Natural Language Processing
Neural Networks II: Transformers

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Announcements

- A2 is due on Friday at 11:59pm
  - Careful with the number of late days you have left! If you used three late days on the last assignment, you have two late days left for the quarter.
  - Make sure to commit/push your **.preds files** by the deadline, in addition to your code and writeup
- Extra office hours this week– the course google calendar lists the OH schedule
- Quiz 5 goes out on Canvas today at the end of lecture
  - Available until Friday at 2:20pm; you'll have 15 minutes to complete it once you start.
  - Remember that you can use your notes during the quiz
  - Will cover material from last Wednesday's lecture through the end of Monday's lecture (so, Viterbi, CRFs, and neural sequence labeling)

Transformers: outline

LSTMs: their pros and cons

The transformer architecture at a high level and how it addresses LSTMs' cons

Attention mechanisms

The transformer architecture at a slightly lower level

The additional idea behind BERT and co. (pretraining and finetuning!)

Things we like about LSTMs

Can deal with arbitrary-length sequences (like text!) while taking the order of the sequence into account (like text does!)

Were the dominant model architecture in NLP for years for a wide range of tasks

Things we don't like as much about LSTMs

Recency bias (references at end)

LSTMs were designed to mitigate this issue compared to Elman RNNs, but still suffer from it

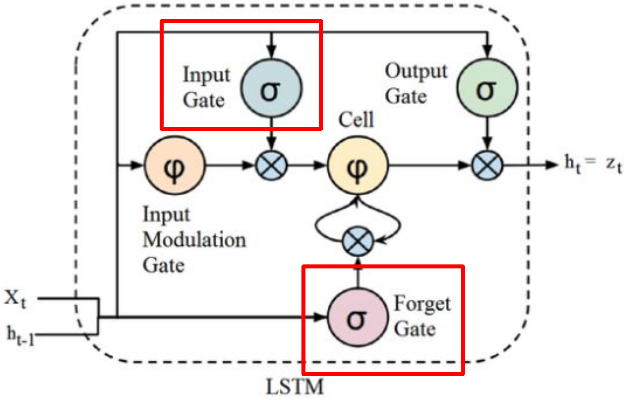
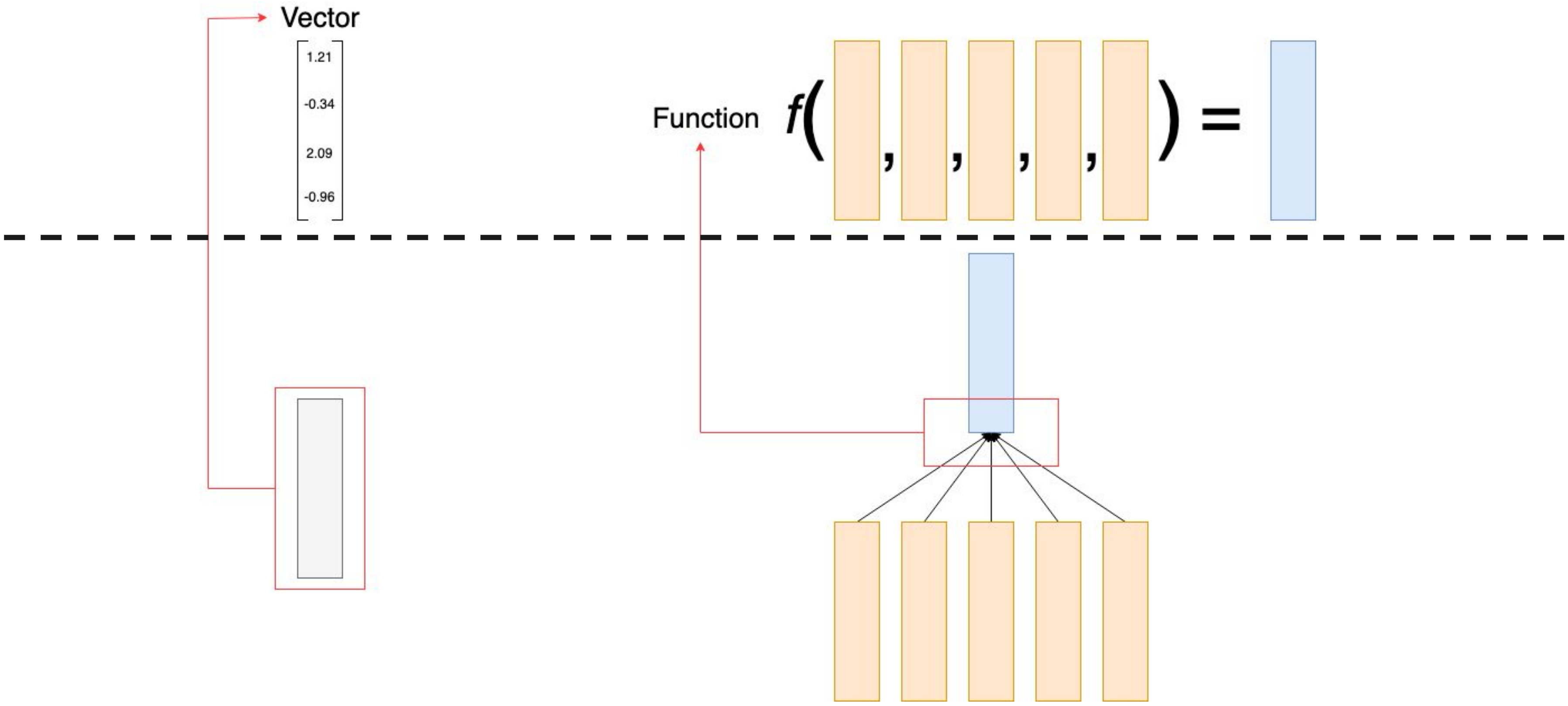


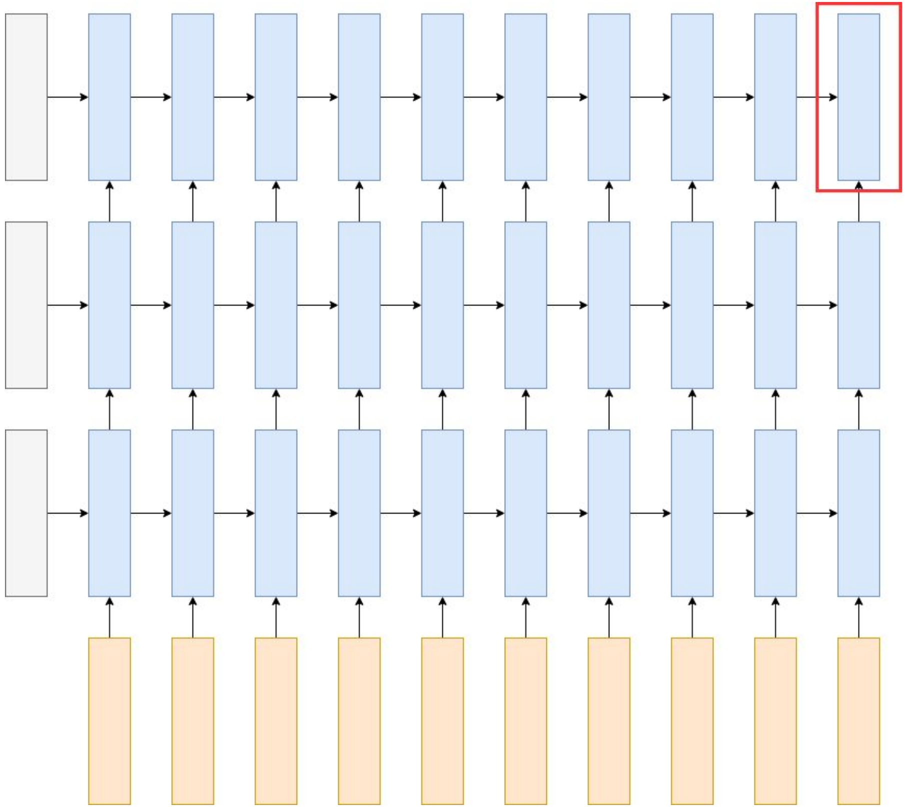
Diagram from a Medium post by Eugine Kang

Time required to train an LSTM

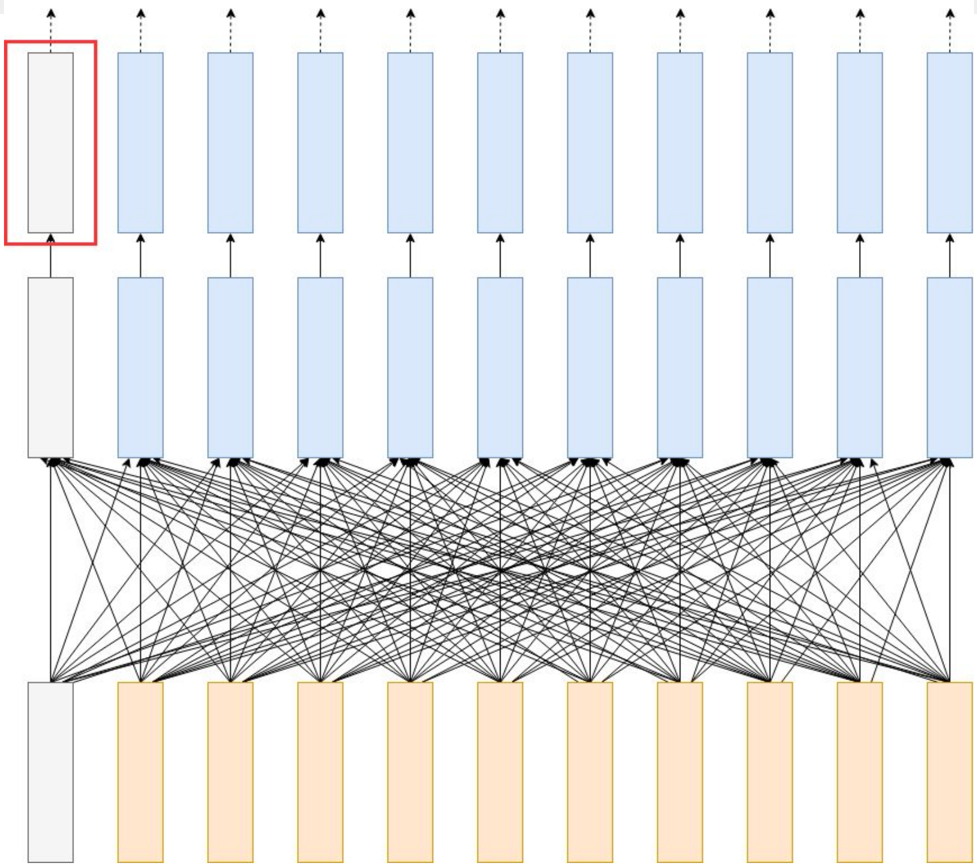
A brief aside about some visual shorthand I'll be using



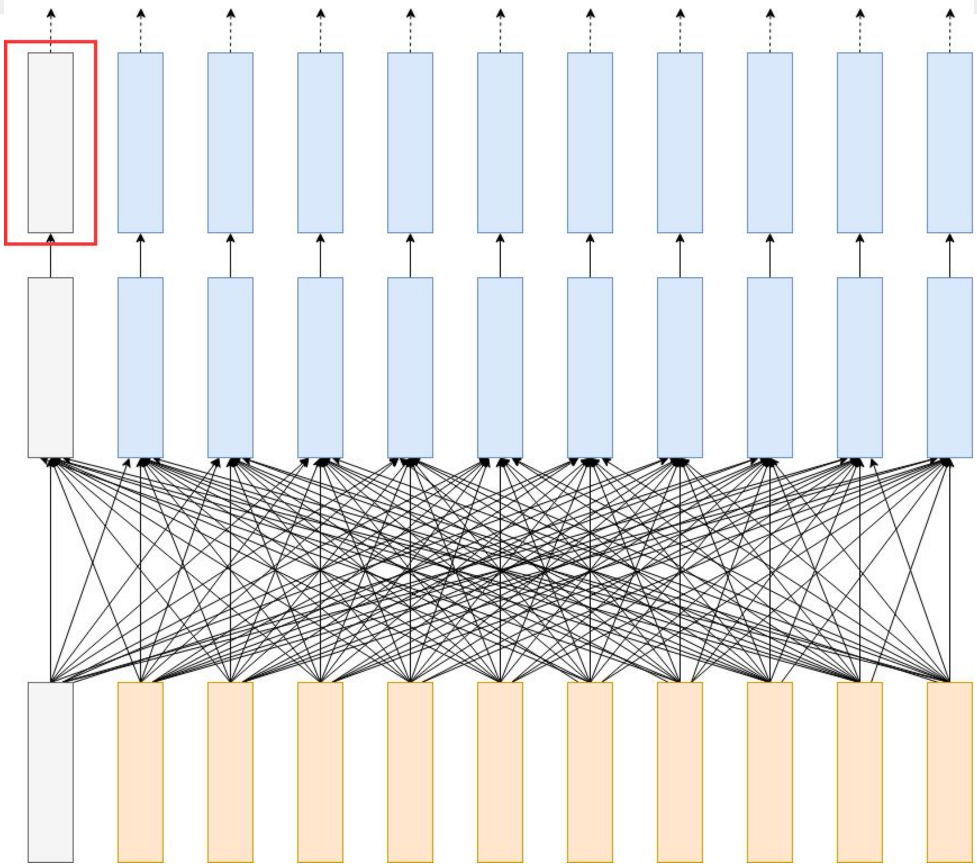
A 3-layer LSTM's calculations for an input of 10 tokens



One layer of the transformer architecture (Vaswani et al. 2017)

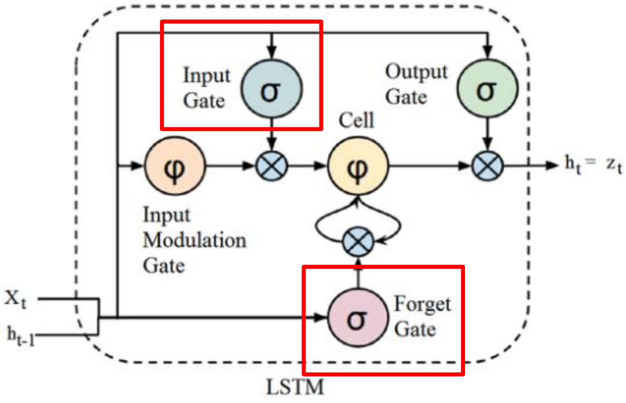


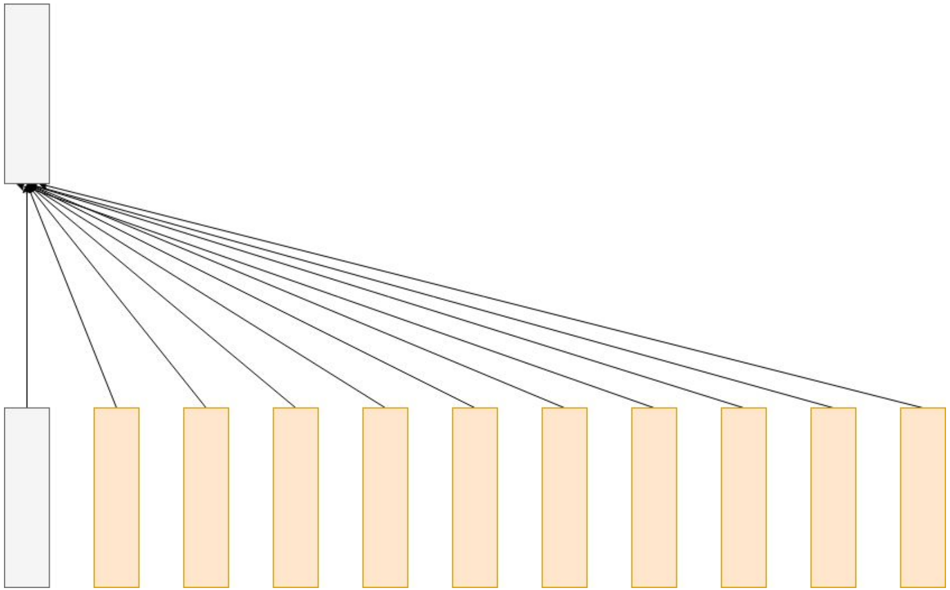
One layer of the transformer architecture (Vaswani et al. 2017)



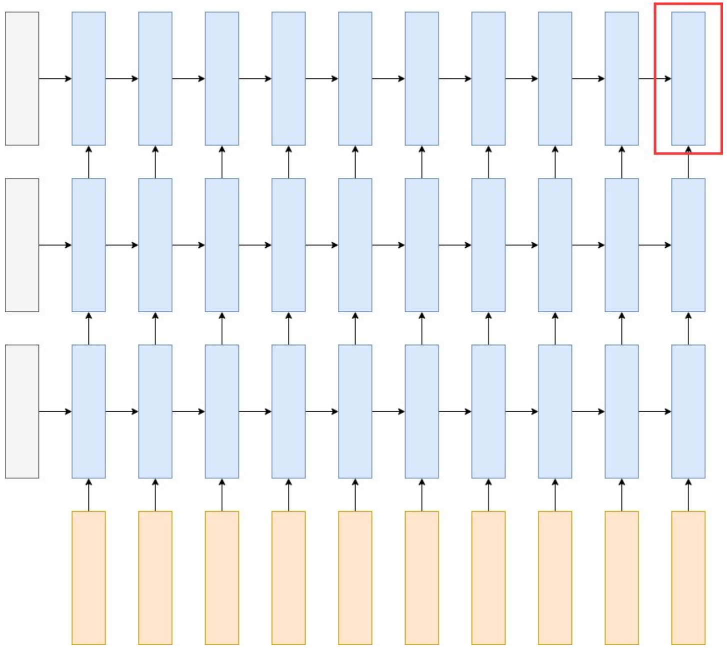
ok but how does this
mess help anything sofia

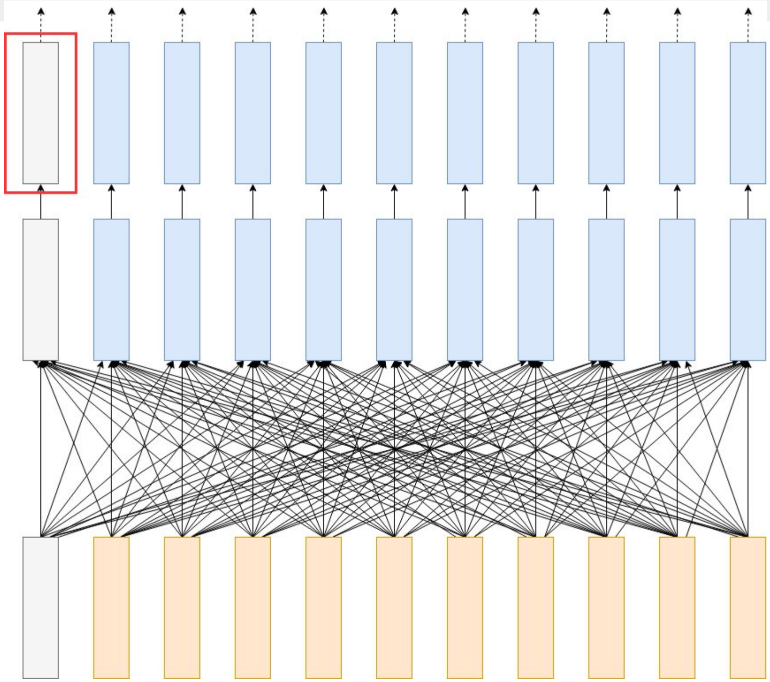
Recency bias is not as much of a problem as in LSTMs





Comparing training times: how many functions do we need to backpropagate through?





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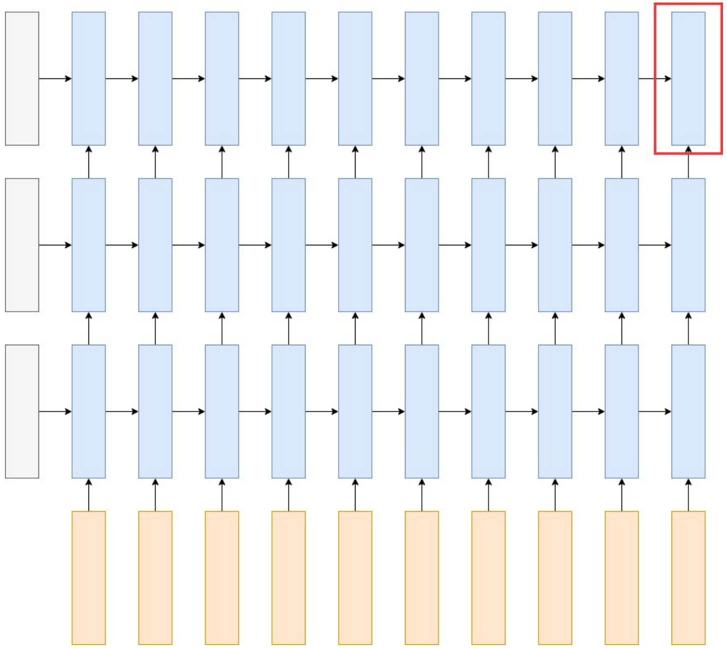
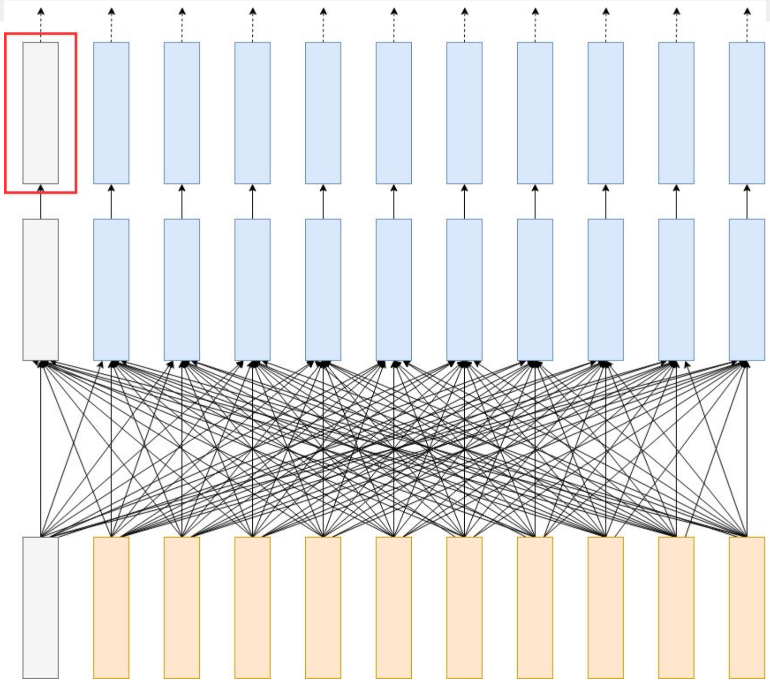
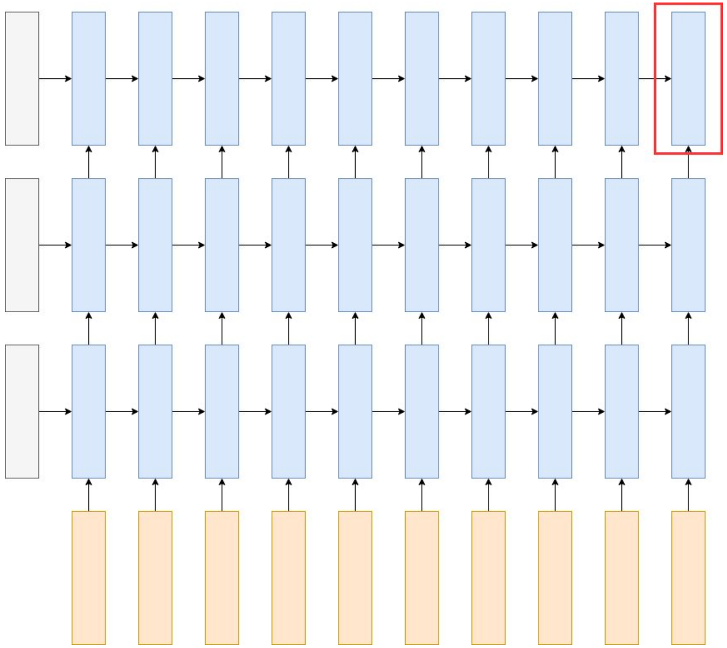
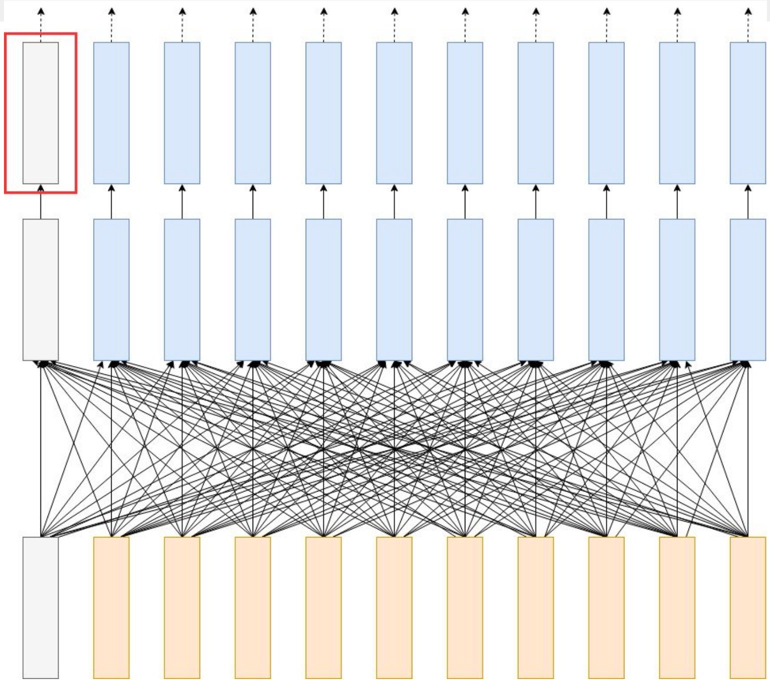




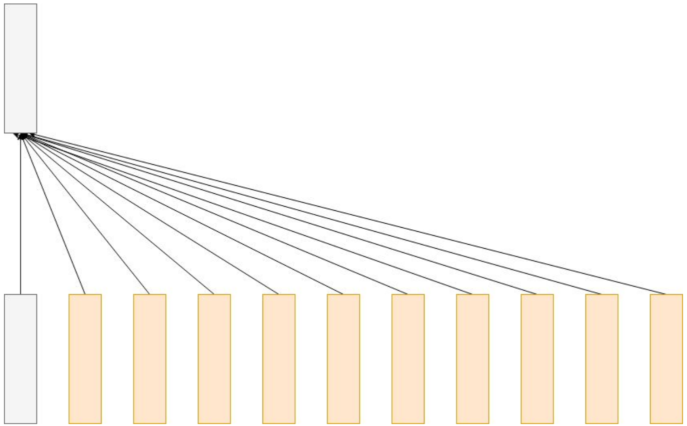
Transformers *parallelize* a lot of the computations that LSTMs make us do in sequence

Comparing training times: how many functions do we need to backpropagate through?





Transformers *parallelize* a lot of the computations that LSTMs make us do in sequence
And (a very specific, but nonempty, subset of) you can therefore train a transformer on a ridiculously large amount of data in a way that you cannot for an LSTM.



What kind of function can take in a variable number of inputs like that without recursively applying an operation a bunch of times?

Attention mechanisms

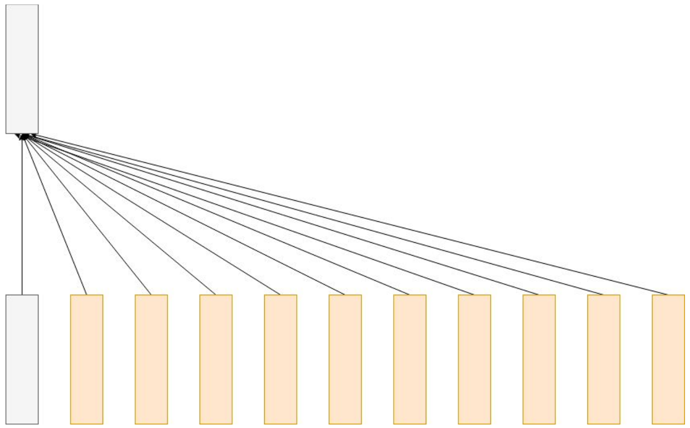
Building up to the attention mechanism

What about an average?

But we probably don't want to weight all input vectors equally...

How about a weighted average?

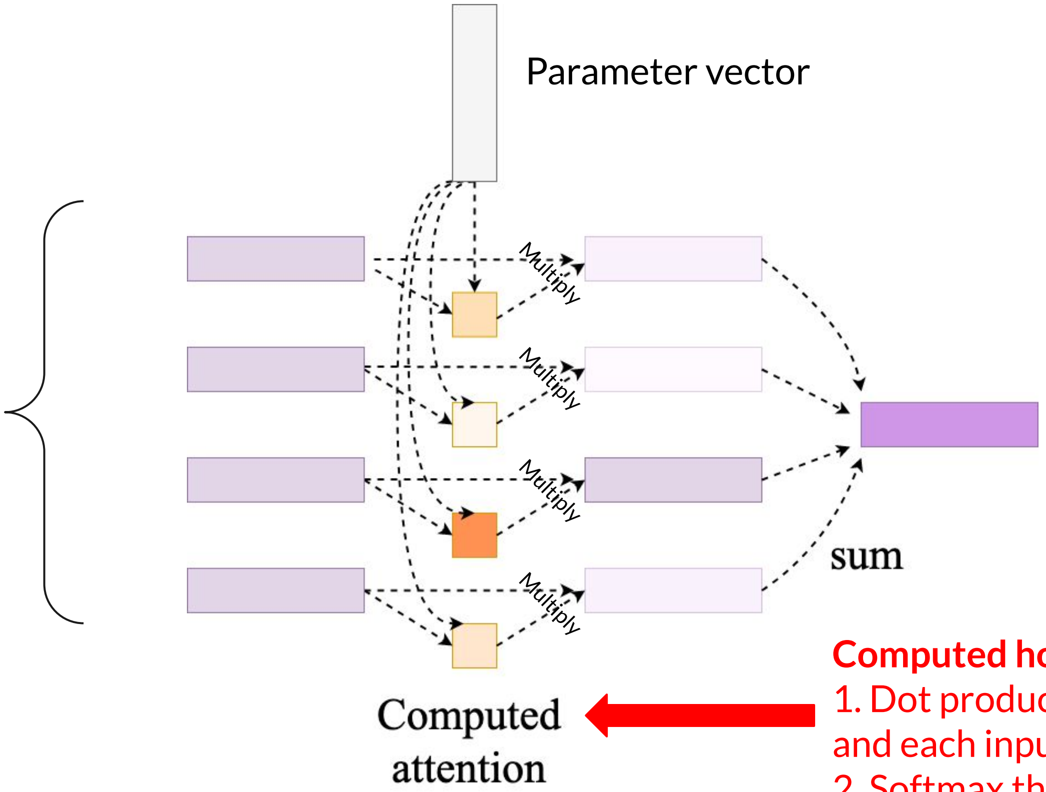
Great idea! **How can we automatically decide the weights for a weighted average of the input vectors?**



What kind of function can take in a variable number of inputs like that without recursively applying an operation a bunch of times?

Bahdanau attention (Bahdanau et al. 2014)

(Variable number of) input vectors

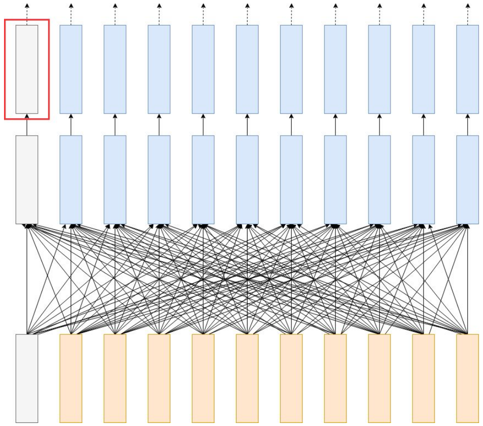


Computed how?
1. Dot product between param vector and each input vector
2. Softmax the set of resulting scalars.

Pros and cons

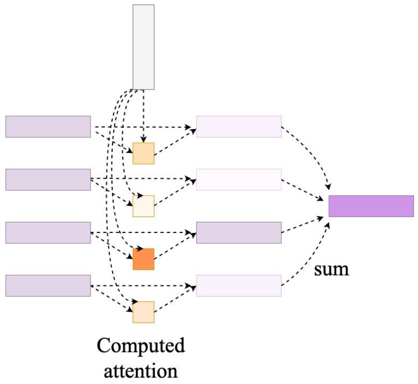
Pros:

- We have a function that can compute a weighted average (largely) in parallel of an arbitrary number of vectors!
- The parameters determining what makes it into our output representation are learned



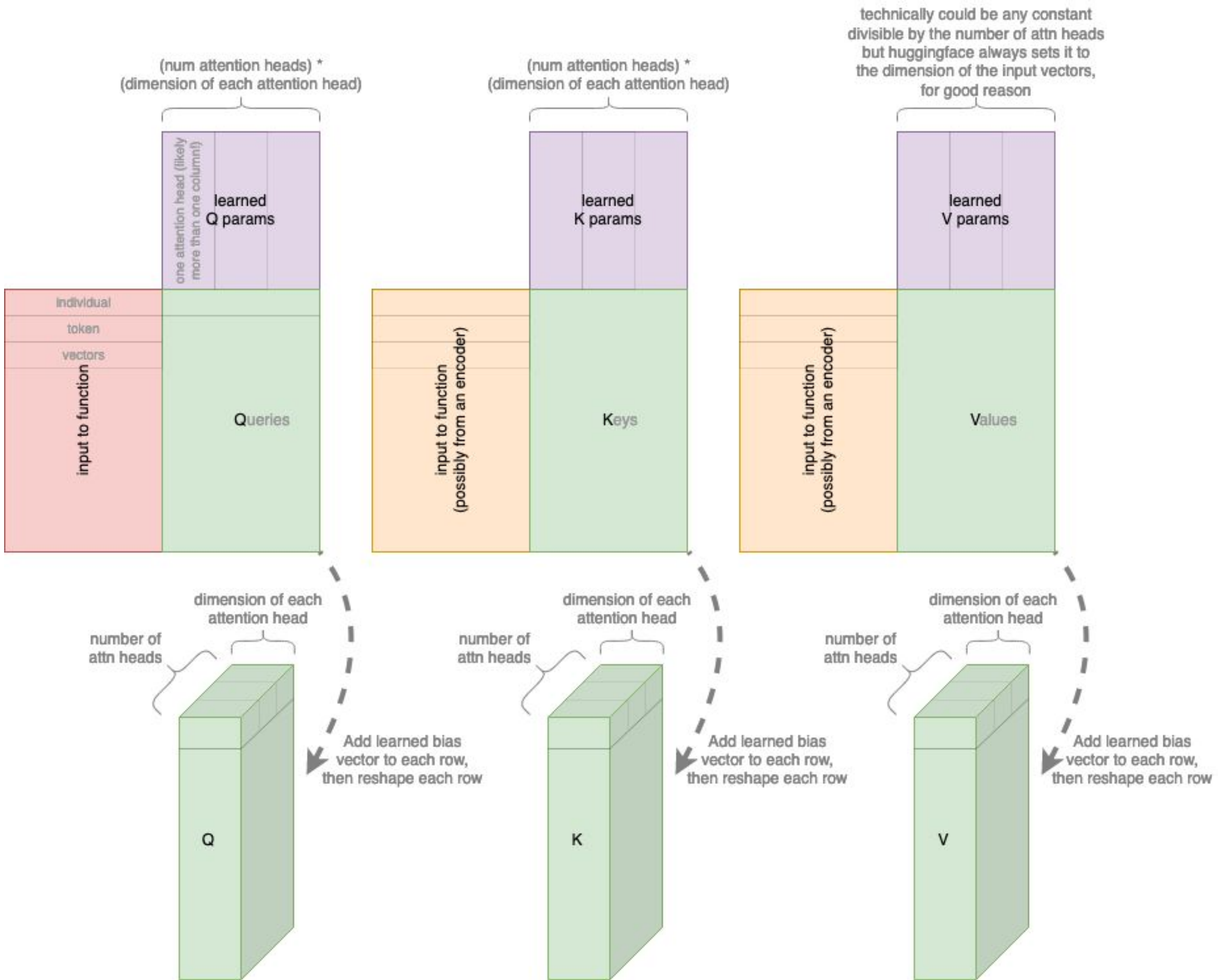
Cons:

- We're also hoping to produce n different output token representations... and this just produces one...

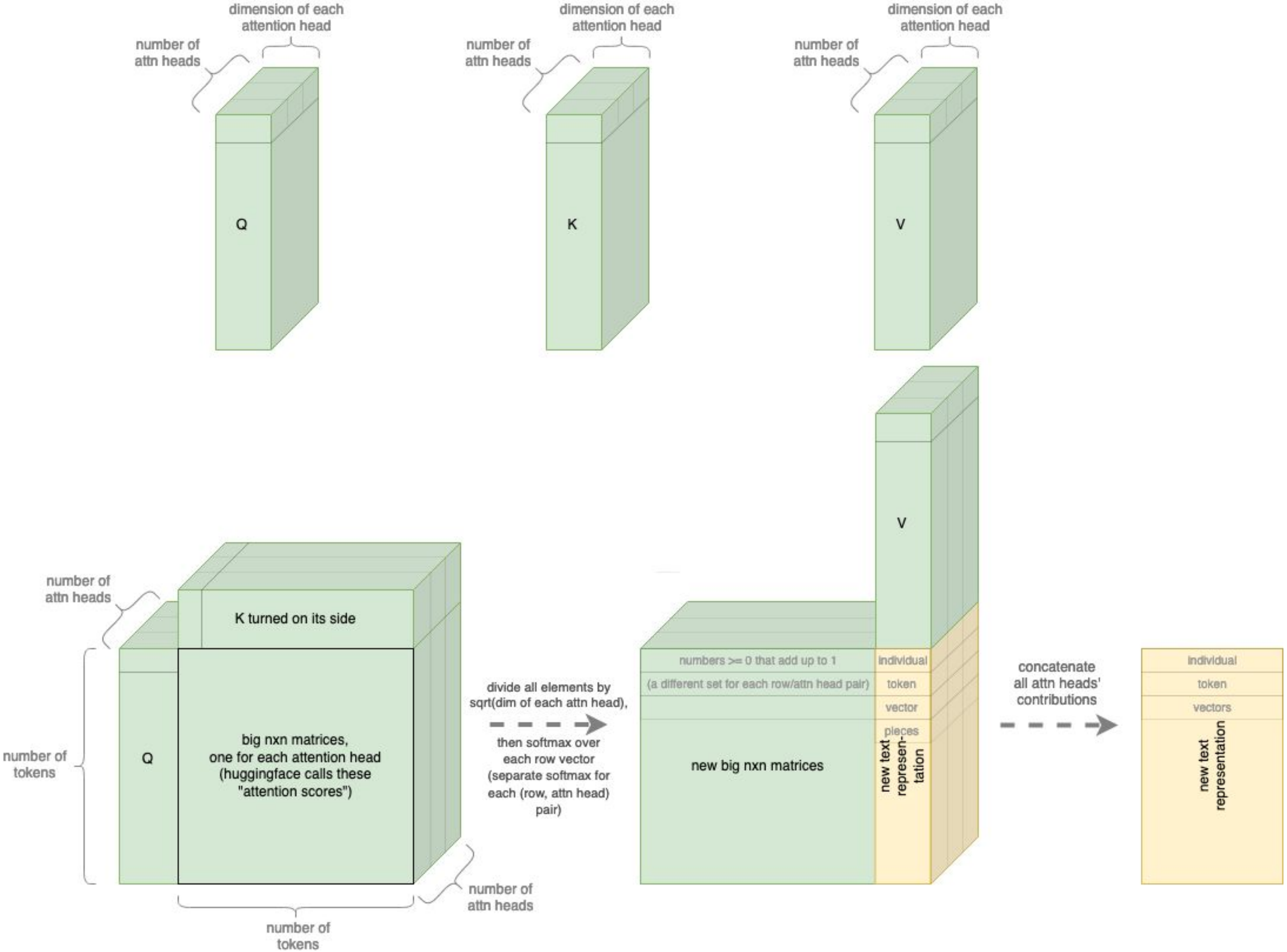


Enter “self attention”

“What if instead of comparing each vector of the sequence to a single learned vector, we compared the sequence to *itself*?”



(num attention heads) *
(dimension of each attention head)
(num attention heads) *
(dimension of each attention head)
technically could be any constant
divisible by the number of attn heads
but huggingface always sets it to
the dimension of the input vectors,
for good reason
one attention head (likely more than one column!)
learned
Q params
learned
K params
learned
V params
individual
token
vectors
input to function
input to function
(possibly from an encoder)
input to function
(possibly from an encoder)
Queries
Keys
Values
dimension of each
attention head
number of
attn heads
dimension of each
attention head
number of
attn heads
dimension of each
attention head
number of
attn heads
Add learned bias
vector to each row,
then reshape each row
Add learned bias
vector to each row,
then reshape each row
Add learned bias
vector to each row,
then reshape each row
Q
K
V

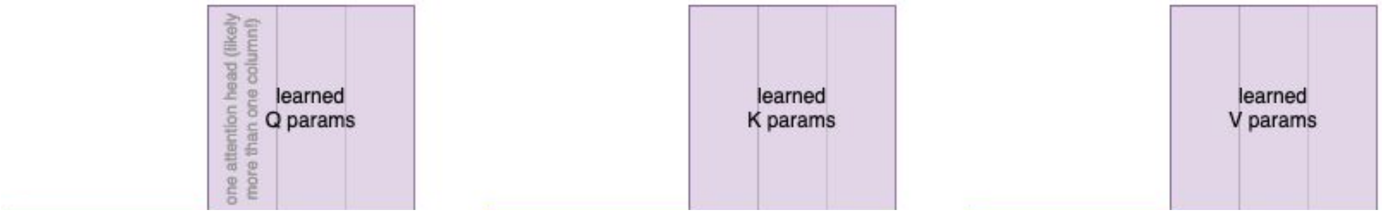


dimension of each attention head
number of attn heads
Q
dimension of each attention head
number of attn heads
K
dimension of each attention head
number of attn heads
V
V
number of attn heads
K turned on its side
number of tokens
Q
big nxn matrices, one for each attention head (huggingface calls these "attention scores")
number of tokens
number of attn heads
divide all elements by sqrt(dim of each attn head),
then softmax over each row vector (separate softmax for each (row, attn head) pair)
numbers >= 0 that add up to 1
(a different set for each row/attn head pair)
new big nxn matrices
individual
token
vector
pieces
new text represen-tation
concatenate all attn heads' contributions
individual
token
vectors
new text representation

Hooray for self attention!

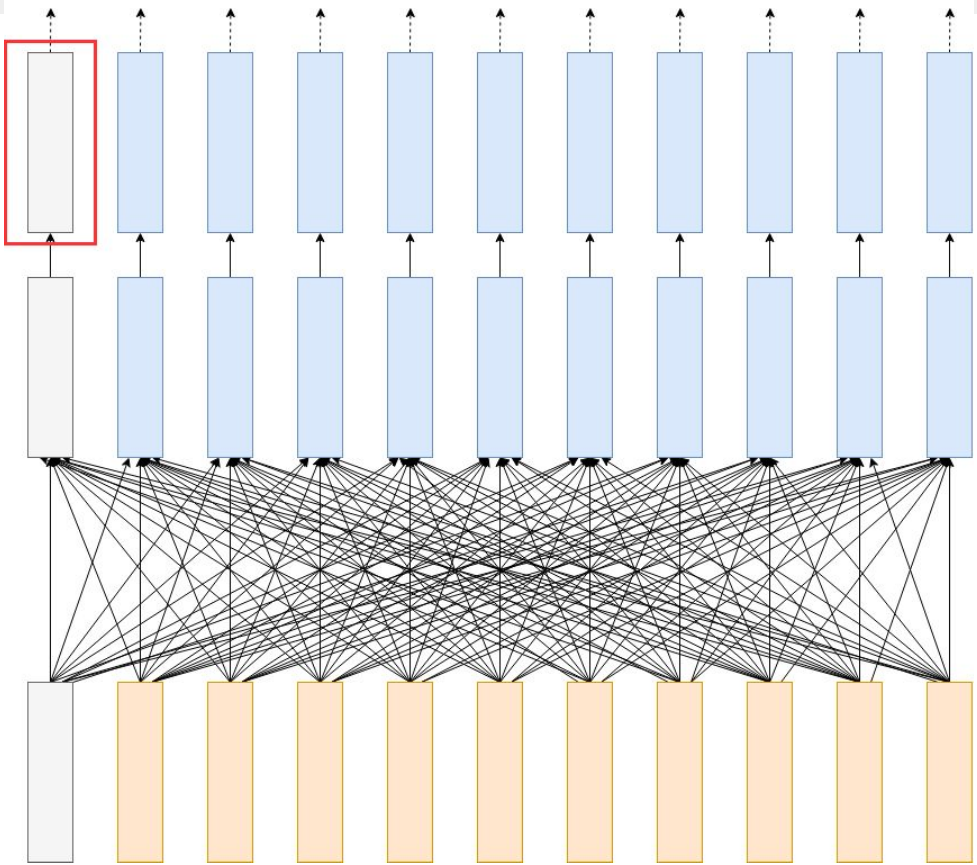
Our function is still made up almost entirely of matrix multiplications! *Which are very parallelizable* (→ efficient!)

We still learn fixed-size blocks of parameters that can be used for a sequence with an arbitrary length



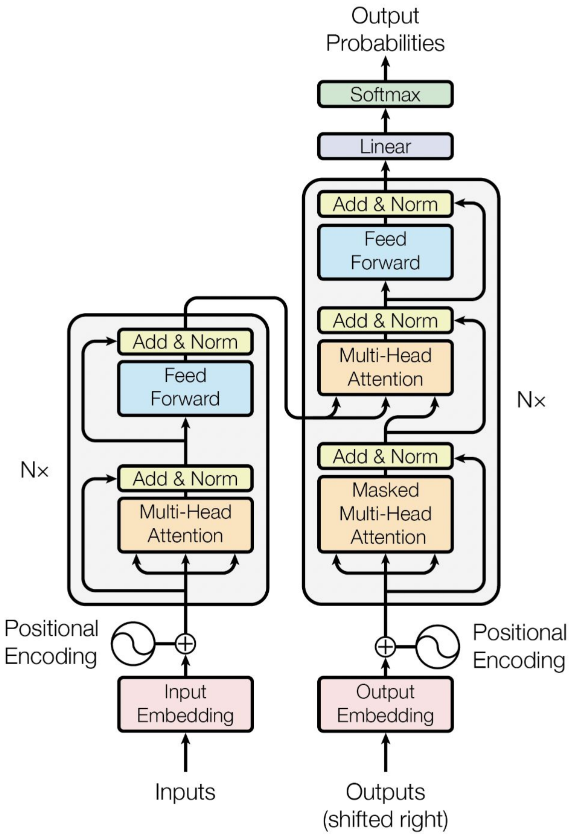
We're now capable of producing *n* different new token representations!

Self attention is the key component of the transformer



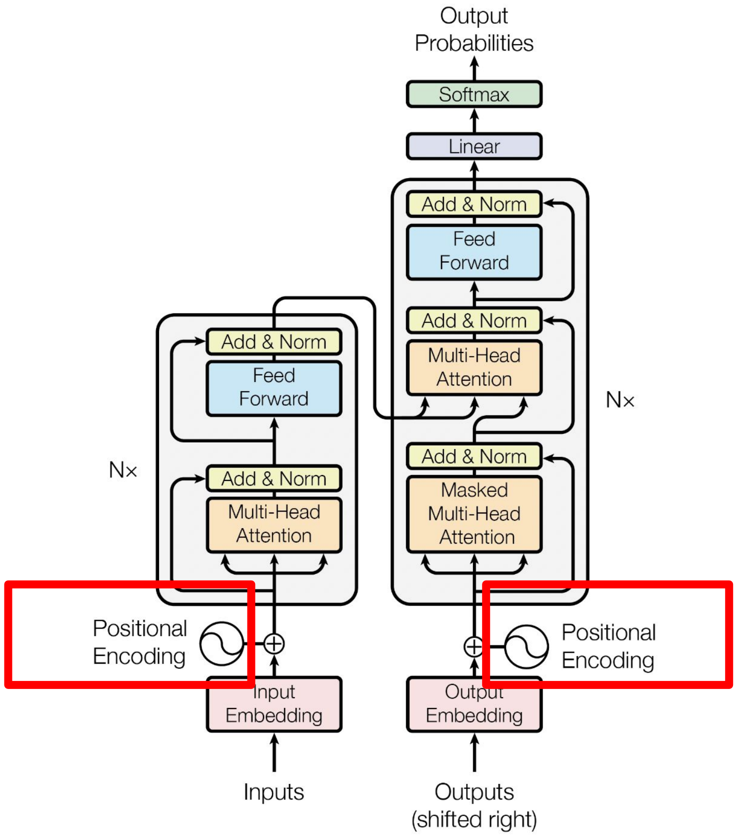
Filling in some last transformer details

The full figure of a layer from the transformer



From [Vaswani et al. 2017]

Position embeddings



From Vaswani et al. 2017

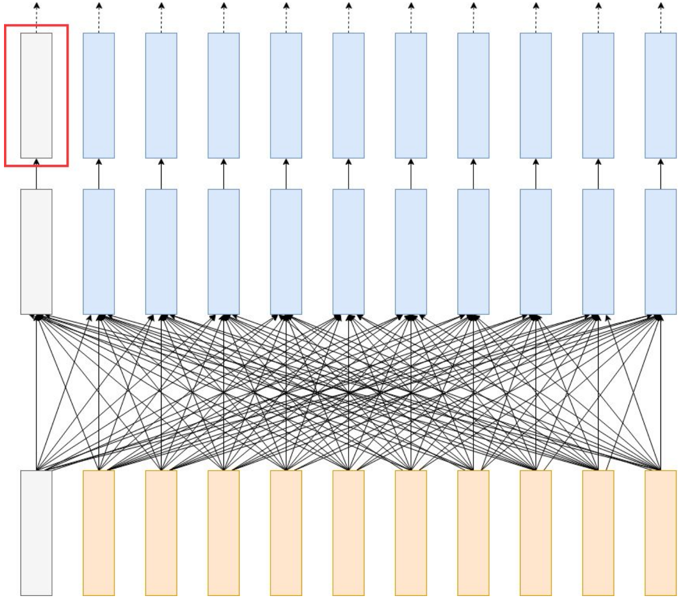
Position embeddings

Probably the least intuitive part of a transformer.

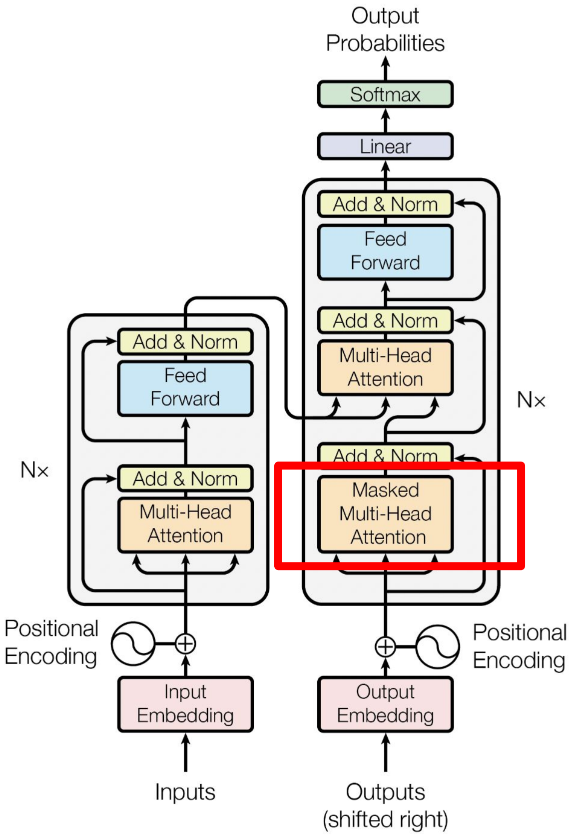
A transformer's only sense of the order of words is a set of position embeddings, one per token index, that are added to the corresponding tokens of an input.

In practice, this also means that unlike for LSTMs, the maximum length of a sequence for a transformer is capped [at the number of position embeddings it's got].

The [original transformer paper]() experimented with both learned positional embeddings and sine/cosine-based positional embeddings (sec 3.5).



Masked attention

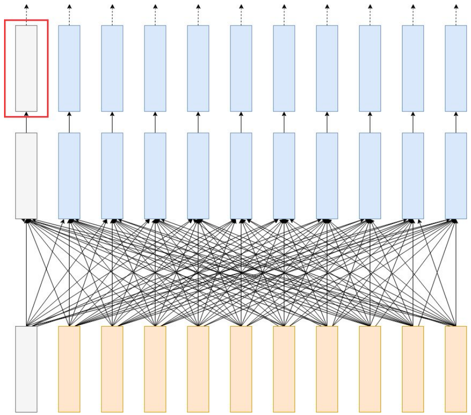


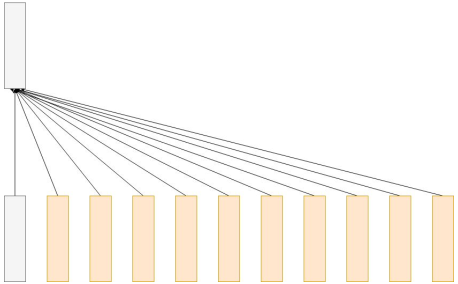
From [Vaswani et al. 2017]

Masked attention

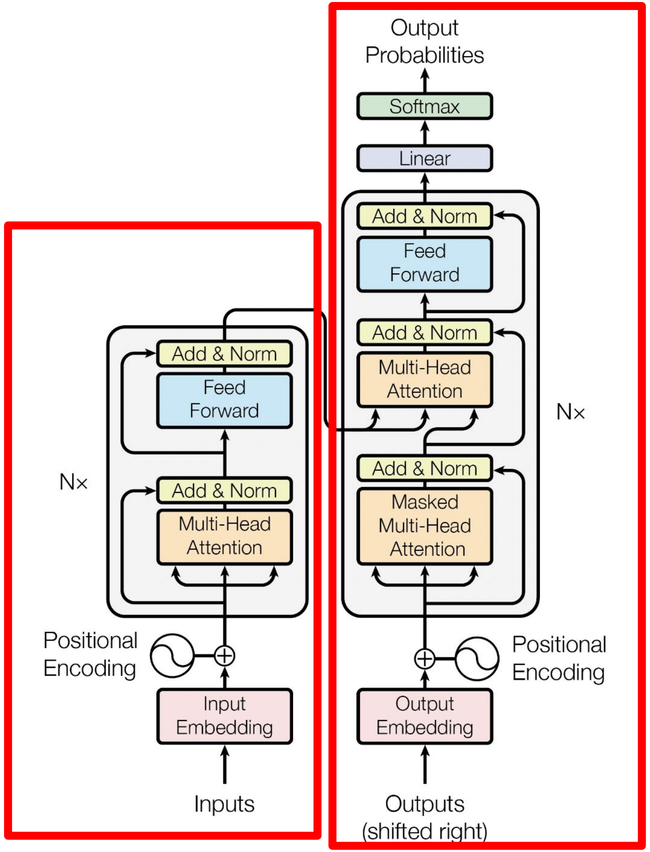
If you're learning a model that's supposed to be able to generate text token by token (an "**autoregressive model**")… then looking ahead to previous tokens during training would be cheating.

In practice, we mask and renormalize the attention distributions to include only the tokens that that time step has seen so far. (In other words, for the token representation at position t, only take an attention distribution over the first t tokens.)





Encoder AND decoder??

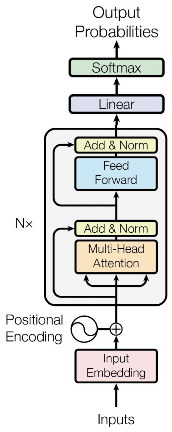


From [Vaswani et al. 2017]

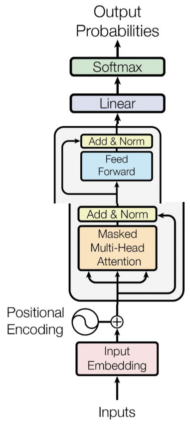
Encoder AND decoder??

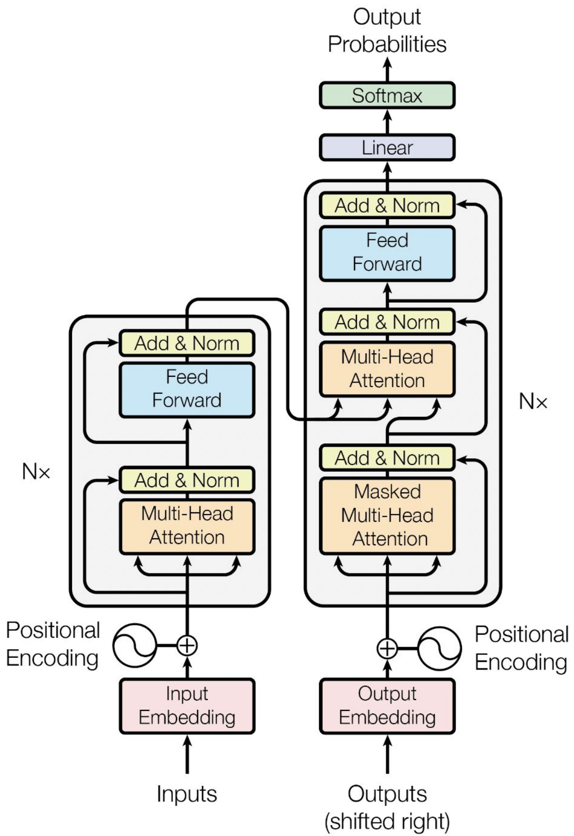
Only for some tasks! (For example, machine translation, where having the input space and output space have different sets of trained word embeddings makes more sense)

Notably, BERT:



GPT___:





So we like this architecture, but what will we train it to do?

Issues with just training the model to do your task of interest

Your task of interest might not have that much labeled data available

Even if that weren't an issue, these models are quite large, and take a lot of resources to properly train

- Feels like a waste to have each separate project consume all those resources
- (Never mind that a lot of people who'd like to use these models don't have access to those kinds of resources)

Pretraining and finetuning

Based on idea of **transfer learning** (not a new idea in machine learning-- Pan and Yang 2010 cite a NeurIPS ‘95 workshop as already discussing this idea)

Pretraining and finetuning is basically transfer learning, BUT with the understanding that the vast majority of training is accomplished in the pretraining stage.

What kinds of tasks make good, generalizable pretraining tasks?

ELMo (Peters et al. 2018)

The big takeaway:

if you train a **language model**,

then just replace the model's output layer and use the parameters from the original language model to adjust your word embeddings in the model's first few layers,

those new word embeddings can help you perform **really** well on a whole range of NLP tasks, especially if you **finetune** the parameters (i.e., train them to perform your actual task of interest).

The BERT training objective ([Devlin et al. 2018]())

Very similar idea to ELMo, but

- used the transformer architecture (unlike ELMo)
- used **masked language modeling** as its pretraining objective instead

The quick brown ______

The quick brown fox _______

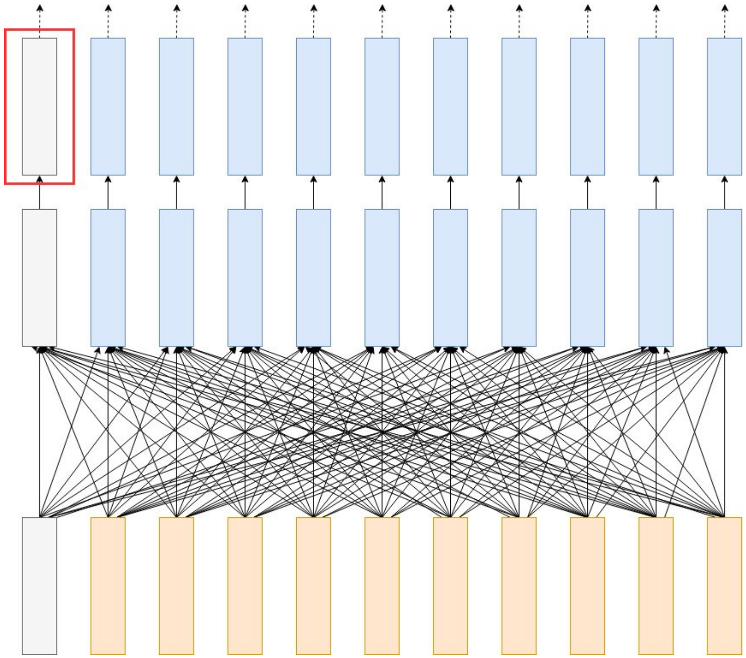
The ______ brown fox jumps ______ the...

The quick _______ ______ jumps over the...

Side note: the reason for this little red box

Want a good representation of a sentence?

It's common to use BERT (or RoBERTa or something) to encode the sentence, and then just take the first representation (corresponding to the special [CLS] token) from the final layer in the transformer as a representation of the sentence as a whole.



Sampling from a trained autoregressive LM transformer

Lots of different sampling strategies proposed

For example, Nucleus Sampling (which we won’t talk about today due to time).

The way in which you sample from a language model’s output probability distribution can have a big effect on the kind of text you get!

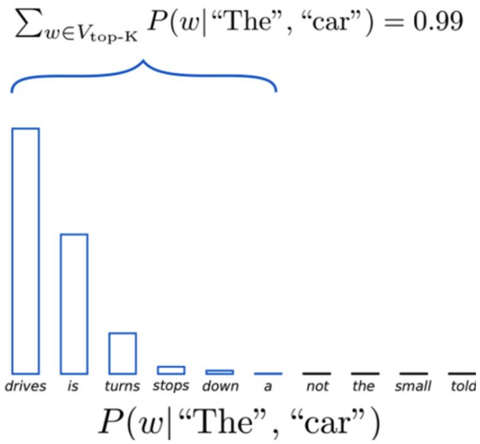
We’ll briefly go over the top-K sampling algorithm as an example.

The top-K sampling algorithm

We will represent $P(\cdot\,|W_{1..i})$ by $p = (p_1, p_2, \ldots, p_{|V|})$, where the elements is sorted that $p_1 \geq p_2 \geq p_3 \ldots \geq p_{|V|}$.
Top-K sampling transforms p to $\hat{p}$ by:

$$\widehat{p_i} = \frac{p_i \cdot 1\{i \leq K\}}{Z}$$

And we sample W_{i+1} from $\hat{p}$.



← from
https://huggingface.co/blog/how-to-generate
(Optional reading)

Slide by Tianxing He

Examples from the GPT2 model

- Prompt: *MIT is a private research university in Cambridge, Massachusetts. It is one of the best universities in the U.S.,*

- GPT2 with naive sampling: but the teaching of traditional African-American studies and African-American literacy continued. Soon thereafter, MIT was renamed The International Comparative University by Lord (then), …
- GPT2 with topk40 sampling: and the home of most of the top international universities in the world. Our alumni are internationally renown, but our mission is unique. We are the only university in the world where there is a chance to take on the challenge of making an impact, …
- topk40 another sample: with a reputation for innovation and open and flexible public systems. Its principal research area deals with autonomous vehicles, robotics and artificial intelligence. To date, MIT has published 40 peer-reviewed papers on this topic, …

- Message: sampling algorithms provide a sweet quality-diversity trade-off.
- (which is the key difference to decoding e.g., beam-search)
- Tianxing did not cherry-pick these examples!

Slide by Tianxing He

References (optional reading)

On recency bias in LSTMs, and comparing LSTMs to the transformer:

- Michał Daniluk et al., "Frustratingly Short Attention Spans in Neural Language Modeling." 2017. https://arxiv.org/abs/1702.04521.
- Jared Kaplan et al., "Scaling Laws for Neural Language Models." 2020. https://arxiv.org/abs/2001.08361.
- Urvashi Khandelwal et al., "Sharp Nearby, Fuzzy Far Away: How Neural Language Models Use Context." 2018. https://arxiv.org/abs/1805.04623.

Sinno Jialin Pan and Qiang Yang, "A Survey on Transfer Learning." 2010. 10.1109/TKDE.2009.191.

Noah A. Smith, "Contextual Word Representations: A Contextual Introduction." 2019. https://arxiv.org/abs/1902.06006.

One Layer of Self-Attention for One Instance in a Batch