

Embeddings

Lecture 3

EN.705.743: ChatGPT from Scratch

Lecture Outline

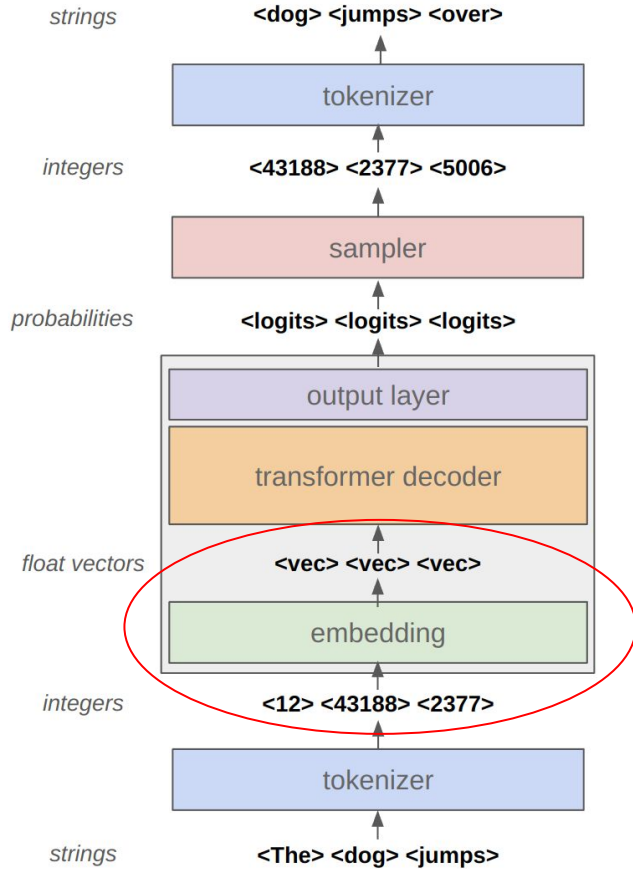
- Review where we are in the GPT3 model
- Intuition behind embeddings
- Word embeddings
 - Learned separately (intuition)
 - Learned directly
- Position Embeddings
 - Learned
 - Pre-computed
 - Rotary (relative)

Embeddings Intuition

Embeddings

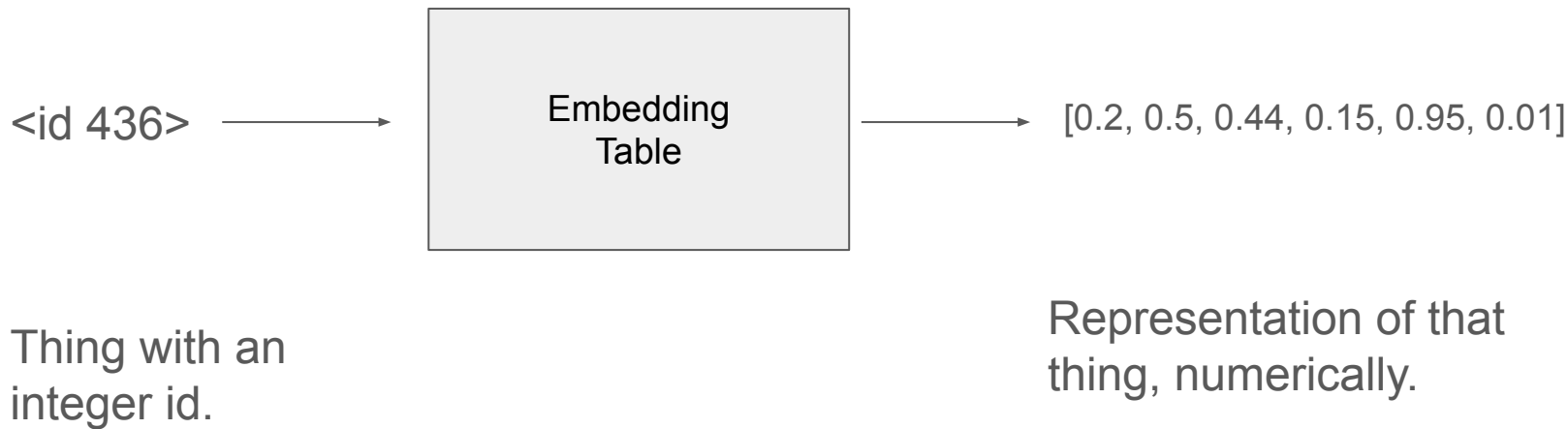
Last lecture, we saw how to convert text into integers so that we finally have numeric inputs for a model.

The first part of the model is an embedding, which does a second conversion: integers to floating point vectors.



Embeddings

In the general sense, an embedding is a vector representation of a specific label or id. An embedding associates a label with floating point features.



Lookup-Table View

One way to think about an embedding is that it is a simple lookup table for vectors that represent various things:

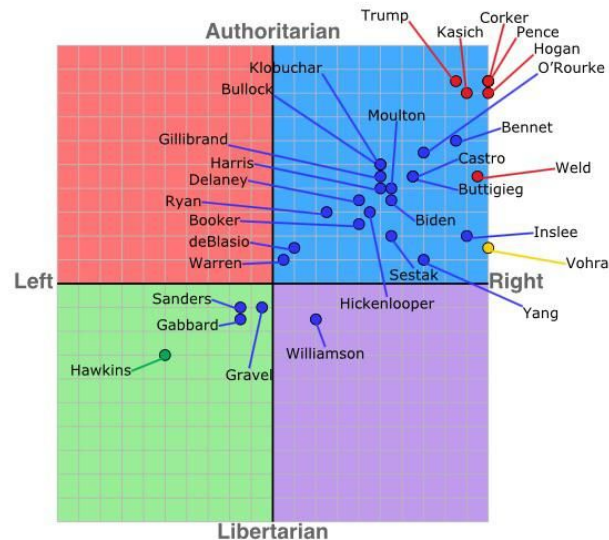
ID	Vector
Bennet	[0.85, 0.6]
Biden	[0.54, 0.36]
Booker	[0.4, 0.25]
Buttigieg	[0.63, 0.46]
...	...

N-Dimensional Space View

Another way to think about this is that an embedding associates each id with a point in N-dimensional space.

ID	Vector
Bennet	[0.85, 0.6]
Biden	[0.54, 0.36]
Booker	[0.4, 0.25]
Buttigieg	[0.63, 0.46]
...	...


The US Presidential Candidates 2020



Word Embeddings

Embeddings are useful because they replace an id with a representation that we can do computation with.

In our case, we want to replace each <id> in our vocabulary with some floating point vector that represents that word.

The dog barks.  tokenizer

<54> <259> <11013>  embedding

[vector embedding 54] [vector embedding 259] [vector embedding 11013]

What are the features?

Our embedding should somehow capture what the word means.

The embedding is N dimensional so it is hard to interpret, but some common properties are things like:

- Similar meanings group (“*dog*” is close to “*canine*” in our N dimensional space)
- Similar concepts group (“*dog*” is also close to “*cat*”)
- Co-occurrences may group (“*boat*” and “*ocean*”)
- Similar usages group (Common proper names might group)

Somehow the N dimensional vector encodes the meaning of the word and how it may be used.

Recap

Our goal is to find, for each <id> in our vocabulary, a vector of length N that represents the given word (or subword).

Typically, N is chosen to be the same input/output dimension as our transformer model (next week's subject). Typically values range from several hundred (512 or 768) to several thousand. GPT3 uses $N=12,288$.

These embeddings are very high dimensional -> hard to construct and hard to interpret. We need to learn them!

Word Embeddings, ~10 Years Ago

Word2Vec (Google, 2013) (Also in this week's reading)

One option is to learn the embeddings with a separate model. Word2Vec is an approach that is based on the idea: **A word should be related to its neighboring words in context.**

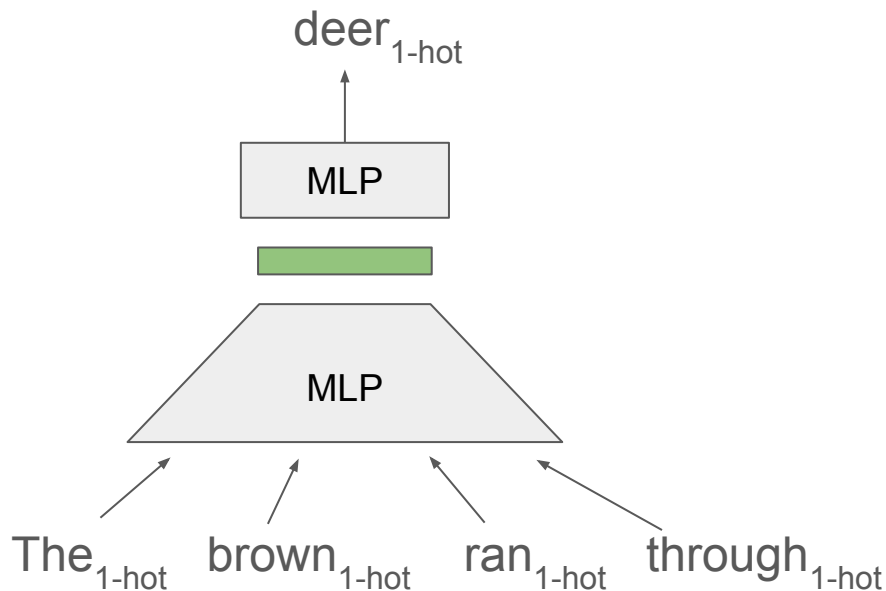
For example, if we have some snippet of text:

The brown deer ran through the meadow.

We have some loose associations between (deer, brown), (deer, meadow), (deer, ran) etc. Over many many examples, these associations should average out into some understanding of the word (“deer”).

Word2Vec Architecture

We can build a model which, given surrounding context, predicts a missing word:



We simply input/output words with a one-hot encoding of their class id:

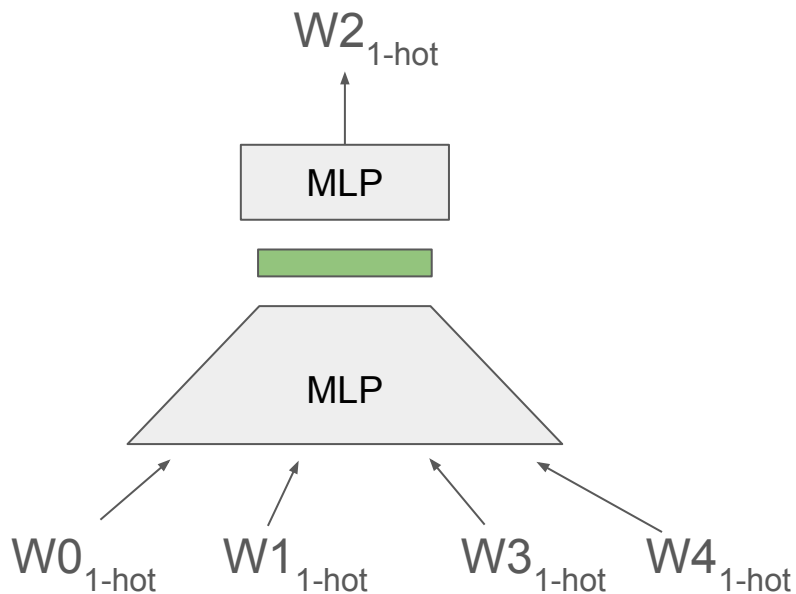
<id=4> becomes [0 0 0 0 **1** 0 0 ...]

The inner representation is taken as the encoding of the missing word.

This is very similar to an autoencoder.

Word2Vec Architecture

We can run this on every sequence of N words in our dataset (here N=5).



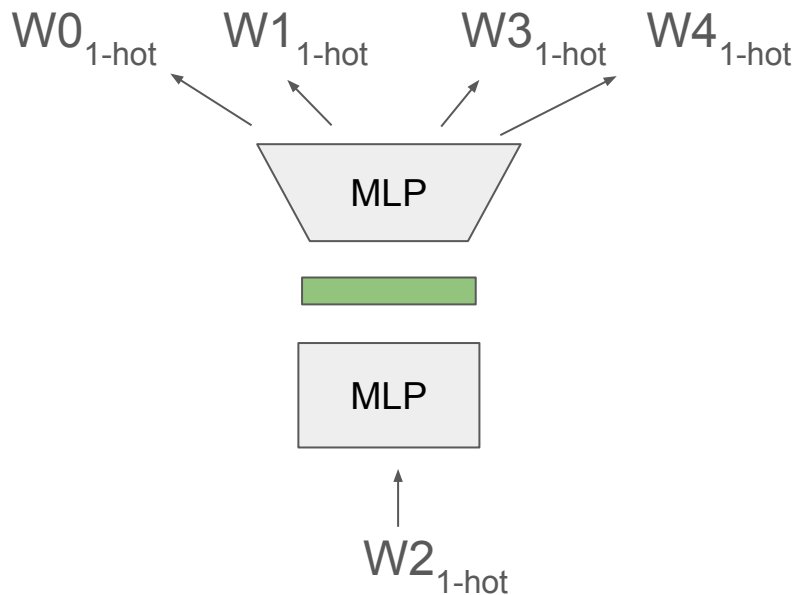
This is called the “**continuous bag-of-words**” method, since we can slide a window of size N over our data, continuously capturing N words.

Question: How do we use this after training?

It's not that easy...

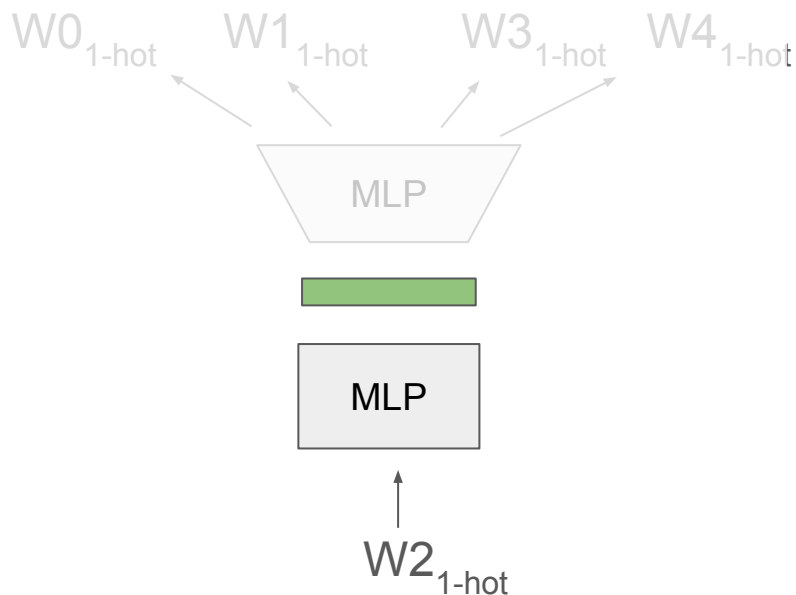
Word2Vec Architecture, Skip-Ngram Method

To make this easier to use, we can actually flip it around:



Word2Vec Architecture, Skip-Ngram Method

To make this easier to use, we can actually flip it around:



This formulation is easier to use after training.

We can input a word and get the associated embedding by using only the first half of the model.

GloVe (**Global Vectors**) (Stanford, 2014)

GloVe is another method you may hear about. Word2Vec computes associations based on local context windows (i.e. group of 5 words).

GloVe instead considers global co-occurrences. i.e., For some word W in the vocabulary, it should be related to the N words that it typically co-occurs with **across the entire dataset**.

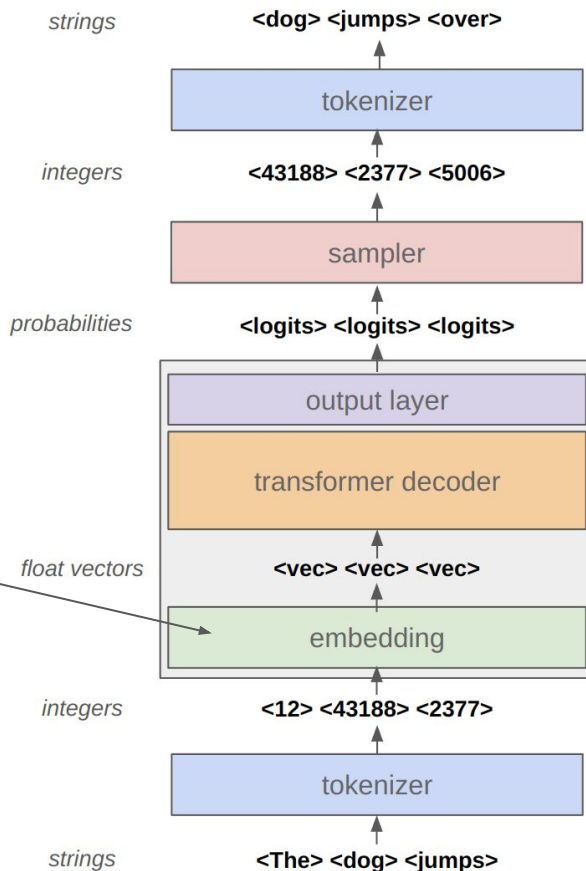
GloVe and Word2Vec are popular methods for learning a **separate embedding model**.

Word Embeddings (Now)

Modern Approach

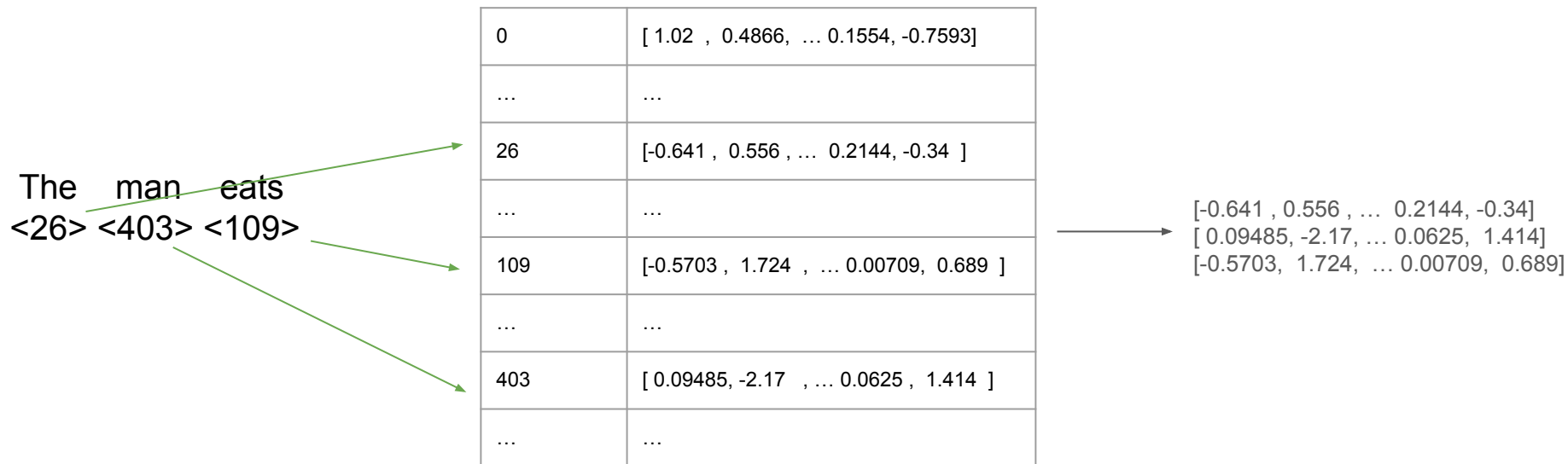
We can also have embeddings learned as a part of the overall optimization of our model.

In the age of transformers, we have an “embedding layer” that we can directly backpropagate through.



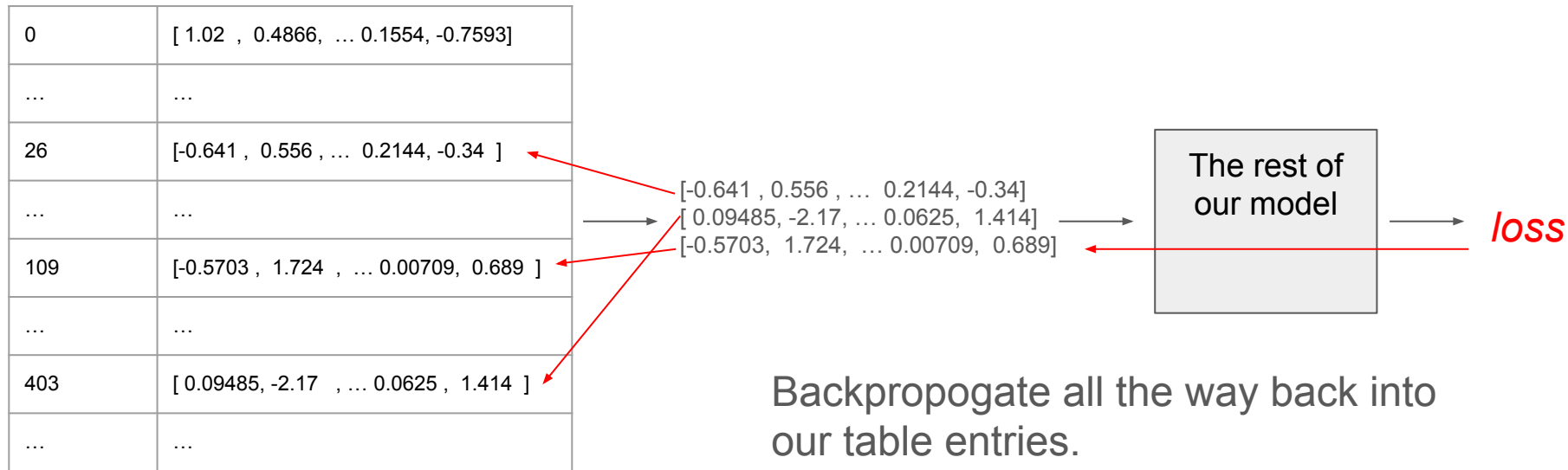
Embedding Layer

Main Idea: We initialize our embedding table randomly. When we train our model, we replace `<ids>` with the associated vectors, even if they are initially meaningless:



Embedding Layer

We feed these vectors into the rest of the model as “input”, and we backpropagate back into the vectors during training.



Embedding Layer

Parallel to MLP: Recall that for a fully connected layer, we have:

$$y = Wx + b$$

And part of updating W is to compute how y changes w.r.t W :

$$dy/dW = x$$

However, we could also compute an update for our input x :

$$dy/dx = W$$

This is exactly what we are doing for our embeddings. We can feed them into the model and compute an update for them. This is also used to pass a gradient to a prior layer from the current layer.

Embedding Layer Notes

A few notes:

- 1) The entries in our embedding table are also the parameters being updated, so sometimes these are called the “parameters” or “weights” of the embedding layer.
- 2) Unlike other NN layers, the embedding layer is outputting these parameters.
- 3) The good news is, if you tell pytorch that the vector require a gradient, it should pretty much figure all this out for you.

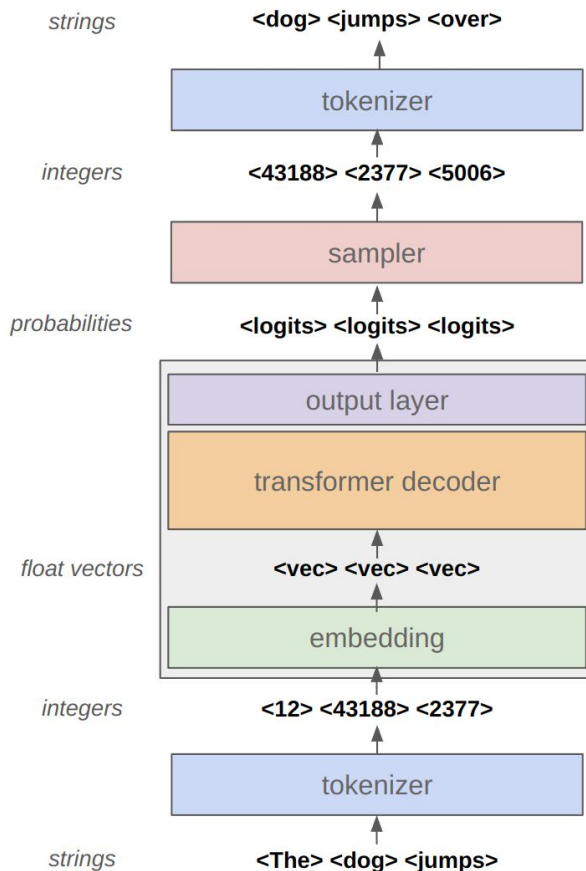
Applying this to our model

So, when building our GPT model, we initialize an embedding layer of size N by D , where N is the size of our vocabulary, and D is the length of the vector representation of each token.

Tokenizer has a pre-built vocabulary of size N .

The rest of our model expects vectors of length D .

So the embedding learns $N \times D$ values.



Side note on size

Good to think about the size of the embedding.

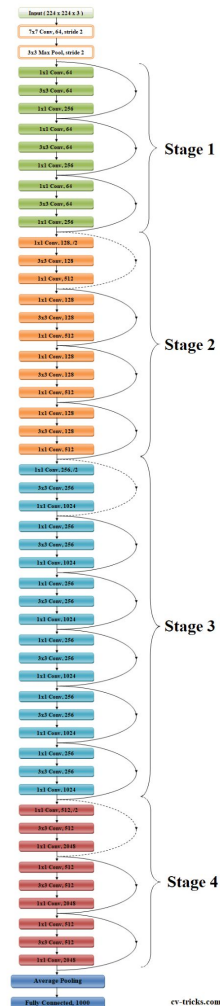
Let's say our vocabulary is size $N \sim 50,000$

And we want to represent each word with a vector of length ~ 1000 .

This is $(50,000) * (1000) = 50$ million parameters!

For a model like GPT3, which has $D=12,288$, the embedding is ~ 600 million parameters.

For comparison, ResNet-50 has 25 million parameters (architecture diagram on right).



Position Embeddings

Two Embeddings for GPT3

Transformers (next week) are technically perform “set” operations, not “sequence” operations. That is, they do not understand ordering. This is critical in language!

*The lion ate the
hyena and the
gazelle.* ? *The lion and
the hyena ate
the gazelle.* ? *The gazelle ate
the hyena and
the lion.*

Without intervention, a transformer treats all of these identically.

Two Embeddings for GPT3

To fix this, we embed each token and its position in the sequence.

Text: The lion ate the gazelle ...

Token: <32> <5364> <27721> <32> <2309>...

Position: <0> <1> <2> <3> <4>...

Our embedding module will have two embeddings, one to convert token ids to vectors, and one to convert position ids to vectors.

Two Embeddings for GPT3

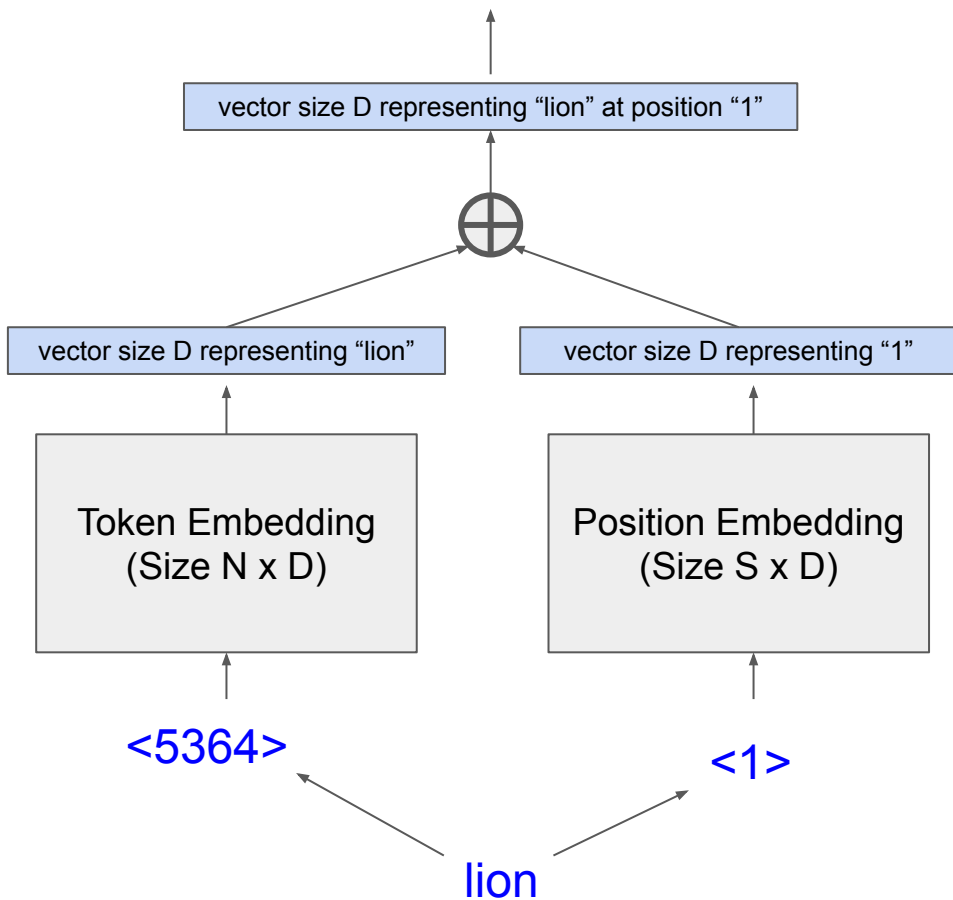
Text: The **lion** ate the gazelle ...

Token: <32> **<5364>** <27721> <32> <2309>...

Position: <0> **<1>** <2> <3> <4>...

Our position embedding has size $S \times D$, where S is the maximum sequence length that we will encounter (the highest possible position).

We simply add the embeddings together to get our final embedding, which describes a token at a specific position.



Position Embeddings

The position embedding is honestly a strange mechanism. Note that we are using D floating point values to represent a single integer.

In the word embedding, an integer input has lots of meaning (it corresponds to a specific word which has meaning, nuance, connotations, context).

In our position embedding, the integer input really is just an integer. The embedding of “23” just means “position 23”.

So they are irksome from a typical software engineering efficiency point of view but... they also work well.

Homework

By far, the easiest thing to do (in terms of the complexity of our model), is to just use the exact same mechanism as word embeddings for positions embeddings.

One learns N vectors of size D , to represent tokens.

The other learns S vectors of size D , to represent position.

Functionally they work exactly the same way. This is a very common approach and it works pretty well. For our homeworks, this is what we will do.

History and Future

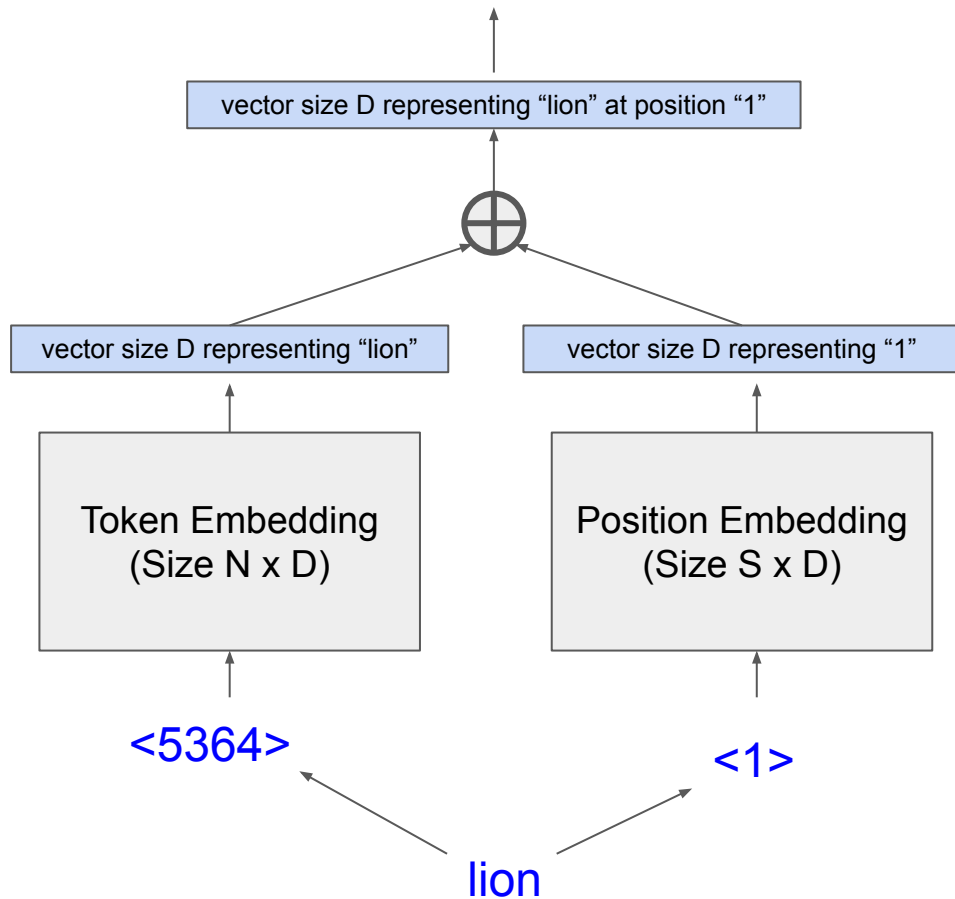
There are a few more complex variants which are worth knowing about for breadth.

Sinusoidal Position Embeddings

Sinusoidal Embeddings

It seems wasteful to learn $S \times D$ values just to represent integers (this may be millions of parameters).

The original transformers paper thought so too, so they had a different approach: Sinusoidal Embeddings

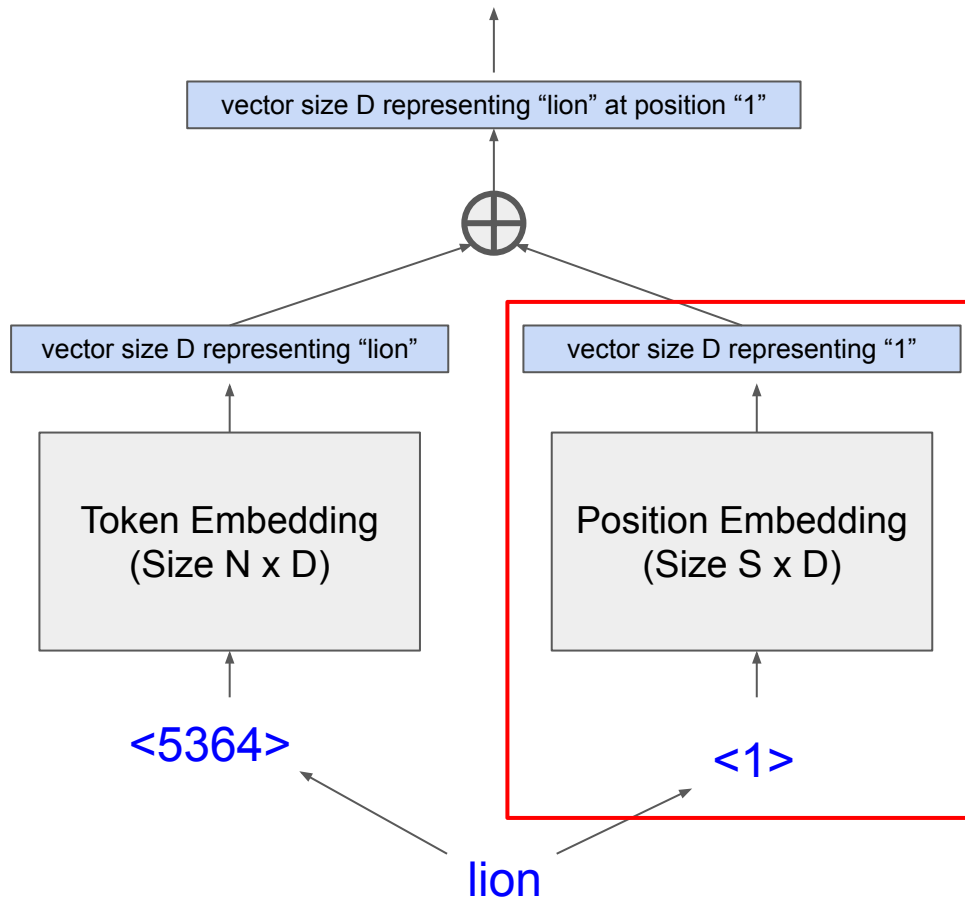


Sinusoidal Embeddings

Revisit the objective of the position embedding module.

We want to express a single integer as D floating-point values.

Could we just construct some set of S vectors of length D , such that each has a unique pattern?



Sinusoidal Embeddings

Rather than learning vectors, construct S vectors of length D which each have a unique pattern. The model will learn to use these on its own.

Specifically:

$$PE_{(pos, 2i)} = \sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos, 2i+1)} = \cos(pos/10000^{2i/d_{\text{model}}})$$

where pos is the position of the token, and i is a floating point value from 0 to

$$D = d_{\text{model}}$$

Sinusoidal Embeddings

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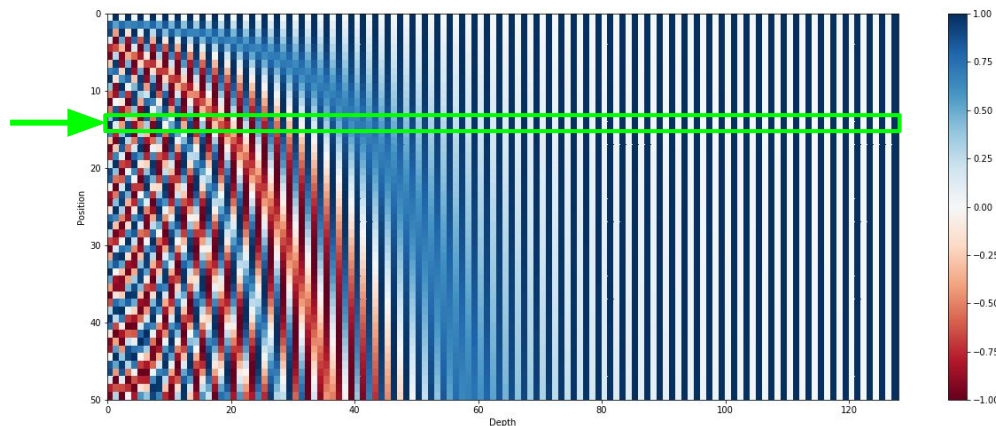
Specifically:

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$$PE_{(pos,2i+1)} = \cos(pos/10000^{2i/d_{model}})$$

where pos is the position of the token, and i is a floating point value from 0 to

$$D = d_{model}$$



For each word, grab row at position of word.

Comparison

Sinusoidal embeddings are pre-computed, so the model has less to learn. On the other hand, you have to compute them!

In practice, both methods work equally well. It's just a matter of preference.

Rotary Position Embeddings

Current Practice

Very modern LLMs (last 1-2 years) use an improvement on these techniques, called Rotary Position Embeddings (RoPE).

A key insight is that a token's meaning is not derived from its absolute position, but from the relative position of other tokens. This is significant in documents hundreds or thousands of tokens long.

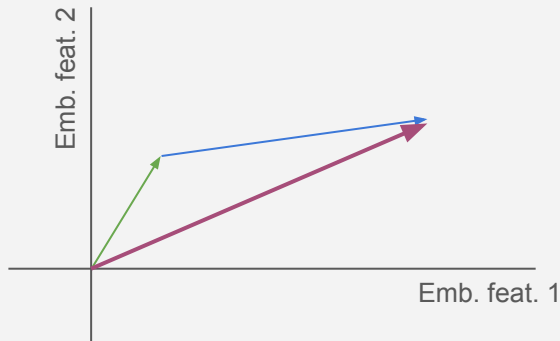


Current Practice

Instead of offsetting embeddings with an addition (absolute embedding), RoPE offsets embeddings by an angle θ . Consider $D=2$, each word embedded by 2 features:

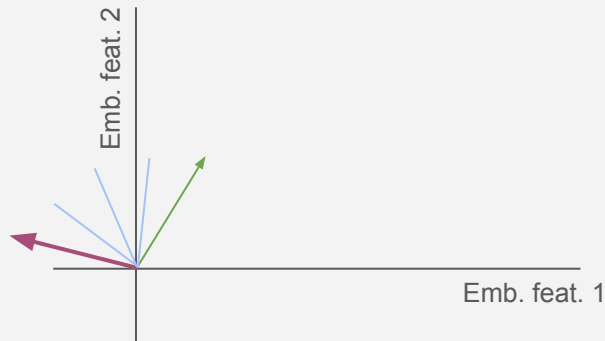
Absolute

$$\begin{array}{l} \text{Lion <id 254>: } [0.1, 0.3] \text{ (from word embedding)} \\ + \text{ Position 3: } [0.4, 0.1] \text{ (from position embedding)} \\ \hline = [0.5, 0.4] \text{ (final embedding of word)} \end{array}$$



Rotary

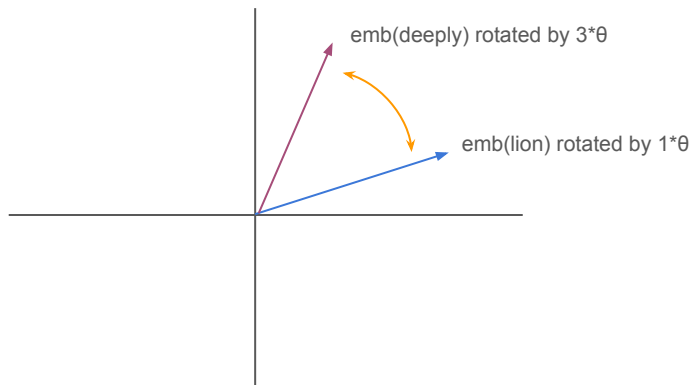
$$\begin{array}{l} \text{Lion <id 254>: } [0.1, 0.3] \text{ (from word embedding)} \\ \text{Rotated by } 3 \times \theta \\ \hline = [-0.31, 0.05] \text{ (final embedding of word)} \end{array}$$



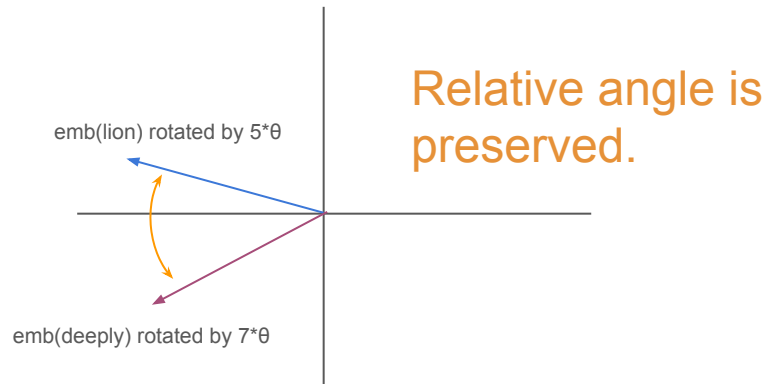
Why is this a good idea?

Rotating by $[\text{position}] * [\text{theta}]$ preserves the relative angle (and angle is a function of position) between two words:

0 1 2 3
The *lion* slept *deeply*.



0 1 2 3 4 5 6 7
After a long day, the *lion* slept *deeply*.



Applying to $D > 2$ features.

Simply rotate each pair of features. Each pair uses a different value for θ :

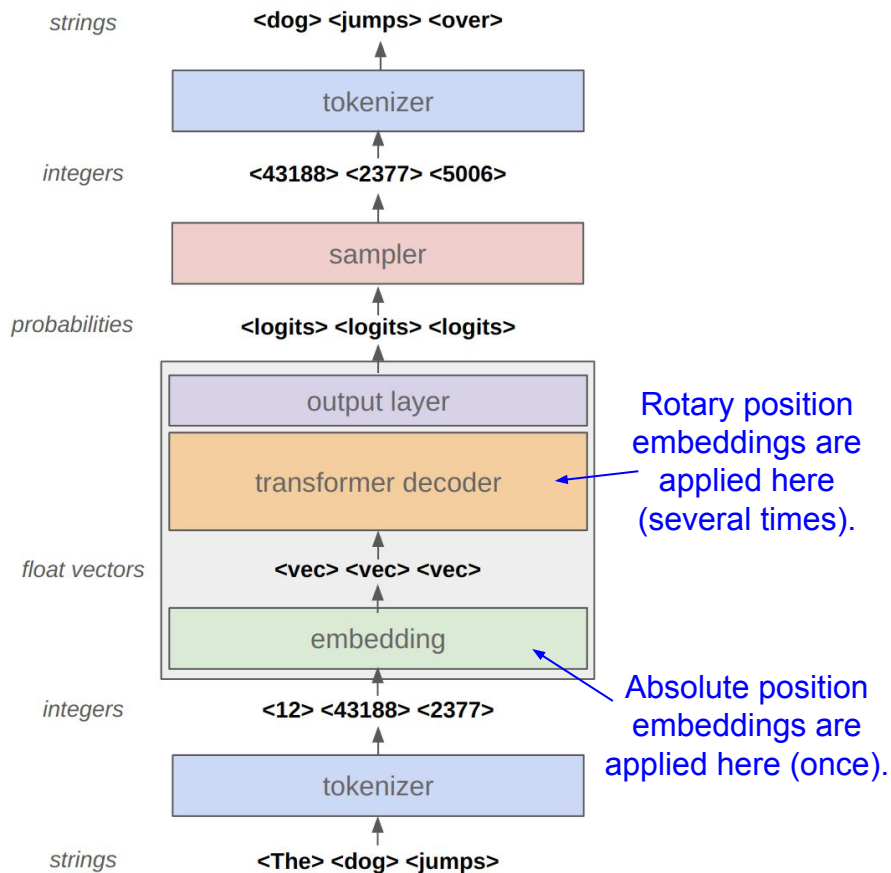
$$\text{Emb}(\langle \text{token id} \rangle) = [0.1, 0.5, 0.3, 0.8, 0.8, 0.1, 0.2, 0.1, 0.8, 0.9 \dots]$$

Rotate by θ_0 Rotate by θ_1 Rotate by θ_2 Rotate by θ_3 Rotate by θ_4

Leftover Notes

RoPE is a little complex to implement in practice, but does result in improved models (RoPE models consistently outperform previous models by a few % better loss).

RoPE is applied many times throughout the model, rather than just at the beginning. As computations are performed on the vectors in the transformer layers, the rotations are applied periodically to keep the position information “fresh”.



Review Assignments