Recurrent Neural Networks and Advanced Architectures for NLP

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Announcements

- Assignment 3 deadline: Monday 18th of April

Overview

1. Neural Language Models
2. Recurrent Neural Networks
3. Fancy RNNs

Neural Language Models

Recap

With language models, we want to compute:

- The probability of a sequence of words: $P(w) = P(w_1, w_2, .., w_n)$.
- The probability of a new word given what came before it: $P(w_n|w_1, w_2, .., w_{n-1})$.
- We have also seen n-gram language models which make use of the Markov assumption. For example, a trigram language model would predict the probability of a sequence of words by conditioning on the two previous words at each step:

$$P(w) = P(w_1)P(w_2|w_1)P(w_3|w_1, w_2) \dots P(w_n|w_{n-2}, w_{n-1})$$

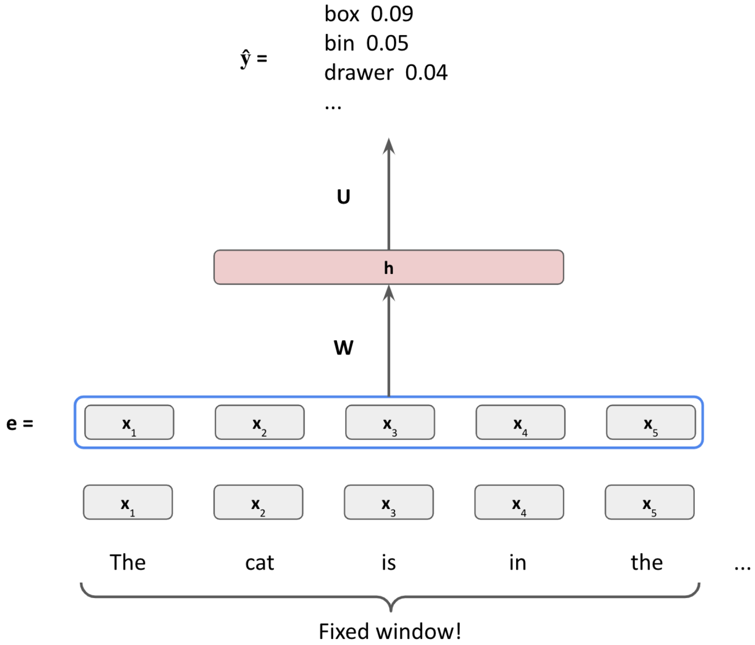
- n-gram language models have some issues, including sparsity and limited use of context.

A first neural language model

We can start by using word embeddings as features for a **fixed-window neural language model**:

- Given a fixed-window sequence of words represented using their embeddings $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_t$;
- we are interested in estimating the probability of the next word $\hat{p}(\boldsymbol{x}_{t+1}|\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_t)$.
- We can use the previous words' embeddings as features, concatenate them and feed them to a hidden layer with a non-linearity, and concluding by estimating probabilities with a softmax.

A first neural language model



A first neural language model

Where:

- Each $\boldsymbol{x}$ is a $1 \times d$ embedding vector of dimensionality d.
- $\boldsymbol{e} = [\boldsymbol{x}_1; \boldsymbol{x}_2; \dots; \boldsymbol{x}_t]$ is the concatenation of the embeddings of the words in the fixed-window preceding w_{t+1}. Therefore $\boldsymbol{e}$ has dimensionality $1 \times dk$, where k is the number of words in the fixed-window.
- $\boldsymbol{h} = f(\boldsymbol{We}^T)$ is the hidden layer, with f an appropriate activation function and $\boldsymbol{W}$ a weight matrix. $\boldsymbol{W}$ has dimensionality $dk \times h$ and $\boldsymbol{h}$ has dimensionality $1 \times h$. The dimensionality of the embeddings and the hidden layer are hyperparameters of the model.
- Finally, $\hat{y} = softmax(\boldsymbol{Uh}^T)$ is the predicted next word probability as estimated using a softmax function. Here $\boldsymbol{U}$ is another weight matrix of dimensionality $|V| \times h$, so that with the softmax we predict a probability distribution over the vocabulary V.

A first neural language model

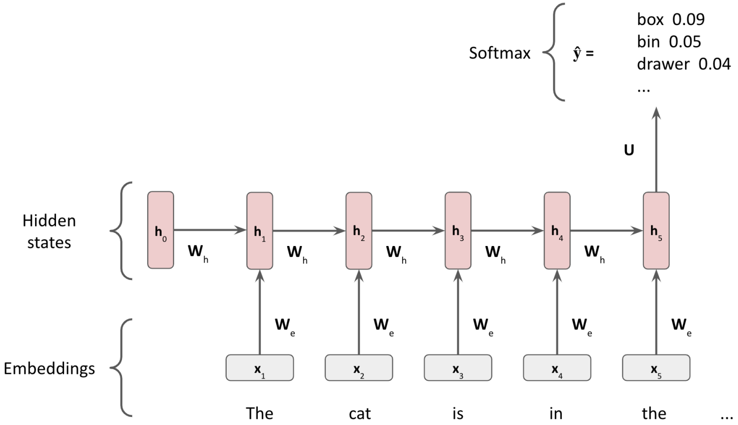
This model is interesting, yet unfortunately:

- it does not solve the use of a broader context with flexible word windows;
- larger windows would mean more parameters so scale is also an issue;
- and it does not make an efficient use of parameters and shared weights.

Can we do better? Yes, with **Recurrent Neural Networks**.

Recurrent Neural Networks

Recurrent architecture

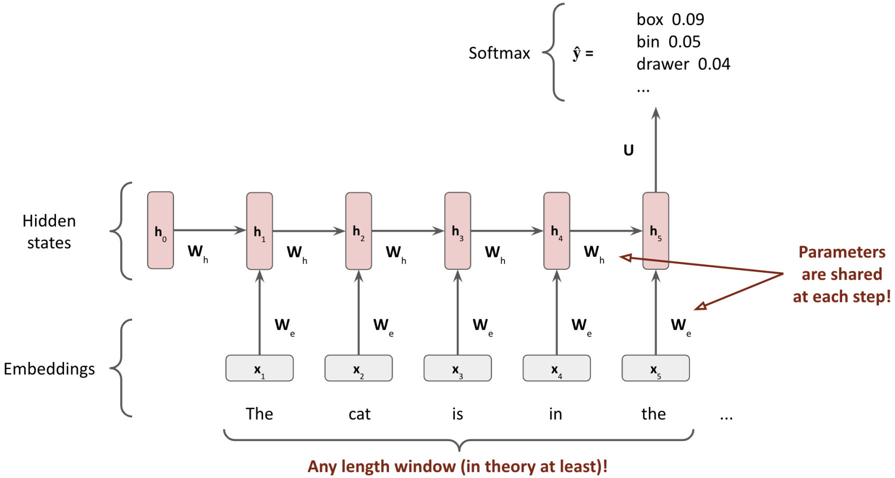


Recurrent architecture

Where:

- Each $\boldsymbol{x}$ is a $1 \times d$ embedding vector of dimensionality d.
- $\boldsymbol{h}_t = f(\boldsymbol{W}_h \boldsymbol{h}_{t-1}^T + \boldsymbol{W}_e \boldsymbol{x}_t^T)$ is the hidden layer, with f an appropriate activation function, $\boldsymbol{W}_e$ and $\boldsymbol{W}_h$ weight matrices. $\boldsymbol{W}_h$ has dimensionality $h \times h$, $\boldsymbol{W}_e$ has dimensionality $h \times d$, and $\boldsymbol{h}$ has dimensionality $1 \times h$. $\boldsymbol{h}_0$ is the initial hidden layer. The dimensionality of the embeddings and the hidden layer are hyperparameters of the model.
- Finally, $\hat{y} = softmax(\boldsymbol{U}\boldsymbol{h}^T)$ is the predicted next word probability as estimated using a softmax function. Here $\boldsymbol{U}$ is another weight matrix of dimensionality $|V| \times h$, so that with the softmax we predict a probability distribution over the vocabulary V.

Recurrent architecture



Why RNNs?

RNNs are a big step forward re. our previous concerns:

- Can process inputs on any length and use previous context of any length (in theory);
- model size does not depend on window size ($\boldsymbol{W}$ matrices remain of the same dimension);
- weights are shared across time steps.

Nevertheless, RNNs can be slow and won't really remember information from many steps back.

Training RNNs

How can we train RNNs?

- Predict the next word at each step, and calculate the loss accordingly.
- The loss at step t is the usual **cross-entropy** (now on multiple classes), calculated for the word to be predicted at $t+1$:

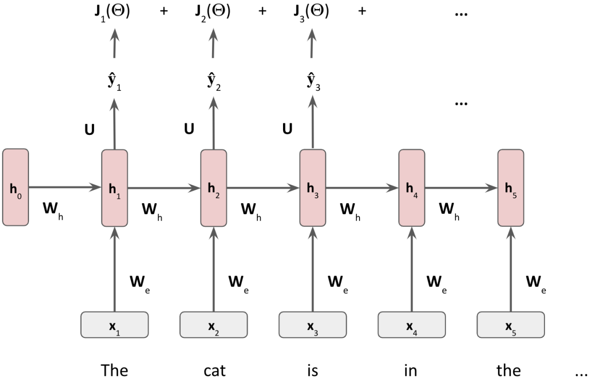
$$\mathcal{L}_t(\boldsymbol{W}) = -\sum_{w \in V} y_{w_{t+1}} log(\hat{y}_{w_{t+1}}) = -log(\hat{y}_{w_{t+1}})$$

- The overall loss is the average of the sum of the losses, calculated at each step:

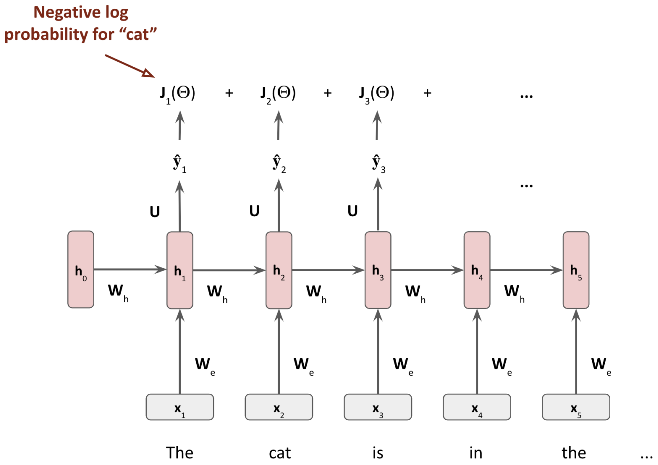
$$\mathcal{L}(\boldsymbol{W}) = \frac{1}{T}\sum_{t=1}^{T} \mathcal{L}_t(\boldsymbol{W}) = \frac{1}{T}\sum_{t=1}^{T} -log(\hat{y}_{w_{t+1}})$$

- Optimization can be done via SGD (backpropagation). Since the parameters $\boldsymbol{W}$ are used repeatedly, this is sometimes called **backpropagation through time**.

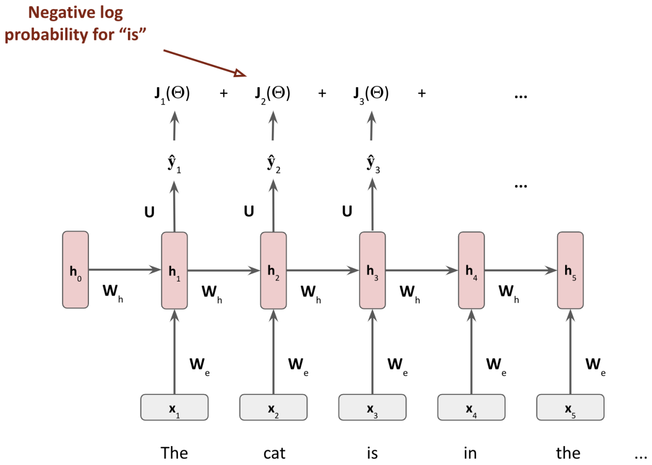
Training RNNs



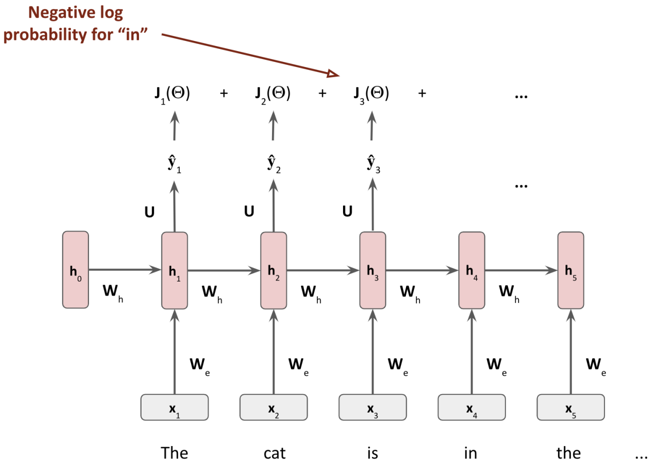
Training RNNs



Training RNNs



Training RNNs



Recall perplexity?

A second look at perplexity:

- We defined it as the inverse probability of the corpus, normalized by the number of words. For a corpus composed of n words:

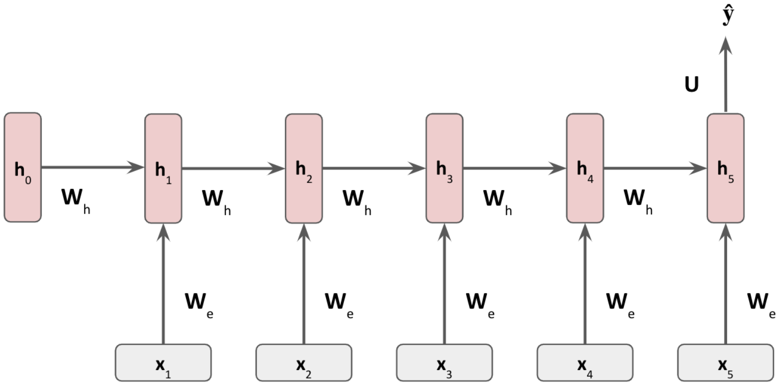
$$PP = P(w_1, w_2, \dots, w_n)^{-\frac{1}{n}} = \prod_{i=1}^{n} \left(\frac{1}{P(w_i | w_1, \dots, w_{i-1})} \right)^{\frac{1}{n}}$$

- It is actually equal to the exponential of the cross-entropy loss:

$$PP = \prod_{i=1}^{n} \left(\frac{1}{\hat{y}_{w_{i+1}}} \right)^{\frac{1}{n}} = exp\left(\frac{1}{n} \sum_{i=1}^{n} -log(\hat{y}_{w_{i+1}}) \right) = exp(\mathcal{L})$$

- So *lower perplexity == lower loss == higher data likelihood*.

RNN flavors: Many to one



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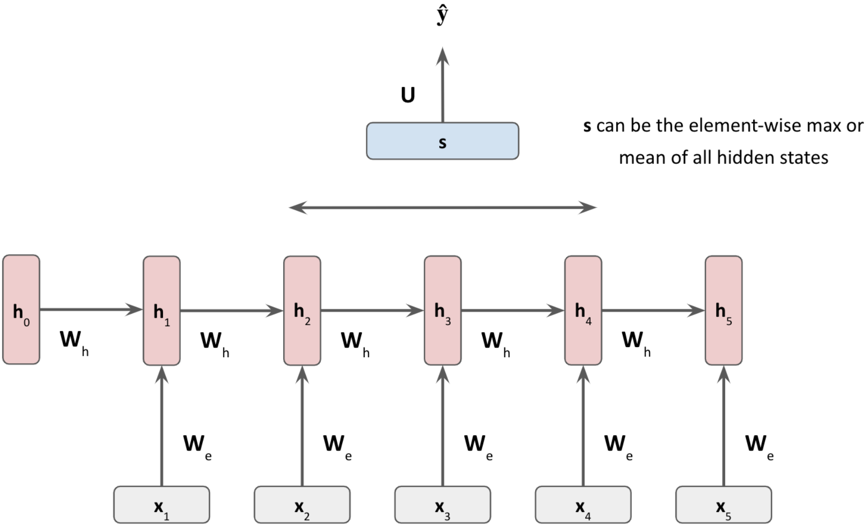
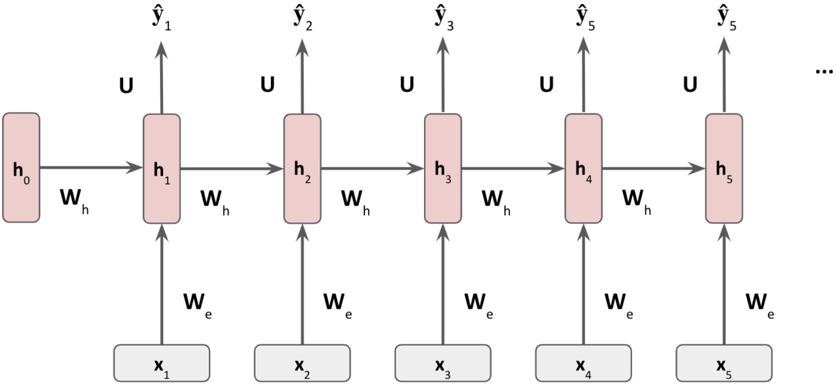


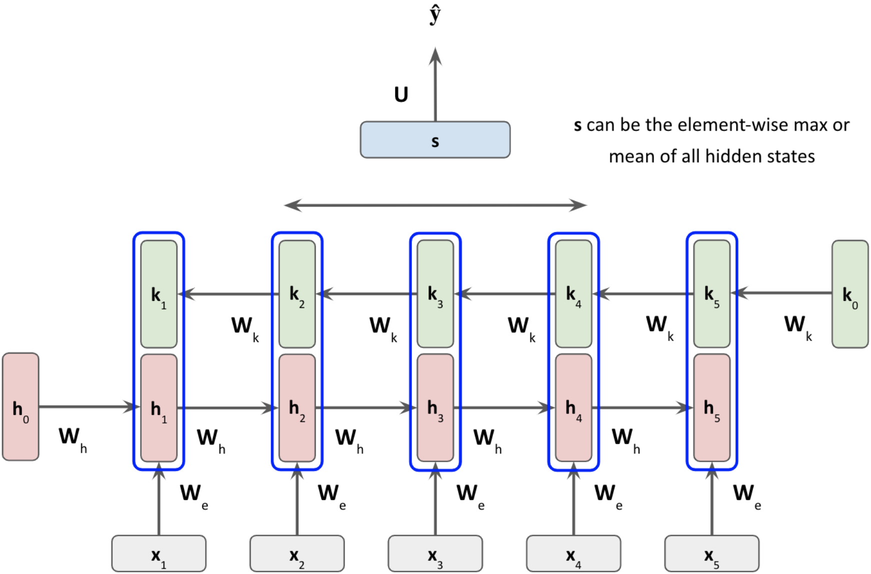
RNN flavors: Many to many



Notes

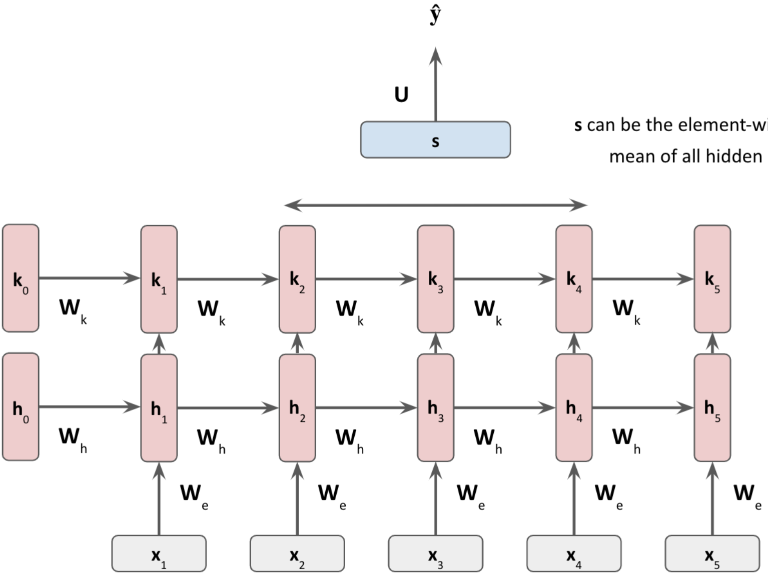
Fancy RNNs

Bi-RNNs



s can be the element-wise max or mean of all hidden states

Multilayer RNNs



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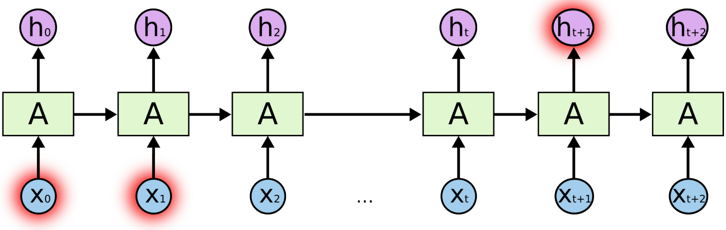
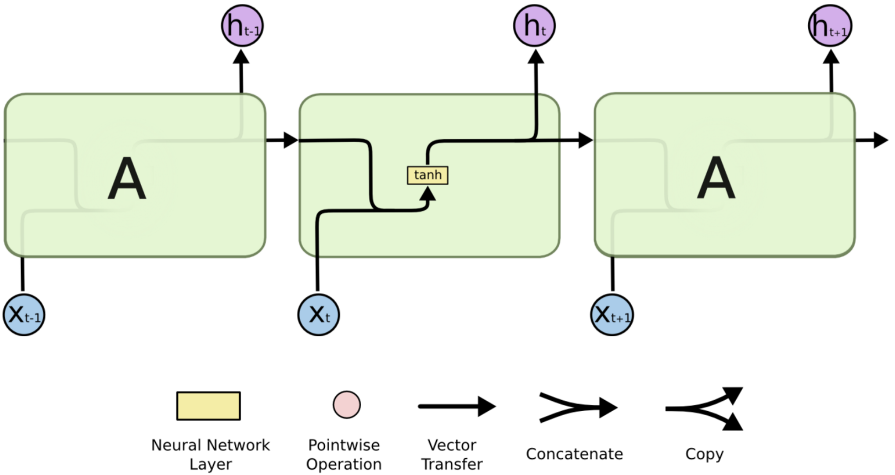
Vanishing Gradients

- RNNs have a crucial issue: **vanishing and exploding gradients**.
- Both occur when we backpropagate through time with multiplying several times by $\boldsymbol{W}$. If $\boldsymbol{W}$'s parameters are small, gradients can vanish to zero. If they are large, they can explode.
- This is an issue as it does not allow to model far away context (vanishing) or to properly converge (exploding).
- Solutions:
  1. Exploding: **gradient clipping**.
  2. Vanishing: **Long Short-Term Memory** networks.



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

A different view on RNNs



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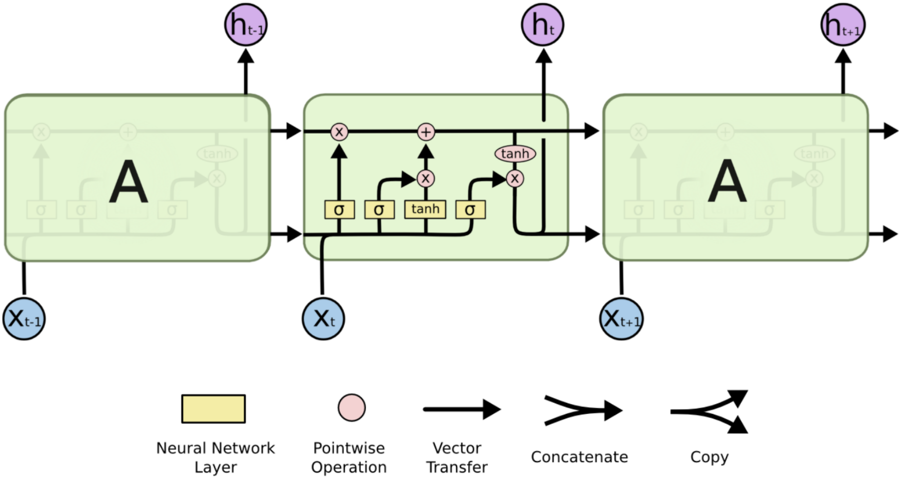
LSTMs



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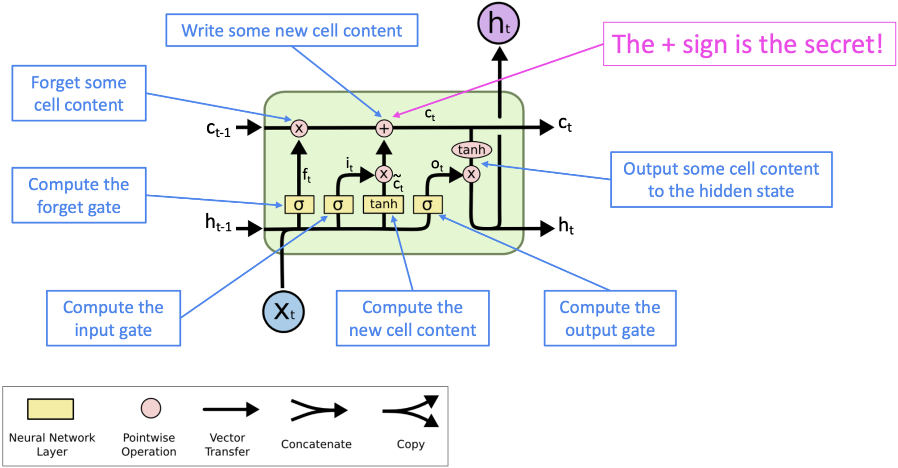
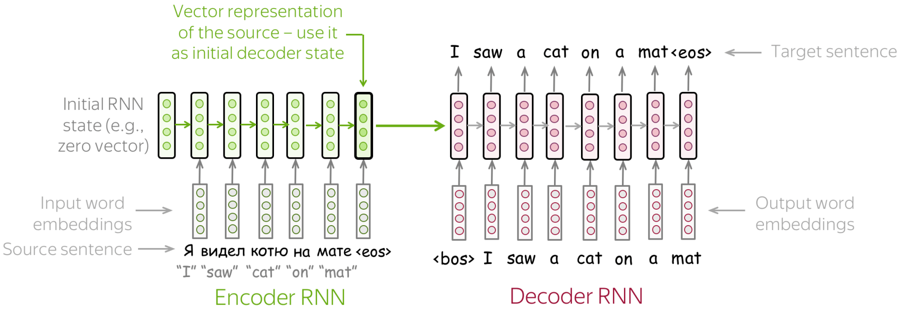
LSTMs



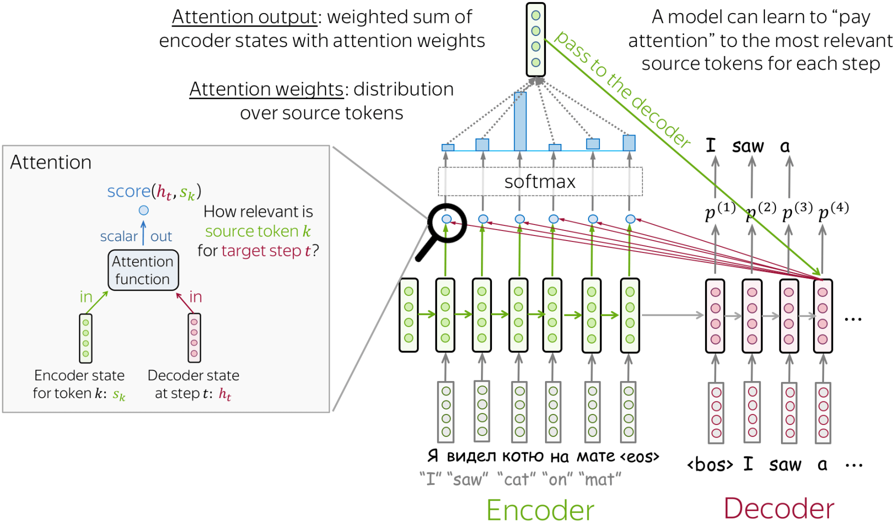
Credit: Stanford CS224N

Seq2Seq



Credit: Lena Voita https://lena-voita.github.io/nlp_course.html

Attention



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What's next

- The most recent advances in neural networks for NLP come from the shift from recurrent architectures to using **attention-based architectures**.
- For your reading assignments, you have explored **transformers** (which combine attention with other ideas from neural networks literature) and will explore **BERT** (which is a neural language model making use of transformers).
- While there is much more to it, in this way you will have a window into contemporary models for NLP.

The next part of the course turns to other topics instead: Web scraping and APIs, recommender systems, corpus annotation, sentiment analysis and clustering with topic modelling, ethics.

Notes