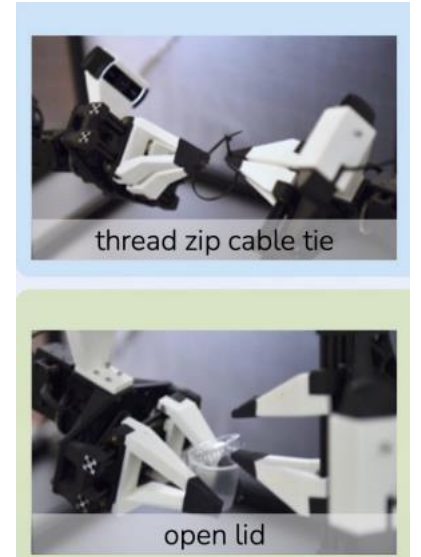
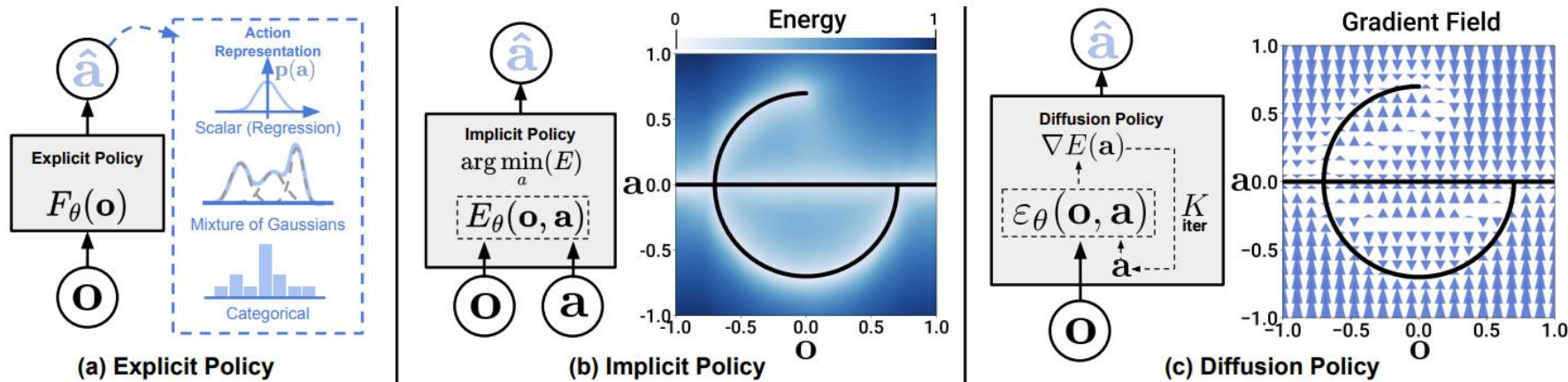


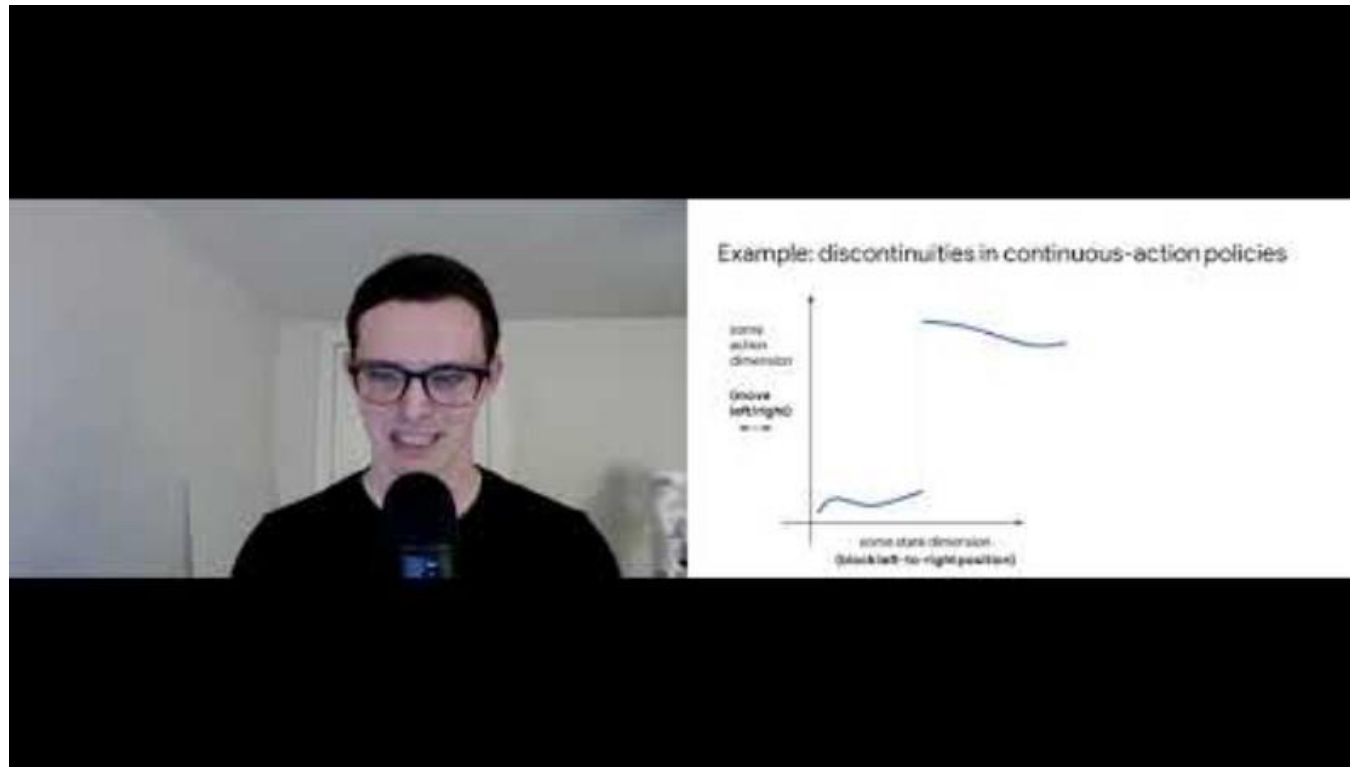
# Advanced Behavioral Cloning



Instructor: Daniel Brown

# Implicit Behavioral Cloning

- Paper: <https://arxiv.org/abs/2109.00137>
- Video: <https://www.youtube.com/watch?v=QsIGqRUSRzs>



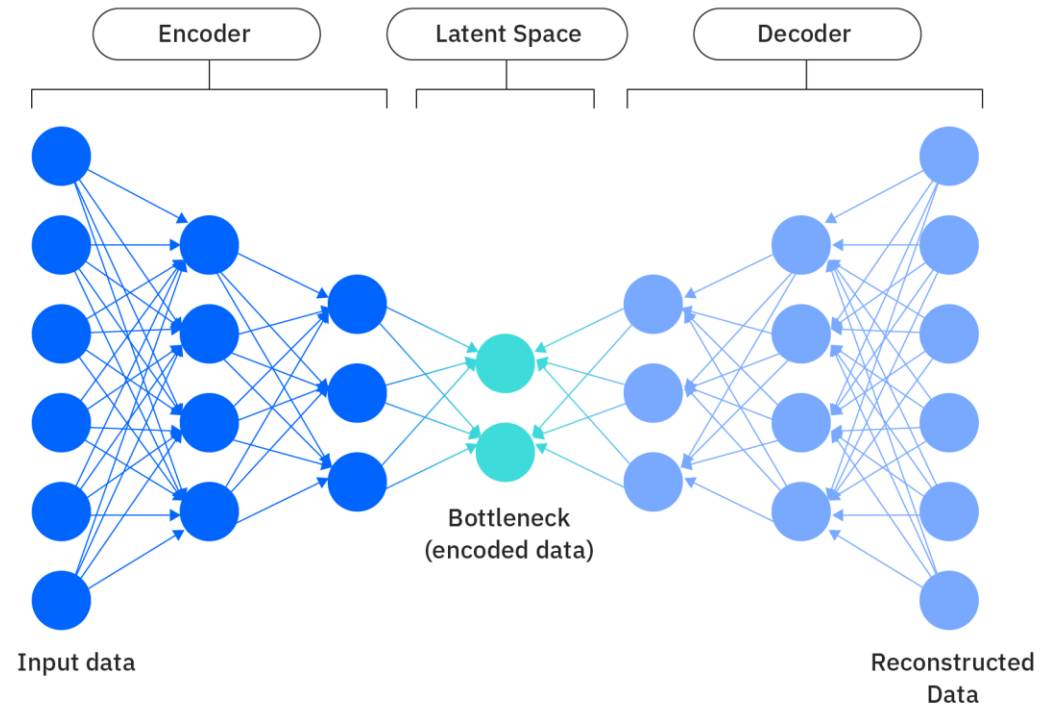
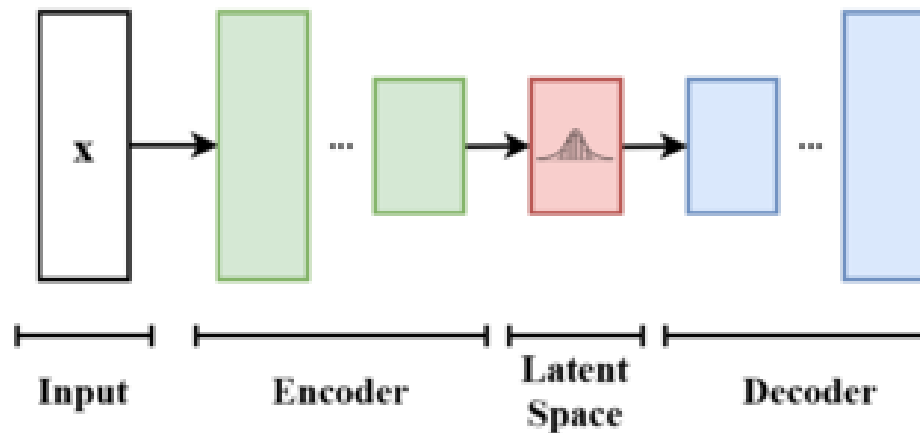


# Action Chunking with Transformers (ACT)

- Paper: <https://arxiv.org/pdf/2304.13705>
- Videos: <https://tonyzhaozh.github.io/aloha/>

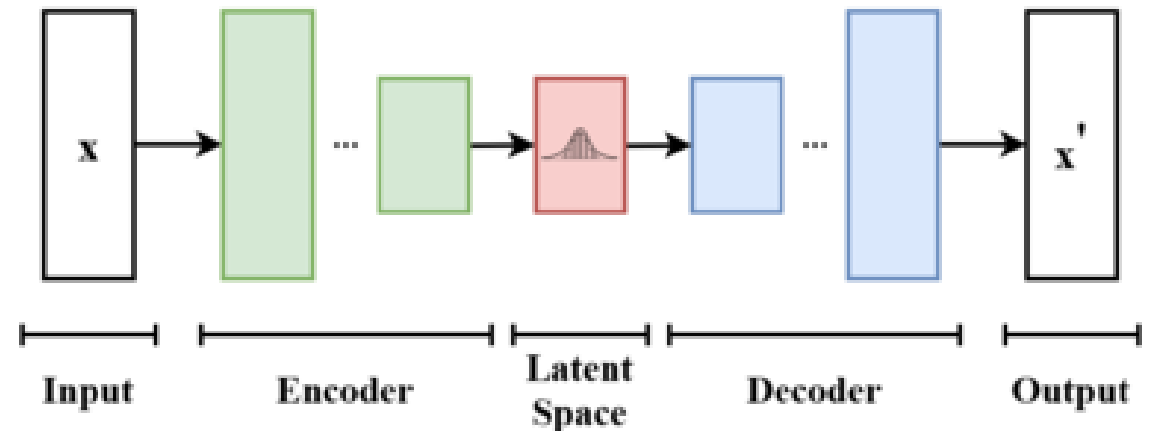
# Variational Autoencoders (VAEs)

- Autoencoders learn latent representations



# Variational Autoencoders (VAEs)

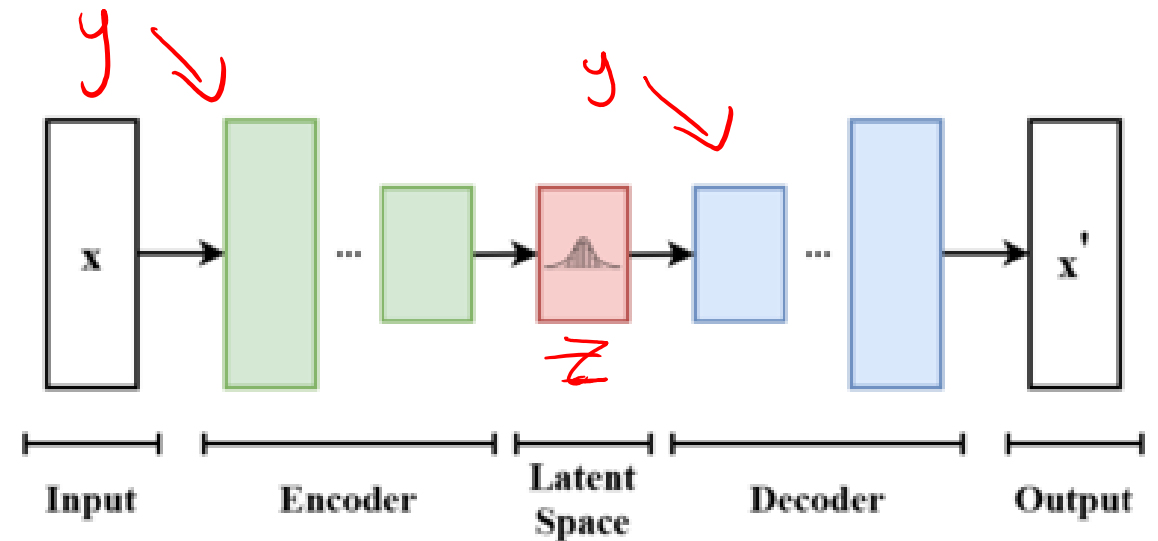
- Autoencoders learn latent representations
- VAEs map input into a distribution over latent variables  $z$
- Loss function is reconstruction plus KL divergence



$$\mathcal{L} = \mathbb{E}_{q(z|x)} [\log p(x|z)] - D_{\text{KL}}(q(z|x) || p(z))$$

# Conditional Variational Autoencoders (CVAEs)

- Encoder and decoder both condition on extra info  $y$



- Loss function is reconstruction plus KL divergence

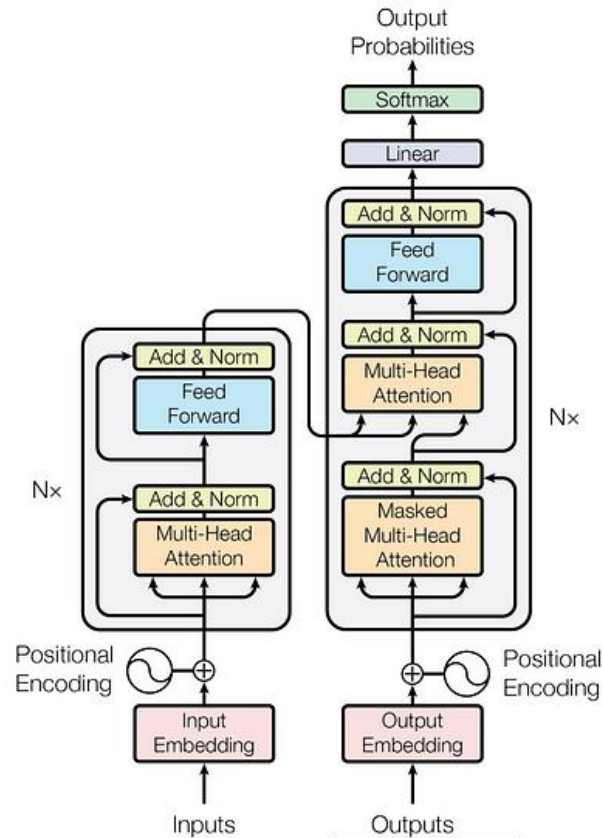
$$\mathcal{L} = \mathbb{E}_{q(z|x,y)} [\log p(x|z, y)] - D_{\text{KL}}(q(z|x, y) || p(z|y))$$

# Transformers

- State of the art ways to ingest and output sequential data.

BERT

Encoder

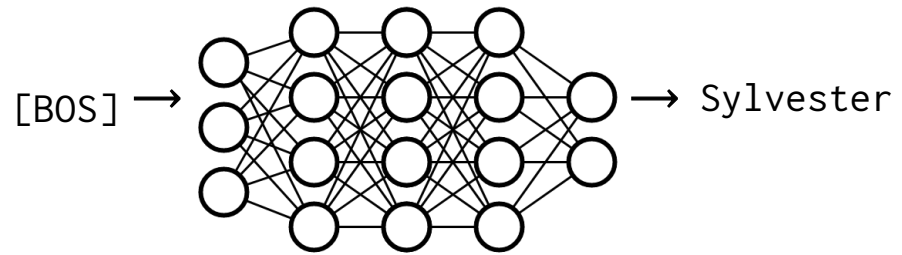


GPT

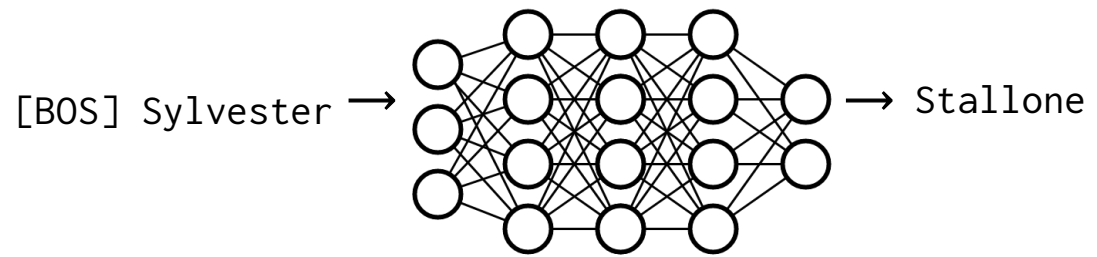
Decoder



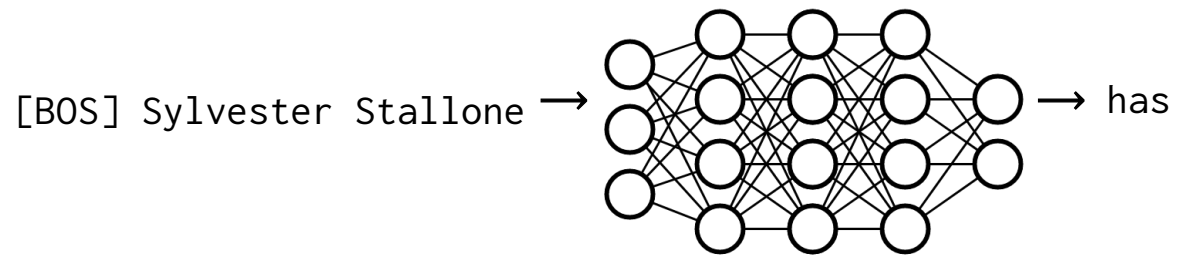
# Neural language modeling



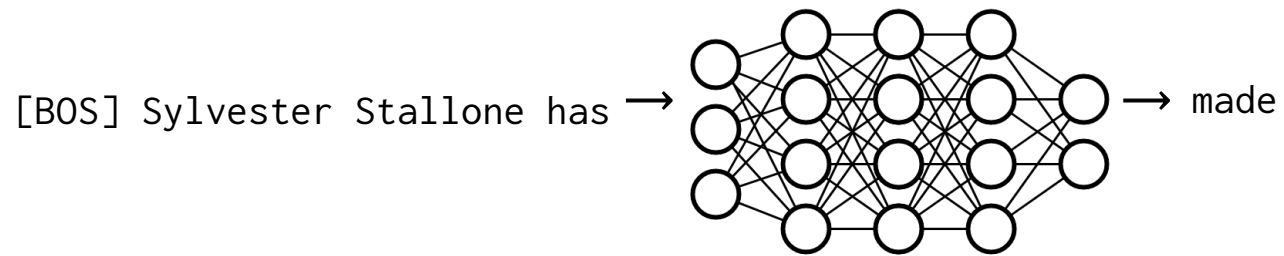
# Neural language modeling

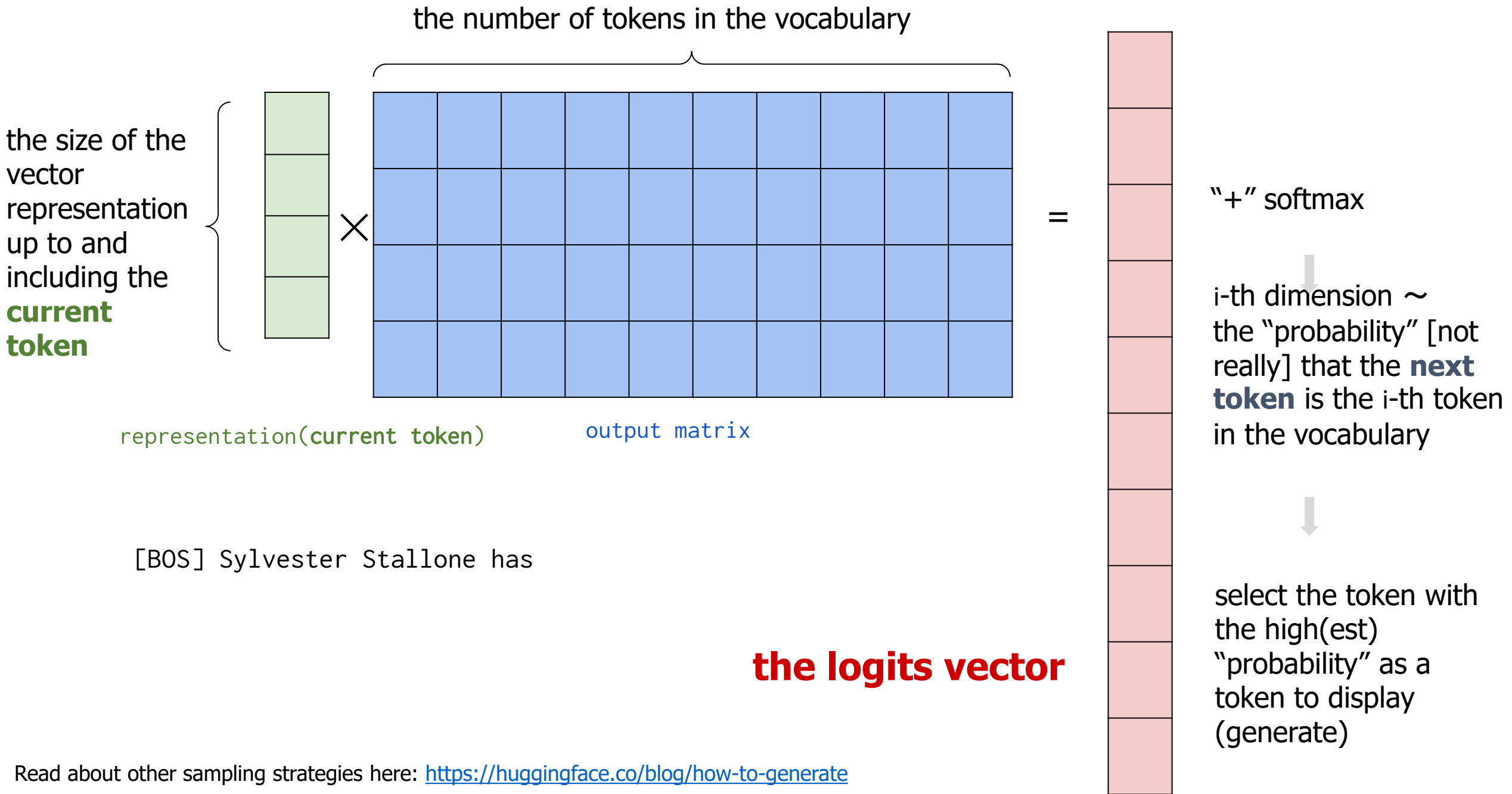


# Neural language modeling

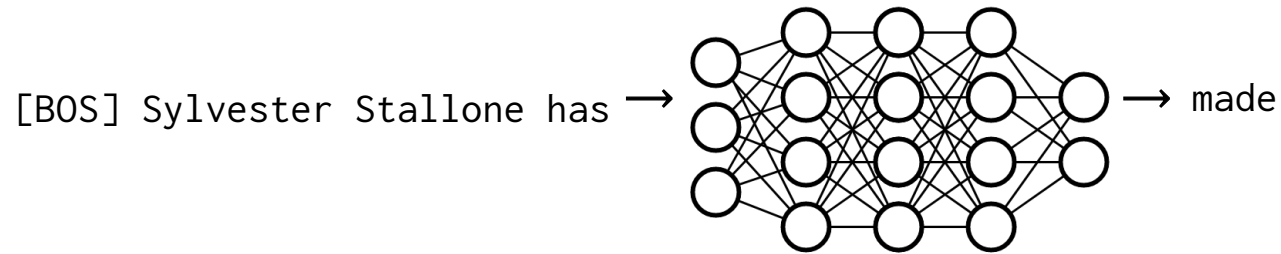


# Neural language modeling





# Neural sequence modeling

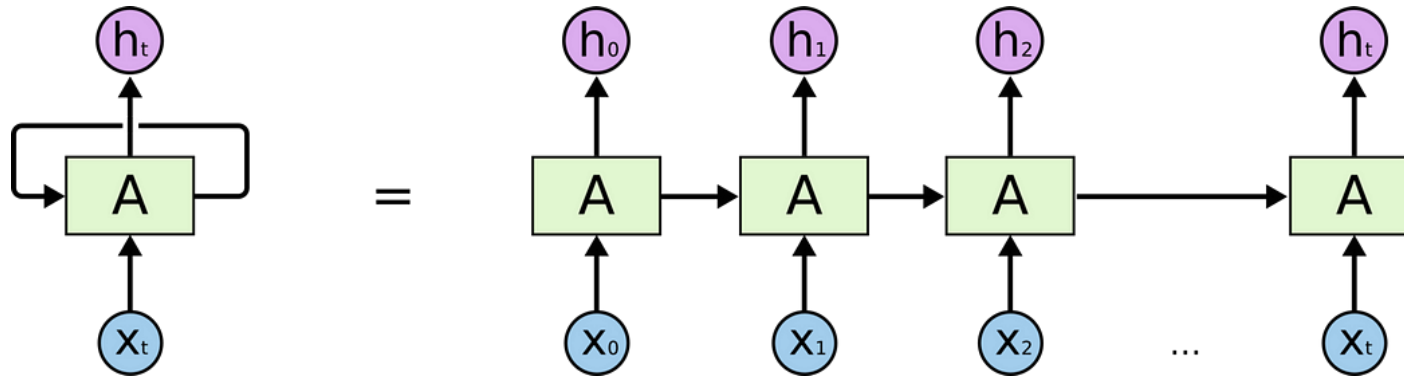


Problems:

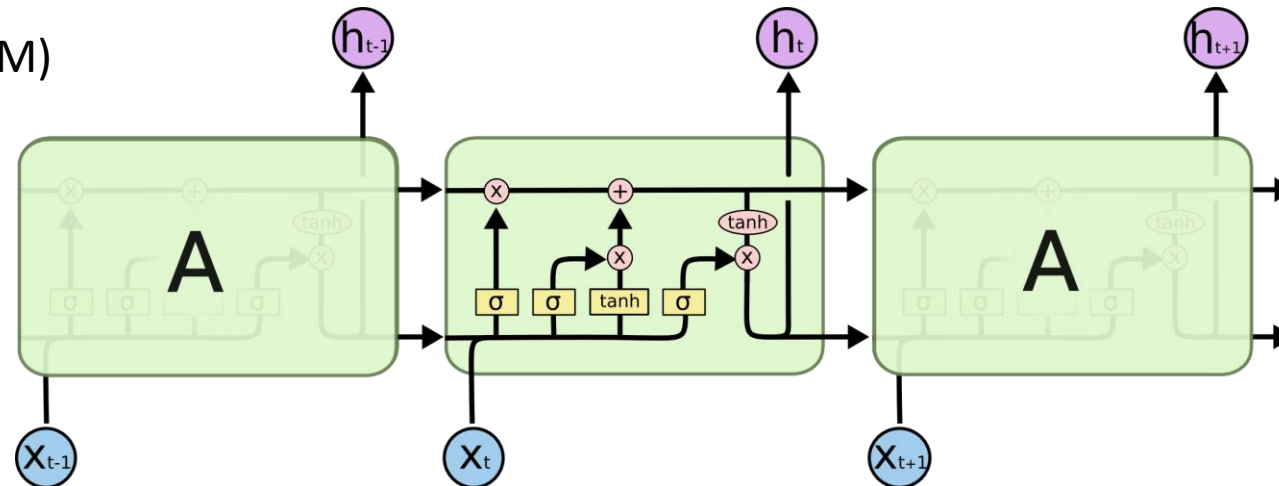
- How do we deal with different length inputs?
- How do we model long-range dependencies?

# Recurrent Neural Networks

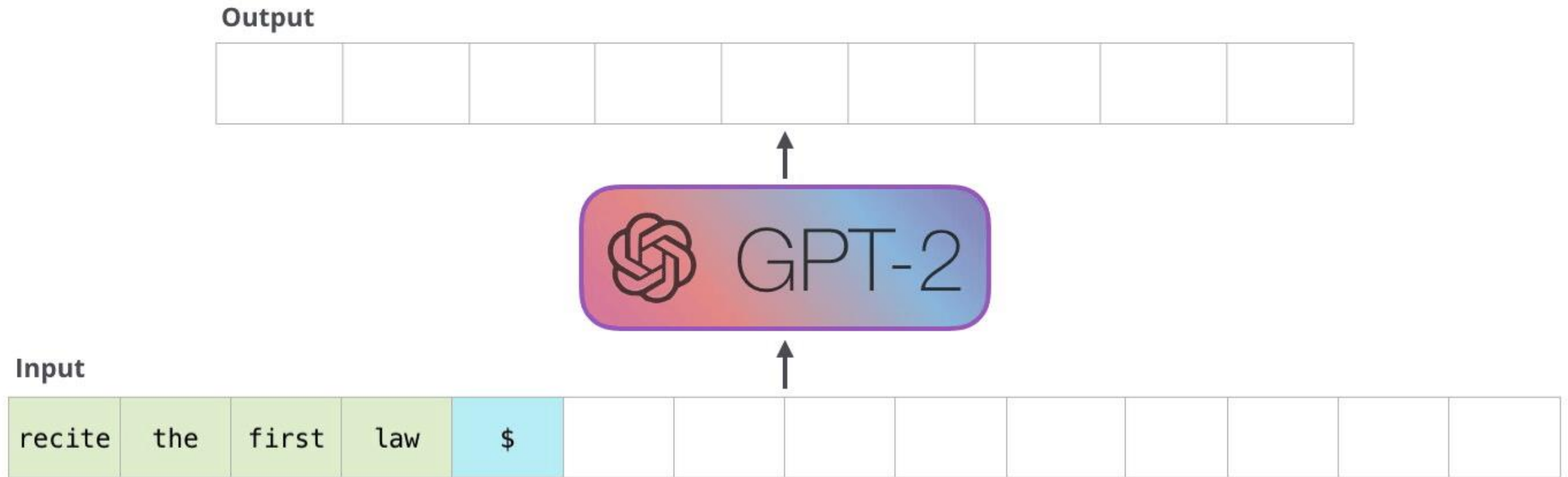
- Standard RNN



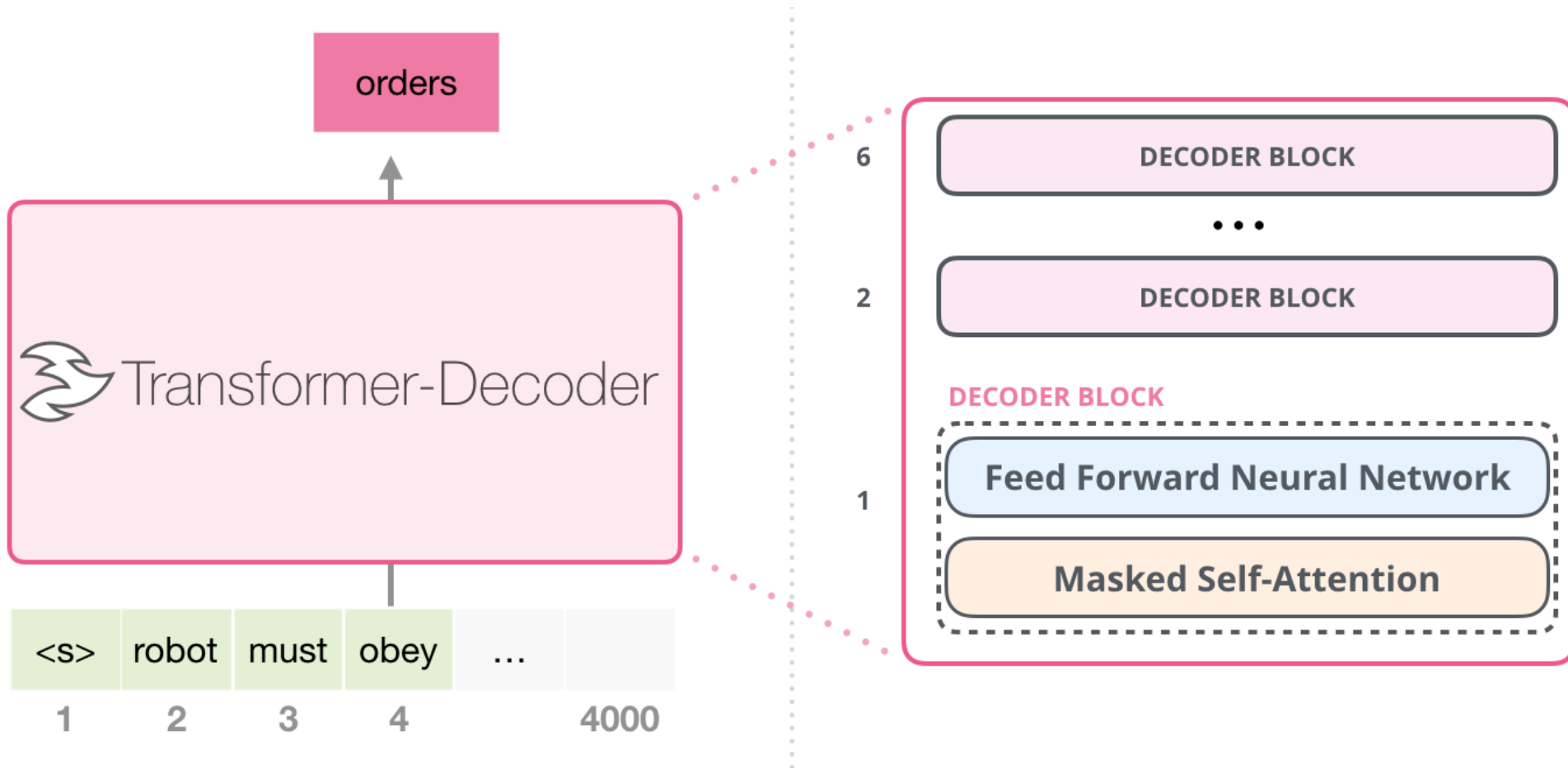
- Long short-term memory (LSTM)

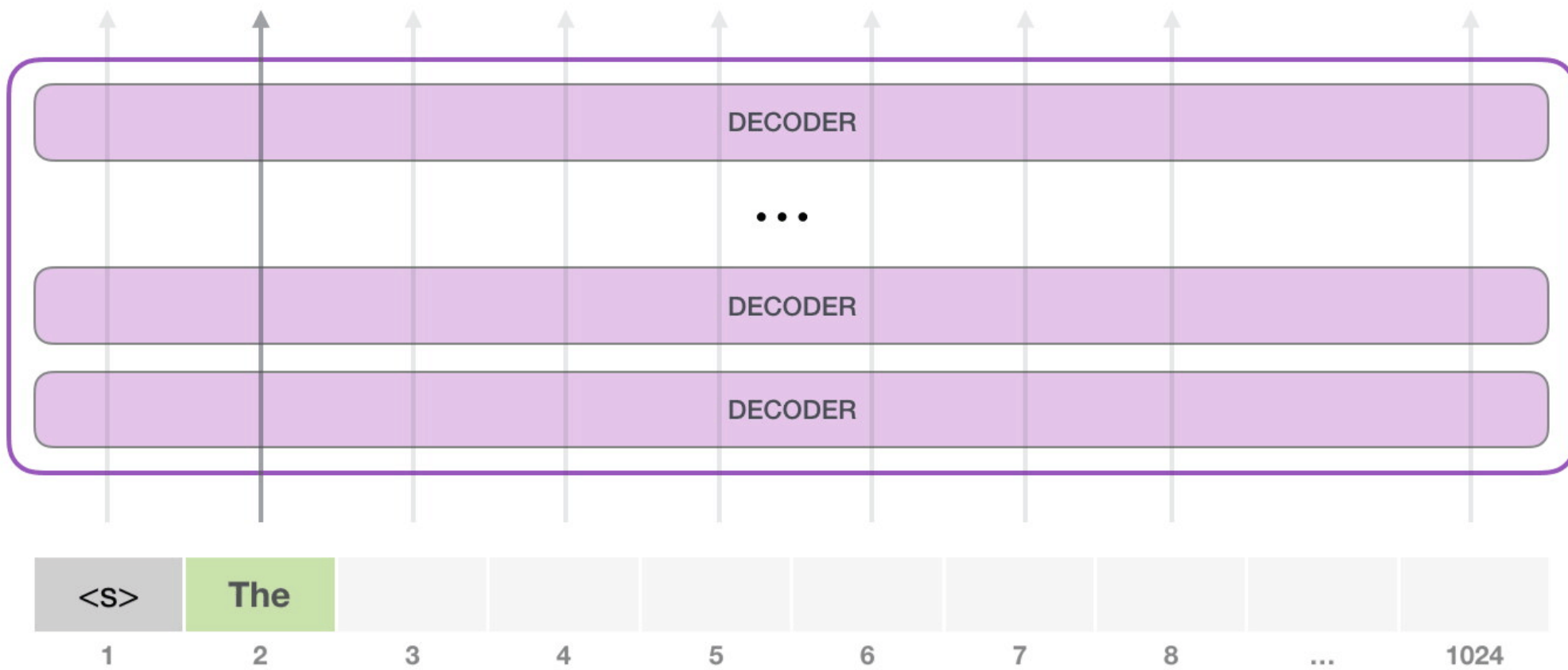


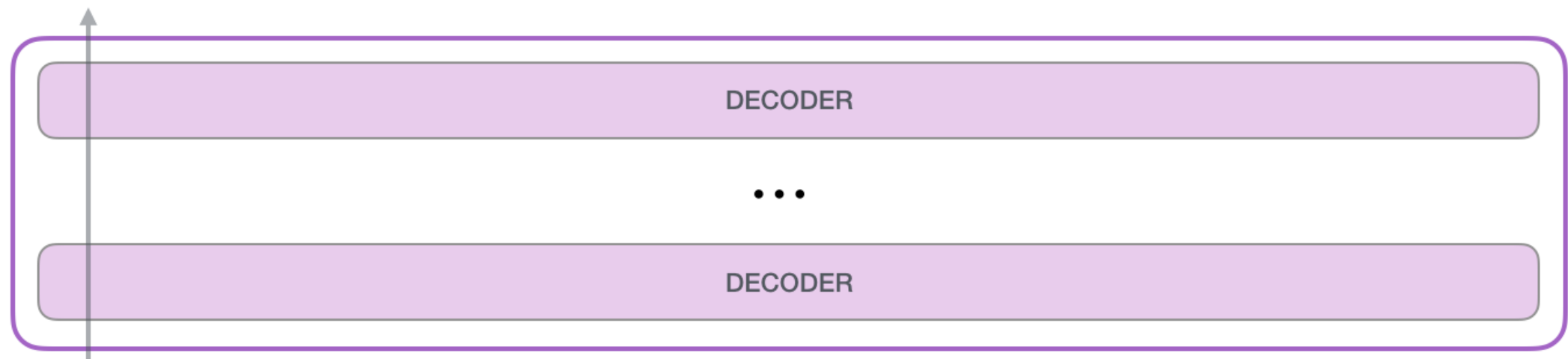
# Large Language Models



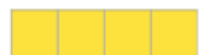






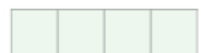


=



Positional encoding for token #1

+



Token embedding of <s>



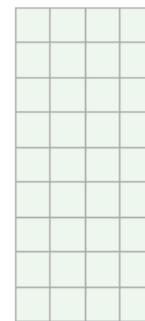
1

2

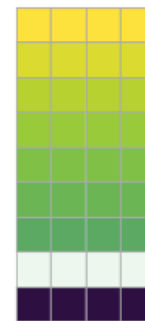
...

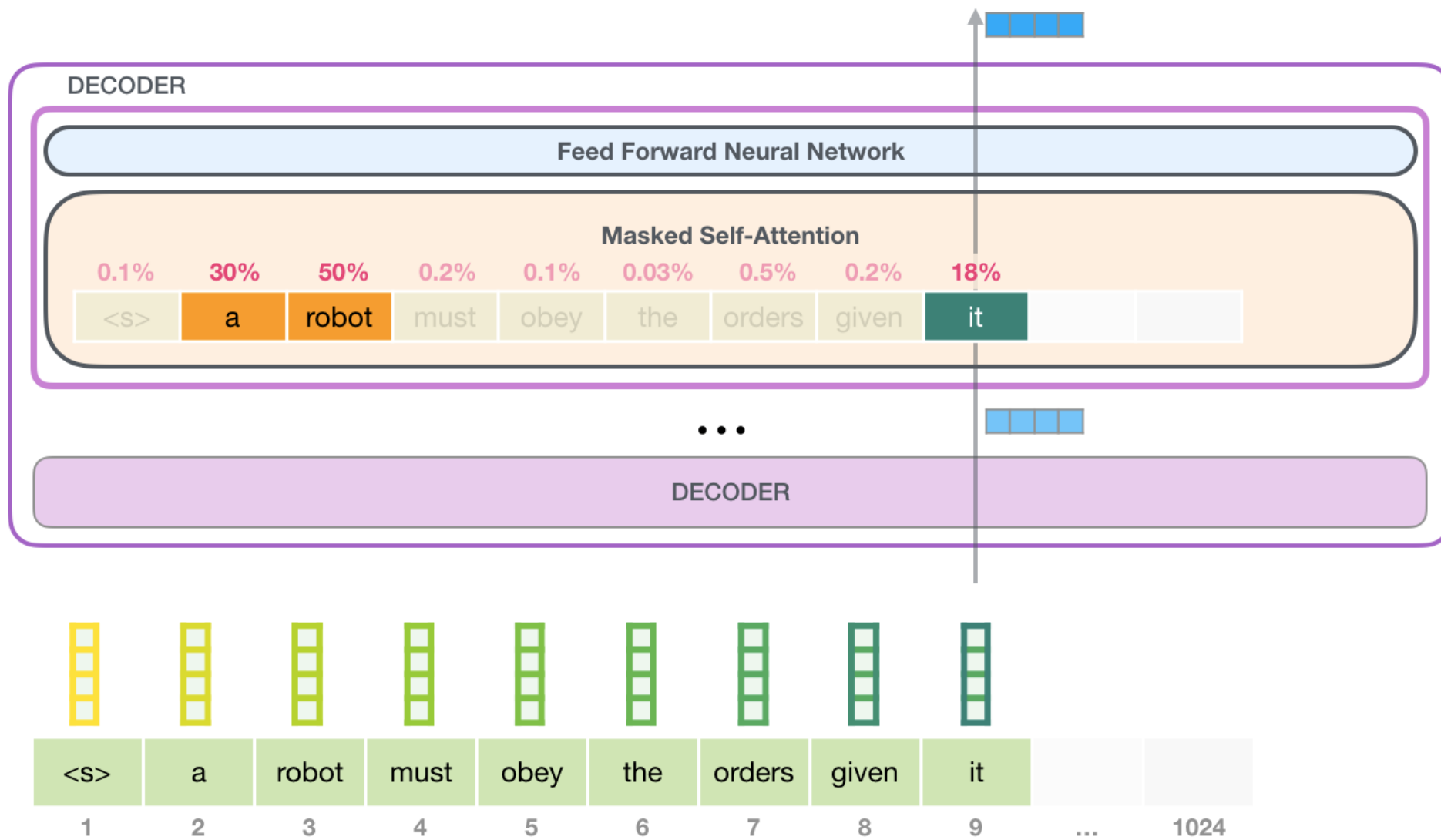
1024

Token  
Embeddings



Positional  
Encodings



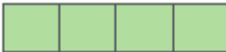


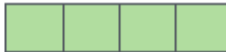
Input

Thinking

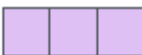
Machines

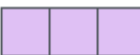
Embedding

$x_1$  

$x_2$  

Queries

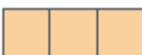
$q_1$  

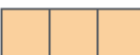
$q_2$  



$W^Q$

Keys

$k_1$  

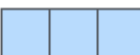
$k_2$  



$W^K$

Values

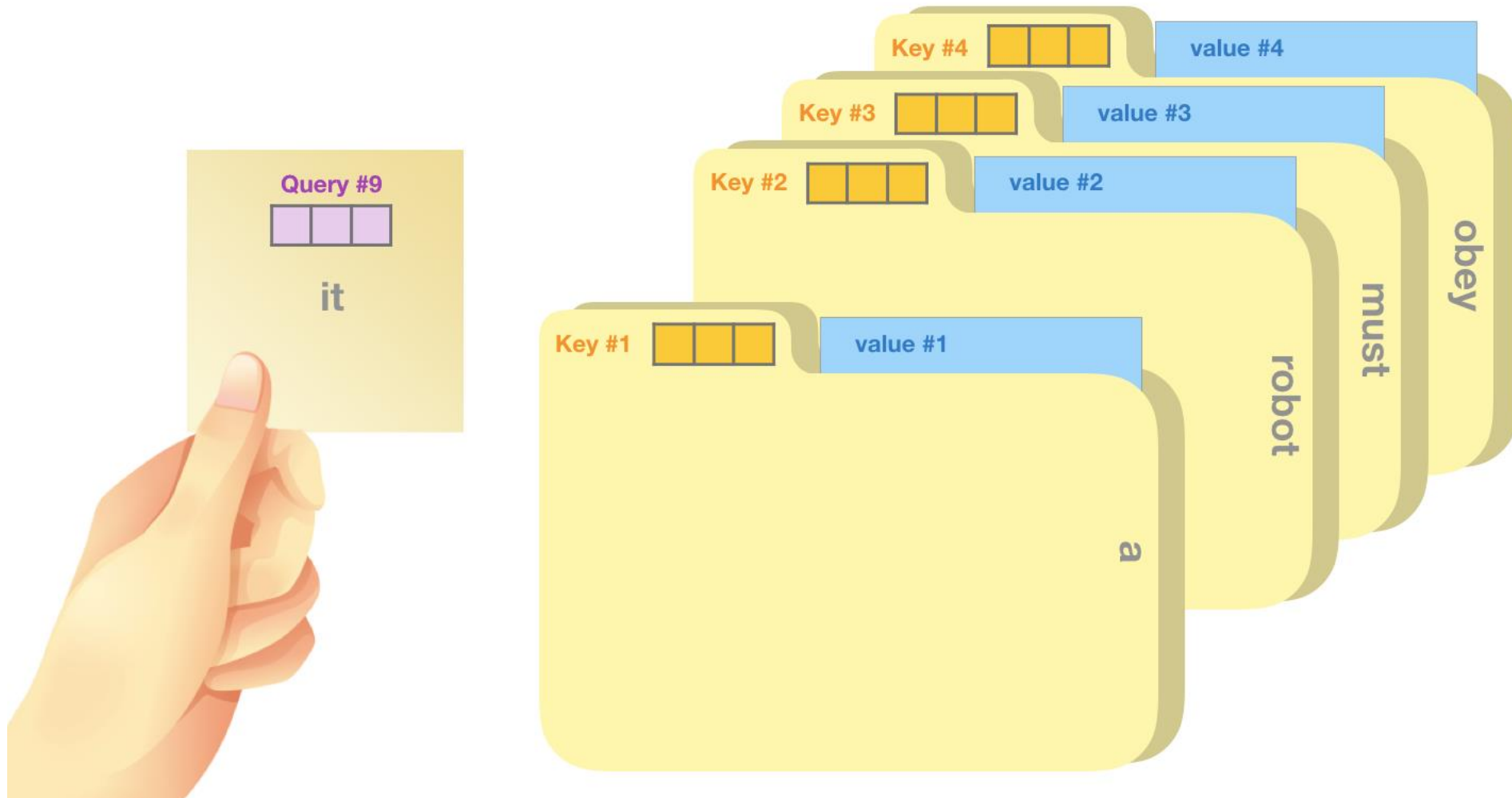
$v_1$  

$v_2$  

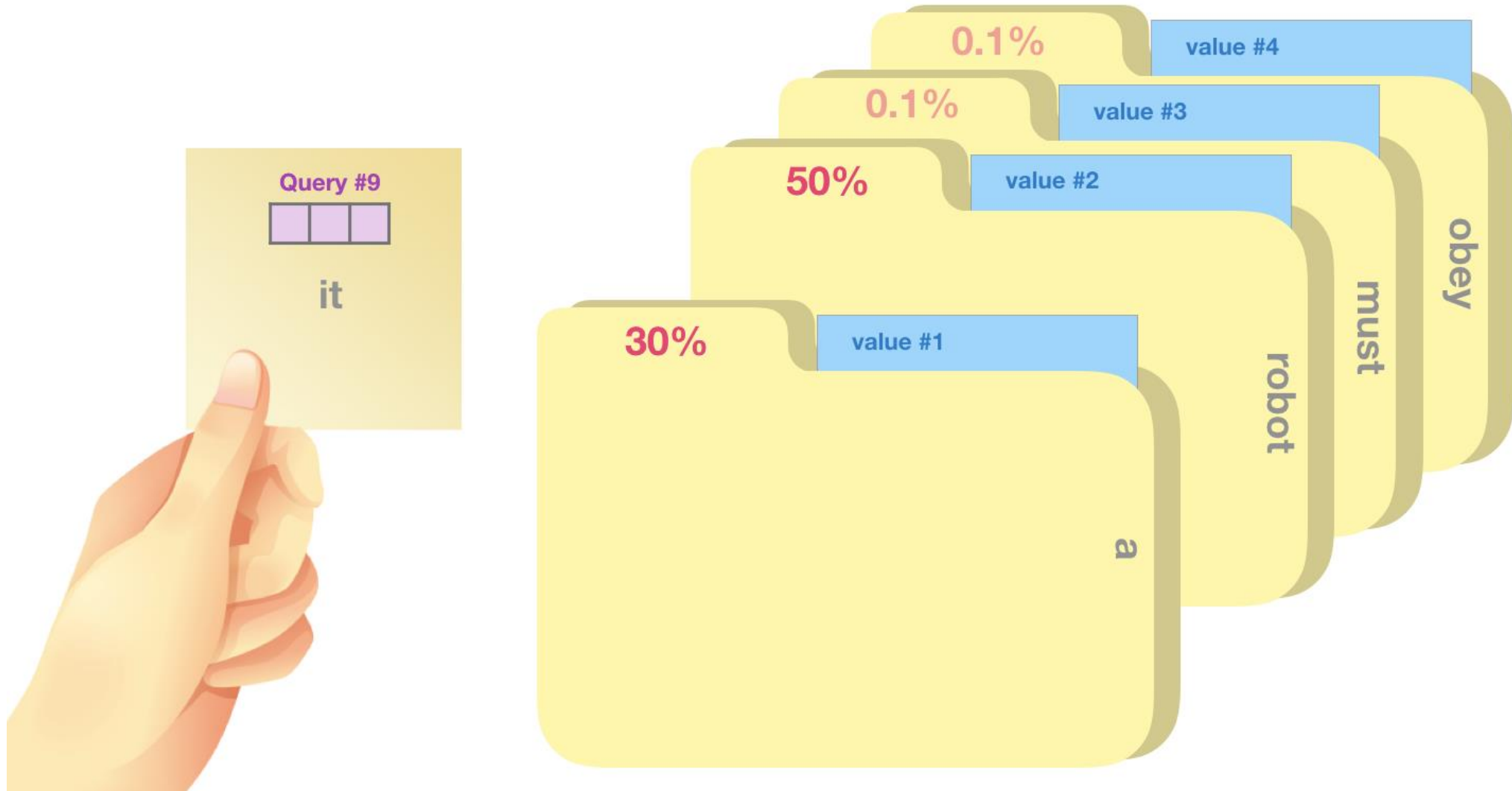





















$W^V$

Perform dot product between query and all keys to get a raw score for each previous word (including current word).

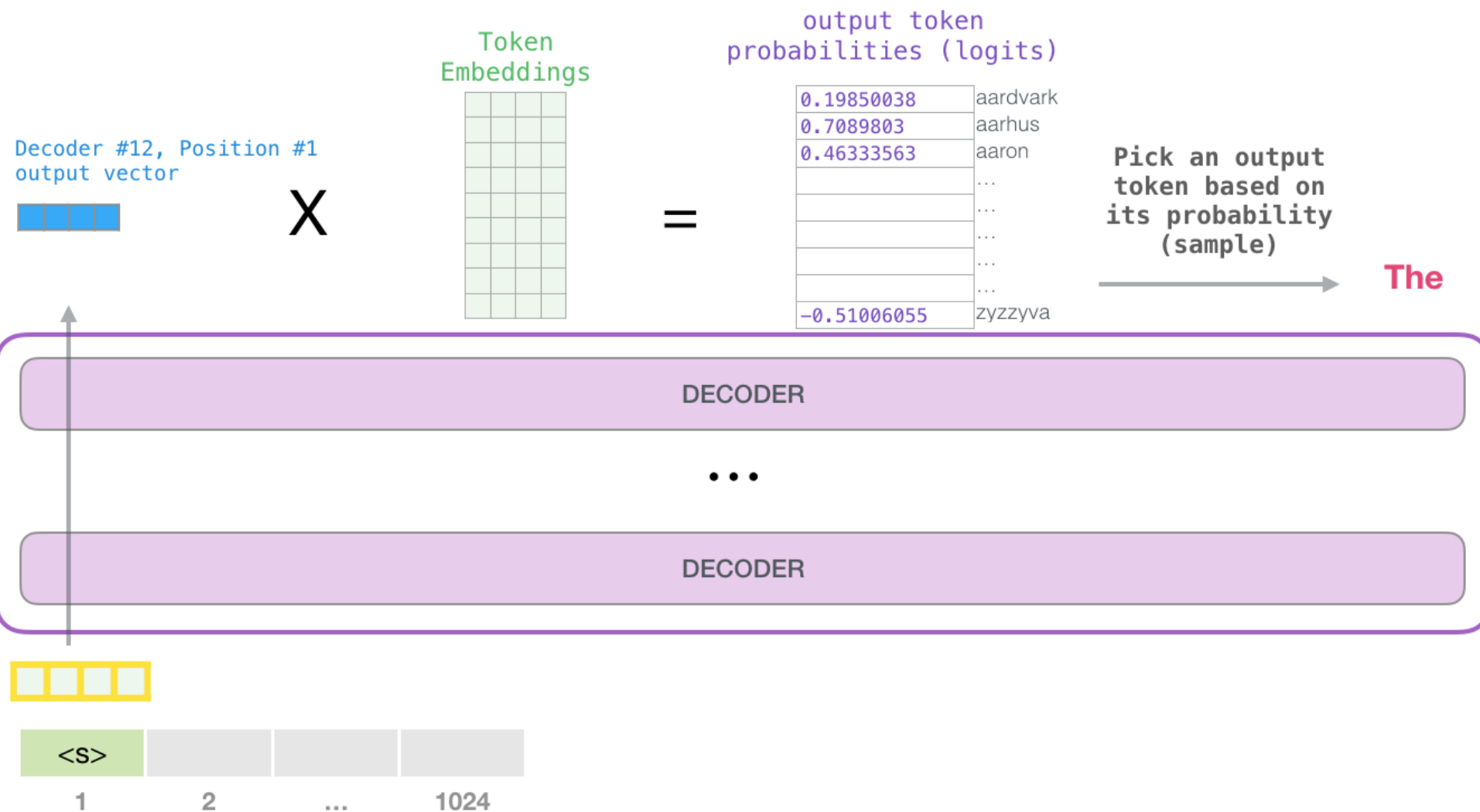


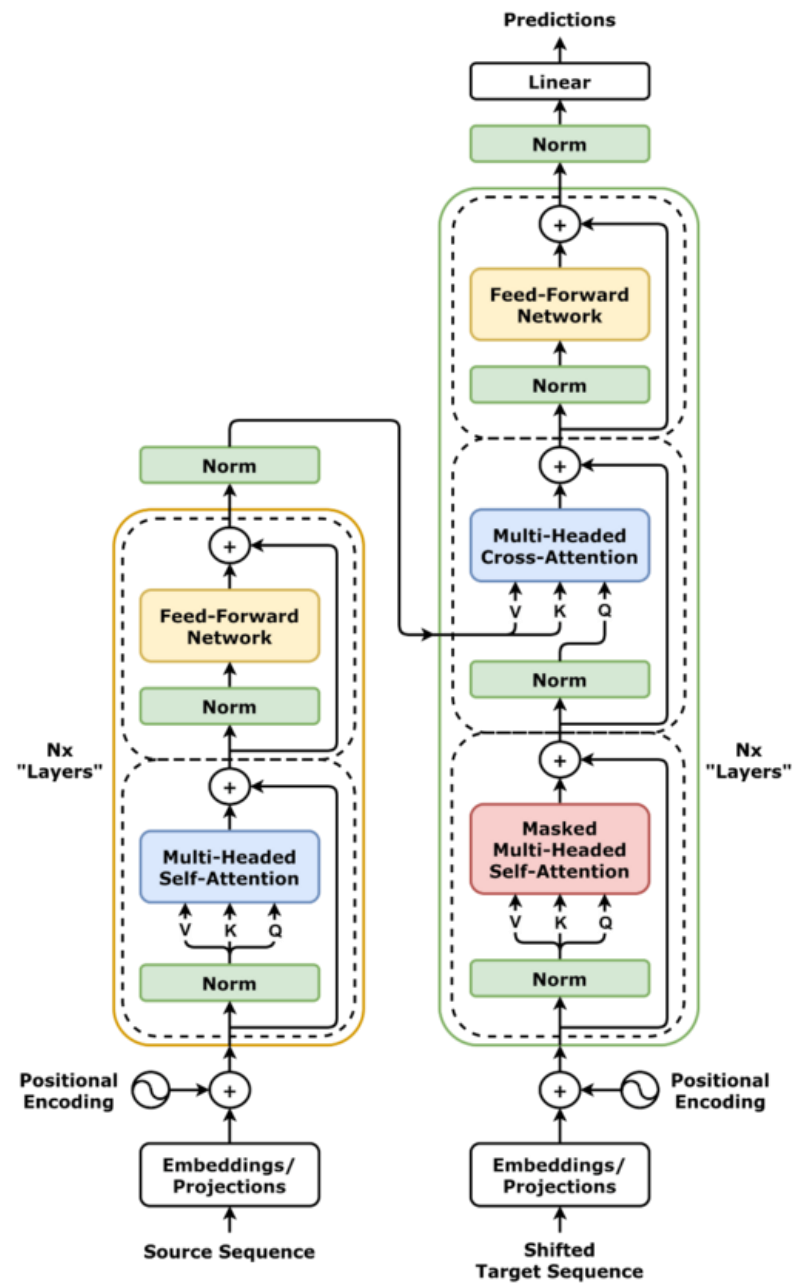
Normalize these scores via a softmax to get a probability distribution. Then return a weighted sum of the values.



Word	Value vector	Score	Value X Score
<S>		0.001	
a		0.3	
robot		0.5	
must		0.002	
obey		0.001	
the		0.0003	
orders		0.005	
given		0.002	
it		0.19	
		Sum:	









# Diffusion Policy

- Paper: <https://arxiv.org/pdf/2303.04137v4>
- Videos: <https://diffusion-policy.cs.columbia.edu/>

# Denoising Diffusion (high-level)

