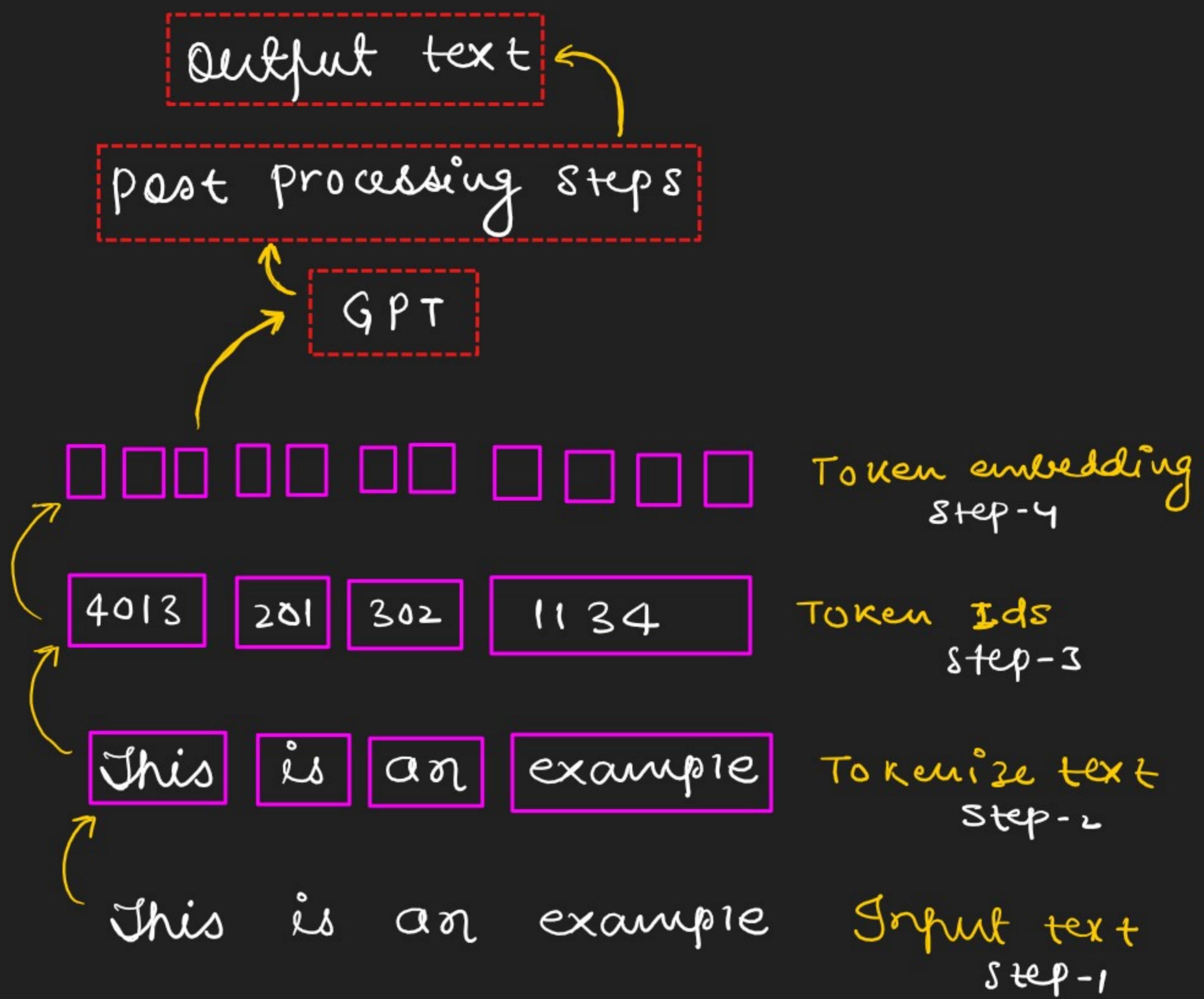


Lecture-10: Token Embedding

vector - embedding



Today, we going to learn about
Step 3: creating token embeddings

- ① conceptual understanding of why token embeddings are needed ?
- ② small hands on demo: playing with token embeddings.
- ③ How are token embeddings created for LLM ?

LLMs from Scratch

What are token embeddings and why we need them?



Representing Words Numerically

- Computers need numerical representation of words
- How can we represent words in numbers?

Can we assign random numbers to each word?

“cat”	→	34
“book”	→	2.9
“tablet”	→	-20
“kitten”	→	-13

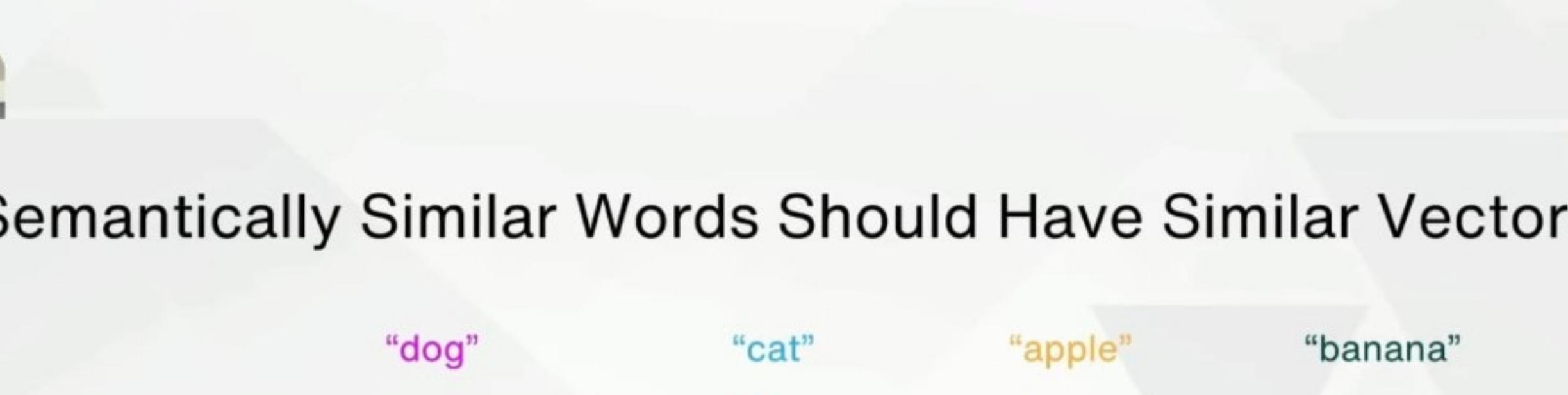


What About One-Hot Encoding?

- 1) Create a dictionary of words
- 2) Assign sequential one-hot encoding to each word



The Problem With One-Hot Encoding



One-hot encoding also fails to capture semantic relationship



Semantically Similar Words Should Have Similar Vectors

	“dog”	“cat”	“apple”	“banana”
has_a_tail	[23]	[31]	[1]	[2]
is_eatable	[2]	[3]	[22]	[38]
has_4_legs	[19]	[21]	[0]	[0]
makes_sound	[12]	[18]	[0.5]	[0.2]
is_a_pet	[35]	[31]	[5]	[7]

Vectors can capture semantic meaning



We Can Train a Neural Network To Create Vector Embedding

“dog” [23, 2, 19, 12, 35]

“cat” [31, 3, 21, 18, 31]

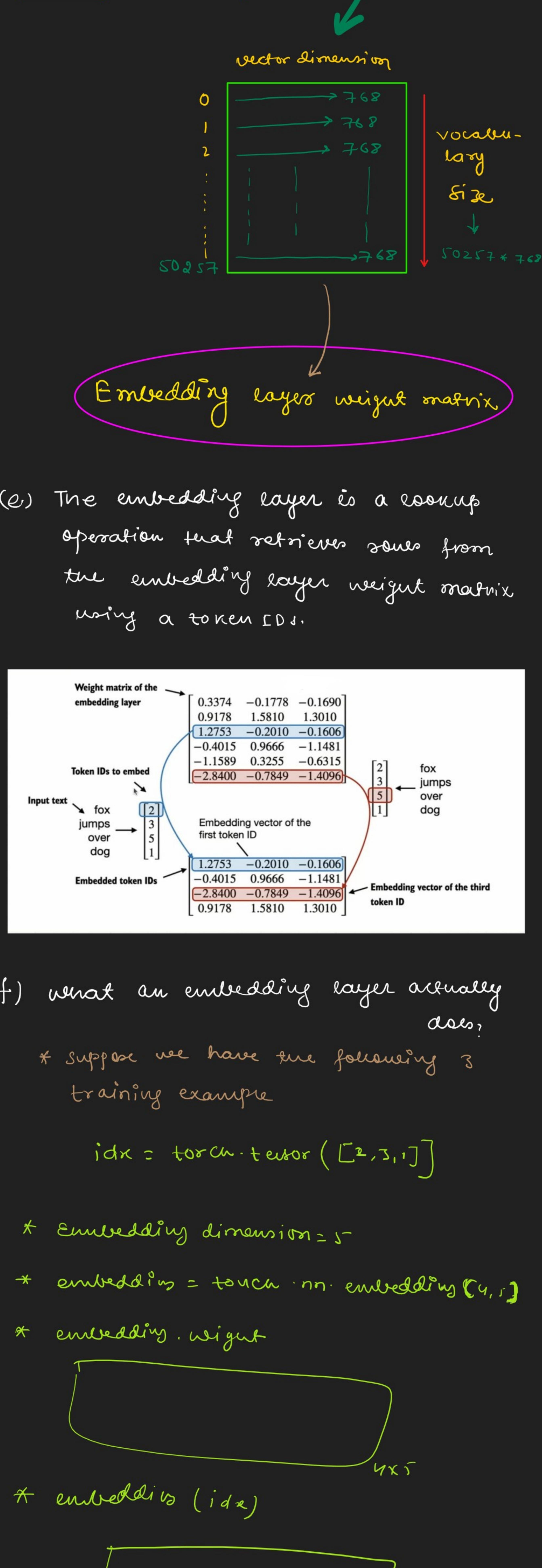
“apple” [1, 22, 0, 0.5, 5]

“banana” [2, 38, 0, 0.2, 7]

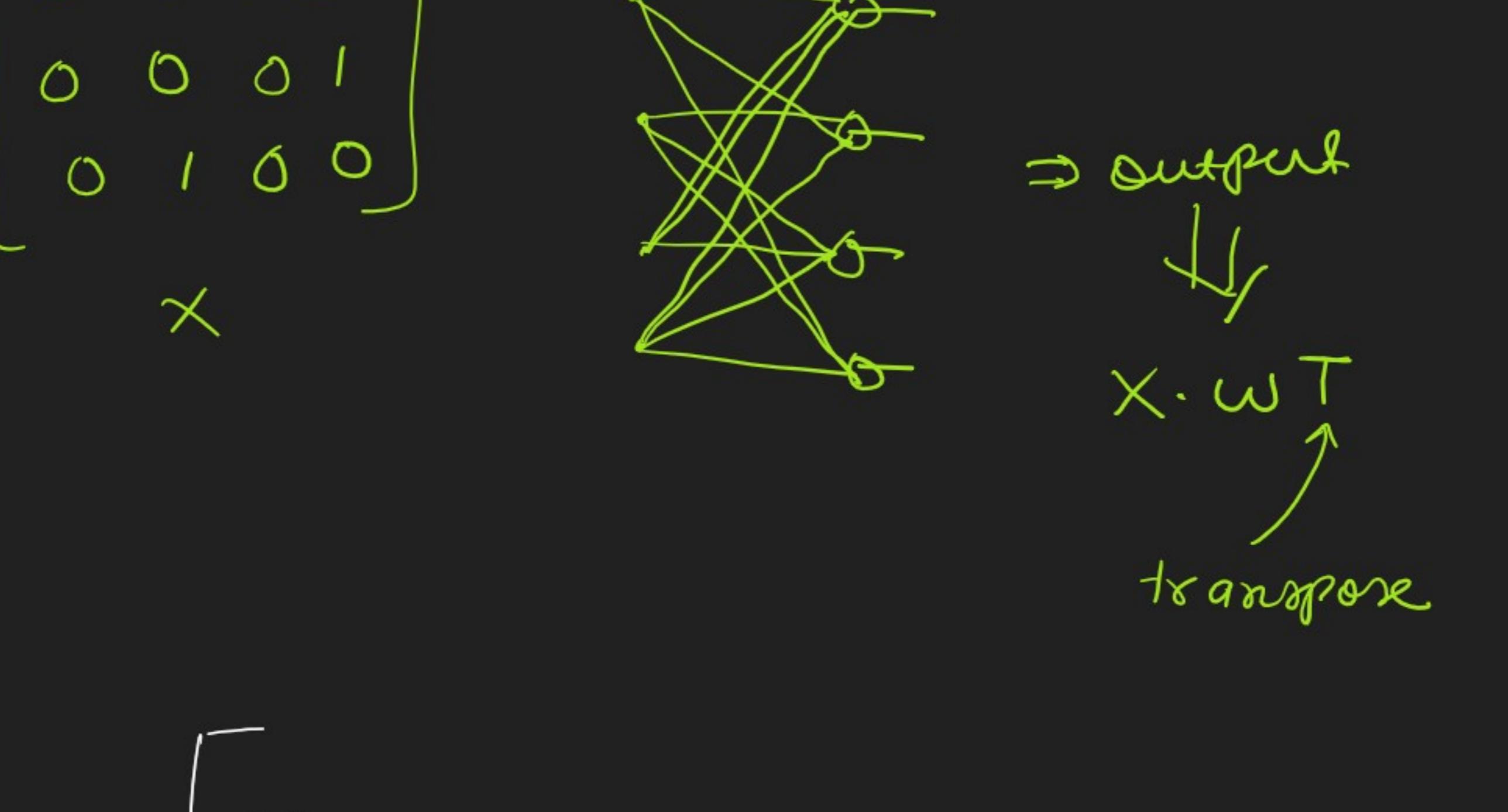


③ How are token embeddings created for LLM?

- (a.) Initialize embedding weights with random values.
- (b.) This initialization serves as the starting point for the LLM learning process.
- (c.) The embedding weights are optimised as part of the LLM training process.
- (d.) vocabulary (usually sorted alphabetically)



- (e.) The embedding layer is a lookup operation that retrieves rows from the embedding layer weight matrix using a token IDs.



This is the same as neural network linear layer.

- * Both embedding layer and NN linear layer lead to some output.

- * Embedding layer is much more computationally efficient, since NN layer has many unnecessary multiplication with zero.

$$\omega^T = \begin{bmatrix} \omega_{11} & \omega_{21} & \omega_{31} & \omega_{41} & \omega_{51} \\ \omega_{12} & \omega_{22} & \omega_{32} & \omega_{42} & \omega_{52} \\ \omega_{13} & \omega_{23} & \omega_{33} & \omega_{43} & \omega_{53} \\ \omega_{14} & \omega_{24} & \omega_{34} & \omega_{44} & \omega_{54} \end{bmatrix}$$

Neuron

Neuron

$$X \cdot \omega^T \rightarrow \text{output}$$

transpose