Sampling and Inference

Lecture 7

EN.705.743: ChatGPT from Scratch

Lecture Outline

- So we have a trained model
- What does the model do?
- Sampling from a trained model
- Practical considerations (kv caching)
- Prompting
- OpenAI Playground Demo

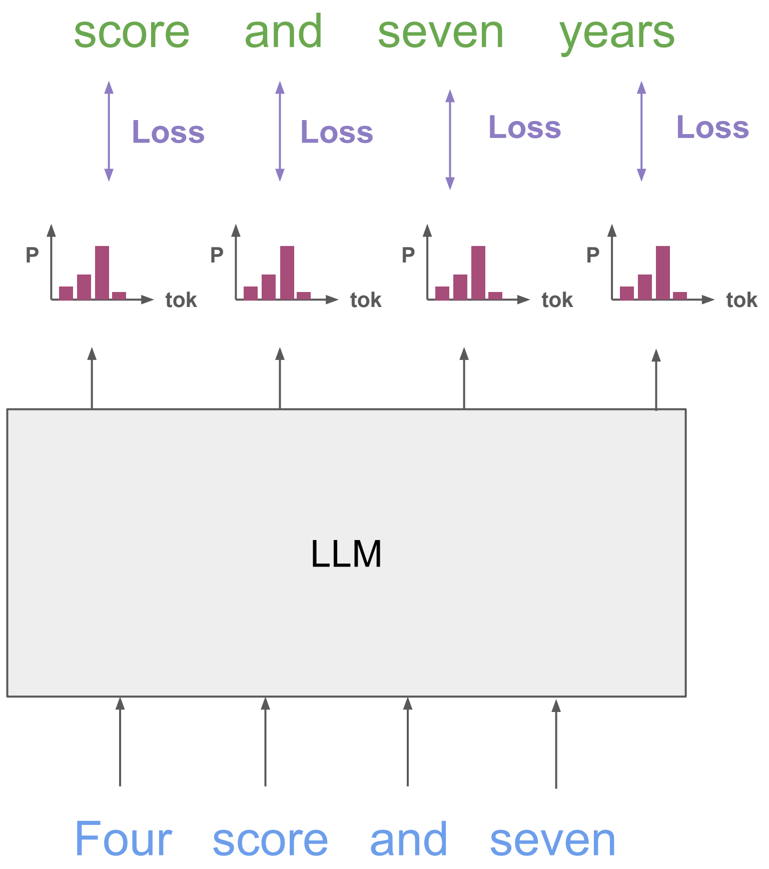
Recap: A Trained Model

Recap

Last week we discussed model training. An LLM is trained on many billions of tokens, often representing large swaths of the internet.

Recap

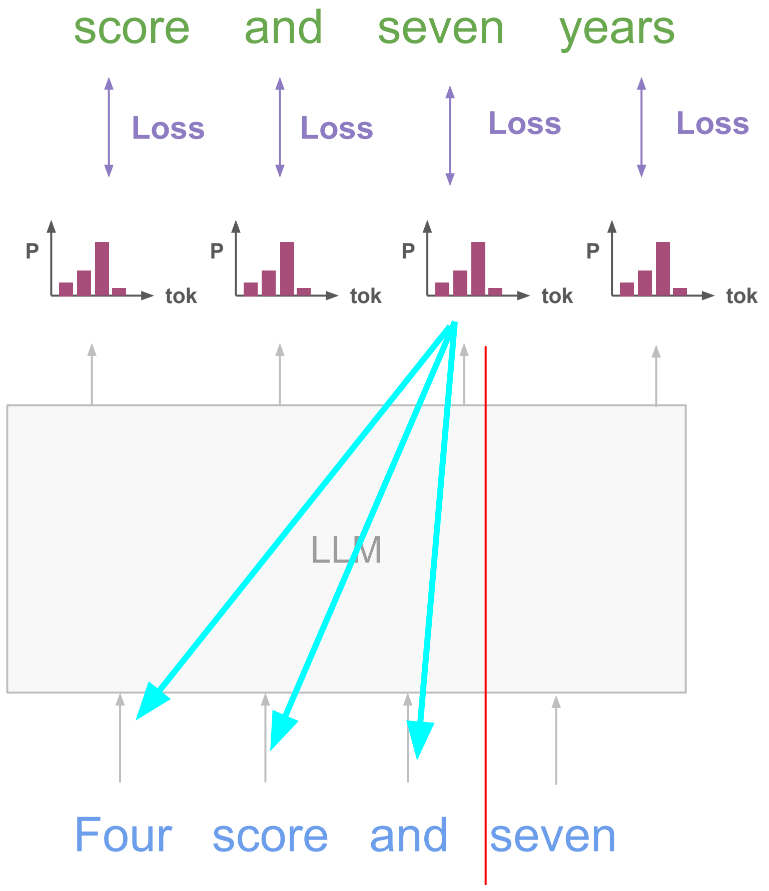
The LLM is trained by taking a sample of text and computing, at each position, a loss between the predicted probabilities over next tokens and the actual token from that sample (cross-entropy loss).



Recap

The LLM is trained by taking a sample of text and computing, at each position, a loss between the predicted probabilities over next tokens and the actual token from that sample (cross-entropy loss).

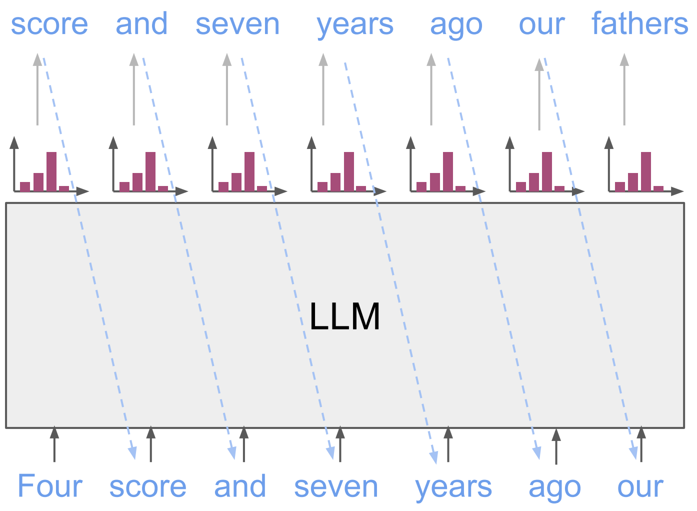
At position i, the output is only dependent on inputs [0 to i], because we use causal masking.



Recap

To generate text with our model, we can start with some initial text, and then sample one token at a time.

Each time we sample a token, we add it to the input and repeat (until we reach some desired length or an <|eos|> token).



Recap

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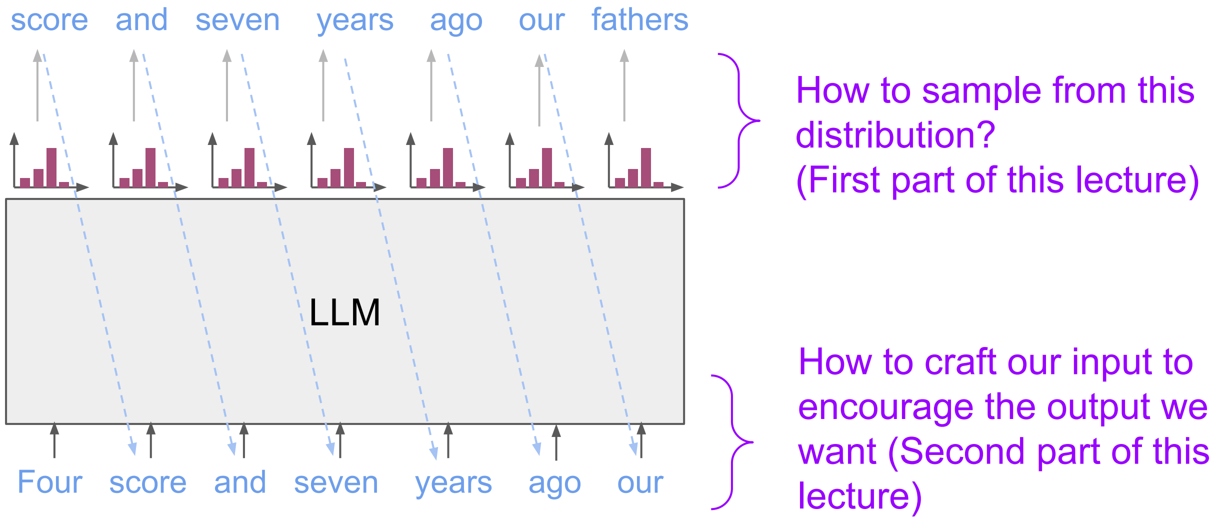

score
and
seven
years
ago
our
fathers
LLM
Four
score
and
seven
years
ago
our
How to sample from this distribution?
(First part of this lecture)
How to craft our input to encourage the output we want (Second part of this lecture)

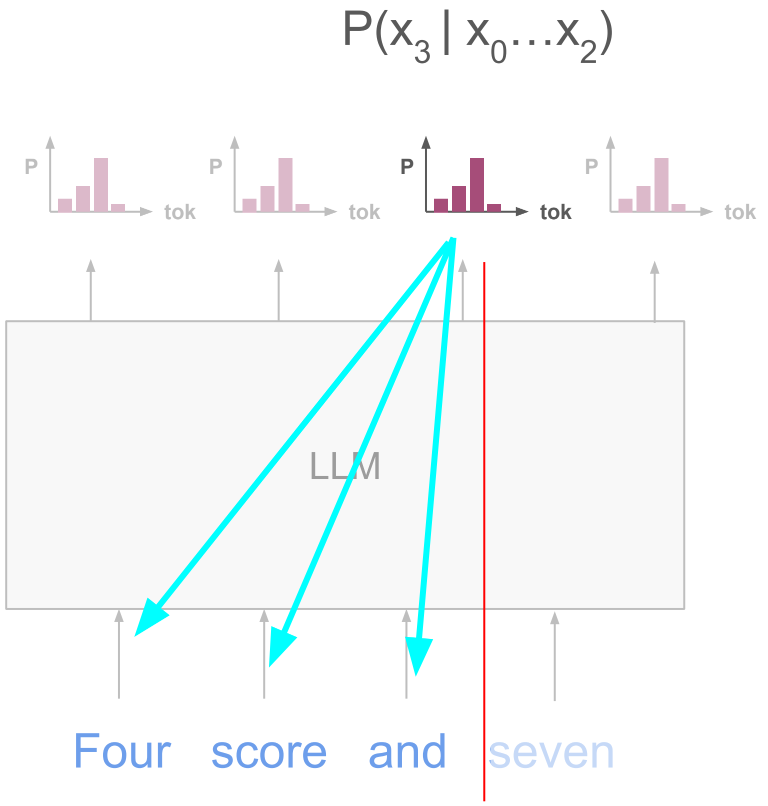
Understanding the Training Objective

Writing out what our model computes

Each output at position i is a probability distribution over the tokens that could appear at this position: $P_{tokens}(x_i)$

But it is conditioned on all previous inputs:

$$\mathbf{P_{tokens}(x_i|x_0\ldots x_{i-1})}$$



Why is this important?

This is important because for each output there are actually two sources of information:

1) The model’s internal weights (what is knows about the world, grammar, patterns of language, spelling, etc)
2) The provided context (which in some cases can be thousands of tokens!)

The model is trying to make use of both of these to provide an output.

Examples

The capital of the United States is *Washington.*

The model needs to know the capital of the U.S. (mainly internal weights)

Red, blue, red, blue, red, blue, red, *blue.*

The model is simply continuing the input pattern (provided context)

Raspberry, blackberry, blueberry, *strawberry.*

A bit of both. The input has a pattern, but the model also needs to know fruit.

Most examples will be in the last category- the model uses knowledge and the context to provide an output distribution.

Behavior

Ultimately, the model has been trained to supply the next token given some context. At this point we have a base model which is purely designed to continue text.

This model is not interactive, it just takes whatever text you give it and keeps going.

What is the capital of France? How many people live there?

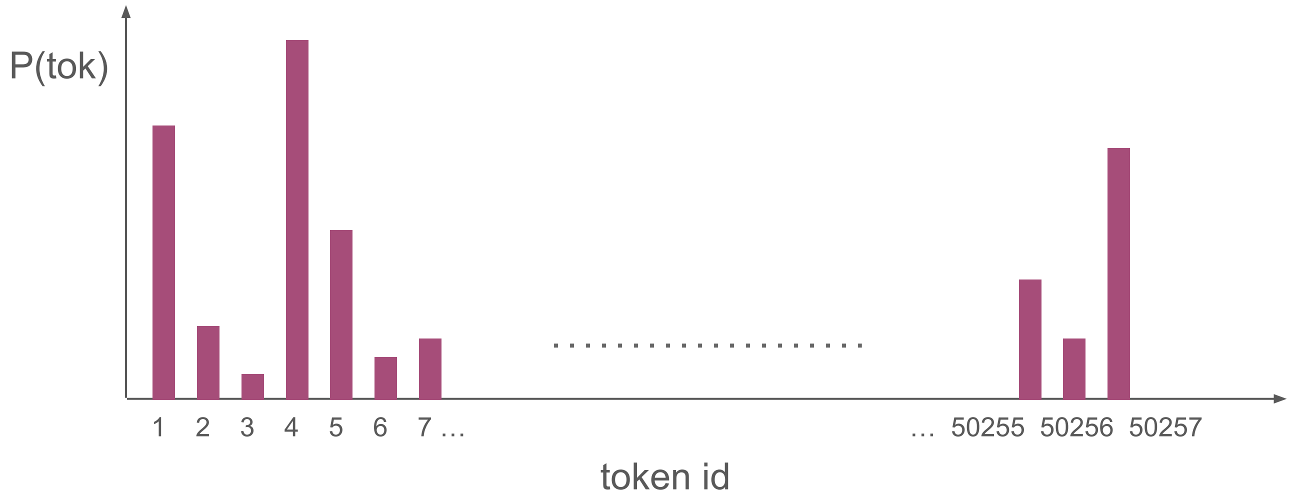
GPT2 completion (Babbage):
Who is the president of France? Is Paris safe to visit? What is the capital of Russia? Which country has the largest army? Which countries have the largest population? What is the language of Russia? How many inhabitants are there in Europe?

Sampling

Thinking about the output distribution

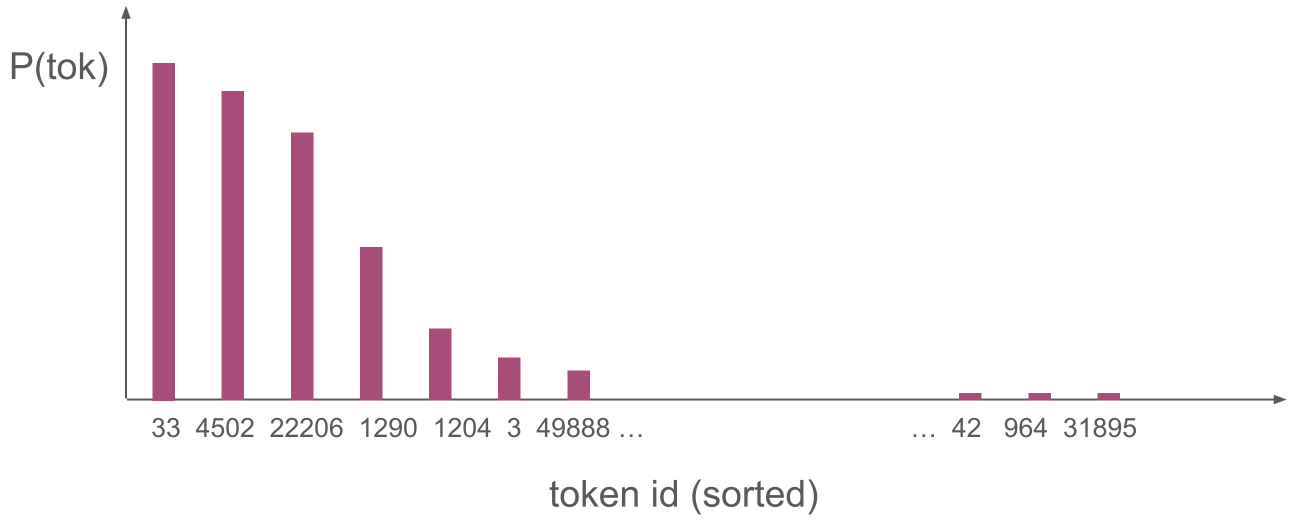
Each output is a probability distribution over our entire vocabulary (something like 50k entries).

This is very difficult to visualize or reason about:



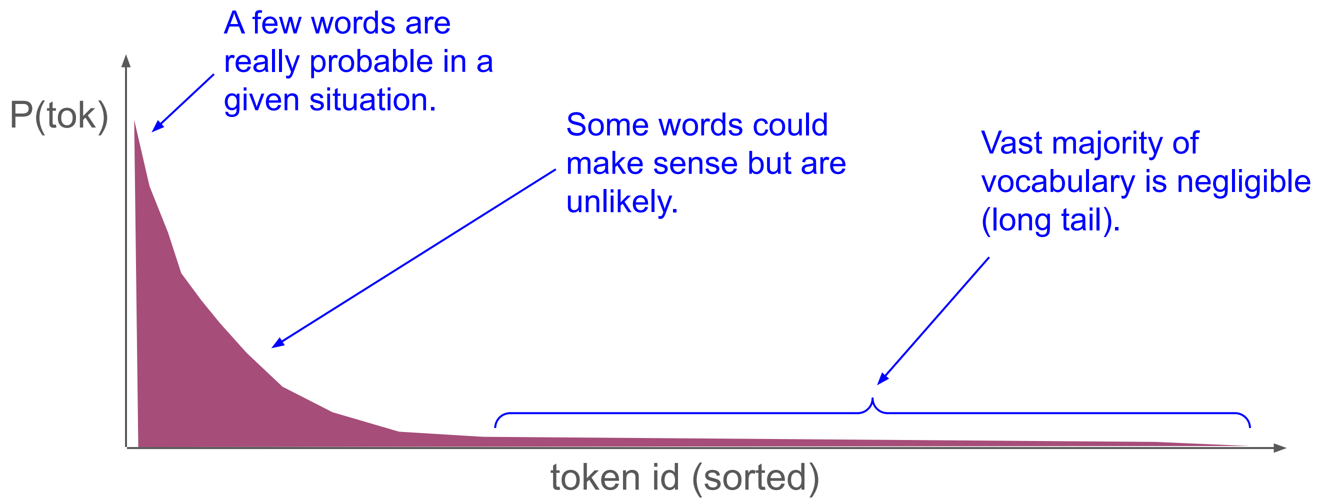
Sorting the distribution

So, we sort this distribution by decreasing probability:



Sorting the distribution

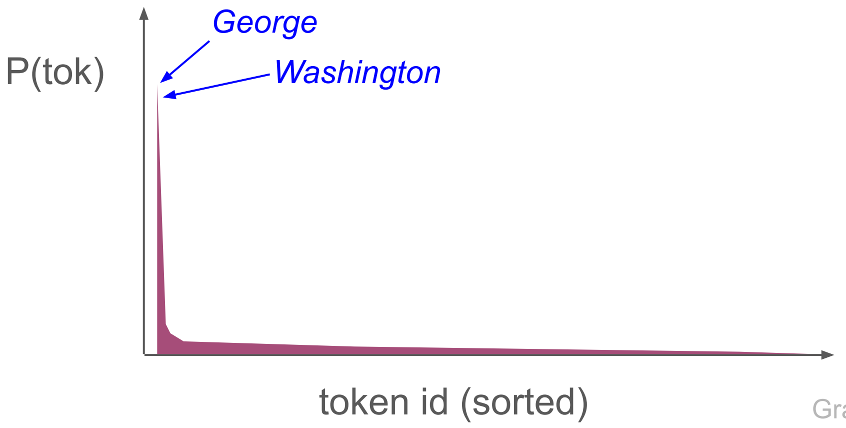
If we zoom out and actually show all ~50k entries, we would see a shape like this:



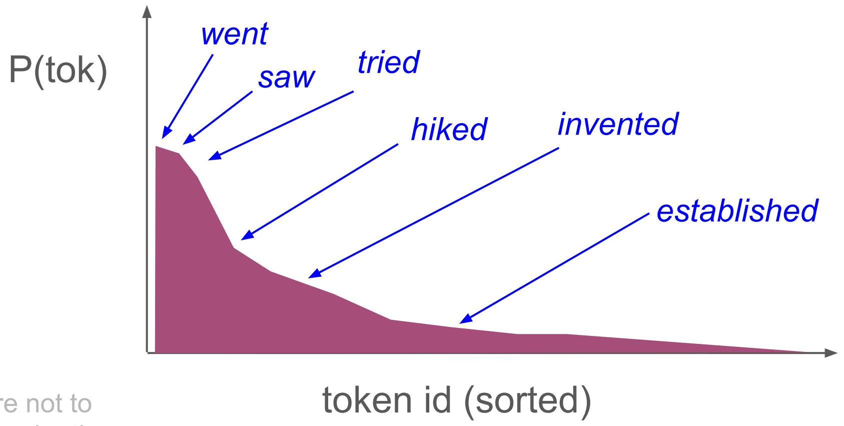
Distribution is a function of the input

The shape of the output distribution is reflective of how many words "fit" when it comes to continuing the input text.

The first president of the U.S. was …



Over the weekend I …



Graphs are not to scale w.r.t. each other

Temperature

Whenever a softmax is used, you can introduce a temperature to adjust it.

$$q_i = \frac{exp(z_i/T)}{\sum_j exp(z_j/T)}$$

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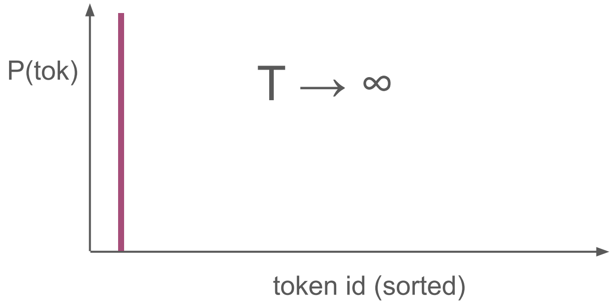
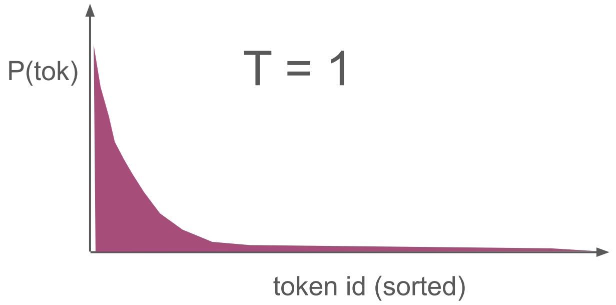
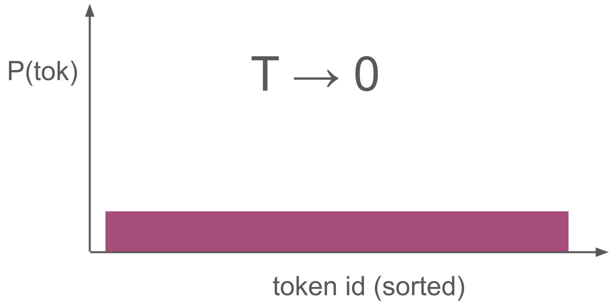


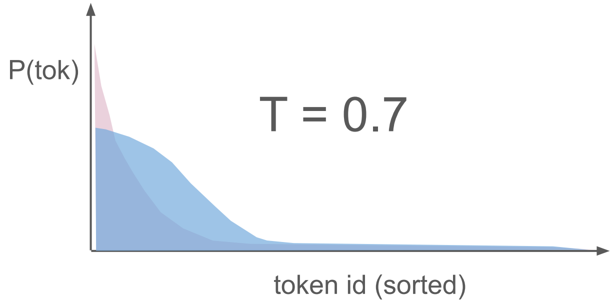


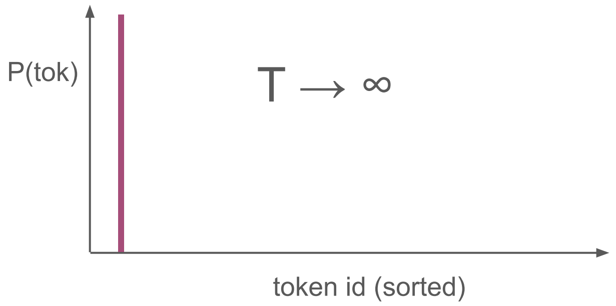


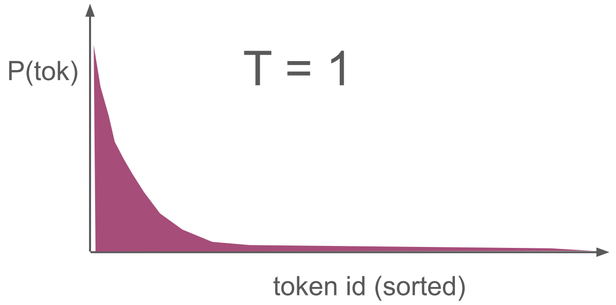
Temperature

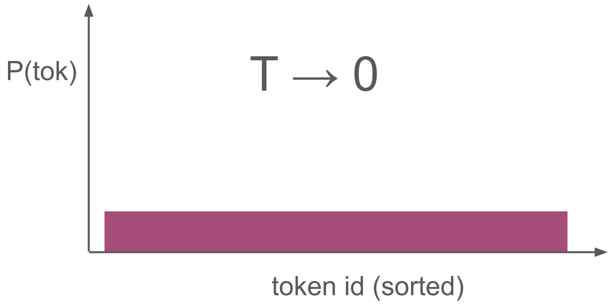
Whenever a softmax is used, you can introduce a temperature to adjust it.

Something less than 1 will smooth out the beginning of this curve, giving more weight to words that are possible but not likely. This can lead to outputs that seem more “creative”.









Problems with naive sampling (Top Choice)

If we always sample the most probable word (entry #1 in our sorted list of tokens), we have a few problems:

First of all, the text is not very exciting (deterministic).

More importantly, text is highly repetitive (detrimentally so).

Problems with naive sampling (Top Choice)

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First of all, the text is not very exciting (deterministic).

More importantly, text is highly repetitive (detrimentally so).

Example Completion (green):
Selecting top word:

Yesterday I went to the gym and I was doing my workout and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press

Problems with naive sampling (Top Choice)

LLMs output is based on the entire input, and once a word appears it is more likely that it will occur again (i.e. it is the topic of conversation).

This can cause feedback loops in which the model creates strong patterns that it then propogates over and over.

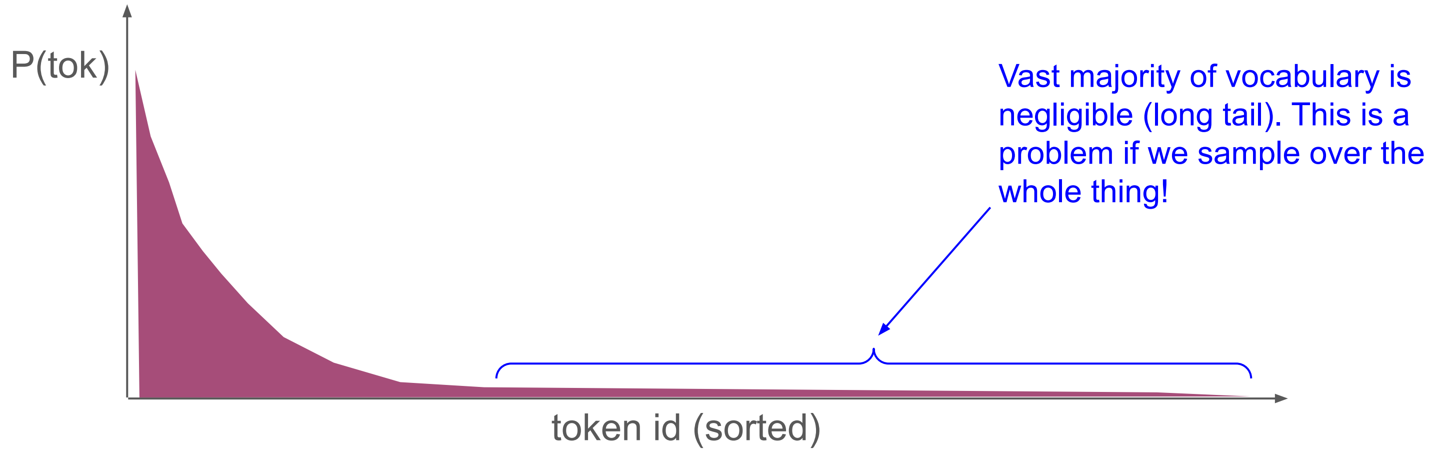
Example Completion (green):
Selecting top word:

Yesterday I went to the gym and I was doing my workout **and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press**

Problems with naive sampling (Full Distribution)

If we sample from the whole distribution, we have a high probability of selecting nonsense. While each low-probability word is unlikely individually, there are so many of them that there is still a chance of selecting something silly.

[Very low probability] X [45,000 choices] = non-negligible probability!



Problems with naive sampling (Full Distribution)

If we sample from the whole distribution, we have a high probability of selecting nonsense. While each low-probability word is unlikely individually, there are so many of them that there is still a chance of selecting something silly.

Example Completion (green):
Sampling the whole distribution:

Yesterday I went to LLBean to pick up some key-rings. Guess who I found in my "hope chest". Woman in White!! In her Believe me! It was a while back so remember to visit Lakeland a few days early. LOLW

back to fishing/love thing >

From ken40946:

Yep, I voted

Problems with naive sampling (Full Distribution)

Example Completion (green):
Sampling the whole distribution:

Once upon a time, there was a young boy who wandered into the forest. He was lost and aimless. One day he met and fell in love with a lovely girl. They danced in the forest all night and two years later, they were married. They welcomed their first child, a boy named Alan. Alan growss up and remembers his mother heavily. He is Mainstream and loves anime. Alan teaches Kun. And that is how Mai

In this example, the LLM makes sense from word to word but the topic “drifts”. Every time an unlikely word is sampled, this pushes us farther away from the original topic.

Problems with naive sampling (Full Distribution)

Example Completion (green):
Sampling the whole distribution:

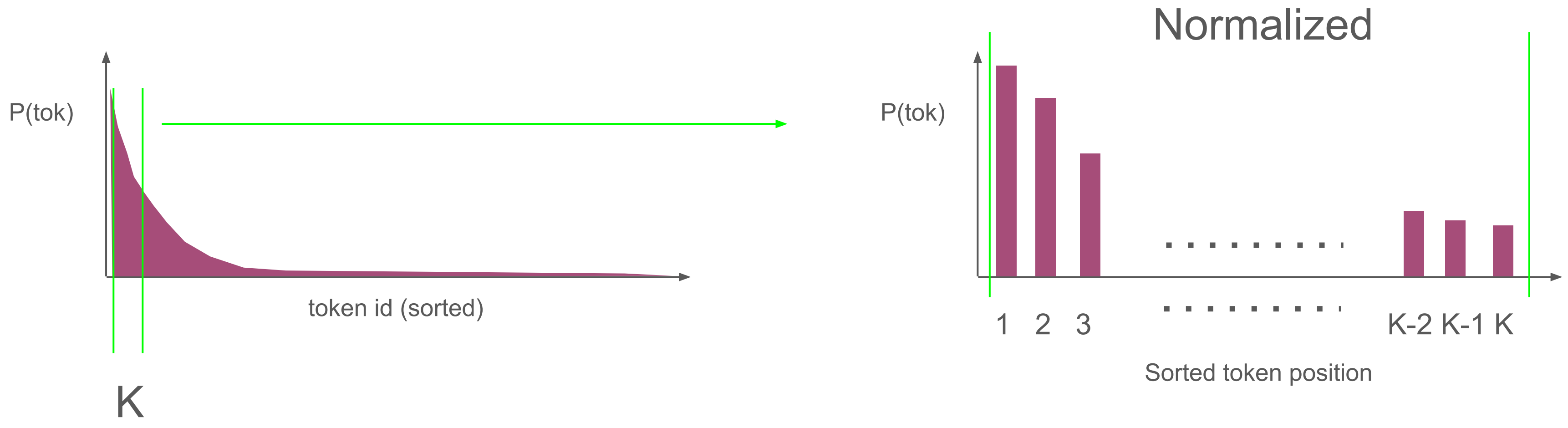
Once upon a time, there was a young boy who wandered into the forest. He was…
Girl, Body, Heart
Spirituality
Things
Turn a Child into An Adult
Clutter Busting
If you love this article you'll also love... Your Self Esteem Declines with every move, change, and imperfection. It's your…
Getting Your Surrender Processed It's the first weekend of November and while people are getting…
Family Business! Congrats Brother But you're not done yet… Once upon a time there were…

In this example, the LLM samples some unlikely words early and quickly degrades into nonsense.

How do we fix this? (Top-K)

The easiest remedy is to only select among the K most probable tokens. This is called “top-k” sampling. (Typically, K=30, 40, 50, something like that).

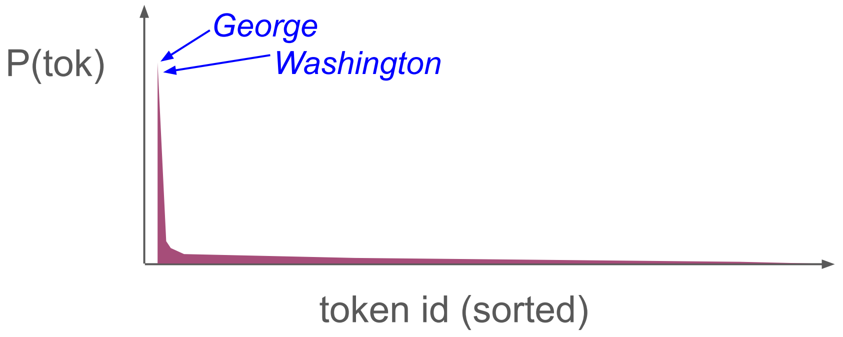
The first K tokens have their probabilities normalized to one and we sample from this new distribution:



Top-P

Top-K is simple and can work pretty well, but it does not account for the shape of the distribution.

The first president of the U.S. was …



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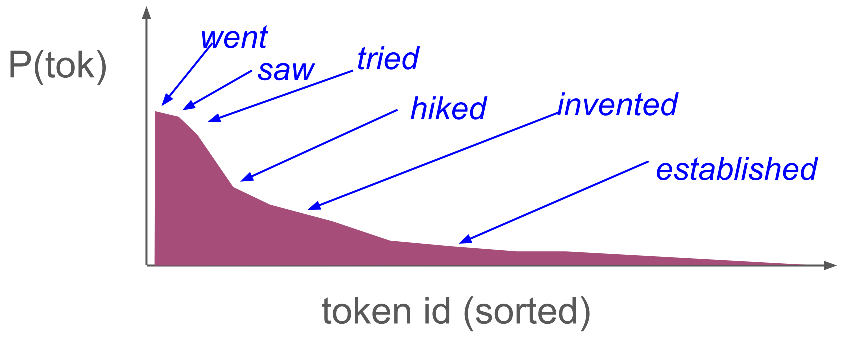


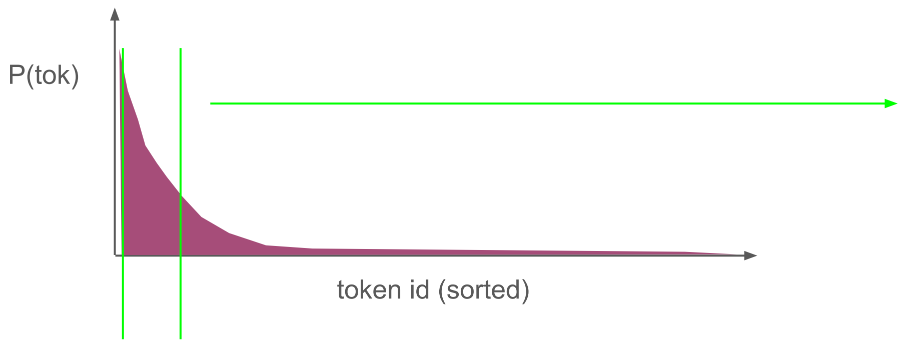
In this example, a few tokens dominate, and we want to only sample from these. A typical value of K=30 might be too big!

In this example, there are lots of possible options. A value of K=30 would be too restrictive!

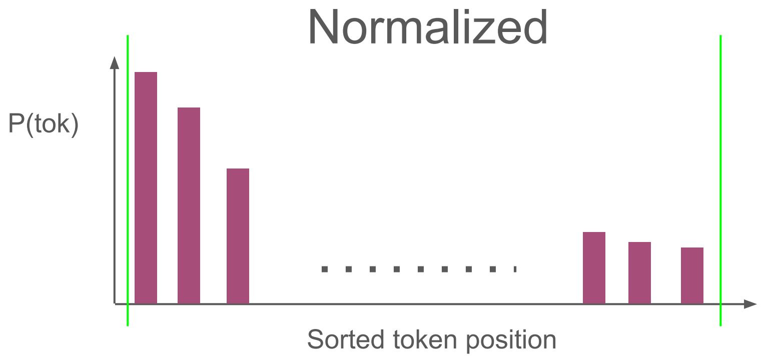
Top-P

Top-P sampling samples from the first N tokens which sum to probability mass P. Typical values of P might be 0.8, 0.9, 0.95.

If only 3 tokens take up 90% of all probability, then we only consider those 3 tokens! However, if 90% is spread over 100 tokens, we will consider all of those.



First P of all probability mass



Problems with Repetition

Top-K or Top-P sampling fix our balance issue- we can consider multiple good choices while ignoring the “long tail” of our distribution.

However, they do not completely fix some problems of the model latching on to patterns and creating feedback loops.

Example Completion (green):
Selecting top word:

Yesterday I went to the gym and I was doing my workout and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press

The problem here is not from the tail- it is that only a few repeated tokens dominate the distribution. Top-P or Top-K would still include these tokens.

Breaking Repetition

There are some common ways we can encourage the model to not repeat itself:

Frequency Penalty - the probability of a token is lowered proportionately to how many times it has occurred so far.

Presence Penalty - the probability of a token is lowered if it is present at all in the previous text.

More generally, these are types of **Repetition Penalties**, which lower the probability of a token (or sequence of tokens) based on previous occurrence.

Breaking Repetition

Repetition Penalty: lowers the probability of a token (or sequence of tokens) based on previous occurrence.

Modify the temperature on a per-token basis by adding a multiplier based on past text.

Important Note: These should be used lightly! They can have adverse effects against common words and punctuation.

$$softmax(x_i) = \frac{exp(x_i/Tk_i)}{\sum_{j=0}^{N} exp(x_j/Tk_j)}$$

Examples:

Frequency of 1.1:
k = 1+(0.1*number of occurrences)

Presence of 1.2:
k = 1+(0.2 if token has occurred)

Sometimes these would be “0.1” and “0.2”- it depends on your deifnition.

Important Note

This only works if the logits are positive! Move the logits to a positive range before doing this.

Dividing by a larger temperature (i.e. a penalty) moves the logit closer to zero. If all the logits are negative, this will actually make that entry more probable relative to the other options.

Breaking Repetition

Generating with both of these added we can break out of repetitive patterns. Here the “leg press” pattern is introduced on purpose, and we can see the model gets out of the feedback loop:

Example Completion (green):
Selecting top word:

Yesterday I went to the gym and I was doing my workout and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was doing the leg press and I was about to finish my workout, my leg pump. And I heard somebody say something. It caught me off guard because it's like someone walked in. So all of a sudden this guy comes up to me while I'm just sitting there going through a workout trying to enjoy myself at the gym…

A Complete Sampling Algorithm

Typically use Top-P of 0.8 or 0.9, generally preferred to Top-K.

Play with temperature if you want to, but not needed.

Add minor frequency and presence penalties.

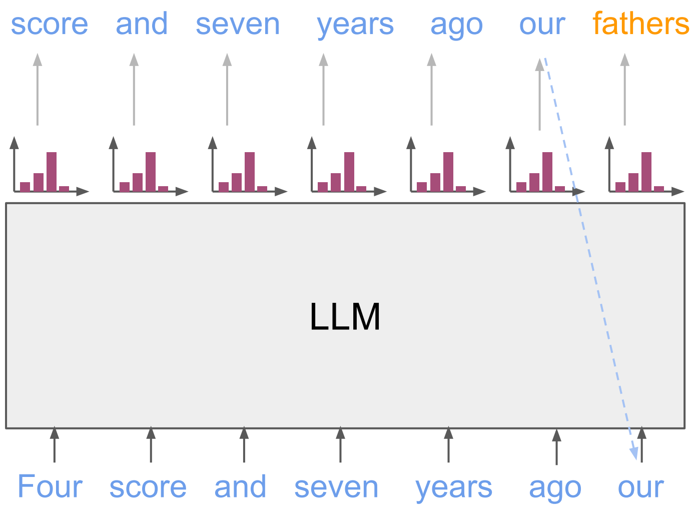
Adjust based on observed behavior.

Example Completion (green):
temp=0.9, top-p=0.9, frequency and presence of 1.2

Yesterday I went to Kavli Institute for Particle Astrophysics and Cosmology, where the astronomers set up a star cluster and took pictures. They were very lovely people who would explain things that I did not understand but to me it was very interesting.

Brief Aside on KV Caching

Efficient Generation

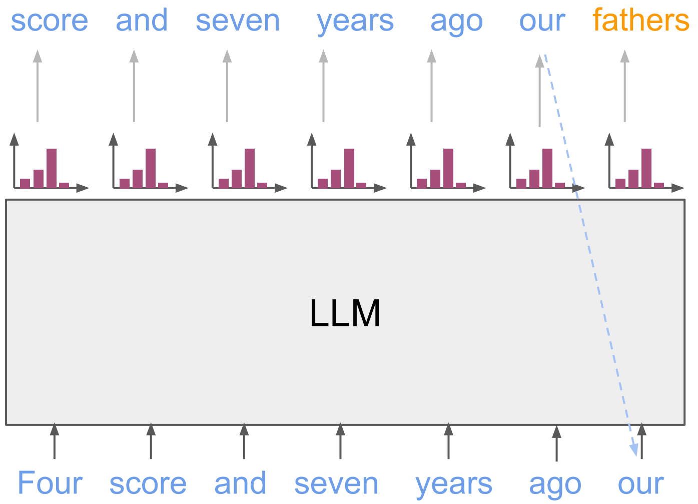


Consider generating the word **“fathers”.** This token is based on all previous inputs.

If we feed “*Four score and seven years ago our*” into the model, we will actually get an output for every input token!

All the outputs except for “fathers” are redundant computation.

Efficient Generation



If we look at the attention equation (simplified here):

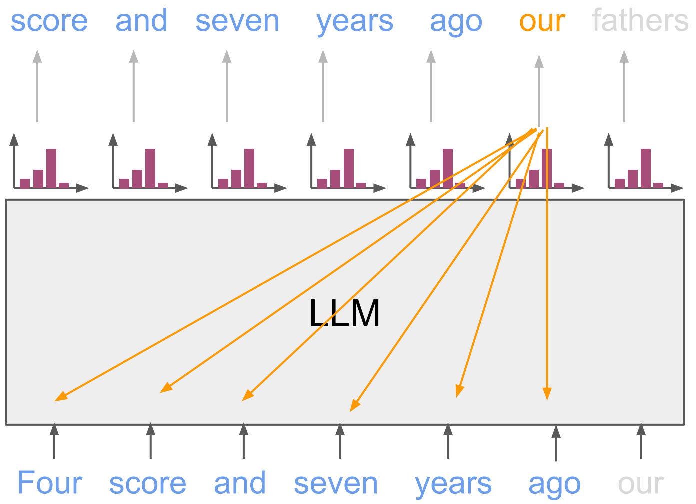
$$y_i = \frac{1}{i}\sum_{j=0}^{i}(q_i \bullet k_j) * v_j$$

Within each transformer layer, the output at position *i* depends on the *ith* query and the keys and values of all previous tokens.

Efficient Generation

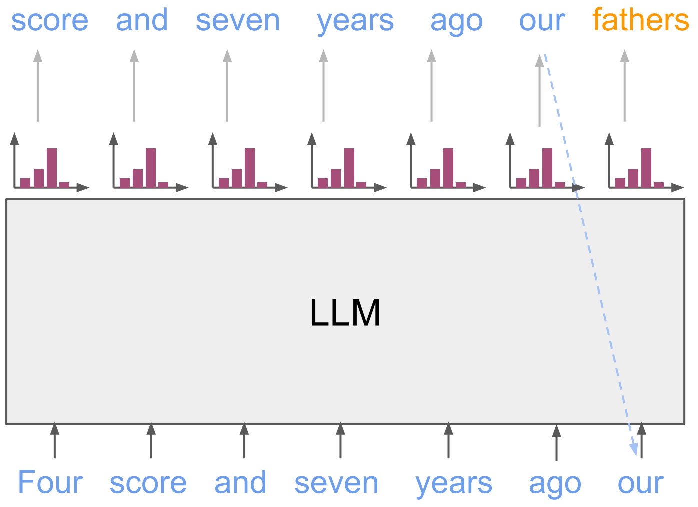
$$y_i = \frac{1}{i}\sum_{j=0}^{i}(q_i \bullet k_j) * v_j$$

y_i depends on q_i, $k_{<=i}$, $v_{<=i}$



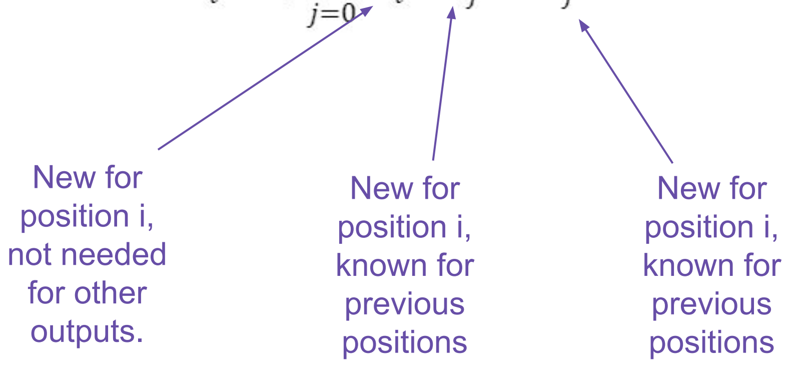
Looking back one token, the keys and values for outputting “our” are only dependent on the previous tokens - they do not change when we are outputting “fathers”.

Efficient Generation



When we generate “fathers”, we should already know the keys and values from all previous tokens.

$$y_i = \frac{1}{i}\sum_{j=0}^{i}(q_i \bullet k_j) * v_j$$


New for position i, not needed for other outputs.
New for position i, known for previous positions
New for position i, known for previous positions

KV-Caching

Store a history of keys K and values V.

In all attention layers, when generating the next token:

- Retrieve K and V for all previous tokens.
- Compute Q, K, and V <u>only for the current token.</u>
- Add K and V for the current token to our history

Prompting

Prompting

We now know how to generate decent quality text from our model (sampling).

We know how to do so efficiently, if we need to (KV-cache).

However, the model is still generating random continuations- how do we get it to output what we want? Output something useful?

Prompting

Remember there are two sources of information for our model:

1) The stored knowledge in the weights
2) Context and patterns in the input

The model loves to pick up on input patterns, and sometimes this is really bad (i.e. feedback loop, repeats the same words over and over again).

However, we can also use this to our advantage.

Prompting

Prompting is the art of introducing context, knowledge, or patterns into the input in order to steer the output of the model.

The easiest here is typically a pattern- craft some text pattern that you want to model to follow. Obviously we can craft some useless patterns:

Input: “red, blue, red, blue, red, blue, red” - Model will output: blue, red, …

Input: “Monday, Tuesday, Wednesday,” - Model will output: Thursday, Friday, …

Prompting

We can also make patterns that demonstrate a behavior:

Input:

“I loved the movie : Positive,

It was way too long : Negative,

The dialogue was fine, but the story didn’t make sense. : Negative,

The leading actress did a wonderful job. : ”

How would you continue this text?

Prompting

We can also make patterns that demonstrate a behavior:

Input:

“I loved the movie : Positive,

It was way too long : Negative,

The dialogue was fine, but the story didn’t make sense. : Negative,

The leading actress did a wonderful job. :

Positive”

By showing examples of sentiment classification, we have turned our model into a sentiment classifier!

We typically show a few examples of the desired behavior, and then end with an example we want the model to process.

Prompting

Another Example:

I love the beach / Ich liebe den Strand

What time is it? / Wie spät ist es?

The beer is ten dollars. / Das Bier kostet zehn Dollar.

Translation examples. Clear English / German pattern.

Where can I get a coffee? /

Incomplete pattern continuation for what we want to translate.

Prompting

Another Example:

I love the beach / Ich liebe den Strand

What time is it? / Wie spät ist es?

The beer is ten dollars. / Das Bier kostet zehn Dollar.

Where can I get a coffee? / Wo kann ich einen Kaffee bekommen?

By continuing the text, the model serves as a translator.

Use your imagination!

This can be very powerful if you brainstorm a bit. Some more interesting examples:

```
# get all files in the ./data/ directory
files = [f for f in os.listdir("./data") if isfile(join("./data", f))]

# Make a 5 by 3 numpy array of zeros
np.zeros((5,3))

# import opencv into python
import cv2

# sort each sublist in the list
y = [x.sorted() for x in y]

# calculate the cumulative sum over my list
sum = 0
for k in y:
    sum += x[k]
```

I see a green car going southbound on I-95.
{vehicle: car, color:green, heading:south}

There is a truck speeding on 295 west.
{vehicle: truck, color: unknown, heading: west}

A pink sedan is driving aggressivly.
{vehicle: sedan , color: pink, heading: unknown}

I'm in a red pickup headed down to Florida.
{vehicle: pickup, color:red, heading:south}

This one took some fiddling to get working. Since there is only one “correct” answer here, I tweaked the sampling to be less random.

Demo

https://platform.openai.com/playground?mode=complete&model=davinci-002

Review Assignments