Word Embedding

Ayoub Bagheri

Outline

- Word embedding
  - Skipgram learning
  - Pre-trained embeddings
- State-of-the-Art

Word Embedding

Slides are partly based on the word embedding lecture by Dong Nguyen in the Applied Text Mining Utrecht summer school ([linkToRCourse](), [linkToPythonCouse]())

Word representations

How can we represent the meaning of words?

So, we can ask:

- How similar is cat to dog, or Paris to London?
- How similar is document A to document B?

Word as vectors

Can we represent words as vectors?

The vector representations should:

- capture semantics
  - similar words should be close to each other in the vector space
  - relation between two vectors should reflect the relationship between the two words
- be efficient (vectors with fewer dimensions are easier to work with)
- be interpretable

Word as vectors

How similar are the following two words? (not similar 0–10 very similar)

smart and **intelligent:**
easy and **big**:
easy and **difficult**:
hard and **difficult**:

Word as vectors

How similar are the following two words? (not similar 0–10 very similar)

smart and **intelligent: 9.20**
easy and **big**: **1.12**
easy and **difficult**: **0.58**
hard and **difficult**: **8.77**

(SimLex-999 dataset, https://fh295.github.io/simlex.html)

Words as Vectors

One-hot encoding

Map each word to a unique identifier

e.g. cat (3) and dog (5).

- Vector representation: all zeros, except 1 at the ID

cat	0	0	1	0	0	0	0
dog	0	0	0	0	1	0	0
car	0	0	0	0	0	0	1

One-hot encoding

Map each word to a unique identifier

e.g. cat (3) and dog (5).

- Vector representation: all zeros, except 1 at the ID

cat	0	0	1	0	0	0	0
dog	0	0	0	0	1	0	0
car	0	0	0	0	0	0	1

What are limitations of one-hot encodings?

One-hot encoding

Map each word to a unique identifier

e.g. cat (3) and dog (5).

- Vector representation: all zeros, except 1 at the ID

cat	0	0	1	0	0	0	0
dog	0	0	0	0	1	0	0
car	0	0	0	0	0	0	1

Even related words have distinct vectors!

High number of dimensions

Distributional hypothesis: Words that occur in similar contexts tend to have similar meanings.

You shall know a word by the company it keeps. (Firth, J. R. 1957:11)

Word vectors based on co-occurrences

documents as context
word-document matrix

	doc_1	doc_2	doc_3	doc_4	doc_5	doc_6	doc_7
cat	5	2	0	1	4	0	0
dog	7	3	1	0	2	0	0
car	0	0	1	3	2	1	1

Word vectors based on co-occurrences

documents as context
word-document matrix

	doc_1	doc_2	doc_3	doc_4	doc_5	doc_6	doc_7
cat	5	2	0	1	4	0	0
dog	7	3	1	0	2	0	0
car	0	0	1	3	2	1	1

neighboring words as context
word-word matrix

	cat	dog	car	bike	book	house	tree
cat	0	3	1	1	1	2	3
dog	3	0	2	1	1	3	1
car	0	0	1	3	2	1	1

Word vectors based on co-occurrences

There are many variants:

- Context (words, documents, which window size, etc.)
- Weighting (raw frequency, etc.)

Vectors are sparse: Many zero entries.

Therefore: Dimensionality reduction is often used (e.g., SVD)

These methods are sometimes called **count-based** methods as they work directly on **co-occurrence** counts.

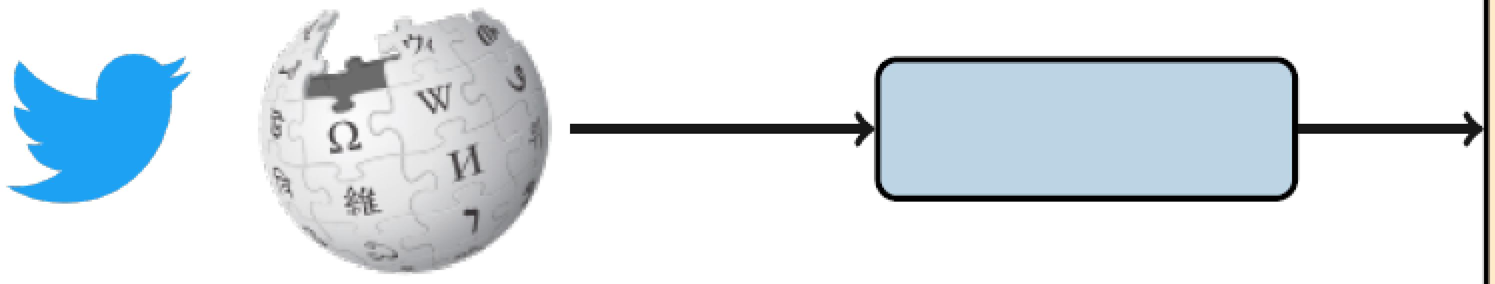
Word embeddings

- Vectors are short; typically 50-1024 dimensions ☺
- Vectors are dense (mostly non-zero values)
- Very effective for many NLP tasks ☺
- Individual dimensions are less interpretable ☹

cat	0.52	0.48	-0.01	⋯	0.28
dog	0.32	0.42	-0.09	⋯	0.78

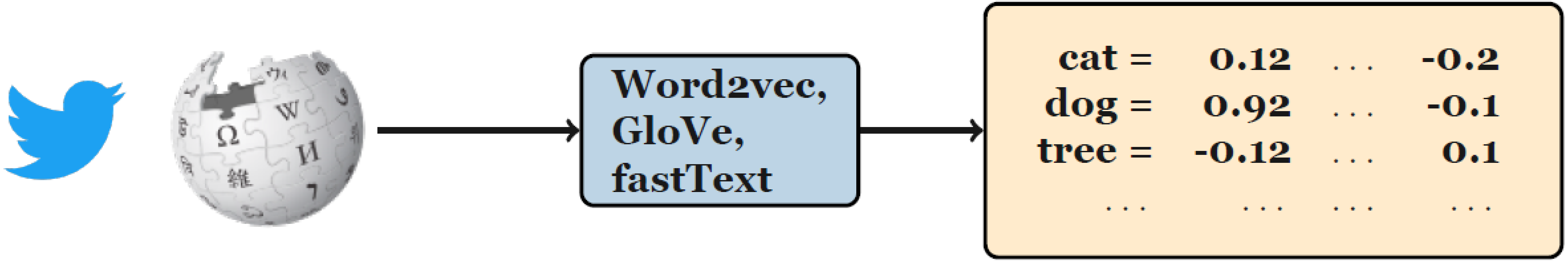
How do we learn word embeddings?

Learning word embeddings



cat =	0.12	...	-0.2
dog =	0.92	...	-0.1
tree =	-0.12	...	0.1
...	...	...	...

Learning word embeddings



Training data for word embeddings

- Use **text itself** as training data for the model!
  - A form of self-supervision.
- Train a **classifier** (neural network, logistic regression, or SVM, etc.) to predict the next word given previous words.

Exercise: Word prediction task

Yesterday I went to the **?**

A new study has highlighted the positive **?**

Which word comes next?

Word2Vec

- Popular embedding method
- Very fast to train
- Idea: **predict** rather than **count**

- https://projector.tensorflow.org/

Word2Vec

The domestic **cat** is a small, typically furry carnivorous mammal

w_{-2} w_{-1} w_0 w_1 w_2 w_3 w_4 w_5

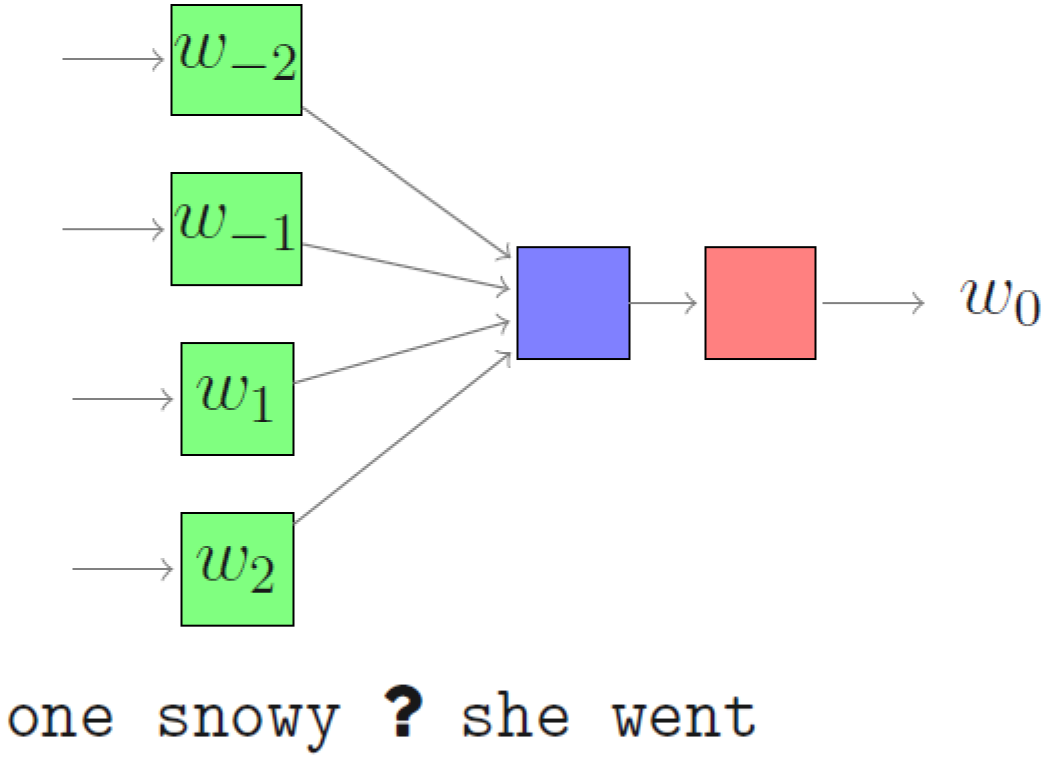
We have **target** words (cat) and **context** words (here: window size = 5).

Word2Vec

- Instead of **counting** how often each word w occurs near a target word
  - Train a classifier on a binary **prediction** task:
    - Is w likely to show up near target?
- We don't actually care about this task
  - But we'll take the learned classifier weights as the word embeddings
- Big idea: **self-supervision**
  - A word c that occurs near target in the corpus as the gold "correct answer" for supervised learning
  - **No need for human labels**
  - Bengio et al. (2003); Collobert et al. (2011)

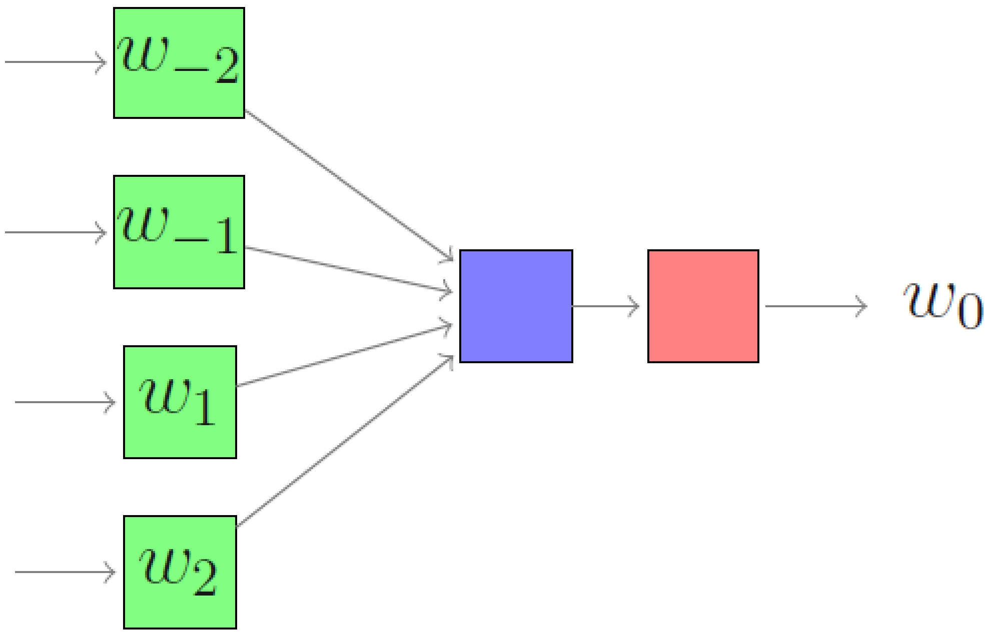
Word2Vec algorithms

Continuous Bag-Of-Words (CBOW)



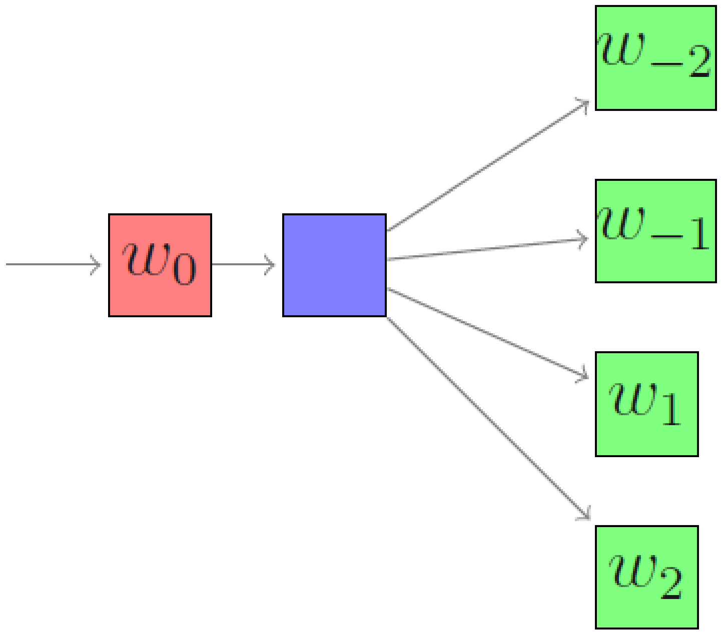
Word2Vec algorithms

Continuous Bag-Of-Words (CBOW)



one snowy ? she went

skipgram



? ? day ? ?

Skipgram overview

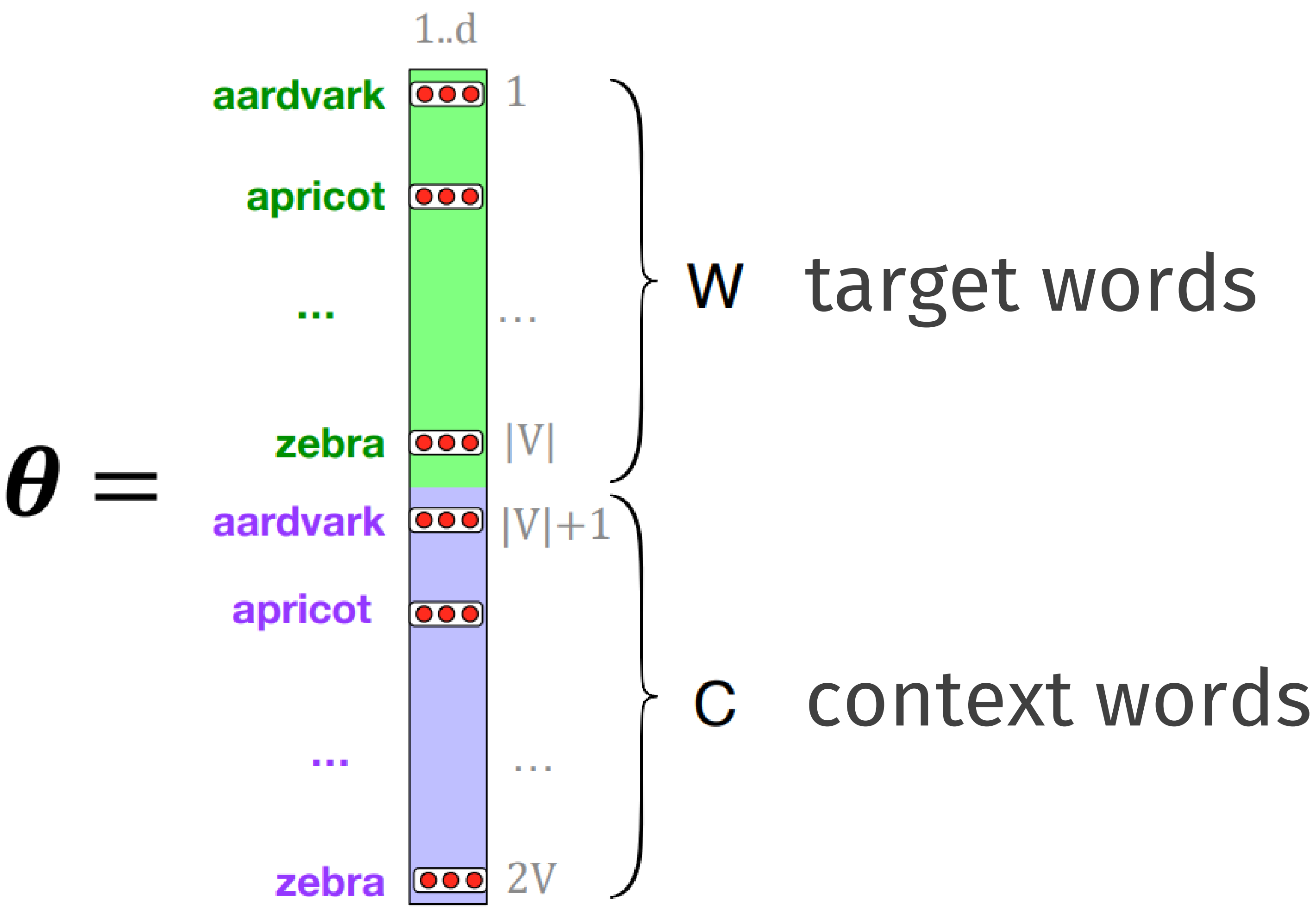
The domestic **cat** is a small, typically furry carnivorous mammal

1. **Create examples**
   - Positive examples: Target word and neighboring context
   - Negative examples: Target word and randomly sampled words from the lexicon (*negative sampling*)
2. Train a **logistic regression** model to distinguish between the positive and negative examples
3. The resulting **weights** are the embeddings!

word (w)	context (c)	label
cat	small	1
cat	furry	1
cat	car	0
...	...	...

Embedding vectors are essentially a byproduct!

Skipgram embeddings



Learning the classifier

- How to learn?
  - **Stochastic gradient descent!**
- SGNS learns two sets of embeddings
  - Target embeddings matrix W
  - Context embedding matrix C
- It's common to just add them together, representing word i as the vector Wi + Ci

Skipgram

1. Treat the target word t and a neighboring context word c as positive examples.
2. Randomly sample other words in the lexicon to get negative examples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights as the embeddings

Skipgram classifier

- A probabilistic classifier, given
  - a test target word w
  - its context window of L words $c_{1:L}$
- Estimates probability that w occurs in this window based on similarity of w (embeddings) to $c_{1:L}$ (embeddings).

- To compute this, we just need embeddings for all the words.

Pre-trained Embeddings

Pre-trained embeddings

- I want to build a system to **solve a task** (e.g., sentiment analysis)
  - Use pre-trained embeddings. Should I **fine-tune**?
    - Lots of data: yes
    - Just a small dataset: no

- **Analysis** (e.g., bias, semantic change)
  - Train embeddings from scratch

State-of-the-Art

State-of-the-Art

- Recurrent neural networks
  - LSTM
  - GRU
  - Bi-directional network
- Transformers
- Contextual embeddings
- ChatGPT

We will discuss the details during the summer text mining courses:

- Click to go to the Intro to Text Mining with R course
- Click to go to the Applied Text Mining course (Python)

Practical
Word embedding

Questions?

Skipgram

The domestic **cat** is a small, typically furry carnivorous mammal

w_{-2} w_{-1} w_0 w_1 w_2 w_3 w_4 w_5

We have **target** words (cat) and **context** words (here: window size = 5).

The probability that c is a real context word, and the probability that c is not a real context word:

$$P(+|w, c)$$
$$P(-|w, c) = 1 - P(+|w, c)$$

Skipgram

Similarity is computed from dot product

- **Intuition**: A word *c* is likely to occur near the target *w* if its embedding is similar to the target embedding.

$$\approx w \cdot c$$

  - Two vectors are similar if they have a high dot product
  - Cosine similarity is just a normalized dot product

Turn this into a probability using the sigmoid function:

$$P(+|w,c) = \sigma(c \cdot w) = \frac{1}{1+\exp(-c \cdot w)}$$

$$\begin{aligned} P(-|w,c) &= 1 - P(+|w,c) \\ &= \sigma(-c \cdot w) = \frac{1}{1+\exp(c \cdot w)} \end{aligned}$$

How Skipgram classifier computes P(+|w, c)

$$P(+|w,c) = \sigma(c \cdot w) = \frac{1}{1+\exp(-c \cdot w)}$$

This is for one context word, but we have lots of context words. We'll assume independence and just multiply them:

$$P(+|w,c_{1:L}) = \prod_{i=1}^{L} \sigma(c_i \cdot w)$$

$$\log P(+|w,c_{1:L}) = \sum_{i=1}^{L} \log \sigma(c_i \cdot w)$$

Word2vec: how to learn vectors

- Given the set of positive and negative training instances, and an initial set of embedding vectors
- The goal of learning is to adjust those word vectors such that we:
- **Maximize** the similarity of the **target word**, **context word** pairs (w , c_{pos}) drawn from the positive data
- **Minimize** the similarity of the (w , c_{neg}) pairs drawn from the negative data.

Loss function for one *w* with *cpos* , *cneg1* ...*cnegk*

- Maximize the similarity of the target with the actual context words, and minimize the similarity of the target with the k negative sampled non-neighbor words.

$$
\begin{aligned}
L_{CE} &= -\log\left[P(+|w,c_{pos})\prod_{i=1}^{k}P(-|w,c_{neg_i})\right] \\
&= -\left[\log P(+|w,c_{pos})+\sum_{i=1}^{k}\log P(-|w,c_{neg_i})\right] \\
&= -\left[\log P(+|w,c_{pos})+\sum_{i=1}^{k}\log\left(1-P(+|w,c_{neg_i})\right)\right] \\
&= -\left[\log \sigma(c_{pos}\cdot w)+\sum_{i=1}^{k}\log \sigma(-c_{neg_i}\cdot w)\right]
\end{aligned}
$$

Learning the classifier

- How to learn?
    - **Stochastic gradient descent!**