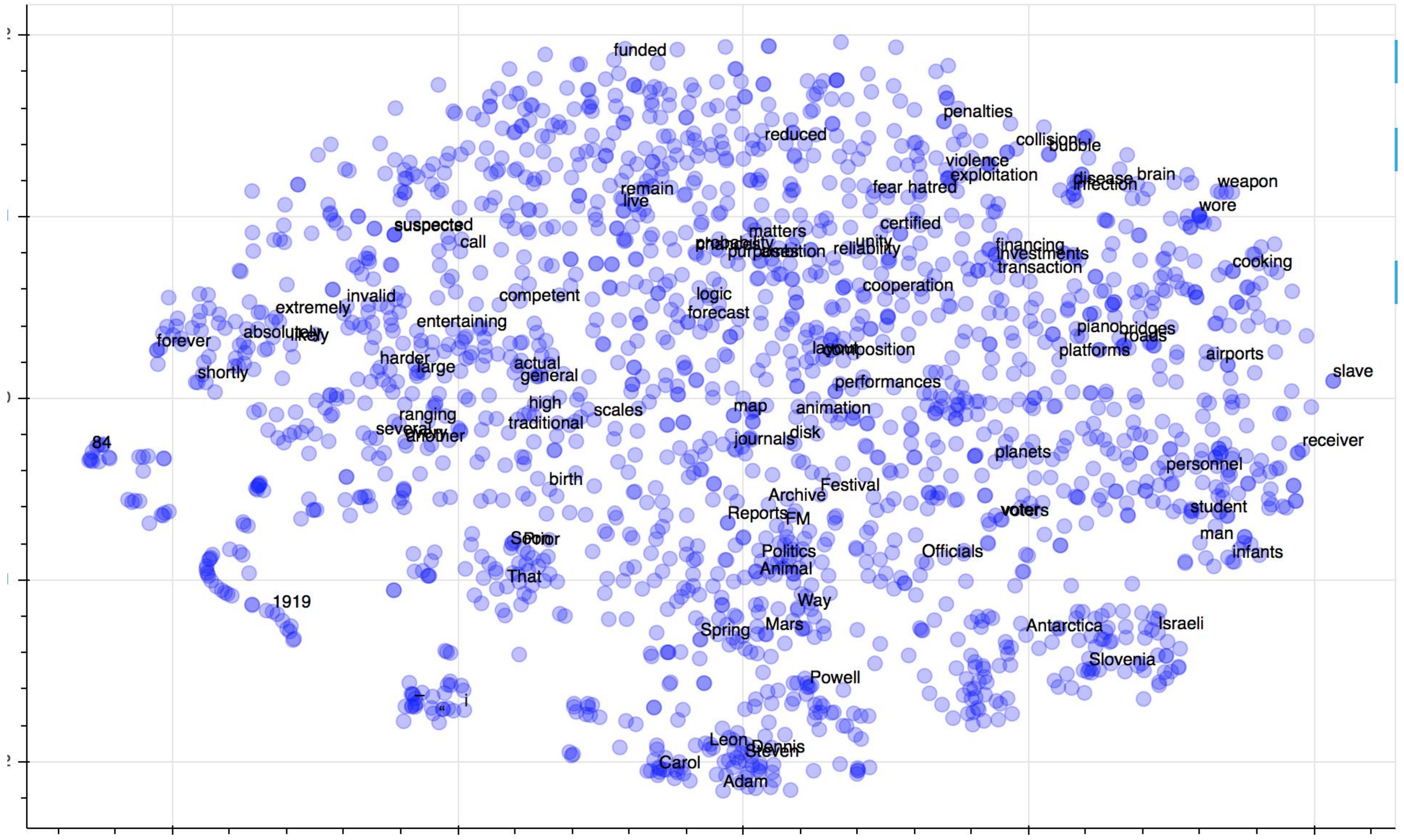
nearest neighbors of *frog*	Litoria	Leptodactylidae	Rana	Eleutherodactylus
Pictures				

(http://nlp.stanford.edu/projects/glove/)

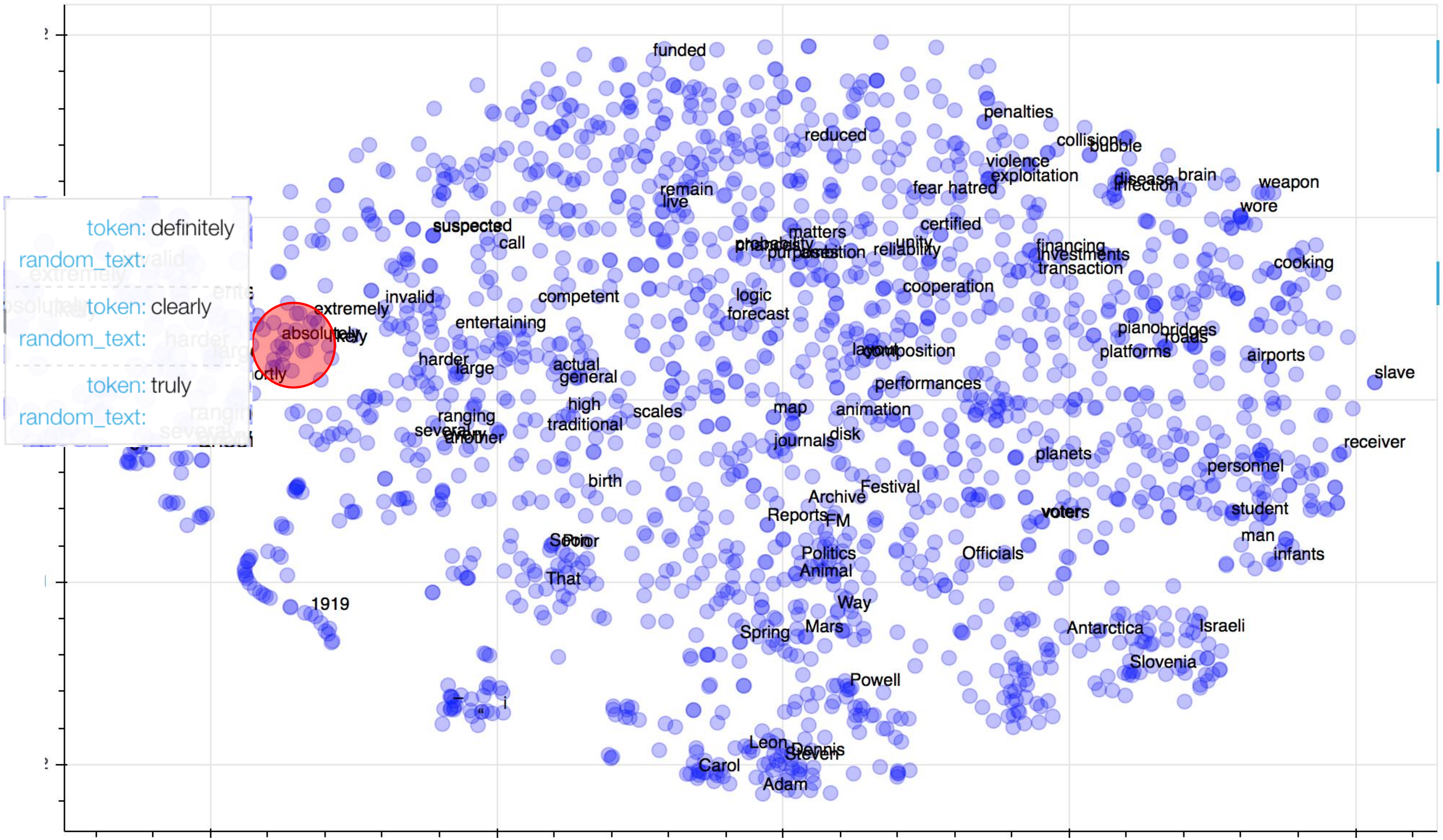
Let’s walk through space…

Let's walk through space…
Semantic space!





https://pste.eu/p/ZRot.html



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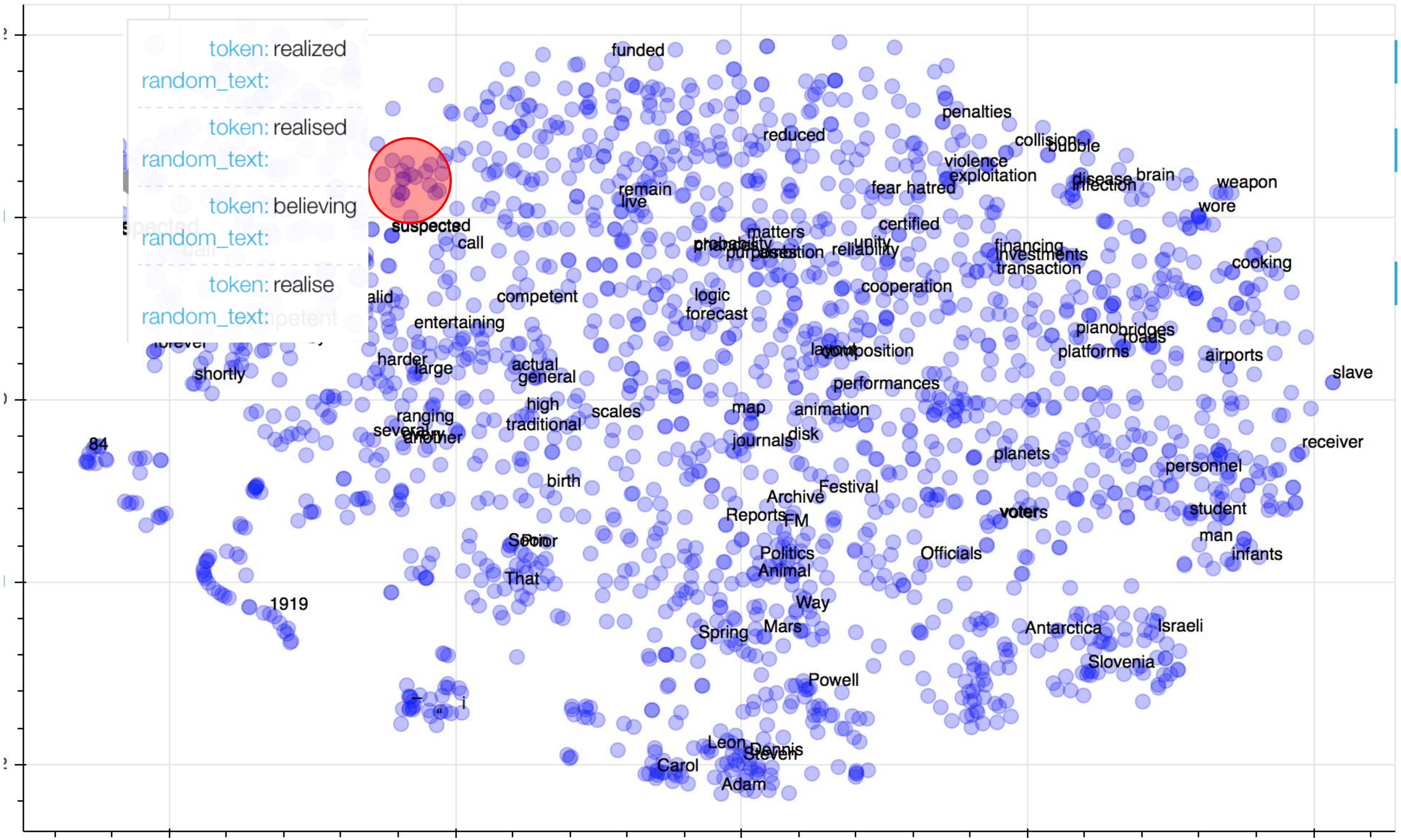

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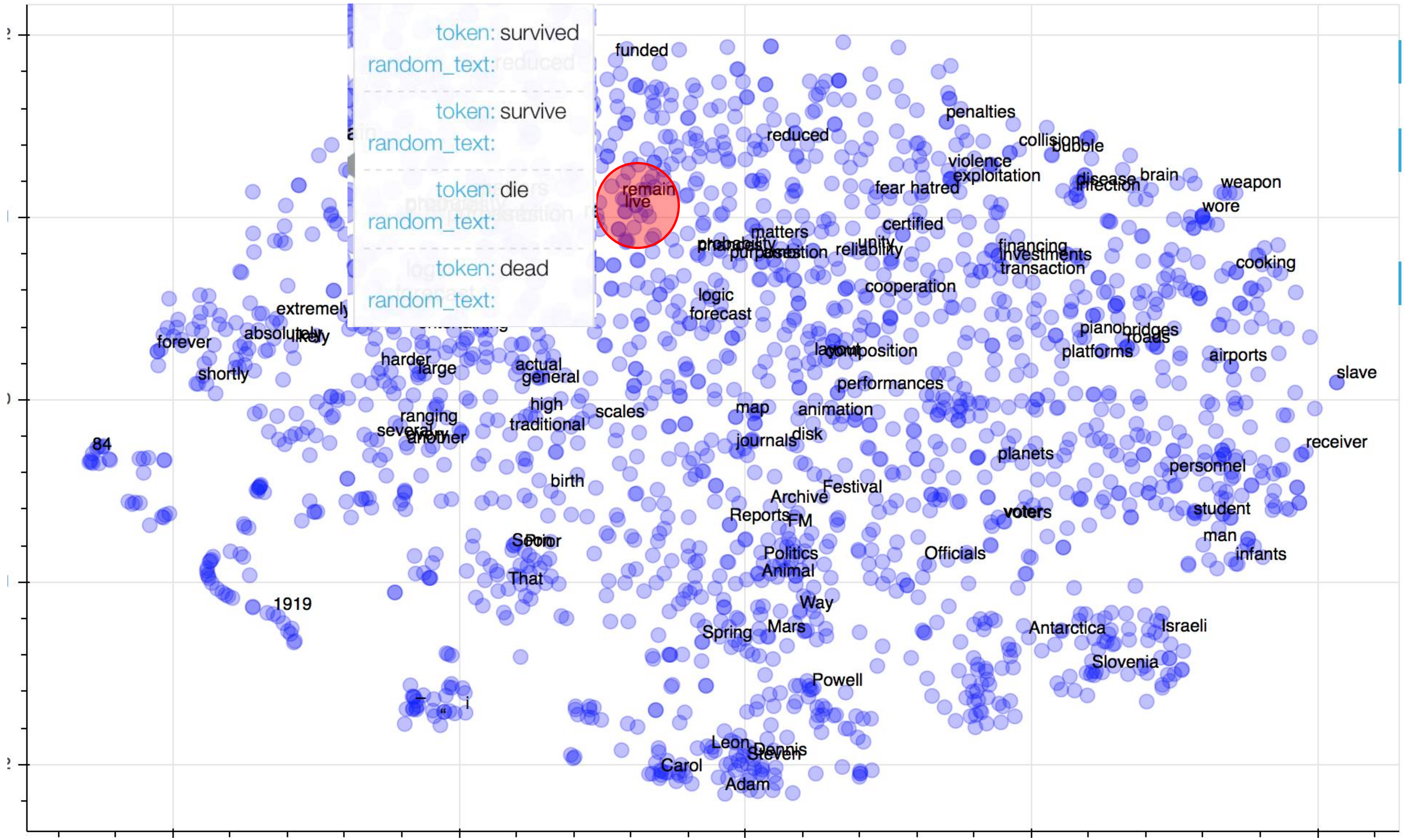

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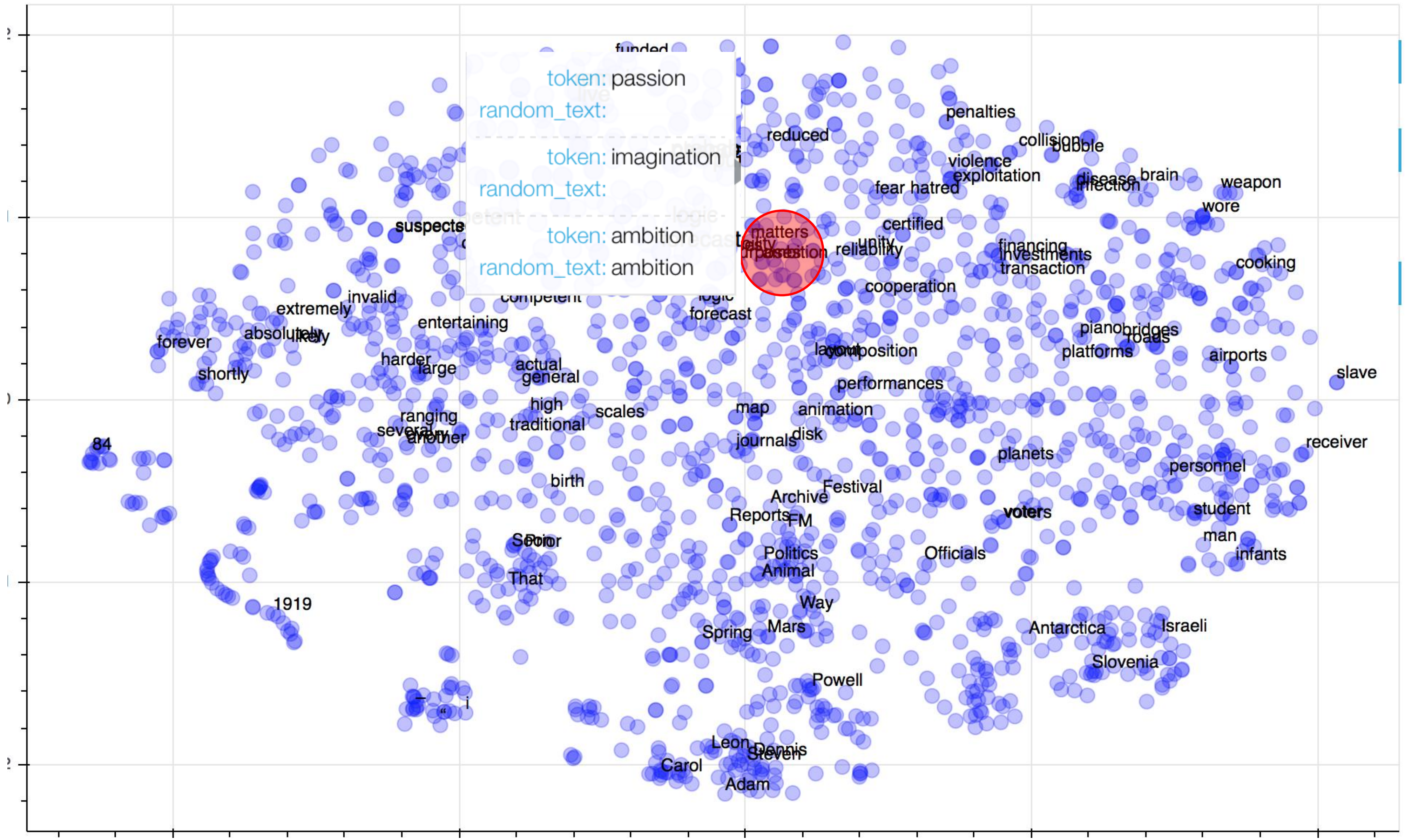

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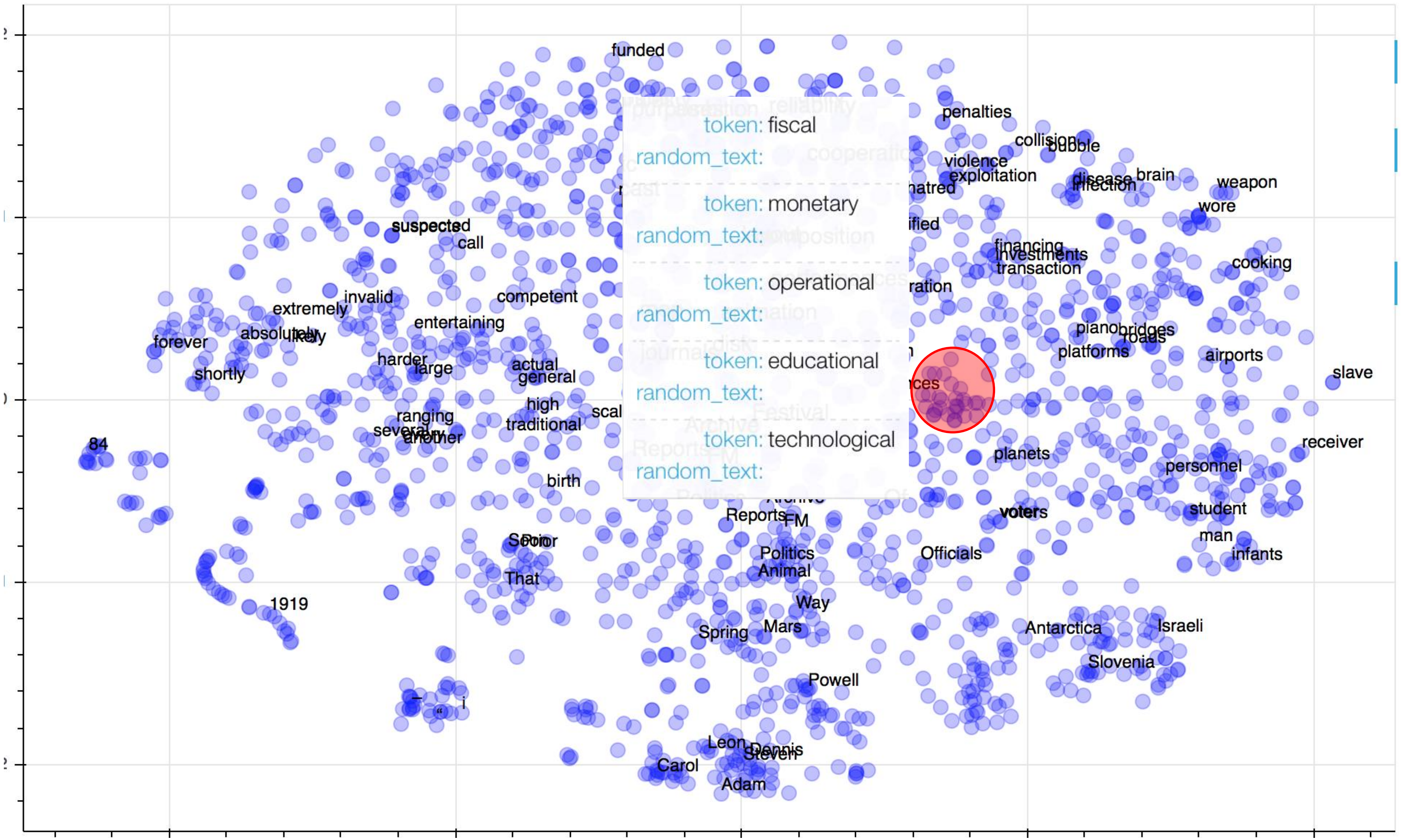

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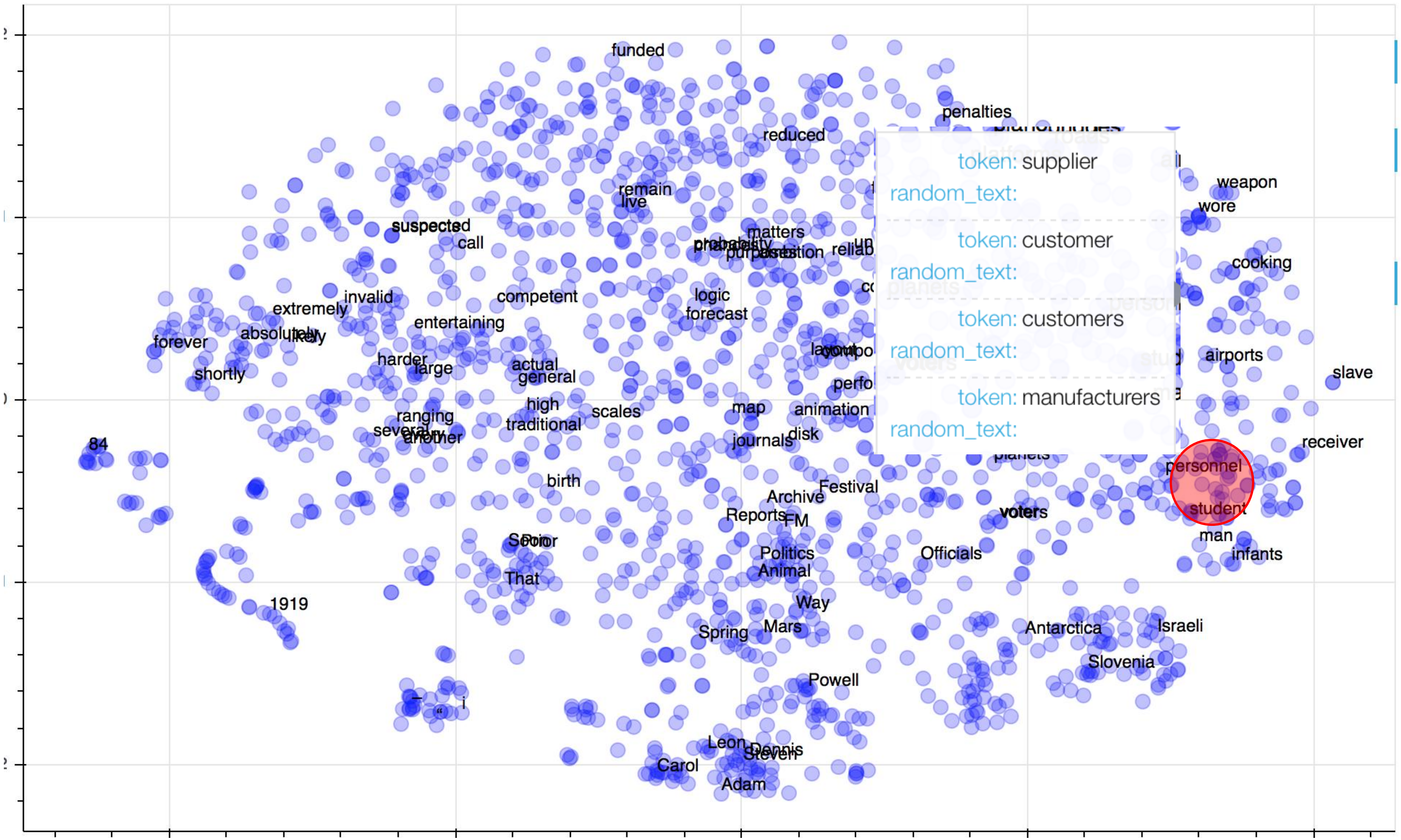

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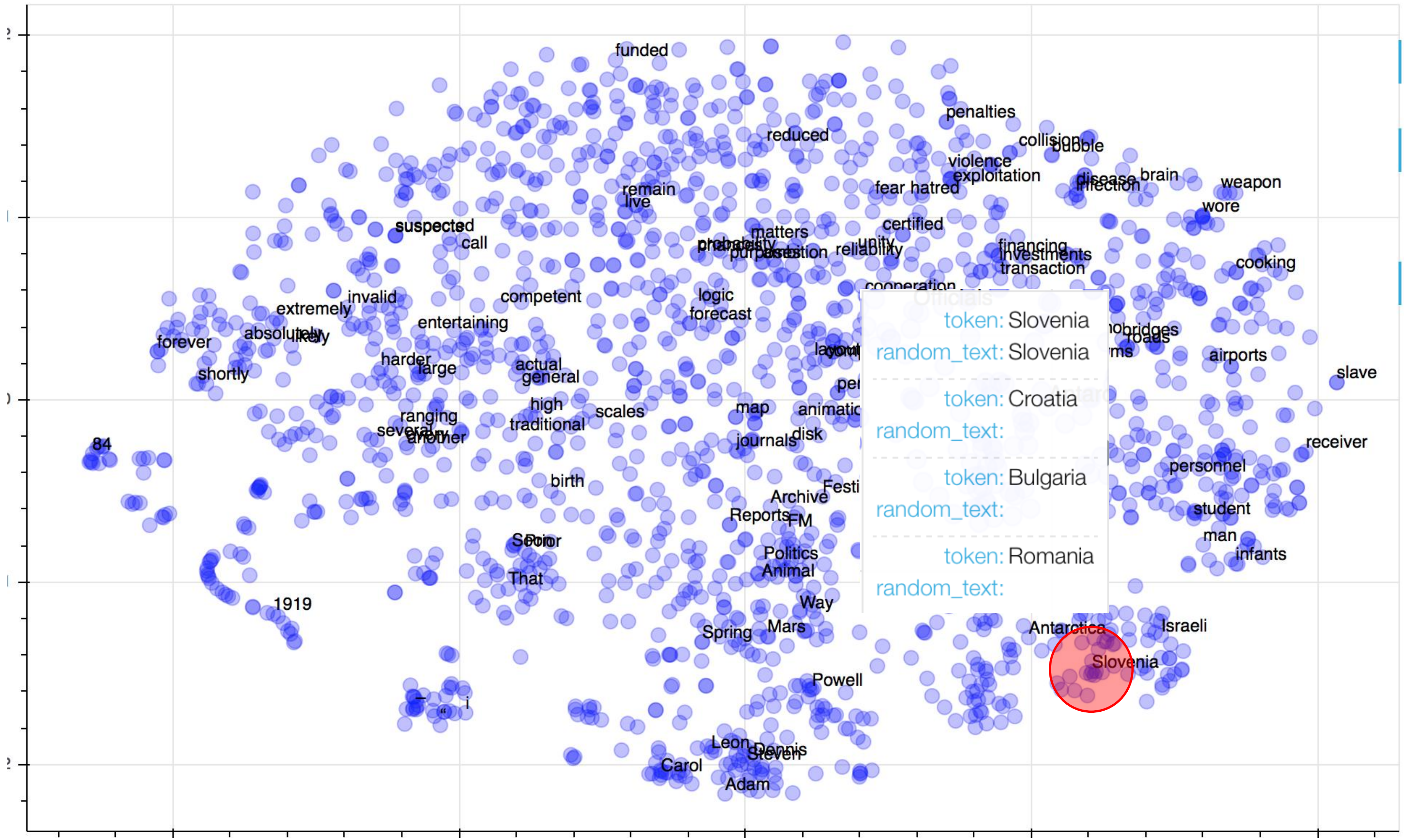

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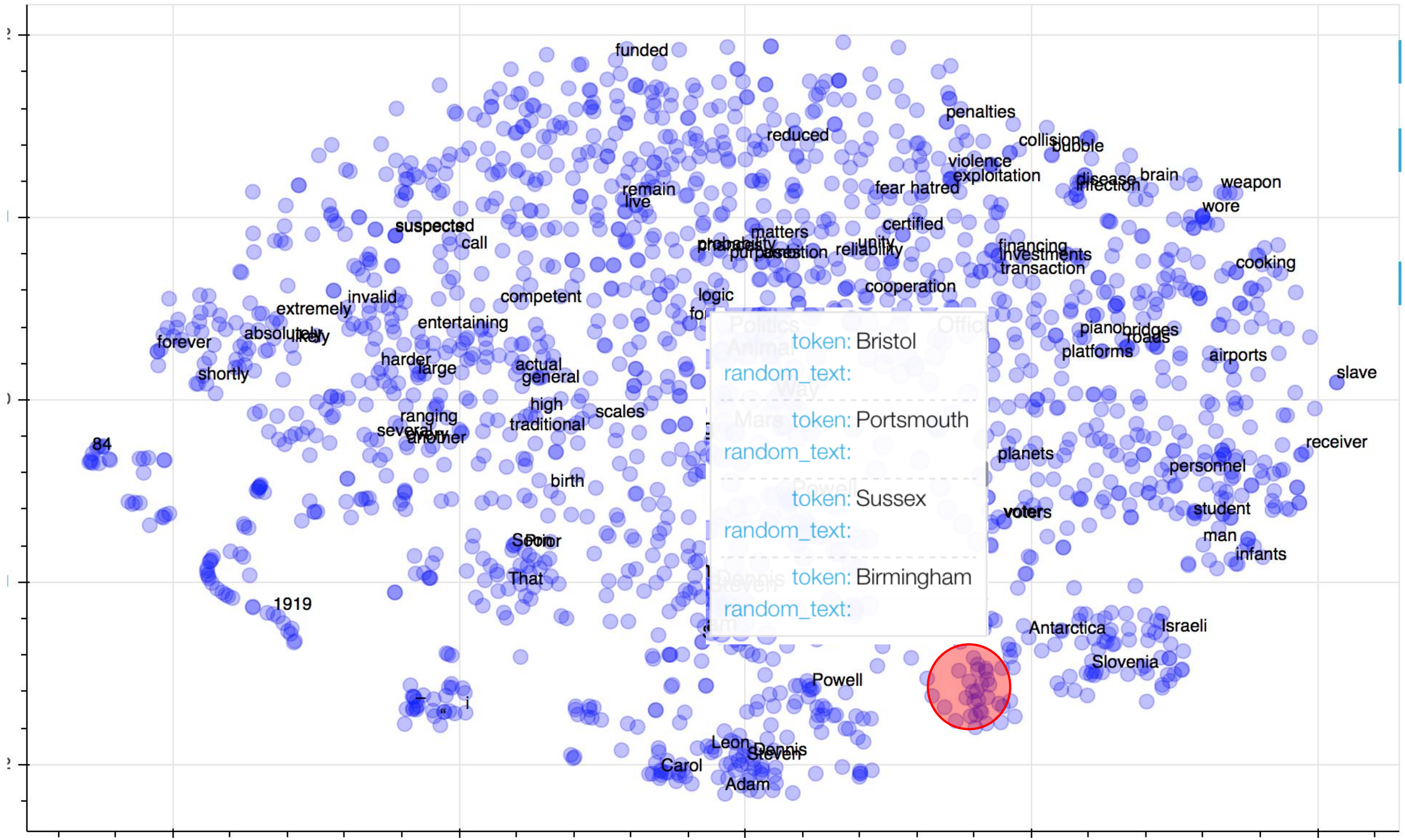

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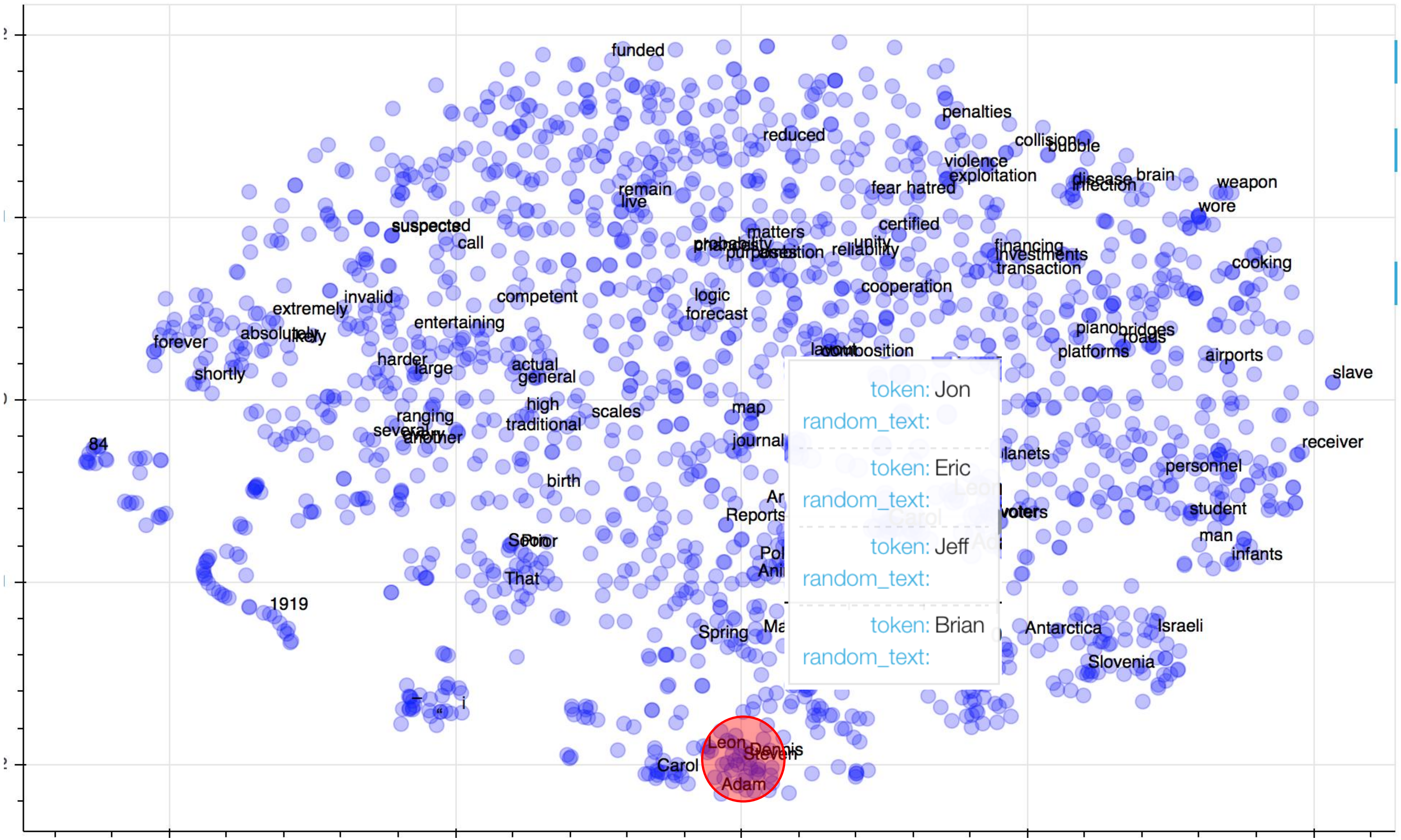

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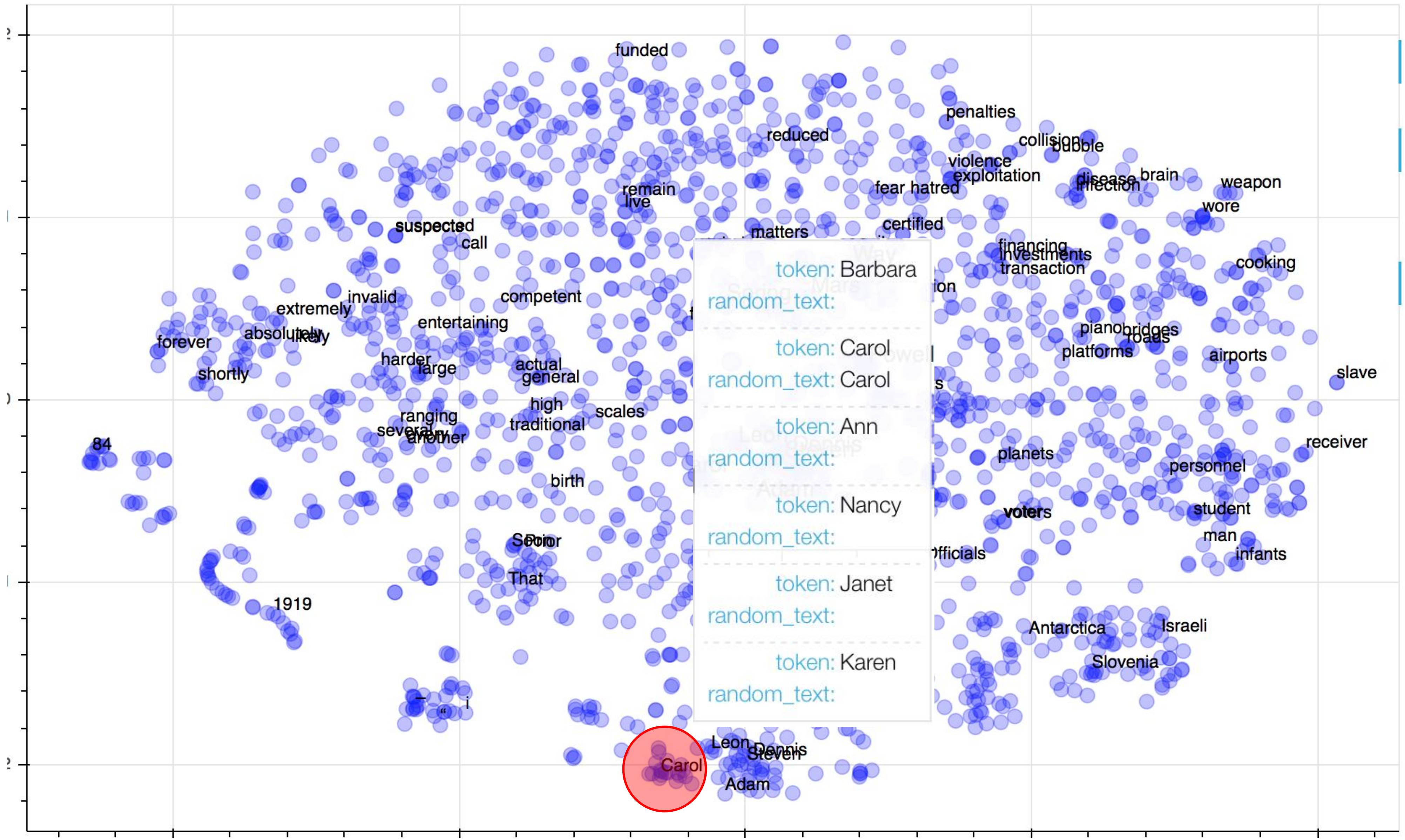

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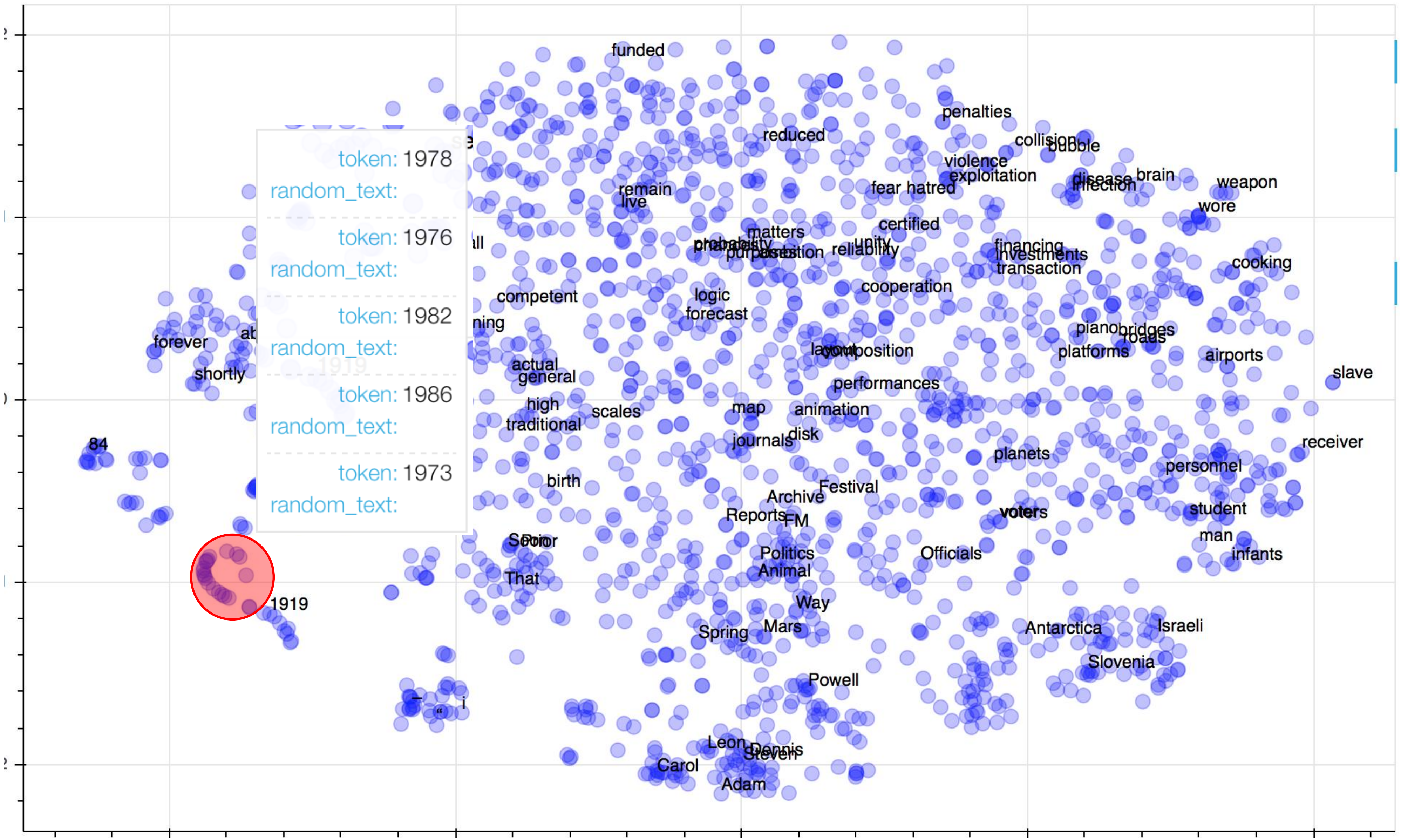


https://pste.eu/p/ZRot.html

How to evaluate embeddings

Intrinsic: evaluation on a specific/intermediate subtask

- word analogies: “*a* is to *b* as *c* is to ___?”
- word similarity: correlation of the rankings
- …

Extrinsic: evaluation on a real task

- take some task (MT, NER, coreference resolution, …) or several tasks
- train with different pretrained word embeddings
- if the task quality is better -> win!

What if..

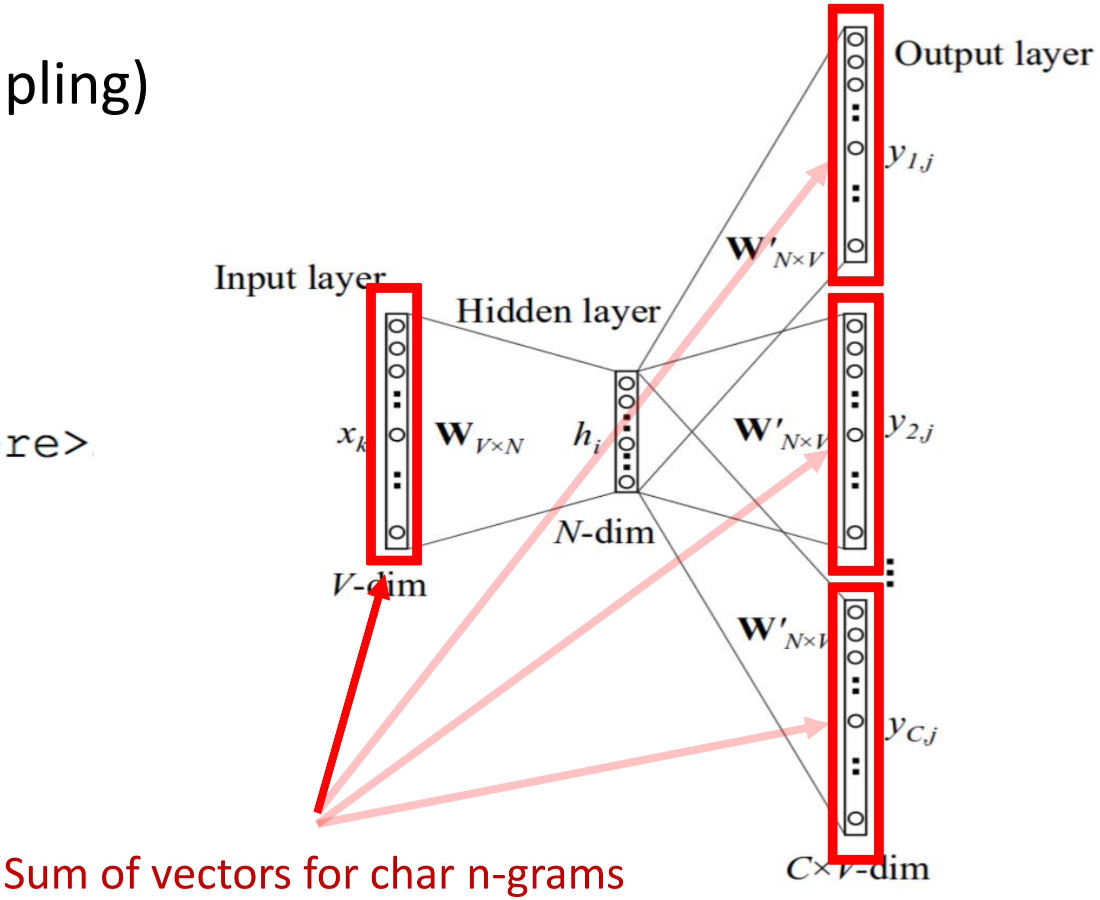
We want to use subword information?

Adding subword information: FastText

Model: SG-NS (skip-gram with negative sampling)

Change the way word vectors are formed:

- each word represented as a bag of character n-gram `<wh, whe, her, ere, re> <where>`
- associate a vector representation to each n-gram
- represent a word by the sum of the vector representations of its n-grams



Bojanovsky et al, TACL 2017 http://aclweb.org/anthology/Q17-1010

Add there any function of chars - get new embeddings!

Char-aware word embedding recipe:

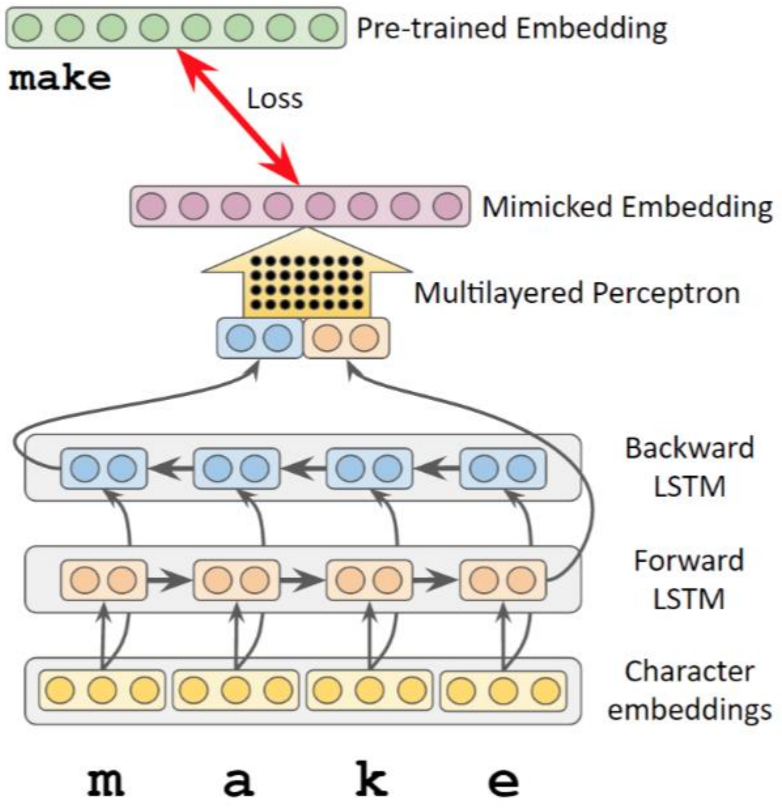
- take any model that learns word embeddings
- choose how to get word representation from representation of chars of char n-grams (RNN, CNN, pooling – mean, sum, etc., - anything reasonable)
- replace word vector in the model with the representation gathered from char/subword representations
- train as before
- DONE!

One example: Ling et al, EMNLP 2015 https://www.aclweb.org/anthology/D/D15/D15-1176.pdf

Or just pretend to be some other embeddings!

Match the predicted embeddings $f(w_k)$ to the pre-trained word embeddings e_{w_k}, by minimizing the squared Euclidean distance:

$$\mathcal{L} = \|f(w_k) - \boldsymbol{e}_{w_k}\|_2^2$$



Pinter et al, EMNLP 2017 http://www.aclweb.org/anthology/D17-1010

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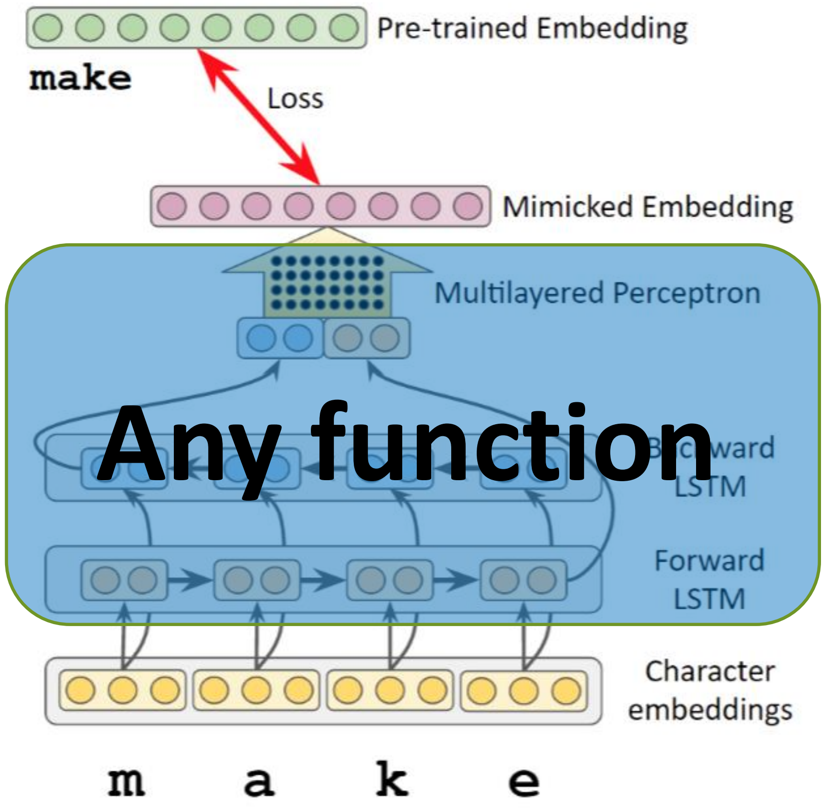


Pinter et al, EMNLP 2017 http://www.aclweb.org/anthology/D17-1010

What if..

We abstract the skip-gram model to the sentence level?

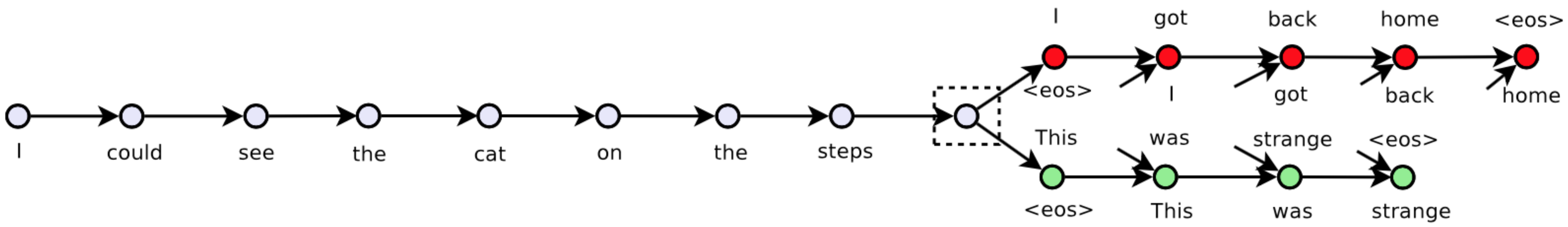
Skip-Thought Vectors

Before:

- ➢ use a word to predict its surrounding context

Now:

- ➢ encode a sentence to predict the sentences around it

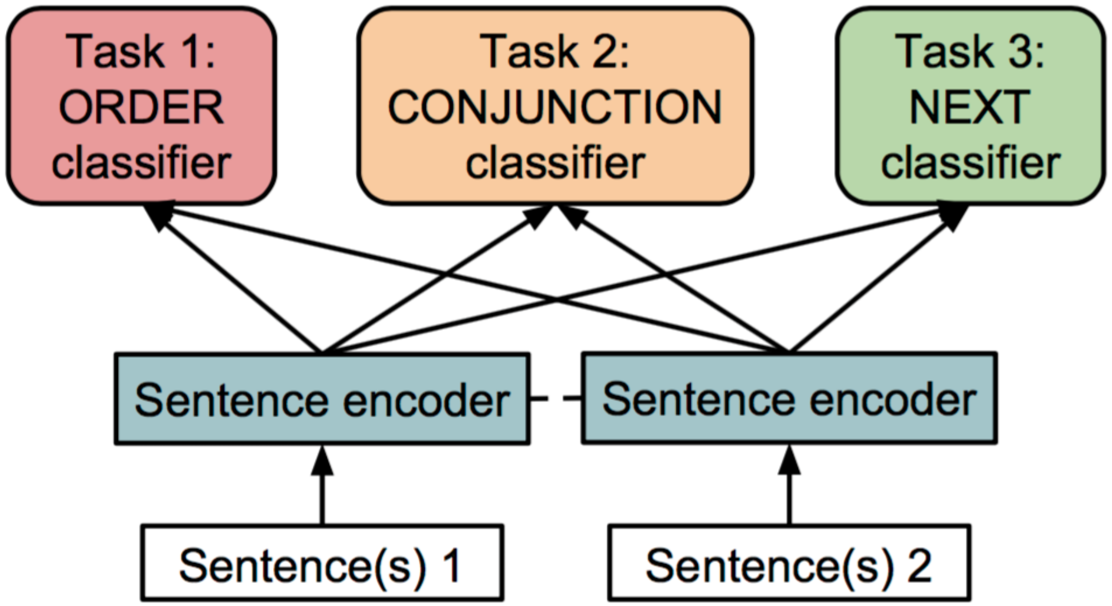


Kiros et al., NIPS 2015 https://papers.nips.cc/paper/5950-skip-thought-vectors.pdf

Discourse-Based Objectives

If for sentence embedding information about neighboring sentences is useful, let's predict something about them:

- Binary Ordering of Sentences
- Next Sentence (classifier)
- Conjunction Prediction (predict a conjunction phrase if the second sentence starts from any)



Jernite et al., 2017, https://arxiv.org/pdf/1705.00557.pdf

What if..

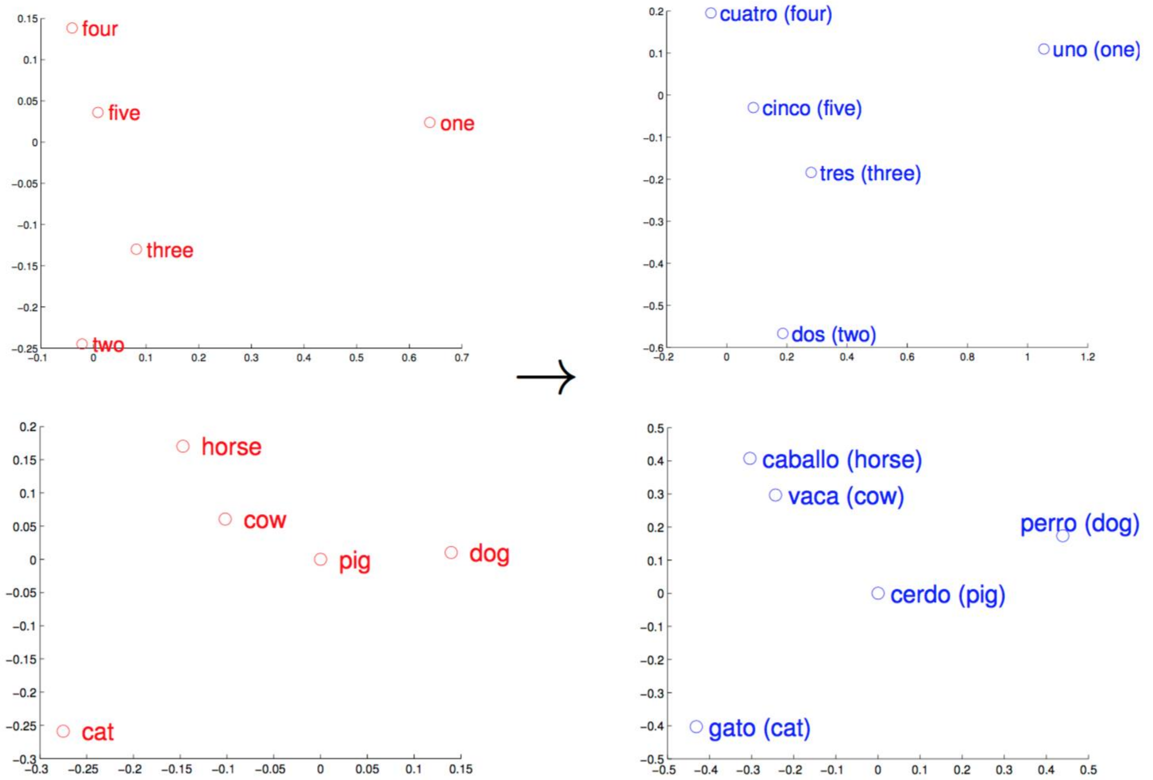
We exploit the structure of semantic space?

Exploiting Similarities among Languages for Machine Translation

- we are given a set of word pairs and their associated vector representations
- find a transformation matrix W

$$\min_{W} \sum_{i=1}^{n} \|W x_i - z_i\|^2$$

- for any given new word we can map it to the other language space



Mikolov et al, 2013, https://arxiv.org/pdf/1309.4168.pdf

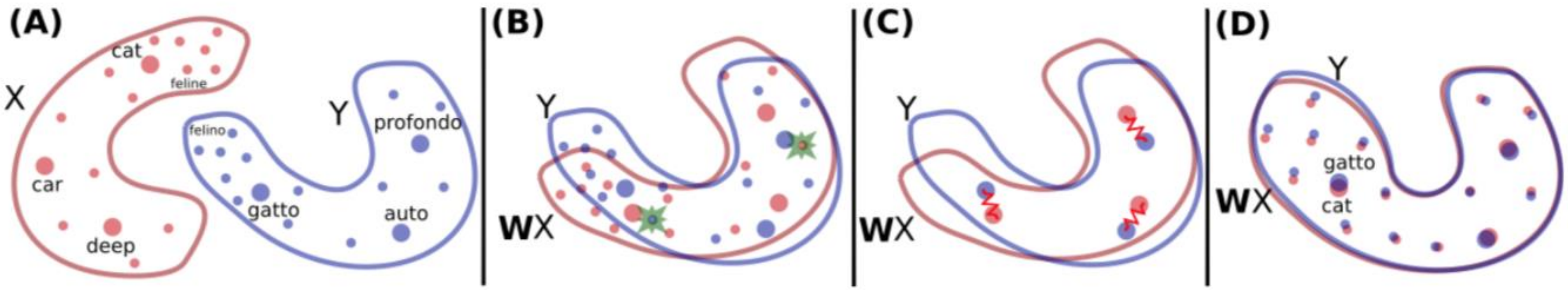
Here we supposed that we already know some word pairs.

But what if we know nothing about the languages?

Word Translation Without Parallel Data

Map semantic spaces so that their samples are indistinguishable

(**Spoiler alert!** You'll know how to do it later in the course)



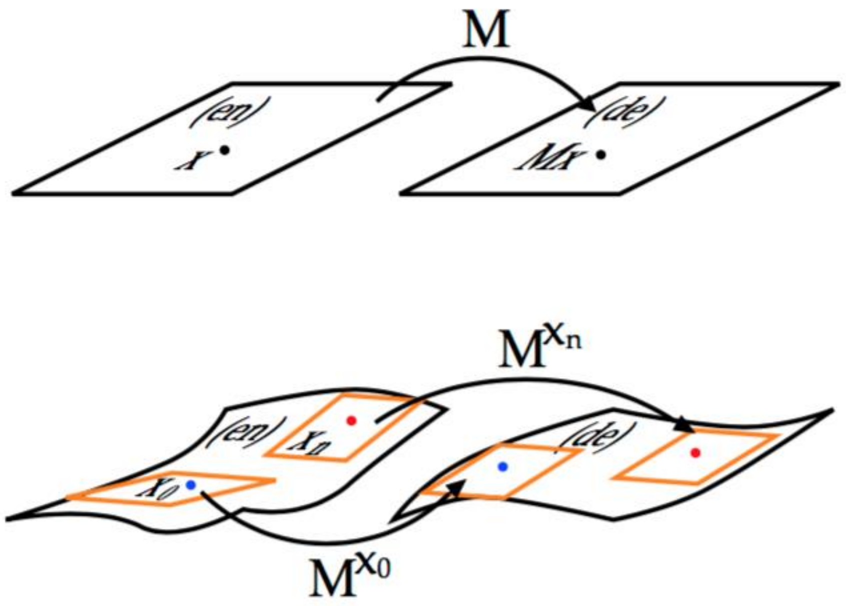
Conneau et al, ICLR 2018, https://arxiv.org/pdf/1710.04087.pdf

Are the underlying maps really linear?

Look at the local linear approximations:

- If they're identical, then the mapping is indeed linear
- If they are not, probably not

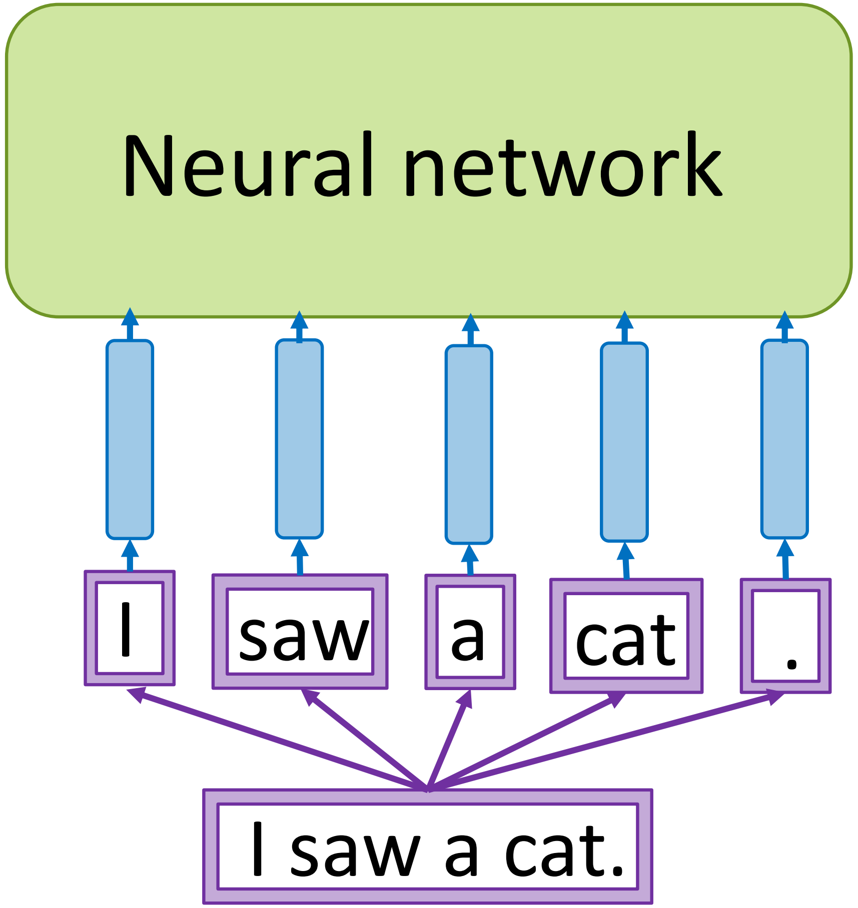
(actually, they're not)



Nakashole & Flauger, ACL 2018, http://aclweb.org/anthology/P18-2036

A piece of practice:
When we really need to learn word representations?

Why do we need word representation?



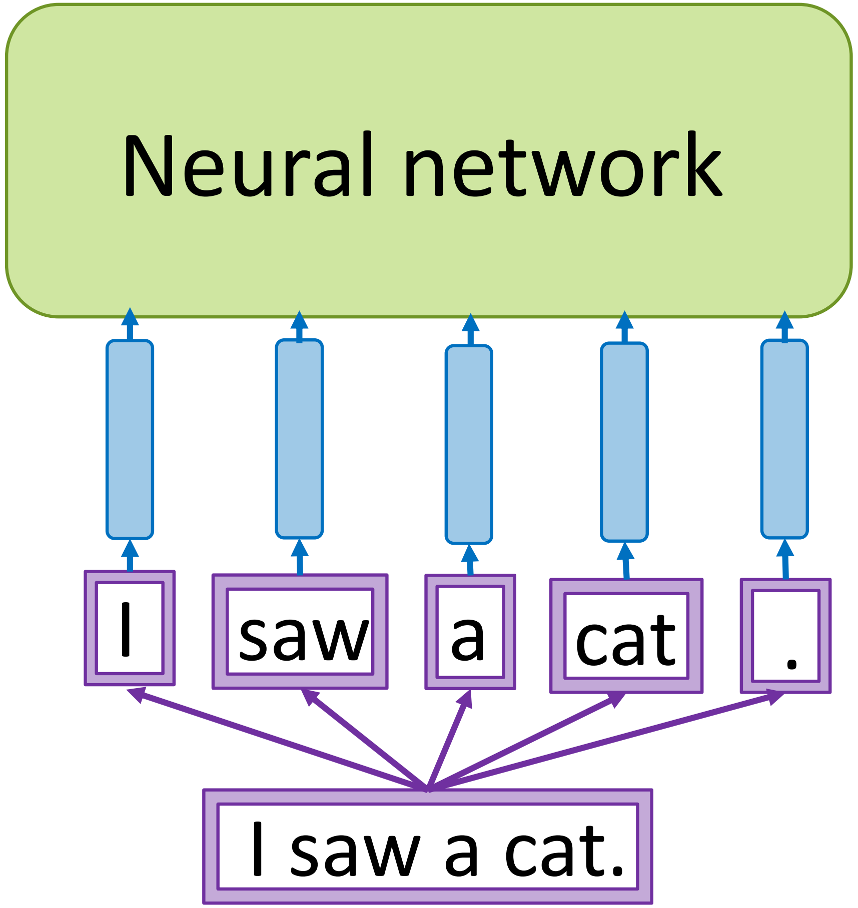
Any NN for solving any task

Word representation - vector
(word embedding)

Sequence of tokens

Text

Do we **REALLY** need to learn word representation in advance?

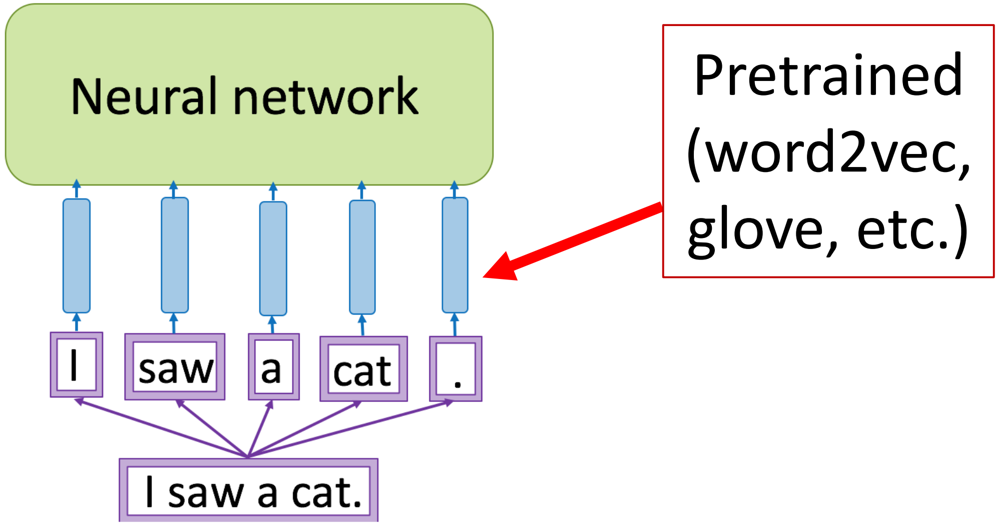


Ok, but if we **already have an NN** for our task, why do we have to learn parameters for word embeddings using **some other NN**?

When to use pretrained embeddings?

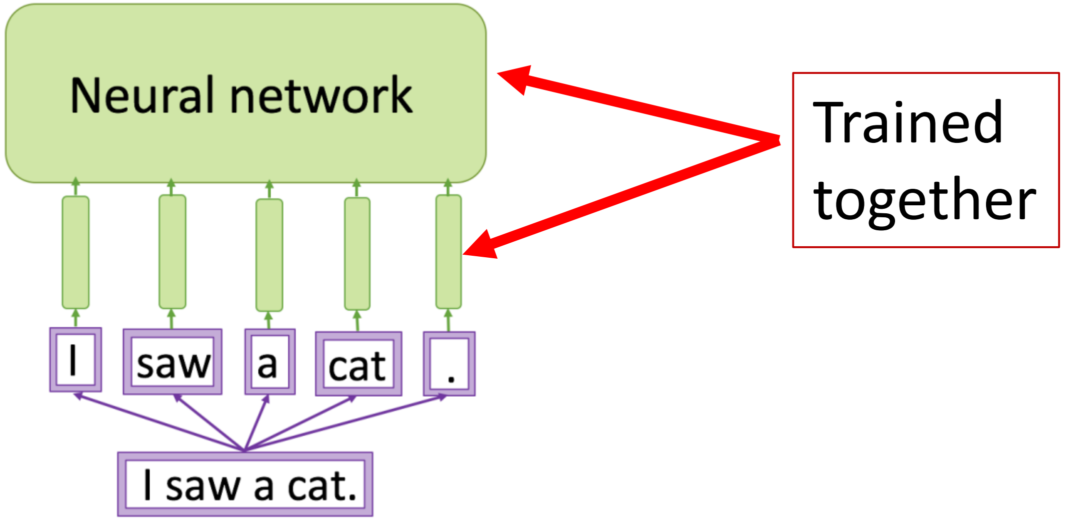
Not enough data or the task is too simple

Use pretrained on the other task

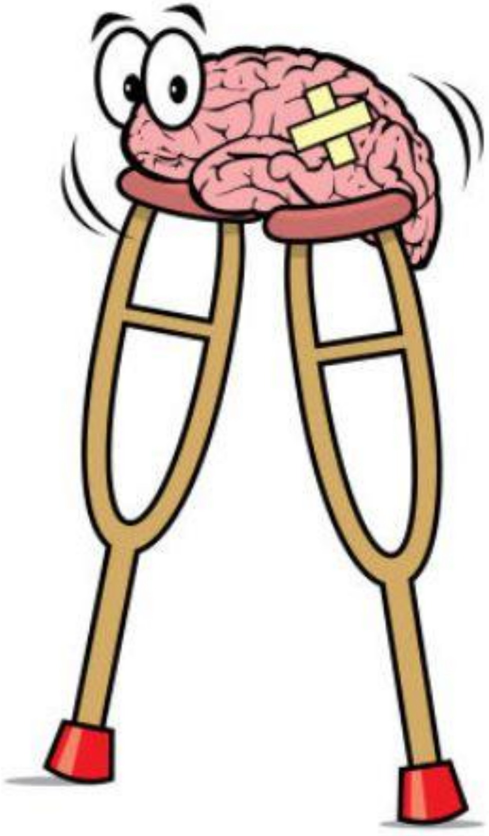


Enough data and a hard task (LM, MT, …)

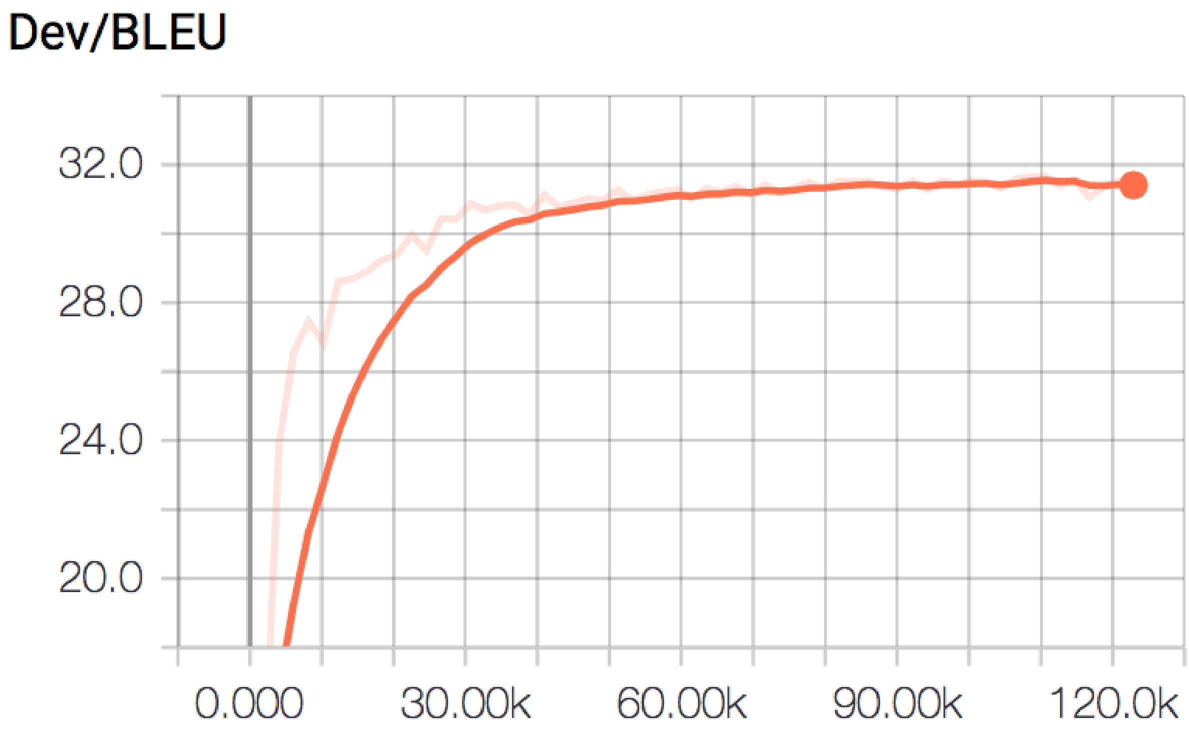
Train with the model

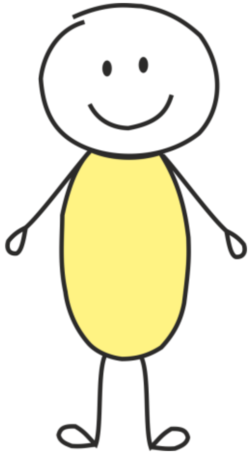


Hack of the day

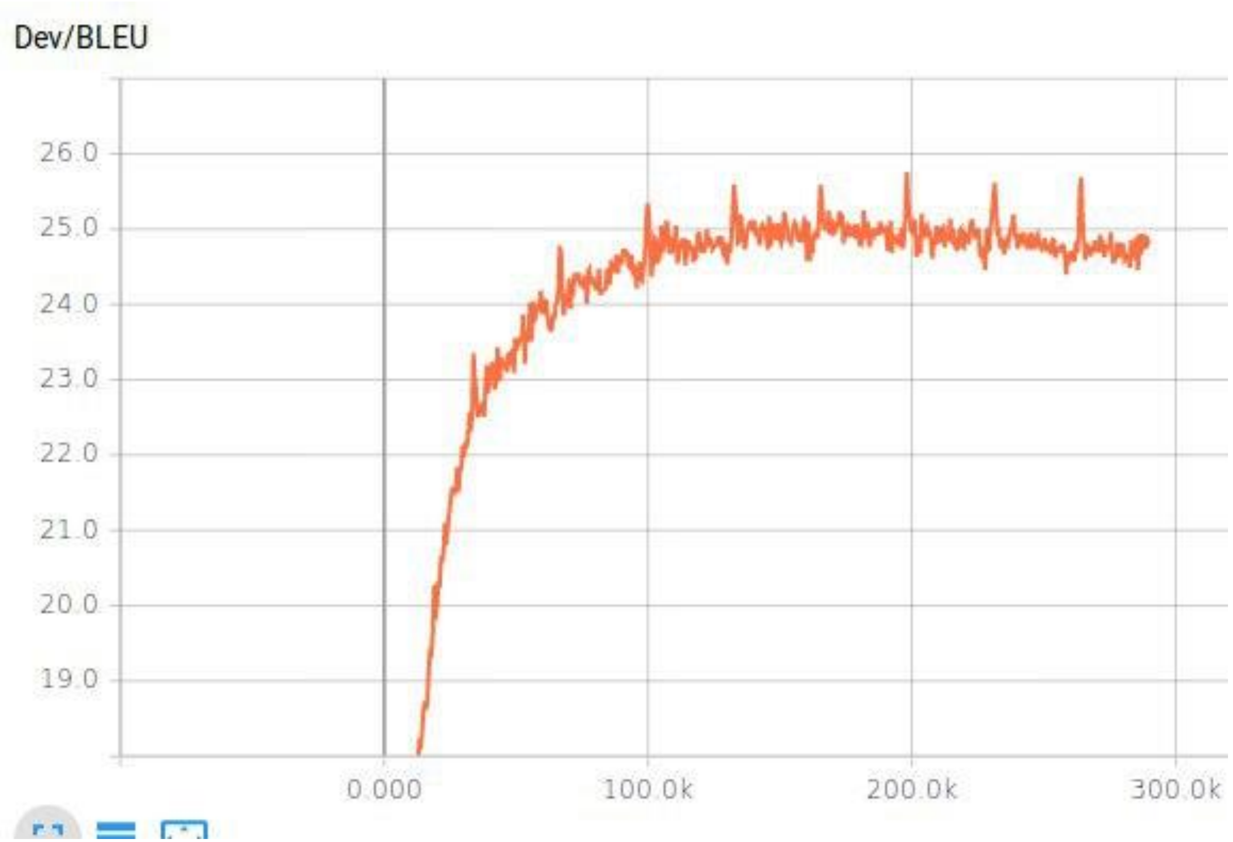


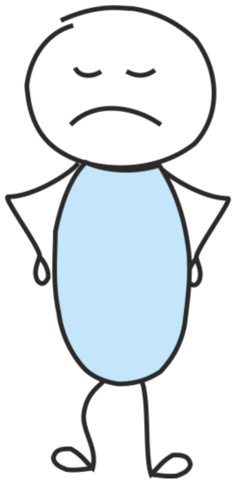
Tensorboard of a healthy man



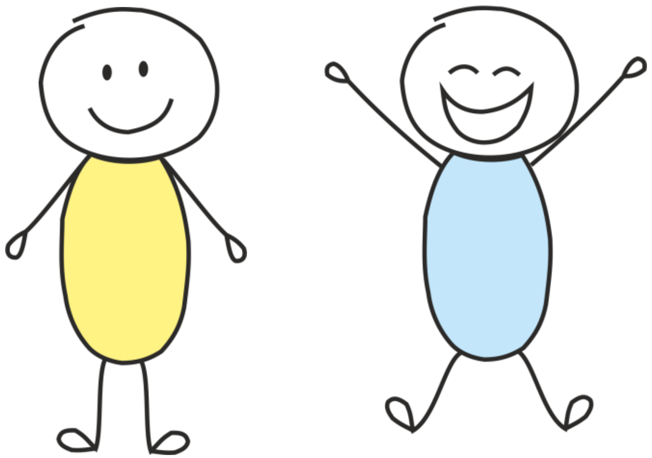


Tensorboard of a man who doesn't shuffle his data





Shuffle your data!



Congratulations, you’ve just survived the first NLP lecture!

Looking forward to the next week's episode…

Sincerely yours,
Yandex Research