Learning from Data

Lecture 4: RNN, LSTM, Seq2Seq

Rik van Noord - 25 September 2023

Assignment 1 feedback

Nothing personal

Read the assignment well

- Check carefully what you are expected to do/answer
  - Not sentiment analysis!
- A few good reports that missed relatively easy points
- Key points are added throughout the assignments

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Github:

- OK to use for submission, but remember to not make changes after
- Always send in a ZIP file with all code anyway
- Check what you are actually sending in

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  - Is 0.1% accuracy improvement really an improvement?

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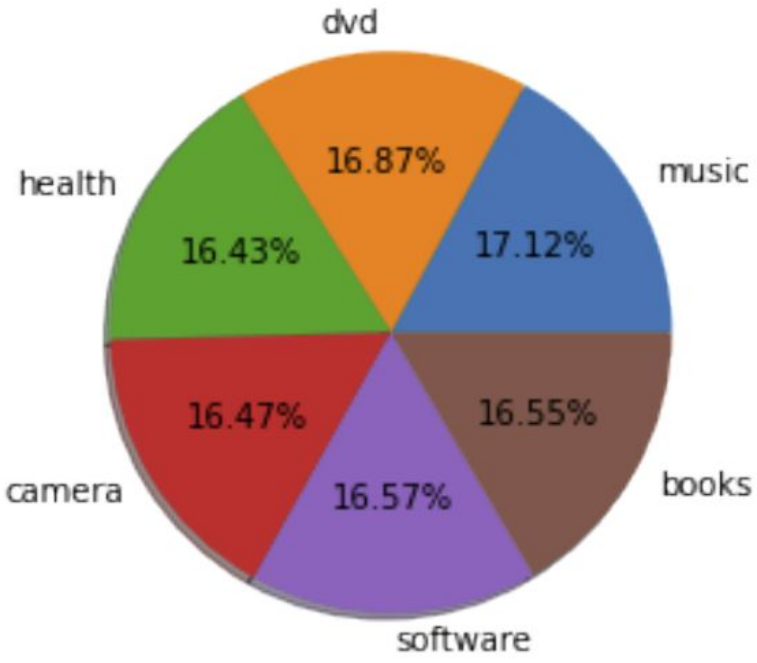
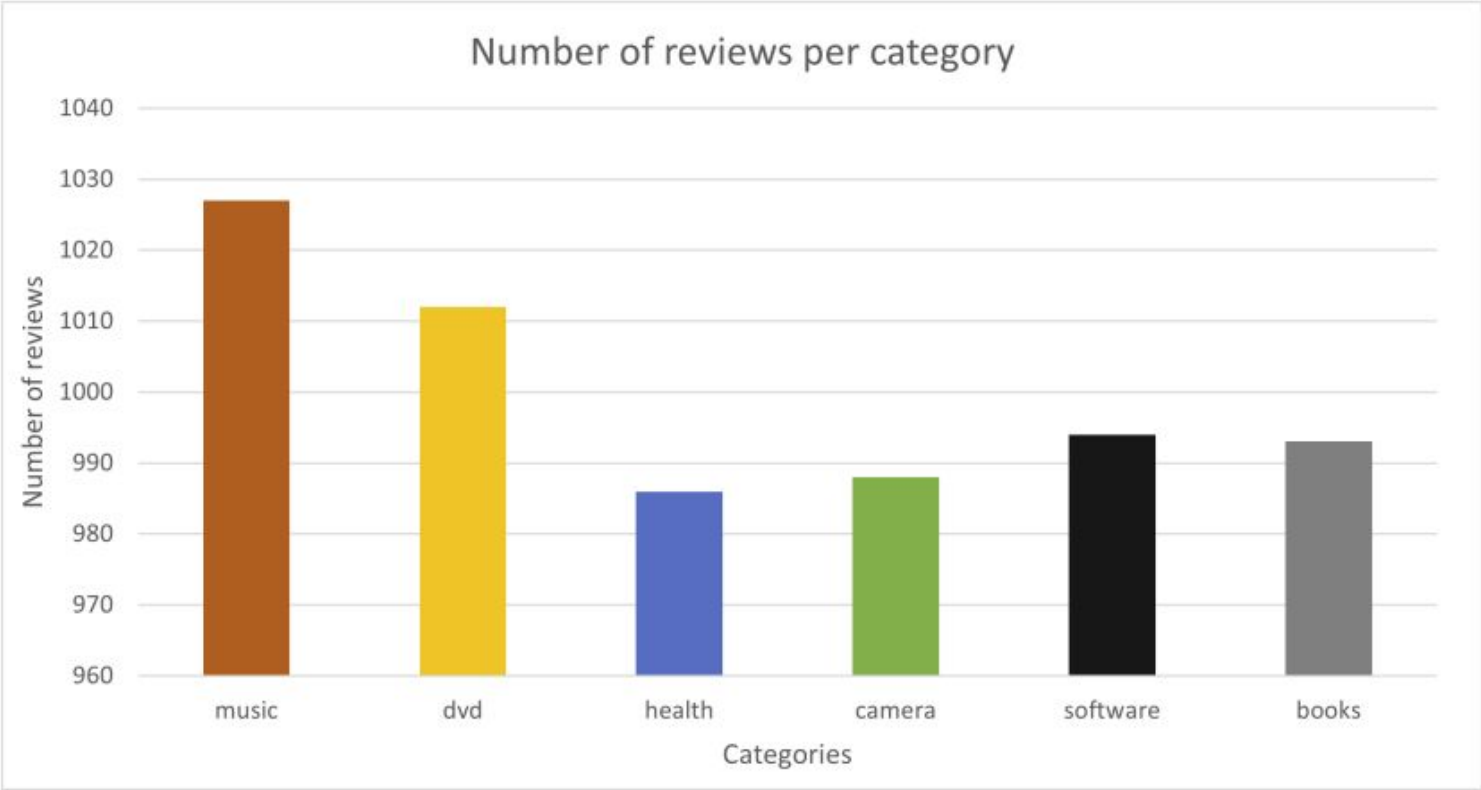
  - Is 0.1% accuracy improvement really an improvement?
- sklearn is the tool, not the method or algorithm
  - No need to describe exactly how to run your code

Data visualization

- Think about what the best option is
  - Often not a bar or pie chart
- Some bad examples will follow


dvd
16.87%
music
17.12%
health
16.43%
16.47%
camera
16.57%
software
16.55%
books


Number of reviews per category
1040
1030
1020
1010
1000
990
980
970
960
Number of reviews
music
dvd
health
camera
software
books
Categories

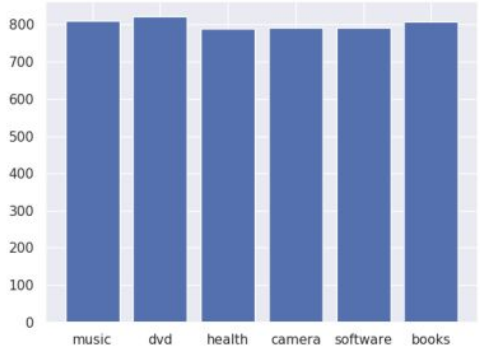


Figure 1: Distribution of the reviews among the topics (training set)

Topic	Count
books	807
camera	790
dvd	821
health	789
music	809
software	790
Total	6000

Table 1: Distribution of the reviews among the topics (training set)

Formatting

- Tables need to be self explanatory, not just caption it “Results of our model”
  - Captions need to end with punctuation
- References to tables/sections/figures are with a capital
  - “See Figure 3”, “This is explained in Section 4”, etc
- Write numbers with a comma: “6,000” instead of “6000”
- Take care of formatting the appendix
  - I’ve seen a 6 page Appendix that would have fit in 3
- No print screens of a terminal, please just create a table
- Check final PDF
  - One group had an empty references section

Table 3: Classification Metrics

	Accuracy without parameters	Best setting
Naive Bayes	89.33%	92%
Decision Trees	77%	79%
Random Forests	85.5%	85.8%
KNN	40.66%	77.66%
SVM	81.66%	92%

Table 4: Accuracy Comparison

This is the lowest accuracy of any of the algorithms or features tested, however the python script for POS tagging might not be completely accurate or fully working which limits the results. The final accuracy in POS tagging may improve if changes to the code are implemented.

4 Discussion/Conclusion

Examining the results from comparatively analyzing our 5 different models showed that the overall accuracy for NB and SVM with adjusted parameters were the highest. The settings we used for both were

Good example

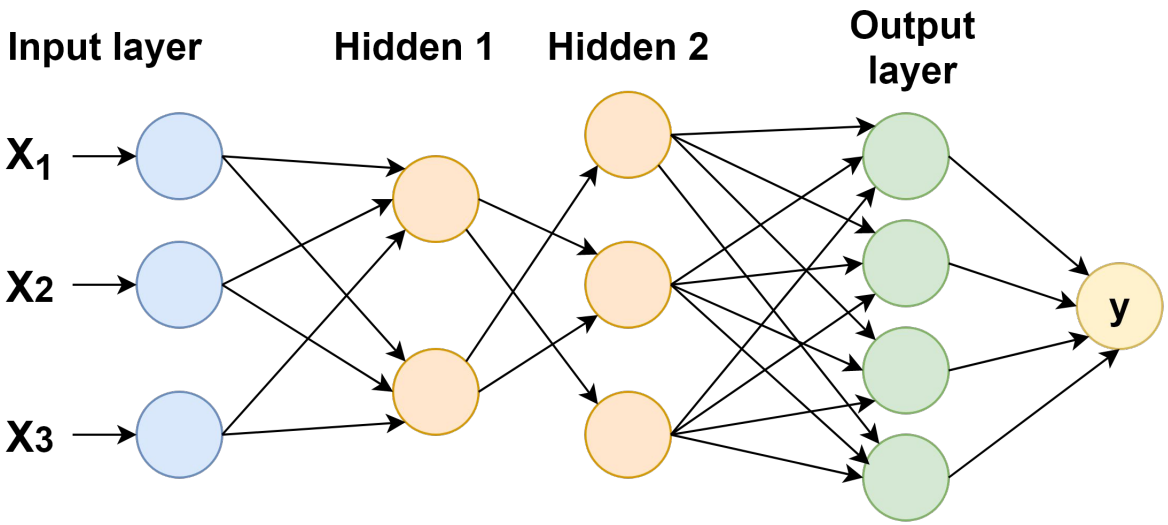
	Train	Dev	Test
Books	659	180	154
Camera	650	170	168
DVD	704	145	163
Health	660	158	168
Music	666	186	175
Software	661	161	172
Total	4,000	1,000	1,000

Today - start of deep learning in NLP

- Assignment feedback
- Recap of Neural Networks
- Recurrent Neural Networks
- LSTMs
- Sequence-to-sequence models (with attention)

Really, this (and next) lecture could be a full course. I will give you highlights, but it might feel like not all details are explained. I will add a reading list on Brightspace.

Last week: multi-layer perceptron



$y = g_2(g_1(W_2(xW_1)))W_3$ ⇨ W_1, W_2 and W_3 are learnable weight matrices

⇨ g_1 and g_2 are non-linear functions

Last week: learning the weights

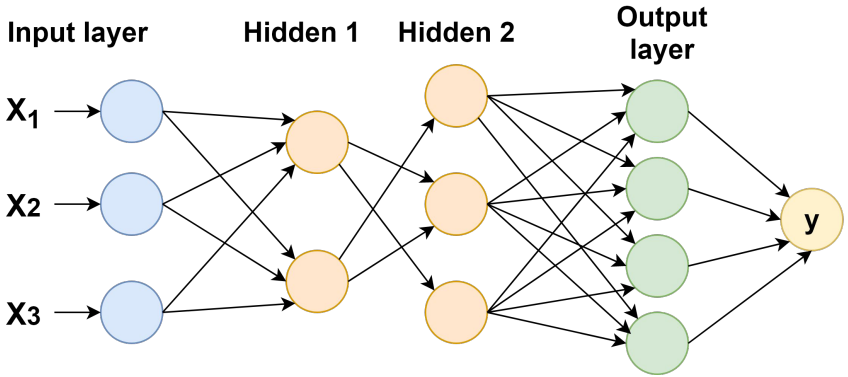
- Changing the weights is how **learning** takes place
- **Intuition:**
  - Pass instance through the network
  - Measure how far off we are (**loss function**)
  - Update weights so that we move in the right direction
  - Loop over instances multiple times until we are happy
  - Save weights as final model so we can predict on unseen data

This **intuition** will stay the same, even though the networks get more complicated.

Last week: creating a neural network

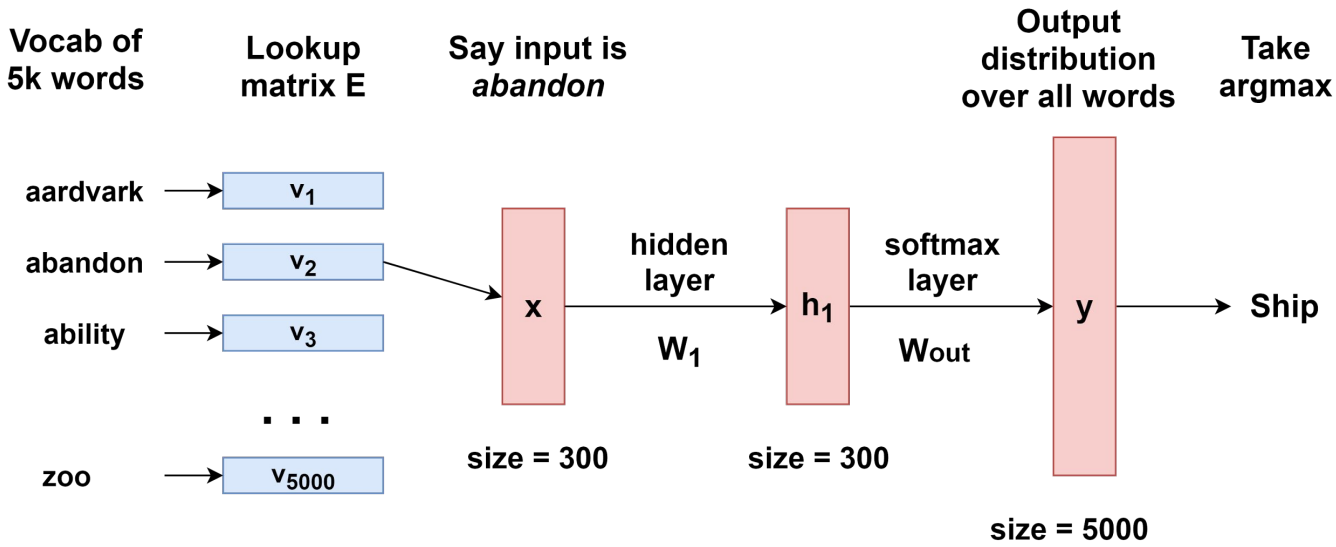
To create a neural net, you have to specify:

- Input features and output categories
- Number of hidden layers
- Activation function (sigmoid, tanh)
- Loss function (MSE, Cross entropy)
- Optimizer (SGD, Adadelta, Adam)
- Where and if to add dropout
- When to stop training



Of course, you don't always know what works in advance. **Experiment!**

Last week: training word embeddings



Each word has an associated **dense vector** that we can use for our own tasks!

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We have a problem: each word has an associated vector, but the input to our neural network also is a single vector. What do we do now?

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- **Averaging** or **max pooling** vectors
  - Could work, but especially for long sentences we lose a lot of information
  - Also, some words are more important than others

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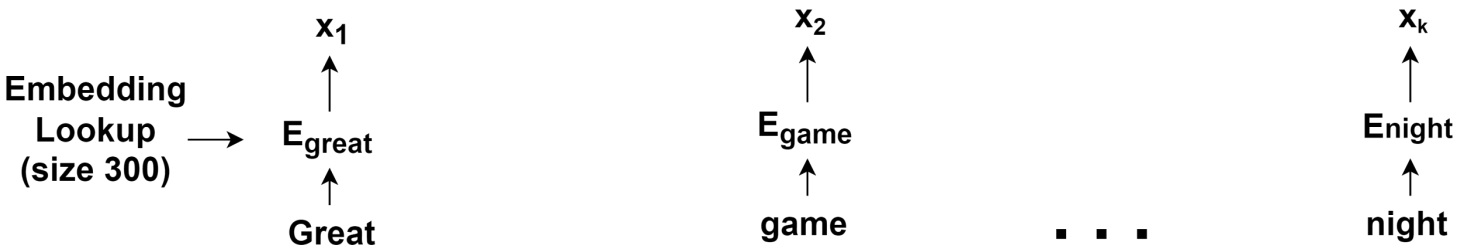
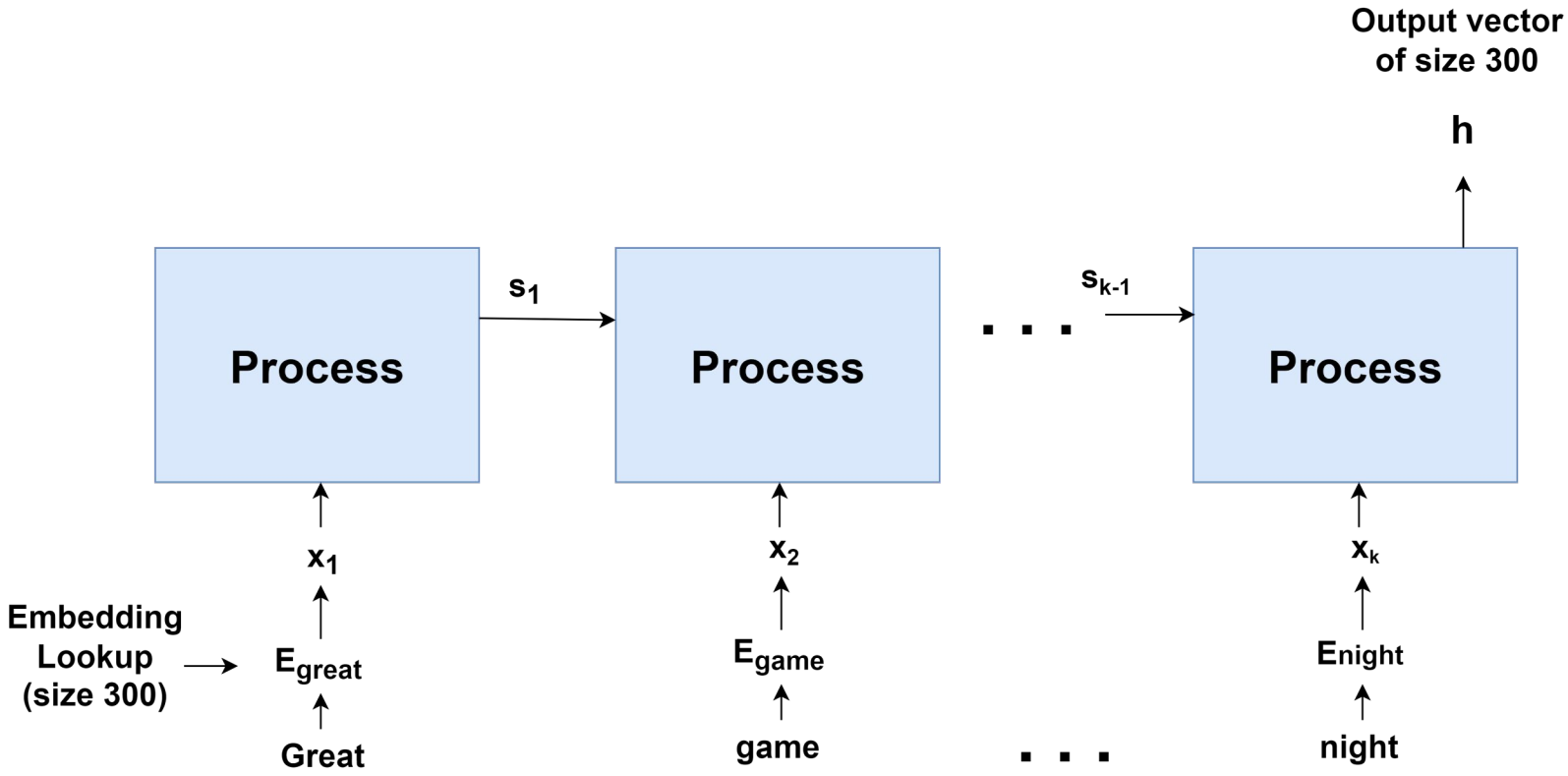
We would like a neural network that can take a **sequence of vectors** as input and automatically **learn** what vectors are important

Recurrent Neural Networks


Embedding
Lookup
(size 300)
x1
Egreat
Great
x2
Egame
game
xk
Enight
night


Output vector
of size 300
h
Process
Process
Process
s_1
s_{k-1}
x_1
x_2
x_k
Embedding
Lookup
(size 300)
E_{great}
E_{game}
E_{night}
Great
game
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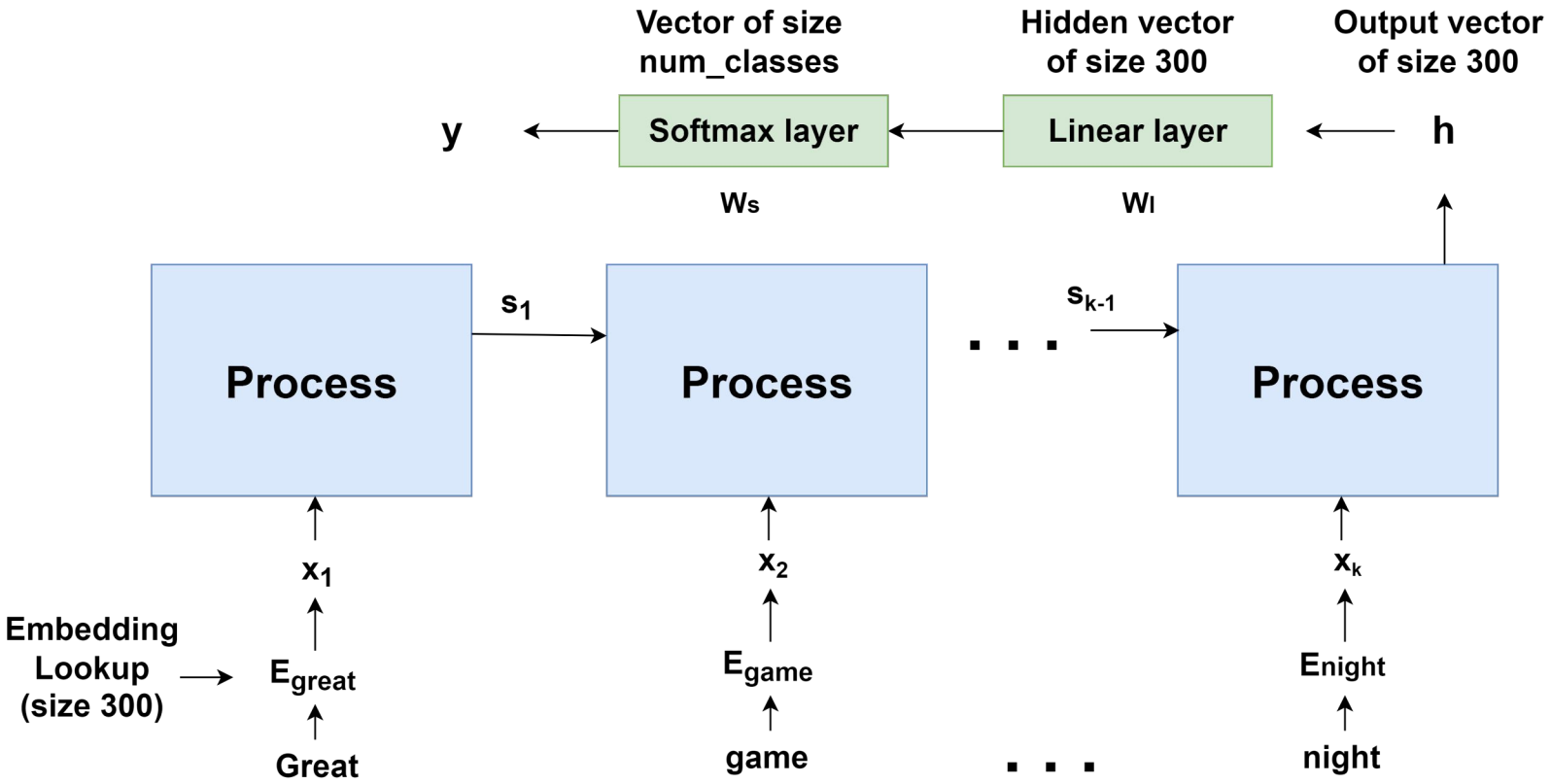
Vector of size num_classes
Hidden vector of size 300
Output vector of size 300
y
Softmax layer
Linear layer
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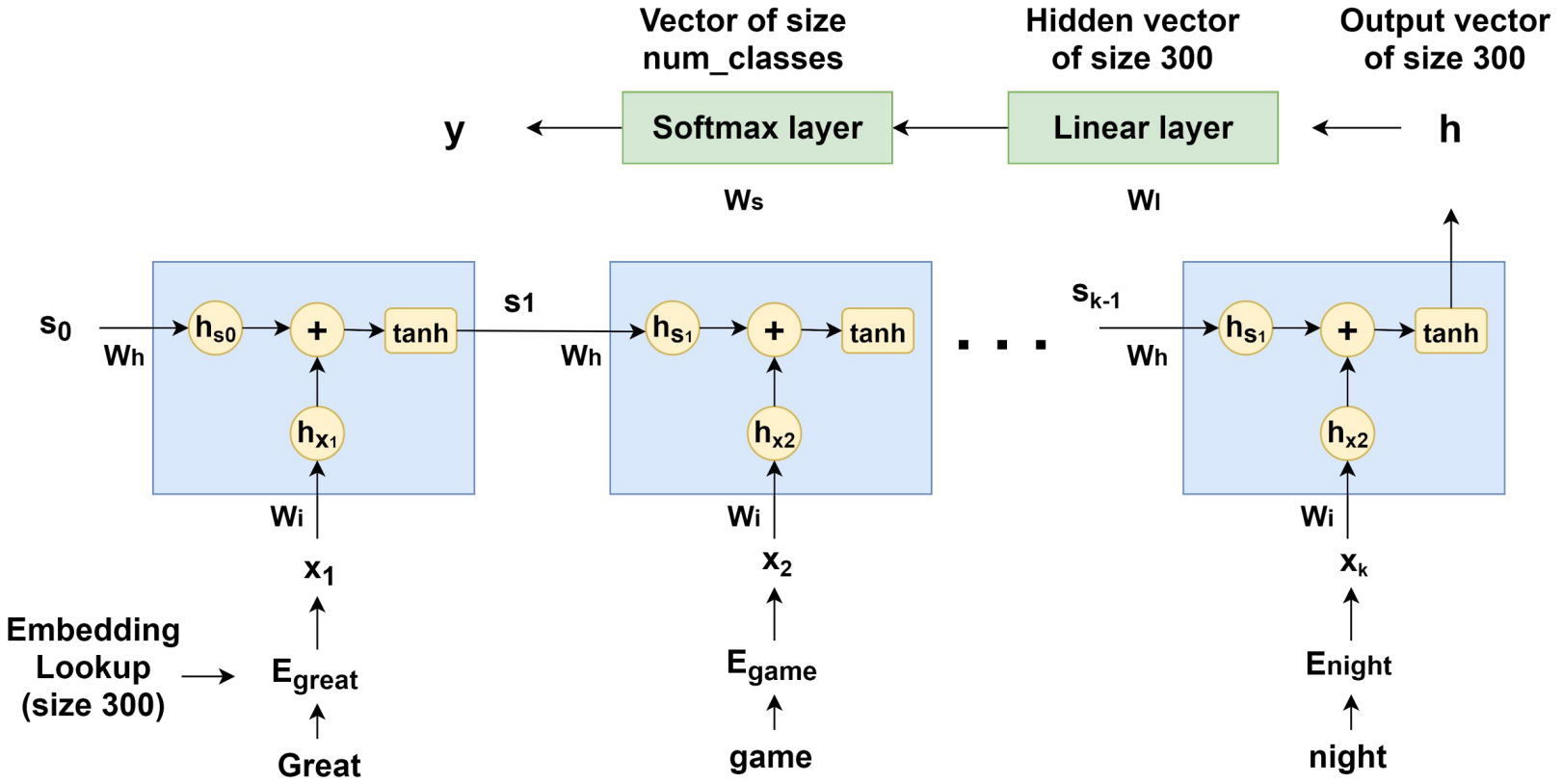
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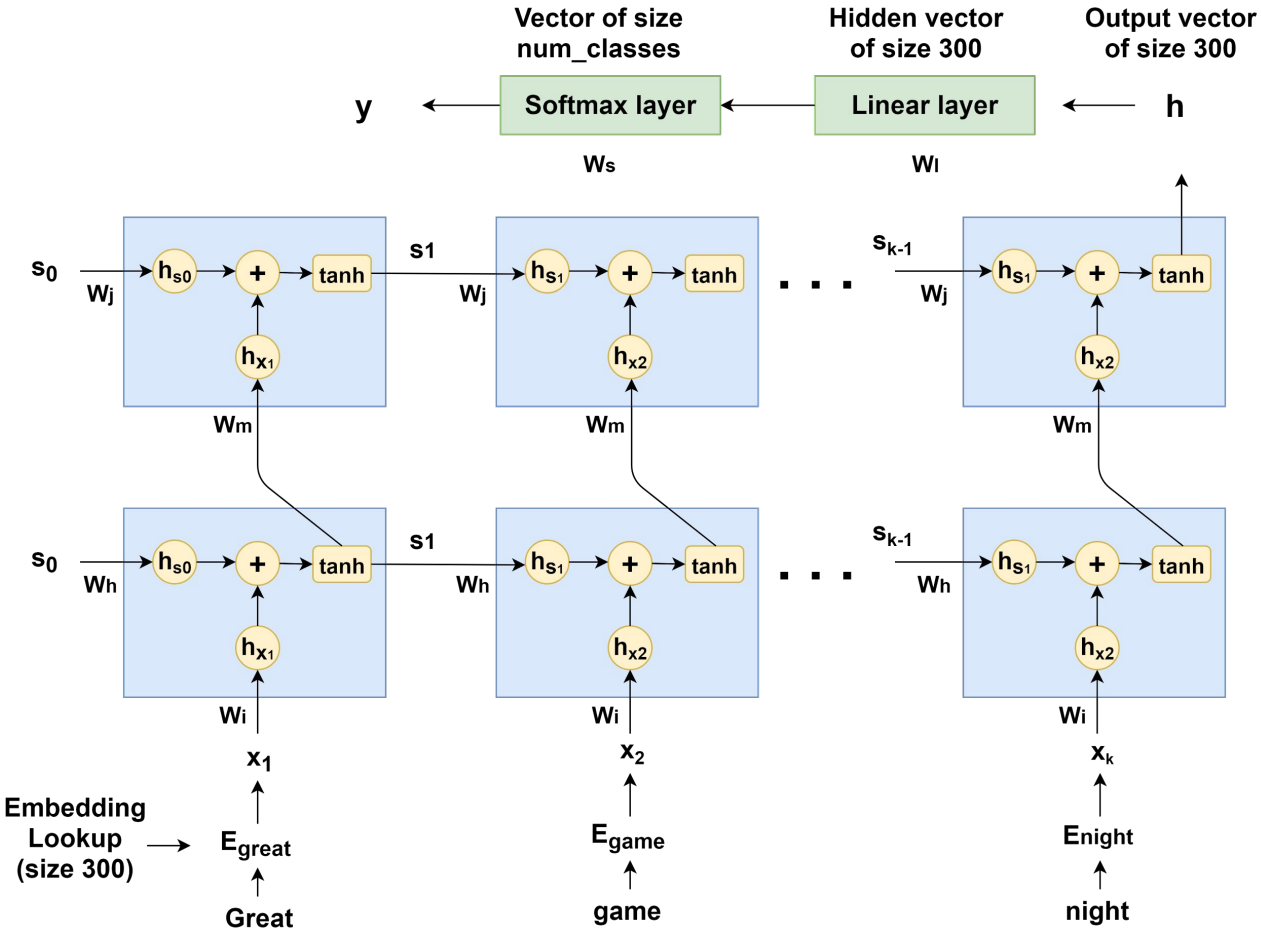
It is possible to have **multiple** RNN layers!


Vector of size num_classes
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sk-1
Wm
Wh
Wi
x1
x2
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Embedding Lookup (size 300)
Egreat
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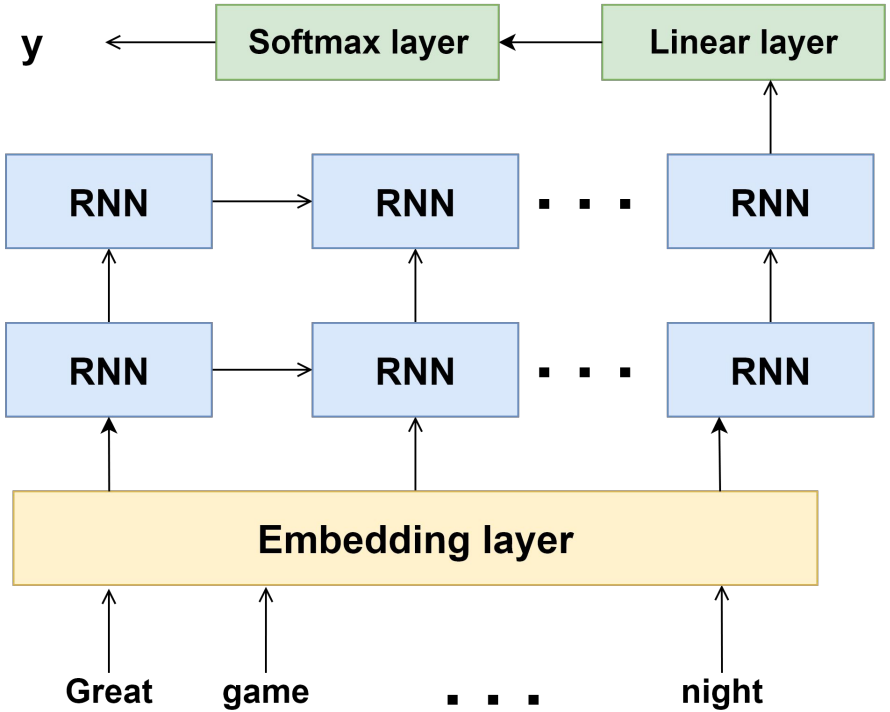
Simplified representation



RNN problem

- All information is condensed in a single vector (hidden state)
- The gradient is dependent on a lot of multiplications
- The gradient tends to either get very small, or very small
  - Small: **vanishing gradients**
  - Large: **exploding gradients**

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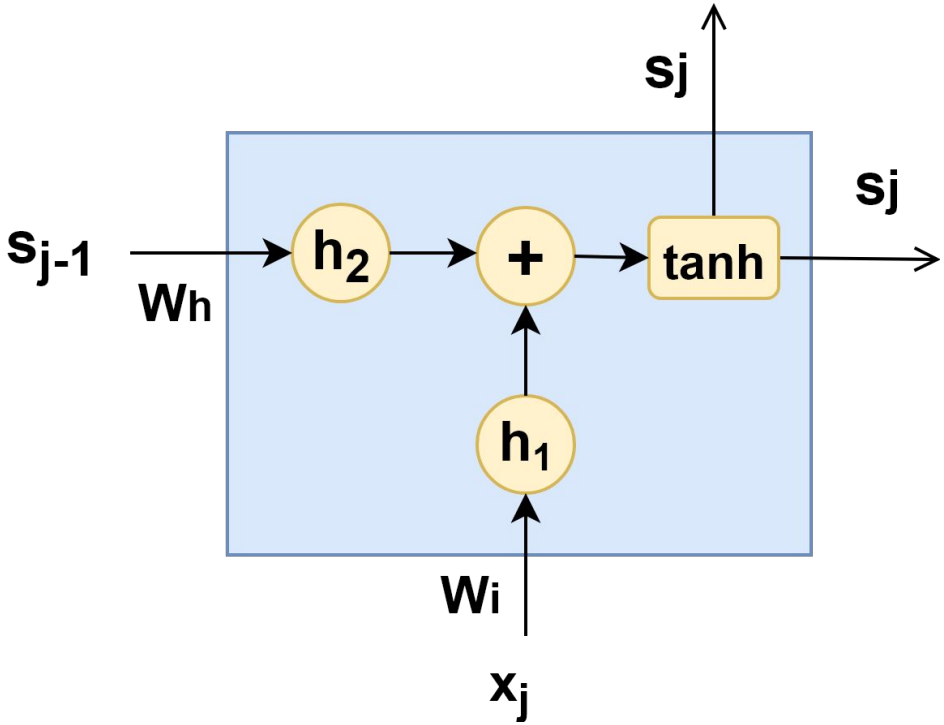
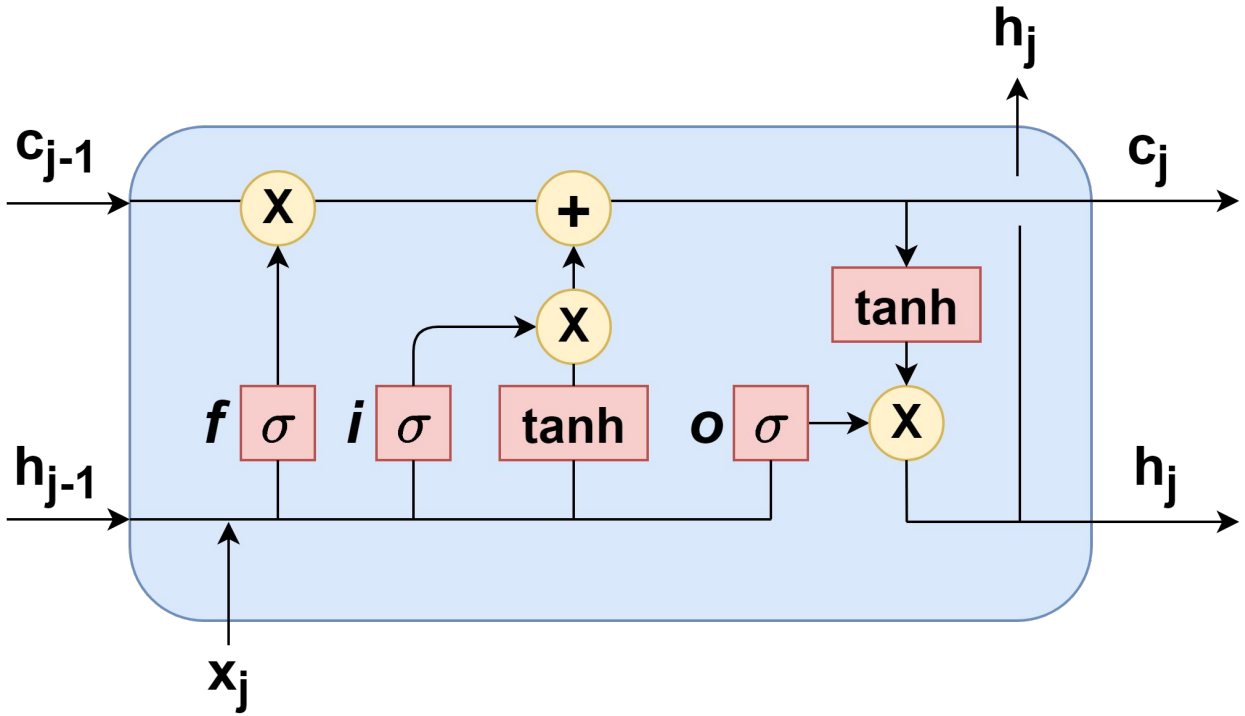
Also: the model has problems learning **long-term dependencies**. Or in other words: at the end of the sequence the model has not retained enough information of the beginning of the sequence.

Model to get around these issues: Long Short Term Memory (LSTM)

Simple RNN cell



LSTM cell

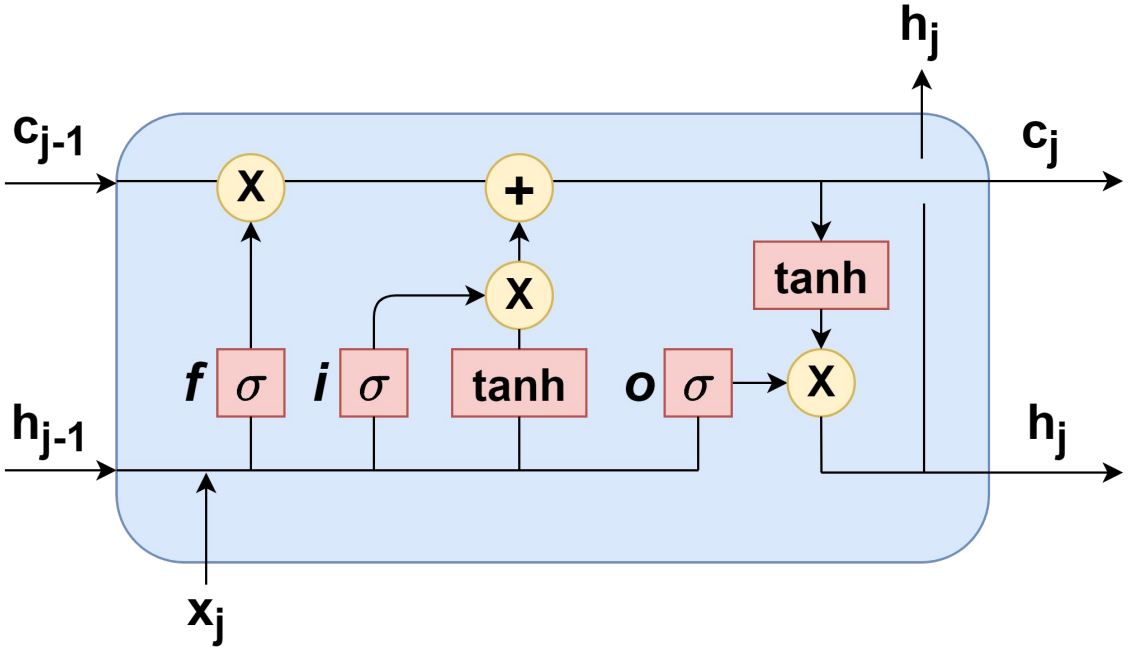


LSTM in formulas

$s_j = \text{LSTM}(s_{j-1}, x_j) = [h_j; c_j]$

$f_j = \sigma(W_f x_j + V_f h_{j-1})$
$i_j = \sigma(W_i x_j + V_i h_{j-1})$
$o_j = \sigma(W_o x_j + V_o h_{j-1})$
$z_j = \tanh(W_z x_j + V_z h_{j-1})$

$c_j = (f_j \odot c_{j-1}) + (i_j \odot z_j)$
$h_j = o_j \odot \tanh(c_j)$



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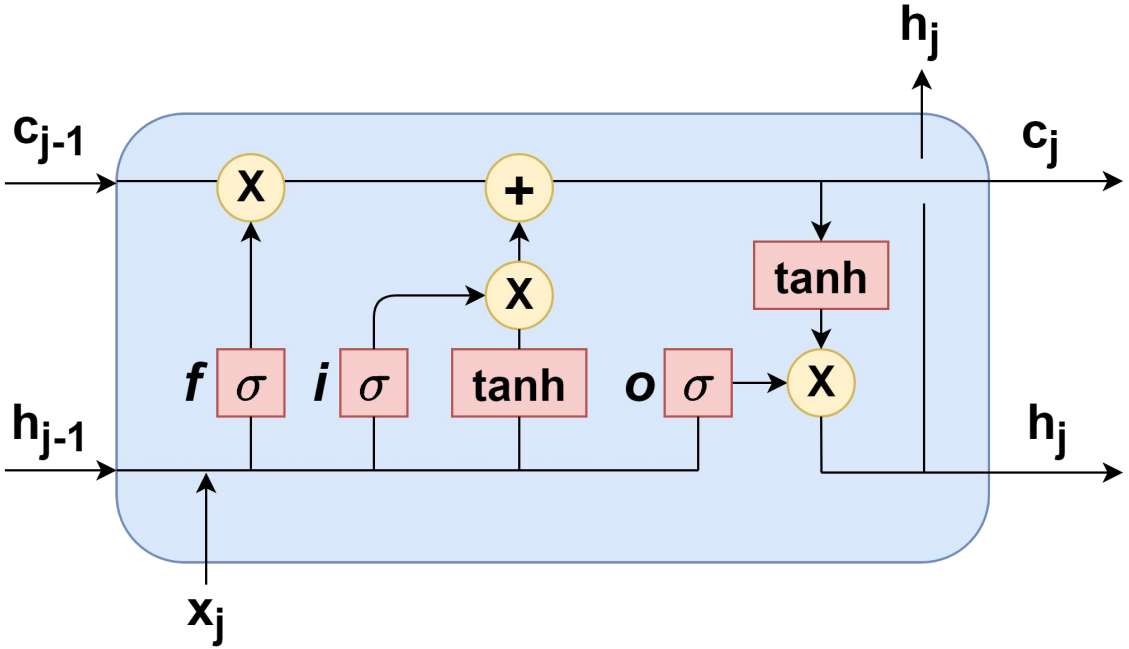

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LSTM in formulas

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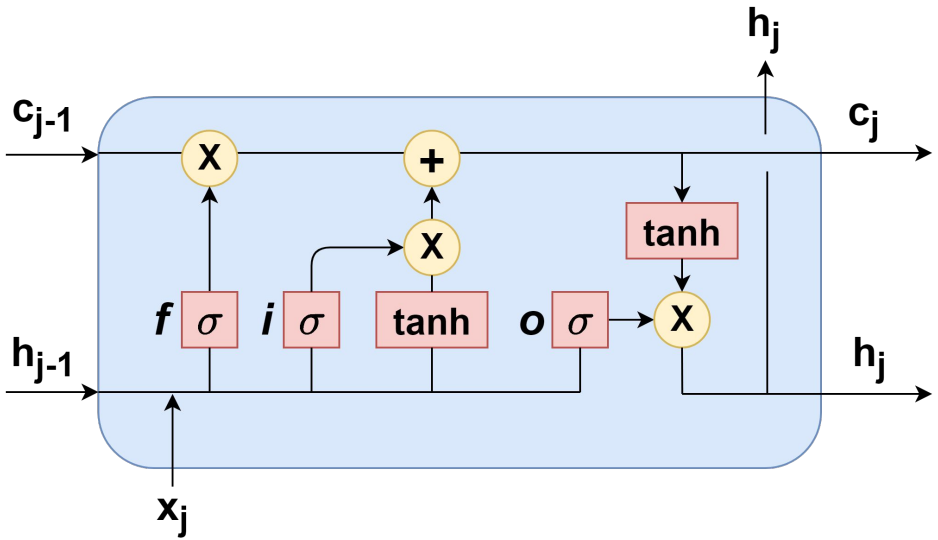

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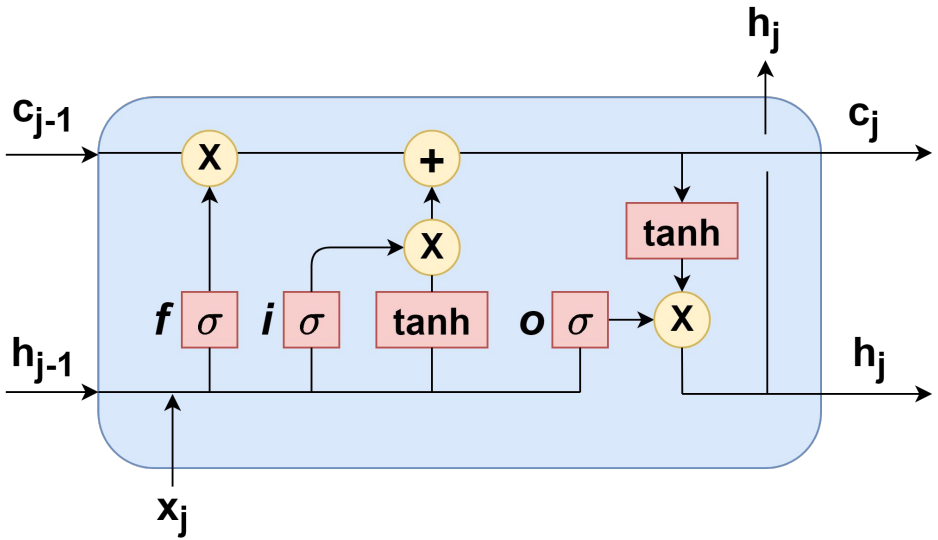

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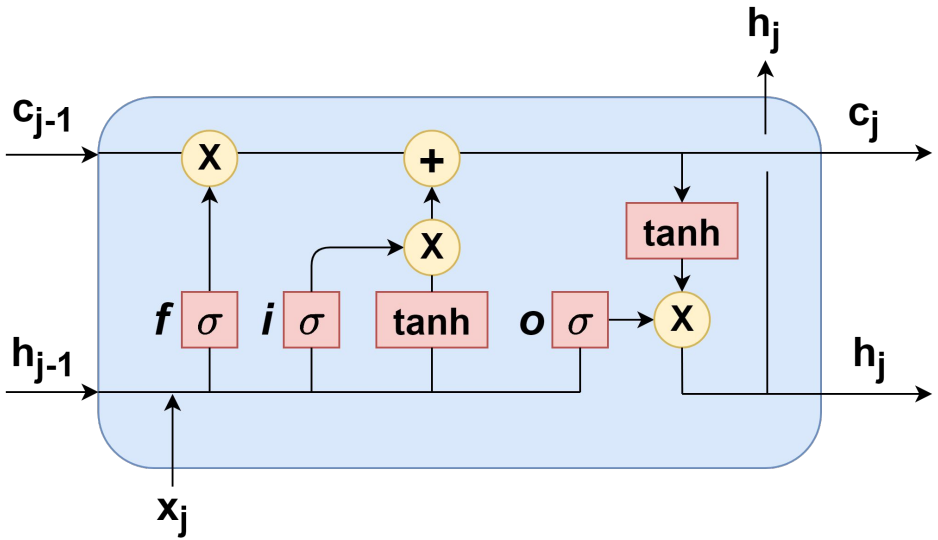

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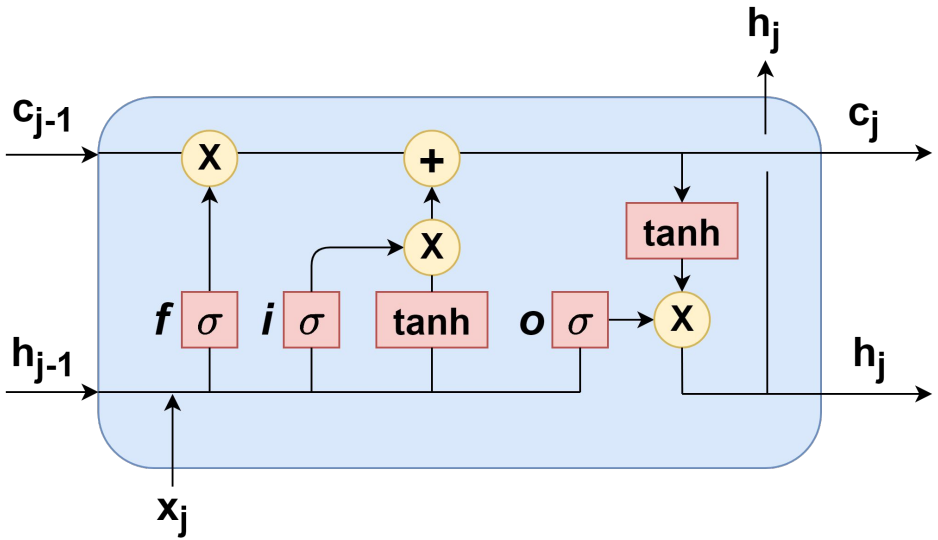

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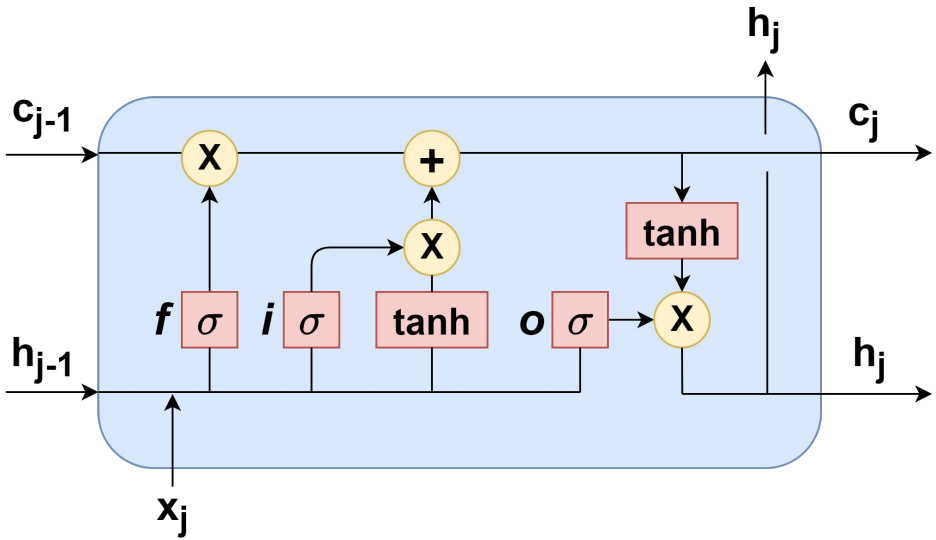

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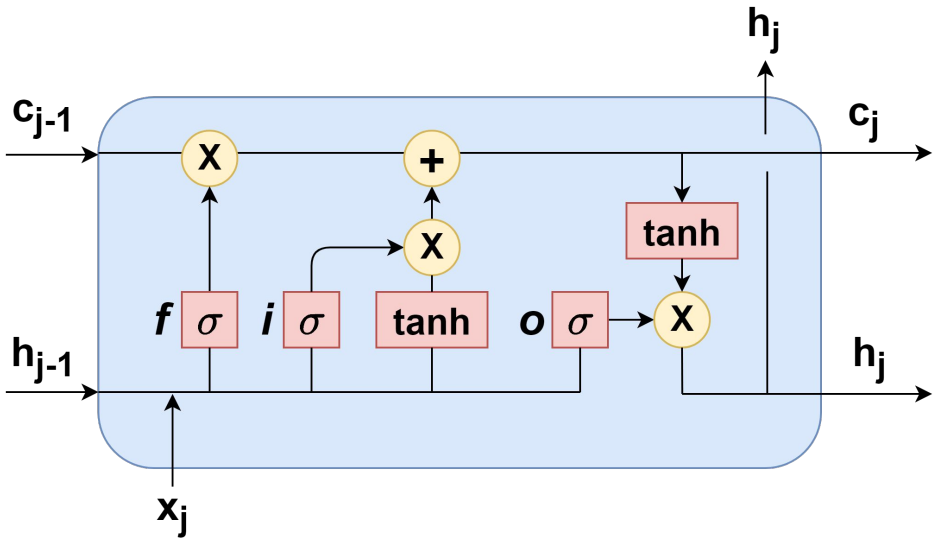


f: forget gate - how much of previous state c_{j-1} do we keep?
i: **input gate** - to what extent do we add new information to c_{j-1}?
o: **output gate** - what do we actually output as our new hidden state h_j?

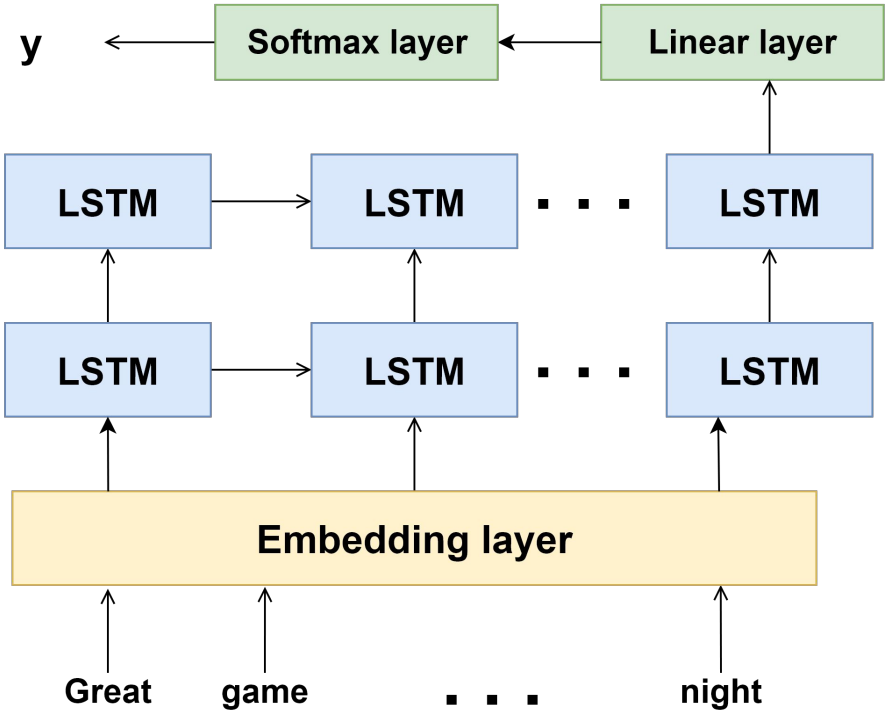
LSTM architecture

This architecture looks a bit random (or ad-hoc), but it's incredible hard to improve on

Jozefowicz et al. (2015) did an architecture search over **thousands** of RNN architectures that were similar to the LSTM architecture. In their own words:

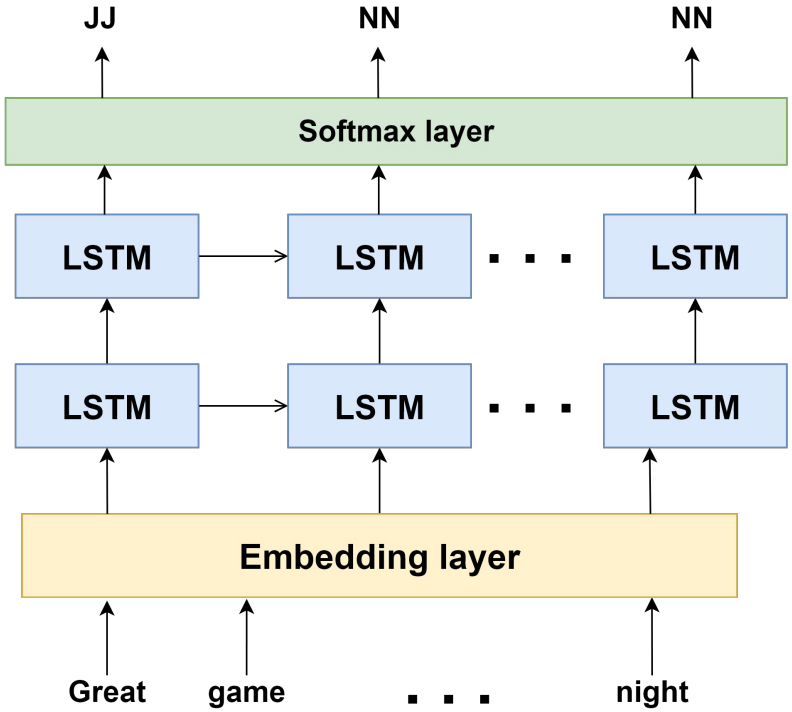
"Though there were architectures that outperformed the LSTM on some problems, we were unable to find an architecture that consistently beat the LSTM [...] in all experimental conditions"

LSTM simplified



What if I want an output for each token?

Sequence Tagging (POS)



LSTM issue

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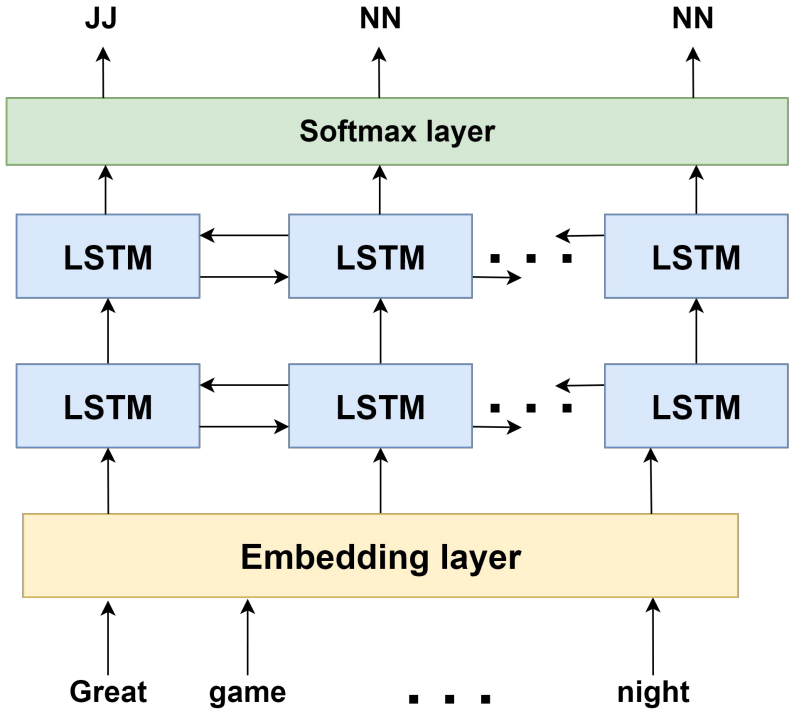
- Weights are **not shared** between the two states

Bi-directional LSTM (bi-LSTM)



But what if we have output of variable length?
For example machine translation?

Encoder-decoder architecture

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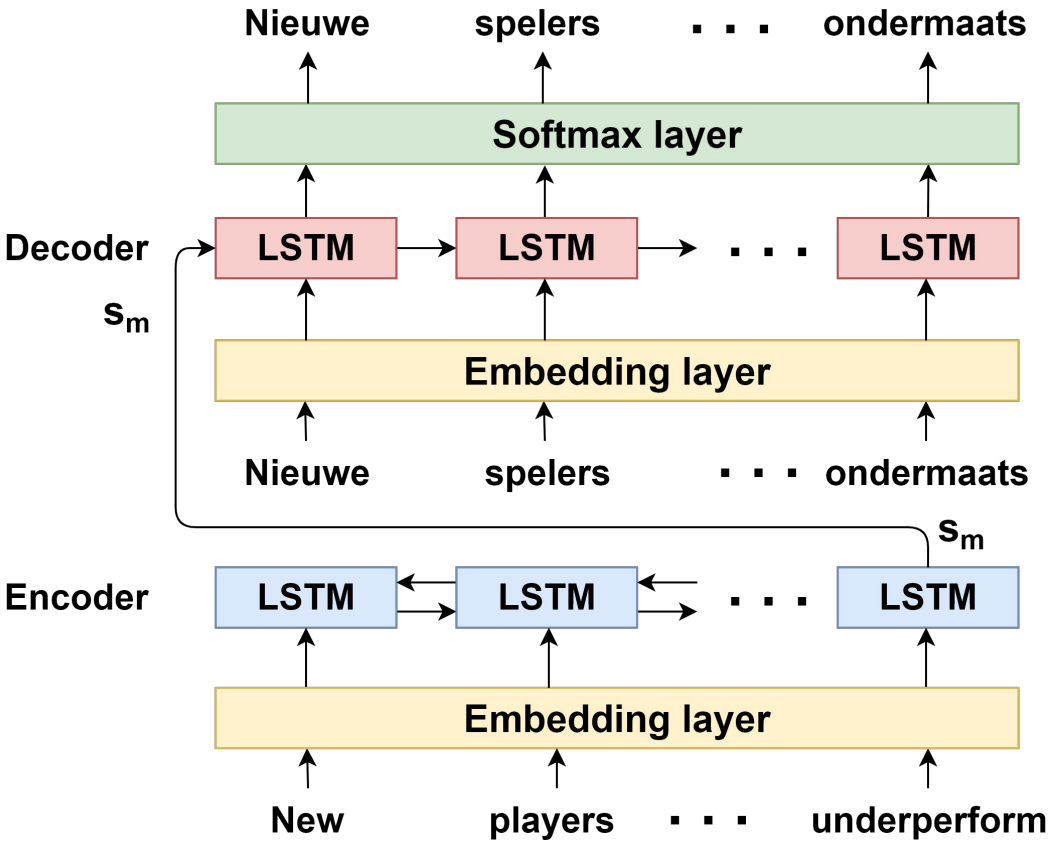
- The decoder outputs a word for each state, which we can compare to our gold standard output (and backpropagate errors ⇒ learning)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. . .
ondermaats
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Decoder
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LSTM
LSTM
. . .
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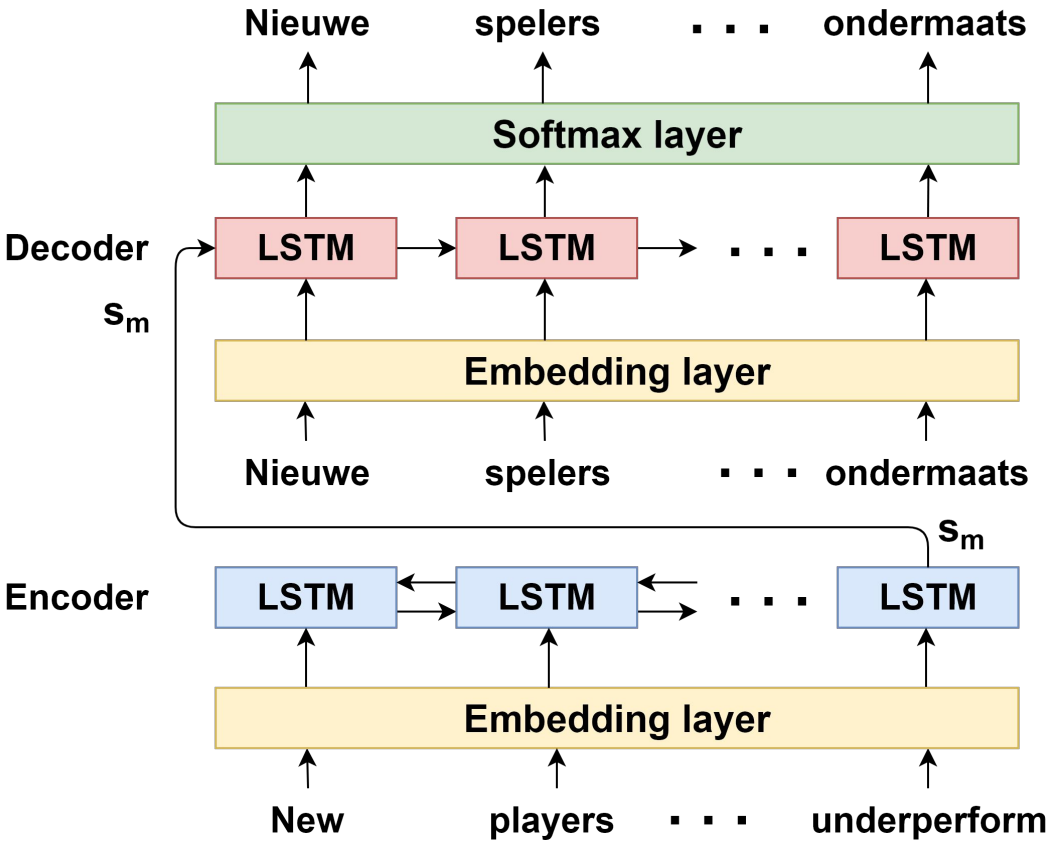
New
players
. . .
underperform

What is the problem here?

This does not work for prediction!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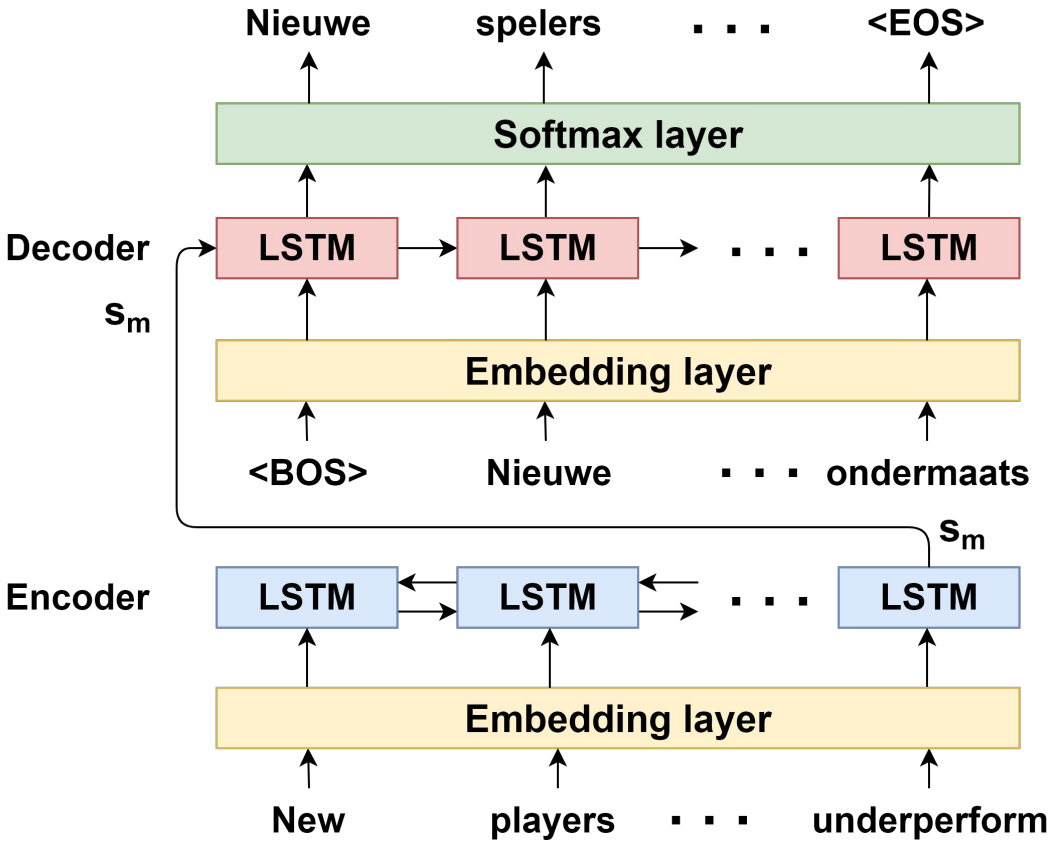
- Once we predict <EOS>, we are **done predicting**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These models are called sequence-to-sequence models

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Currently, we always output the **most probable** token at each step in the decoder

However, say that for the first token we want to output we have two good options:

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This process is called **beam search**

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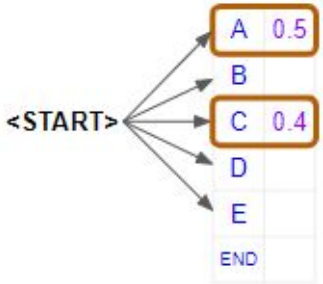
Solution:

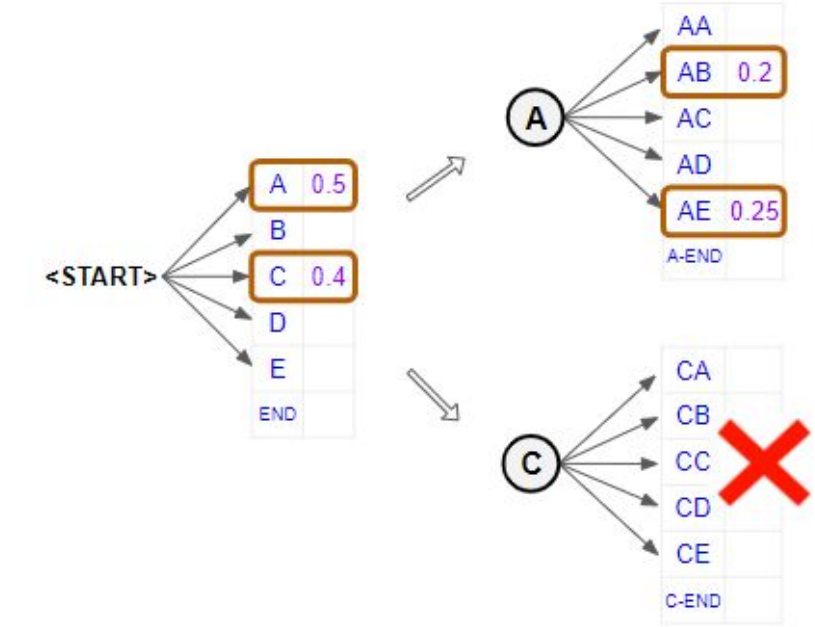
- Specify a beam size **b**: number of hypotheses we keep in memory
- At each step, prune the least likely hypotheses to keep only **b**
- Do this by simply multiplying probabilities of the current path
- Finally, select the path with the highest probability
    - Note that we do normalize by length as not to punish longer sequences

Let’s do an example
with a beam size of 2



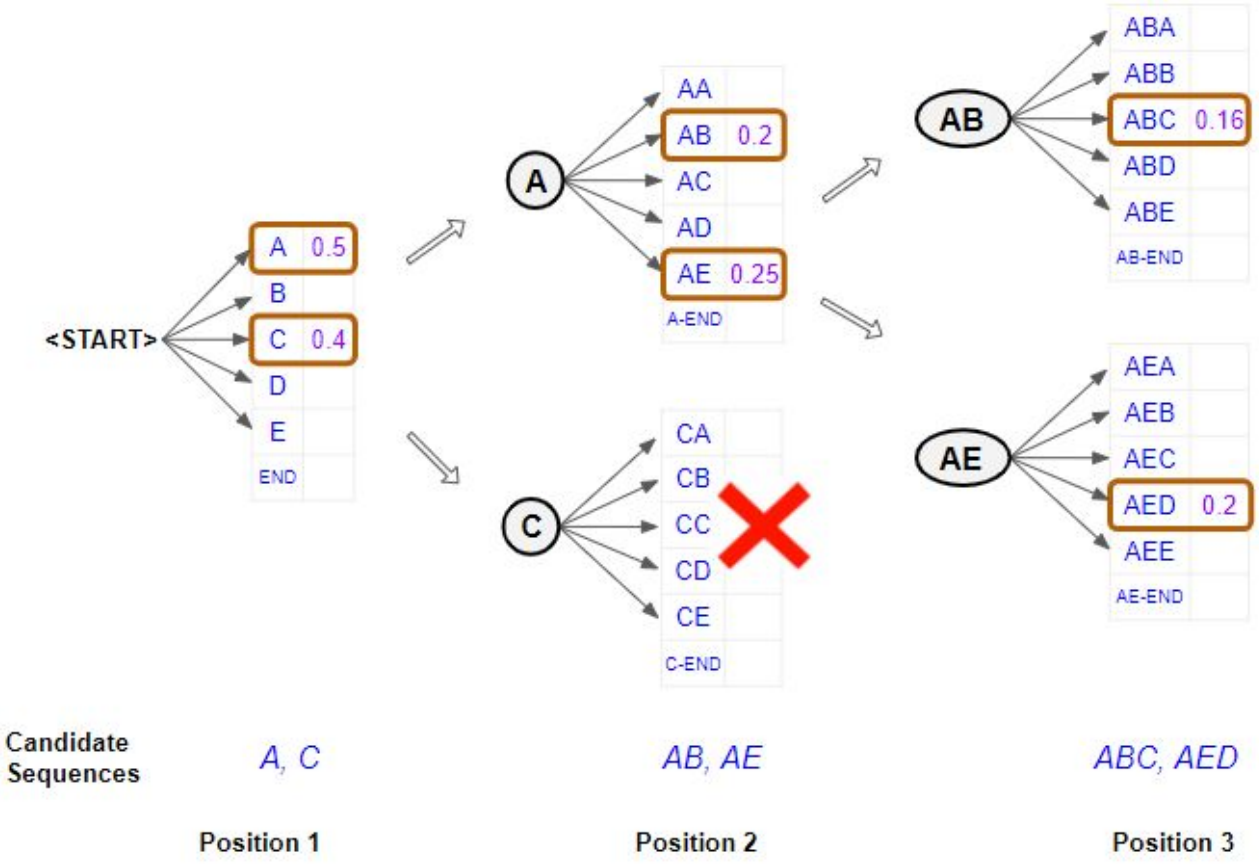
Candidate Sequences *A, C*

Position 1



Candidate Sequences *A, C* *AB, AE*

Position 1 **Position 2**


<START>
A 0.5
B
C 0.4
D
E
END
A
AA
AB 0.2
AC
AD
AE 0.25
A-END
C
CA
CB
CC
CD
CE
C-END
AB
ABA
ABB
ABC 0.16
ABD
ABE
AB-END
AE
AEA
AEB
AEC
AED 0.2
AEE
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Candidate Sequences
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Position 3

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Famous quote by Ray Mooney: you can't cram the meaning of whole f*cking sentence in a single f*cking vector

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- We pay **attention** to the encoder states that are relevant for the current state

Intuition: get a single vector based on all encoder states that takes into account what encoder states are most relevant for the current decoder state by taking a weighted average of them

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Say I have three vectors for my input words:

- v_1= [4, 10, 15], v_2 = [15, 6, 9], v_3 = [12, 5, 3]

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Final weighted vector: [8.9, 7.8, 10.8]

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- Continue the process as before

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Attention calculations

Attention output

$$c^{(t)} = a_1^{(t)} s_1 + a_2^{(t)} s_2 + \cdots + a_m^{(t)} s_m = \sum_{k=1}^{m} a_k^{(t)} s_k$$

"source context for decoder step t"

(weighted sum)

Attention weights

$$a_k^{(t)} = \frac{\exp(\text{score}(h_t, s_k))}{\sum_{i=1}^{m} \exp(\text{score}(h_t, s_i))}, \text{k} = 1..\text{m}$$

"attention weight for source token k at decoder step t"

(softmax)

Attention scores

$$\text{score}(h_t, s_k), \text{k} = 1..\text{m}$$

"How relevant is source token k for target step t?"

Attention input

$s_1, s_2, \ldots, s_m$ all encoder states

h_t one decoder state

Source: https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

Attention score

- We have yet to define the function score($\mathbf{s_k}$, $\mathbf{h_t}$)
- There are multiple variants that usually work well
  - **Dot-product:** score($\mathbf{s_k}$, $\mathbf{h_t}$) = $h_t s_k$
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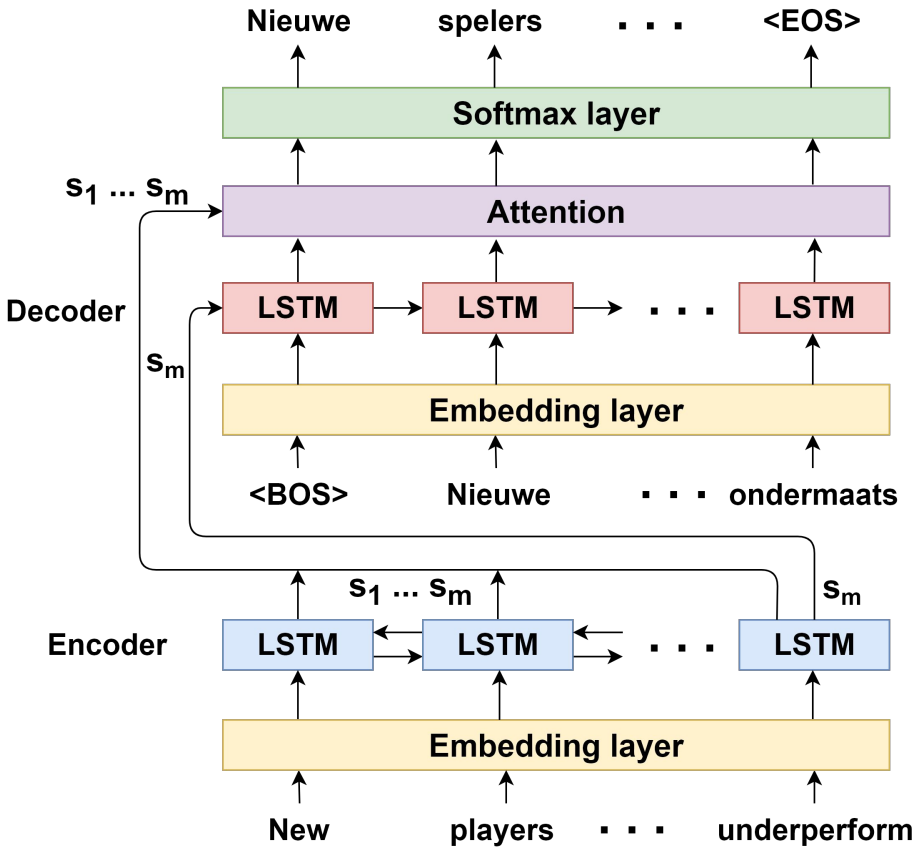
The nice thing about dot-product is that it doesn't introduce any extra weights that need to be learned. It turns out we can automatically learn weights for the other layers so that they work well with dot-product attention!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Deep learning wave: almost all NLP tasks could be modeled by using one of these models, lots and lots of papers with state-of-the-art results

Improving on word embeddings

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Surely we must be able to do better than a fixed vector per word!

ELMo: Deep Contextualized Word Representations

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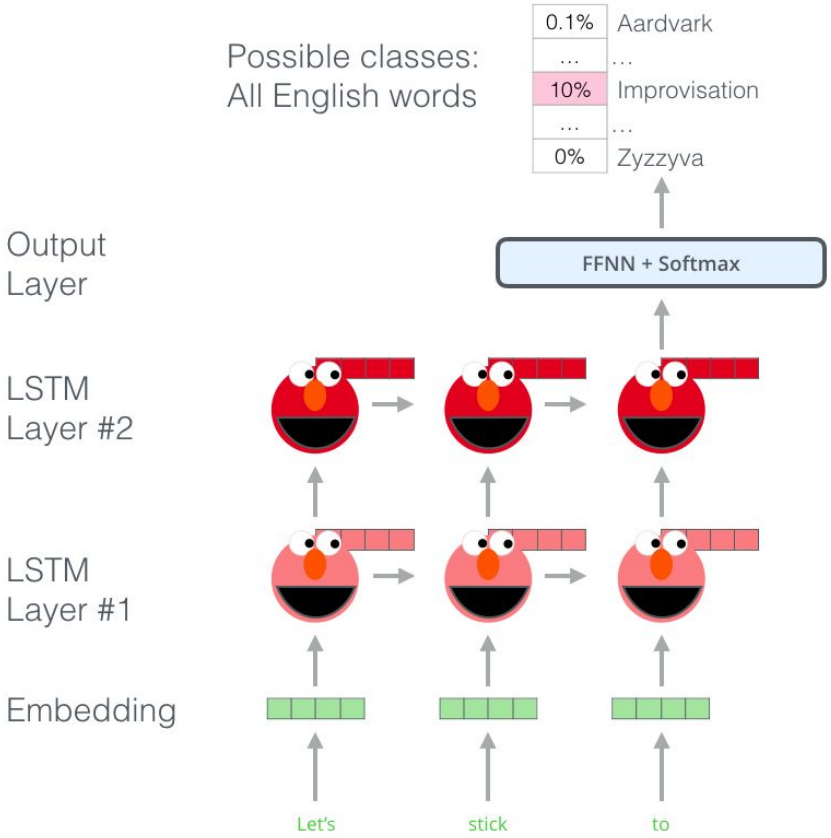
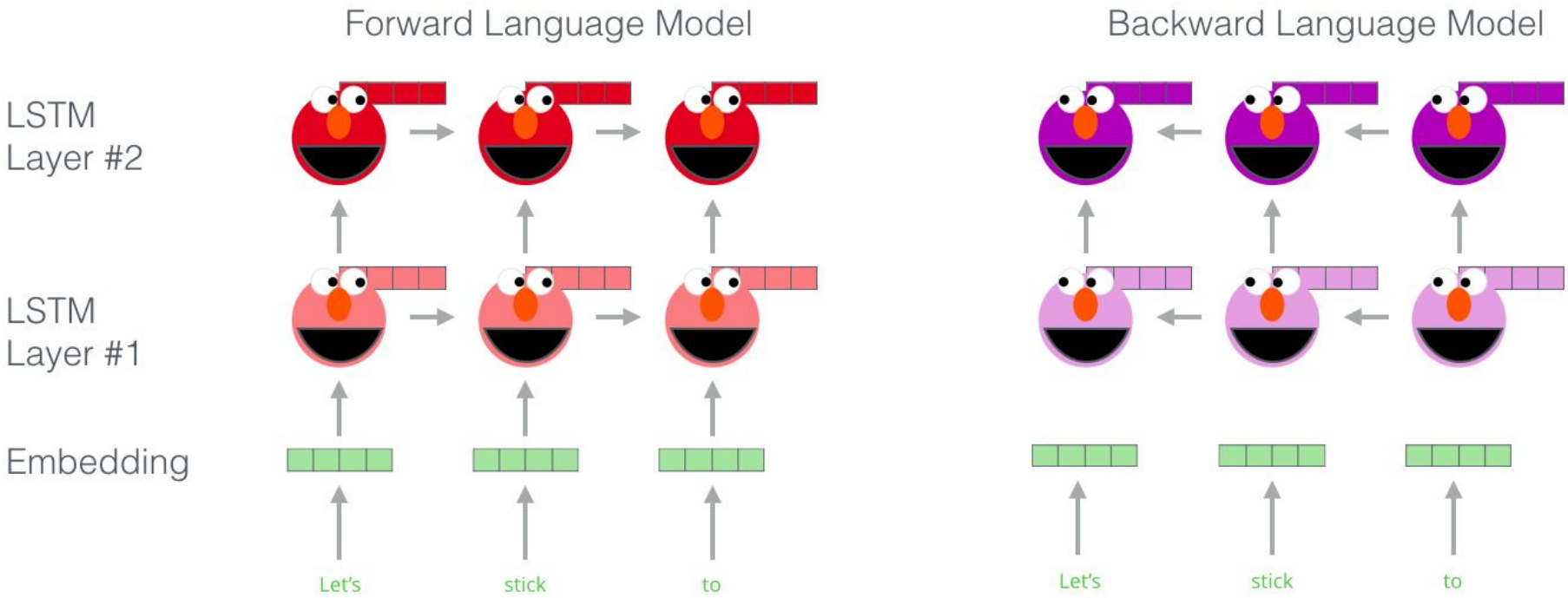
Intuition: use the pretrained LSTM model to initialize our own embeddings. Since the LSTM takes context into account, so do our input vectors now!

Source: https://jalammar.github.io/illustrated-bert/


Possible classes:
All English words
0.1%
Aardvark
...
...
10%
Improvisation
...
...
0%
Zyzzyva
Output Layer
FFNN + Softmax
LSTM Layer #2
LSTM Layer #1
Embedding
Let's
stick
to

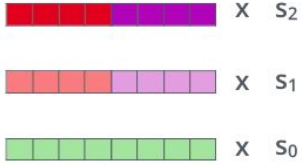
Embedding of “stick” in “Let’s stick to” - Step #1



Embedding of “stick” in “Let’s stick to” - Step #2

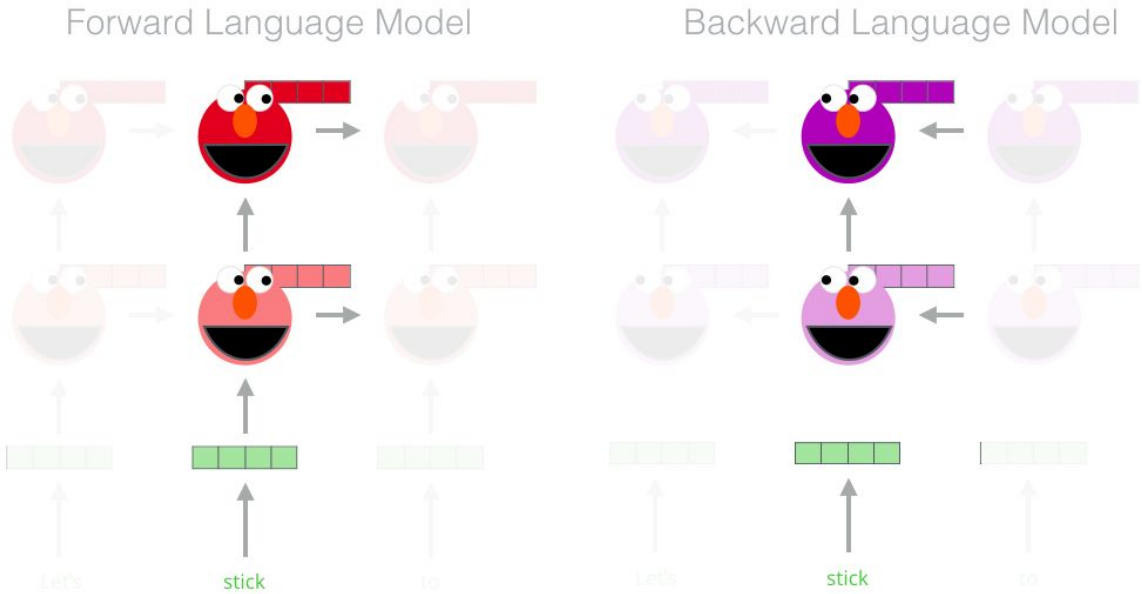
1- Concatenate hidden layers

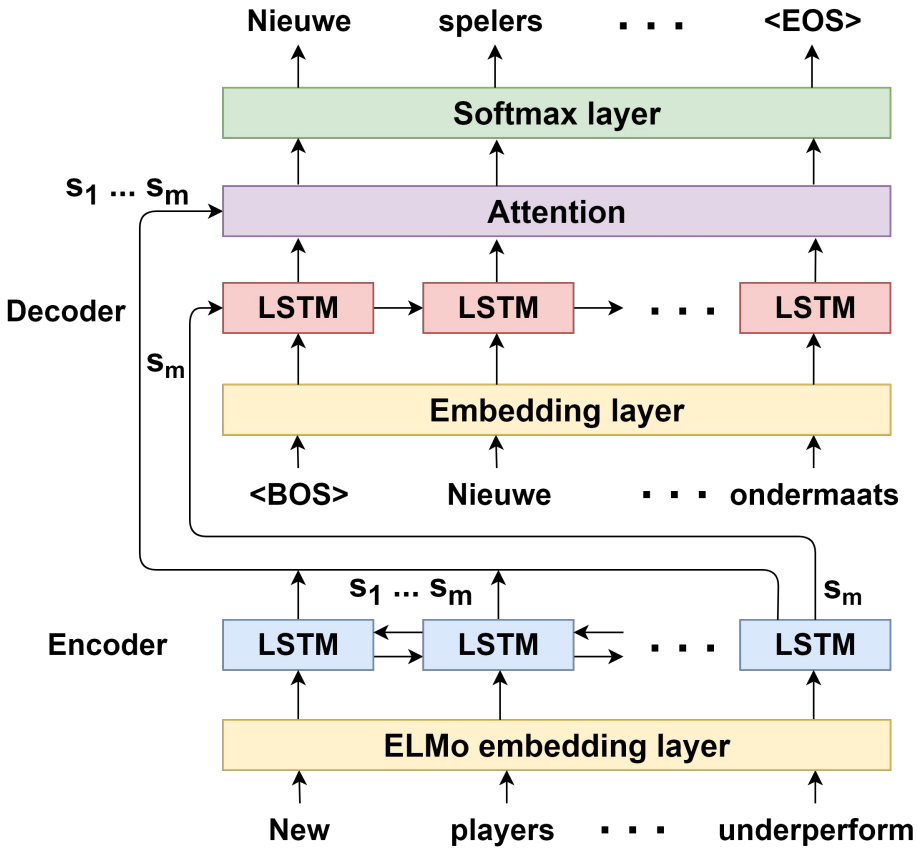
2- Multiply each vector by a weight based on the task

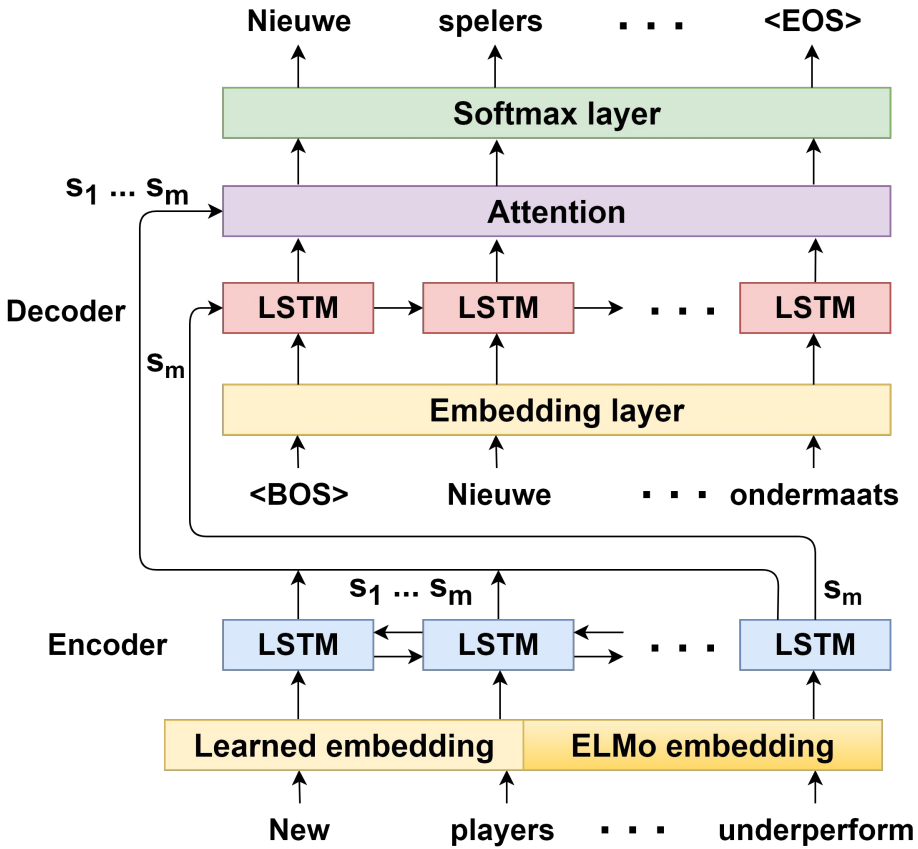


3- Sum the (now weighted) vectors

ELMo embedding of “stick” for this task in this context




Nieuwe
spelers
. . .
<EOS>
Softmax layer
s1 ... sm
Attention
Decoder
LSTM
LSTM
. . .
LSTM
sm
Embedding layer
<BOS>
Nieuwe
. . .
ondermaats
s1 ... sm
sm
Encoder
LSTM
LSTM
. . .
LSTM
ELMo embedding layer
New
players
. . .
underperform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Why does this work so well?

Transfer learning: the model learns how to do task X well (in this case language modelling). This knowledge can then **transfer** towards different tasks. The weights of the model have acquired some sort of general “understanding” of language.

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Of course, they start out being far from perfect. Training a model on a different task might also not be perfect, but it’s easy to do better than a **random** initialization!

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Word embeddings: the embedding layer should not be randomly initialized
Transfer learning: as much weights as possible should not be randomly initialized

Assignment 3

- In groups of 3. Write a report structured like a research paper again
- Experiment with LSTMs and pretrained word embeddings
- Experiment with fine-tuning pretrained language models
  - This will all be explained next week!
  - Work with Google Colab for access to GPU
- Extra requirement: paragraph on who did what
  - Potentially grades can be changed based on this information
- Please check Brightspace for a long list of papers and resources

Deadline: 16 October 10:59