Natural Language Processing

Word Embedding, Recurrent Neural Networks & Transformers

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Based on Ayoub Bagheri's slides

Last week

- Text mining
- Pre-processing text data
- Vector space model
- Topic modeling

Today

- Natural language processing
- Word embedding
  - Skipgram learning
  - Pre-trained embeddings
- Recurrent neural networks
  - LSTM
  - Extensions
- State-of-the-Art: Transformers

Natural Language Processing (NLP)

NLP vs text mining

- Natural language processing, or NLP, is a research field dedicated to giving machines the ability to manipulate natural languages (Bird, Klein, & Loper, 2009).
- Text mining focuses on application and pattern learning

Word Embedding

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

&

And partly from chapter 6 of Speech and Language Processing (3rd ed. draft), Dan Jurafsky and James H. Martin https://web.stanford.edu/~jurafsky/slp3/

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 (relative 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.

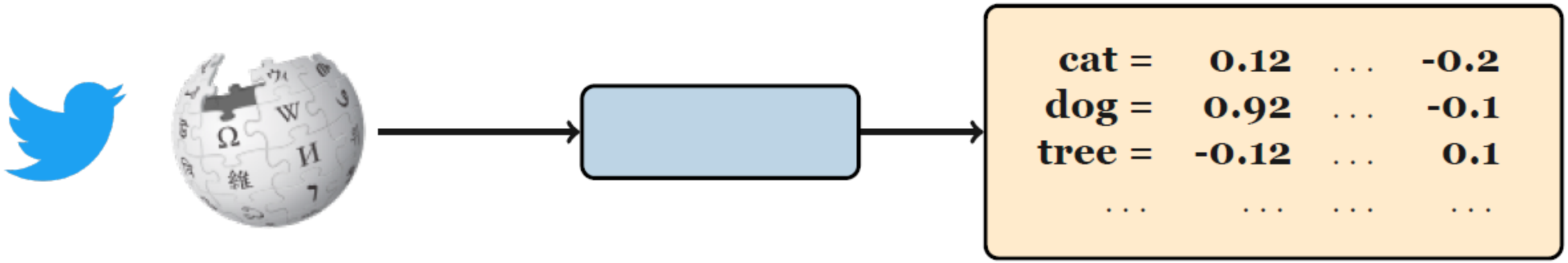
Word embeddings are better!

- 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 ☹

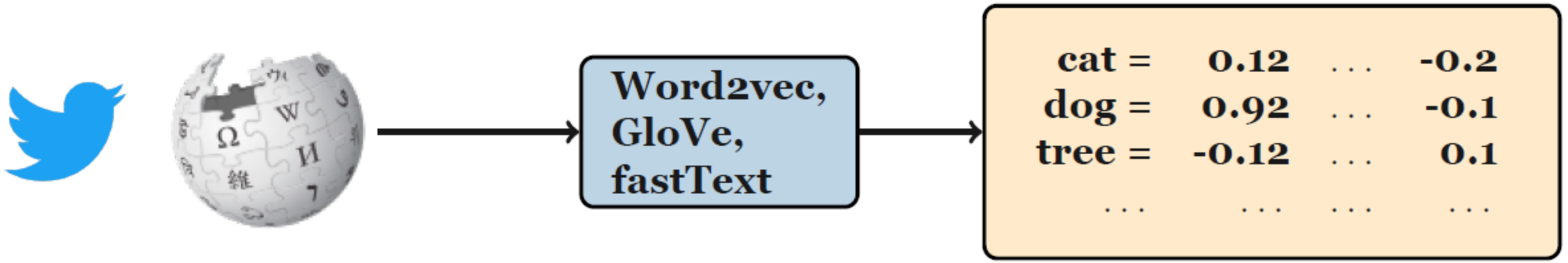
cat	0.52	0.48	-0.01	...	0.28
dog	0.32	0.42	-0.09	...	0.78

How do we learn word embeddings?

Learning word embeddings



Learning word embeddings



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

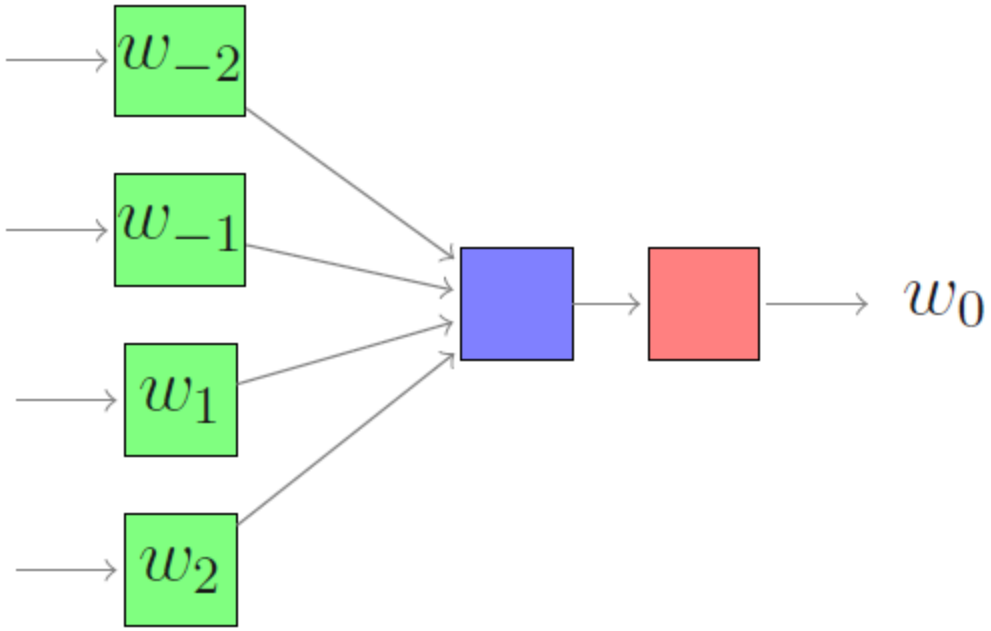
We have **target** words (cat) and **context** words (here: window size = 5).

Word2Vec

- Instead of **counting** how often each word occurs near a target word
  - Train a classifier on a binary **prediction** task:
    - Is a word likely to show up near the target word?
- We don’t actually care about this task
  - But we'll take the learned classifier weights as the word embeddings
- Main idea: **self-supervision**
  - A word that occurs near the target word 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

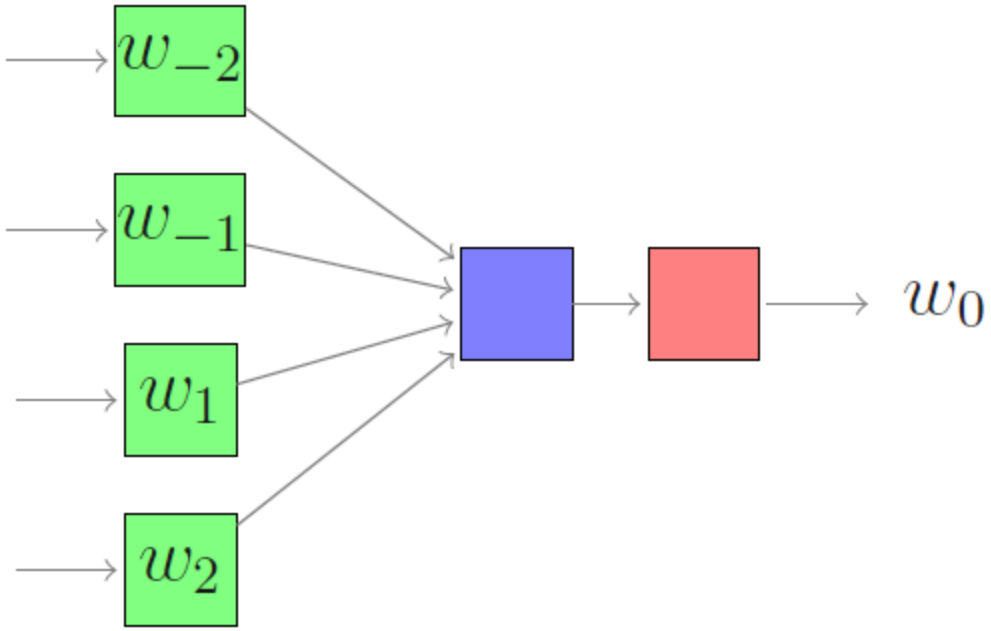
Continuous Bag-Of-Words (CBOW)



one snowy **?** she went

Word2Vec algorithms

Continuous Bag-Of-Words (CBOW)



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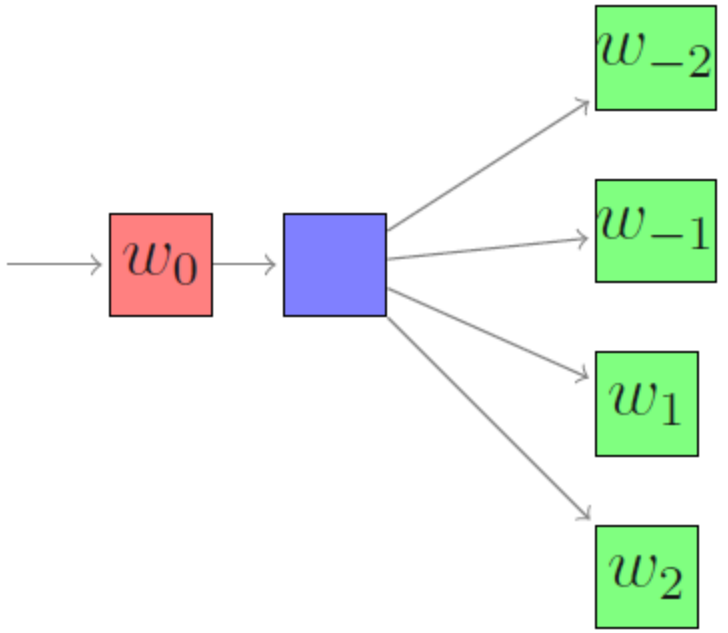
skipgram



? **?** 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 **two-layered neural network** 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

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:

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

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

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

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 weights/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 c_{pos} , c_{neg1} ...c_{negk}

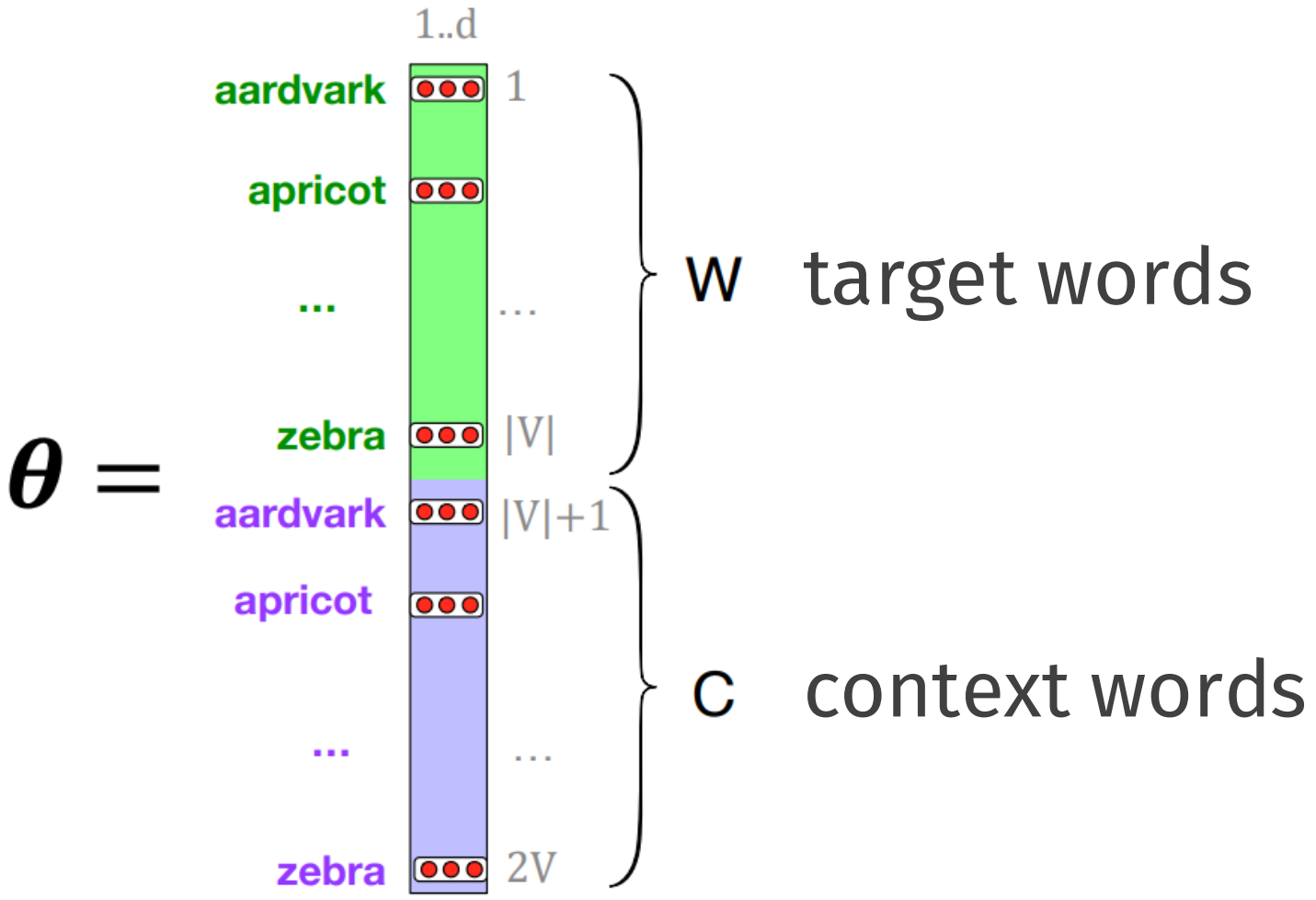
- Maximize the similarity of the target with the actual context words, and minimize the similarity of the target with the k negative sampled non-neighbor words.

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

Learning the classifier

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

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 W_i + C_i

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

- **But, for analysis** of bias, semantic change across corpora etc.
  - Train embeddings from scratch

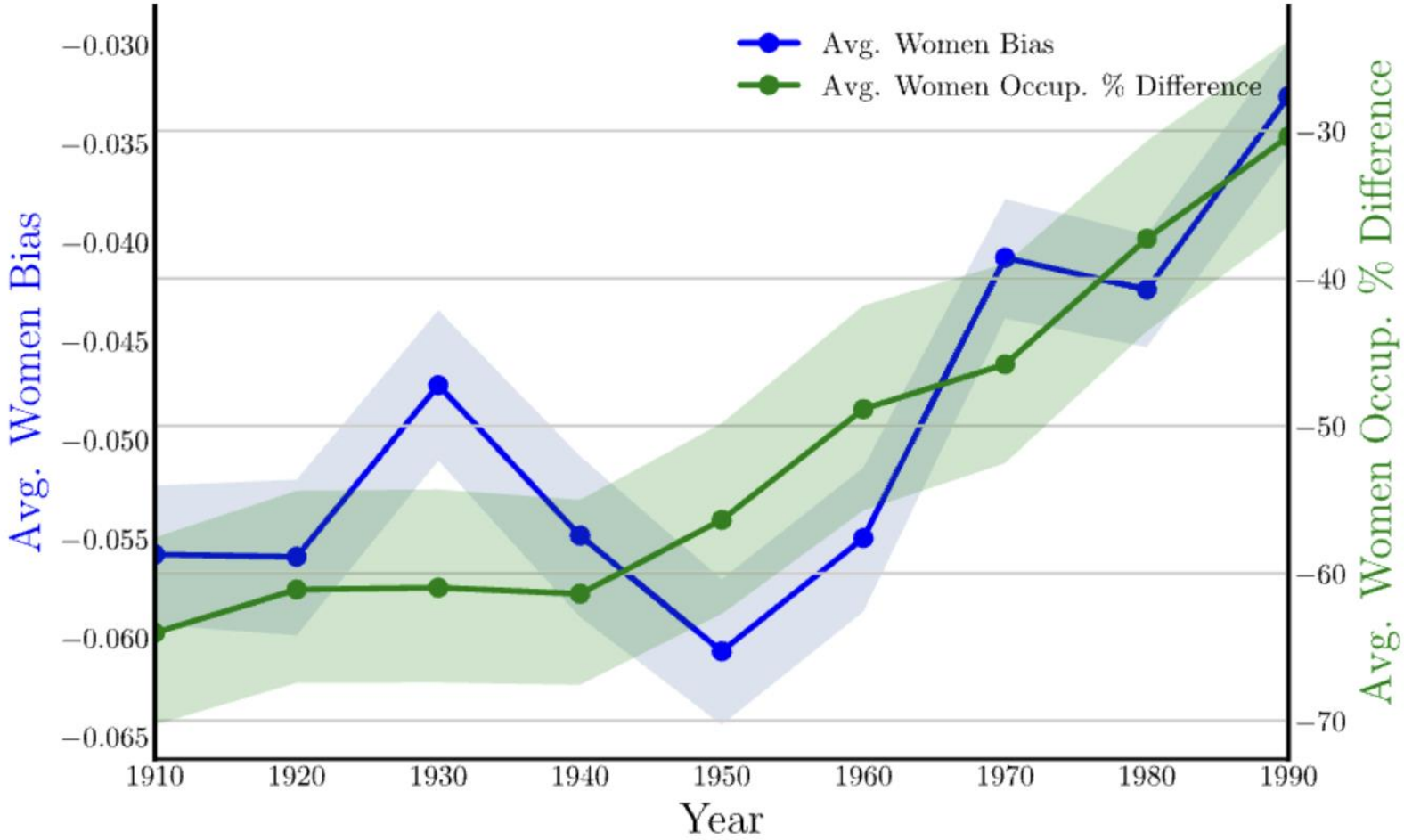


Fig. 2. Average gender bias score over time in COHA embeddings in occupations vs. the average percentage of difference. More positive means a stronger association with women. In blue is relative bias toward women in the embeddings, and in green is the average percentage of difference of women in the same occupations. Each shaded region is the bootstrap SE interval.

Word embedding in R

Word2Vec embeddings in R

```
library(word2vec)

cbow_model = word2vec(x = data, type = "cbow", dim = 15,
                      iter = 20)

# finding lookalike
cbow_lookslike <- predict(cbow_model, c("hotel", "airbus"),
                          type = "nearest", top_n = 5)

print("The nearest words for hotel and airbus in CBOW model
prediction is as follows ")

print(cbow_lookslike)
```

GloVe embeddings in R

```
library(text2vec)
# https://www.rdocumentation.org/packages/text2vec/versions/0.5.1/topics/GlobalVectors

glove <- GlobalVectors$new(word_vectors_size, vocabulary, x_max, learning_rate = 0.15,
                           alpha = 0.75, lambda = 0.0, shuffle = FALSE, initial = NULL)

# target word vectors
# x is the input data, a term co-occurence matrix.
wv_main <- glove$fit_transform(x, n_iter = 10L, convergence_tol = -1, n_check_convergence = 1L,
                               n_threads = RcppParallel::defaultNumThreads())
# context word vectors
wv_context <- glove$components

# we can also use their summation
word_vectors <- wv_main + t(wv_context)
```

Layer embedding in keras

```
layer_embedding(input_dim = max_words, output_dim = dim_size,
                input_length = maxlen,
                # put weights into list and do not allow training
                weights = list(word_embeds), trainable = FALSE)
```

https://www.rdocumentation.org/packages/keras/versions/2.7.0/topics/layer_embedding

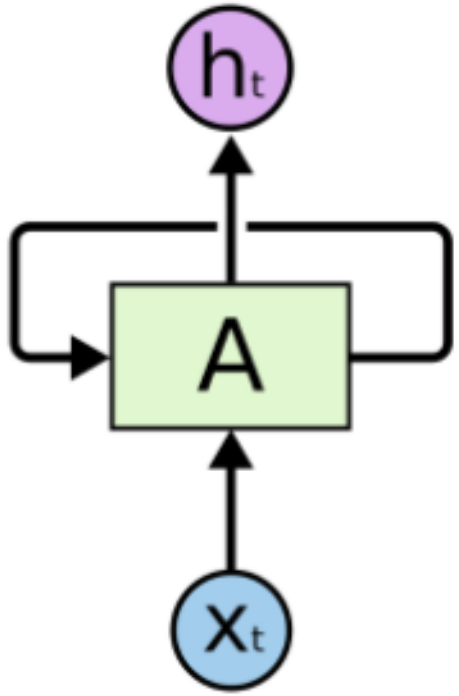
Recurrent Neural Network (RNN)

Recurrent Neural Network

- Another famous architecture of **Deep Learning**
- Preferred algorithm for sequential data
  - **text**, time series, speech, financial data, audio, video, weather and much more.
  - **text**: sentiment analysis, sequence labeling, part of speech tagging, machine translation, etc.

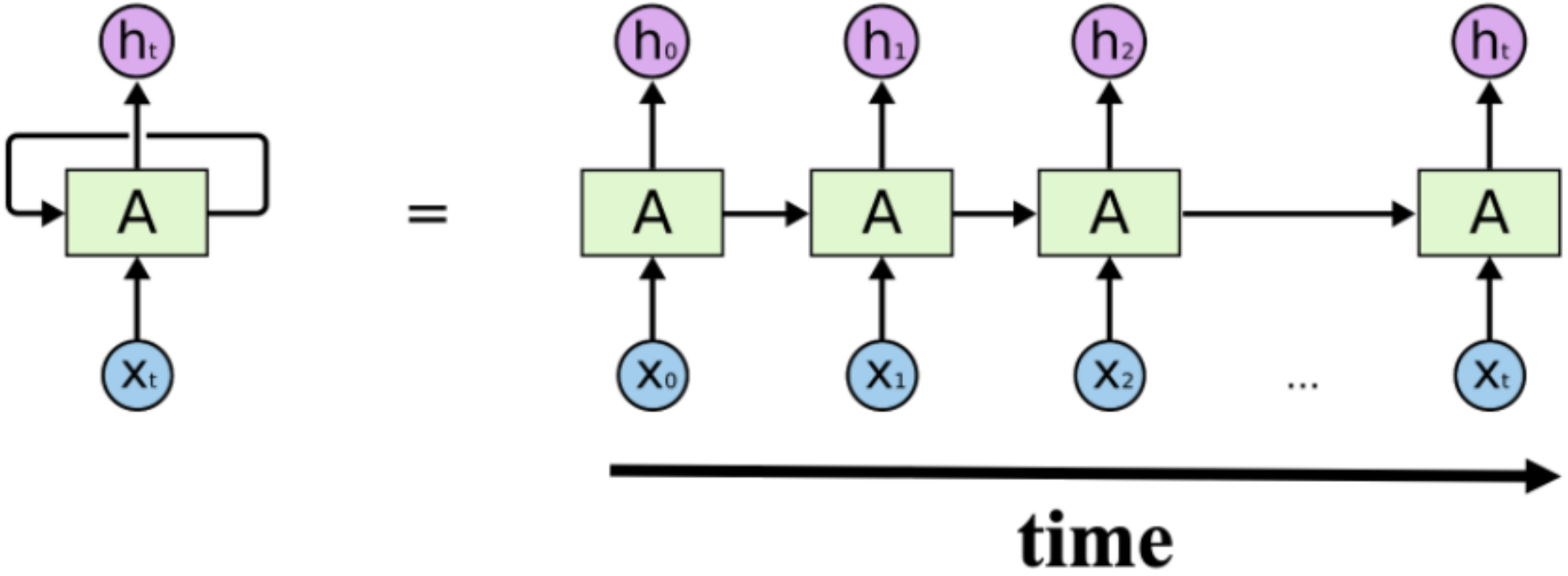
- Maintains **internal memory**, thus can remember its previous inputs

Simple recurrent network

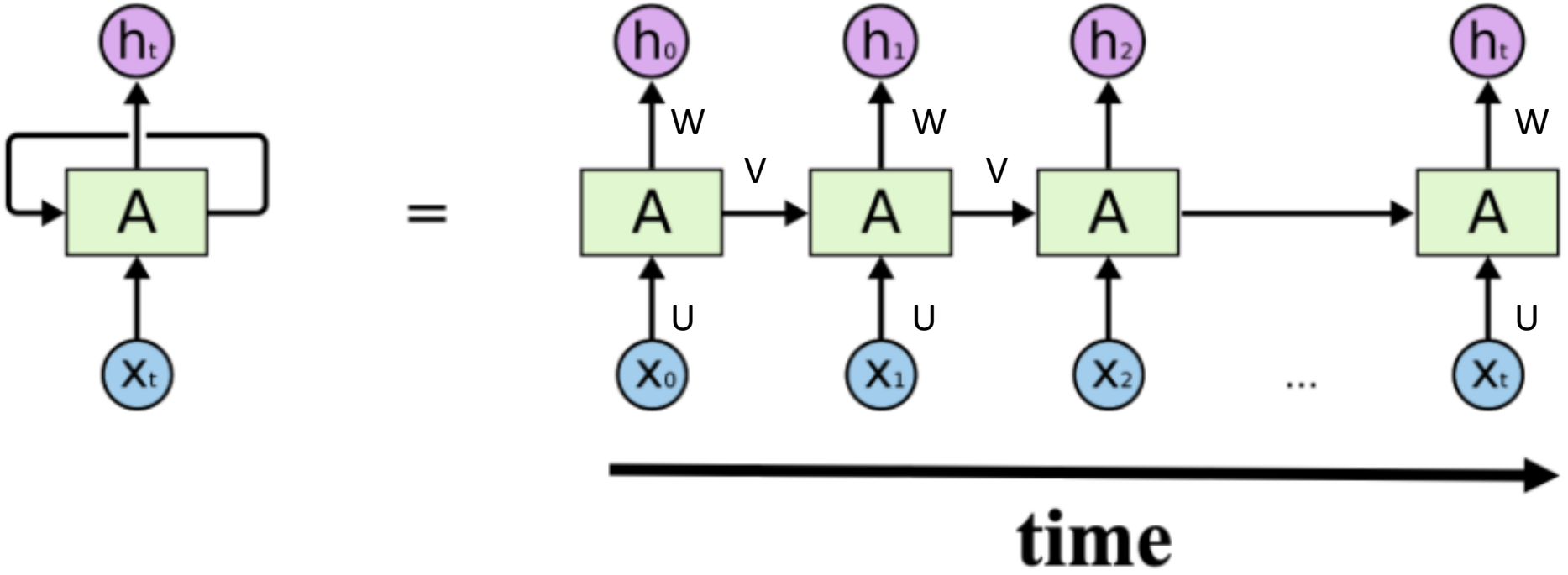


http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Simple recurrent network



Simple recurrent network



The problem of Vanishing Gradient

- Consider a **RNN** model for a **machine translation** task from English to Dutch.
- It has to read an English sentence**, store as much information as possible** in its hidden activations, and output a Dutch sentence.
- The information about the first word in the sentence doesn’t get used in the predictions until it starts generating Dutch words.
- There’s **a long temporal gap** from when it sees an input to when it uses that to make a prediction.
- It can be hard to learn **long-distance dependencies**.
- In order to adjust the input-to-hidden weights based on the first input, the error signal needs to travel backwards through this entire pathway.

Vanishing / Exploding gradient

$$\frac{\partial \mathbf{L}}{\partial W} = \sum_{i=0}^{T} \frac{\partial \mathcal{L}_i}{\partial W} \propto \sum_{i=0}^{T} \left(\prod_{i=k+1}^{y} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}$$

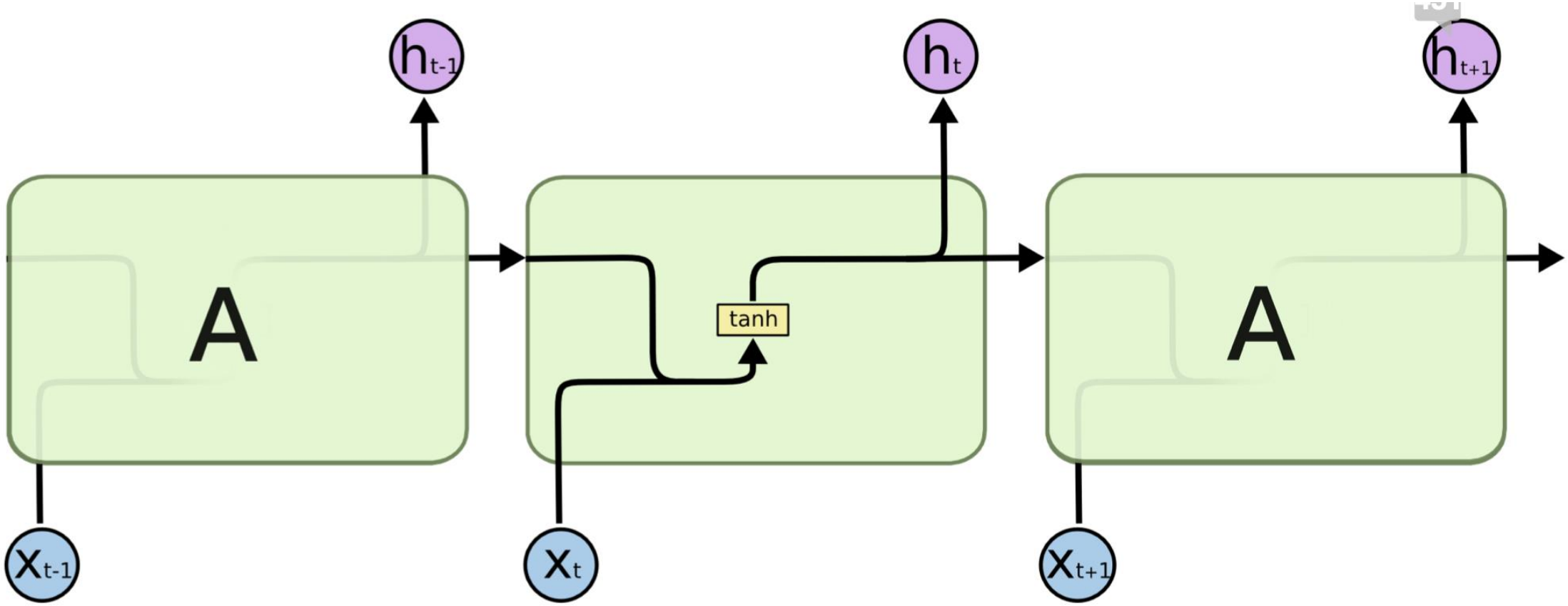
- **Vanishing gradient:** the term goes to zero exponentially fast, which makes it difficult to learn some long period dependencies.
- **Exploding gradient:** the term goes to infinity exponentially fast, and their value becomes a NaN due to the unstable process.

Long Short-Term Memory (LSTM)

Long Short-Term Memory

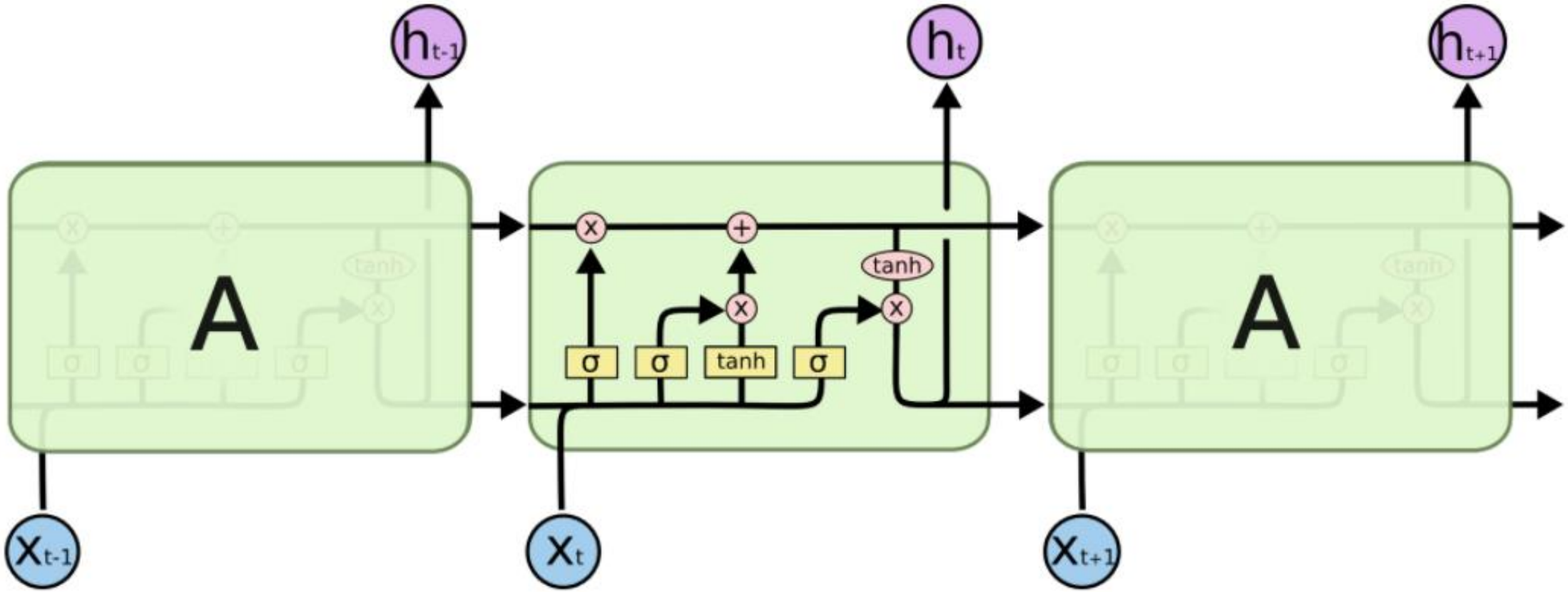
- Prevents vanishing/exploding gradient problem by:
  - introducing a **gating** mechanism
  - turning multiplication into addition
- Designed to make it easy to remember information over long time periods.
- Considers both short-term and long-term memory.

Standard RNN



The repeating module in a standard RNN contains a single layer.

LSTM architecture



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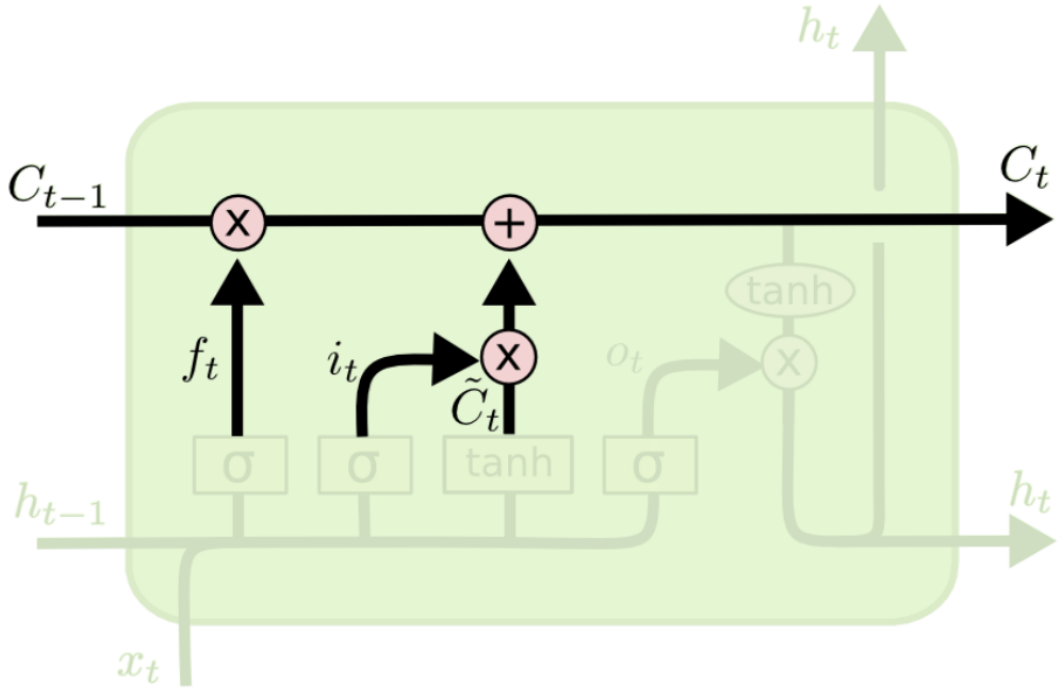
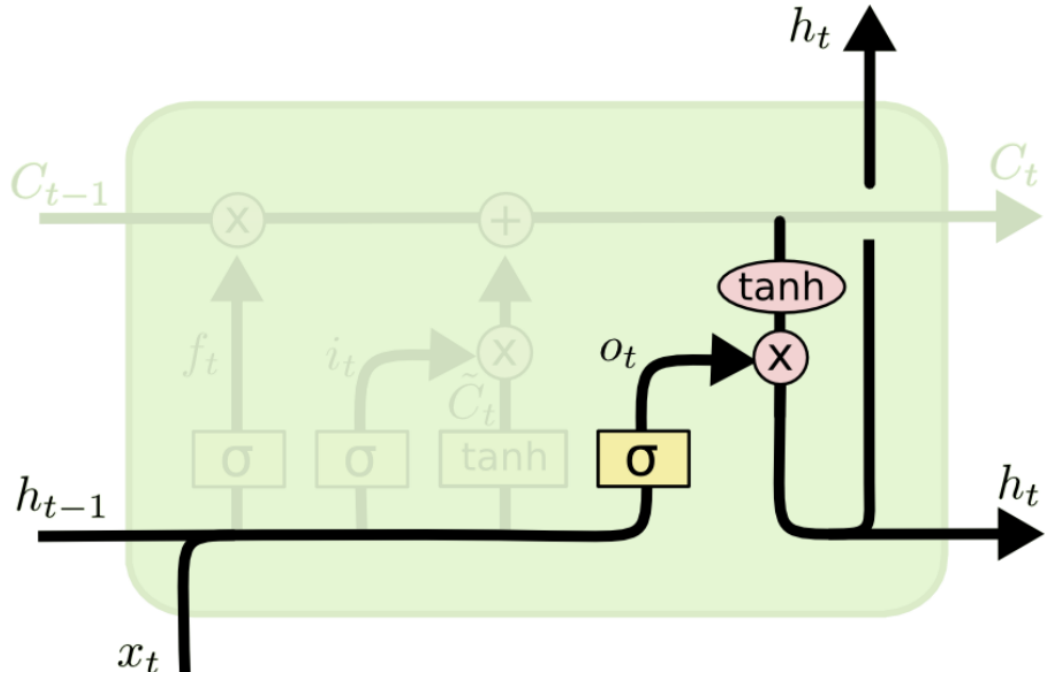
LSTM architecture



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM architecture



$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Extensions

- **Drop-out layer**
- **Bi-directional** network: separate LSTMs process forward and backward sequences, and hidden layers at each time step are concatenated to form the cell output.
- **Gated Recurrent Unit (GRU):** LSTM that uses fewer gates, combines forget and input gates into “update” gate, eliminates cell state vector.
- **Attention:** Allows network to learn to attend to different parts of the input at different time steps, shifting its attention to focus on different aspects during its processing.

Transformers

Problems with RNN

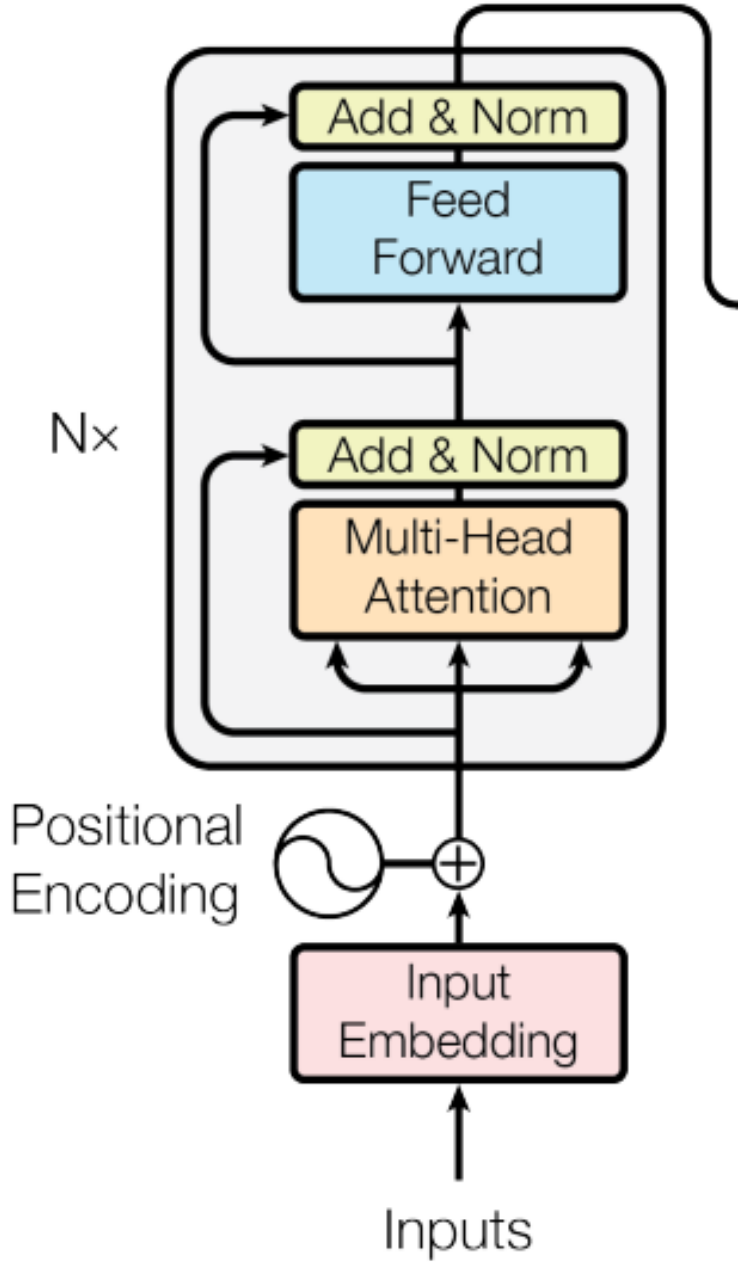
- Pros:
  - Arbitrary input length
  - Fast and cheap inference
- Cons:
  - Forward-looking
  - No parallelization
  - Gradient explosion or vanishing (for long sequences), even for LSTMs

Transformer architectur

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Self-attention
Probability score matrix

	Hello	I	love	you
Hello	0.8	0.1	0.05	0.05
I	0.1	0.6	0.2	0.1
love	0.05	0.2	0.65	0.1
you	0.2	0.1	0.1	0.6



Transformer architecture

- Pros:
  - Parallelization
  - Bi-directional contextual representations
- Cons:
  - Quadratic memory
    - Limited input sequence length

Conclusion

- Word2vec
  - Dense vectors
  - Representation is created by training a classifier to predict whether a word is likely to appear nearby
- RNN -> LSTM -> Transformers

Practical
Word embedding with GloVe and Keras

Questions?