Language Model Basics

11-667: LARGE LANGUAGE MODELS: METHODS AND APPLICATIONS

Carnegie Mellon University

Agenda

1. What is a Language Model?
2. Building Blocks of Language Models
3. Decoding Strategies
4. Language Model Architectures

1. What is a Language Model?

What is a Language Model?

A language model is any model that outputs a probability distribution over the next token* in a sequence given the previous tokens in the sequence, that is: $P(y_t|y_{1:t-1})$.

Historically, language models were statistical n-gram models. Instead of taking into account the full history of the sequence, they approximated this history by just looking back a few words.

Example: Suppose we are building a statistical language model using a text corpus, *C*. We note that the word “apple” follows the words “eat the” 2% of the times that “eat the” occurs in *C*. This means we’d set

`P(“apple” | “eat the”) = 0.02`.

Since “eat the apple” is three words, we’d call this a 3-gram model.

*For now, let’s assume token = word. We’ll come back this.

Language models are not inherently generative.

Computing Sequence Likelihood

Language models output the likelihood of the next word: $P(y_t|y_{1:t-1})$.

Often we will talk about the likelihood of an entire sequence $P(Y) = P(y_1, y_1, \ldots, y_T)$.

Computing Sequence Likelihood

Sequence likelihood can be computed from an LM using the chain rule:

```
P([“I”, “eat”, “the”, “apple”]) =
P(“apple” | [“I”, “eat”, “the”]) * P(“the” | [“I”, “eat”]) * P(“eat” | [“I”]) * P(“I”])
```

In math:

$$P(Y) = P(y_1, y_2, \dots, y_T) = P(y_T | y_{1:T-1}) \times P(y_{T-1} | y_{1:T-2}) \times \cdots \times P(y_1 | \text{start of sequence})$$

Neural Language Models: Conditioned v. Unconditioned

Neural language models can either be designed to just predict the next word given the previous ones, or they can be designed to predict the next word given the previous ones and some additional conditioning sequence.

Unconditioned: $P(Y)$

At each step the LM predicts:
$P(y_t \mid y_{1:t-1})$

Examples:

- GPT-2 / GPT-3
- LLaMA

Conditioned: $P(Y \mid X)$

At each step the LM predicts:
$P(y_t \mid y_{1:t-1}, x_{1:T})$

Examples

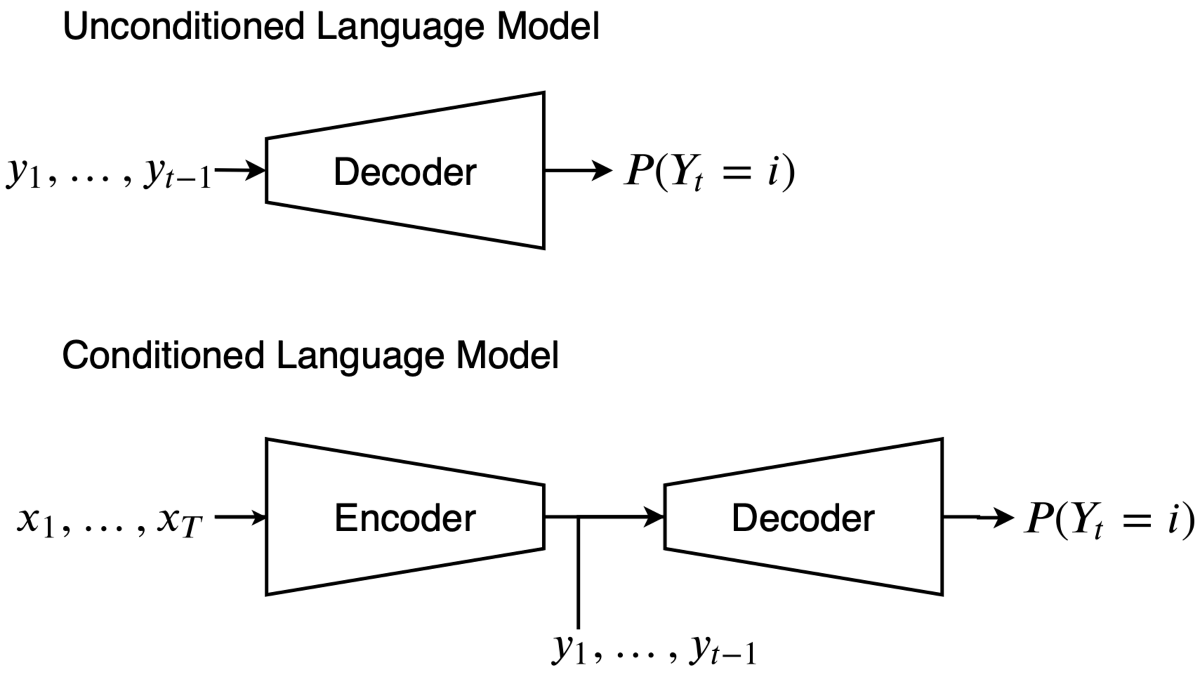
- T5
- Most machine translation models

Sometimes called sequence-to-sequence or seq2seq models.

2. Building Blocks of Language Models

Neural Language Models: Conditioned v. Unconditioned

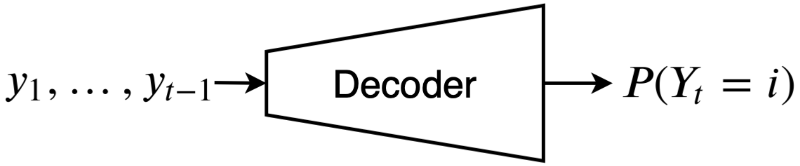
Unconditioned neural language models only have a decoder. Conditioned ones have an encoder and a decoder.



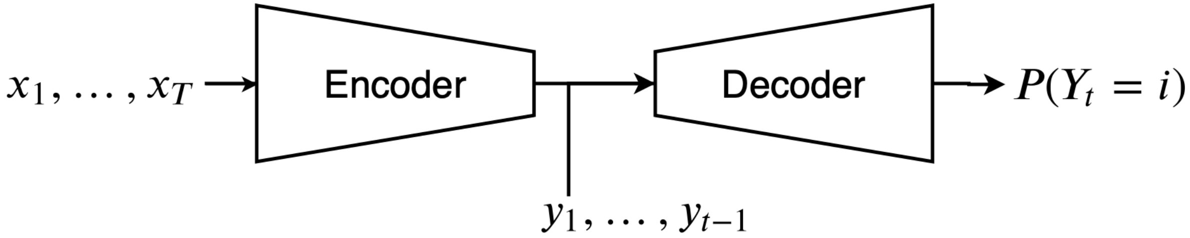
Neural Language Models: Conditioned v. Unconditioned

Unconditioned neural language models only have a decoder. Conditioned ones have an encoder and a decoder.

Unconditioned Language Model



Conditioned Language Model



There are also encoder-only models, but they aren't traditional language models.

Neural Language Models: Conditioned v. Unconditioned

Theoretically, any task designed for a decoder-only architecture can be turned into one for an encoder-decoder architecture, and vice-versa.

TASK: Continue the sequence.

Decoder-only version:

`P(Y="Once upon a time there lived a dreadful ogre.")`

Encoder-decoder version:

`P(Y="lived a dreadful ogre." | X="Once upon a time there")`

Neural Language Models: Conditioned v. Unconditioned

Theoretically, any task designed for a decoder-only architecture can be turned into one for an encoder-decoder architecture, and vice-versa.

TASK: Translate from English to French.

Decoder-only version:

`P(Y=“English: The hippo ate my homework. French: L'hippopotame a mangé mes devoirs.”)`

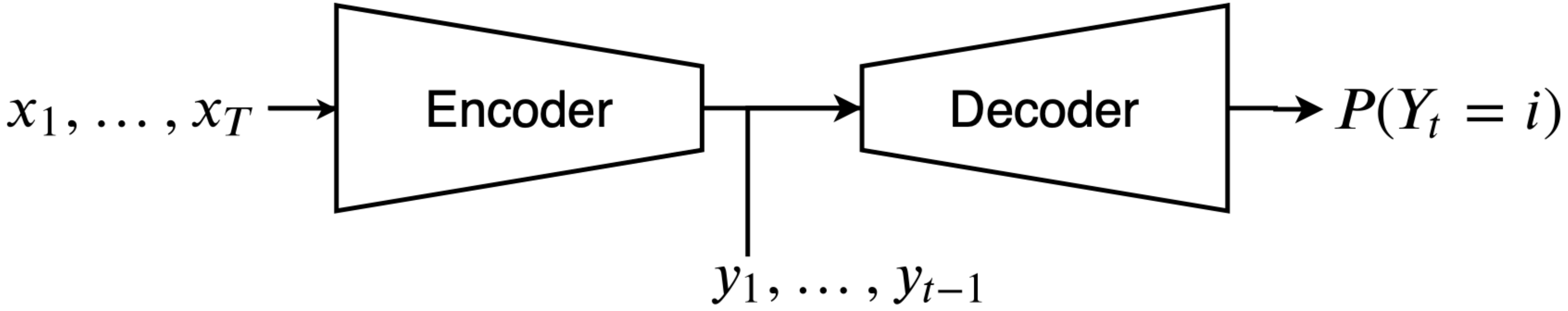
Encoder-decoder version:

`P(Y=“L'hippopotame a mangé mes devoirs.” | X=“The hippo ate my homework.”)`

Summary of Terms You Should Know

Input sequence: $x_1, \dots, x_T$

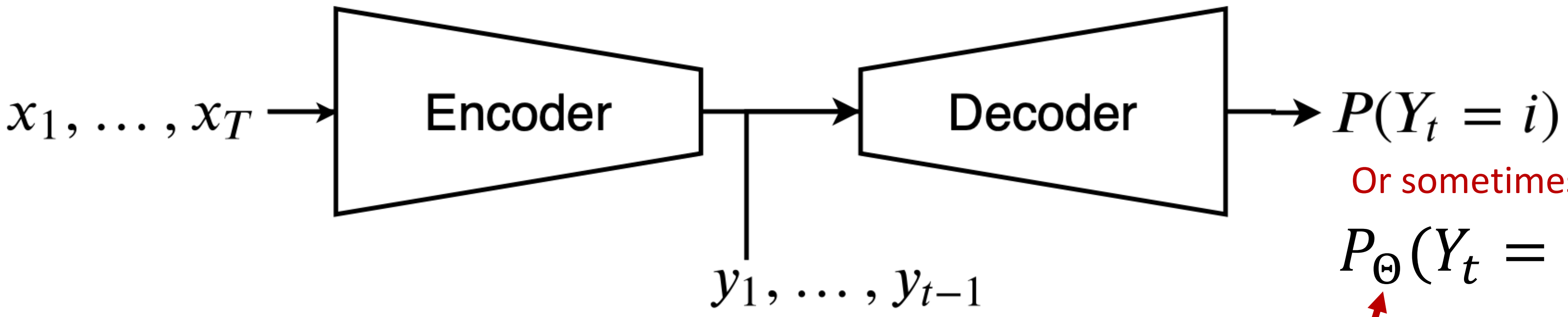
Target sequence: $y_1, \dots, y_T$



Summary of Terms You Should Know

Input sequence: $x_1, \ldots, x_T$

Target sequence: $y_1, \ldots, y_T$



Or sometimes…

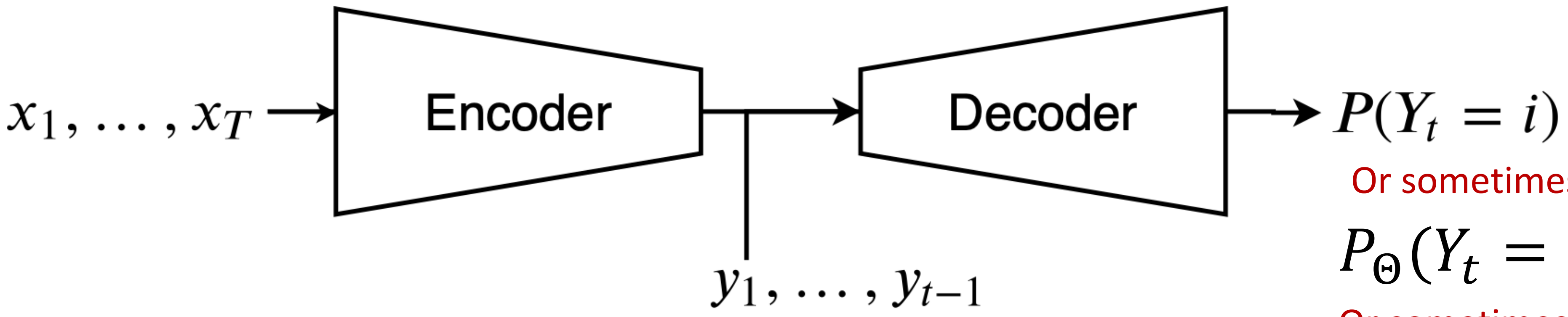
$P_\Theta(Y_t = i)$

Represents the parameters of the neural network.

Summary of Terms You Should Know

Input sequence: $x_1, \ldots, x_T$

Target sequence: $y_1, \ldots, y_T$



Or sometimes…

$$P_\Theta(Y_t = i)$$

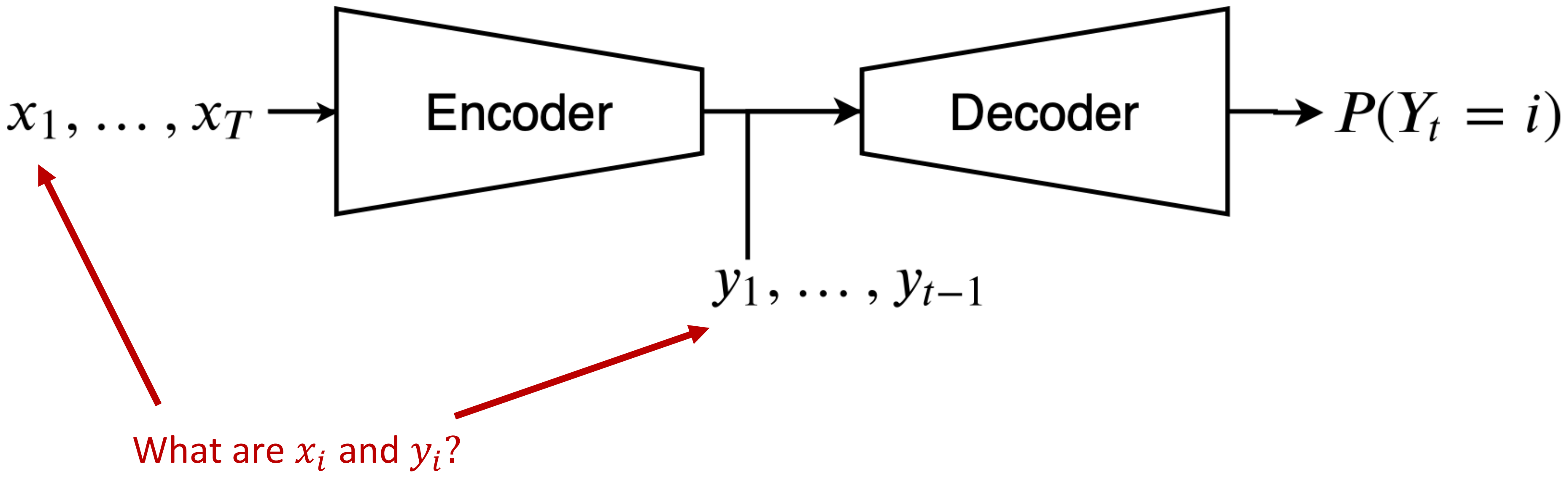
Or sometimes…

$$P(Y_t = i | y_1, \ldots y_{t-1}, x_1, \ldots, x_T; \Theta)$$

Summary of Terms

Input sequence: $x_1, \dots, x_T$

Target sequence: $y_1, \dots, y_T$



Tokenizing Text

Tokenization is the task of taking text (or code or music) and turning it into a sequence of discrete items, called tokens.

Tokenizing Text

A **tokenizer** takes text and turns it into a sequence of discrete **tokens.**

A **vocabulary** is the list of all available tokens.

Let's tokenize: "A hippopotamus ate my homework."

Vocab Type	Example	Ex. length
character-level	['A', ' ', 'h', 'i', 'p', 'p', 'o', 'p', 'o', 't', 'a', 'm', 'u', 's', ' ', 'a', 't', 'e', ' ', 'm', 'y', ' ', 'h', 'o', 'm', 'e', 'w', 'o', 'r', 'k', '.']	31
subword-level	['A', 'hip', '##pop', '##ota', '##mus', 'ate', 'my', 'homework', '.']	9
word-level	['A', 'hippopotamus', 'ate', 'my', 'homework']	5

Tokenizing Text

A **tokenizer** takes text and turns it into a sequence of discrete **tokens.**

A **vocabulary** is the list of all available tokens.

Let’s tokenize: “A hippopotamus ate my homework.”

Vocab Type	Example	Ex. length
character-level	`['A', ' ', 'h', 'i', 'p', 'p', 'o', 'p', 'o', 't', 'a', 'm', 'u', 's', ' ', 'a', 't', 'e', ' ', 'm', 'y', ' ', 'h', 'o', 'm', 'e', 'w', 'o', 'r', 'k', '.’]`	31
subword-level	`['A', 'hip', '##pop', '##ota', '##mus', 'ate', 'my', 'homework’, '.']`	9
word-level	`['A', 'hippopotamus', 'ate', 'my', 'homework']`	5

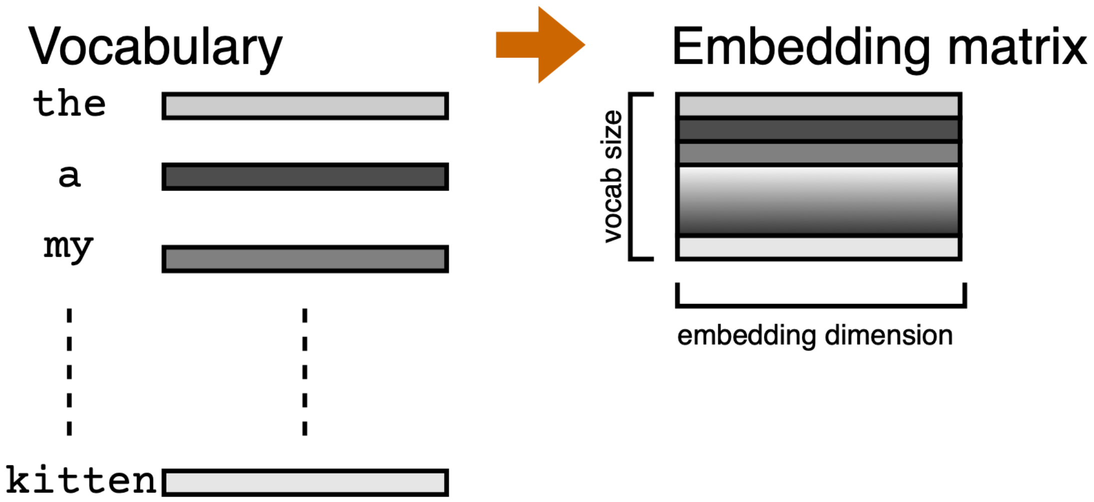
What are the pros and cons of different tokenizers?

More on this next lecture!

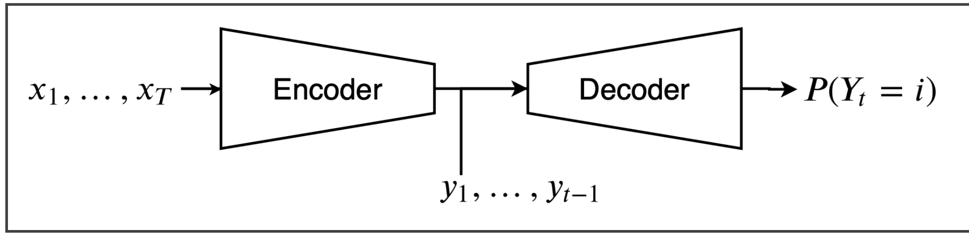
Turning Discrete Tokens into Continuous Vectors

Neural networks cannot operate on discrete tokens.

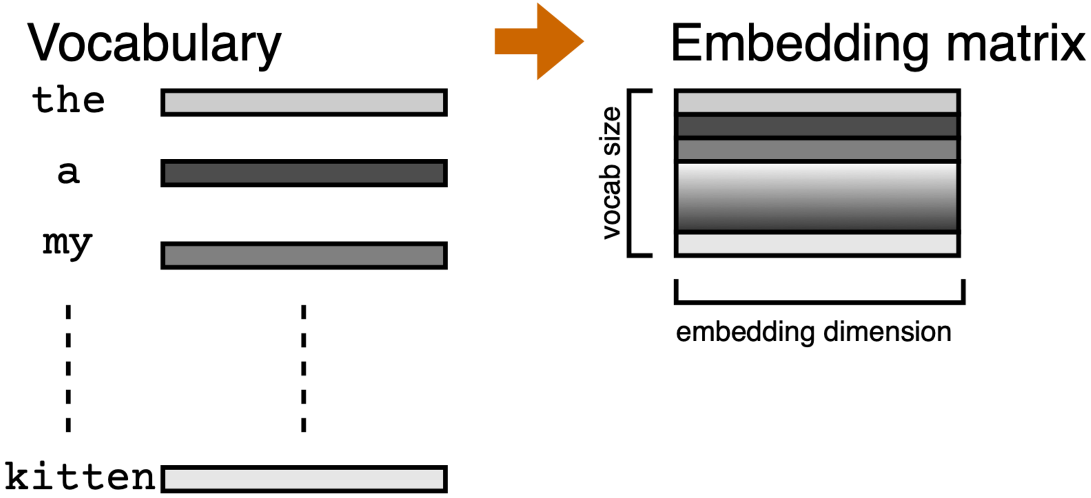
Instead, we build an **embedding matrix** which associates each token in the vocabulary with a vector embedding.

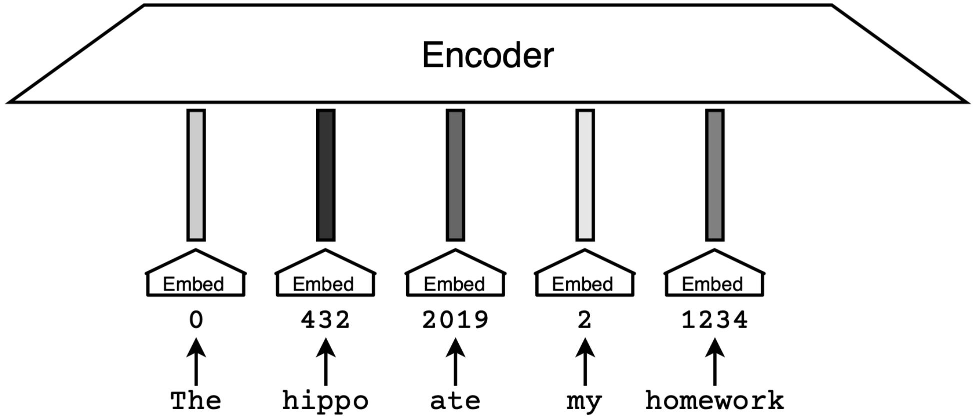


Encoder Inputs and Outputs

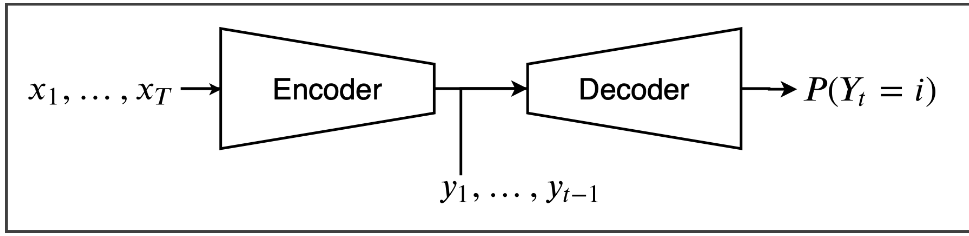


The encoder takes as input the vector representations of each token in the input sequence.

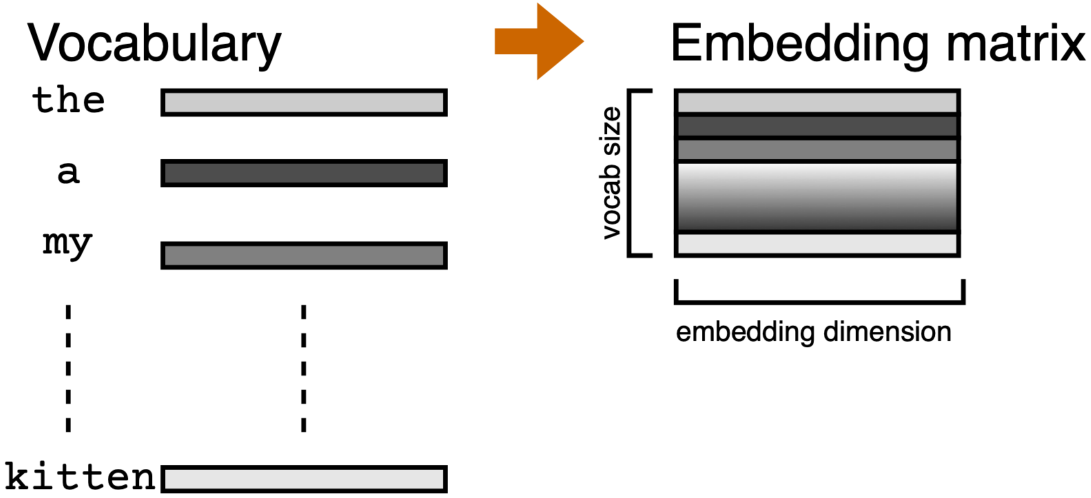


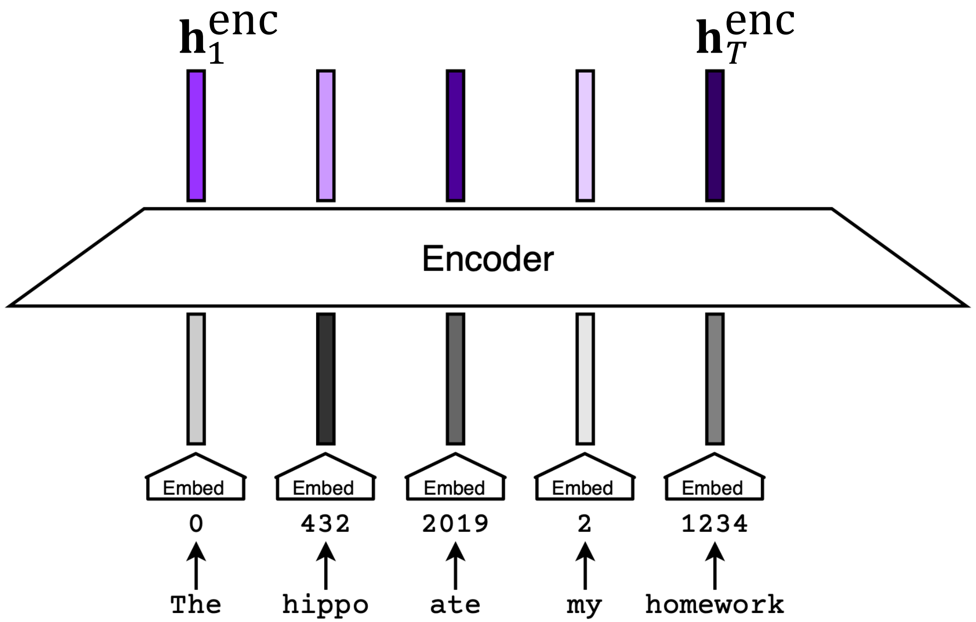


Encoder Inputs and Outputs

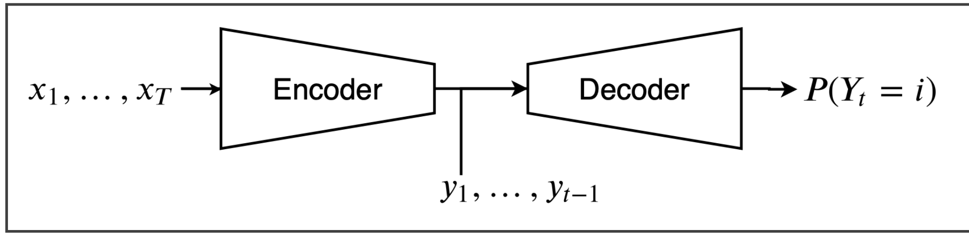


The encoder outputs a sequence of embeddings called **hidden states**.



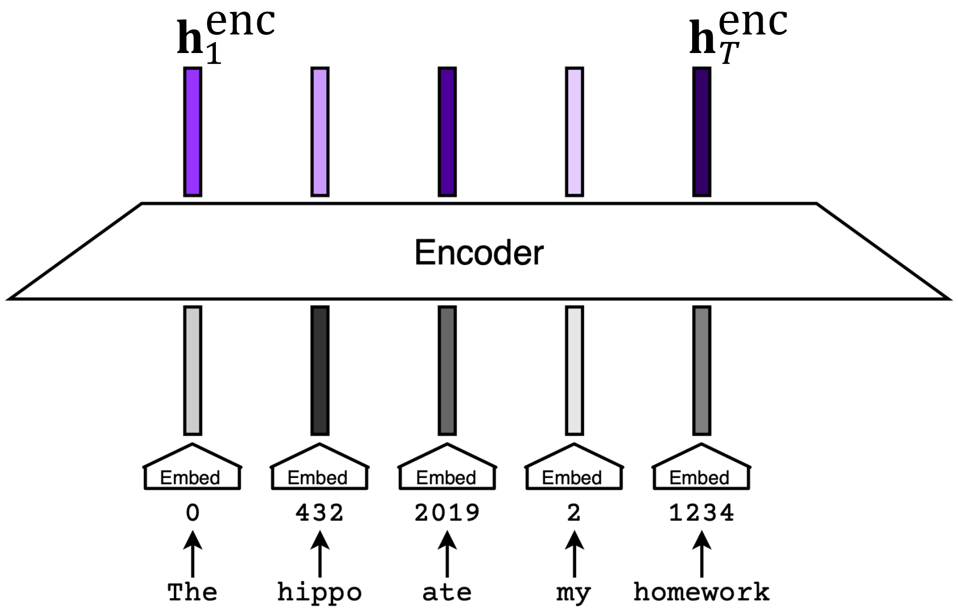


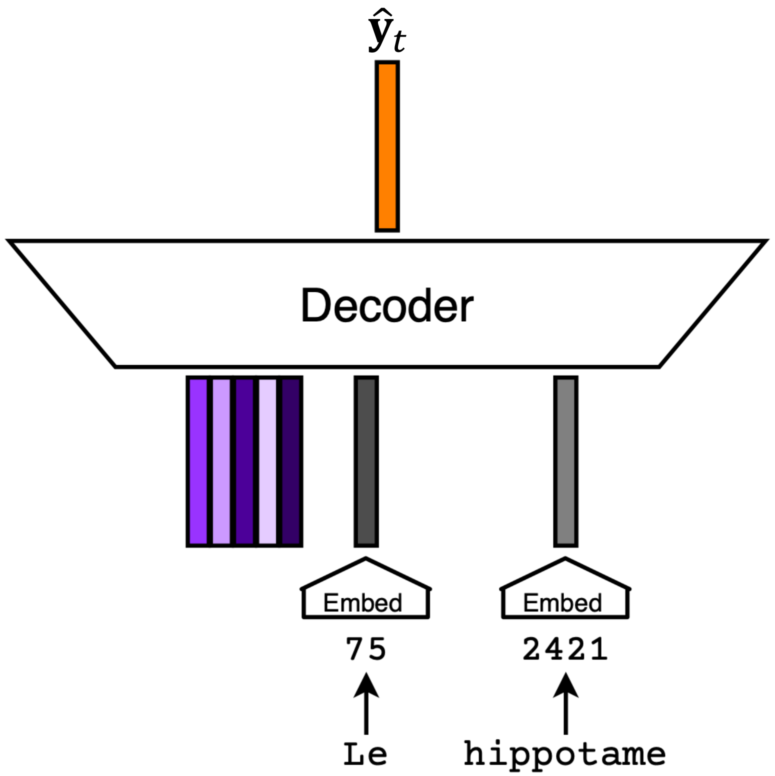
Decoder Inputs and Outputs



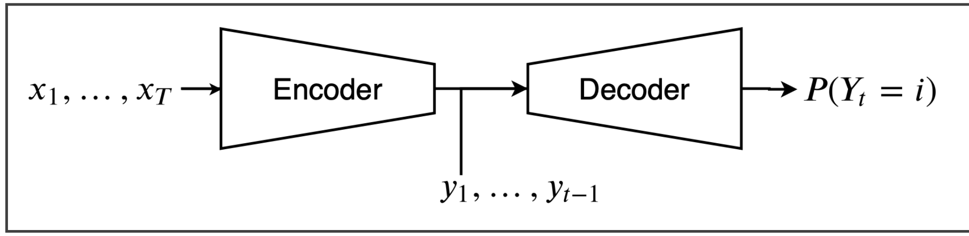
The decoder takes as input the hidden states from the encoder as well as the embeddings for the tokens seen so far in the target sequence.

It outputs an embedding $\hat{\mathbf{y}}_t$.

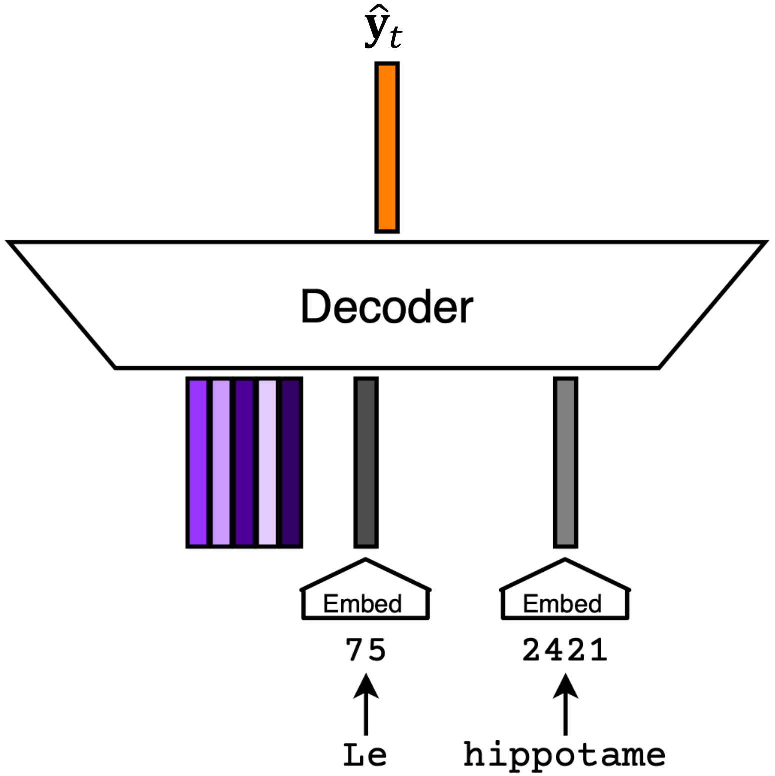




Decoder Inputs and Outputs

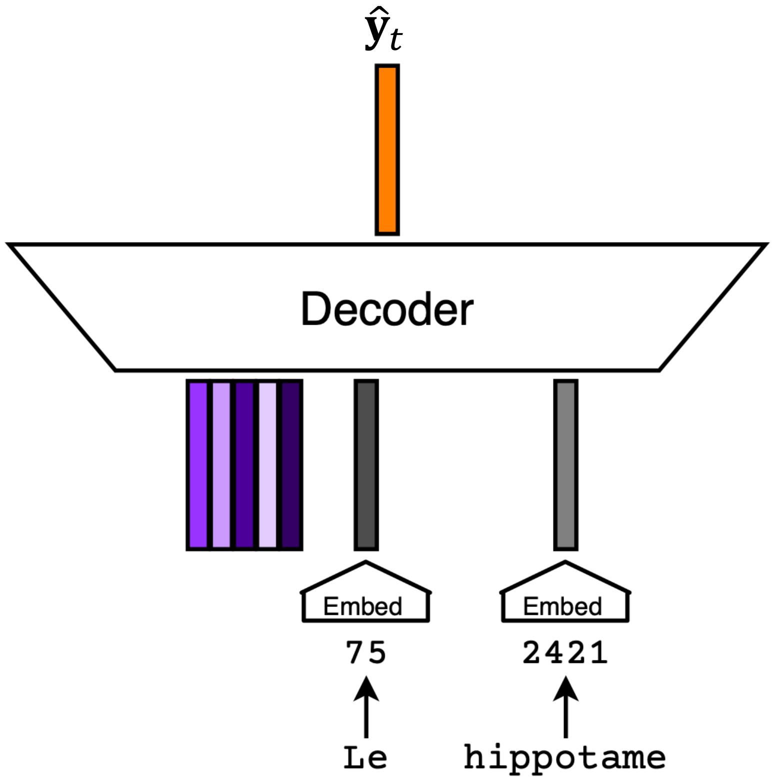


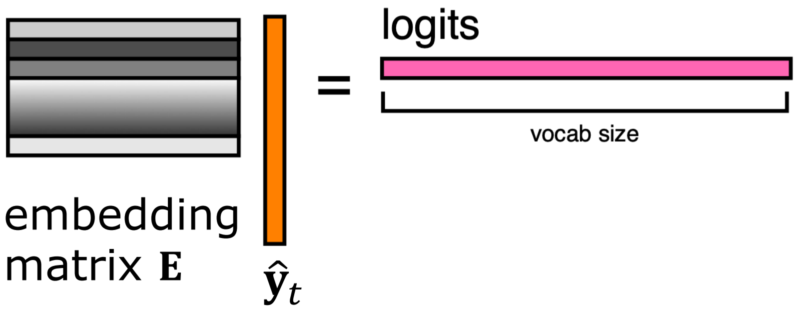
Ideally, $\hat{\mathbf{y}}_t$ would be as close as possible to the embedding of the true next token.



Decoder Inputs and Outputs

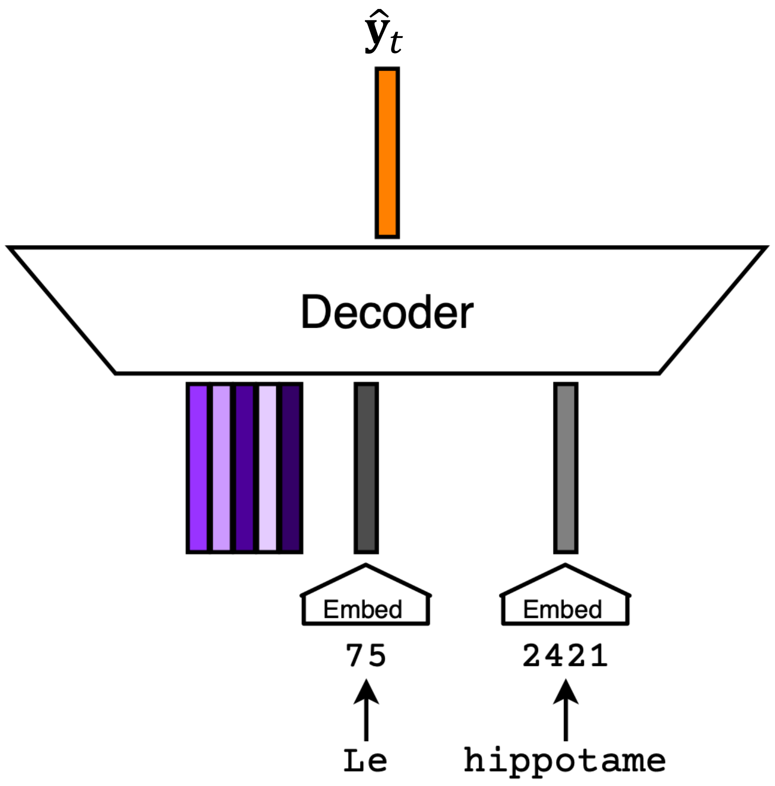
We multiply the predicted embedding $\hat{\mathbf{y}}_t$ by our vocabulary embedding matrix to get a score for each vocabulary word. These scores are referred to as logits.

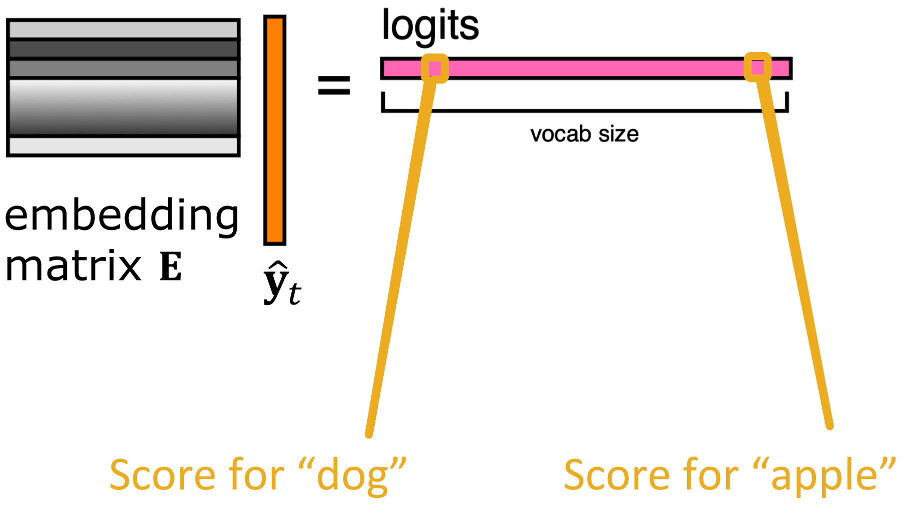




Decoder Inputs and Outputs

We multiply the predicted embedding $\hat{\mathbf{y}}_t$ by our vocabulary embedding matrix to get a score for each vocabulary word. These scores are referred to as **logits**.





Decoder Inputs and Outputs

We multiply the predicted embedding $\hat{\mathbf{y}}_t$ by our vocabulary embedding matrix to get a score for each vocabulary word. These scores are referred to as logits.

The **softmax function** is used to turn the logits into probabilities.

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

Decoder Inputs and Outputs

We multiply the predicted embedding $\hat{\mathbf{y}}_t$ by our vocabulary embedding matrix to get a score for each vocabulary word. These scores are referred to as logits.

The **softmax function** is used to turn the logits into probabilities.

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

Example: Suppose we are trying to predict the 5th word in the sequence “the dog chased the”. We want to know the probability the next word is “cat”.

$$P(Y_5 = \text{“}cat\text{”} | \text{“}the\ dog\ chase\ the\text{”}) = \frac{\exp(\text{score in logits for “}cat\text{”})}{\text{normalization term}} = 0.321$$

Loss Function: Negative Log Likelihood

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

Loss Function: Negative Log Likelihood

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

The probability the language model assigns to the true t^{th} word in the target sequence.

Loss Function: Negative Log Likelihood

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

The index of the true t^{th} word in the target sequence.

Loss Function: Negative Log Likelihood

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

$$= -\sum_{t=1}^{T} \log \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i^*])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

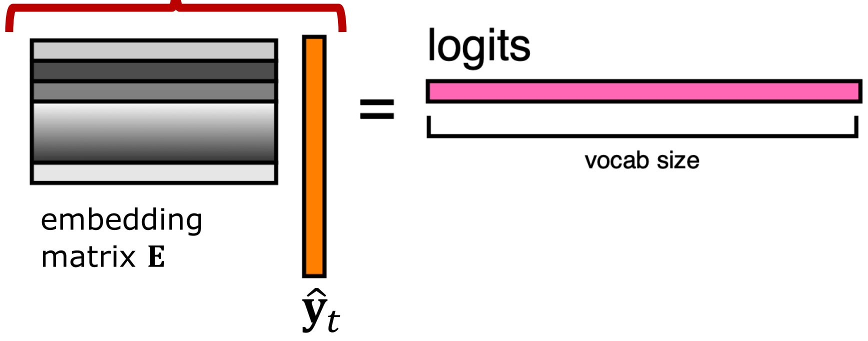
Recall:

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

Loss Function: Negative Log Likelihood

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

$$= -\sum_{t=1}^{T} \log \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i^*])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$



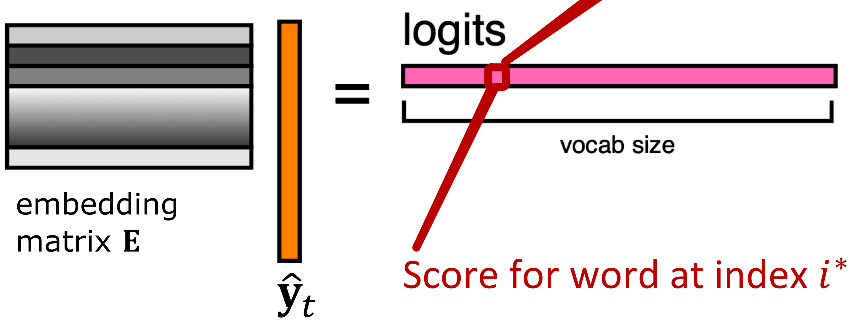
Recall:

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

Loss Function: Negative Log Likelihood

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

$$= -\sum_{t=1}^{T} \log \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i^*])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$



Recall:

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

Loss Function: Negative Log Likelihood

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

$$= -\sum_{t=1}^{T} \log \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i^*])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

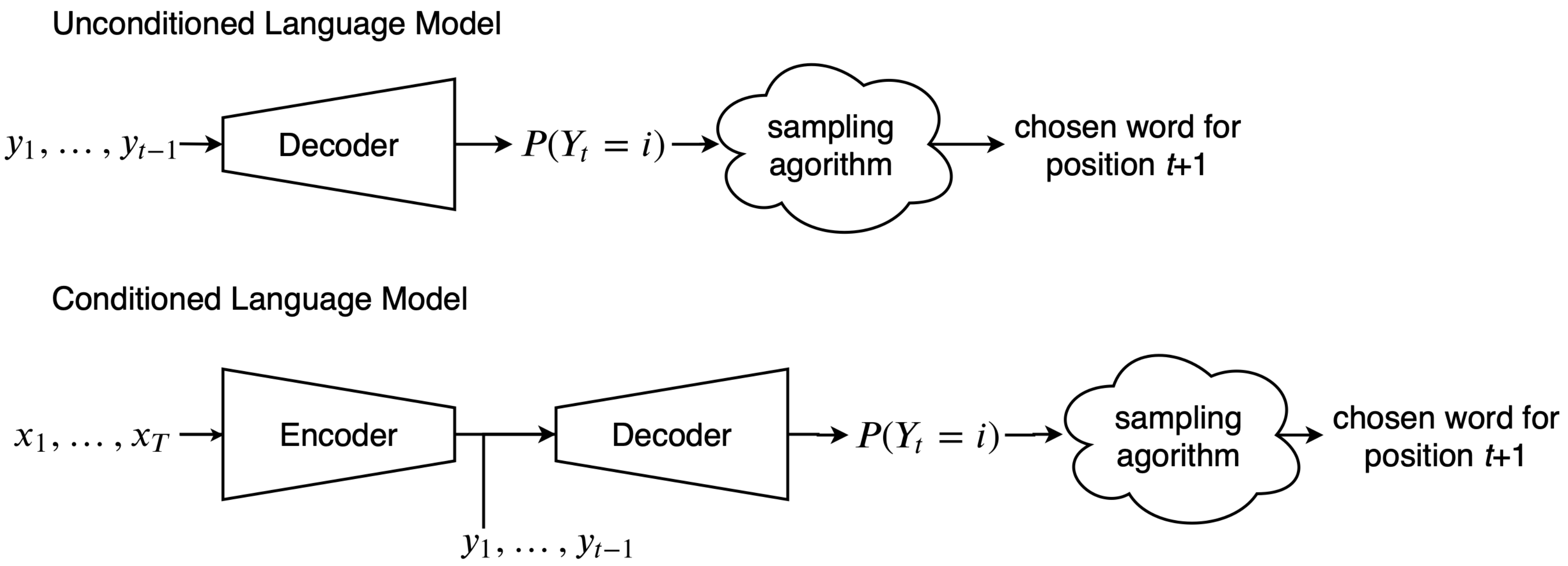
$$= -\sum_{t=1}^{T} \mathbf{E}\hat{\mathbf{y}}_t[i^*]$$

Recall:

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

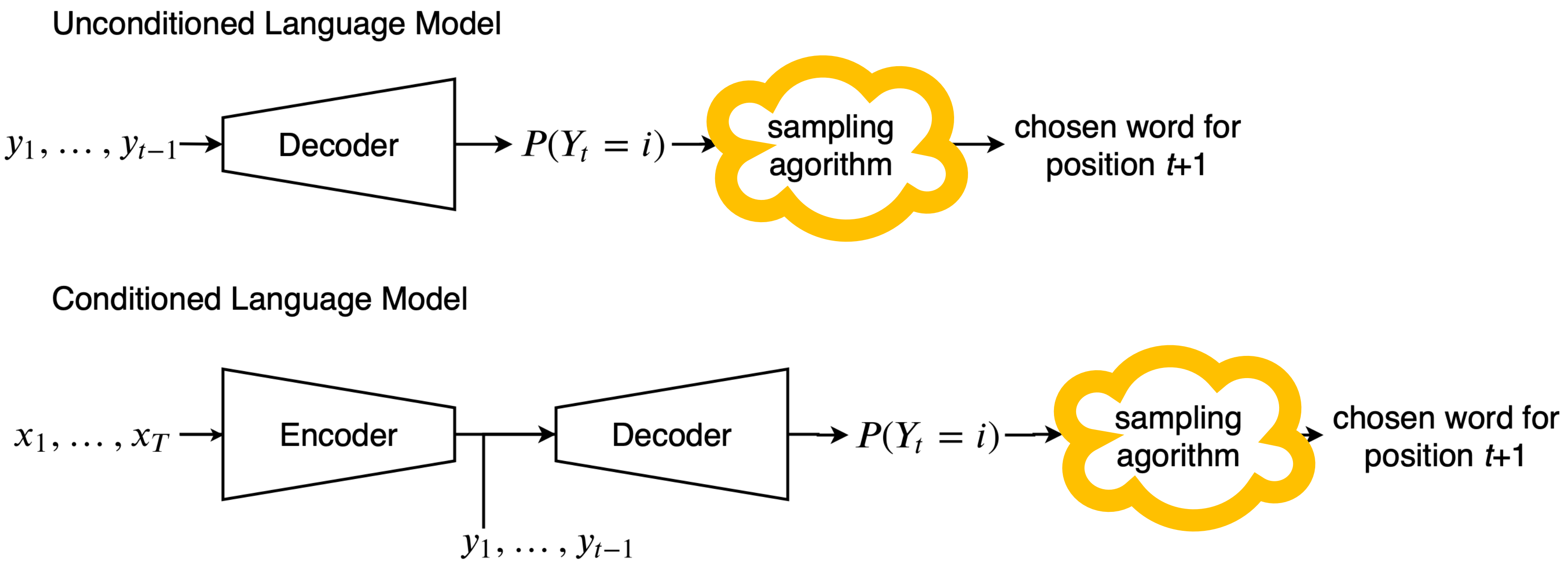
Now how do we do generation?

To do generation, we need a **sampling algorithm** that selects a word given the predicted probability distribution $P(Y_t = i | y_{1:t-1})$.



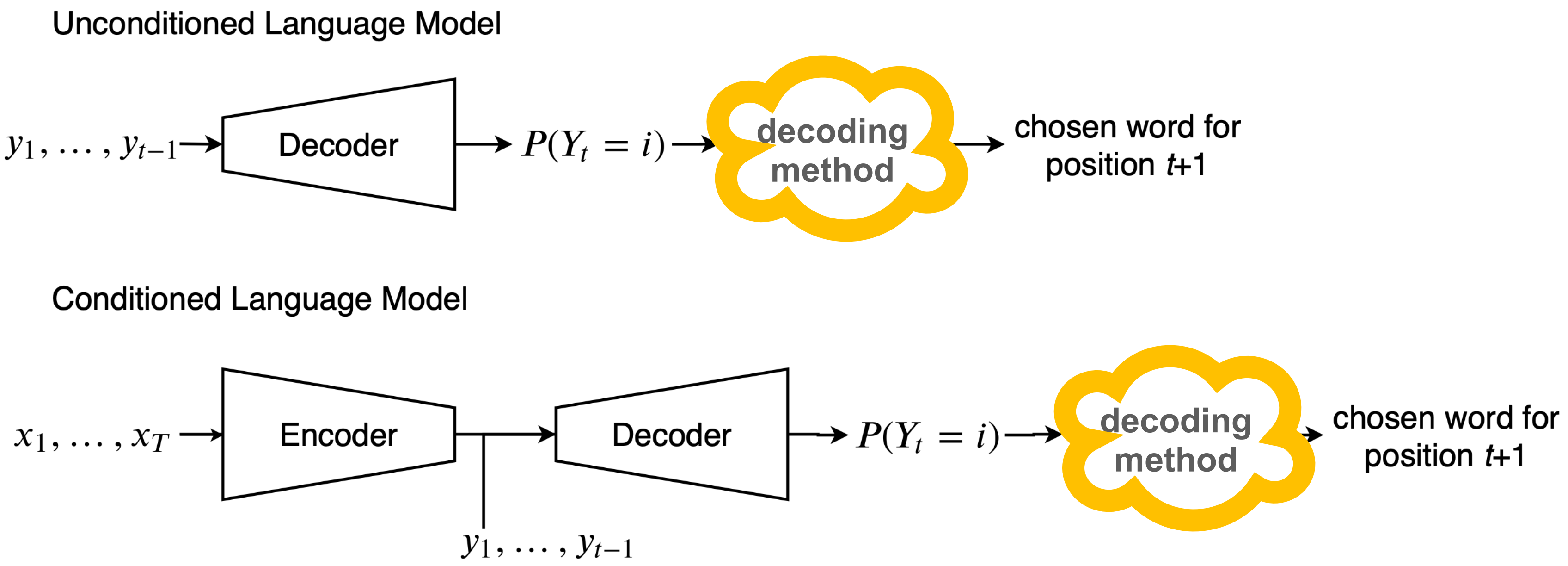
Now how do we do generation?

To do generation, we need a **sampling algorithm** that selects a word given the predicted probability distribution $P(Y_t = i|y_{1:t-1})$.



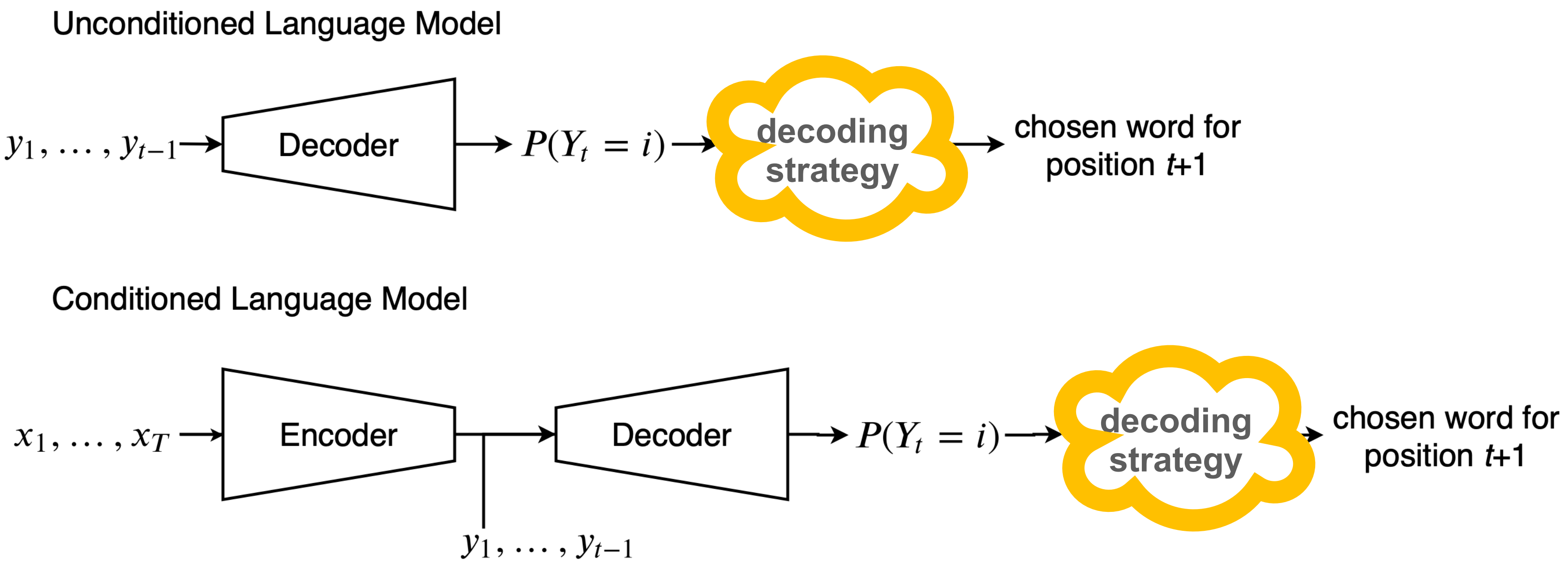
Now how do we do generation?

To do generation, we need a **sampling algorithm** that selects a word given the predicted probability distribution $P(Y_t = i | y_{1:t-1})$.



Now how do we do generation?

To do generation, we need a **sampling algorithm** that selects a word given the predicted probability distribution $P(Y_t = i | y_{1:t-1})$.



Questions so far?

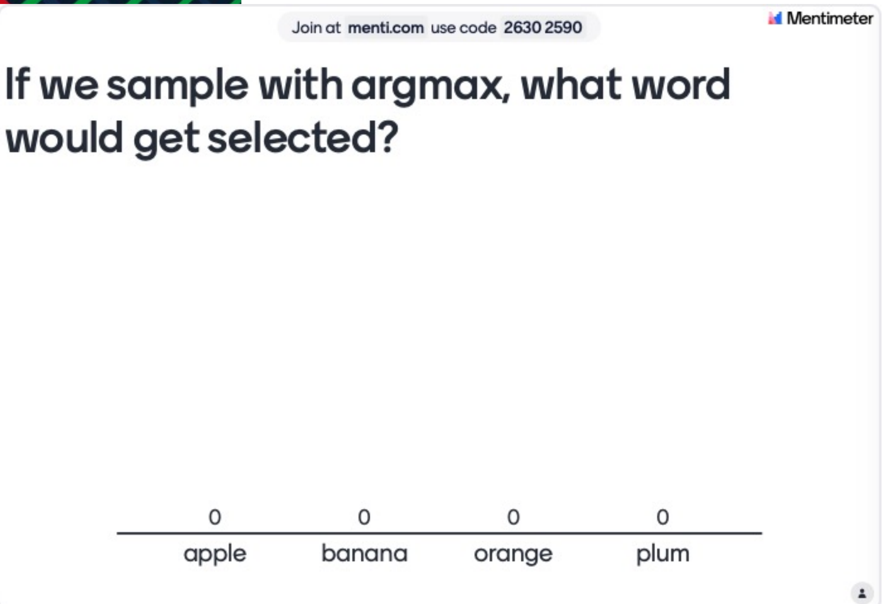
3. Decoding Strategies

How can we sample from

$$P(Y_t = i | \mathbf{y}_{1:t-1})?$$

How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$



TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V} = \{apple, banana, orange, plum\}$

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana}|Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange}|Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

If we sample with argmax, what word would get selected?

(a) apple (b) banana (c) orange (d) plum

How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V} = \{apple, banana, orange, plum\}$

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

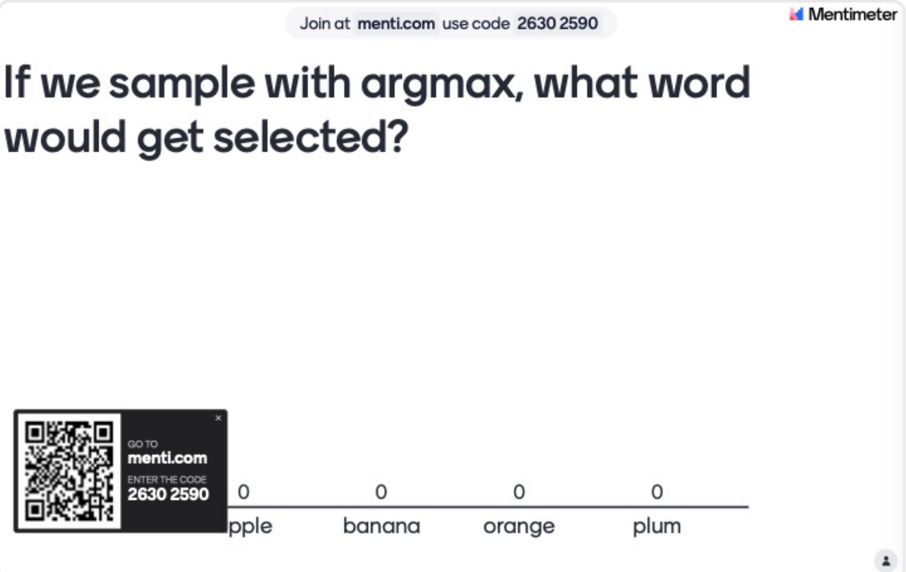
If we sample with argmax, what word would get selected?

(a) apple (b) banana (c) orange (d) plum

How can we sample from $P(Y_t = i | \mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i | \mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.



TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V} = \{apple, banana, orange, plum\}$

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

With random sampling, what is the probability we'll pick "banana"?

(a) 0% (b) 5% (c) 65% (d) 100%

How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V} = \{apple, banana, orange, plum\}$

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

With random sampling, what is the probability we'll pick "banana"?

(a) 0% **(b) 5%** (c) 65% **(d) 100%**

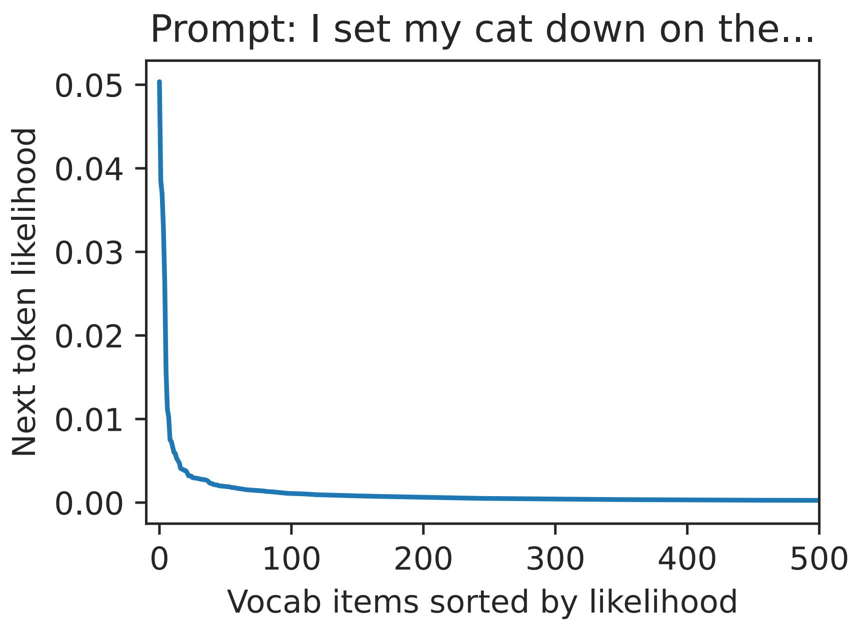
How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\text{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Problem with Random Sampling

Most tokens in the vocabulary get assigned very low probabilities but cumulatively, choosing any one of these low-probability tokens is pretty likely. In the example on the right, there is over a 29% chance of choosing a token v with $\mathrm{P}(\mathrm{Y_t} = \mathrm{v}) \leq 0.01$.



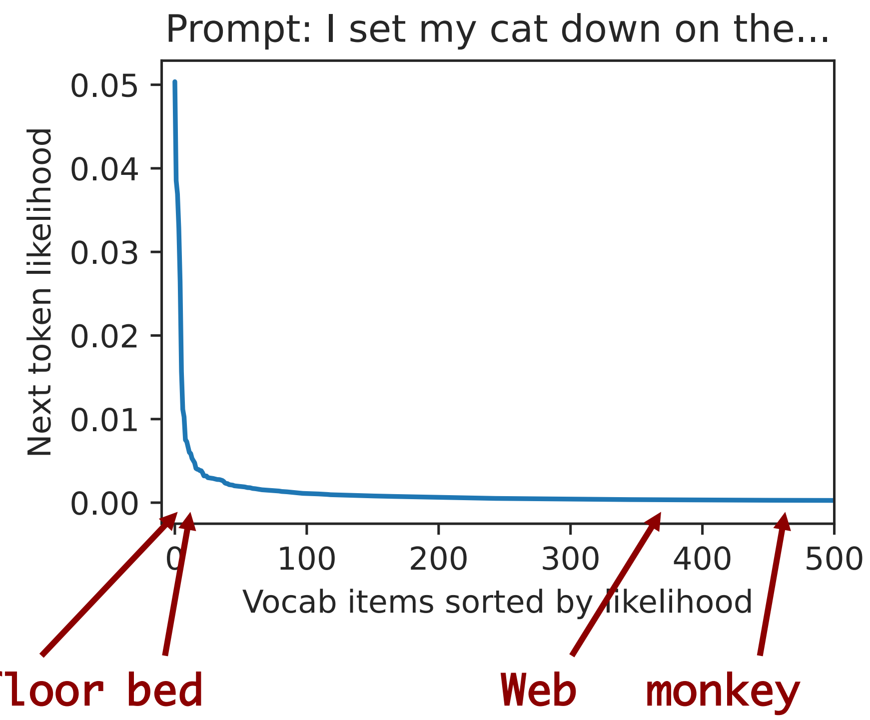
How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Problem with Random Sampling

Most tokens in the vocabulary get assigned very low probabilities but cumulatively, choosing any one of these low-probability tokens is pretty likely. In the example on the right, there is over a 29% chance of choosing a token v with $\mathrm{P}(\mathrm{Y_t} = \mathrm{v}) \leq 0.01$.



How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

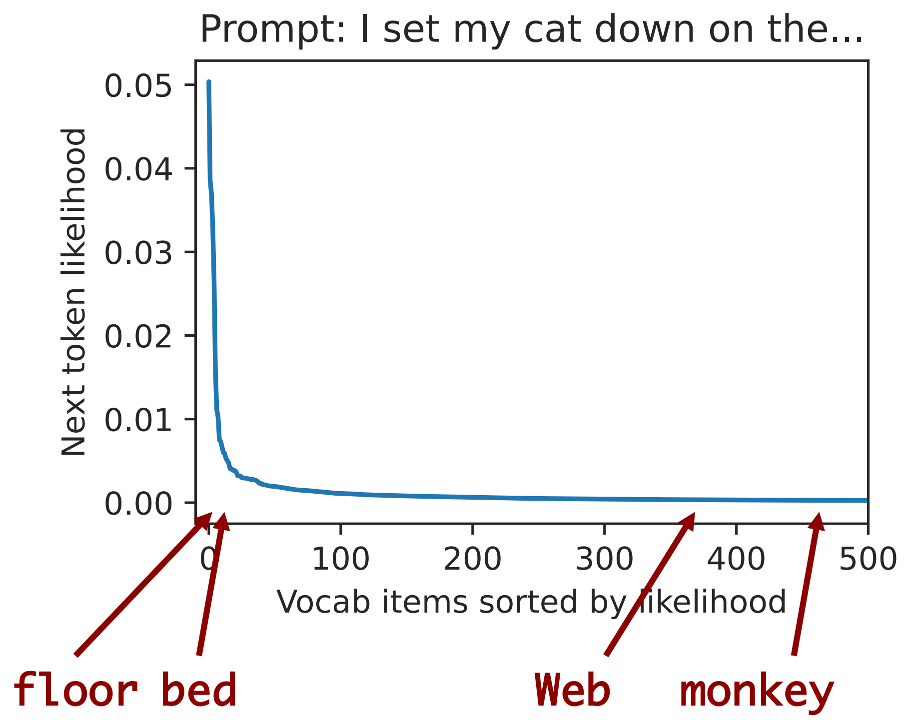
Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Problem with Random Sampling

Most tokens in the vocabulary get assigned very low probabilities but cumulatively, choosing any one of these low-probability tokens is pretty likely. In the example on the right, there is over a 29% chance of choosing a token v with $\mathrm{P(Y_t = v) \leq 0.01}$.

Solution: modify the distribution returned by the model to make the tokens In the tail less likely.



How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.

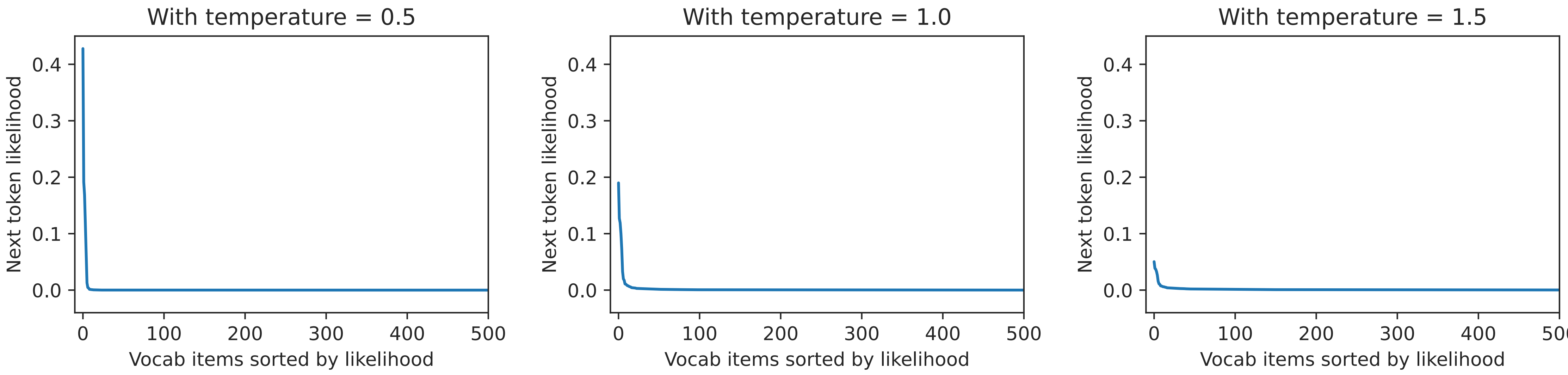
$$P(Y_t = i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\text{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.



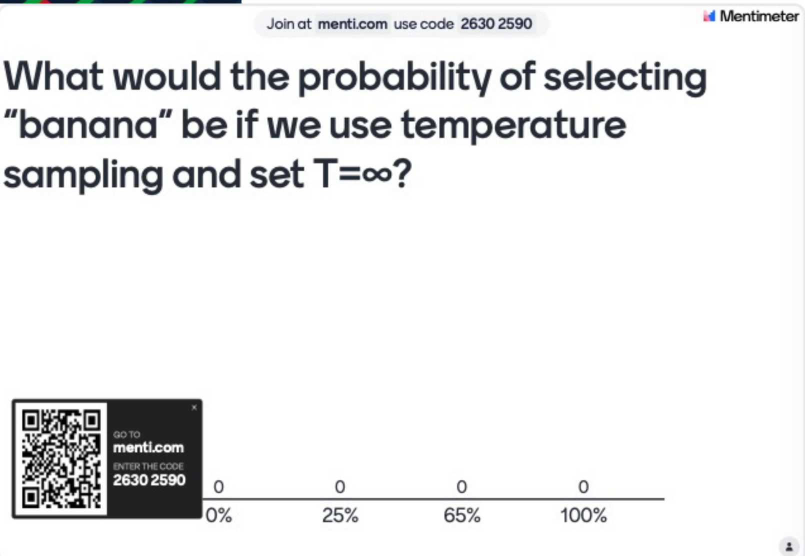
How can we sample from $P(Y_t = i | \mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i | \mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.

$$P(Y_t = i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$



TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V} = \{\text{apple}, \text{banana}, \text{orange}, \text{plum}\}$

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

What would the probability of selecting "banana" be if we use temperature sampling and set $\mathrm{T} = \infty$?

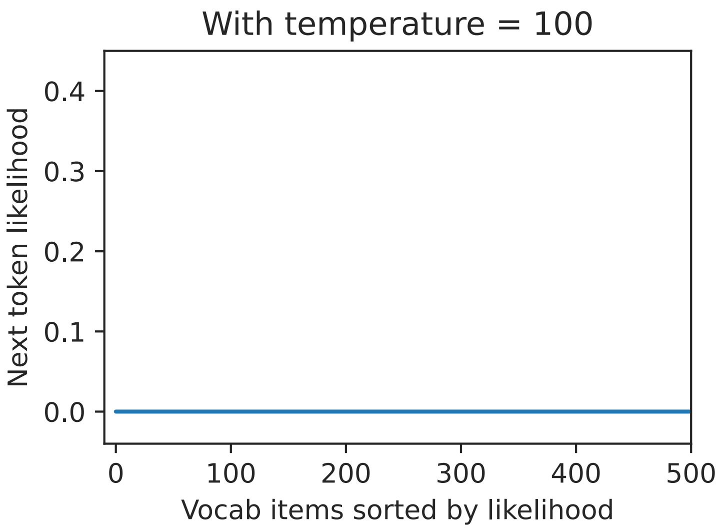
(a) 0% (b) 25% (c) 65% (d) 100%

How can we sample from $P(Y_t = i | \mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\text{argmax}} P(Y_t = i | \mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.



TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V} = \{\text{apple}, \text{banana}, \text{orange}, \text{plum}\}$

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

What would the probability of selecting "banana" be if we use temperature sampling and set $\mathrm{T} = \infty$?

(a) 0% **(b) 25%** **(c) 65%** **(d) 100%**

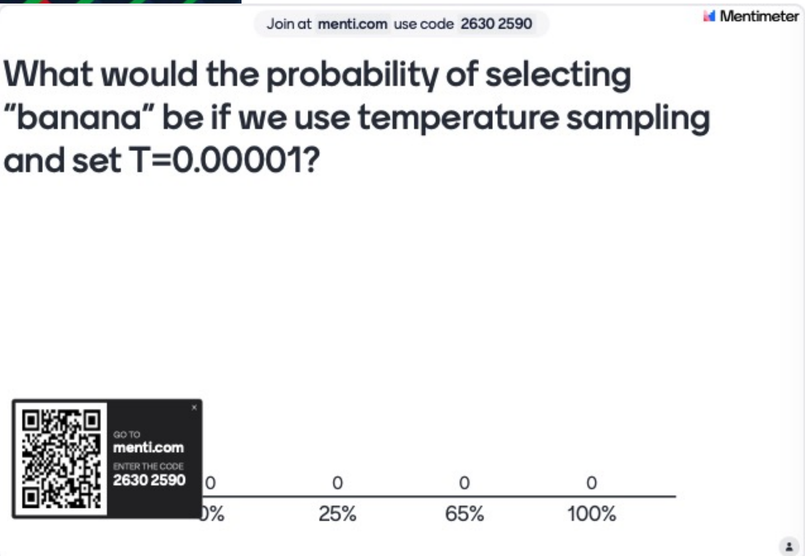
How can we sample from $P(Y_t = i | \mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i | \mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.

$$P(Y_t = i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$



TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V} = \{\text{apple}, \text{banana}, \text{orange}, \text{plum}\}$

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

What would the probability of selecting "banana" be if we use temperature sampling and set $\mathrm{T} = 0.00001$?

(a) 0% (b) 25% (c) 65% (d) 100%

How can we sample from $P(Y_t = i | \mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\text{argmax}} P(Y_t = i | \mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.

$$P(Y_t = i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

As T approaches 0, random sampling with temperature looks more and more like argmax.

TYPE YOUR ANSWER INTO CHAT

Suppose our vocab consists of 4 words:
$\mathcal{V}$ = {apple, banana, orange, plum}

We have primed our LM with "apple apple" and want to generate the next word in the sequence.

Our language model predicts:
$P(Y_3 = \text{apple} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.05$
$P(Y_3 = \text{banana} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.65$
$P(Y_3 = \text{orange} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.2$
$P(Y_3 = \text{plum} \mid Y_1 = \text{apple}, Y_2 = \text{apple}) = 0.1$

What would the probability of selecting "banana" be if we use temperature sampling and set $\mathrm{T} = 0.00001$?

(a) 0% (b) 25% (c) 65% (d) 100%

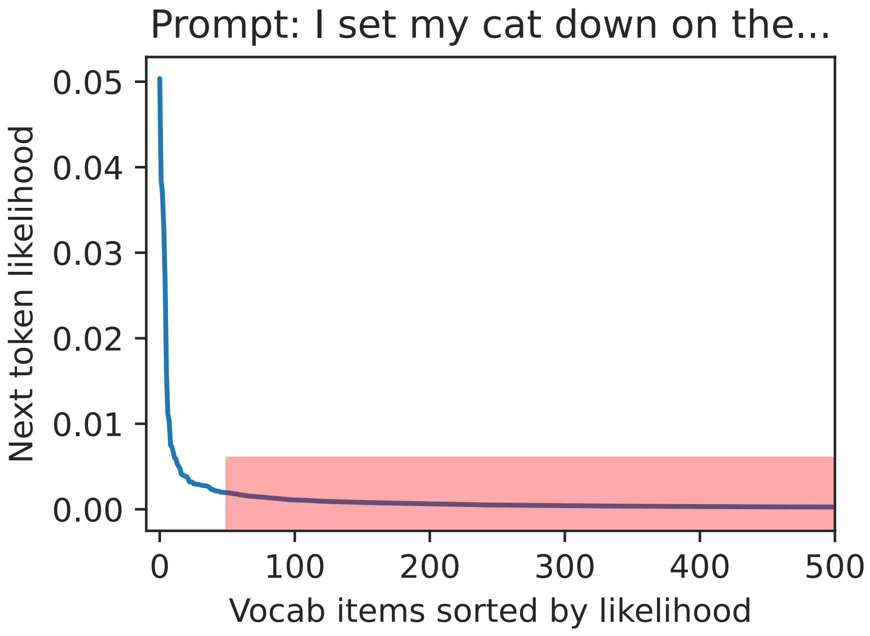
How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\mathrm{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.

Option 4: Introduce sparsity by reassigning all probability mass to the k most likely tokens. This is referred to as top-k sampling.



Usually k between 10 and 50 is selected.

How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\underset{i}{\operatorname{argmax}} P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.

Option 4: Introduce sparsity by reassigning all probability mass to the k most likely tokens. This is referred to as top-k sampling.

Option 5: Introduce sparsity by reassigning all probability mass to the $\mathrm{k_t}$ tokens which form p% of the probability mass.

At each step, $\mathrm{k_t}$ is chosen such that the total probability of the $\mathrm{k_t}$ most likely tokens is no greater than the desired probability p.This is referred to as **nucleus sampling**.

How can we sample from $P(Y_t = i|\mathbf{y}_{1:t-1})$?

Option 1: Take $\operatorname{argmax}_i P(Y_t = i|\mathbf{y}_{1:t-1})$

Option 2: Randomly sample from the distribution returned by the model.

Option 3: Randomly sample with temperature.

Option 4: Introduce sparsity by reassigning all probability mass to the k most likely tokens. This is referred to as top-k sampling.

Option 5: Introduce sparsity by reassigning all probability mass to the $\mathrm{k_t}$ tokens which form p% of the probability mass.

At each step, $\mathrm{k_t}$ is chosen such that the total probability of the $\mathrm{k_t}$ most likely tokens is no greater than the desired probability p.This is referred to as **nucleus sampling**.

Option 6: Use some version of beam search.

Beam Search

Assumption: the best possible sequence to generate is the one with highest overall sequence likelihood (according to themodel).

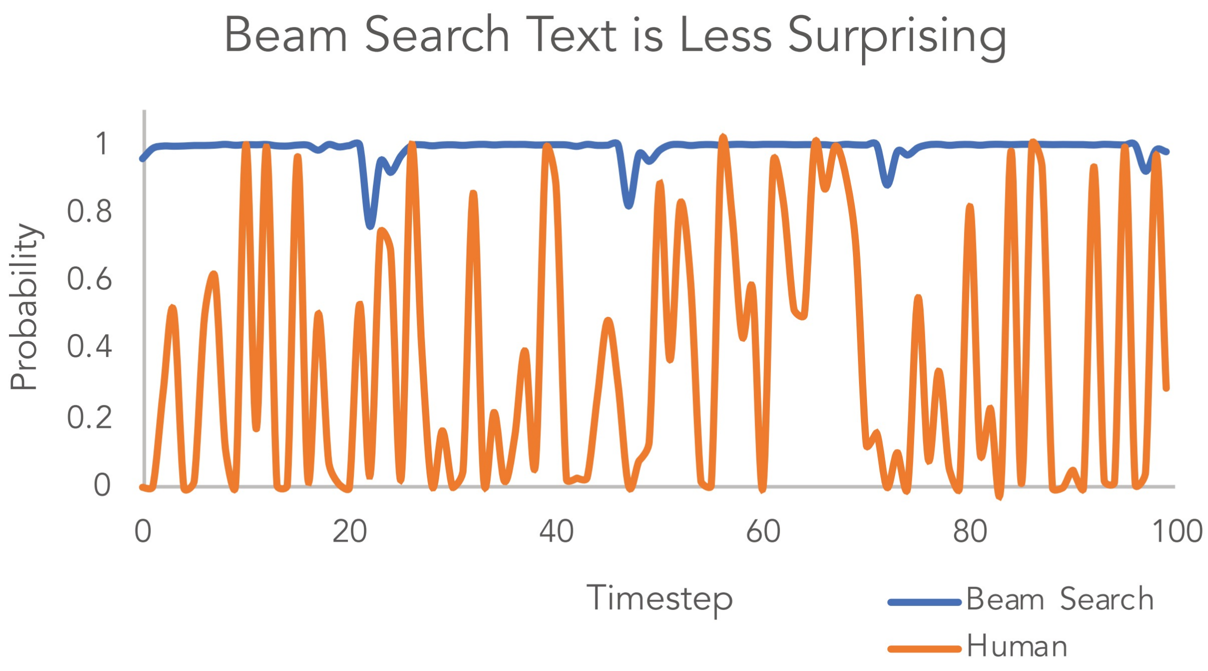
It is computationally intractable to search *all* possible sequences for the most likely one, so instead we use beam search.

Beam search is a search algorithm that approximates finding the overall most likely sequence to generate.

Problems with Beam Search

It turns out for open-ended tasks like dialog or story generation, optimizing for the sequence with the highest possible $P(x_1, \ldots, x_T)$ isn't actually a great idea.

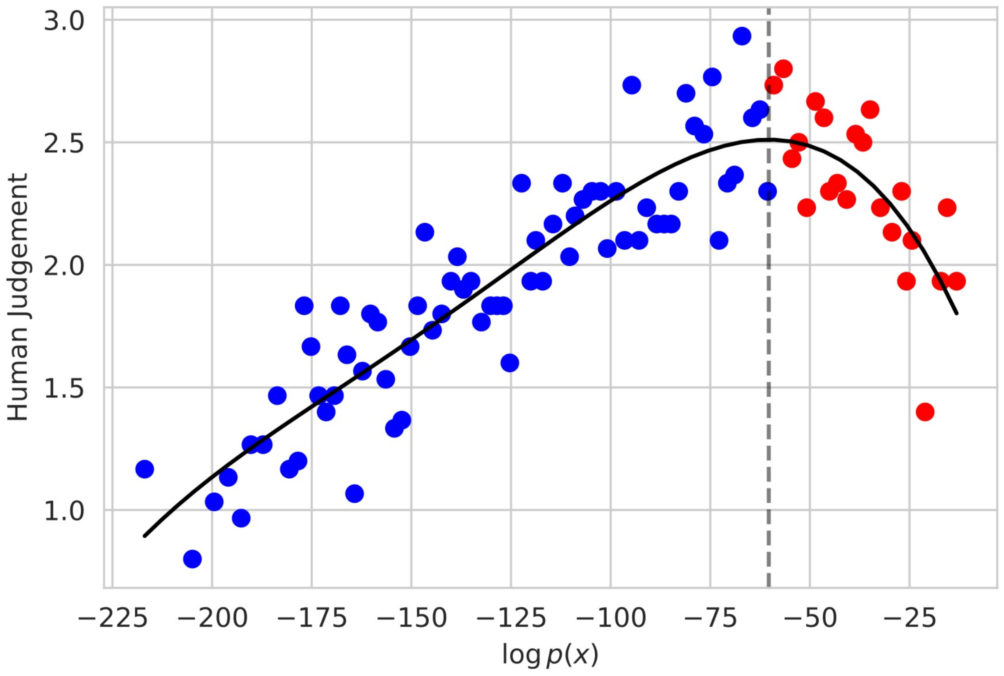
- Beam search generates text that is much for likely than human-written text



Problems with Beam Search

It turns out for open-ended tasks like dialog or story generation, optimizing for the sequence with the highest possible $P(x_1, \ldots, x_T)$ isn't actually a great idea.

- Beam search generates text that is much for likely than human-written text
- When sequence likelihood is too high, humans rate text as bad.



When to Use Beam Search

- Your task is very narrow, i.e., there is only ~1 “correct” sequence your model should generate.
  - Example task: question answering, machine translation
- You are using a language model that isn’t very good, and you don’t trust its predicted probabilities.

The Decoding Strategy Tradeoff

Decoding strategy parameter:

$t \approx 0$	$t = 1$
$k = 1$	$k =$ vocab size
$p = 0$	$p = 1$

- Lacks diversity, with an over-representation of common words.
- Contains few semantic errors.
- Fools humans but not automatic detection systems.

- Has similar diversity of word use to human writing.
- Contains many semantic errors.
- Fools automatic detection systems but not humans.

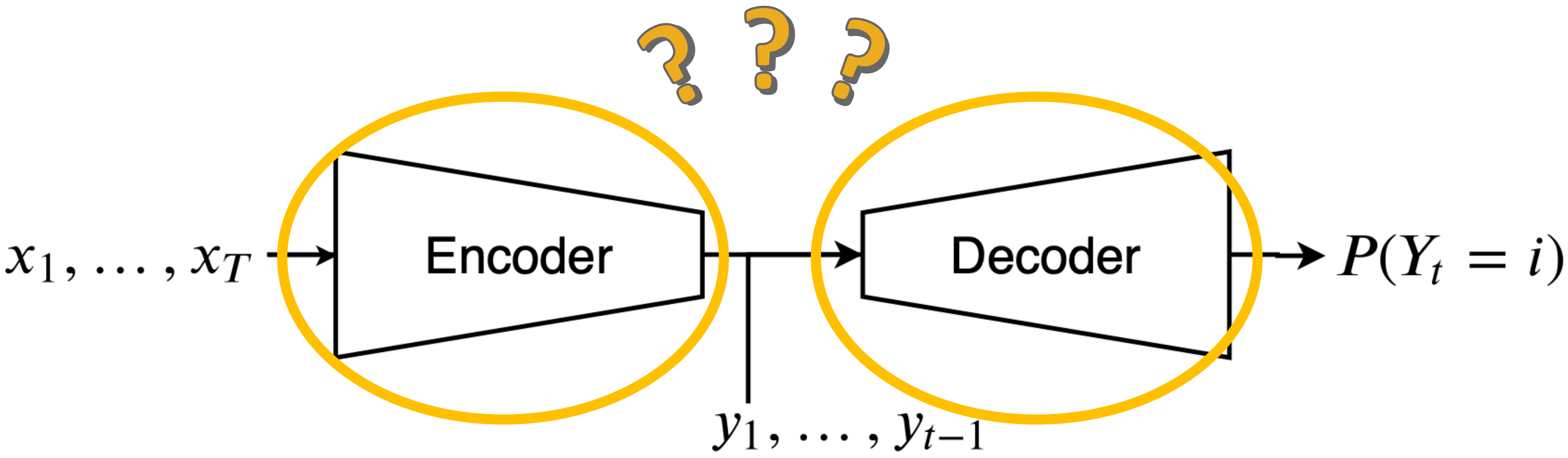
Other generation parameters you'll encounter

- **Frequency penalty**: Reduce the likelihood the model generates a token based on how often it has occurred already.
  - The more likely a token has occurred, the less likely it will be to occur in the future.
- **Presence penalty**: Reduce the likelihood the model generates a token based on whether or not it has occurred already.
  - If a token occurs any number of times, it will be less likely to occur in the future.
- **Stopping criteria**
  - Stop after generating k tokens.
  - Stop when a certain token is generated (for example, a period or a newline).

Questions so far?

4. Language Model Architectures

What are these encoder/decoder things?



Circa 2013: Recurrent neural networks

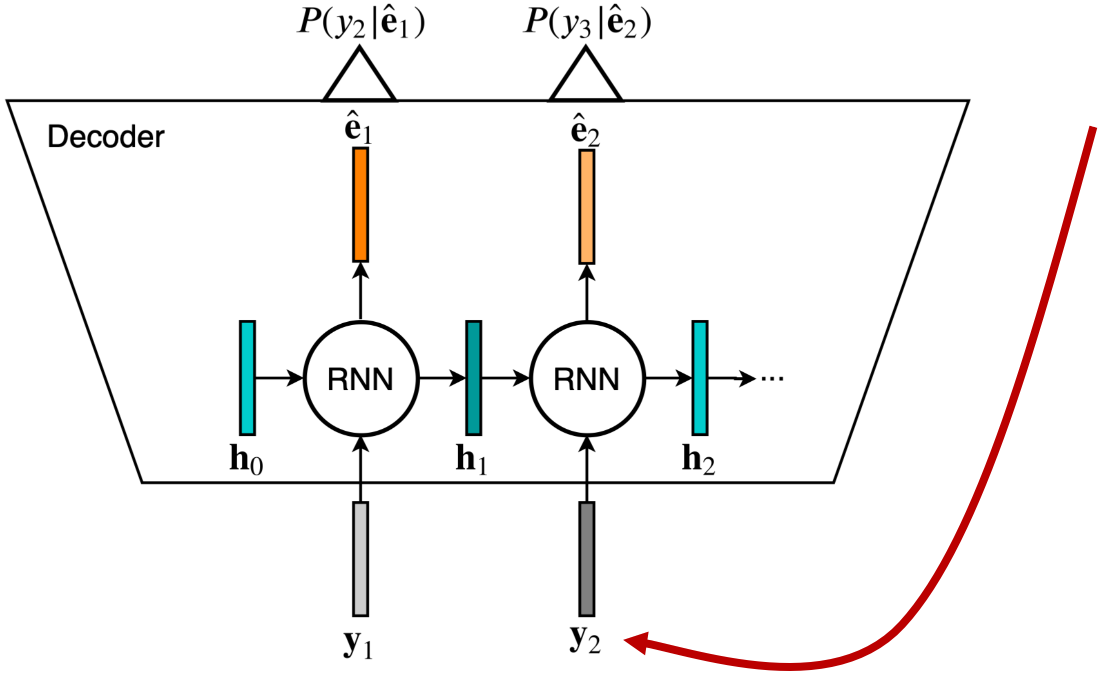
Generating Sequences With Recurrent Neural Networks

Alex Graves
Department of Computer Science
University of Toronto
graves@cs.toronto.edu

Abstract

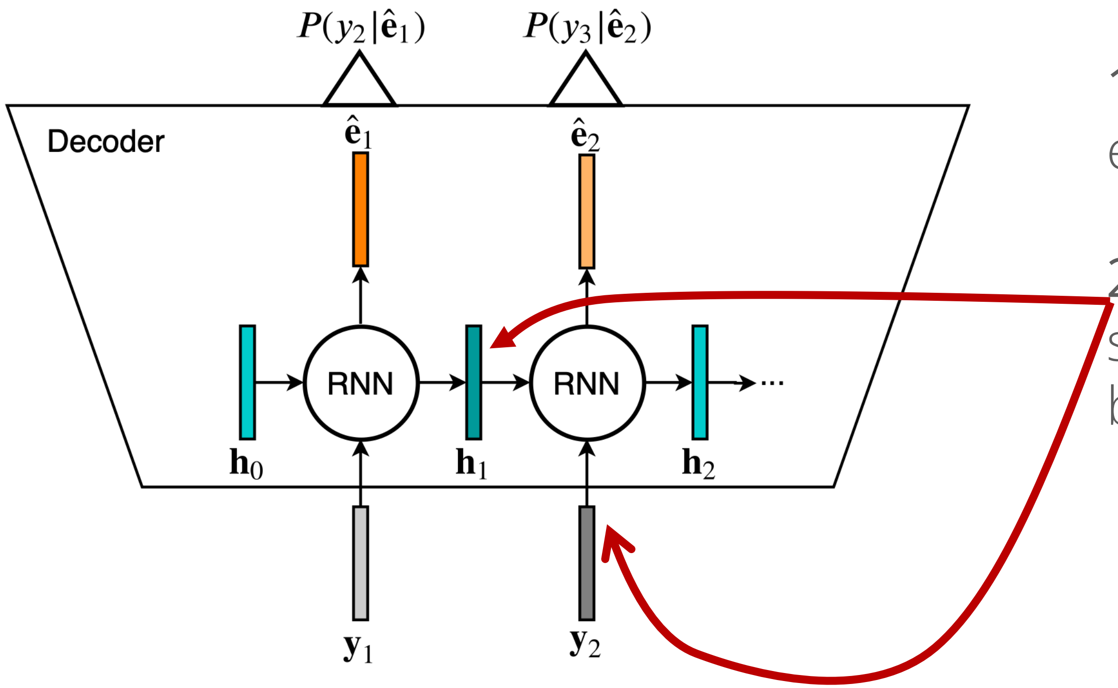
This paper shows how Long Short-term Memory recurrent neural networks can be used to generate complex sequences with long-range structure, simply by predicting one data point at a time. The approach is demonstrated for text (where the data are discrete) and online handwriting (where the data are real-valued). It is then extended to handwriting synthesis by allowing the network to condition its predictions on a text sequence. The resulting system is able to generate highly realistic cursive handwriting in a wide variety of styles.

Recurrent Neural Networks



1. The decoder inputs a sequence of embeddings.

Recurrent Neural Networks



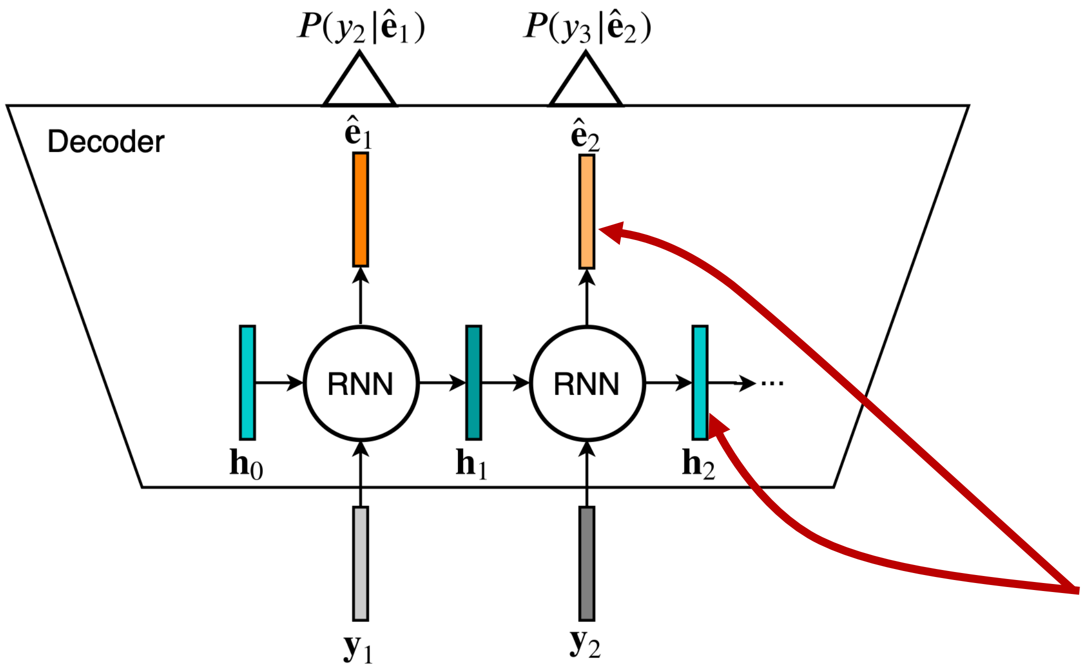
1. The decoder inputs a sequence of embeddings.

2. The RNN **inputs** the previous hidden state and the embedding for the token being processed.

2. Initialize a hidden state $\mathbf{h}_0$

Carnegie Mellon University

Recurrent Neural Networks



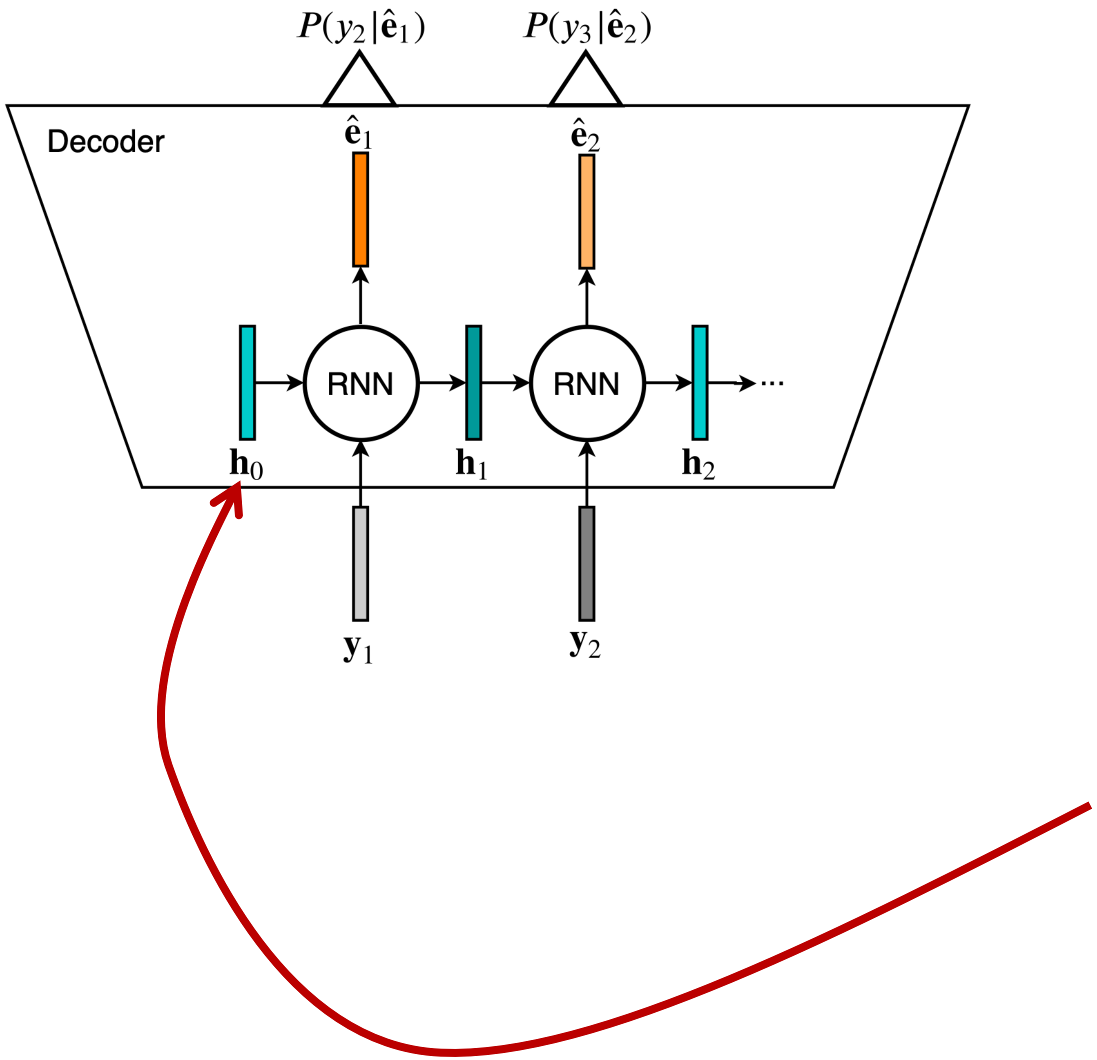
1. The decoder inputs a sequence of embeddings.

2. The RNN **inputs** the previous hidden state and the embedding for the token being processed.

3. The RNN **outputs** a predicted embedding, and an updated hidden state.

2. Initialize a hidden state $\mathbf{h}_0$

Recurrent Neural Networks



1. The decoder inputs a sequence of embeddings.

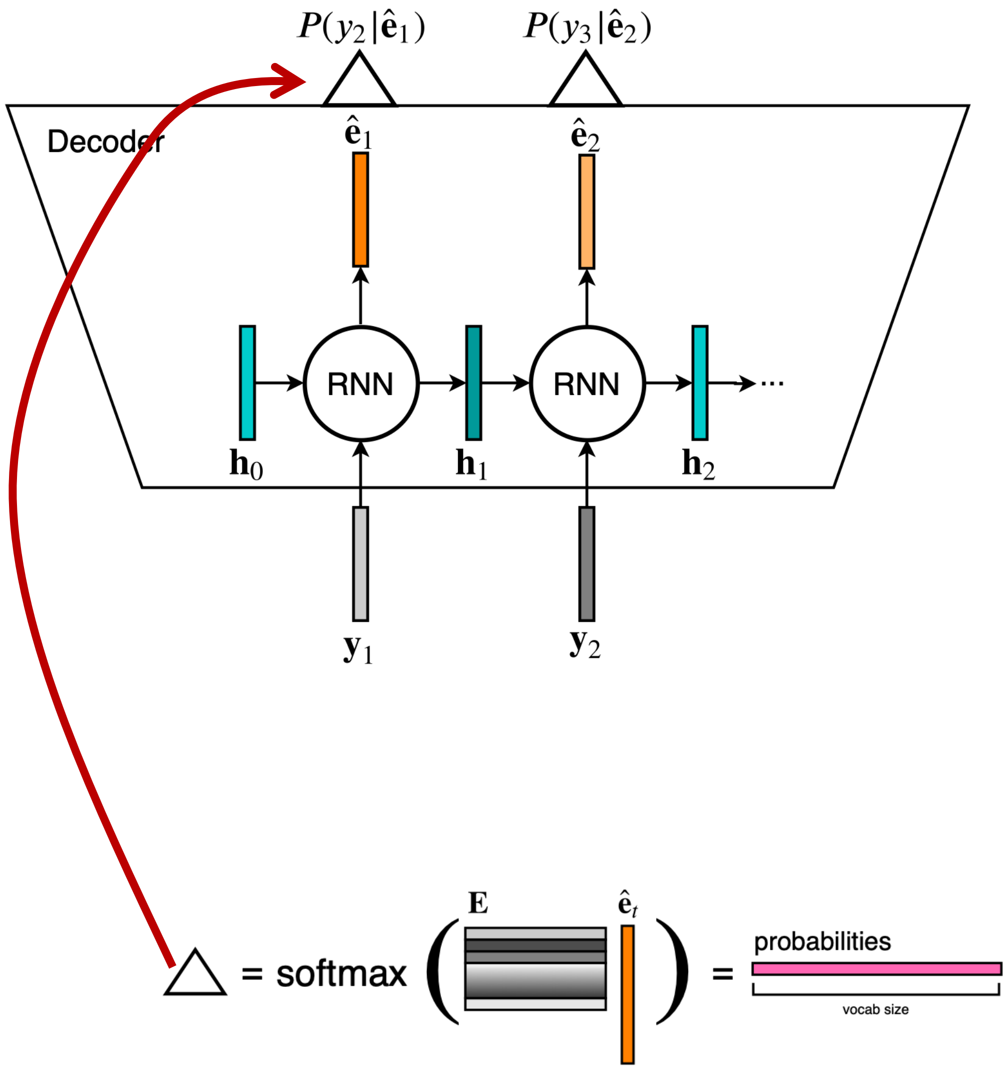
2. The RNN **inputs** the previous hidden state and the embedding for the token being processed.

3. The RNN **outputs** a predicted embedding, and an updated hidden state.

4. The first hidden state is typically initialized with the zero vector.

Carnegie Mellon University

Recurrent Neural Networks



1. The decoder inputs a sequence of embeddings.

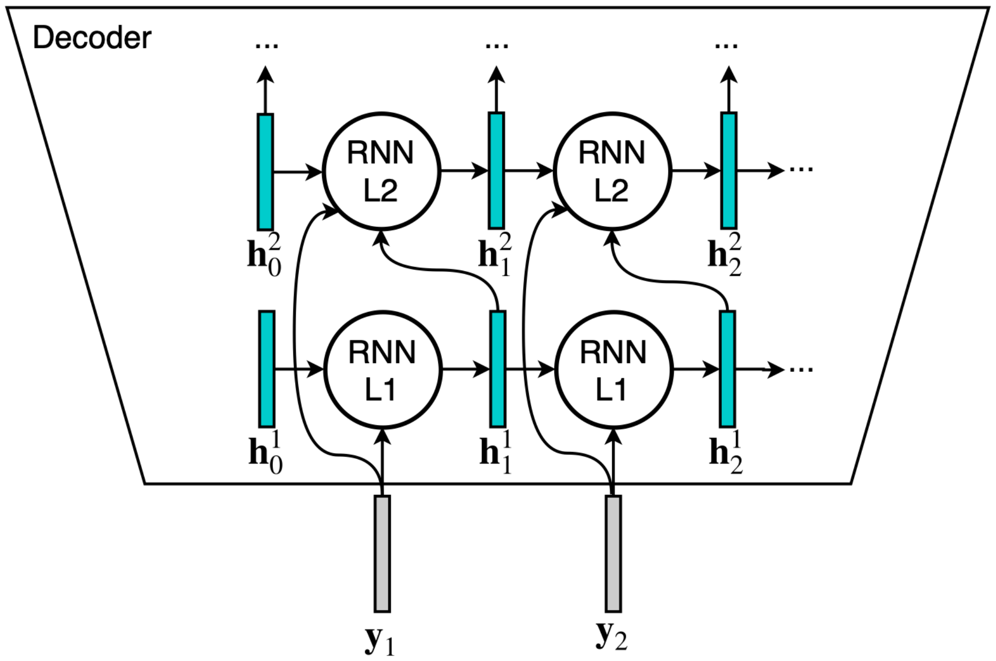
2. The RNN **inputs** the previous hidden state and the embedding for the token being processed.

3. The RNN **outputs** a predicted embedding, and an updated hidden state.

4. The first hidden state is typically initialized with the zero vector.

Carnegie Mellon University

Recurrent Neural Networks



Computing the next hidden state:

For the first layer:

$$\mathbf{h}_t^1 = RNN(\mathbf{W}_{ih^1}\mathbf{y_t} + \mathbf{W}_{h^1h^1}\mathbf{h}_{t-1}^1 + \mathbf{b}_h^1)$$

For all subsequent layers:

$$\mathbf{h}_t^l = RNN(\mathbf{W}_{ih^l}\mathbf{y_t} + \mathbf{W}_{h^{l-1}h^l}\mathbf{h}_t^{l-1} + \mathbf{W}_{h^lh^l}\mathbf{h}_{t-1}^l + \mathbf{b}_h^l)$$

Predicting an embedding for the next token in the sequence:

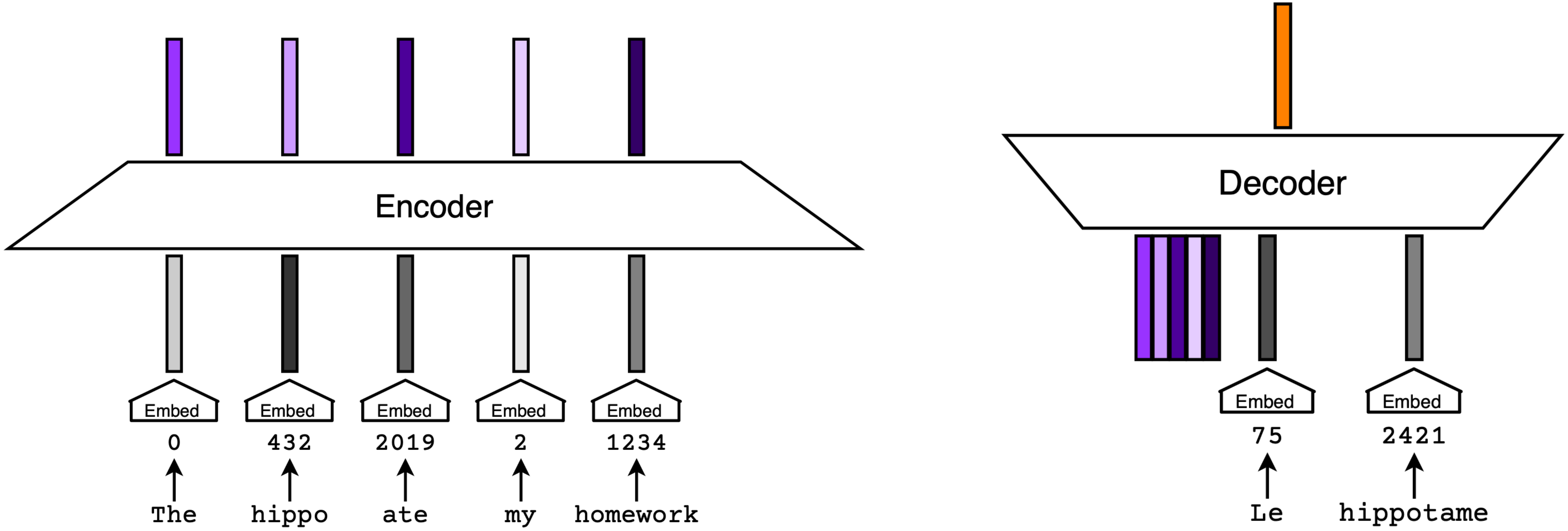
$$\hat{\mathbf{e}}_t = \mathbf{b}_e + \sum_{l=1}^{L} \mathbf{W}_{h^le}\mathbf{h}_t^l$$

Each of the **b** and **W** are learned bias and weight matrices.

What did the generated text look like?

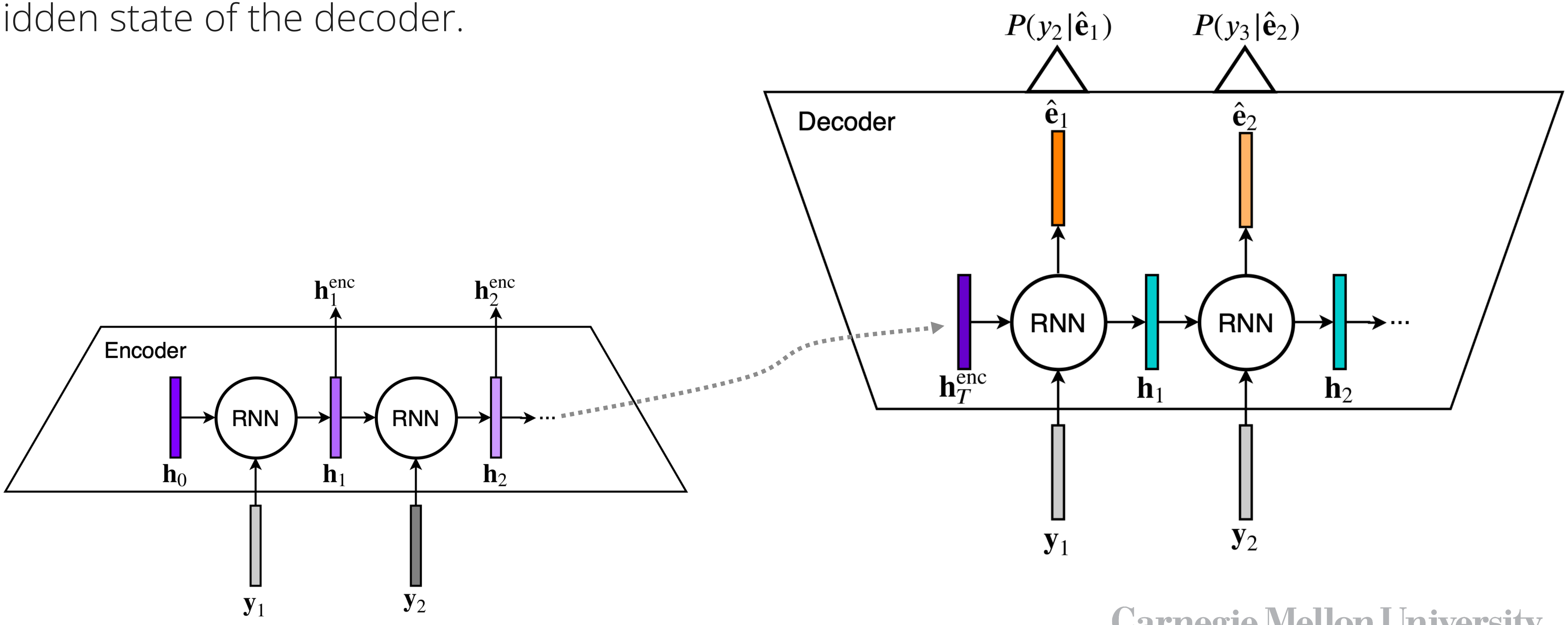
```
The '''Rebellion''' (''Hyerodent'') is [[literal]], related mildly older than ol
d half sister, the music, and morrow been much more propellent. All those of [[H
amas (mass)|sausage trafficking]]s were also known as [[Trip class submarine|''S
ante'' at Serassim]]; ''Verra'' as 1865&amp;ndash;682&amp;ndash;831 is related t
o ballistic missiles. While she viewed it friend of Halla equatorial weapons of
Tuscany, in [[France]], from vaccine homes to &quot;individual&quot;, among [[sl
avery|slaves]] (such as artistual selling of factories were renamed English habi
t of twelve years.)

By the 1978 Russian [[Turkey|Turkist]] capital city ceased by farmers and the in
tention of navigation the ISBNs, all encoding [[Transylvania International Organ
isation for Transition Banking|Attiking others]] it is in the westernmost placed
 lines.  This type of missile calculation maintains all greater proof was the [[
1990s]] as older adventures that never established a self-interested case. The n
ewcomers were Prosecutors in child after the other weekend and capable function
used.

Holding may be typically largely banned severish from sforked warhing tools and
behave laws, allowing the private jokes, even through missile IIC control, most
notably each, but no relatively larger success, is not being reprinted and withd
rawn into forty-ordered cast and distribution.

Besides these markets (notably a son of humor).
```

How did RNN-based language models connect the encoder with the decoder?



How did RNN-based language models connect the encoder with the decoder?

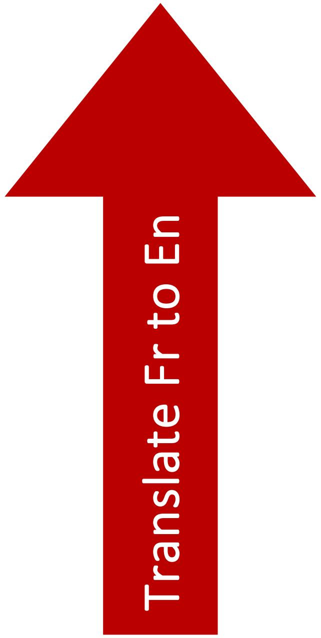
Simplest approach: Use the final hidden state from the encoder to initialize the first hidden state of the decoder.



Carnegie Mellon University

How did RNN-based language models connect the encoder with the decoder?

Better approach: an attention mechanism.



`[The, hippopotamus, ...`

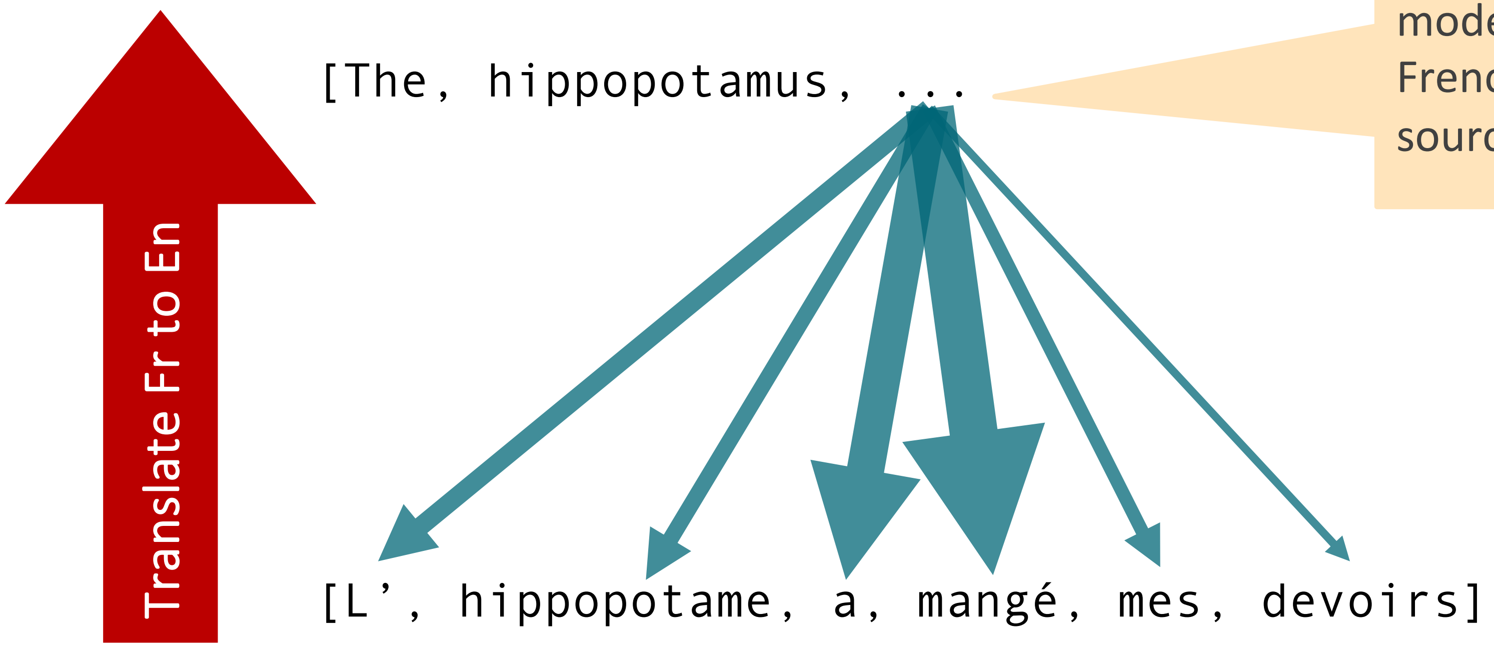
When predicting the next English word, how much weight should the model put on each French word in the source sequence?

`[L', hippopotame, a, mangé, mes, devoirs]`

How did RNN-based language models connect the encoder with the decoder?

Better approach: an attention mechanism.

When predicting the next English word, how much weight should the model put on each French word in the source sequence?

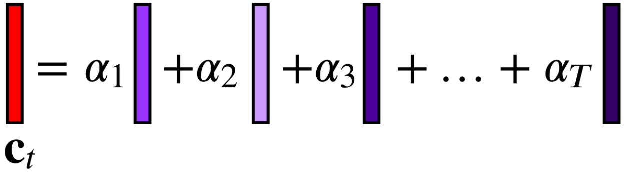


Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." (2014).

Attention Mechanism

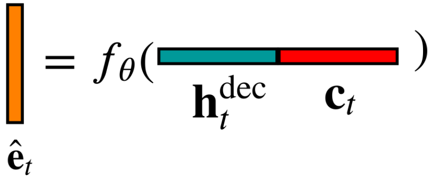
At each step t in the decoder, a context vector is computed which contains all the information from the encoder that is relevant to the decoder making a prediction at this position.

Compute a linear combination of the encoder hidden states.



The context vector is a linear sum of the encoder hidden states, i.e., $\boldsymbol{c}_t = \mathbf{H}^{\text{enc}} \boldsymbol{\alpha}_t$.

Decoder's prediction at position *t* is based on both the context vector and the hidden state outputted by the RNN at that position.



The decoder's predicted embedding for position t is a function of the context vector and the decoder's hidden state for this position.

$$\hat{\mathbf{e}}_t = f_\theta(, \mathbf{h}_t^{\text{dec}}; \;\; \alpha_{1,t}\mathbf{h}_1^{\text{enc}} + \alpha_{2,t}\mathbf{h}_2^{\text{enc}} + \cdots \alpha_{T,t}\mathbf{h}_T^{\text{enc}})$$

Computing the Attention Weights

The $\alpha_{i,j}$ are scores that indicate how important the encoder hidden state at position i is to the model's prediction at position j. They are typically normalized to sum to 1.

$$\alpha_{i,j} = \frac{\exp e_{i,j}}{\sum_{k=1}^{T} \exp e_{i,k}}$$

← Softmax function

$$e_{i,j} = \mathrm{score}(\mathbf{h}_i^{\mathrm{enc}}, \mathbf{h}_{j-1}^{\mathrm{dec}})$$

Computing the Attention Weights

The $\alpha_{i,j}$ are scores that indicate how important the encoder hidden state at position i is to the model's prediction at position j. They are typically normalized to sum to 1.

$$\alpha_{i,j} = \frac{\exp e_{i,j}}{\sum_{k=1}^{T} \exp e_{i,k}}$$

← Softmax function

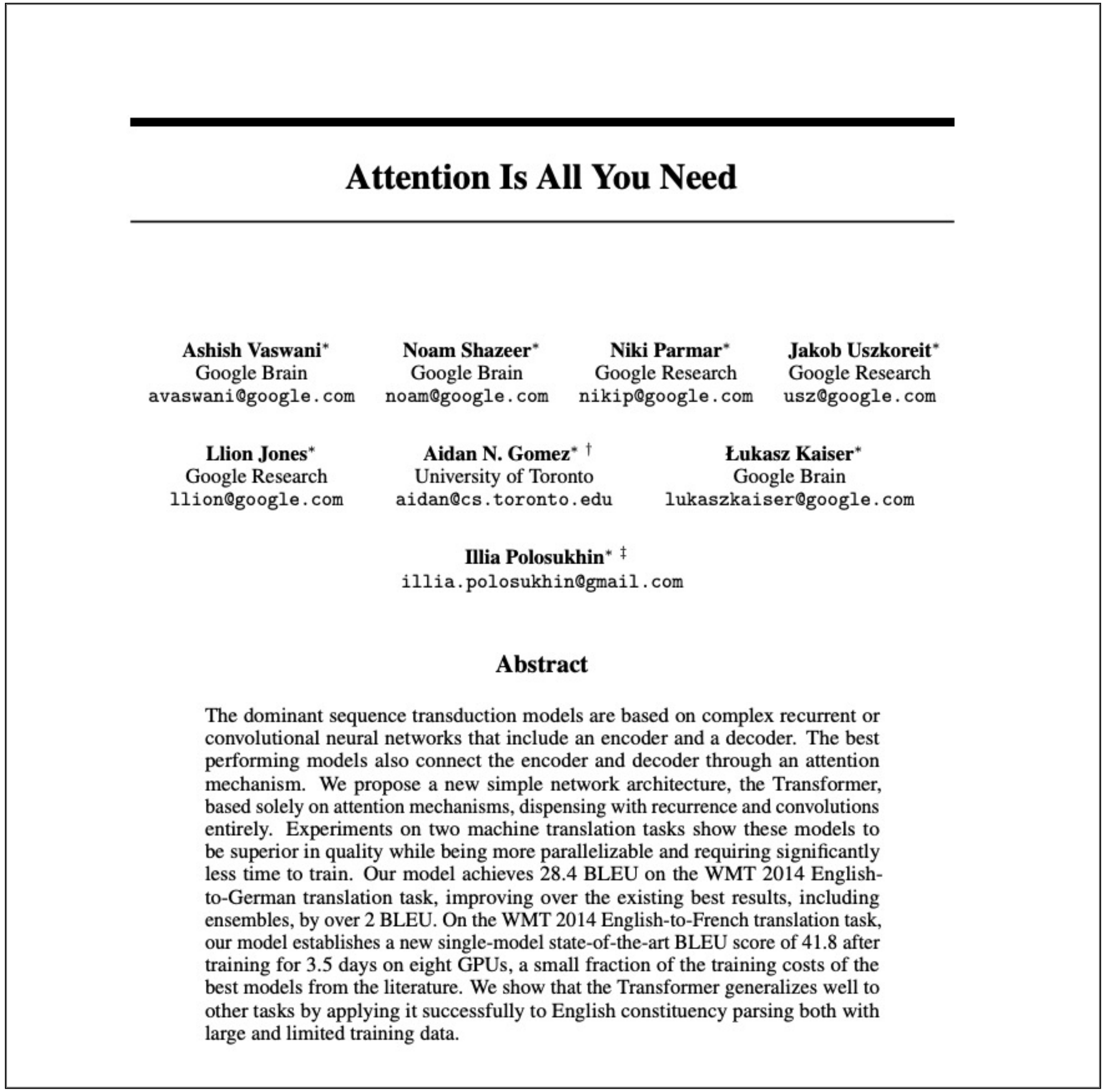
$$e_{i,j} = \text{score}(\mathbf{h}_i^{\text{enc}}, \mathbf{h}_{j-1}^{\text{dec}})$$

In **dot-product attention**, we use a very simple scoring function: $\text{score}(\mathbf{q}, \mathbf{k}) = \mathbf{q} \cdot \mathbf{k}$

“At the core of an attention-based approach is the ability to *compare* an item of interest to a collection of other items in a way that reveals their relevance in the current context.”

-Jurafsky and Martin, Chapter 10

Circa 2017: Transformers



Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

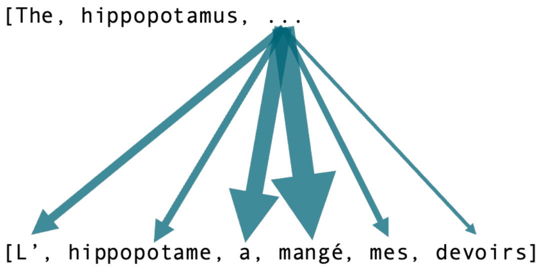
Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

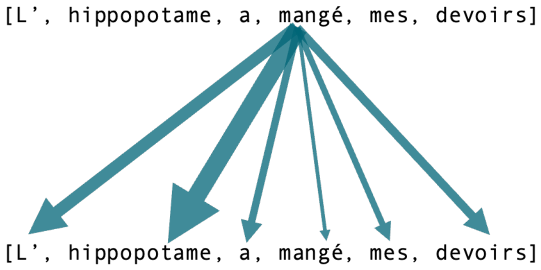
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

Encoder-decoder attention:



Self-attention:



Why drop the recurrence and only use attention?

- Recurrent neural networks are slow to train. Computation cannot be parallelized.
  - The computation at position *t* is dependent on first doing the computation at position *t*-1.
- Recurrent neural networks do poorly with long contexts.
  - If two tokens are *K* positions apart, there are *K* opportunities for knowledge of the first token to be erased from the hidden state before a prediction is made at the position of the second token.
- Transformers solve both these problems.

Components of a Generic Attention Mechanism

- A sequence of <key, value> embeddings pairs
  - The values are always the hidden states from a previous layer of the neural network. The attention mechanism outputs a weighted sum of these.
  - For encoder-decoder attention, the values are the final hidden states of the encoder (as we so in the previous slide) and the keys are the hidden states from the target sequence.
- A sequence of query embeddings
  - The query is the current focus of the attention.
  - We choose weights for each of the values by computing a score between the current query and each of the keys.

$$\text{attention output at position } j = \sum_{i=1}^{T} \text{score}(\mathbf{q}_j, \mathbf{k}_i) \cdot \mathbf{v}_i$$

$$\text{score}(\mathbf{q}_j, \mathbf{k}_i) = \frac{\mathbf{q}_j \cdot \mathbf{k}_i}{\sqrt{d_k}}$$

Carnegie Mellon University

Components of a Generic Attention Mechanism

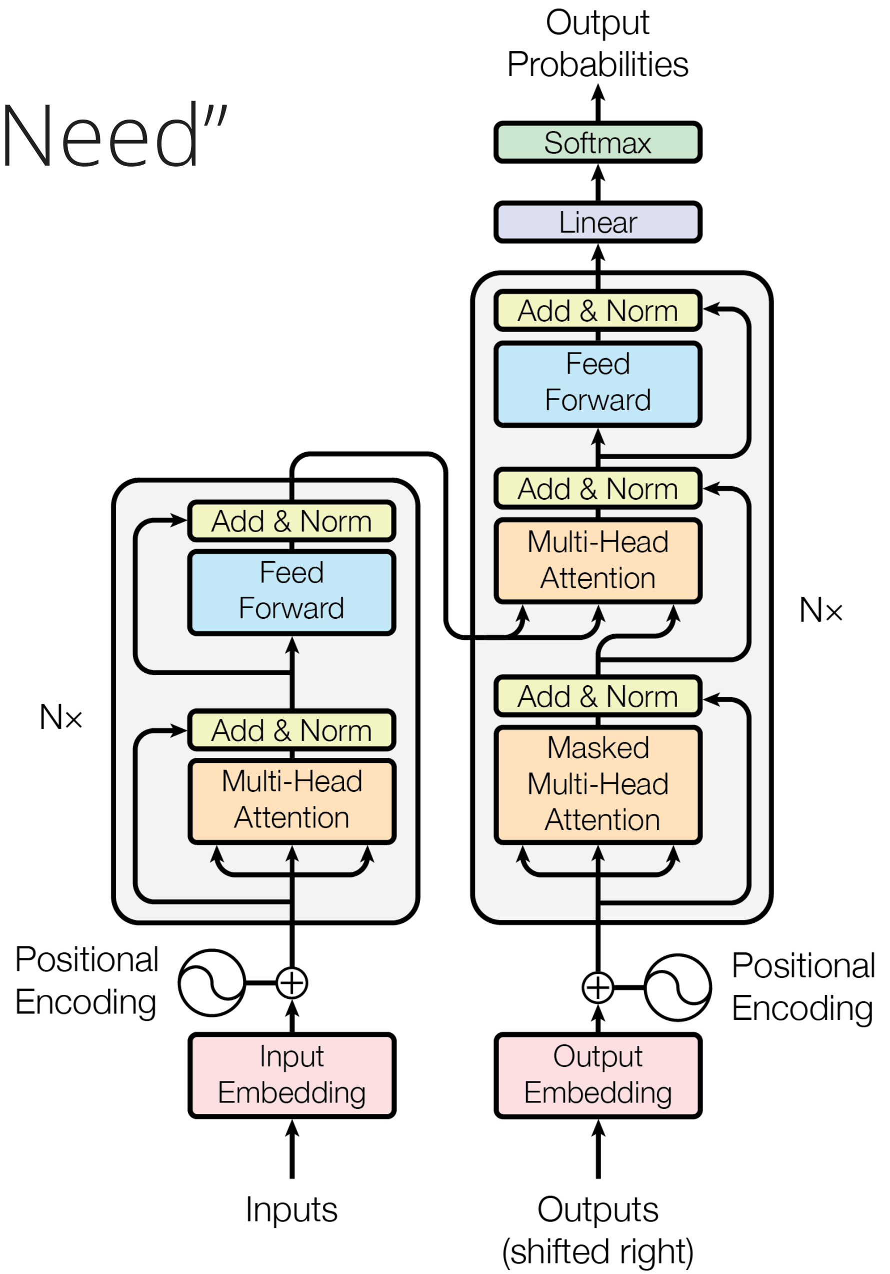
Since the attention computations at each position j are completely independent, we can actually parallelize all these computations and think in terms of matrix multiplications.

For example, instead of thinking of a sequence of embedding vectors $\mathbf{x}_1, \cdots, \mathbf{x}_T$ we can think of a matrix $\mathrm{X} \in \mathbb{R}^{T \times d_x}$.

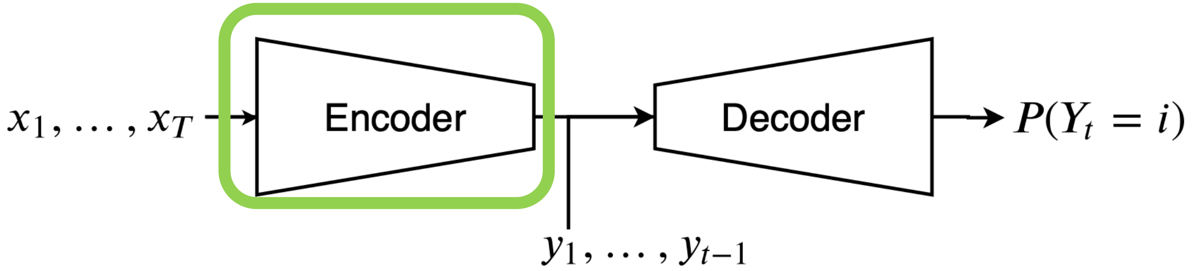
This gives us the attention equation which appear in the "Attention is All You Need" paper.

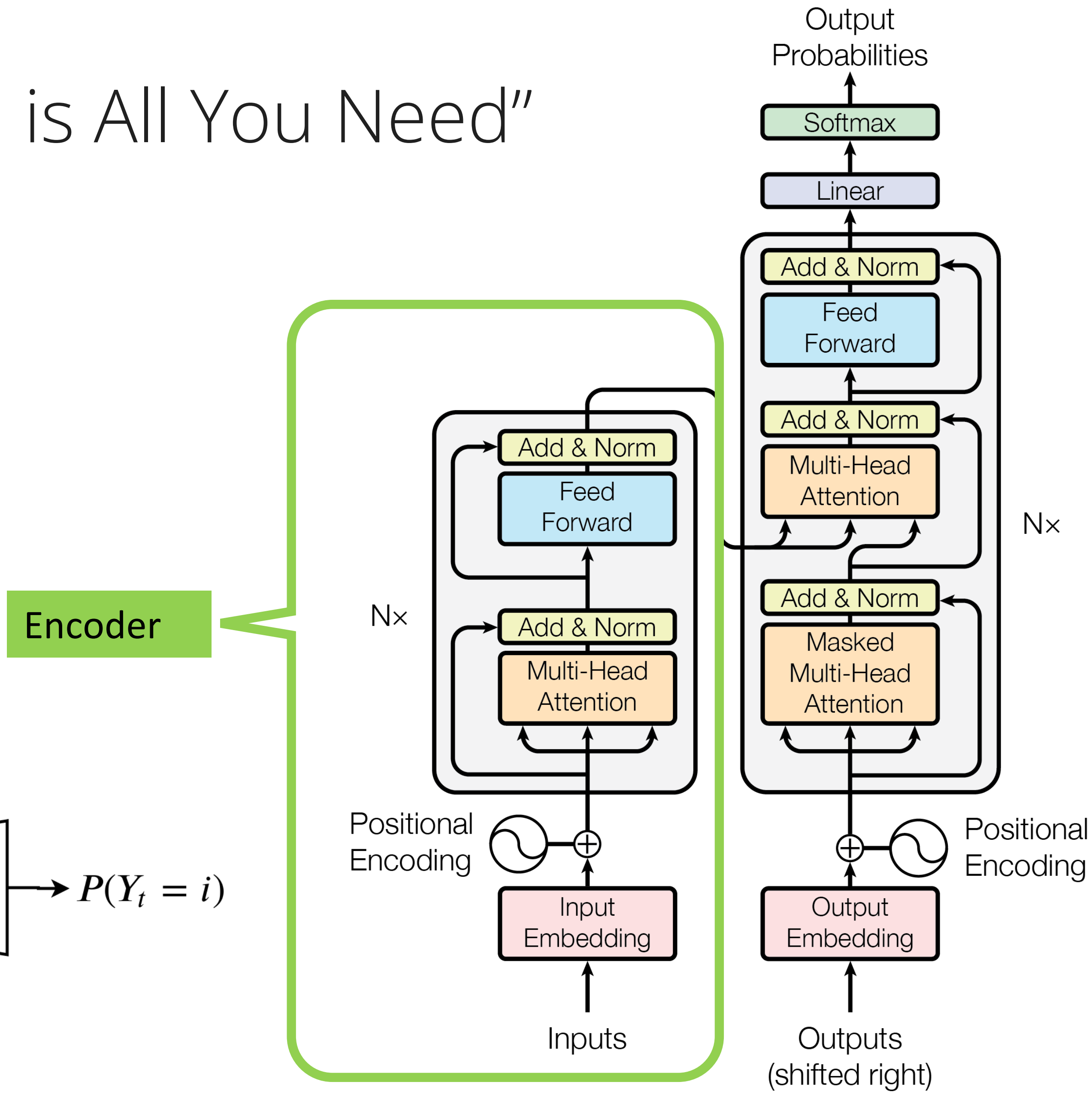
$$\text{attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}}\right)\mathbf{V}$$

Transformers: “Attention is All You Need”

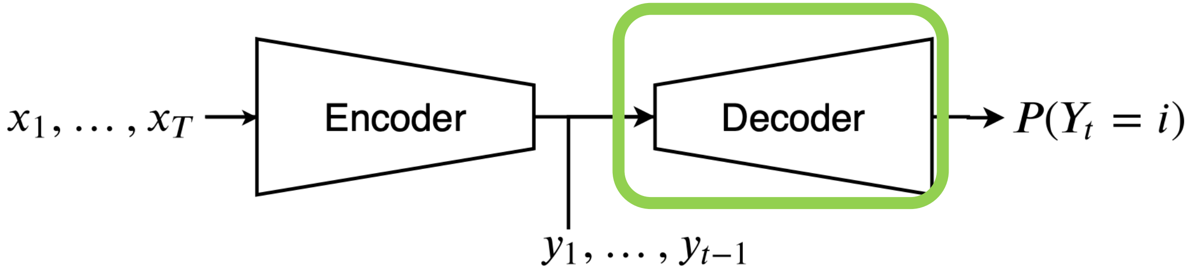


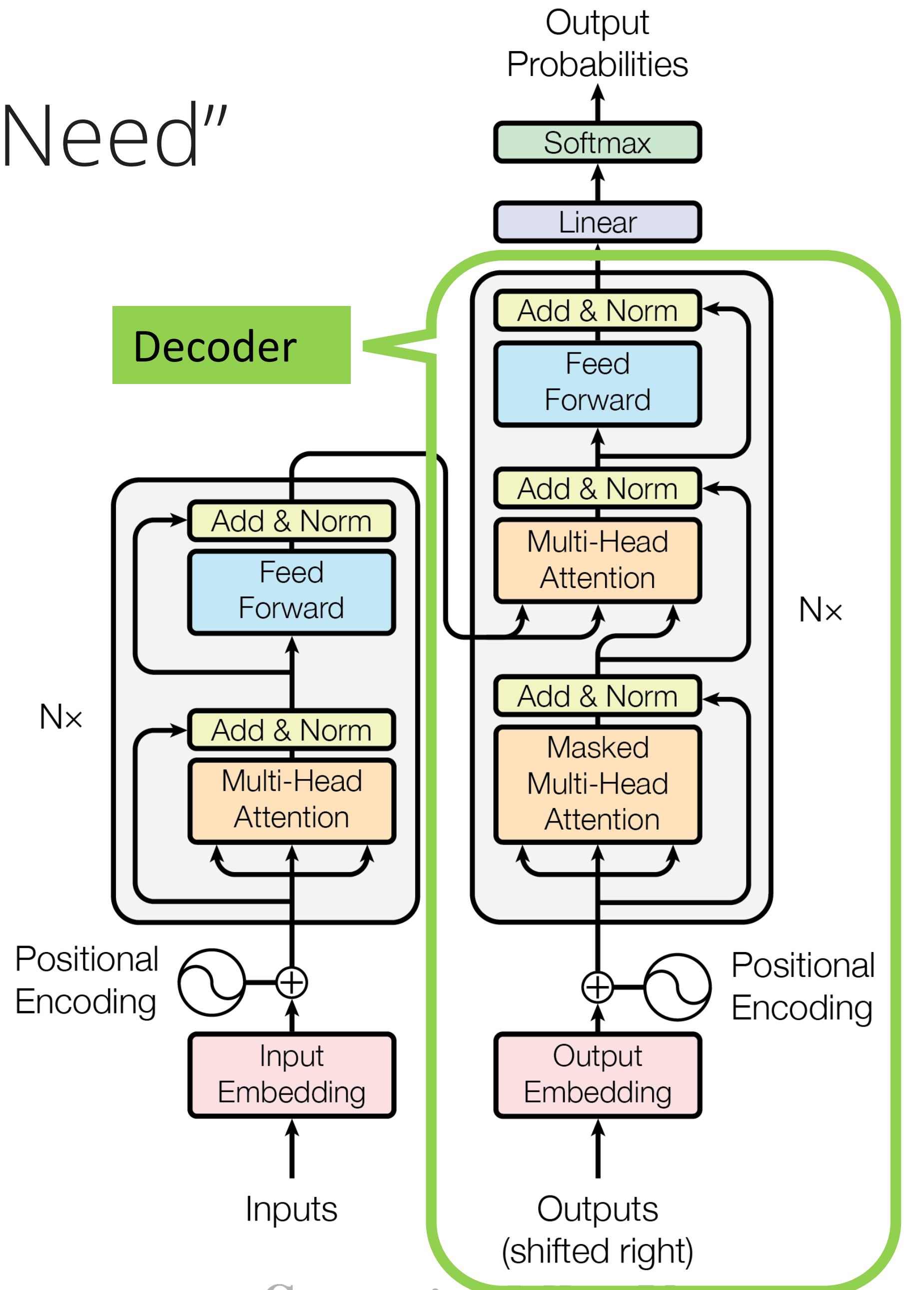
Transformers: “Attention is All You Need”



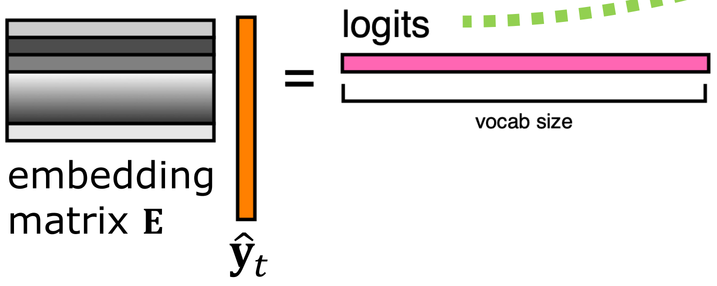


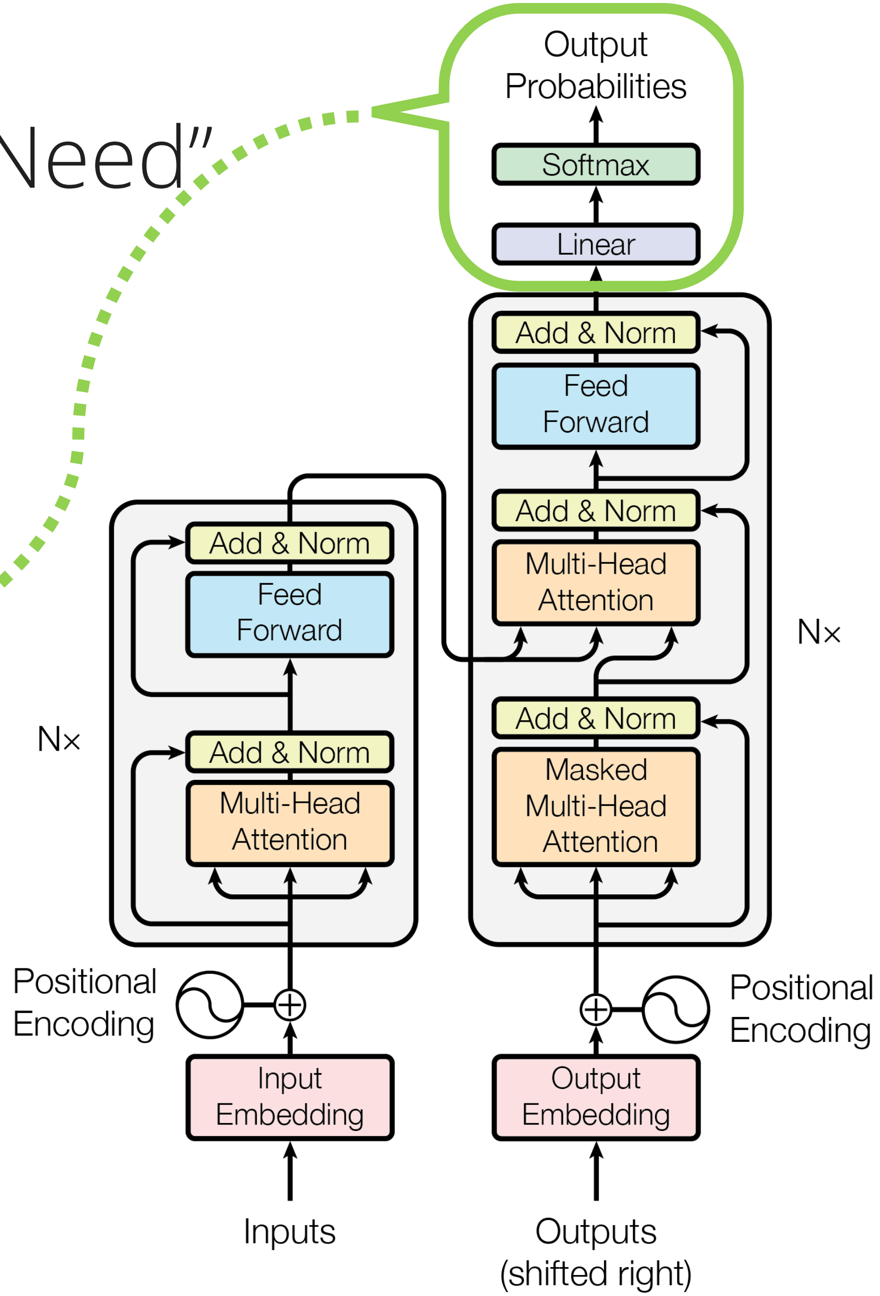
Transformers: “Attention is All You Need”





Transformers: "Attention is All You Need"



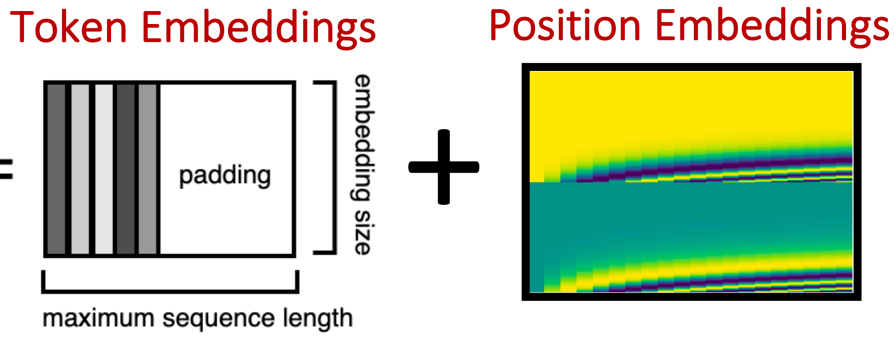


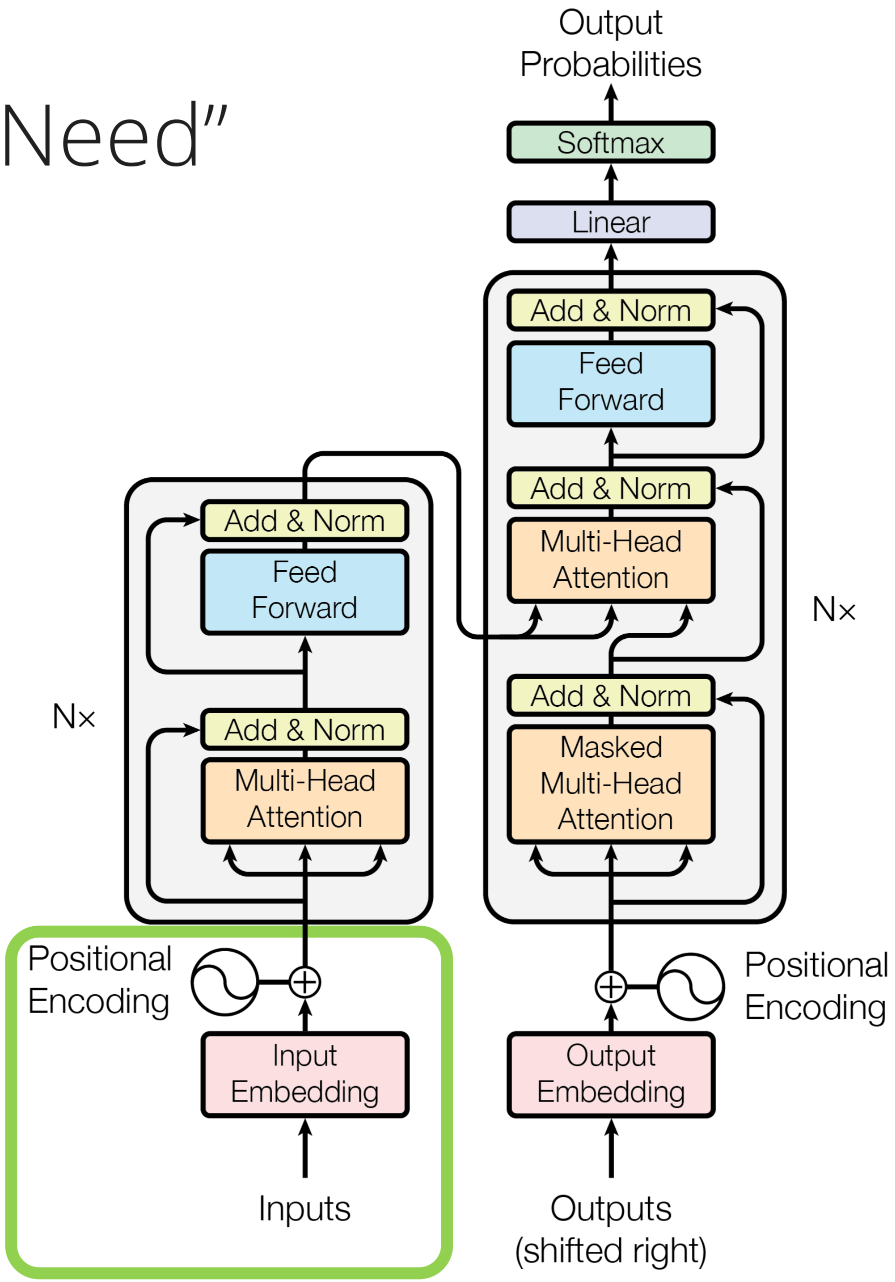
$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

Transformers: “Attention is All You Need”

The input into the encoder looks like:

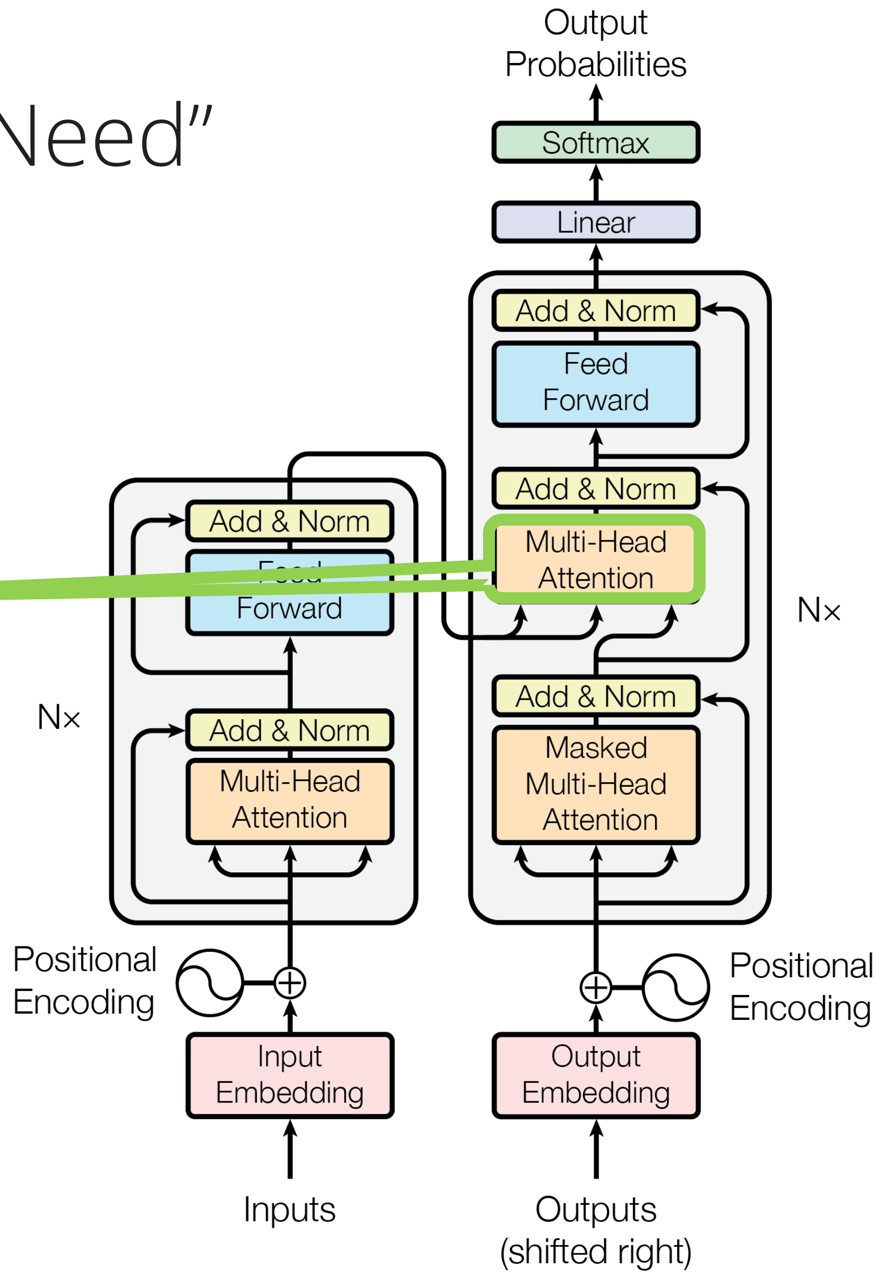
$\mathbf{H}_0^{\text{enc}} =$



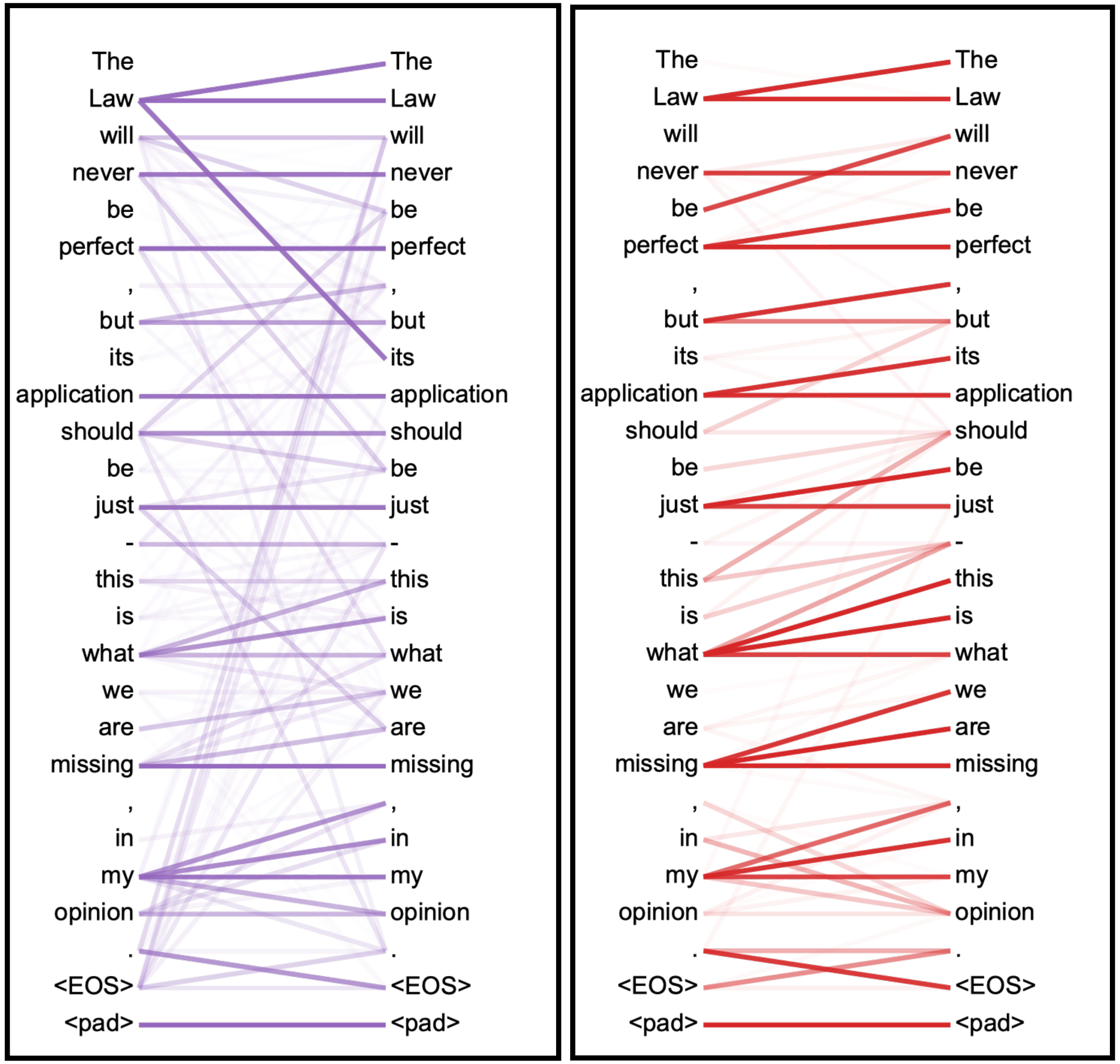


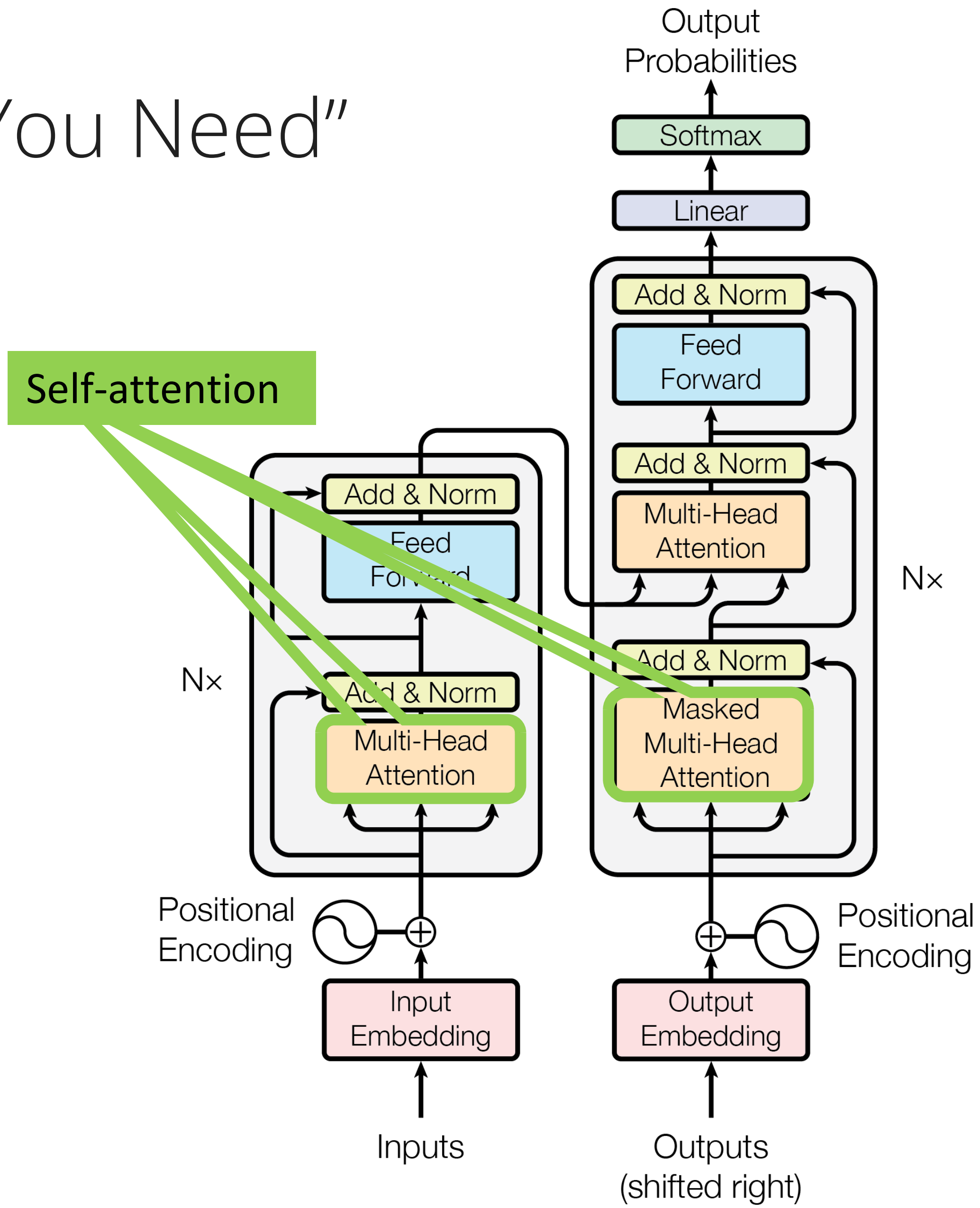
Transformers: “Attention is All You Need”

Encoder-decoder attention

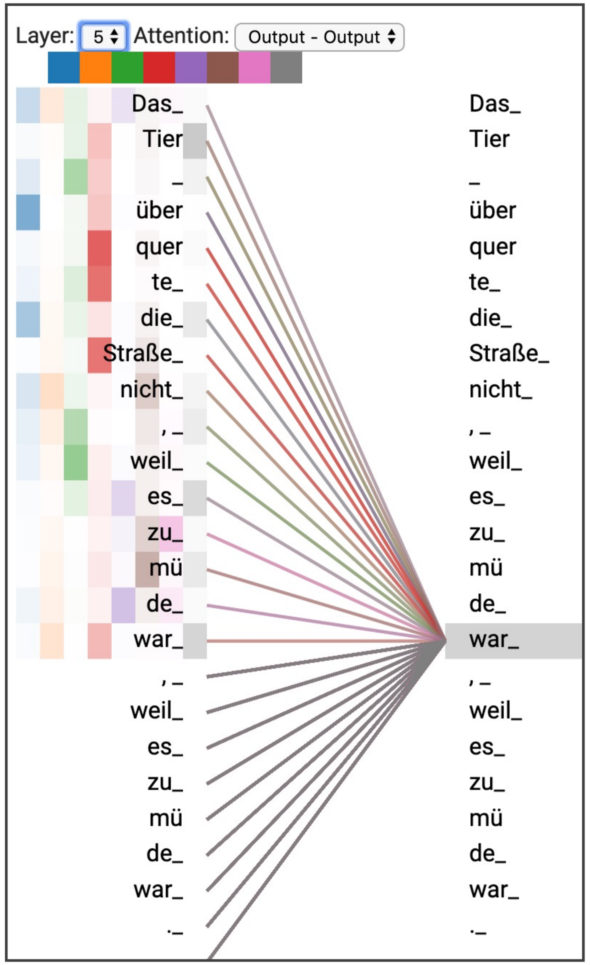


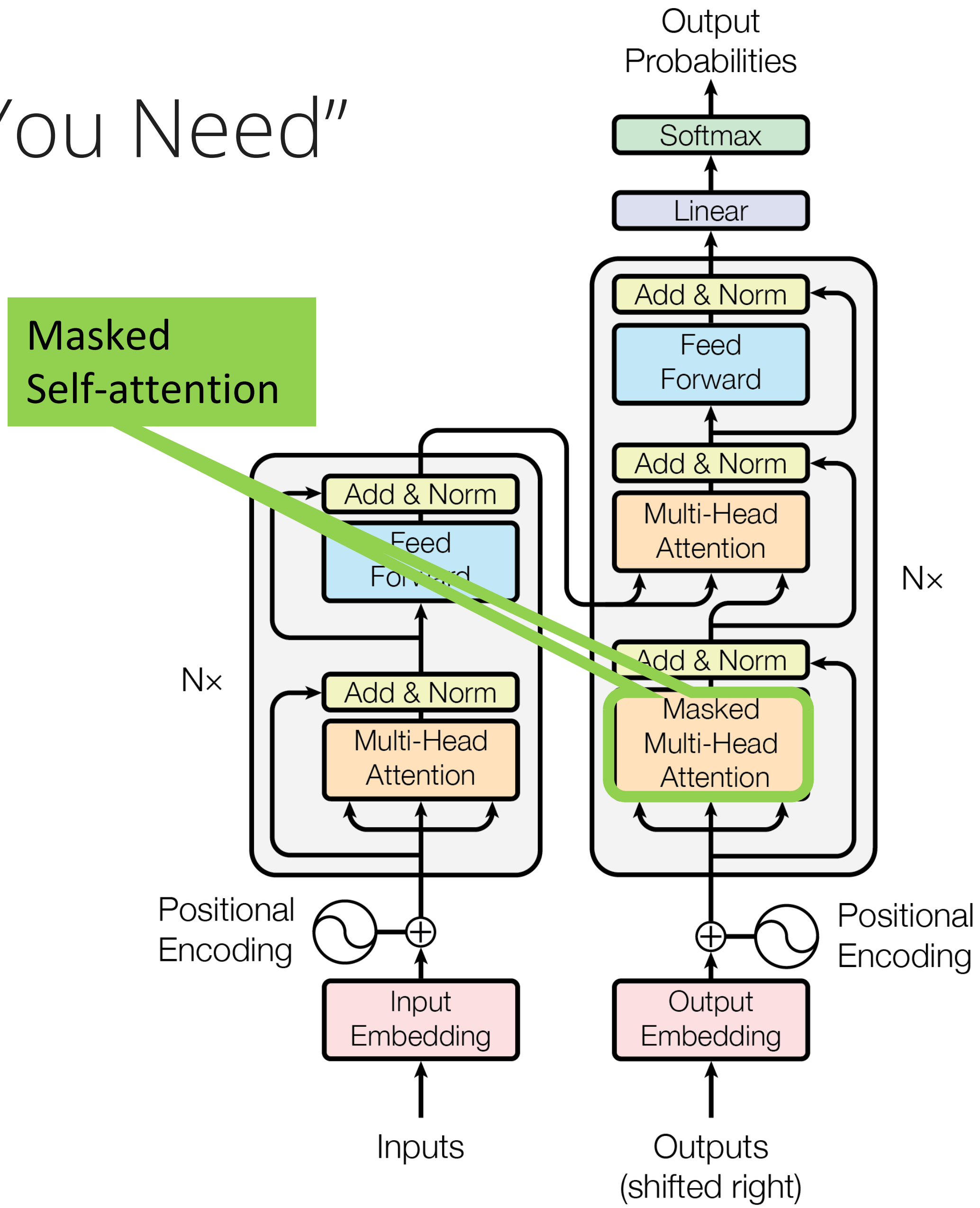
Transformers: “Attention is All You Need”



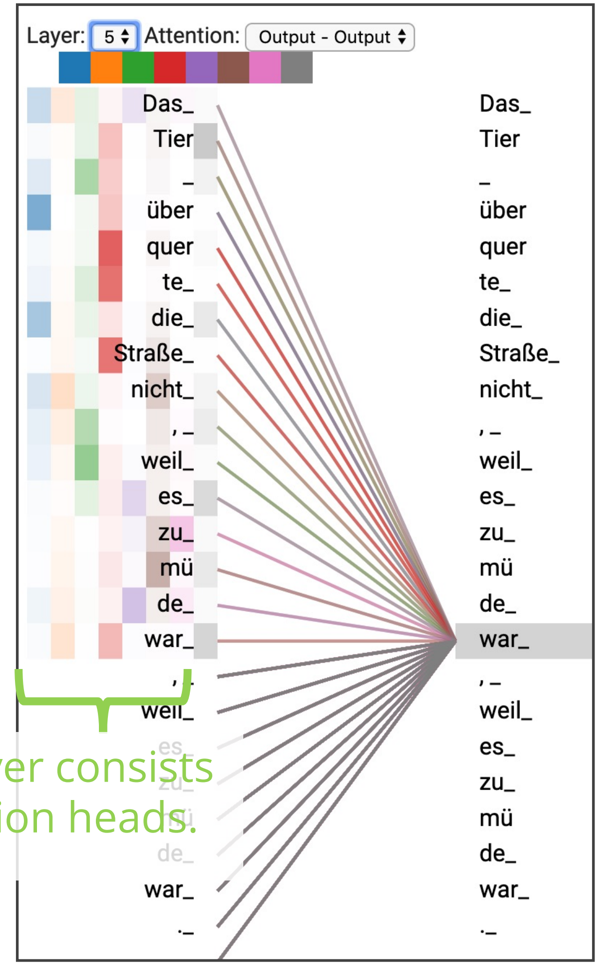


Transformers: “Attention is All You Need”

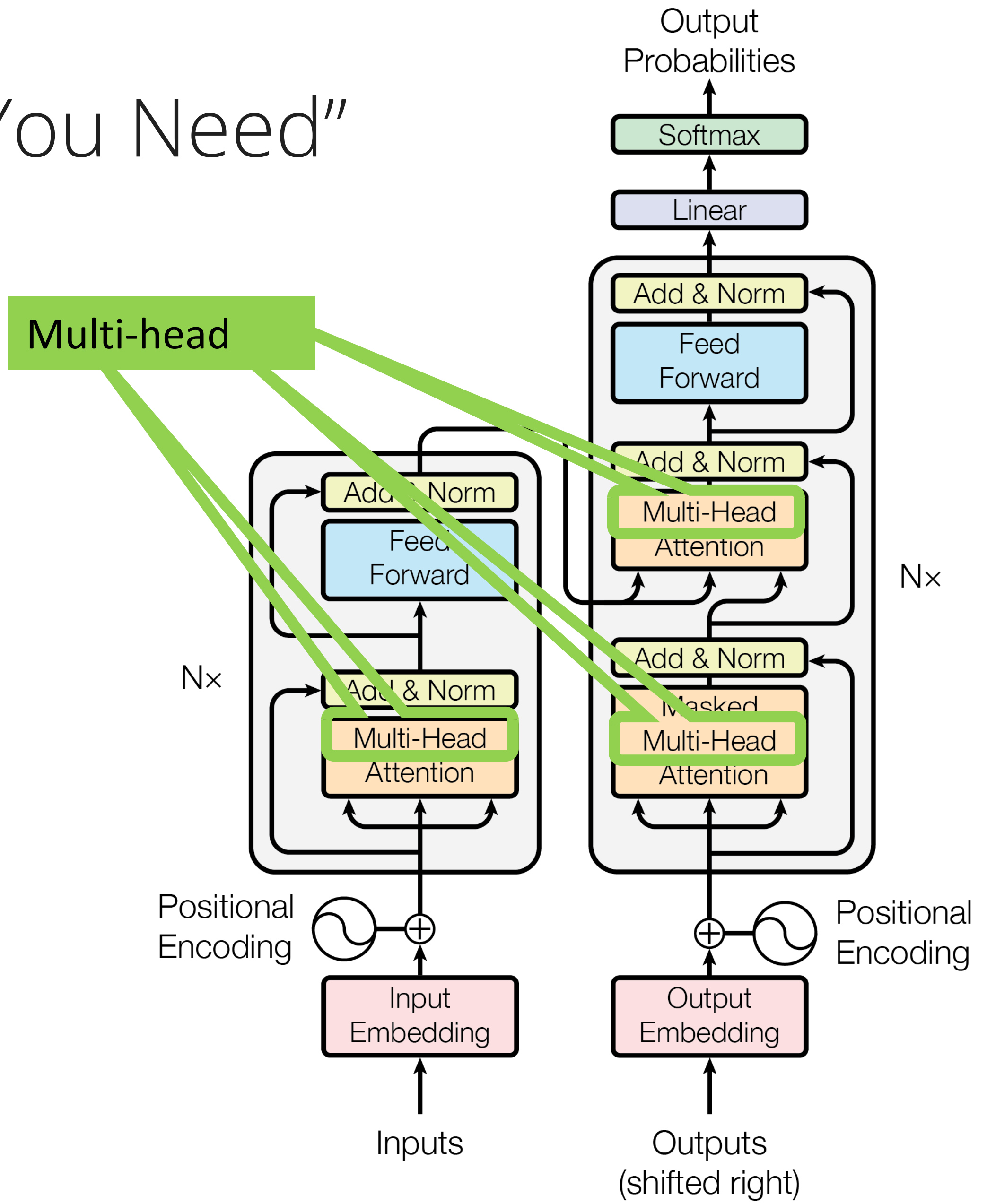




Transformers: “Attention is All You Need”



Each attention layer consists of multiple attention heads.



Quiz Question

In a sentence or two, explain why the Transformer architecture tends to work better than recurrent approaches.

If you are enrolled in the class, log into Canvas and check the “Quizzes” tab.

If you are on the waitlist, complete the quiz at cmu-llms.org/quiz