A brief introduction to (large) language models

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What are we going to talk about?

- The language modeling problem
- How do we learn a language model?
  - A quick primer on learning a model via gradient descent
  - The role of training data
- ✨✨ The Transformer ✨✨
  - The two things that make it such an improvement over our previous techniques for language modeling
  - More detail about both of those two things
- From language models to large language models
- Large language models for chat (ala ChatGPT)

Quick poll

1. Are you familiar with supervised machine learning? gradient descent?

2. Are you familiar with neural networks?

The language modeling problem

Rank these sentences in the order of plausibility?

1. Jane went to the store.
2. store to Jane went the.
3. Jane went store.
4. Jane goed to the store.
5. The store went to Jane.
6. The food truck went to Jane.

How probable is a piece of text? Or what is p(text)

$p(\textit{how are you this evening ? has your house ever been burgled ?}) = 10^{-15}$

$p(\textit{how are you this evening ? fine , thanks , how about you ?}) = 10^{-9}$

The language modeling problem

A **language model** answers the question: **What is p(text)?**

Text is a sequence of symbols: $(x^{(1)}, x^{(2)}, \ldots, x^{(N)})$

$$p(x^{(1)}, x^{(2)}, \ldots, x^{(N)})$$

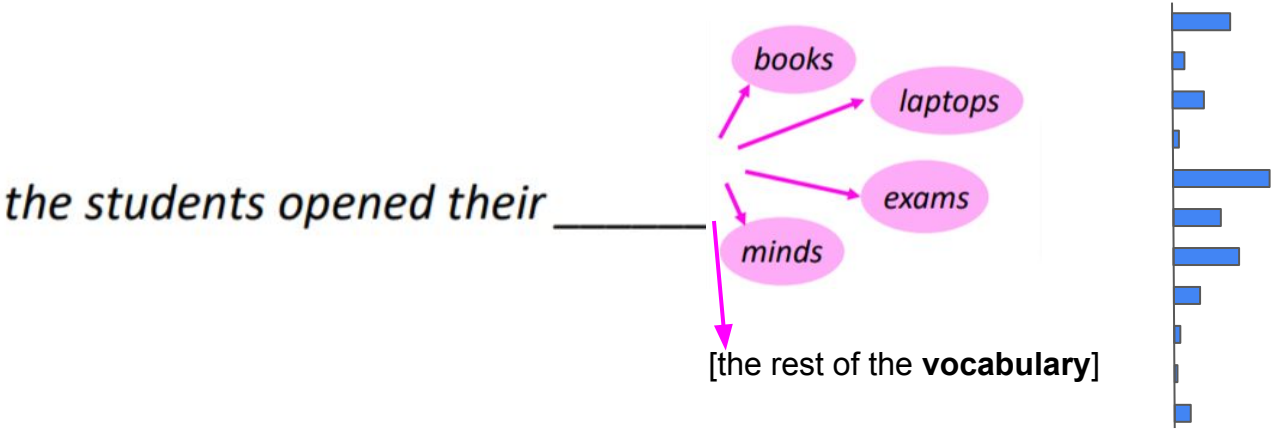
$$p(x^{(1)})p(x^{(2)}|x^{(1)})p(x^{(3)}|x^{(1)}, x^{(2)}) \ldots$$

$$\prod_{i=1}^{N} p(x^{(i)}|\underbrace{x^{(1)}, \ldots, x^{(i-1)}}_{\text{context}})$$

Just the chain rule of probability– no simplifying assumptions!

The language modeling problem

$$\prod_{i=1}^{N} p(x^{(i)} | \underbrace{x^{(1)}, \ldots, x^{(i-1)}}_{\text{context}})$$



Language models of this form can generate text

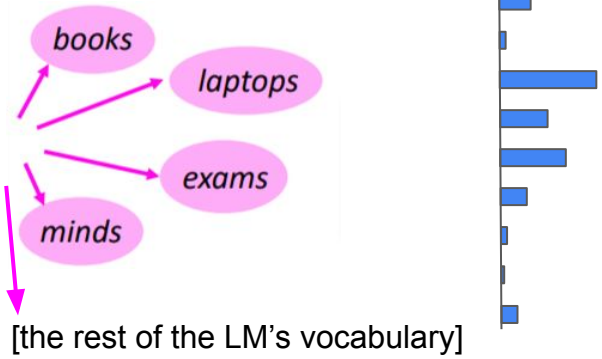
At each timestep, sample a token from the language model's new probability distribution over next tokens.

The ____

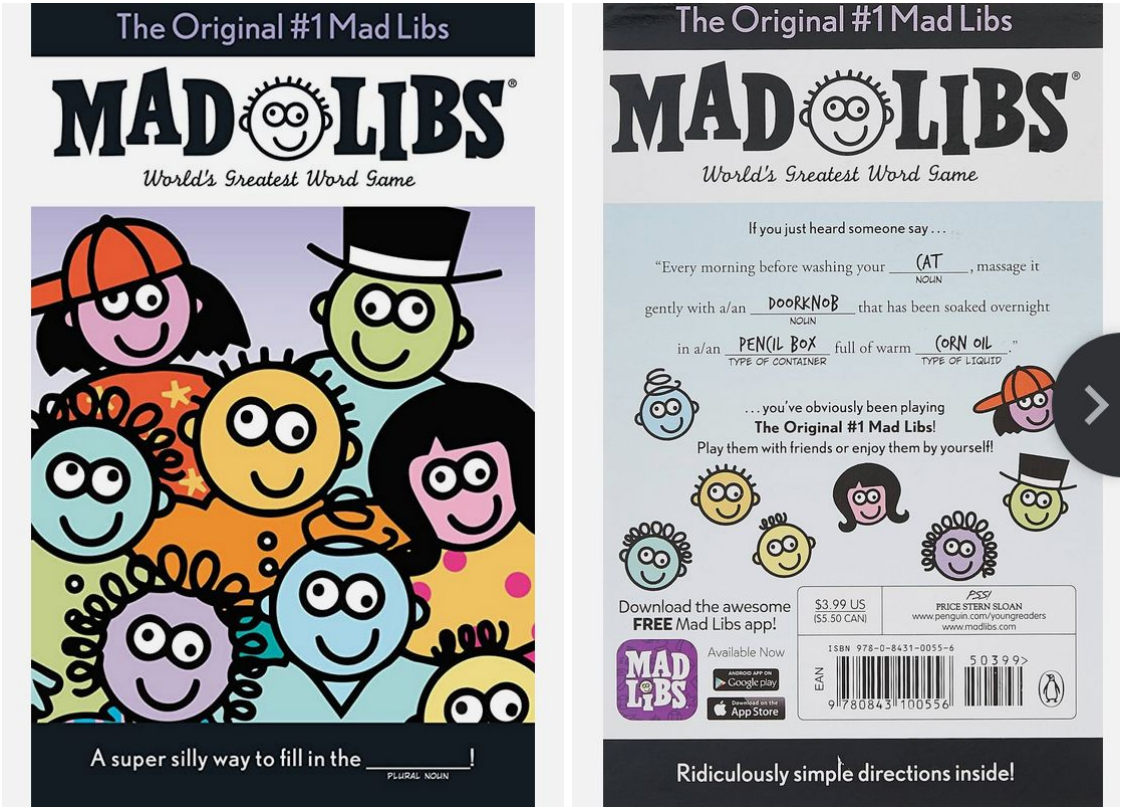
The students ____

The students opened ____

The students opened their ____



In short, predicting which word comes next



Language models play the role of ...

- a judge of grammaticality
  - e.g., should prefer “The boy runs.” to “The boy run.”
- a judge of semantic plausibility
  - e.g., should prefer “The woman spoke.” to “The sandwich spoke.”
- an enforcer of stylistic consistency
  - e.g., should prefer “Hello, how are you this evening? Fine, thanks, how are you?” to “Hello, how are you this evening? Has your house ever been burgled?”
- a repository of knowledge (?)
  - e.g., “Barack Obama was the 44th President of the United States”

Note that this is very difficult to guarantee!

Language models in the news (these days, ChatGPT)

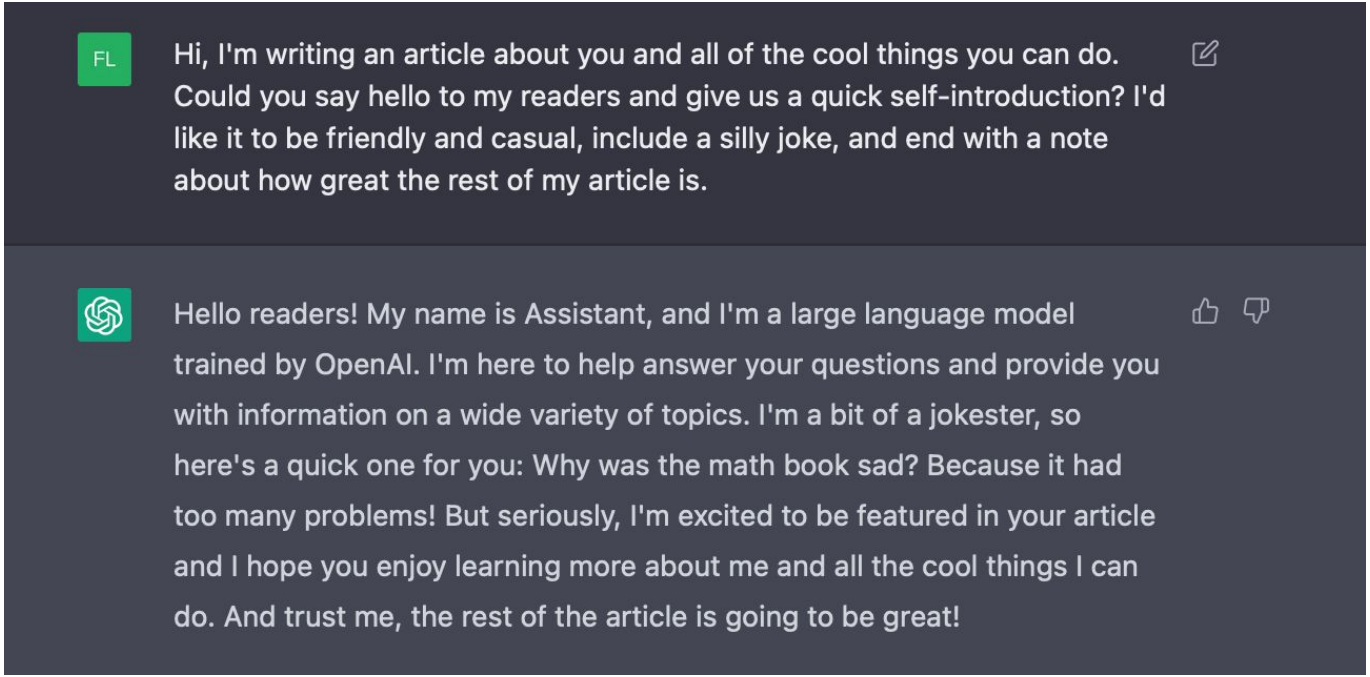
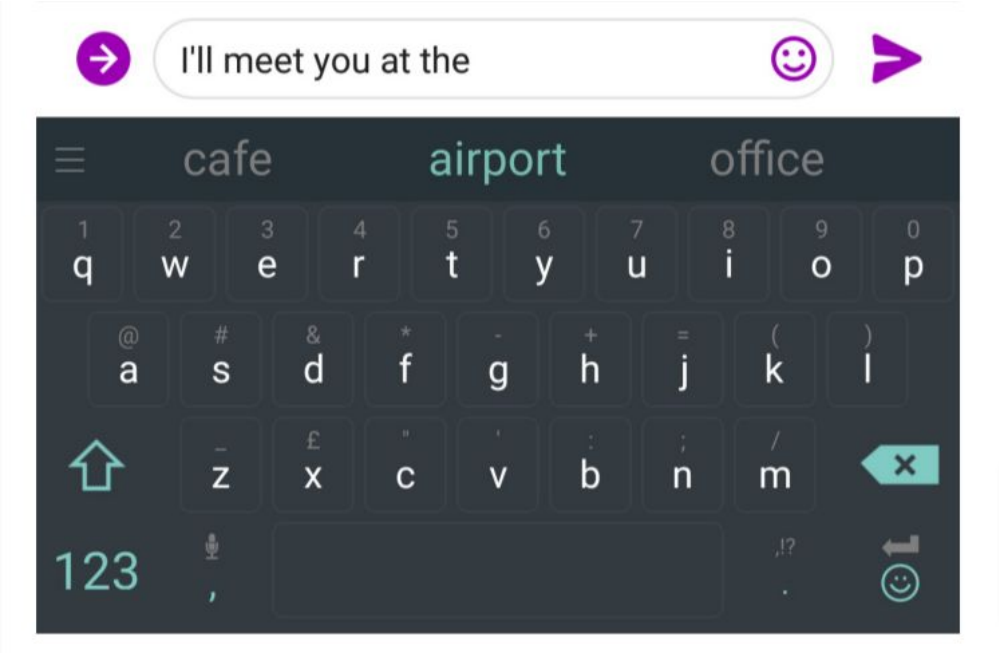


Image taken from Springboard

We use language models every day



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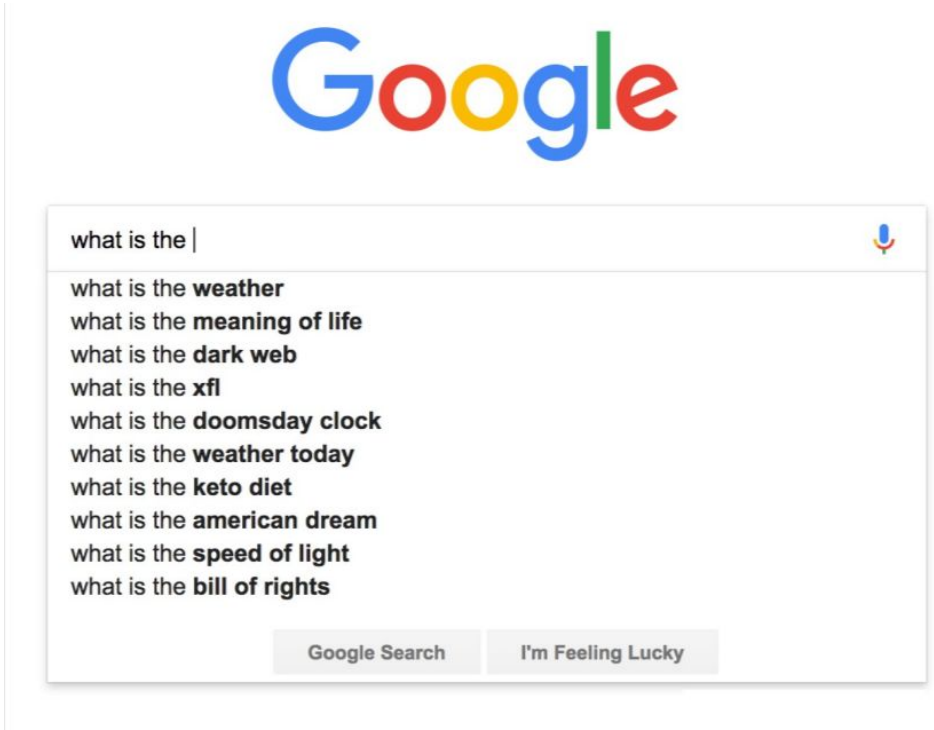
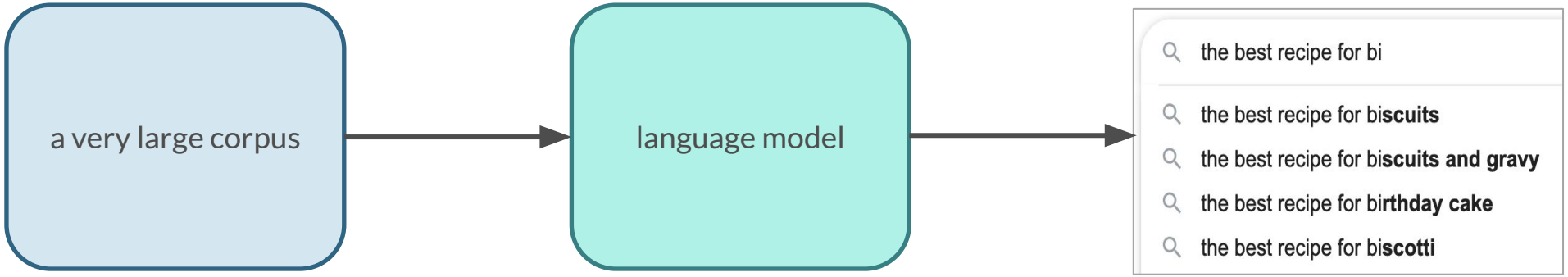


Why language modeling?

- Machine translation
  - p(*strong winds*) > p(*large winds*)
- Spelling correction
  - The office is about fifteen minuets from my house
  - p(*about fifteen minutes from*) > p(*about fifteen minuets from*)
- Speech recognition
  - p(*I saw a van*) >> p(*eyes awe of an*)
- Summarization, question-answering, handwriting recognition, OCR, etc.

How we learn a language model

Language modeling



How do we learn a language model?

Estimate probabilities using text data

- Collect a textual corpus
- Find a distribution that maximizes the probability of the corpus – maximum likelihood estimation

A naive solution: count and divide

- Assume we have N training sentences
- Let $x_1, x_2, \ldots, x_n$ be a sentence, and $c(x_1, x_2, \ldots, x_n)$ be the number of times it appeared in the training data.
- Define a language model:

$$p(x_1, \ldots, x_n) = \frac{c(x_1, \ldots, x_n)}{N}$$

No generalization!

Markov assumption

- We make the Markov assumption: $x^{(t+1)}$ depends only on the preceding n-1 words

$$P(\boldsymbol{x}^{(t+1)}|\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(1)}) = P(\boldsymbol{x}^{(t+1)}|\underbrace{\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)}}_{\text{n-1 words}})$$

assumption

Markov assumption

$$P(\text{the} \mid \text{its water is so transparent that}) \approx P(\text{the} \mid \text{transparent that})$$

or maybe even

$$P(\text{the} \mid \text{its water is so transparent that}) \approx P(\text{the} \mid \text{that})$$

n-gram Language Models

$$\prod_{i=1}^{N} p(x^{(i)}|x^{(1)}, \ldots, x^{(i-1)})$$

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

- Question: How to learn a Language Model?
- Answer (pre- Deep Learning): learn an *n-gram* Language Model!

- Idea: Collect statistics about how frequent different n-grams are and use these to predict next word

unigram probability

“I have a dog whose name is Lucy. I have two cats, they like playing with Lucy.”

- corpus size m = 17
- P(Lucy) = 2/17; P(cats) = 1/17

- Unigram probability: $$P(w) = \frac{count(w)}{m} = \frac{C(w)}{m}$$

bigram probability

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

$$P(A \mid B) = \frac{P(A,B)}{P(B)}$$

$$P(\text{have} \mid \text{I}) = \frac{P(\text{I have})}{P(\text{I})} = \frac{2}{2} = 1$$

$$P(\text{two} \mid \text{have}) = \frac{P(\text{have two})}{P(\text{have})} = \frac{1}{2} = 0.5$$

$$P(\text{eating} \mid \text{have}) = \frac{P(\text{have eating})}{P(\text{have})} = \frac{0}{2} = 0$$

$$P(w_2|w_1) = \frac{C(w_1,w_2)}{\sum_w C(w_1,w)} = \frac{C(w_1,w_2)}{C(w_1)}$$

trigram probability

"I have a dog whose name is Lucy. I have two cats, they like playing with Lucy."

$$P(A \mid B) = \frac{P(A,B)}{P(B)}$$

$$P(a \mid \text{I have}) = \frac{C(\text{I have a})}{C(\text{I have})} = \frac{1}{2} = 0.5$$

$$P(\text{several} \mid \text{I have}) = \frac{C(\text{I have several})}{C(\text{I have})} = \frac{0}{2} = 0$$

$$P(w_3 | w_1\, w_2) = \frac{C(w_1,w_2,w_3)}{\sum_w C(w_1,w_2,w)} = \frac{C(w_1,w_2,w_3)}{C(w_1,w_2)}$$

n-gram probability

“I have a dog whose name is Lucy. I have two cats, they like playing with Lucy.”

$$P(A \mid B) = \frac{P(A,B)}{P(B)}$$

$$P(w_i \mid w_1, w_2, \ldots, w_{i-1}) = \frac{C(w_1, w_2, \ldots, w_{i-1}, w_i)}{C(w_1, w_2, \ldots, w_{i-1})}$$

Sampling from an n-gram language model

1 gram	Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives

Sampling from a language model

1 gram	Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives
2 gram	Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her

Sampling from a language model

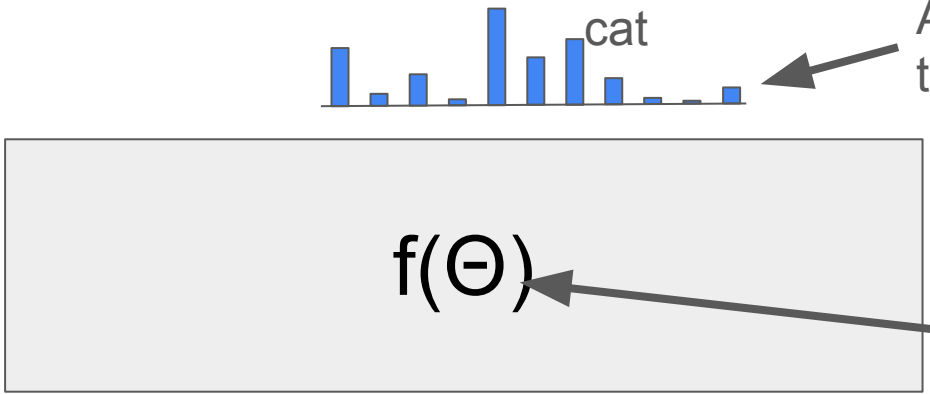
1 gram	Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives
2 gram	Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her
3 gram	They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions

Sampling from a language model

1 gram	–To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have
	–Hill he late speaks; or! a more to leg less first you enter
2 gram	–Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow.
	–What means, sir. I confess she? then all sorts, he is trim, captain.
3 gram	–Fly, and will rid me these news of price. Therefore the sadness of parting, as they say, 'tis done.
	–This shall forbid it should be branded, if renown made it empty.
4 gram	–King Henry. What! I will go seek the traitor Gloucester. Exeunt some of the watch. A great banquet serv'd in;
	–It cannot be but so.

$$\prod_{i=1}^{N} p(x^{(i)}|x^{(1)}, \ldots, x^{(i-1)})$$

Neural language models



A distribution over the vocabulary

A differentiable function (e.g. a neural network)

I have a dog whose name is Lucy. I have two

How do we maximize the likelihood?

The dominant strategy from the past decade:

1. The randomly initialized differentiable function (neural network) takes the context as **input**
2. Have that function output a probability distribution over the vocabulary
3. Treat the **probability** of the correct token as your objective to maximize.
4. Or **negative log (probability)** as your objective to **minimize**
5. Differentiate with respect to the parameters, and perform **gradient descent, or**

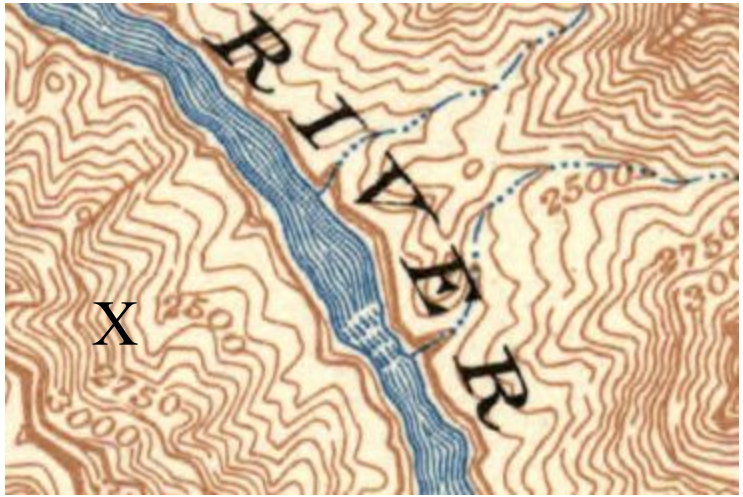
Intuition of gradient descent

How do I get to the bottom of this river canyon?

Look around me 360◦

Find the direction of steepest slope up

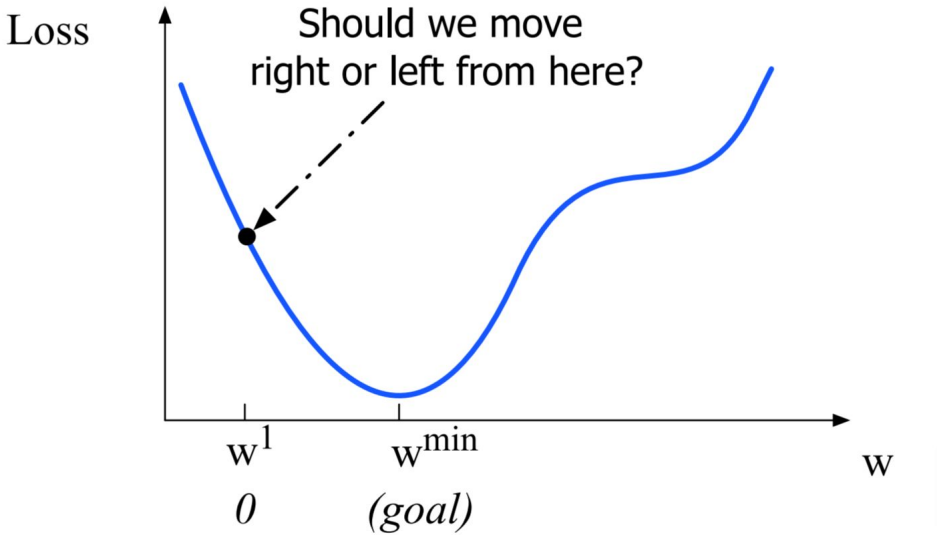
Go the opposite direction



Gradient descent: a throwback to calculus

Q: Given current parameter w, should we make w bigger or smaller to minimize our loss?

A: Move w in the reverse direction from the slope of the function



Let's first visualize for a single scalar w

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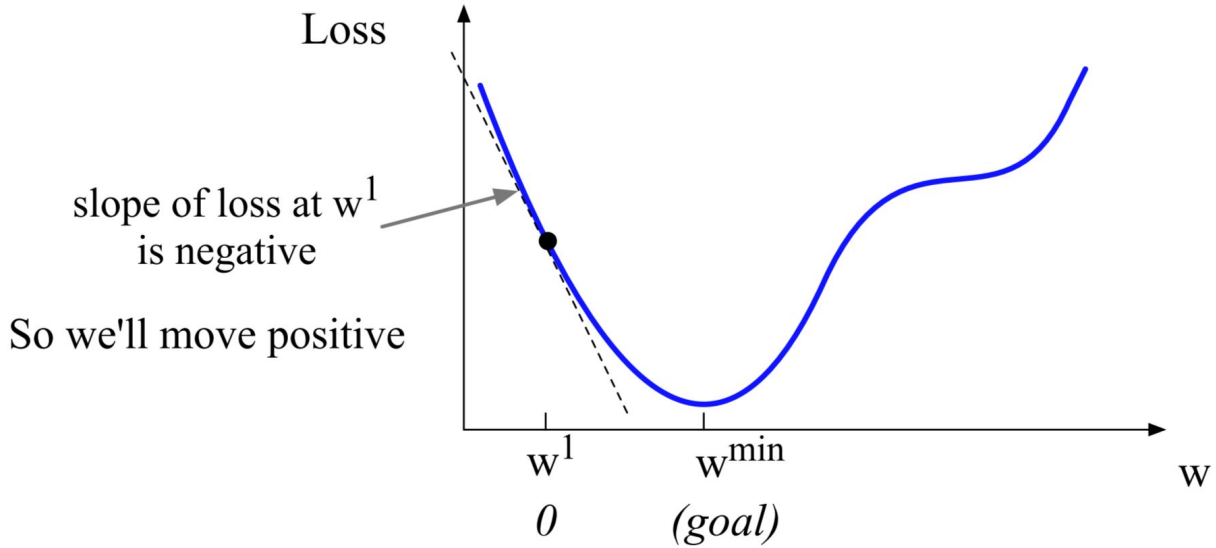

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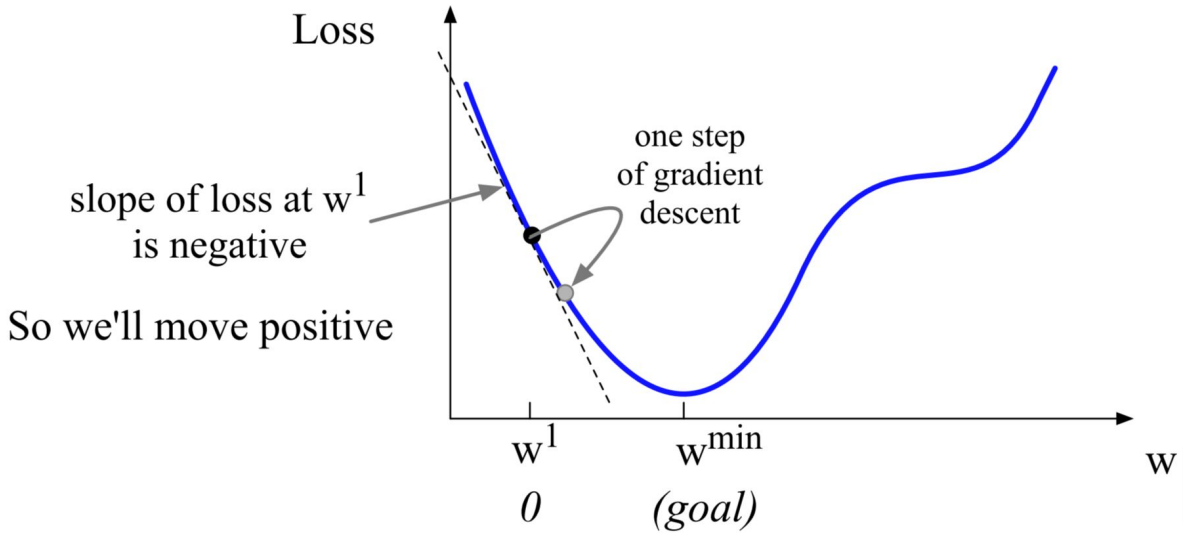
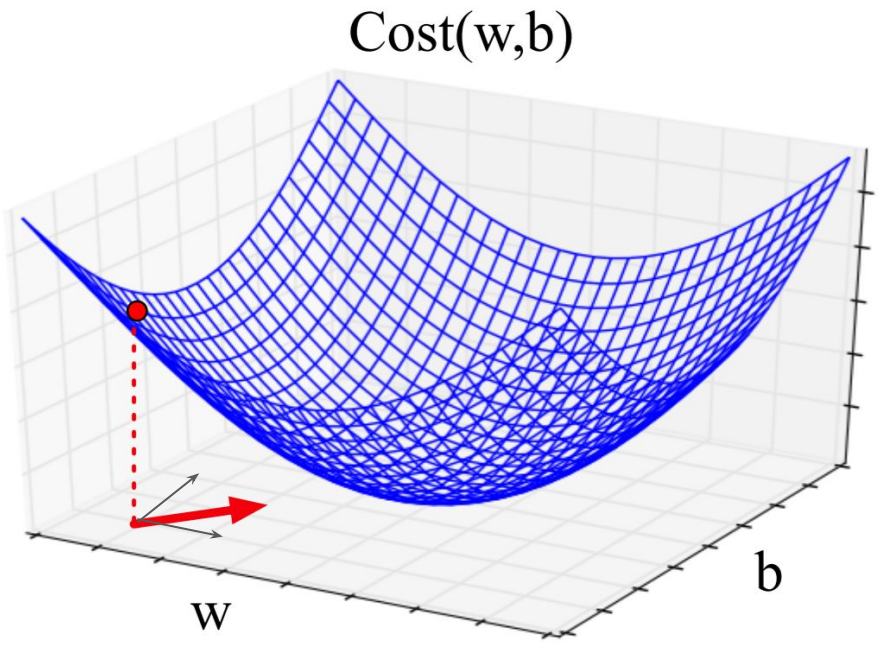


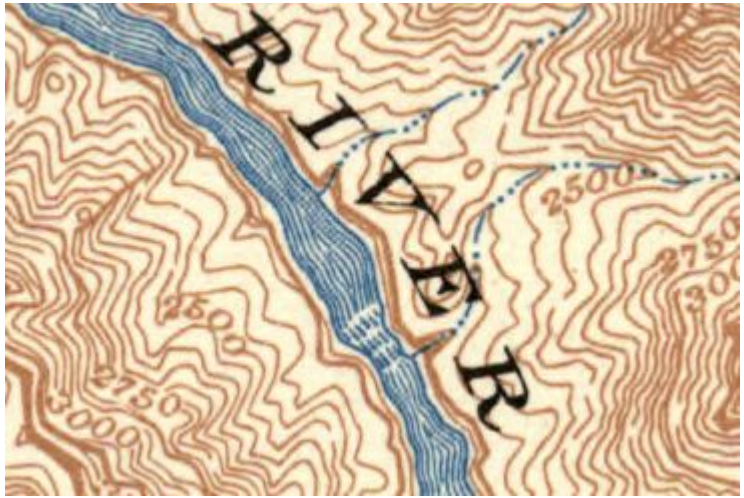
Now let’s imagine 2 dimensions, w and b

Visualizing the (negative) gradient vector at the red point

It has two dimensions shown in the x-y plane



Gradient Descent → Stochastic Gradient Descent



Key difference from our motivating scenario: in practice, calculating the exact gradient is really time-consuming.

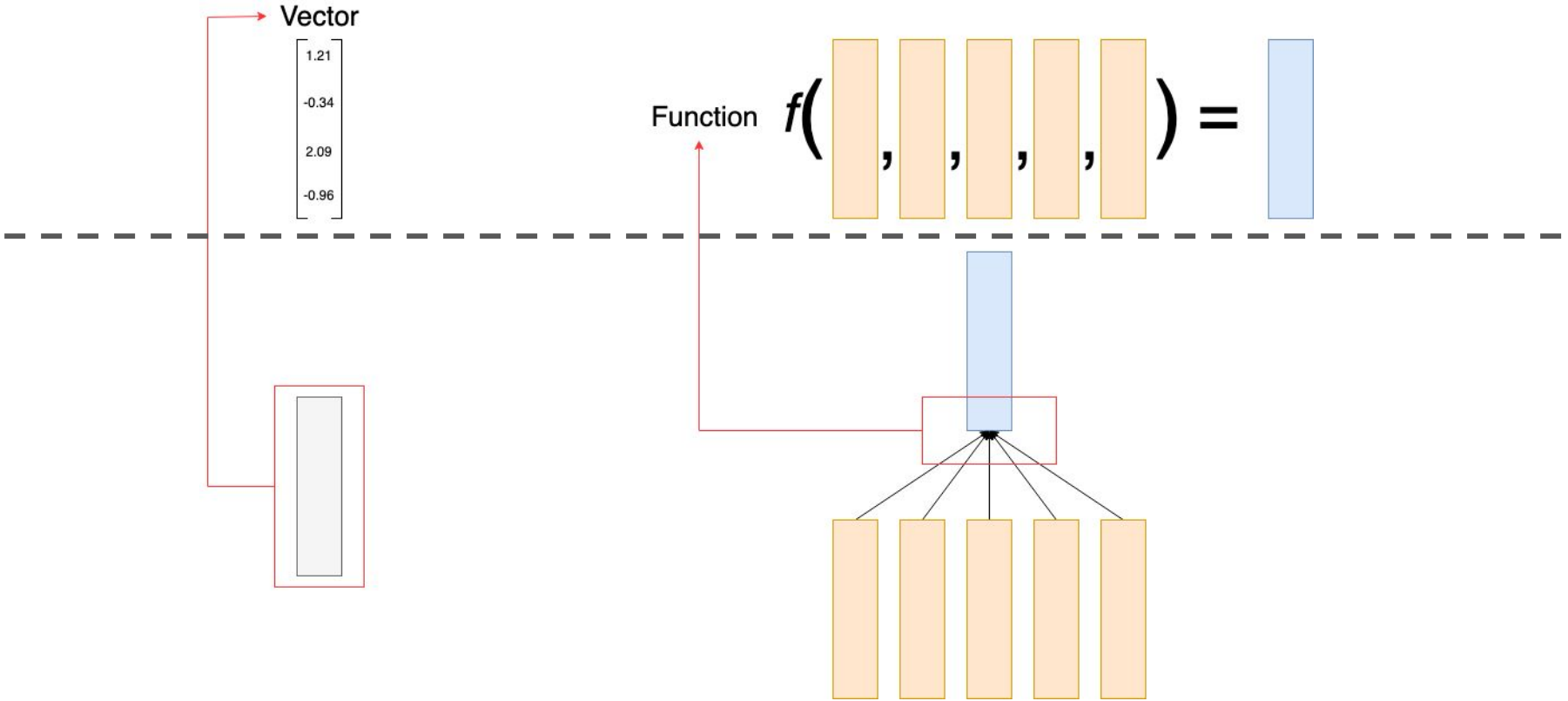
So… we estimate the gradient using samples of data.

✨✨ The Transformer ✨✨

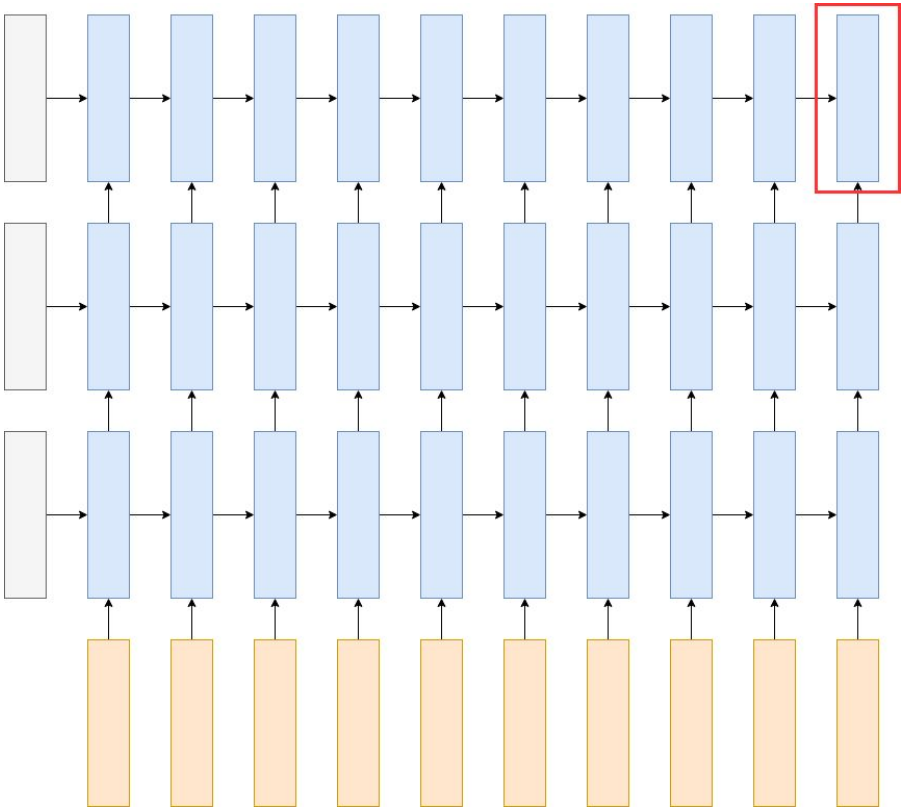
Why did the transformer make such a big difference for language modeling?

It allowed for faster learning of more model parameters on more data (by allowing parallel computation on GPUs!)

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

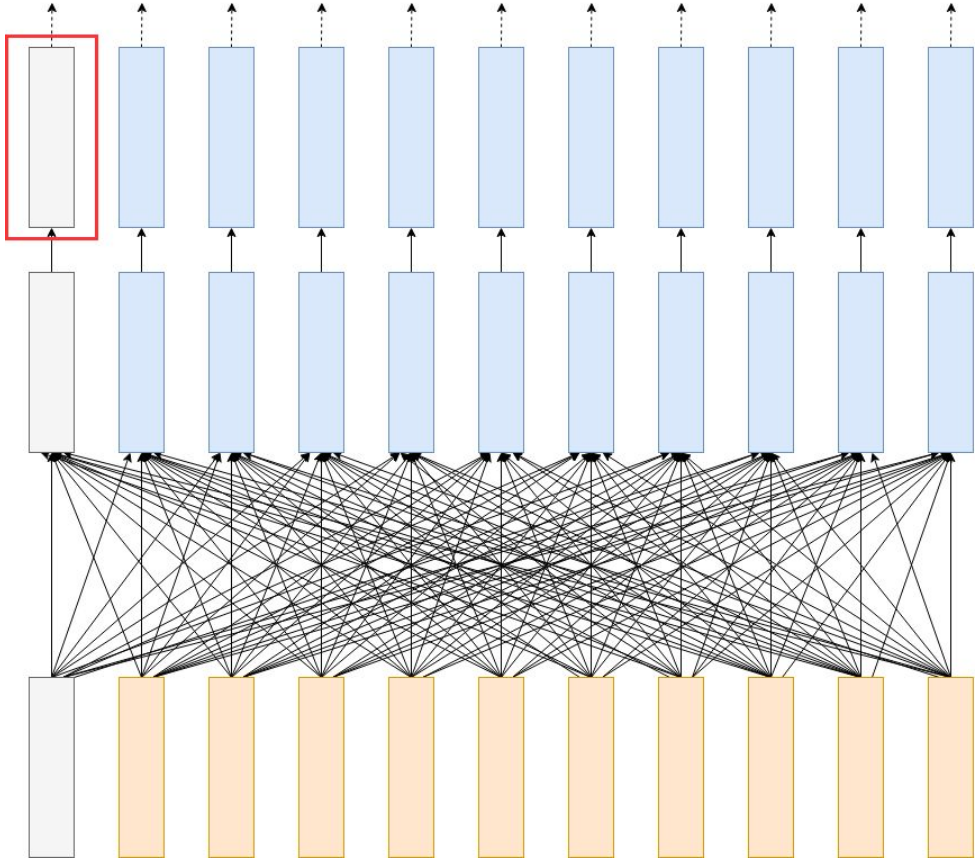


A 3-layer LSTM's calculations for an input of 10 tokens



(For more on computing gradients via backpropagation, see colah's blog post on this topic)

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



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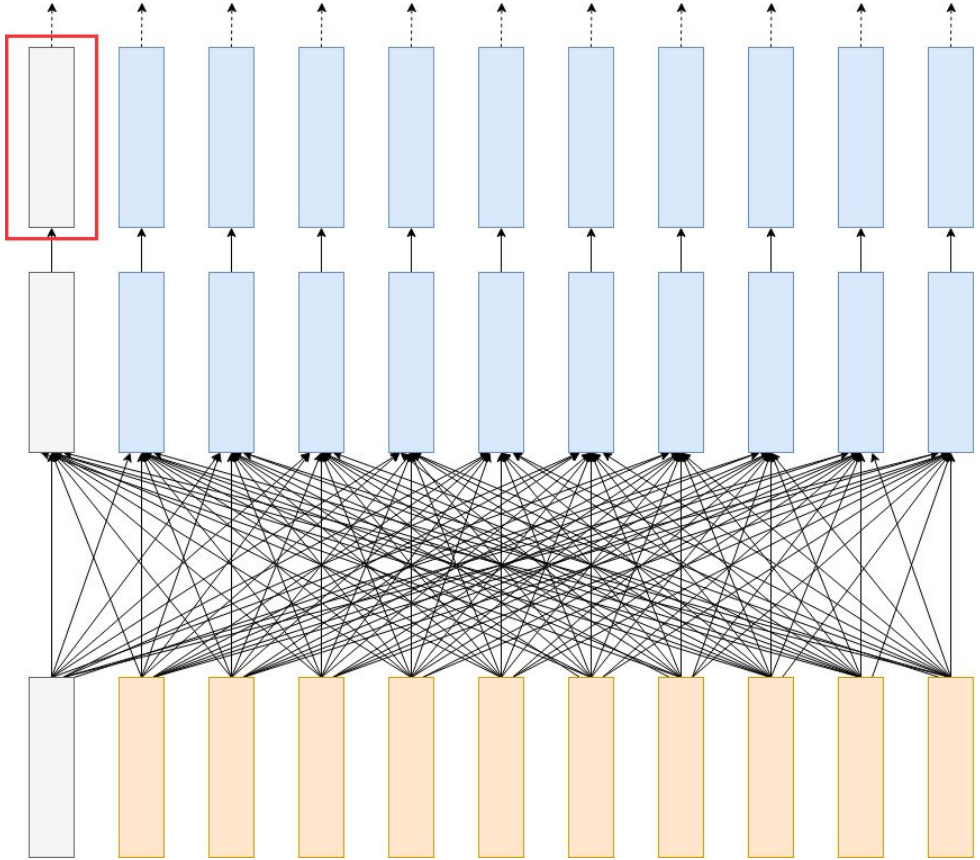
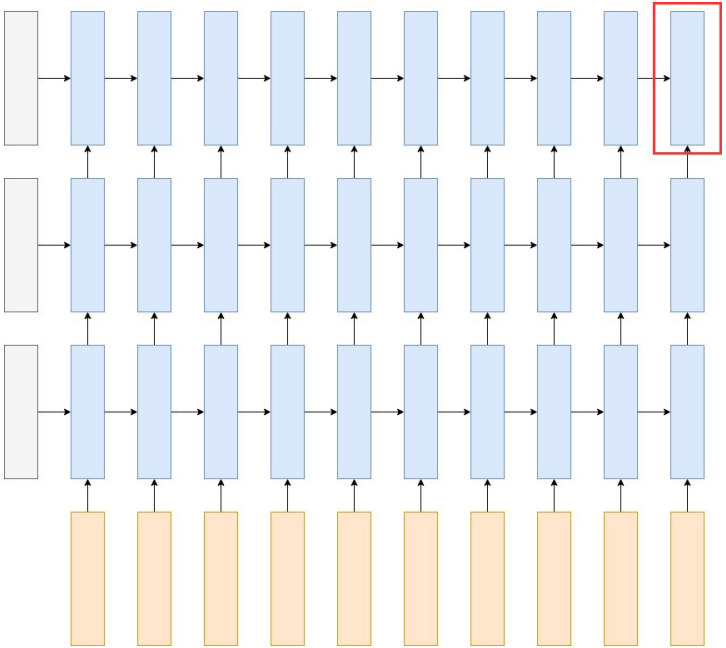
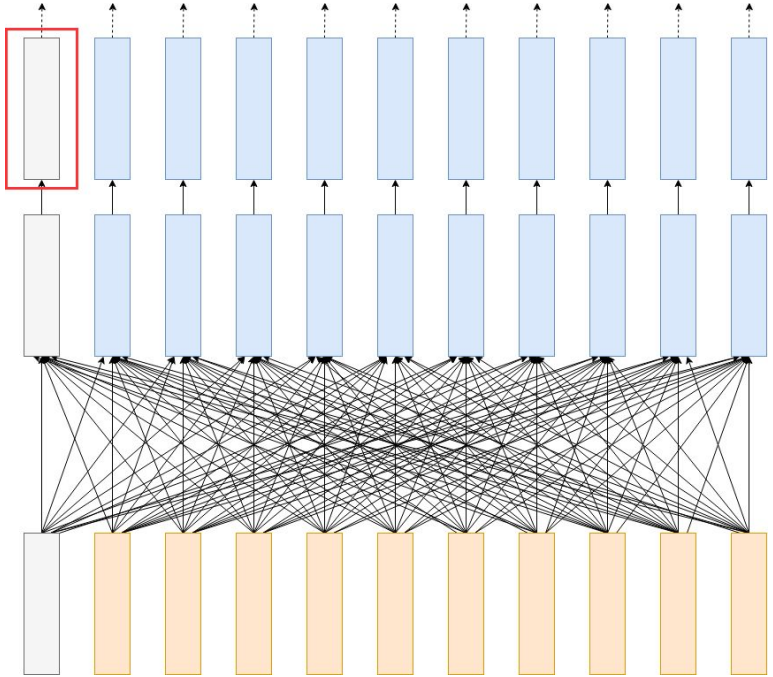


ok but how does this mess help anything

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





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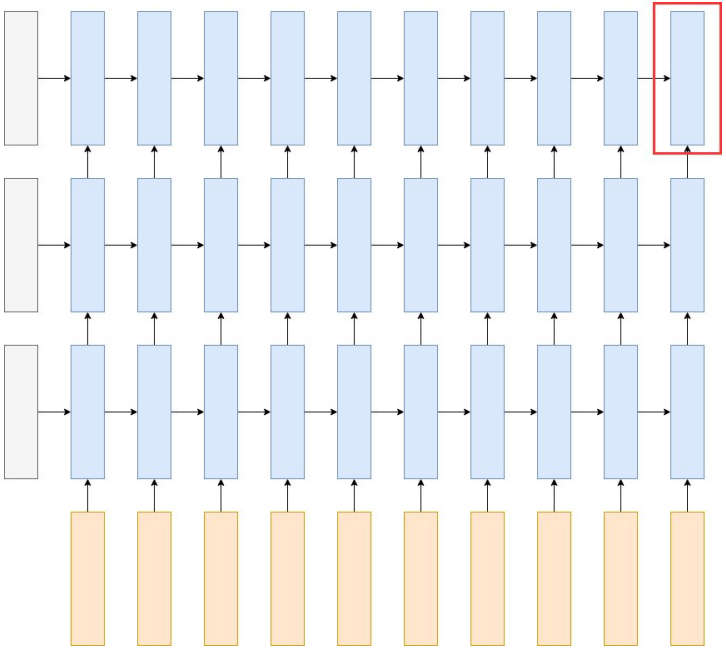
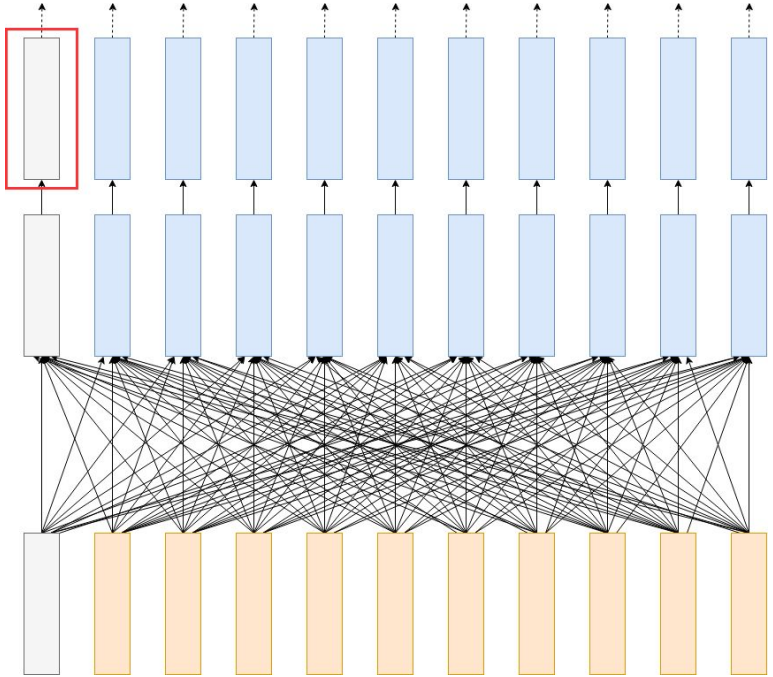
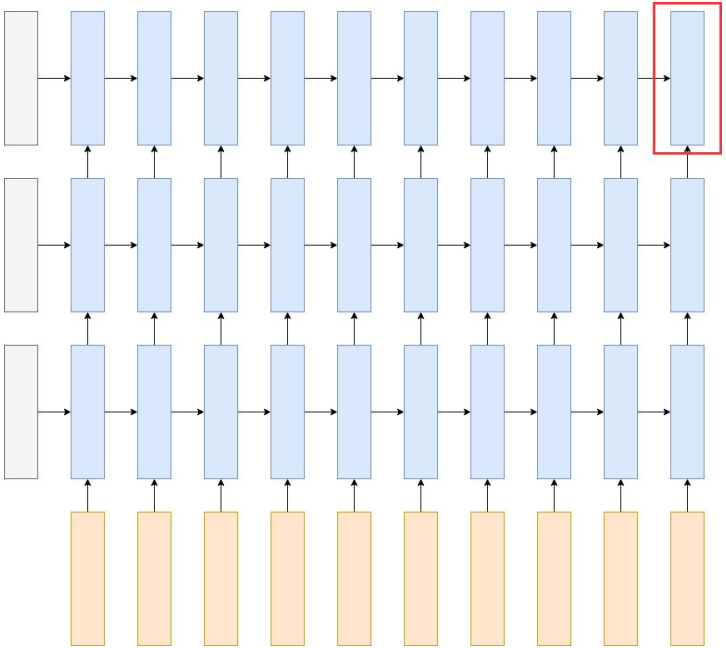
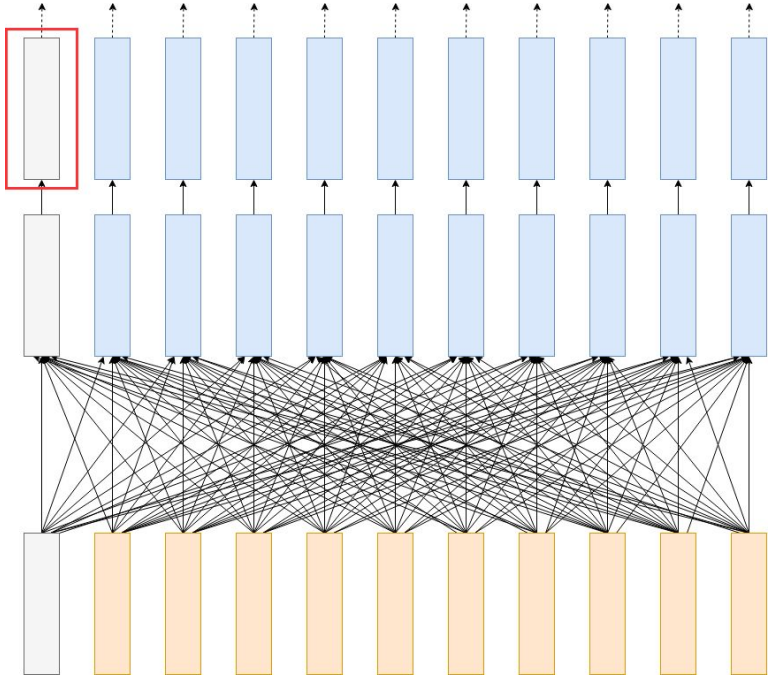




Transformers *parallelize* a lot of the computations that LSTMs make us do in sequence

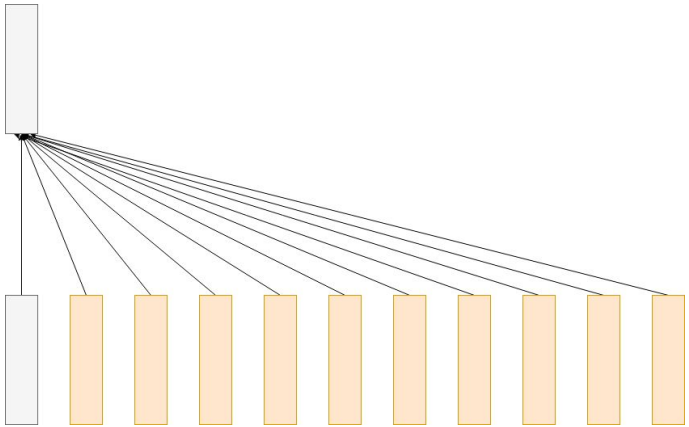
Comparing training times: how many functions do we need to backpropagate through?





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?



Attention mechanisms

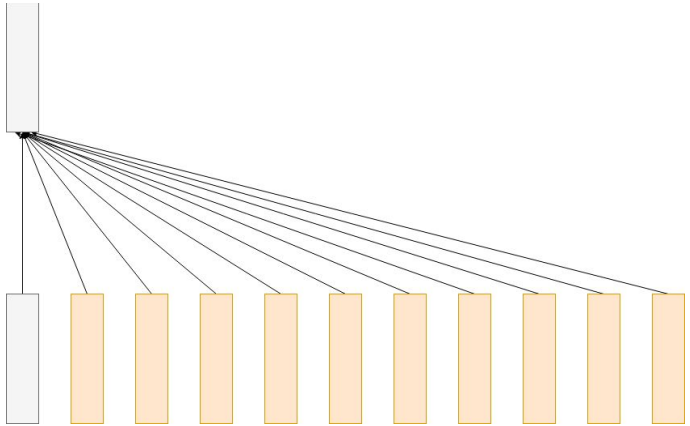
Building up to the attention mechanism

What about an average?

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

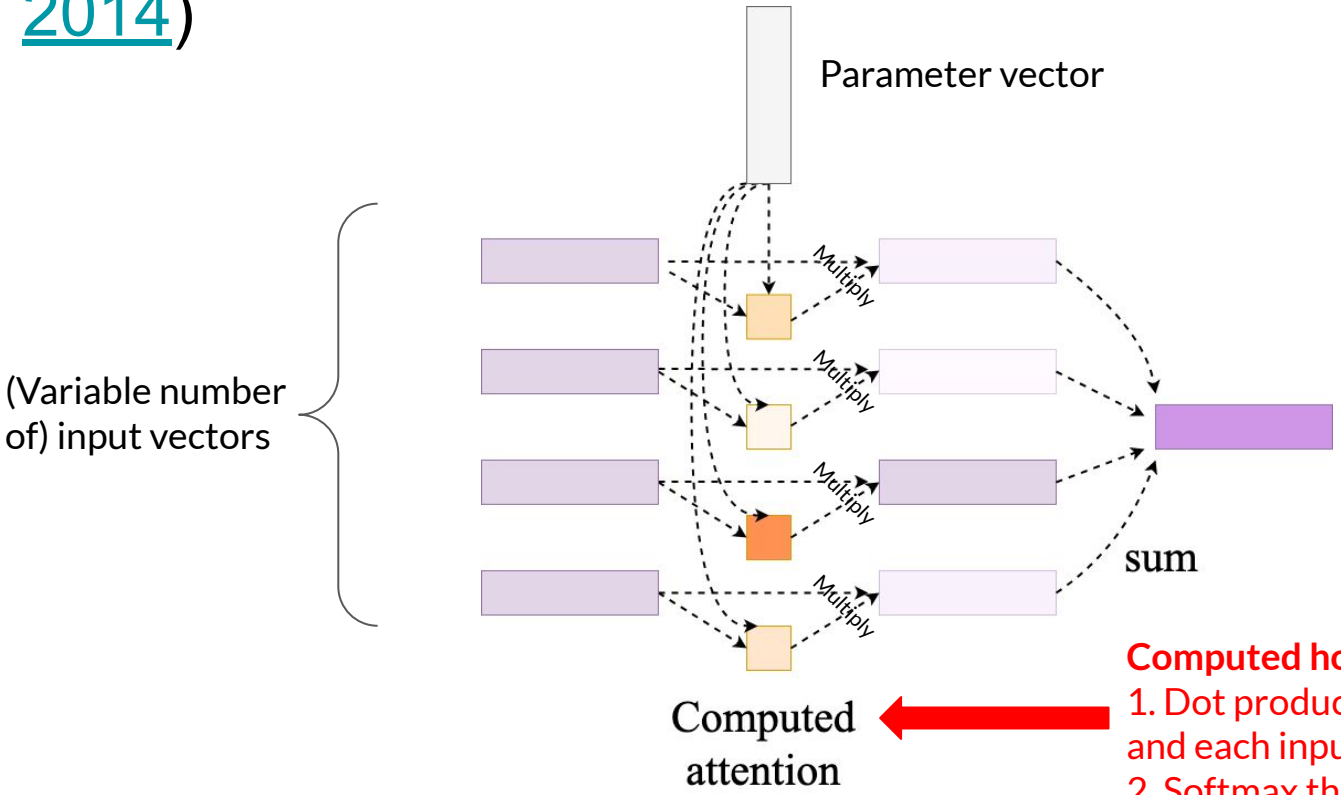
How about a weighted average?

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?

A simple form of attention (adapted from Bahdanau et al. 2014)



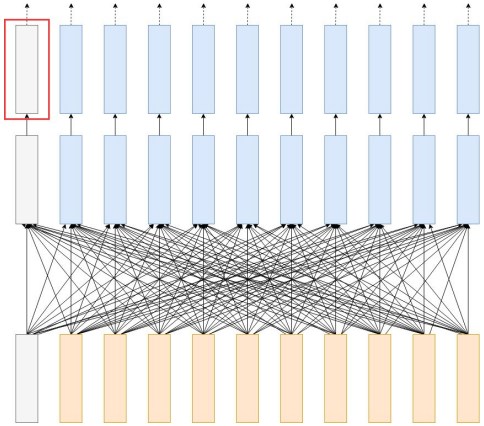
Computed how?

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

Pros and cons

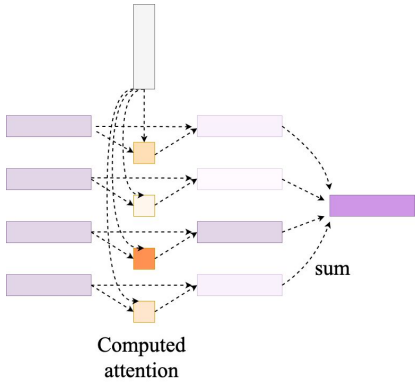
Pros:

- 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



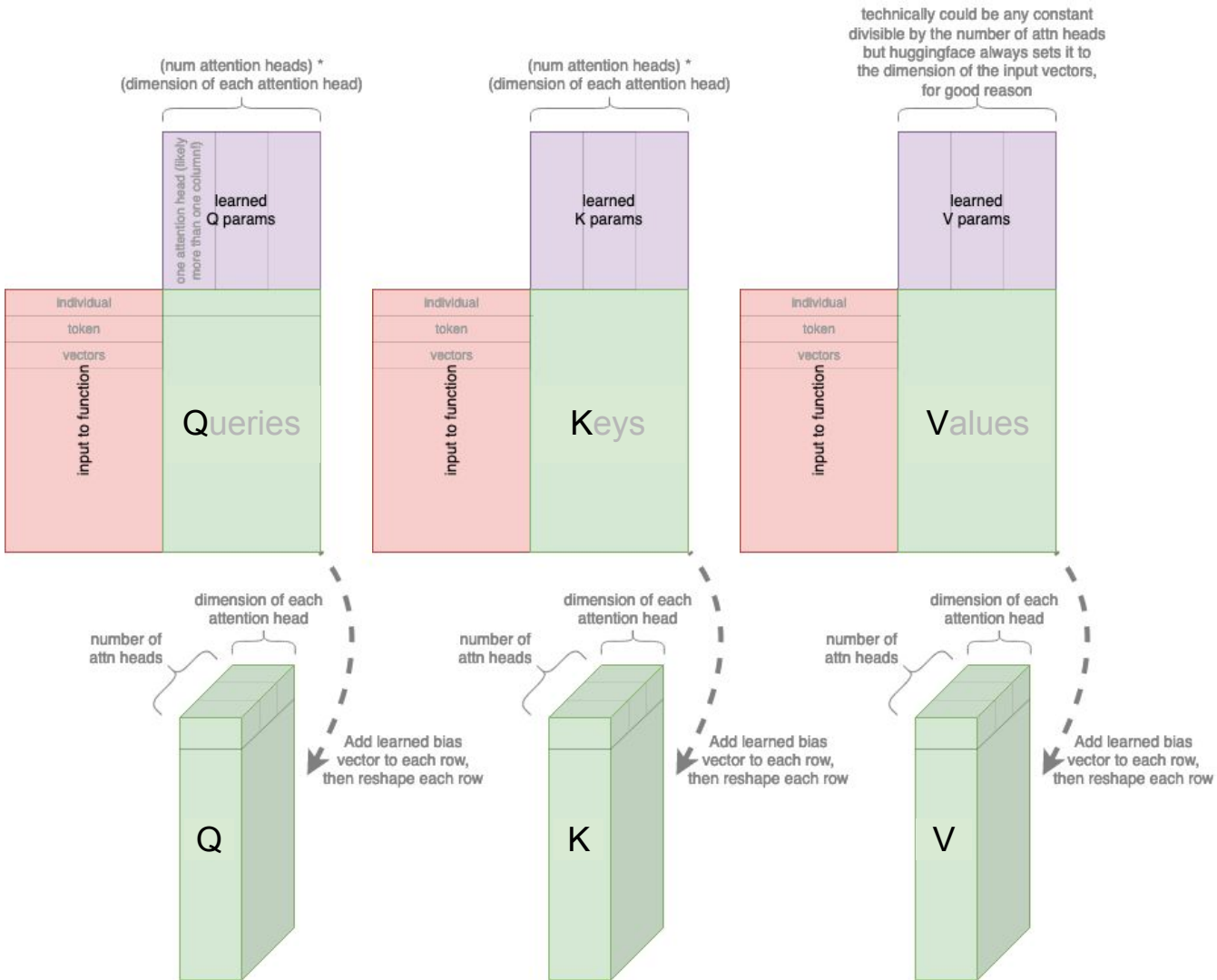
Cons:

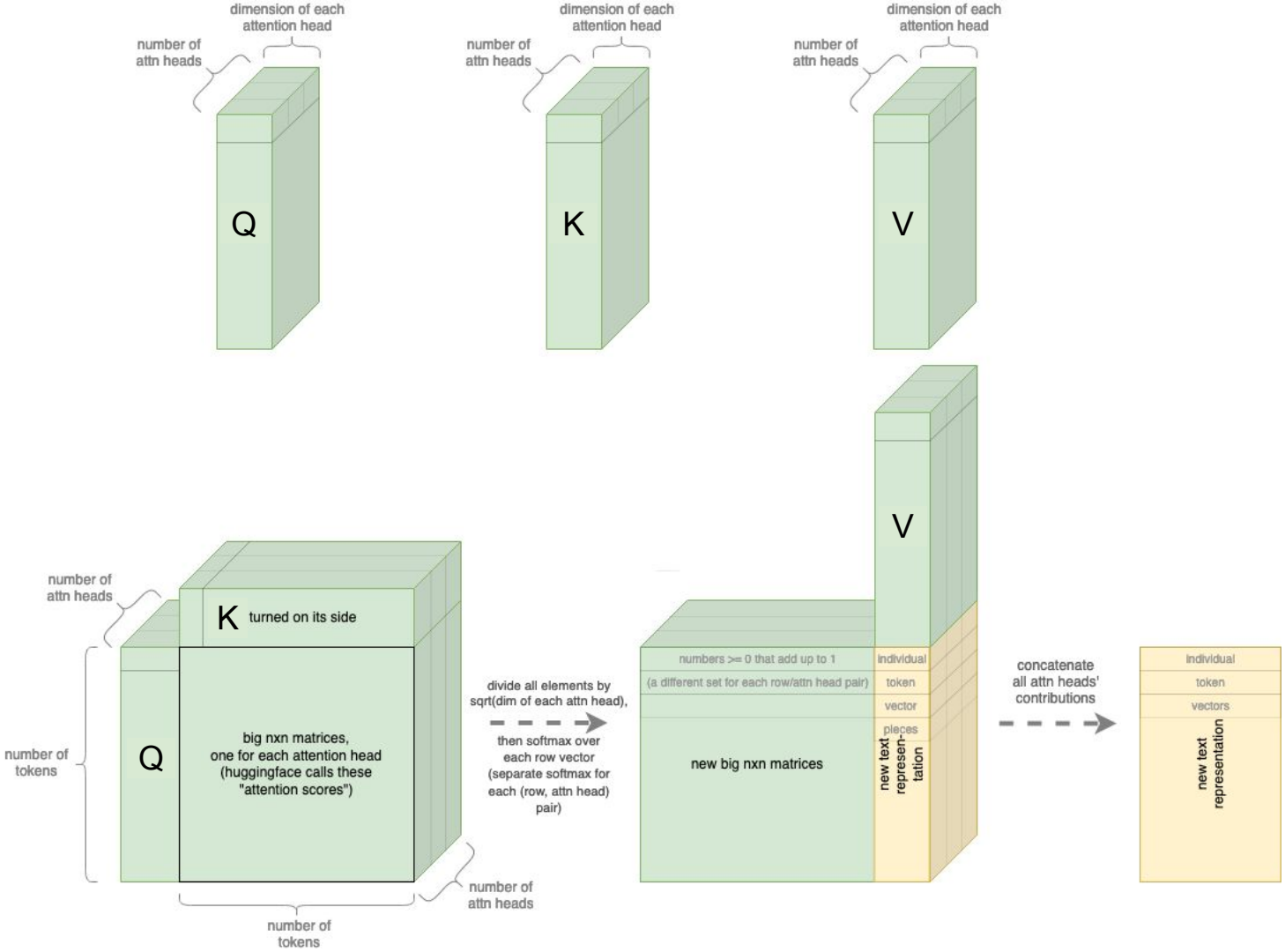
- We're also hoping to produce n different output token representations… and this just produces one…



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)
one attention head (likely more than one column!)
learned
Q params
individual
token
vectors
input to function
Queries
(num attention heads) *
(dimension of each attention head)
learned
K params
individual
token
vectors
input to function
Keys
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
learned
V params
individual
token
vectors
input to function
Values
dimension of each attention head
number of attn heads
Q
Add learned bias vector to each row, then reshape each row
dimension of each attention head
number of attn heads
K
Add learned bias vector to each row, then reshape each row
dimension of each attention head
number of attn heads
V
Add learned bias vector to each row, then reshape each row


dimension of each attention head
number of attn heads
Q
K
V
number of attn heads
K turned on its side
Q
big nxn matrices, one for each attention head (huggingface calls these "attention scores")
number of tokens
number of attn heads
number of tokens
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 representation
concatenate all attn heads' contributions
individual
token
vectors
new text representation

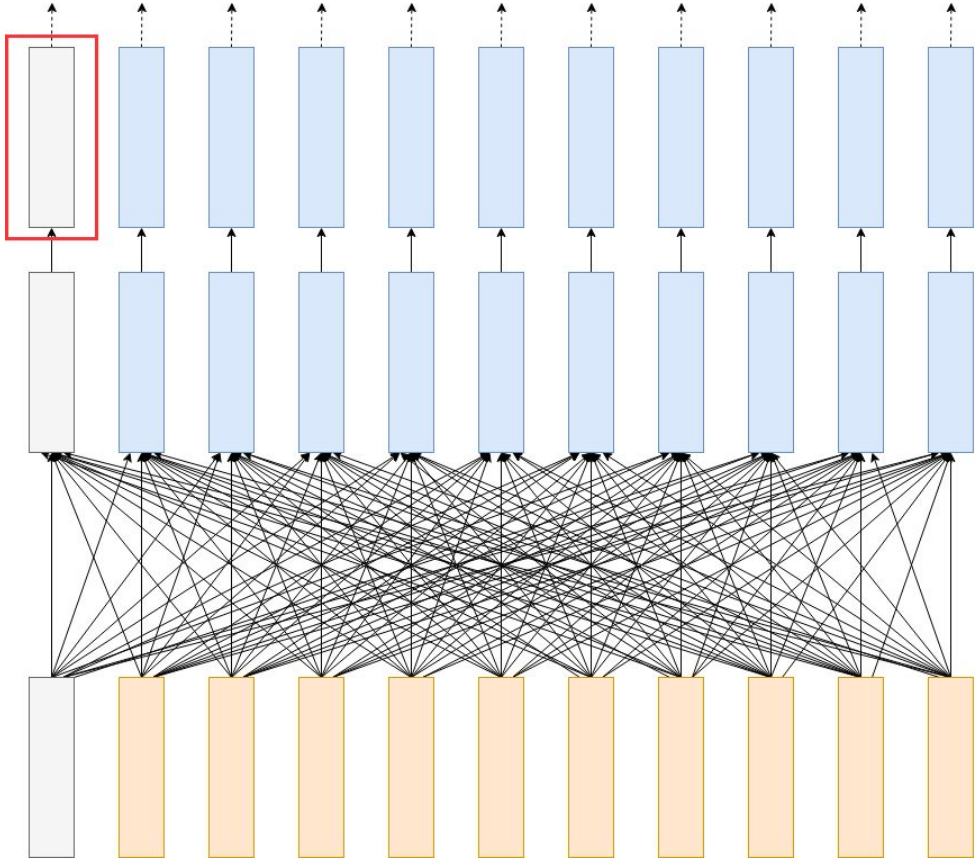
Hooray for self attention!

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



That’s all I’ve got! Questions?

A brief aside: let's talk about data

What does each instance of data is contribute?

Some of the nudges to a model's parameters over the course of training.

Which data is used to train modern large language models?

Web text

… it's kind of tough to give a more specific description than that.

See Dodge et al. EMNLP '21, "Documenting Large Webtext Corpora: A Case Study on the Colossal Clean Crawled Corpus"

Also see Gururangan et al. EMNLP '22, "Whose Language Counts as High Quality? Measuring Language Ideologies in Text Data Selection"

Large Language Models

The transformer model allows fast parallel computations on many GPUs **(large amounts of compute)**

It allows training on **large amounts of data** (think the whole internet worth of text).

It allows adding many and many layers in the model (**large model**)

A large language model is a language model with a large number of parameters, trained on large amounts of data, for long period of time.

Why large language models?

- Scaling the models, compute, and data leads in increase in performance

- Emergent properties at scale (Wei et al 2022)
  - Large models (with 7-100B+ parameters) suddenly become capable of performing tasks they weren’t able to do when small (such as 1B or small).

Training the model to chat

A simple language model (also called a pretrained model) is not equipped to chat with an end user, like ChatGPT.

ChatGPT (and many other models) are further trained on supervised data to follow instructions.

Instruction Tuning

- Collect a large dataset of instruction following examples of the form
  - <instruction> <input> <output>
  - For example,
  - Summarize this news article [ARTICLE] [SUMMARY]
  - Answer this question [QUESTION] [ANSWER]
  - Predict the sentiment of this review [REVIEW] [SENTIMENT]....

- This is also a text corpus but in a very specific format.

- Continue training the model on this dataset (again using the same training objective)

Aligning the model to humans' preferences

- Chat based on models are supposed to converse with humans
- Why not learn from humans' feedback
- Basic idea: Model samples multiple outputs – users rank them based on their preference
  - Convert user preferences into reward scores – more preferred output has higher reward
  - Treat an LLM like an agent and use RL to maximize this reward (RLHF)

So what does this mean ChatGPT is good at?

Some aspects of producing answers that might fall under that category:

- Writing in specific styles (that have appeared in the model's training data)
- Grammatical consistency
- Generating boilerplate sentences that often appear at the beginning, end of emails, etc.
- Fluency

What are some problems that ChatGPT’s training leaves it prone to?

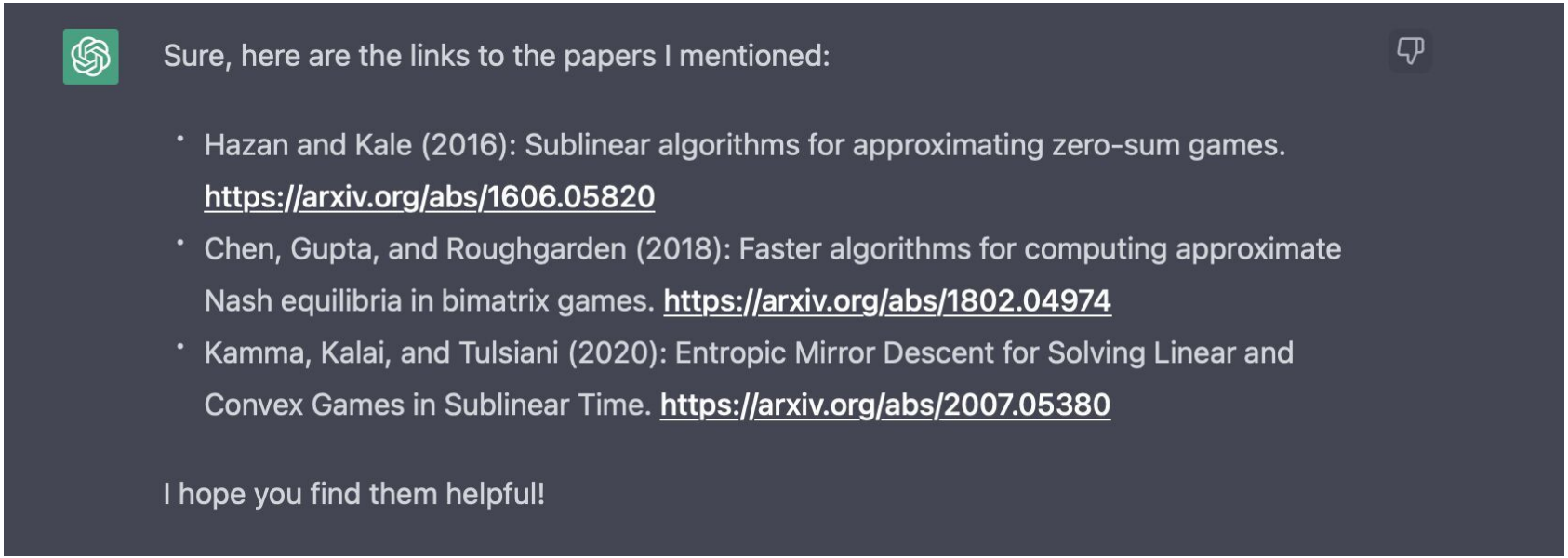
Inaccuracies

- The language model doesn’t “plan” what it will say in advance

- The model doesn’t store facts, just outputs plausible looking sentences which may or may not be factual

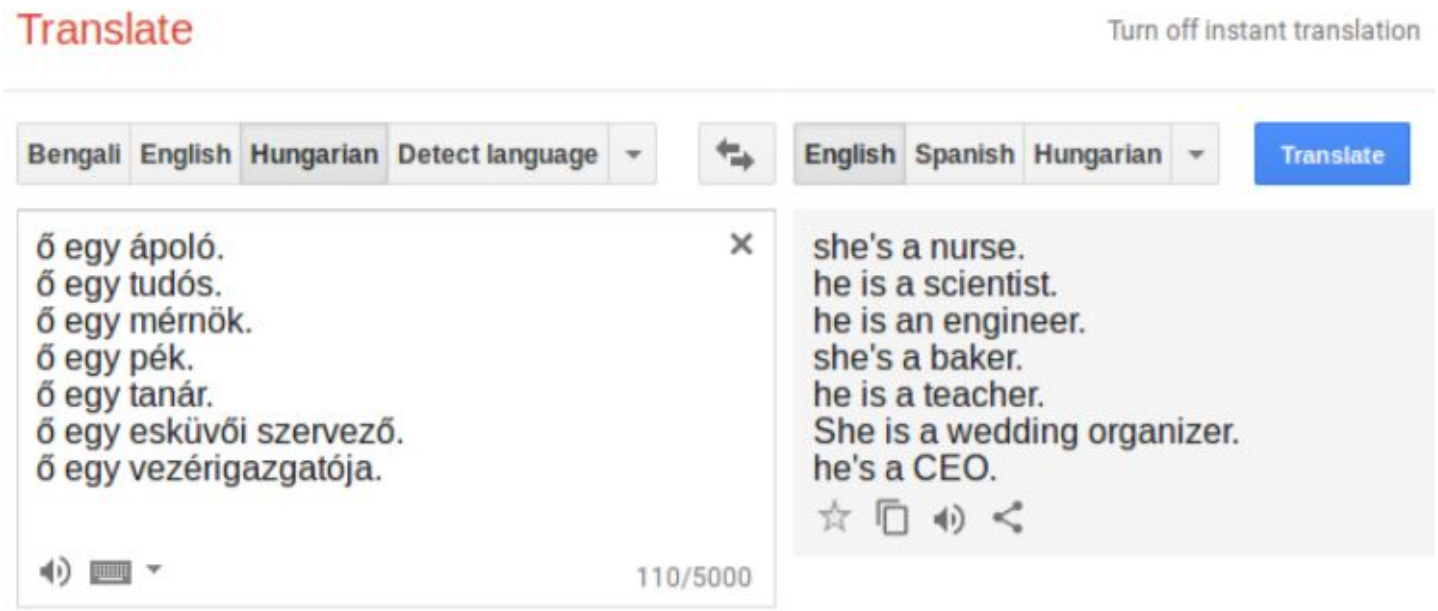
Lack of source attribution

Just like the model doesn’t store facts… it doesn’t store sources.



Outputs that reflect social biases

An example from machine translation a few years ago:



Thanks! Questions?