Natural Language and Speech Processing

Lecture 8: Neural Attention

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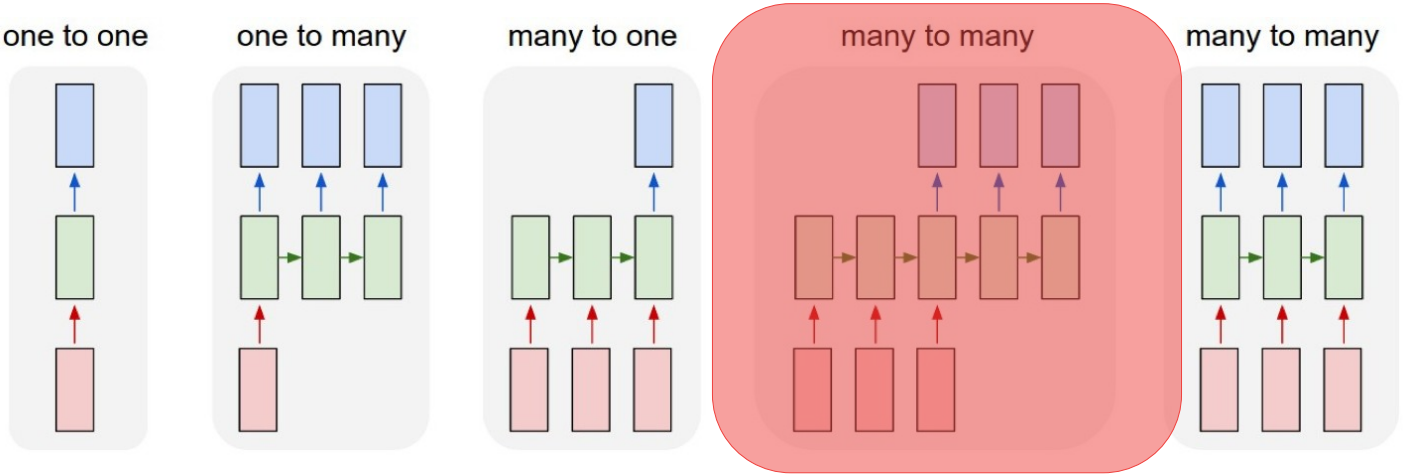
Recurrent model types

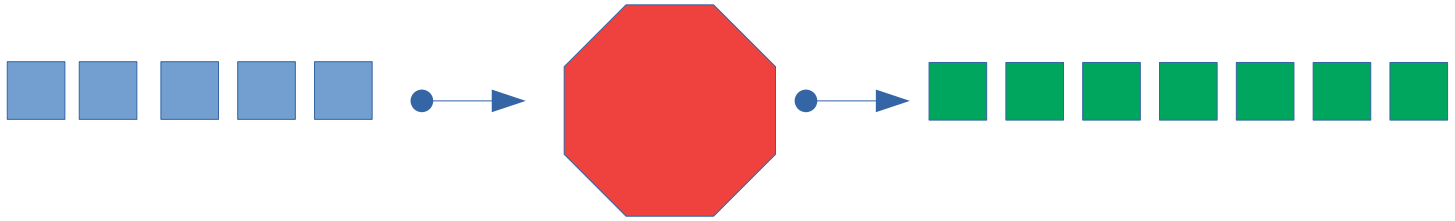
- Using recurrent neural networks, we can:
  - Classify items in a sequence
    - e.g., classify words in a sentence
  - Classify sequences (using hidden state corresponding to the last item of the sequence)
  - Generate sequences from the model
- **But how to deal with a problem when both the input and output are sequences, but of different length?**



Sequence-to-sequence

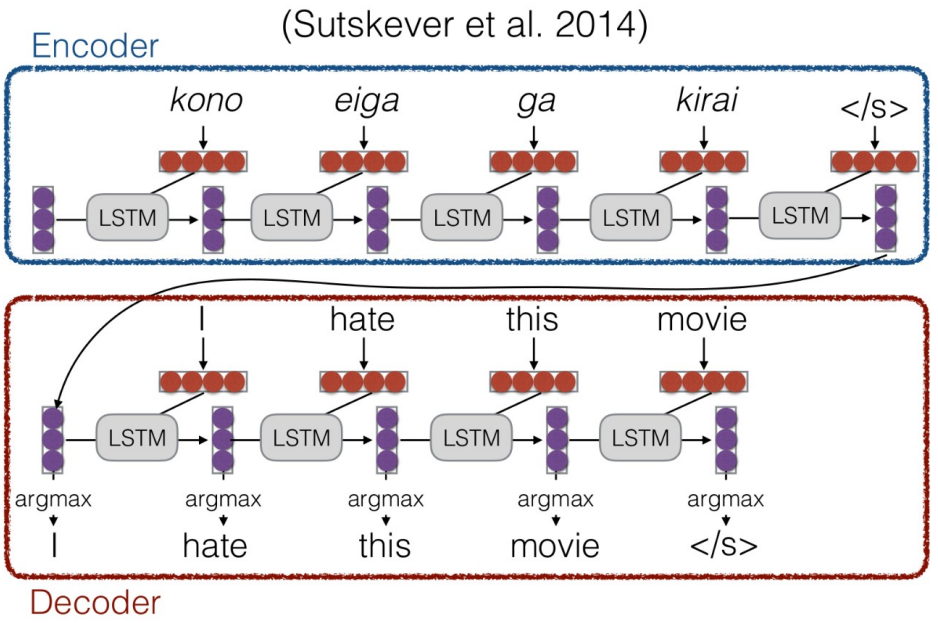
- Encoder-decoder models
- Also know as sequence-to-sequence (seq2seq models)

- Useful for
  - Machine translation
  - Summarization
  - Question answering
  - Chat bots



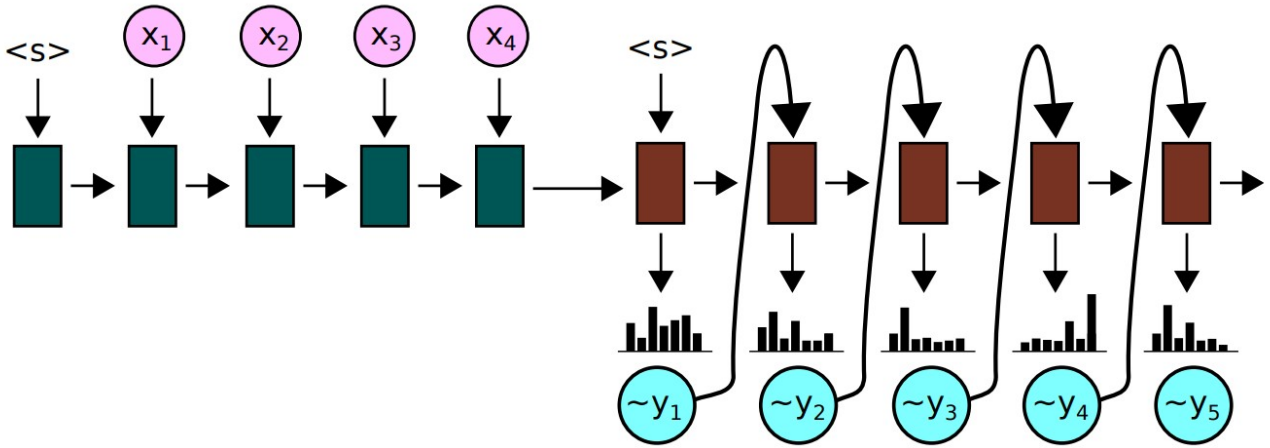
Basic idea

- Basic idea on RNN-based seq2seq models:
  - Use one RNN (**encoder**) to process the input sequence
  - Take the hidden state after processing the last item in the input
  - Feed the hidden state to the second RNN (**decoder**) as the initial state
  - Generate until </s>!



Sequence-to-sequence

- Advantage:
  - Can be trained end-to-end (i.e., there is just one model, and all you need is a lot of input-output pairs as training data
- Does it work?
  - Kind of

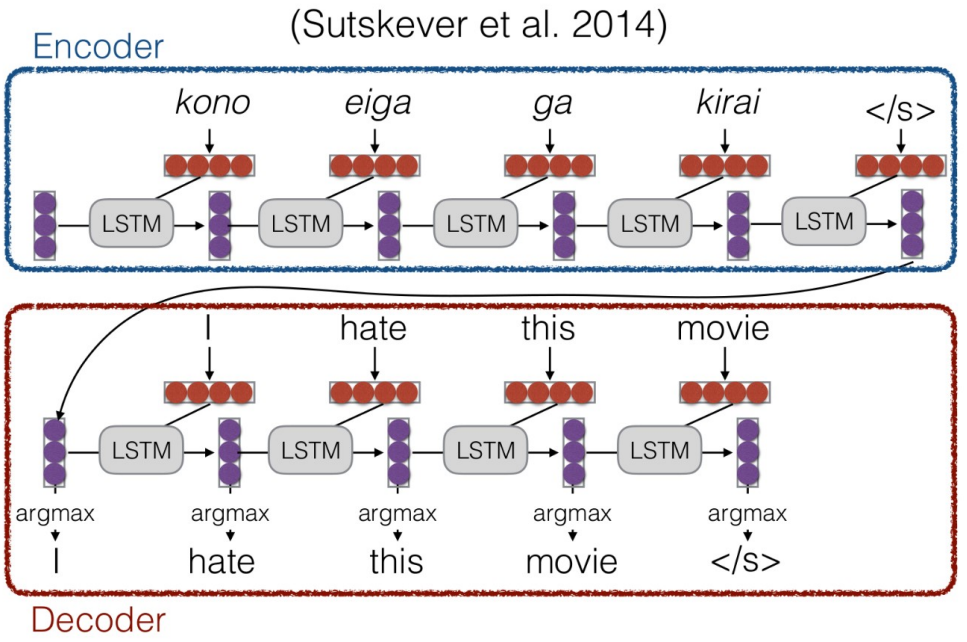


Early neural machine translation

- Before neural MT, statistical MT was used
- Statistical MT retained most of the meaning, but the syntax of the generated sentence was often horrible
- Output of neural MT is very different from statistical MT
  - Always very fluent
  - But sometimes the meaning is completely lost!

Problem with this architecture

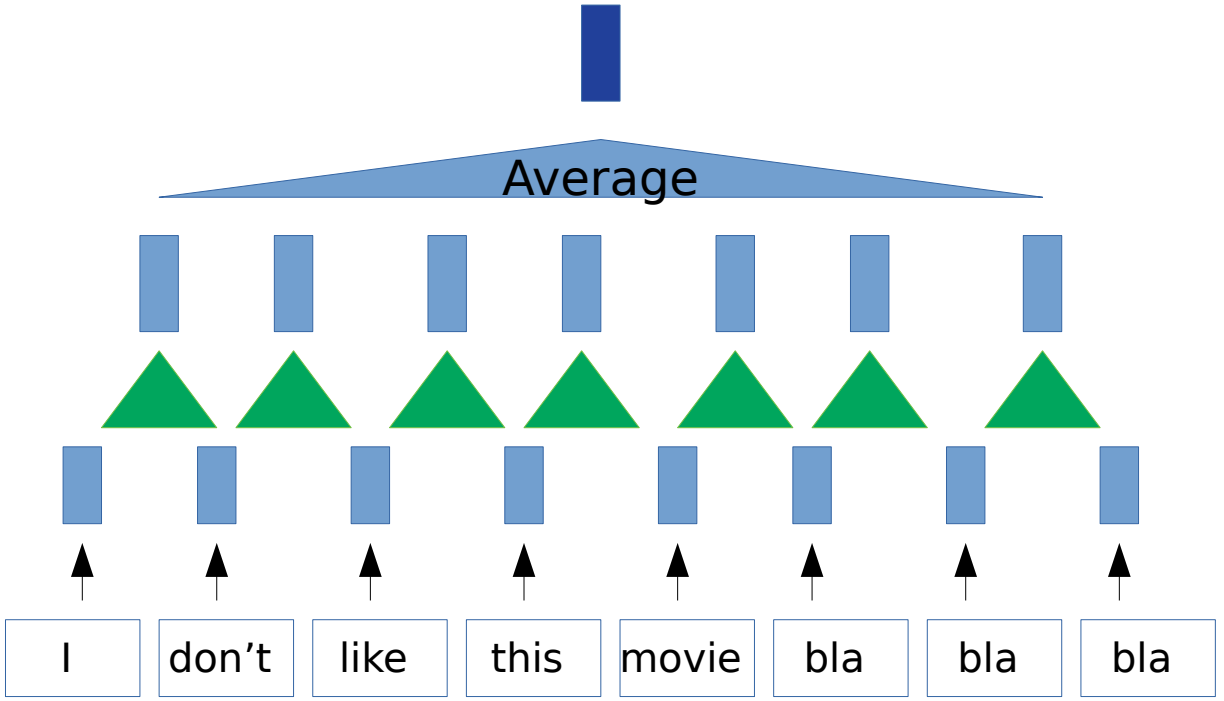
- The whole source sentence is compressed into one vector
- The vector has fixed dimensions, regardless of the sentence
- “You can’t cram the meaning of a whole *%&!$ing* sentence into a single *$&!*ing* vector!” — *Ray Mooney*
- Fixed-length vector makes it difficult to translate longer sequences
- Often it has forgotten the earlier parts of the sequence once it has processed the entire the sequence.



Neural Attention

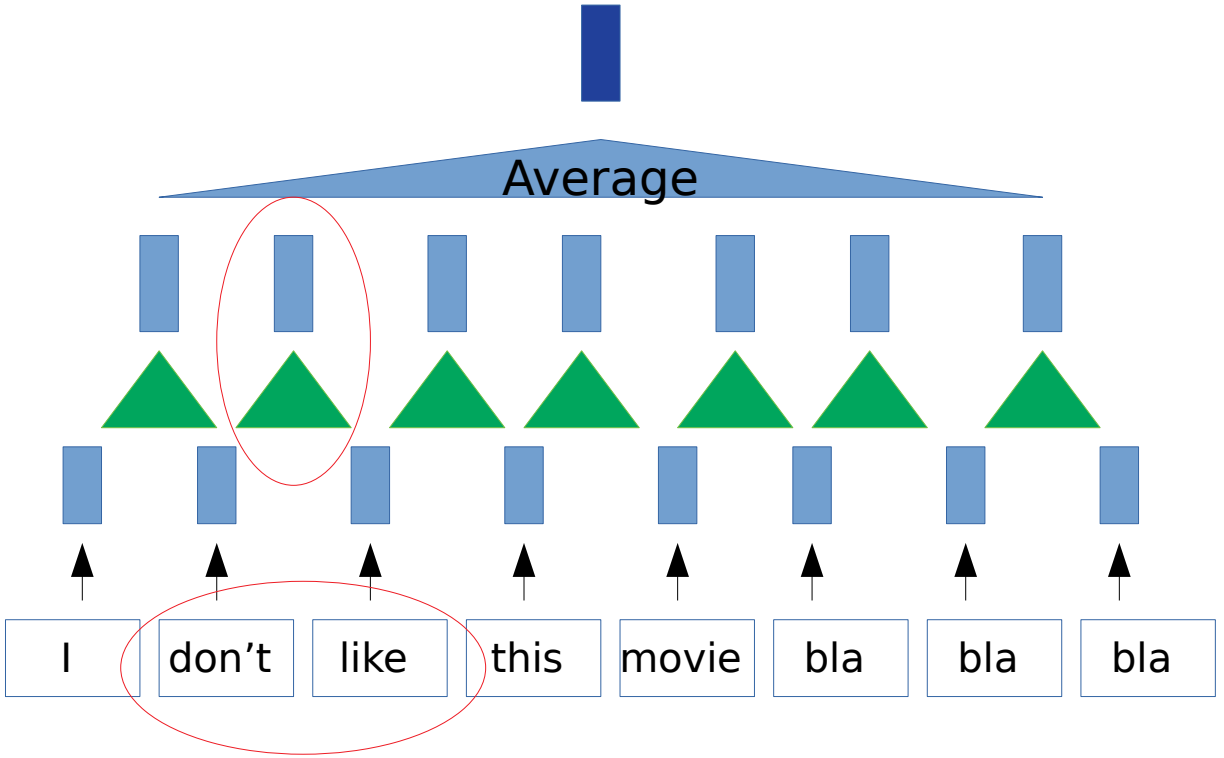
Global pooling

- Remember convolutional neural networks?
- When applied for sequence classification (e.g. sentiment analysis), global (average or max) pooling is often applied to find the fixed-length vector of the whole text



Problem with global pooling

- Global pooling is too generic:
  - E.g., the bigram „don’t like” is really useful for sentiment analysis, but we „bla bla bla” can be discarded
- In other words, we need something like a **weighted average**



Sentence vector

Global pooling

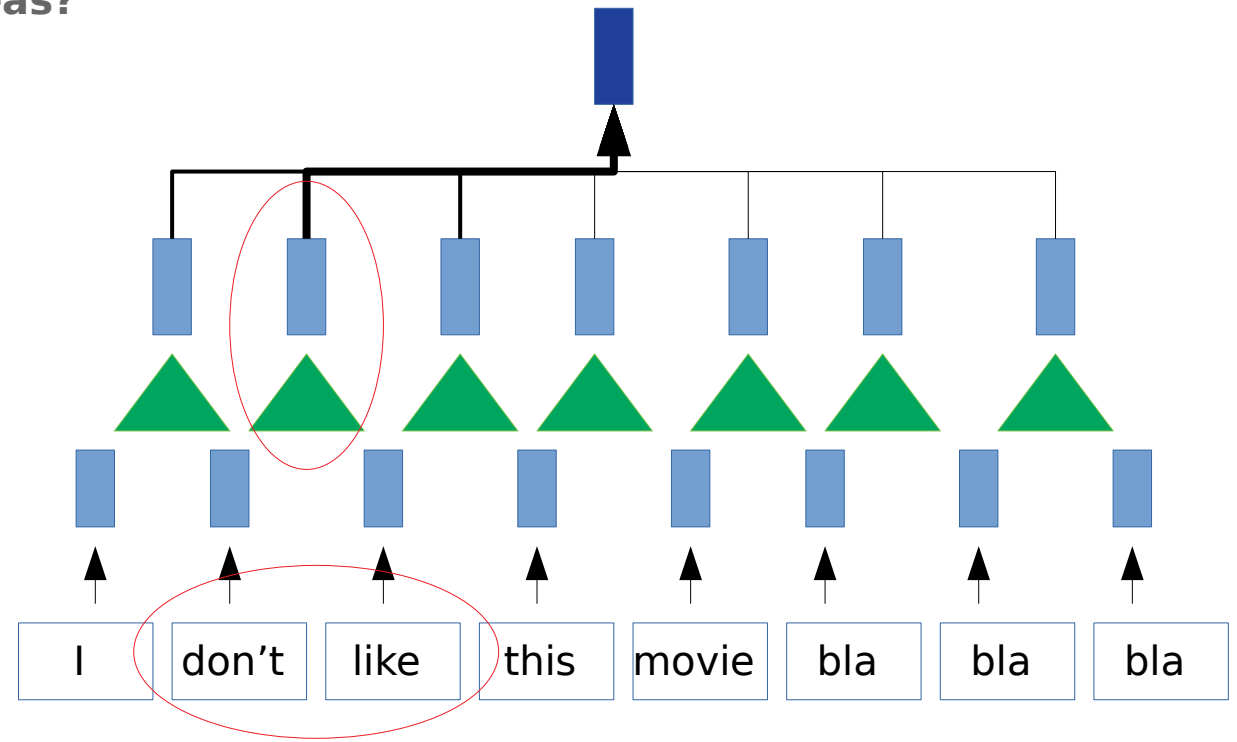
Bigram vectors

Convolution

Word embeddings

Weighted average?

- Weighted average would allow us to combine the sentence vector out of only the most relevant parts of the sentence
- **But how to get the weights for the weighted average?**
- The weights must depend on the input sentence
  - i.e., we cannot expect that bigrams 2 and 3 are always most important
- **Any ideas?**



Sentence vector

Global pooling

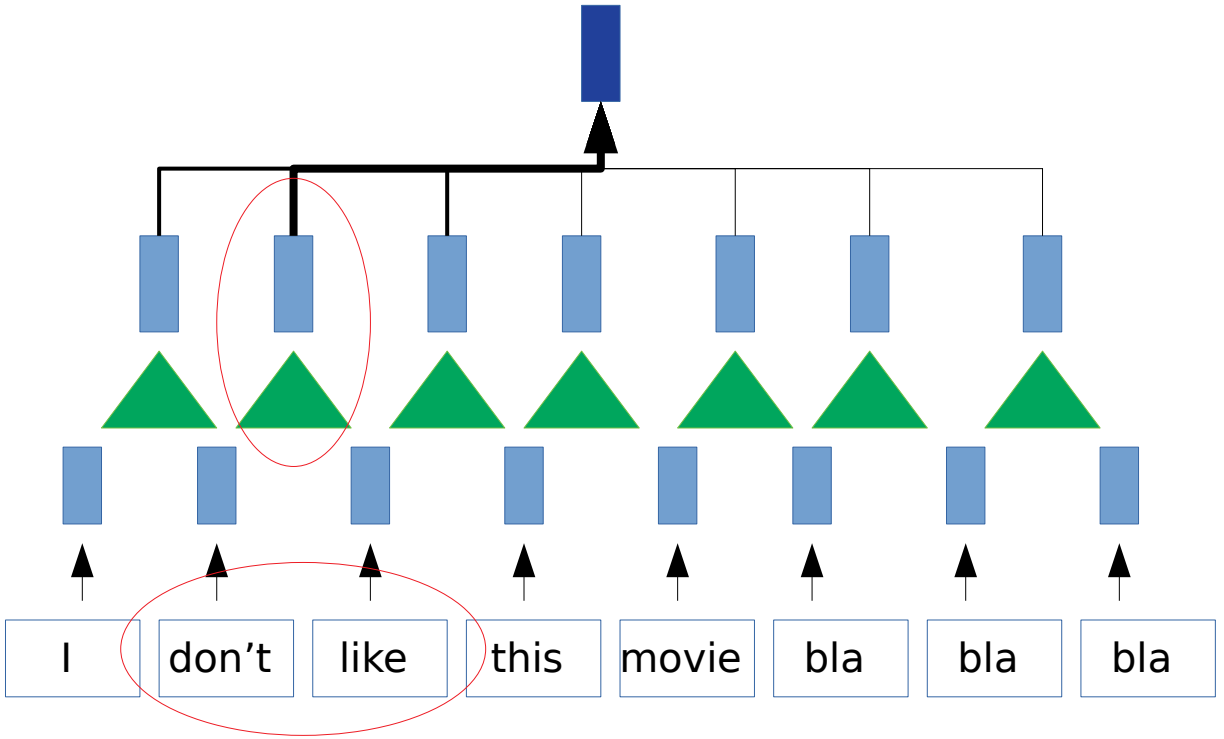
Bigram vectors

Convolution

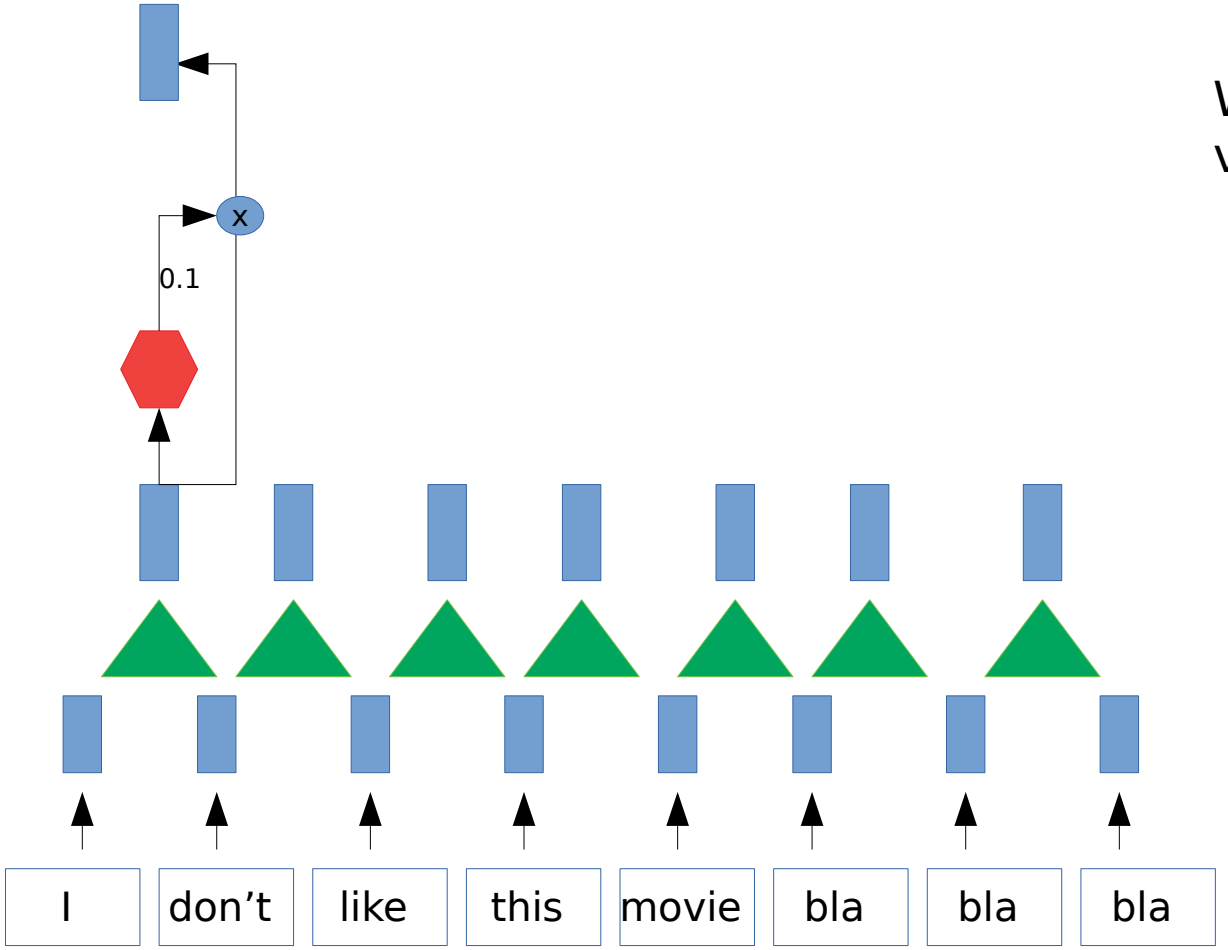
Word embeddings

Weighted average

- How to get the weights for the weighted average?
- Solution: use a small neural network!
- We feed each **bigram vector** into the small neural network, and it will tell us the weight



Computing the weights



Weighted bigram vector

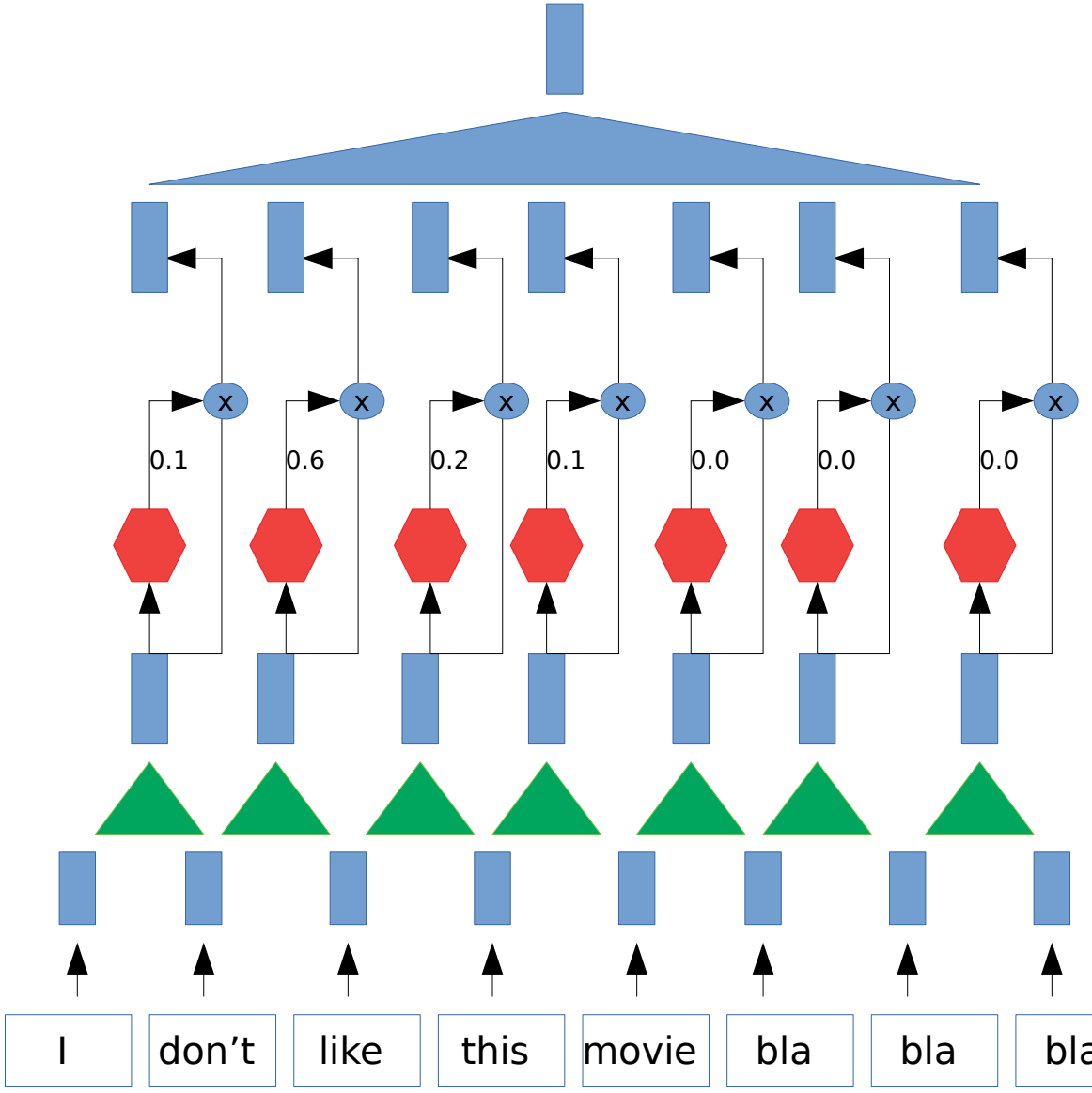
„Weight computer”

Bigram vectors

Convolution

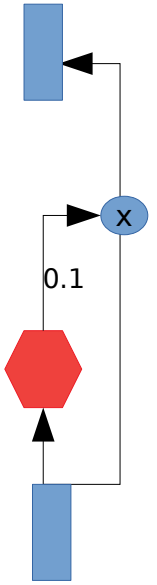
Word embeddings

Computing the weights



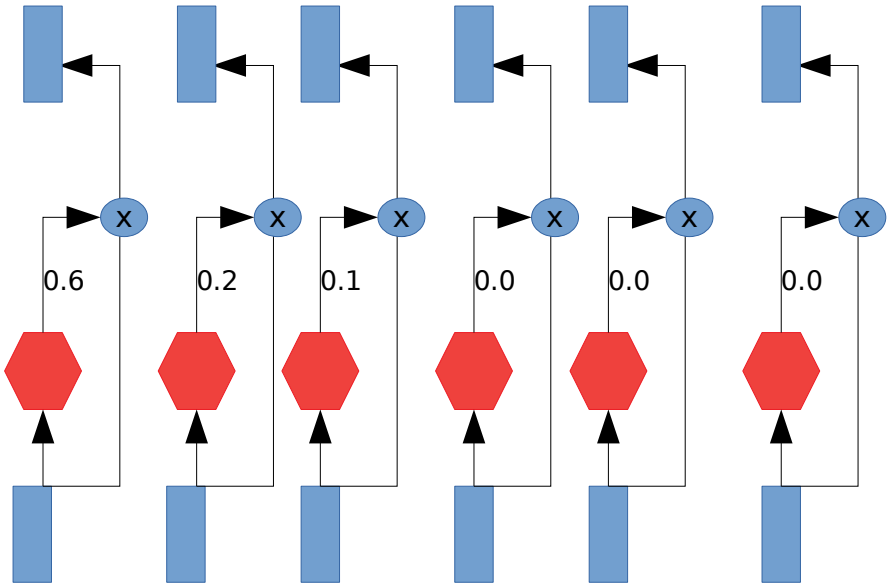
Weight computer

- What kind of neural network the weight computer (the red hexagon) is?
  - Usually just one hidden layer (+ nonlinearity like ReLU) is enough
- But „who” gives this neural network to us?
  - We simply train it, like other parts of the neural network
- Intuition: in the context of sentiment analysis, the weight computer will learn to recognize „emotional” phrases, like „don’t like” „loved the plot”, „hated the music”, etc, and assign higher weights to them



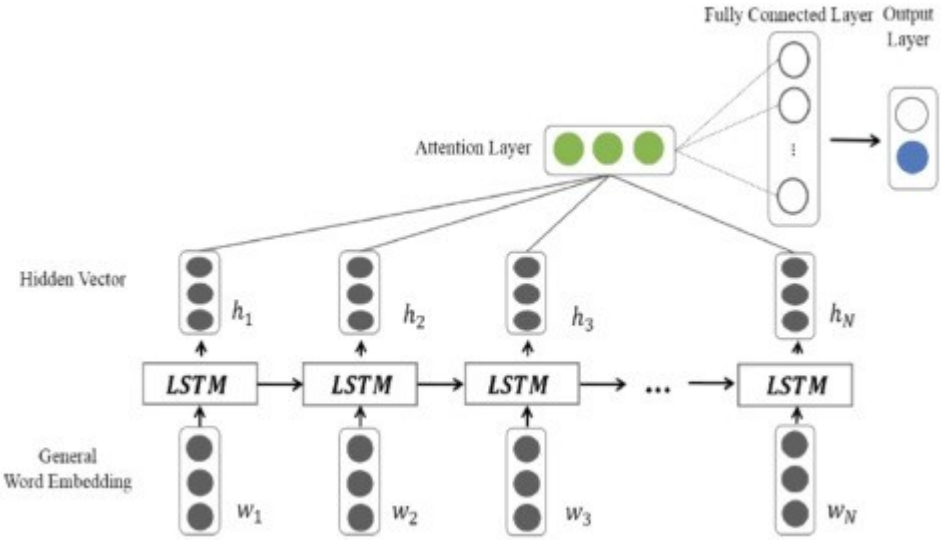
Weighted average: sum to 1

- Of course, when we compute the weighted average, the weights should sum to 1
- This is can be achieved using *softmax*
  - Output of the *weight computer NN* is normalized using softmax over the whole sentence/document
  - This guarantees that the weights/scores are all positive and sum to one



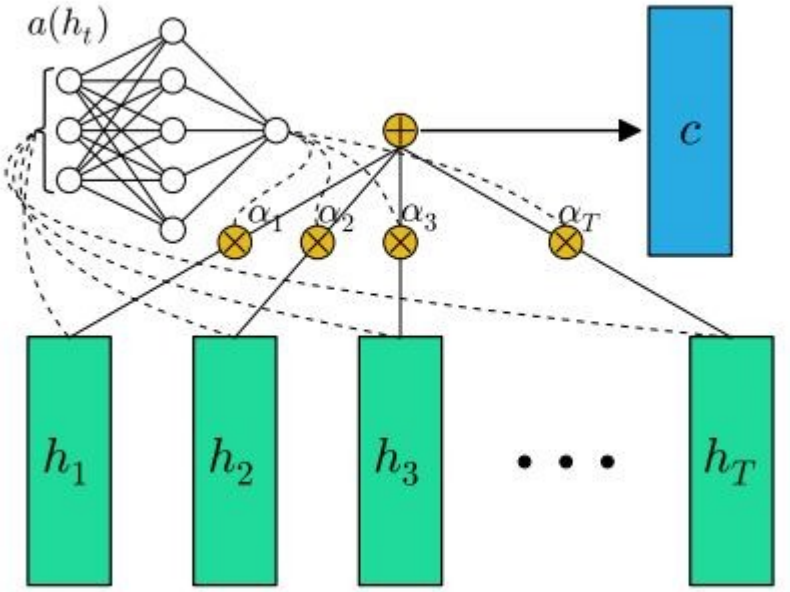
LSTMs and Attention

- In our example, we used convolutional neural network for getting intermediate representations (bigram vectors)
- We can also use RNN (LSTM) to give us the intermediate vectors, and apply attention to them



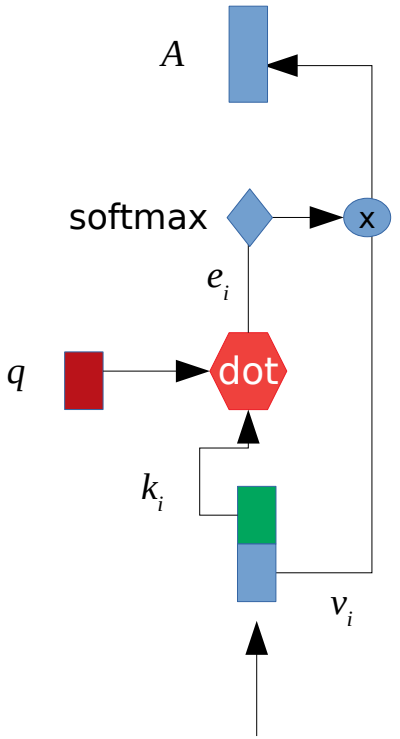
Attention mechanism

- This kind of weighted average using learned weight computer is called **attention mechanism**
- Attention mechanism is a bit similar to RNN: it also allows compressing a sequence of varying length into a fixed-length vector
  - But it is also quite different



Attention with query, key and value

- Often attention mechanism is implemented using **query, key and value**:
  - The underlying DNN (CNN or RNN) generates a representation (vector) that is viewed as consisting of two parts: **key** and **value**
  - The weight finder is not a small DNN but **a vector** („**query**"), **with same dim as key**
  - Score (e_i) is simply computed as a **dot product (similarity) between key and query**
  - Weights over a sequence are softmaxed
  - The softmaxed weight is multiplied with the **value**

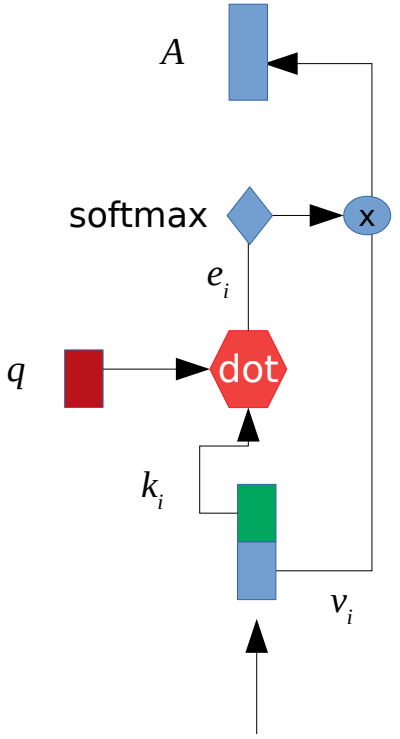


$$e_i = q^T k_i$$

$$A(q, K, V) = \sum_i \frac{\exp(e_i)}{\sum_j \exp(e_j)} v_i$$

Attention with query, key and value, cont.

- In practice, simple dot product is not the best metric for calculating the score of key, given the query
- Instead, use an additional weight matrix $\boldsymbol{W_s}$ between query and key
- This allows the model to learn which aspects of similarity between the key and query states are important

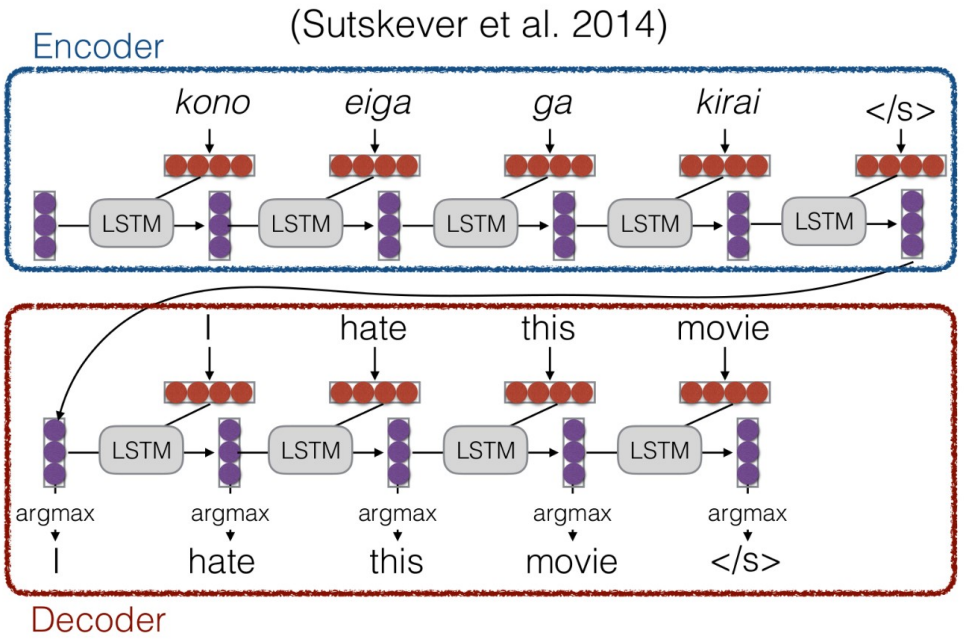


$$e_i = q W_s k_i$$

$$A(q, K, V) = \sum_i \frac{\exp(e_i)}{\sum_j \exp(e_j)} v_i$$

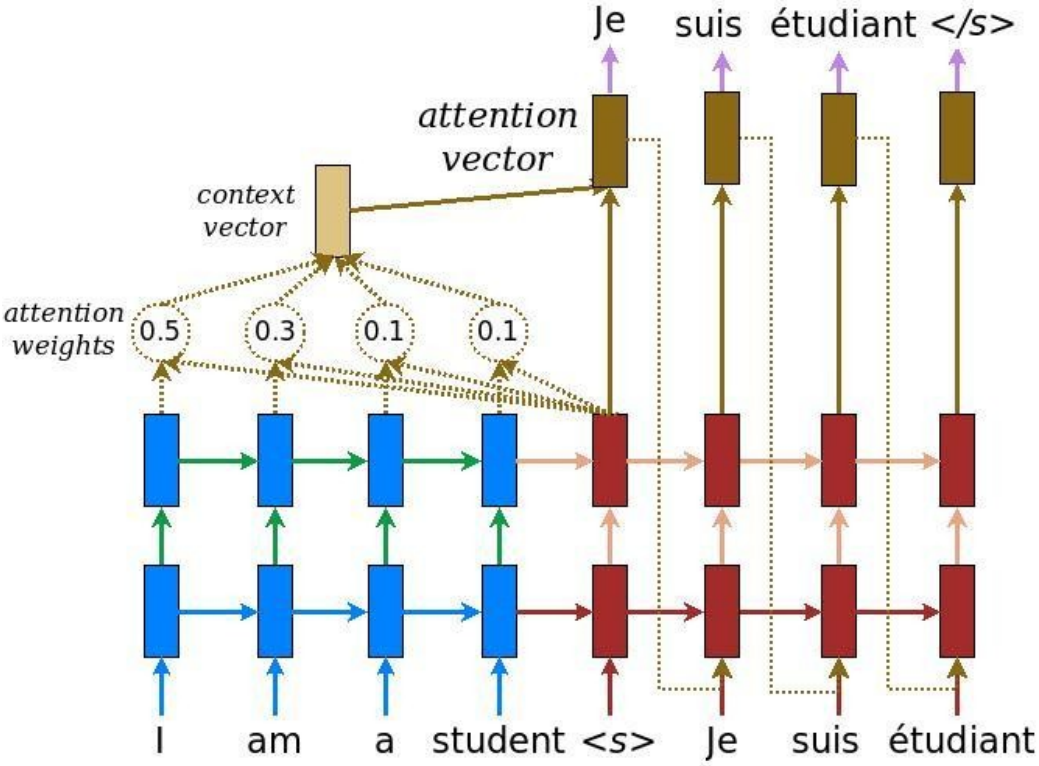
Attention in seq2seq

- But what does attention have to do with the information bottleneck problem in seq2seq models?
- It turns out that attention can be effectively used to give the decoder a view over the whole input sequence at each decoding step
- Then, we don't have to put encode the full source sentence into the hidden state that is passed from encoder to decoder



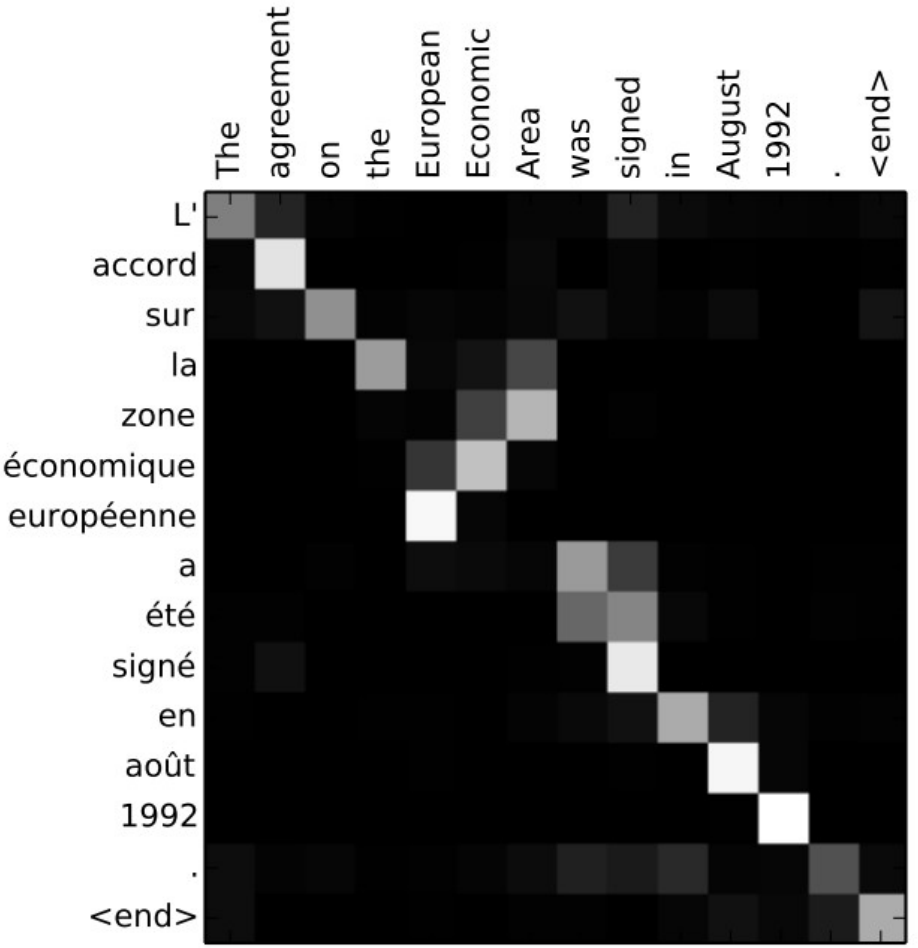
Attention in seq2seq

- Pass the source sentence through a RNN
- When generating a target sentence, use the **current hidden state of the decoder as the query vector** in attention
- Use the query vector to compute a new context vector from source sentence
- Use the result („attention vector”) as additional input when generating the next word



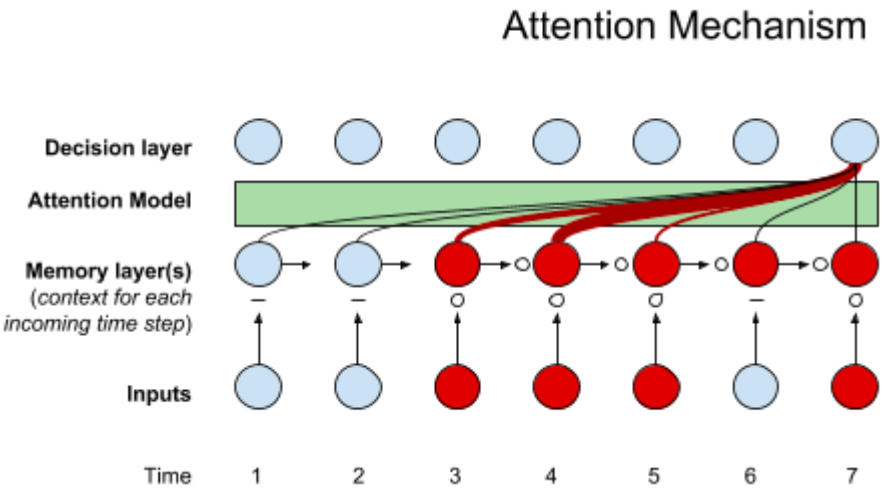
Visualizing attention

- We can check which words in the source sentence had highest weights for each target word
- In other words, which words were **attended to**
- You can see how the model paid attention correctly when outputing "European Economic Area"
- In French, the order of these words is reversed ("européenne économique zone") as compared to English



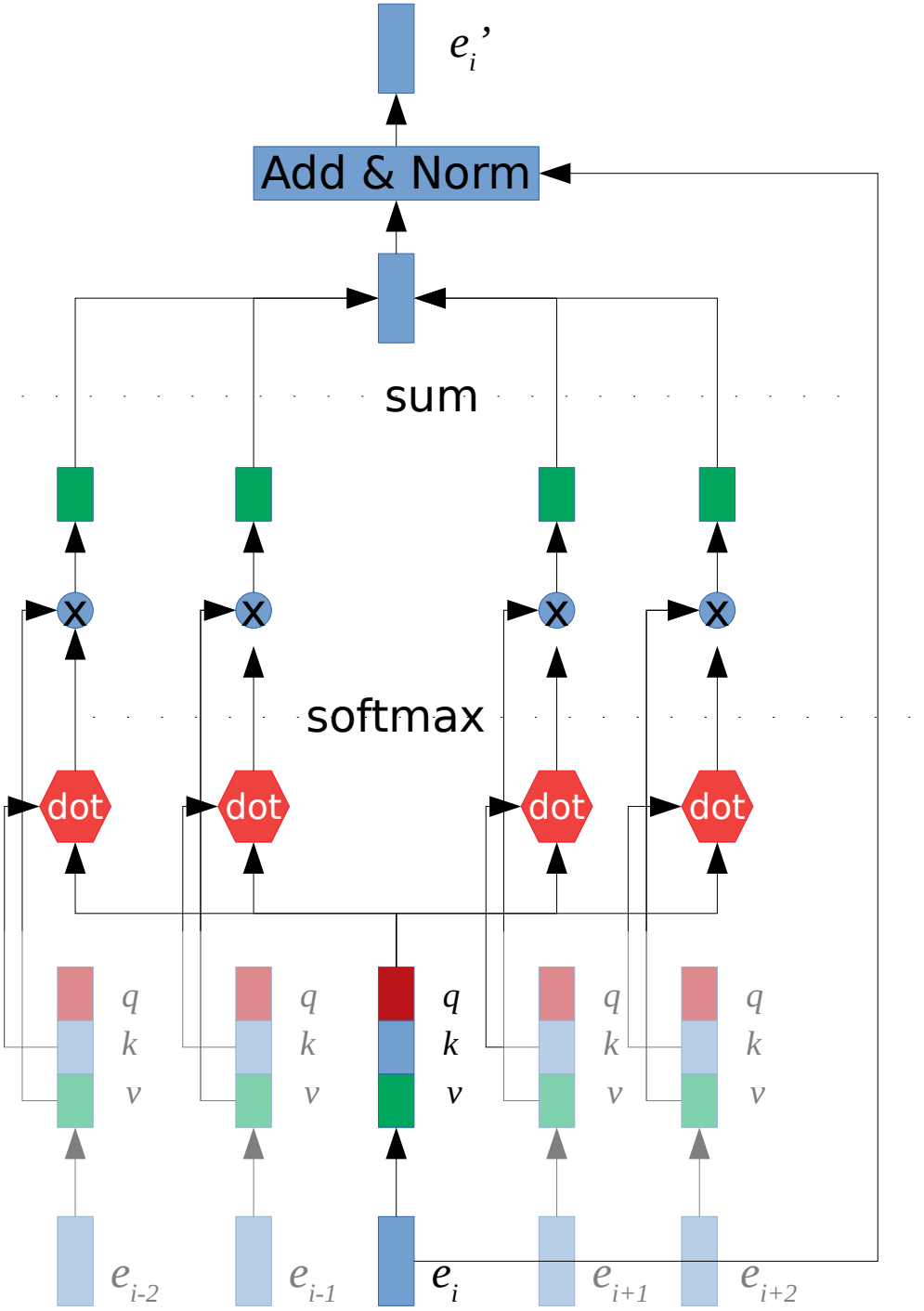
Self-attention

- So far, we looked at how to use attention for classifying a sequence
  - Attention acts as a weighted average over the sequence
- But attention can be also used for sequence tagging or next-word prediction
  - In this case, attention over the whole sequence is computed for each word independently, using the current word itself as a query vector
- This is called **self-attention**



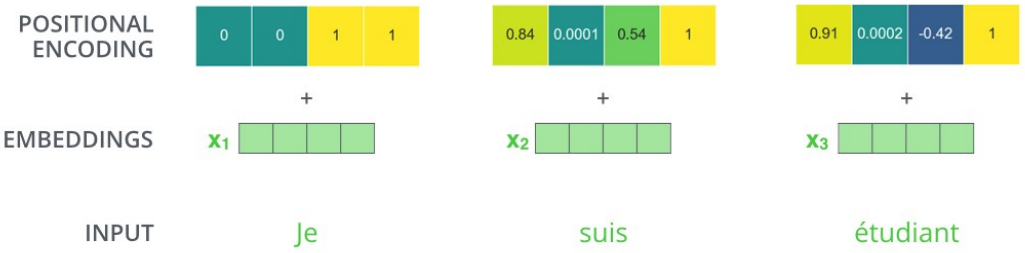
Self-attention explained

- Self-attention transforms word embeddings *e* to new word embeddings *e'*
  - Each *e* is transformed to *q*, *k* and *v*, using matrix multiplication (using shared matrices for each position)
  - Vector *q* of position *i* is compared to vectors *k* of all other words, using dot product
  - Result is softmaxed over the whole sequence
  - Softmax values are used to compute weighted *v* vectors
  - Result is summed
  - Initial e is added to the new weighted sum, and the result is normalized, producing new *e'*



Positional encodings

- Attention loses all information about word order
  - When computing the attention weights (and the resulting weighted average), word order is not taken into account in any way!
- Positional encoding is a way to deal with sequential data when no recurrency or temporal information is available due to the lack of RNNs
- Solution: for each input word, the input embedding is a sum of two vectors:
  - The word embedding
  - A vector describing the word's position



Positional encodings, cont.

- Usually, sinusoidal embeddings are used
  - Positional embeddings have the same dimensionality as word embeddings (e.g. 200)
  - Each dimension is a sine/cosine of the current timestep, using different frequency
- This allows to encode both absolute and relative position of the word

$$\overrightarrow{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases}$$

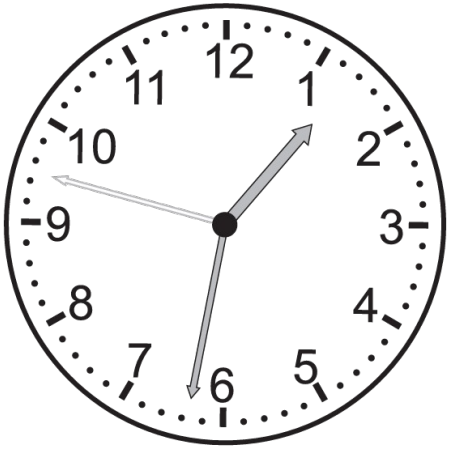
where

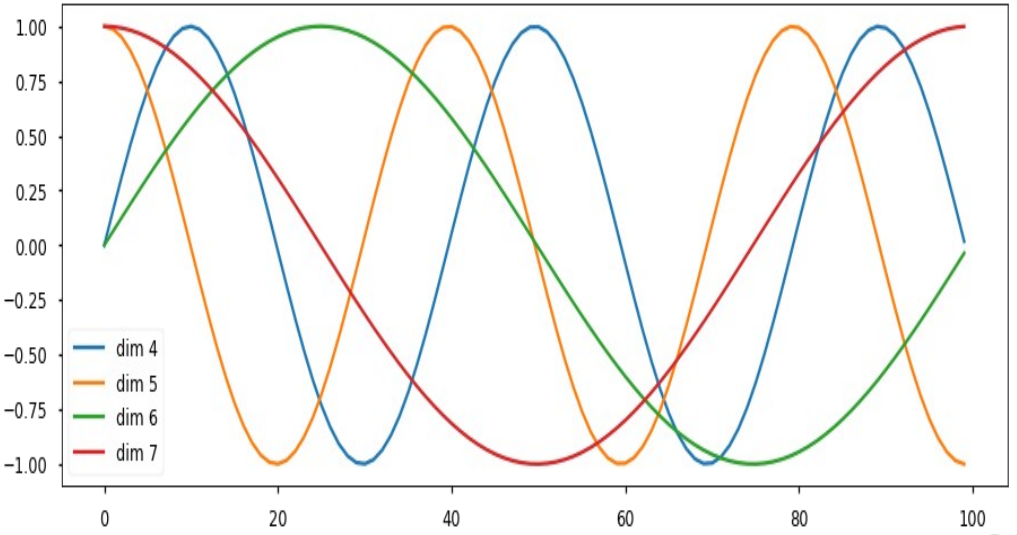
$$\omega_k = \frac{1}{10000^{2k/d}}$$

$$\overrightarrow{p_t} = \begin{bmatrix} \sin(\omega_1 . t) \\ \cos(\omega_1 . t) \\ \\ \sin(\omega_2 . t) \\ \cos(\omega_2 . t) \\ \\ \vdots \\ \\ \sin(\omega_{d/2} . t) \\ \cos(\omega_{d/2} . t) \end{bmatrix}_{d \times 1}$$

Positional encodings, cont.

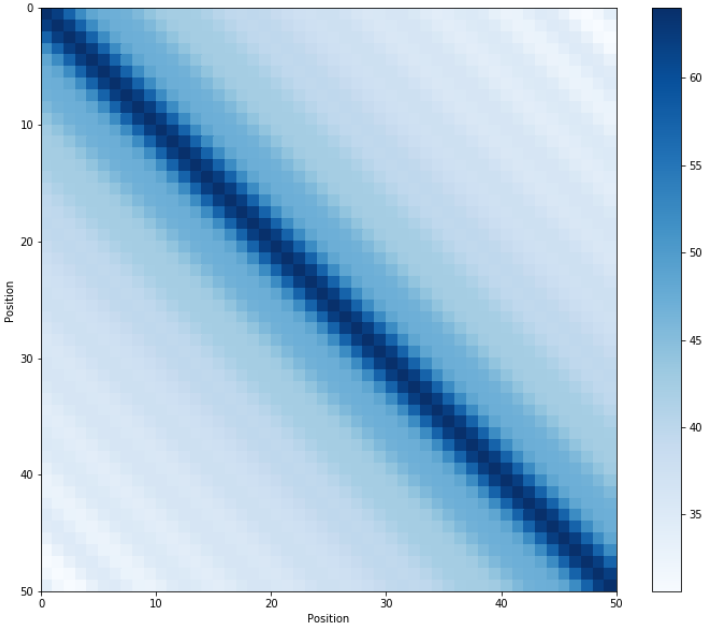
- Intuitive explanation of positional embedding is to think about it as a clock
  - Clock is a positional encoding with **three** dimensions
    - Hours hand, minutes hand, seconds hand
  - Moving from one position to the next position is just rotating those hands at different frequencies
    - (Thanks to Jiaxuan Wang for this great explanation)





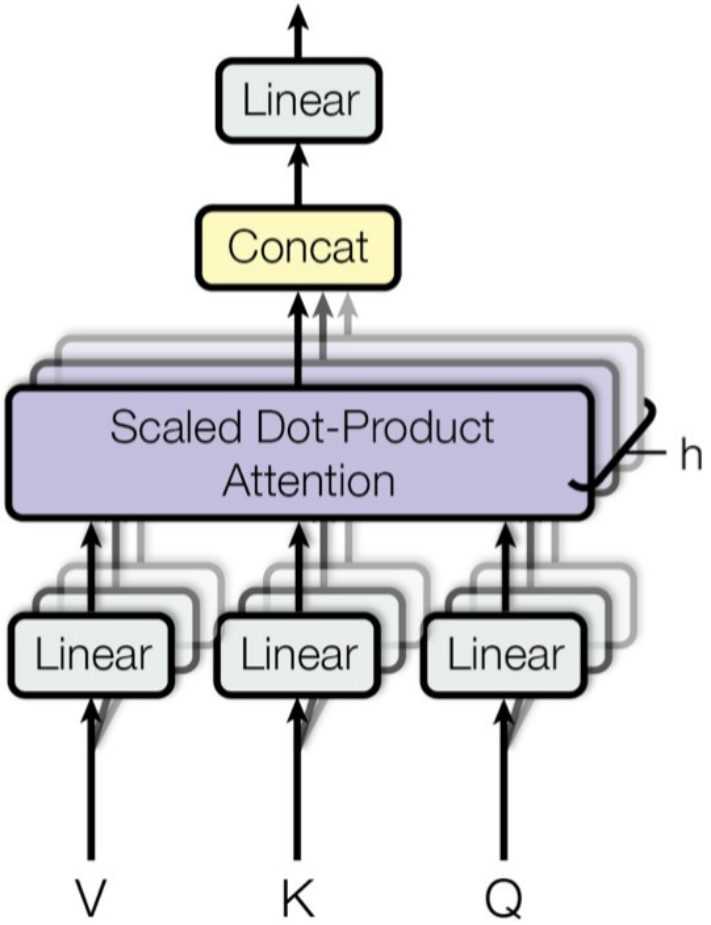
Positional encodings, more

- Another property of sinusoidal positional encoding is that the **distance** between neighboring time-steps are **symmetrical** and decays nicely with time
- That is, words that are close to each other in the text have embeddings that are closer to each other than words far apart!



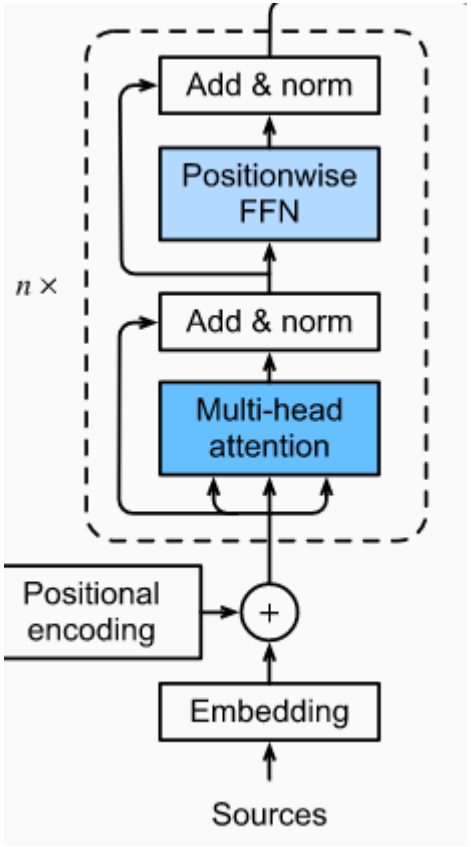
Multi-head attention

- Attention mechanism is used as a way for the model to focus on relevant information based on what it is currently processing
- It is difficult to capture various different aspects of the input, using a single attention weighted sum
- To solve this problem the Transformer uses the **Multi-Head Attention** block
- This block computes multiple attention weighted sums instead of a single attention pass over the values



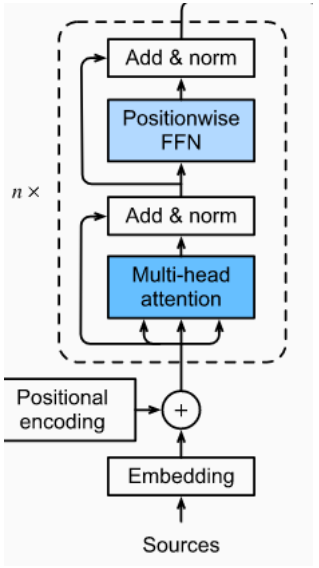
Sequence processing using attention

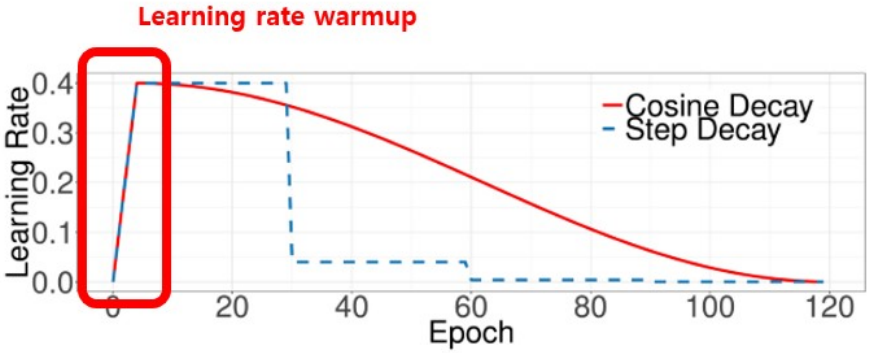
- Modern NLP sequence processing:
  - Positional encoding
  - Several layers of:
    - Multi-head self-attention
    - Add & norm
    - Positionawise feed-forward layer (same as convolution with kernel size 1)
    - Add & norm



Why better/worse than RNN?

- RNN (incl LSTMs):
  - Long distance dependencies still difficult, despite LSTMs
- Attention:
  - Each step has **direct** access to all the other steps (self-attention)
- However: Attention based models
  - Require more data
  - Training more difficult (often require learning-rate warmup)

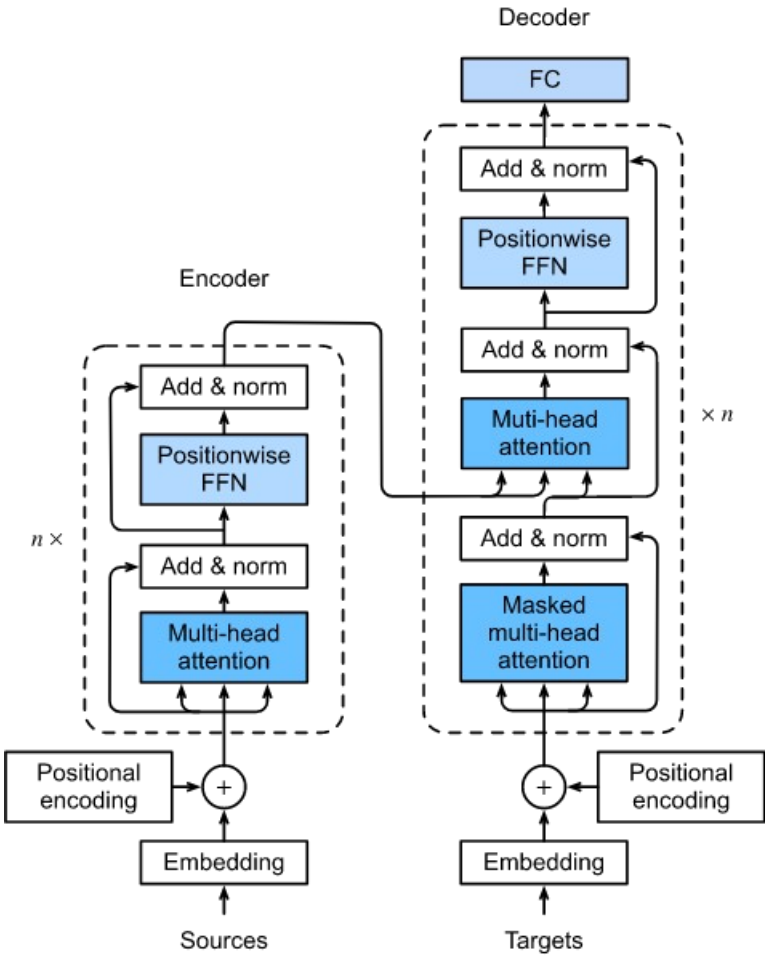




(a) Learning Rate Schedule

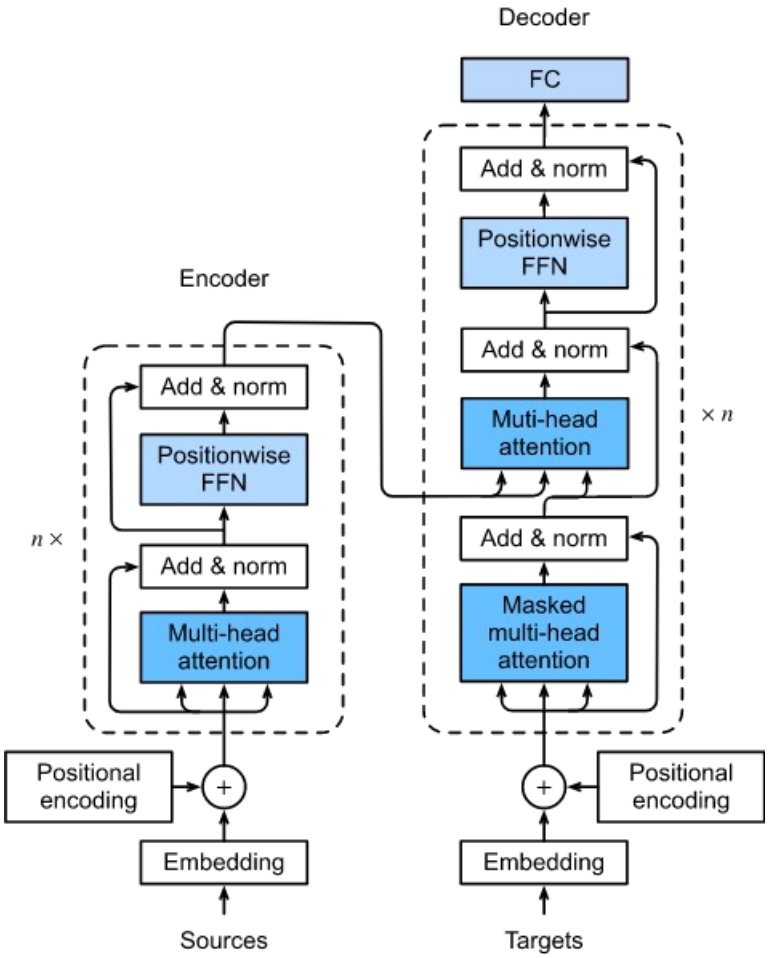
The Transformer

- Transformer is a sequence-to-sequence model where both encoder and decoder only use attention blocks (i.e., **no RNNs**)
- Proposed in the paper „**Attention is all you need**” (Vaswani et al., 2017)
- Probably the most important architecture currently in NLP
- Used in machine translation, summarization, speech recognition (with some modifications)



The Transformer

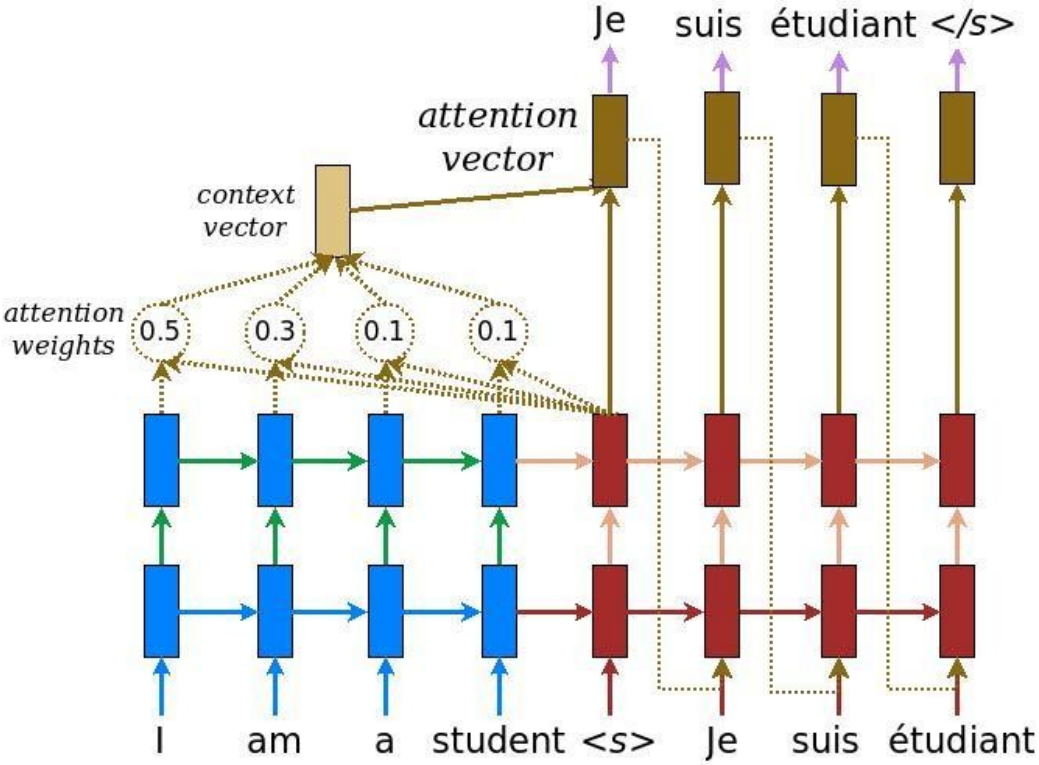
- Encoder is a sequence processing model that applies a series of multi-head attention layers (+ add & norm) to position-encoded input embeddings
- Decoder is a language model that uses attention over both inputs (that is, encoder outputs) as well as already generated tokens (self-attention)
  - Decoder is exactly as encoder, but with a intermediate block that attend over the encoder outputs



Beam Search

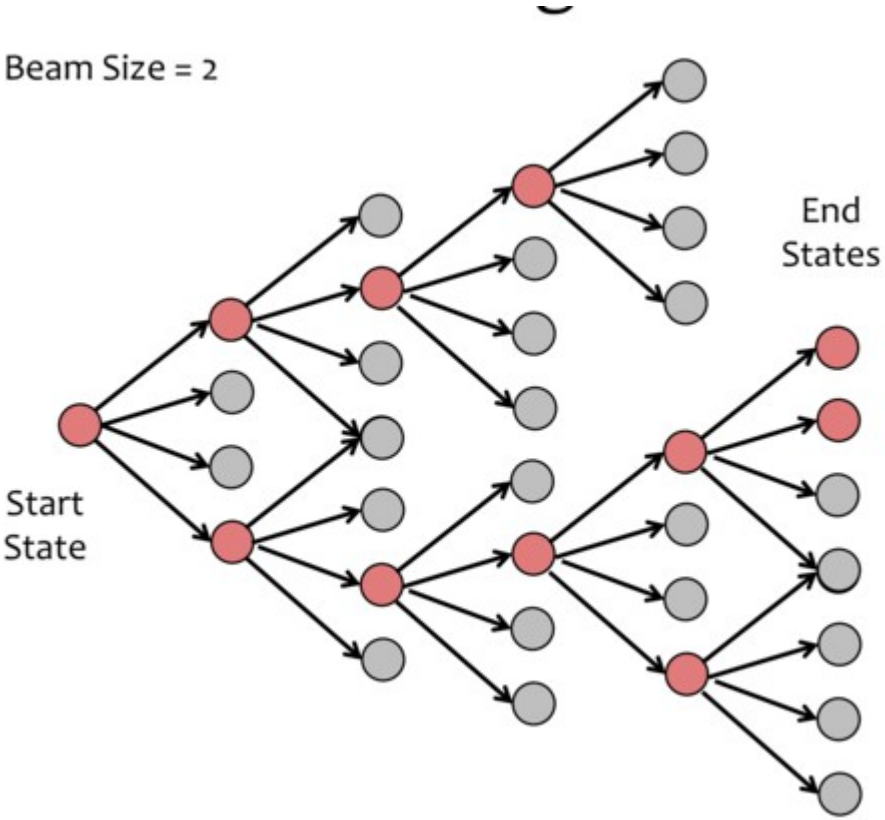
Greedy Search

- How to generate the best output sequence from the decoder?
- Greedy search: at each time step, select the word with the highest probability
- It doesn't guarantee that the individual choices being made make sense together and combine into a coherent whole
- Can we sample from the output probability distribution instead?
  - In the case of MT, this leads to strange and usually incorrect output
- We also cannot track all alternatives, since this leads to $|V|^k$ alternatives, where |V| is the vocabulary size and k length of the sentence



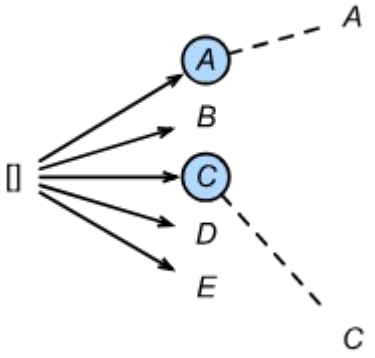
Beam Search

- Beam search tracks *k* (beam size) best alternatives in parallel
- At first time step, *k* best alternatives are kept, together with their probabilities
- This is called the *frontier*
- At each next timestep, we expand each candidate in the frontier, and multiply the probabilities along each path
- After each expansion step, we *prune* the candidates to *k* best alternatives



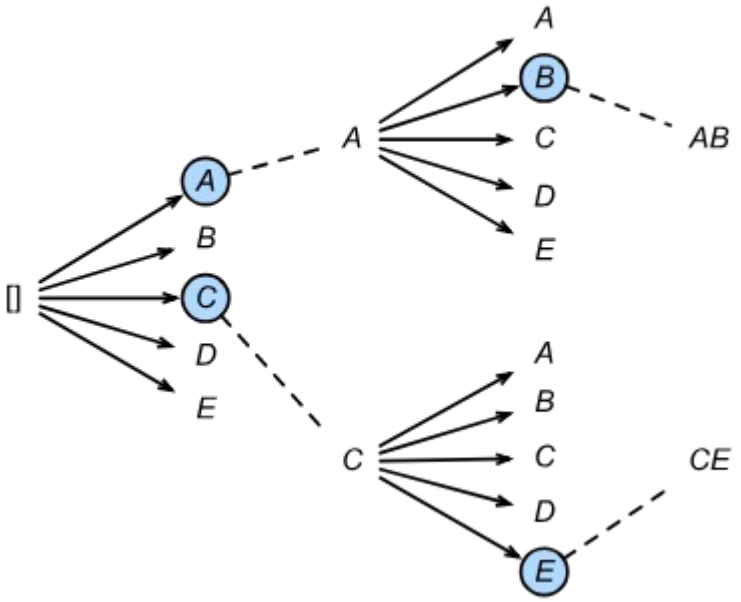
Beam Search, example

- k=2
- Time step 1:
  - Keep A, C



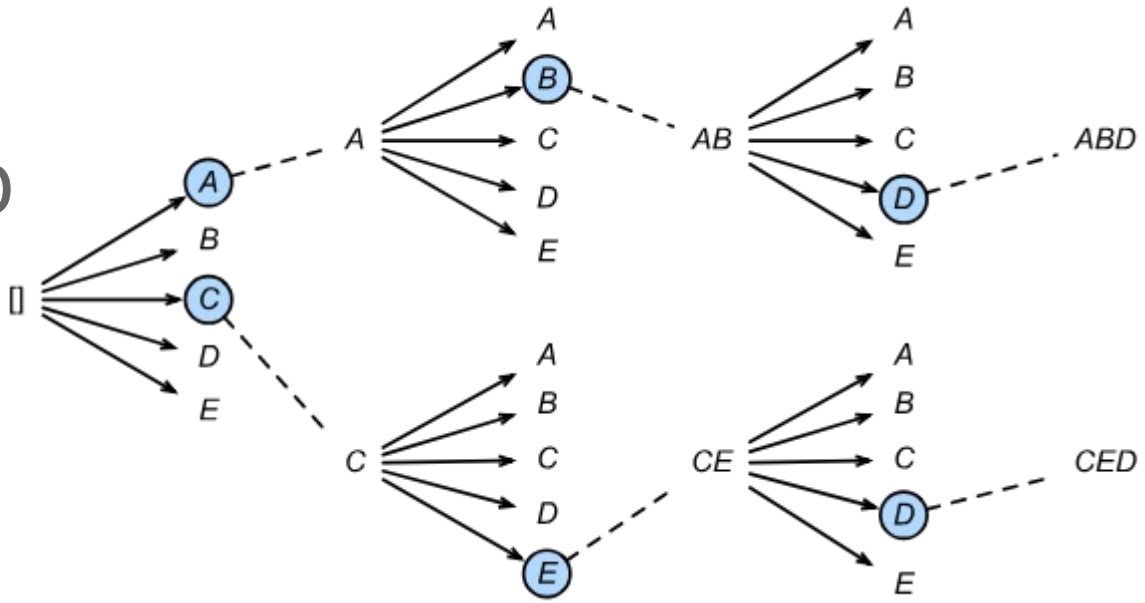
Beam Search, example

- k=2
- Time step 2:
  - Keep AB, CE



Beam Search, example

- k=2
- Time step 3:
  - Keep ABD, CED



Beam Search, cont.

- If </s> is generated at certain branch, this branch is not expanded further
- Beam search continues until only hypotheses ending with </s> are among the best *k* hypotheses
- Different hypotheses could have different length
  - Longer hypotheses will naturally look worse than shorter ones just based on their length
  - The usual solution to this is to apply some form of length normalization to each of the hypotheses

Questions?