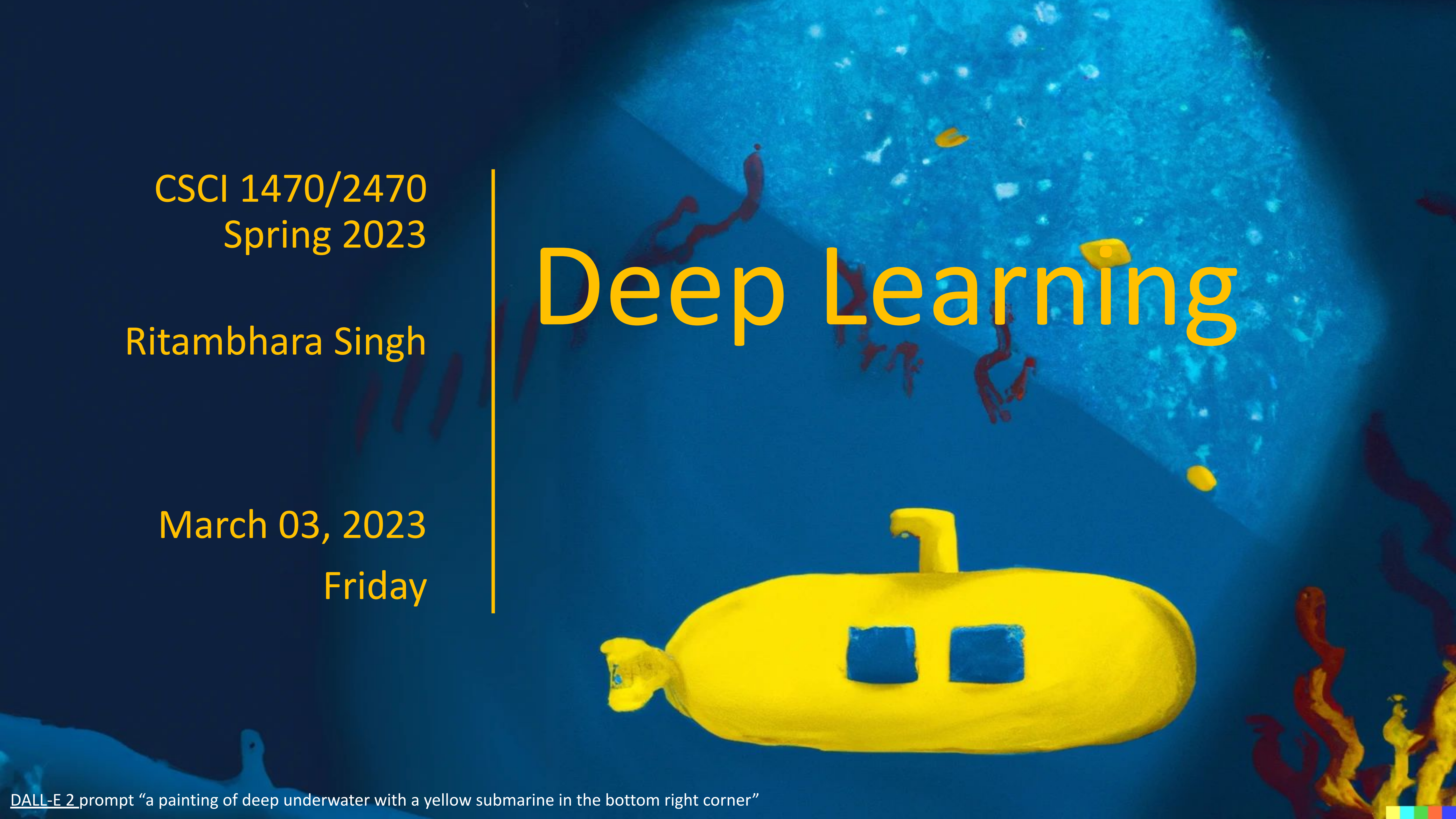
CSCI 1470/2470
Spring 2023

Deep Learning

Ritambhara Singh

March 03, 2023
Friday



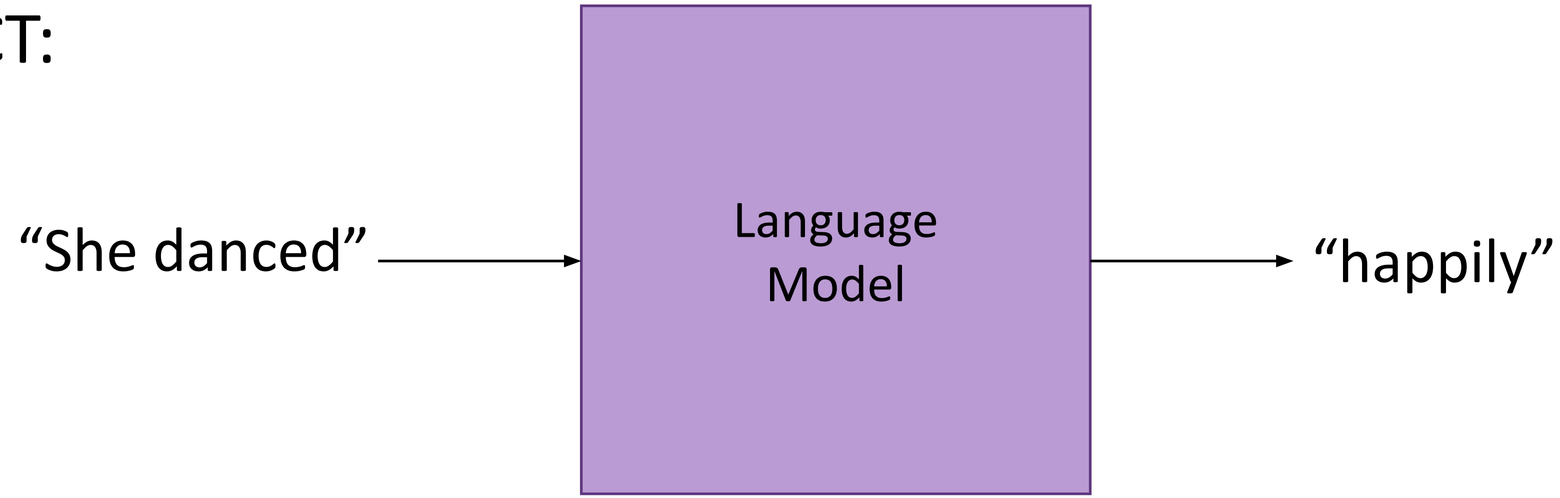
DALL-E 2 prompt “a painting of deep underwater with a yellow submarine in the bottom right corner”

Review: Language Modeling

Goal: Predict future words in a sentence given previous words:

TRAIN: “She danced happily. They sang beautifully.”

PREDICT:



Review: N-gram counting

Improvement: **N-gram** model – only look at **N** words at a time

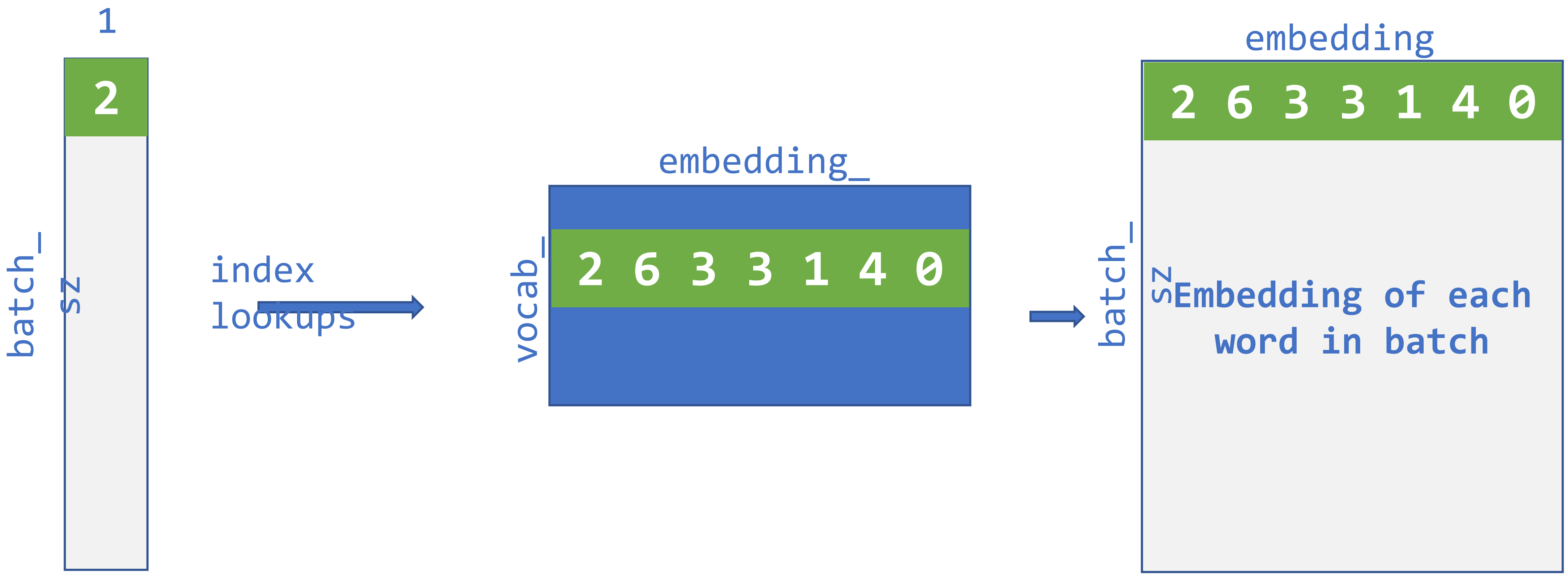
(in this case, **bi**grams look at **2** words at a time)

- ***"danced happily"***
- ***"sang beautifully"***
- ***"danced energetically"***
- ***"sang happily"***
- ***"danced gracefully"***

"He danced happily" now has 1/3 probability!

Review: Embeddings

Represent words as embedding vectors using:
`tf.nn.embedding_lookup`



Today’s goal – Building a ***Deep*** Language Model

(1) Learning a deep bigram model

(2) Improve upon the deep bigram model

(3) Evaluating language models

Once upon a time…

"The dog barked loudly."

"The cat meowed softly"

Data Preprocessing

First, we extract all of the bigrams from the training corpus.

"The dog barked loudly."
"The cat meowed softly."

→

(***"The"***, ***"dog"***)
(***"dog"***, ***"barked"***)
(***"barked"***, ***"loudly"***)
(***"The"***, ***"cat"***)
(***"cat"***, ***"meowed"***)
(***"meowed"***, ***"softly"***)

Corpus: a collection of written texts

Data Preprocessing

First, we extract all of the bigrams from the training corpus.

Create training batches by pairing up first and second words:

"The dog barked loudly."
"The cat meowed softly."

→

("The", "dog")
("dog", "barked")
("barked", "loudly")
("The", "cat")
("cat", "meowed")
("meowed", "softly")

→

inputs	labels
"The"	"dog"
"dog"	"barked"
"barked"	"loudly"
"The"	"cat"
"cat"	"meowed"
"meowed"	"softly"

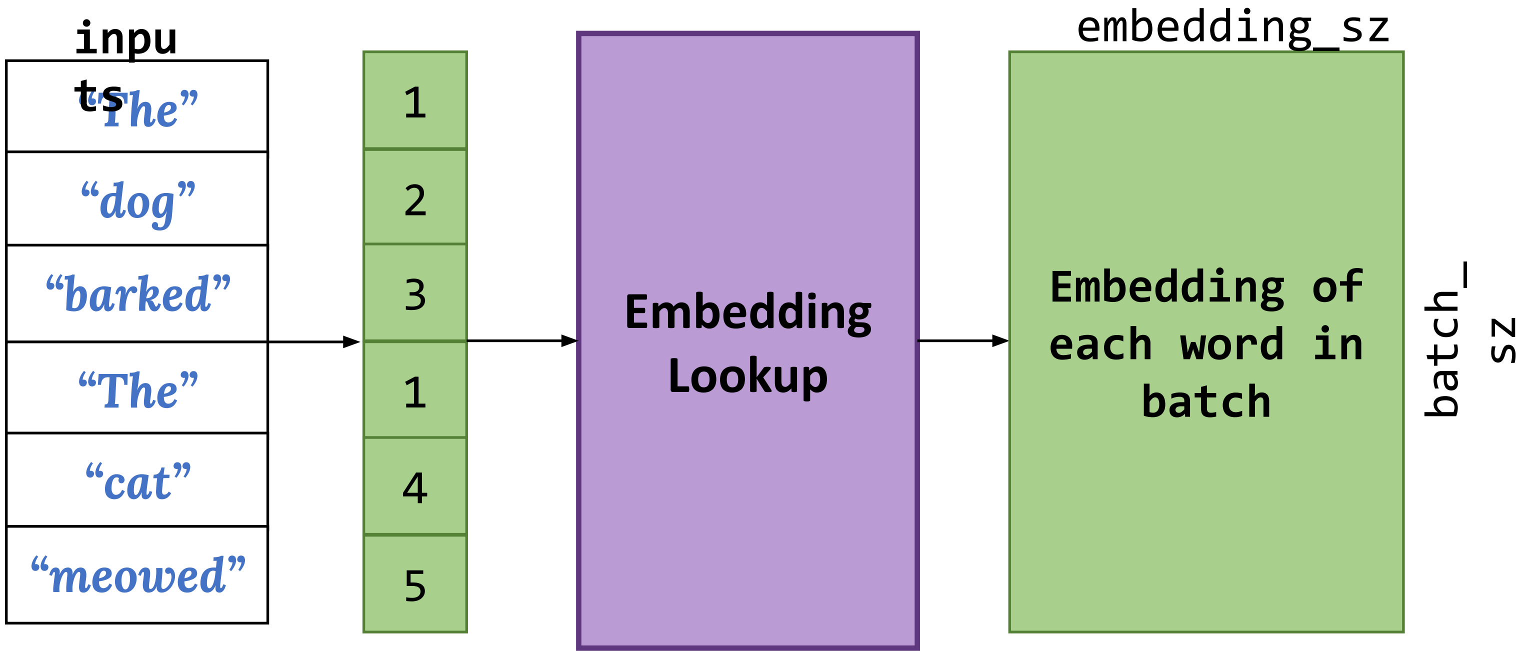
Corpus: a collection of written texts

Bigram Language Model Architecture

We convert all words to their corresponding vocab indices.

Bigram Language Model Architecture

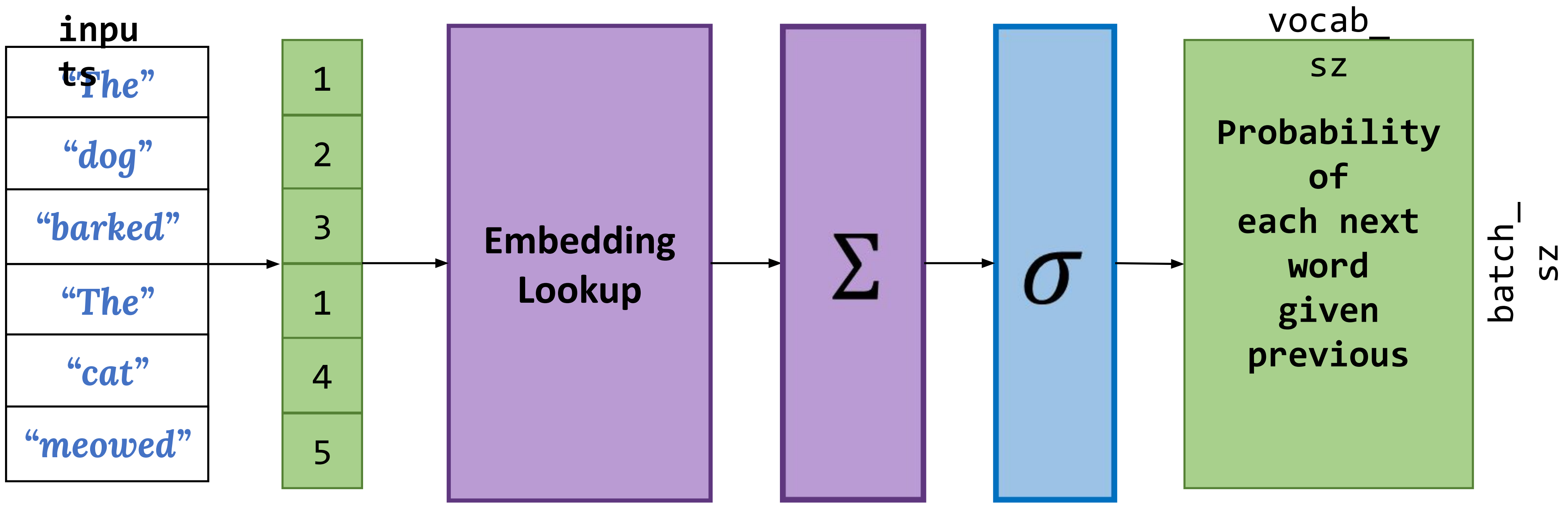
Applying **`tf.nn.embedding_lookup`** to our entire batch gets the embedding for each word in the batch.



What do we do next?

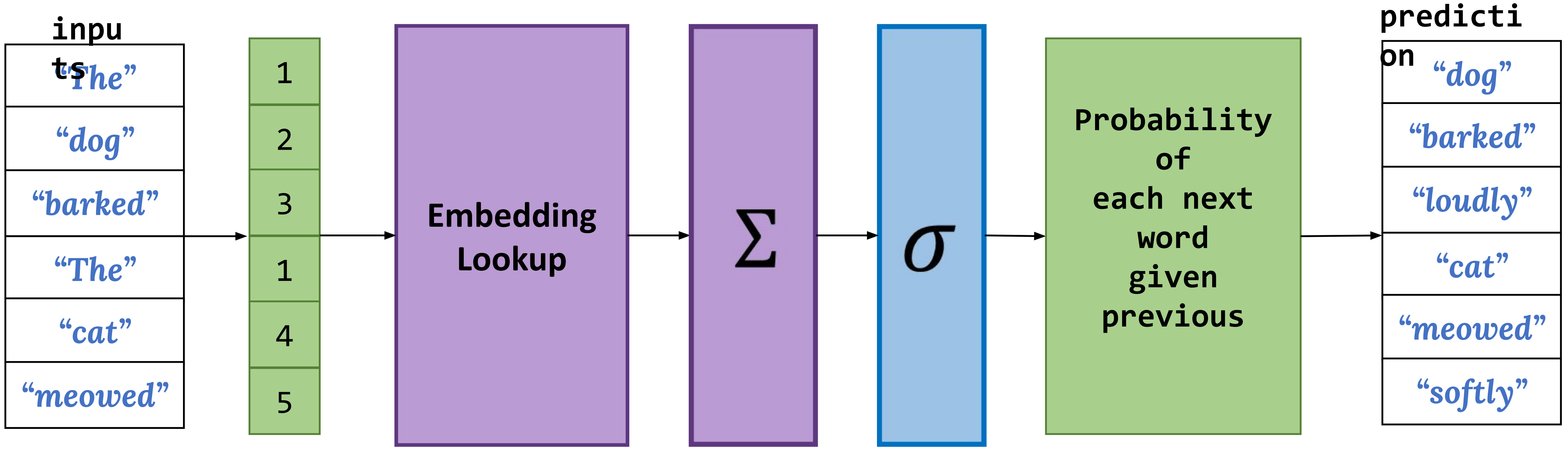
Bigram Language Model Architecture

We feed our batch of embeddings to a fully connected layer with softmax activation to get probability of each word in vocab.



Bigram Language Model Architecture

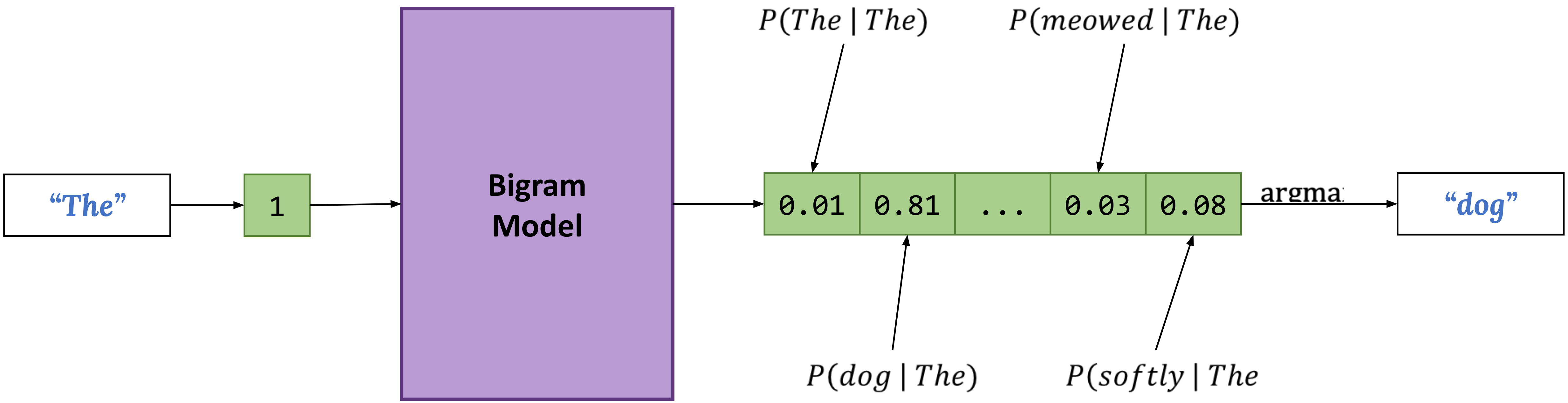
Finally, we choose the word with the max probability as our prediction.



Bigram Language Model Output

Should we be concerned about a large vocabulary making the probabilities small?

The output of our model gives us the probability of each word in our vocabulary appearing next, given the previous word.



Why might the bigram model not be sufficient?

Improving on the Bigram model

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Consider slightly more *distant* sentence relationships:

“The dog was barking.”

“The cat was meowin

Improving on the Bigram model

Why might the bigram model not be sufficient?

Consider slightly more *distant* sentence relationships:

"The dog was barking."

"The cat was meowing."

We want to capture *context* farther than the immediately preceding word.

Using the bigram model, we would need to predict ***"barking"*** and ***"meowing"*** based only on the word ***"was"***.

Can we do better?

Trigram Language Model

"The dog was barking."
"The cat was meowing."

("The", "dog", "was")
("dog", "was", "barking")
("The", "cat", "was")
("cat", "was", "meowing")

For the trigram model, we treat the first two words of each trigram as the input, and the third word as the target.

inpu

"The"	"dog"
"dog"	"was"
"The"	"cat"
"cat"	"was"

labe
ls

"was"
"barking"
"was"
"meowing"

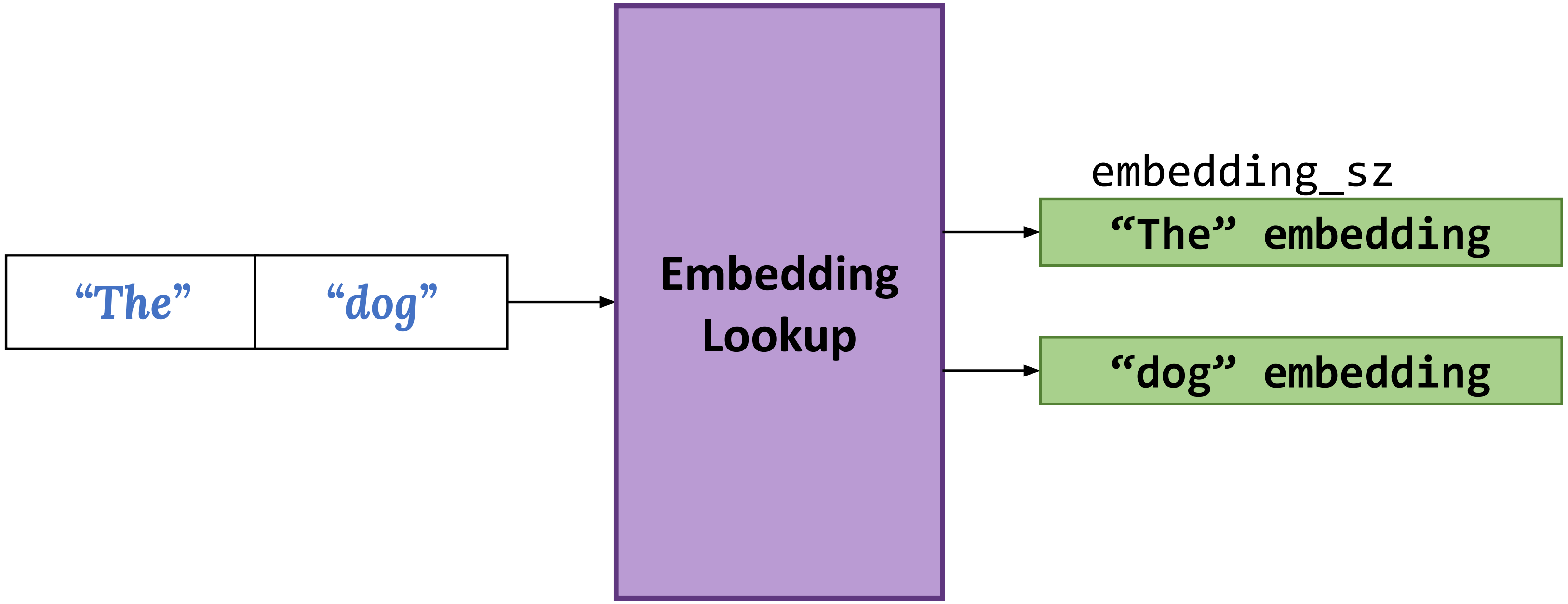
Trigram Language Model Input

Now our network input is two words…

…how do we turn these into a tensor to feed into our network?

Handling Multi-Word Input

Get the embeddings for each word as before



Handling Multi-Word Input

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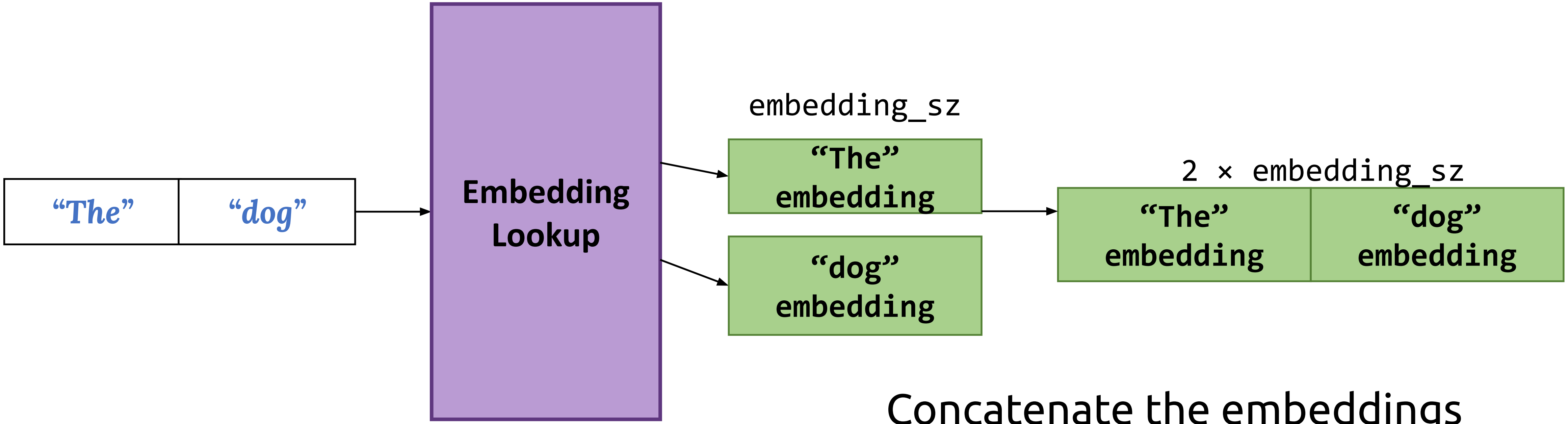
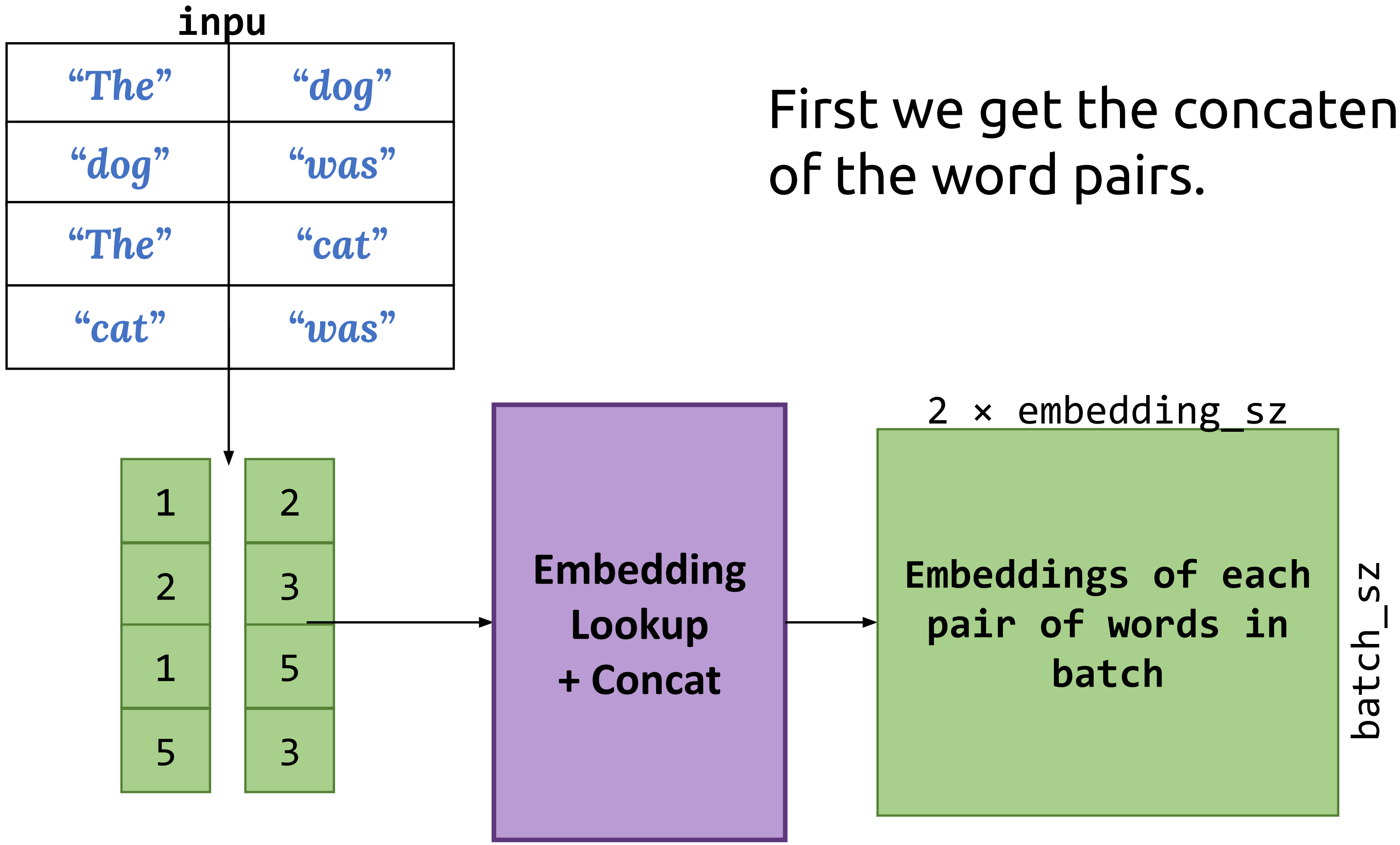


Concatenate the embeddings

Complete Trigram Language Model

First we get the concatenated embeddings of the word pairs.

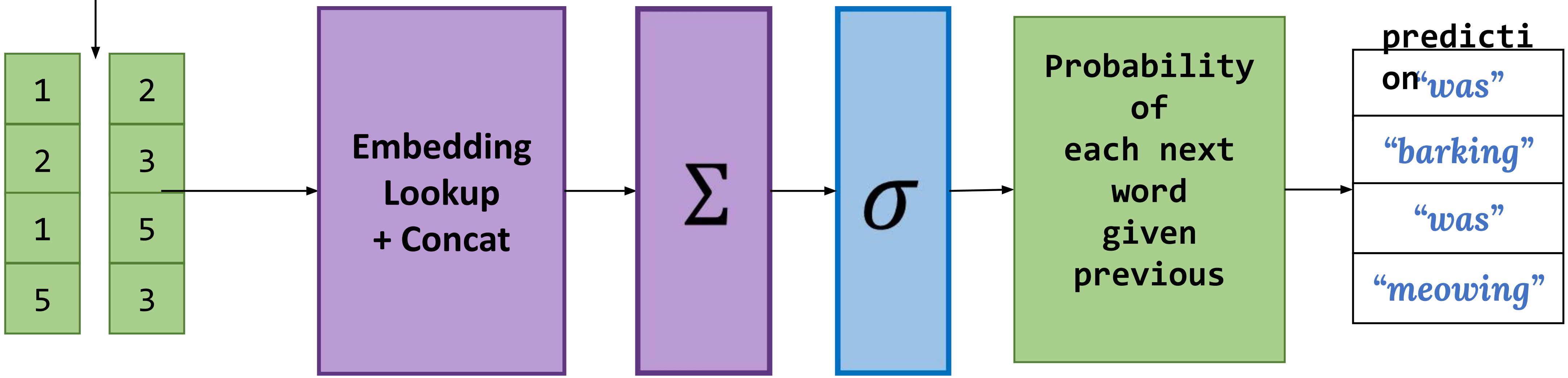


Complete Trigram Language Model

inpu

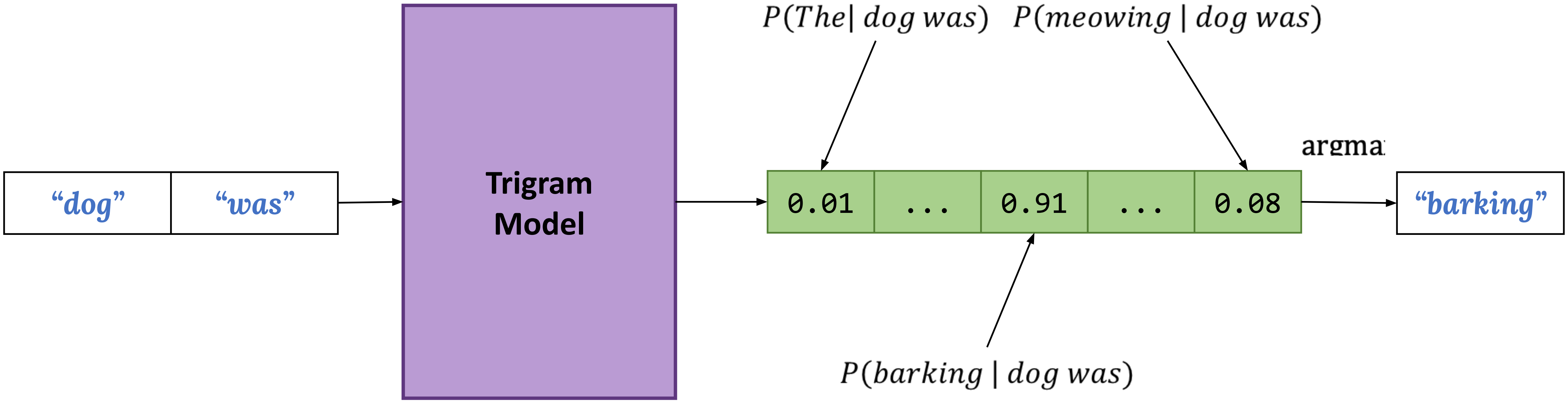
"The"	*"dog"*
"dog"	*"was"*
"The"	*"cat"*
"cat"	*"was"*

The model proceeds identically as in the bigram model from there.



Trigram Language Model Output

In the trigram version, the probabilities are now conditioned on two previous words rather than just one.



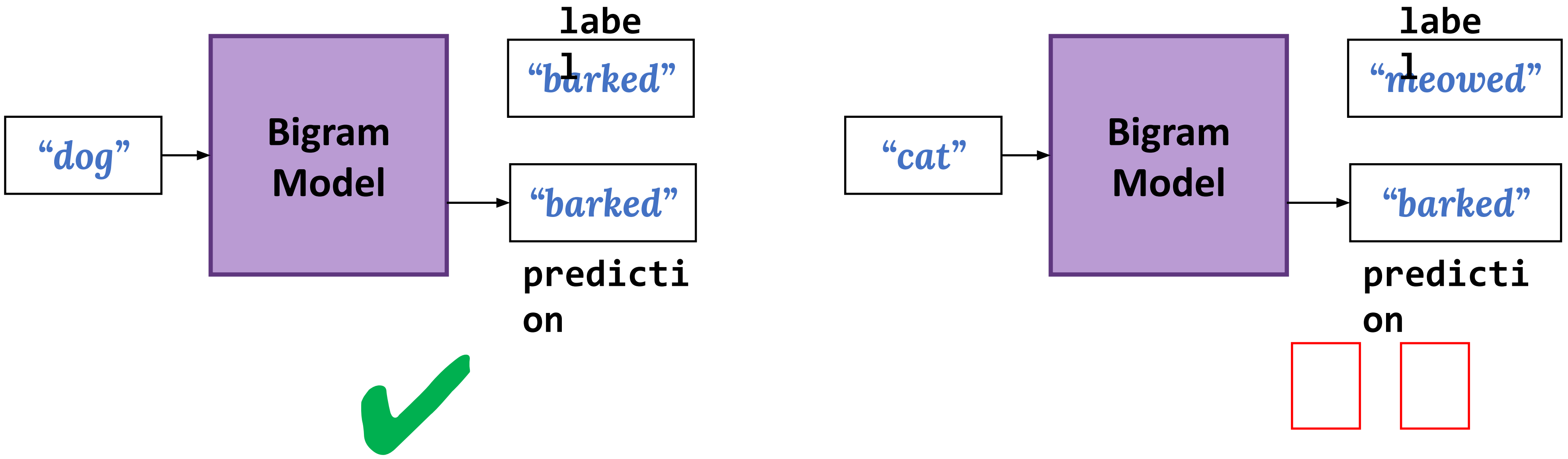
Language Model Assessment

How do we know when our model is performing well?

Language Model Assessment

How do we know when our model is performing well?

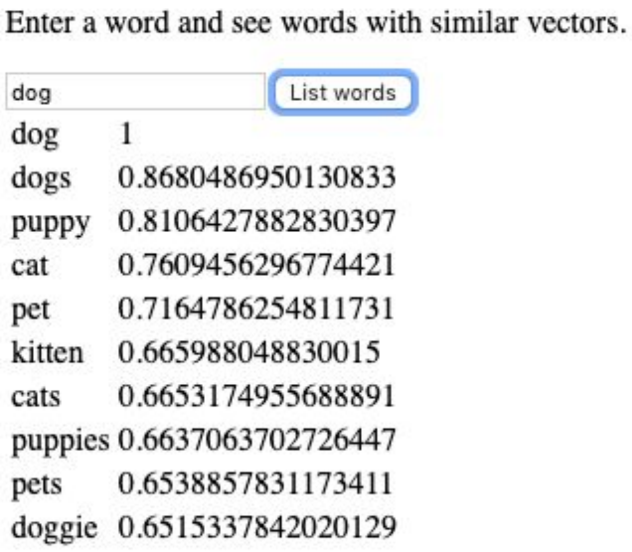
For starters, we can print some predictions and judge for ourselves:



Language Model Assessment

How do we know when our model is performing well?

Or, we can examine similarities between embedding vectors


Enter a word and see words with similar vectors.

dog | List words

dog	1
dogs	0.8680486950130833
puppy	0.8106427882830397
cat	0.7609456296774421
pet	0.7164786254811731
kitten	0.665988048830015
cats	0.6653174955688891
puppies	0.6637063702726447
pets	0.6538857831173411
doggie	0.6515337842020129

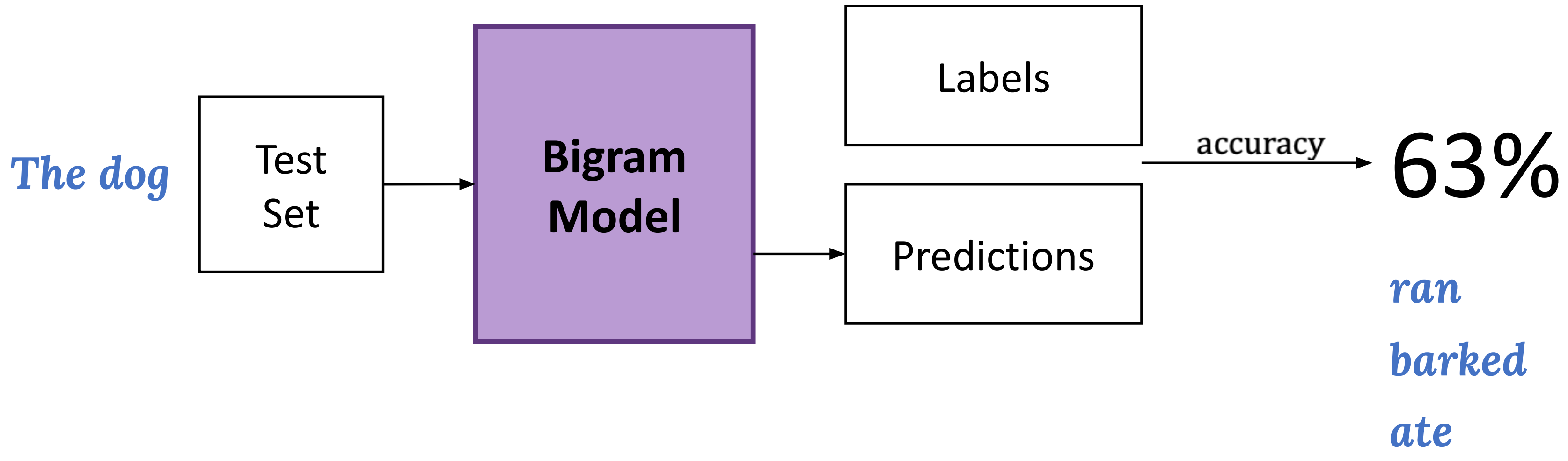
These are forms of ***qualitative*** evaluation

What about ***quantitative*** evaluation?

Language Model Assessment: Quantitative

How do we know when our model is performing well?

We can evaluate the per-word accuracy on a test set:



Is there an issue with this metric?

Language Model Assessment: Quantitative

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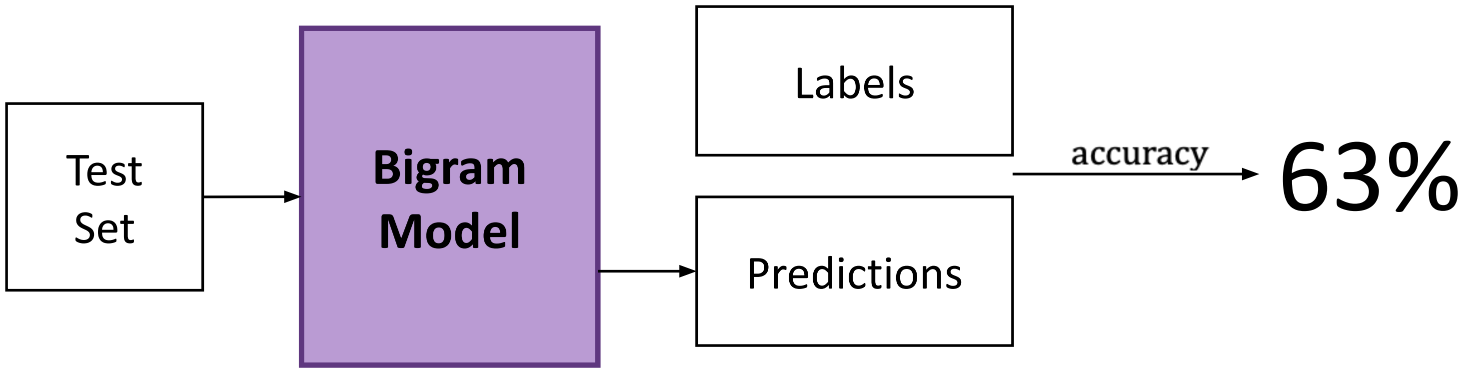


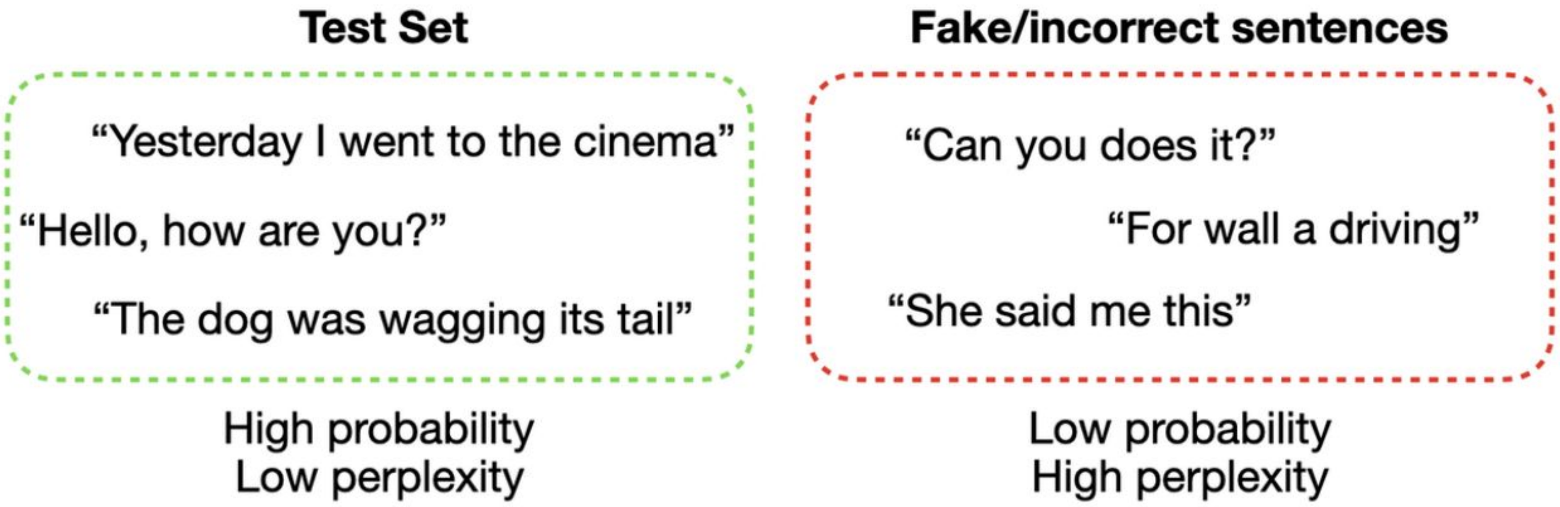
Is there an issue with this metric?

When you've got thousands of possible words, this is not a great measure (i.e. the top 1 prediction is going to differ from the ground truth label ***a lot*** of the time)

Perplexity

What is a good language model?

Assigns high probabilities to sentences that are real and syntactically correct, and low probabilities to fake, incorrect, or highly infrequent sentences



Intuitively – A model assigning high probability to a sentence means it not "not perplexed" by this new sentence (low perplexity)!

https://towardsdatascience.com/perplexity-in-language-models-87a196019a94

Perplexity

- The standard quantitative metric in NLP for assessing language models

$$\text{Perplexity}(D) = e^{\frac{\sum_{s\in D}\sum_{w_i\in s}\frac{-\log p\left(w_i^s \mid w_1^s \ldots w_{i-1}^s\right)}{|s|}}{|D|}}$$

where

- $D =$ an unseen test dataset of sentences
- $s =$ a sentence in the test set
- $w_i^s =$ the i^{th} word of sentence s
- $p(\cdot) =$ the probability of the next word under our learned model

Making Perplexity less perplexing...

-

$$\text{Perplexity}(D) = e^{\frac{\sum_{s \in D} \sum_{w_i \in s} \boxed{\frac{-\log p(w_i^s \mid w_1^s \ldots w_{i-1}^s)}{|s|}}}{|D|}}$$

Making Perplexity less perplexing...

•

$$\text{Perplexity}(D) = e^{\frac{\sum_{s\in D} \boxed{\sum_{w_i\in s} \frac{\text{cross entropy loss for } w_i^s}{|s|}}}{|D|}}$$

Why normalize by the sentence length?

Making Perplexity less perplexing...

•

$$\text{Perplexity}(D) = e^{\boxed{\frac{\sum_{s \in D} \text{avg cross entropy loss for } s}{|D|}}}$$

Any questions?

Making Perplexity less perplexing...

-

$$\text{Perplexity}(D) = e^{\text{avg cross entropy loss for all words in } D}$$

Let’s tie it together

$$\text{Perplexity}(D) = e^{\text{avg cross entropy loss for all words in } D}$$

V = {“the”, “dog”, “cat”, “barked”, “meowed”, “was”, “barking”, “meowing”, “loudly”, “softly” }

“The dog barked loudly.”

“The cat meowed softly”

inputs

“The”
“dog”
“barked”
“The”
“cat”
“meowed”

Bigram Model

labels

“dog”
“barked”
“loudly”
“cat”
“meowed”
“softly”

(1) What is the perplexity for a randomly initialized language model?

[What output probabilities would you assign if you had no idea about the data]

Perplexity: Intuitive Meaning

- “If a model has a perplexity of X, then it has the same odds of predicting the correct next word as a fair die with X sides”

- For a randomly-initialized model:
  - All words in the vocab V have equal probability $\frac{1}{|V|}$

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  - i.e. predicting from a randomly-initialized model is equivalent to rolling a $|V|$-sided die (which is consistent with our intuition)

Let’s tie it together

$$\text{Perplexity}(D) = e^{\text{avg cross entropy loss for all words in } D}$$

V = {“the”, “dog”, “cat”, “barked”, “meowed”, “was”, “barking”, “meowing”,
“loudly”, “softly” }

“The dog barked loudly.”

“The cat meowed softly”

inputs		labels
“The”	→ Bigram Model →	“dog”
“dog”		“barked”
“barked”		“loudly”
“The”		“cat”
“cat”		“meowed”
“meowed”		“softly”

(1) What is the perplexity for a randomly initialized language model?

Let’s tie it together

$$\text{Perplexity}(D) = e^{\text{avg cross entropy loss for all words in } D}$$

V = {“the”, “dog”, “cat”, “barked”, “meowed”, “was”, “barking”, “meowing”, “loudly”, “softly” }

“The dog barked loudly.”

“The cat meowed softly”

inpu			labels
“The”		0.6	“dog”
“dog”		0.5	“barked”
“barked”	→ Bigram Model →	0.4	“loudly”
“The”		0.3	“cat”
“cat”		0.5	“meowed”
“meowed”		0.5	“softly”

(2) What is the perplexity for a trained language model with the shown output probabilities?

Any questions?

Perplexity: Intuitive Meaning

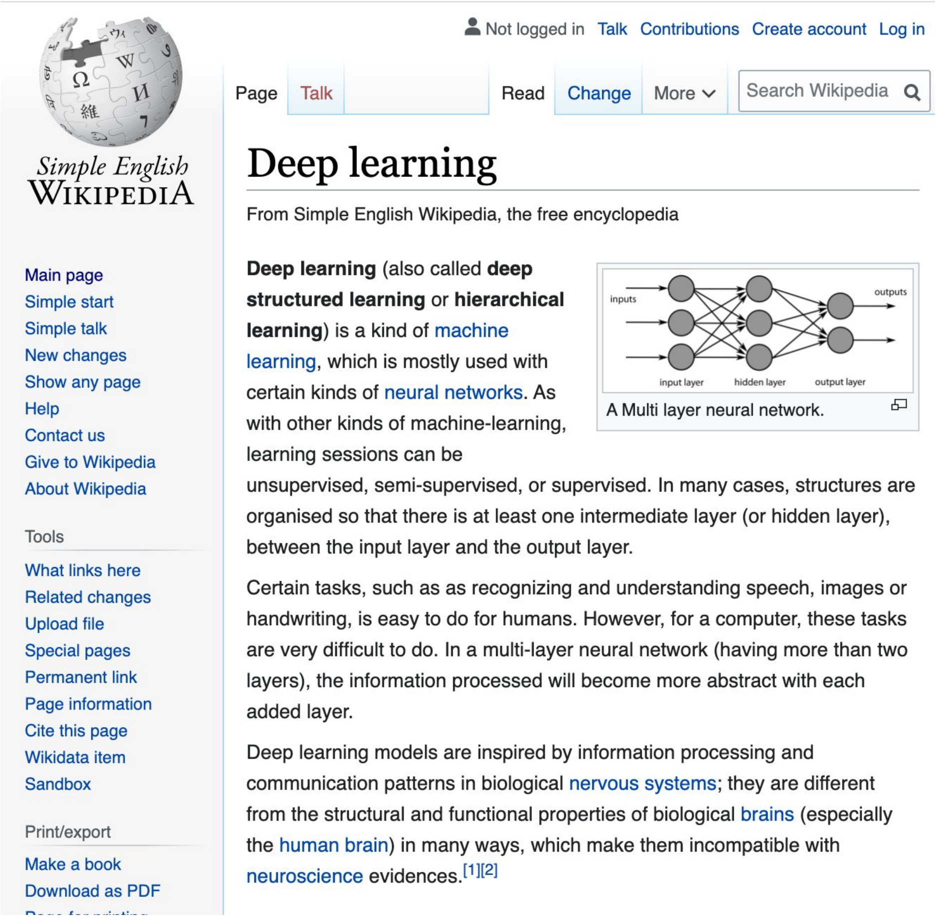
- "If a model has a perplexity of X, then it has the same odds of predicting the correct next word as a fair die with X sides"

- Example: for a well-trained trigram model on a known NLP dataset (Penn Tree Bank with |V|~10,000):
  - Can expect perplexity < 240
    - Much better to 'guess' words via a ~200 sided die than a ~10,000 sided die!
  - A perplexity threshold is what the hw4 autograder checks for, in fact ;)

Speaking of hw4...

Hw4: Language Modeling

- Build and train a trigram language model
  - Perplexity < 165
- Build and train a recurrent language model (next lecture!)
  - Perplexity < 95
- Dataset
  - Articles scraped from [Simple English Wikipedia]
  - Focused on technology-related topics (for a smaller, more consistent vocabulary)



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Deep learning

From Simple English Wikipedia, the free encyclopedia

inputs
outputs
input layer
hidden layer
output layer

A Multi layer neural network.

Deep learning (also called **deep structured learning** or **hierarchical learning**) is a kind of machine learning, which is mostly used with certain kinds of neural networks. As with other kinds of machine-learning, learning sessions can be unsupervised, semi-supervised, or supervised. In many cases, structures are organised so that there is at least one intermediate layer (or hidden layer), between the input layer and the output layer.

Certain tasks, such as as recognizing and understanding speech, images or handwriting, is easy to do for humans. However, for a computer, these tasks are very difficult to do. In a multi-layer neural network (having more than two layers), the information processed will become more abstract with each added layer.

Deep learning models are inspired by information processing and communication patterns in biological nervous systems; they are different from the structural and functional properties of biological brains (especially the human brain) in many ways, which make them incompatible with neuroscience evidences.[1][2]

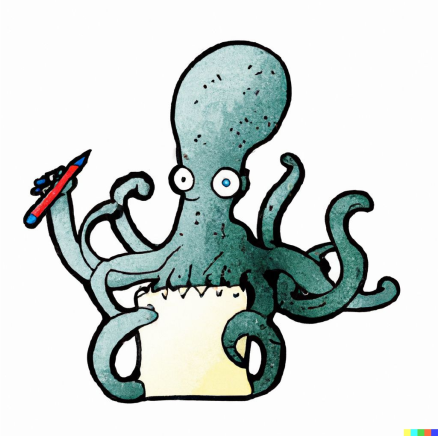
Recap

Feedforward Language Models

- Bigram model
- Limitations of bigram model
- Trigram model

Evaluating Language Models

- Qualitative assessment
- Quantitative assessment
- Perplexity and its intuition



"The dog barked loudly."

"The cat meowed softly"