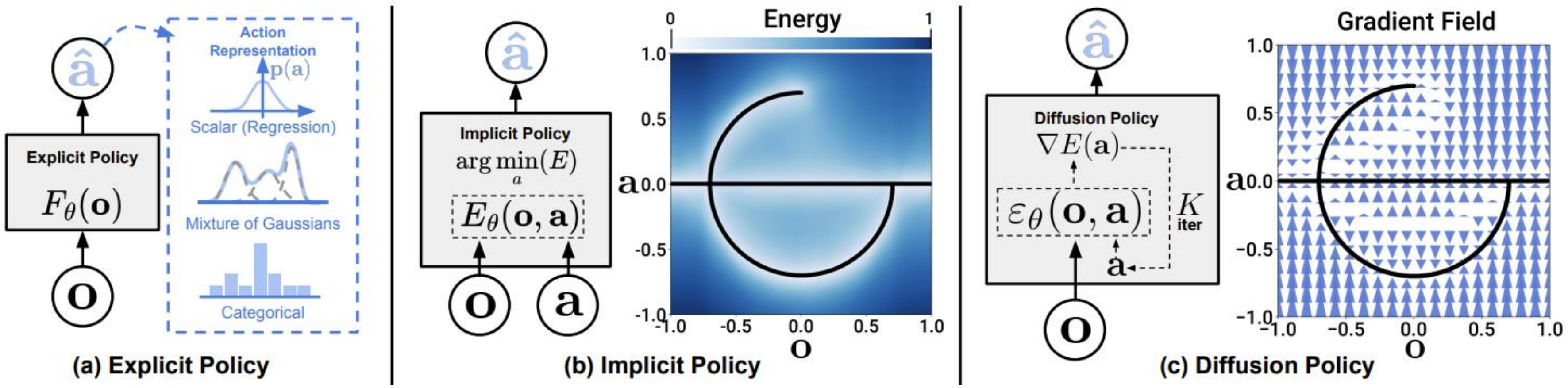
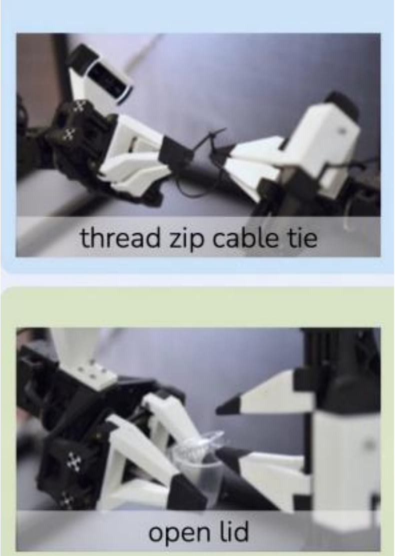
Advanced Behavioral Cloning



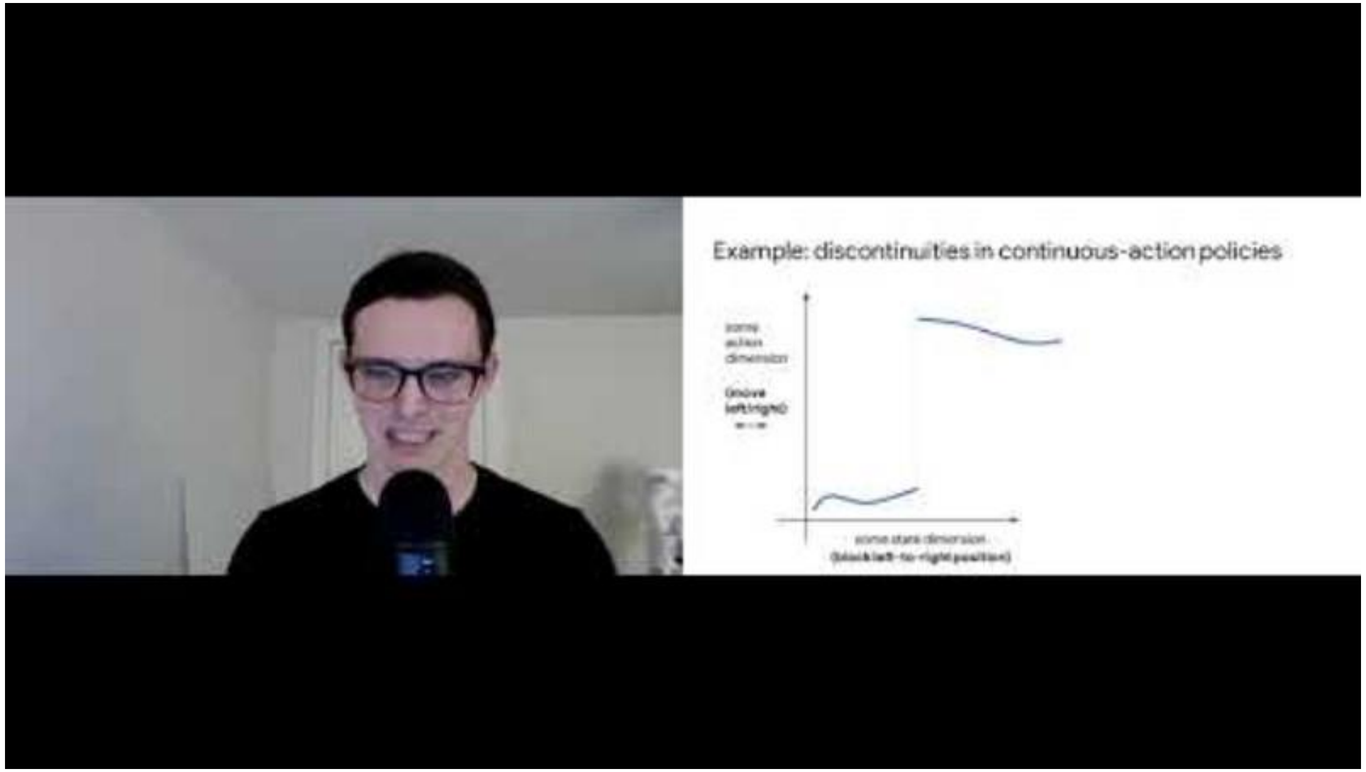


$D = \{(o,a)\ldots\}$

Instructor: Daniel Brown

Implicit Behavioral Cloning

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



$D = \{ (o_1, a_1), (o_1, a_2) \dots$

$o \rightarrow$ BC $\rightarrow a$

$o \rightarrow$, $a \rightarrow$ IBC $\rightarrow E(o, a) \in \mathbb{R}$

E_θ

$E(o, a) \downarrow$

$E(o, c) \uparrow$

Test time

- BC input $o' \rightarrow a'$
- IBC input $o' \; ? \rightarrow E$

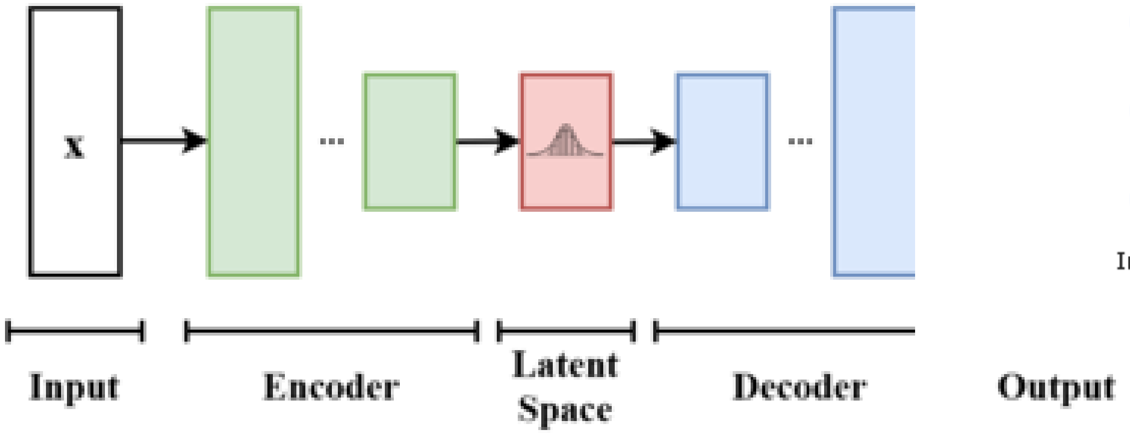
$a' = \arg\min_a E_\theta(o', a)$

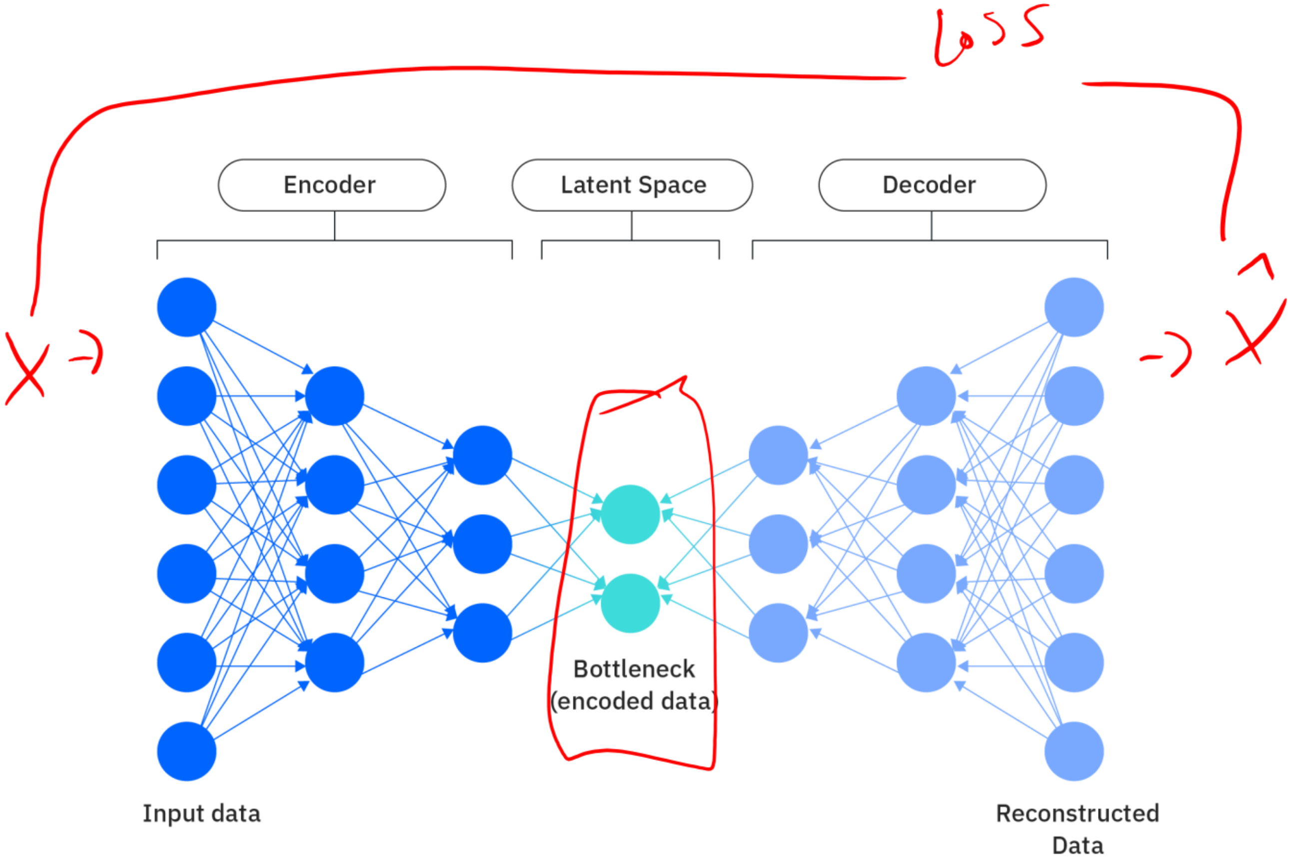
Action Chunking with Transformers (ACT)

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

Variational Autoencoders (VAEs)

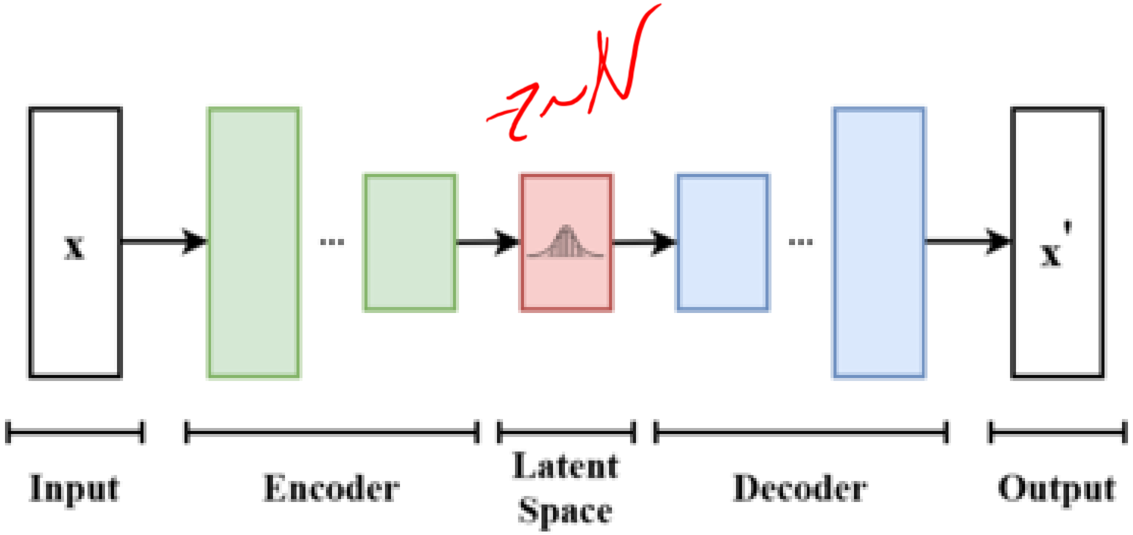
- Autoencoders learn latent representations





Variational Autoencoders (VAEs)

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

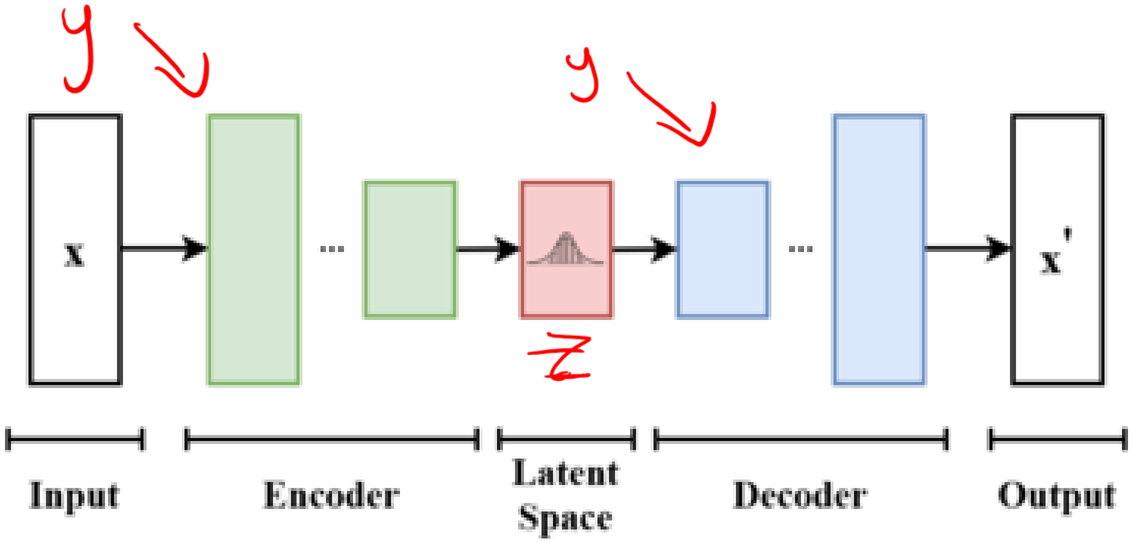


prior $N(0,I)$

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

Conditional Variational Autoencoders (CVAEs)

- Encoder and decodre both condition on extra info y



- Loss function is reconstruction plus KL divergence

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

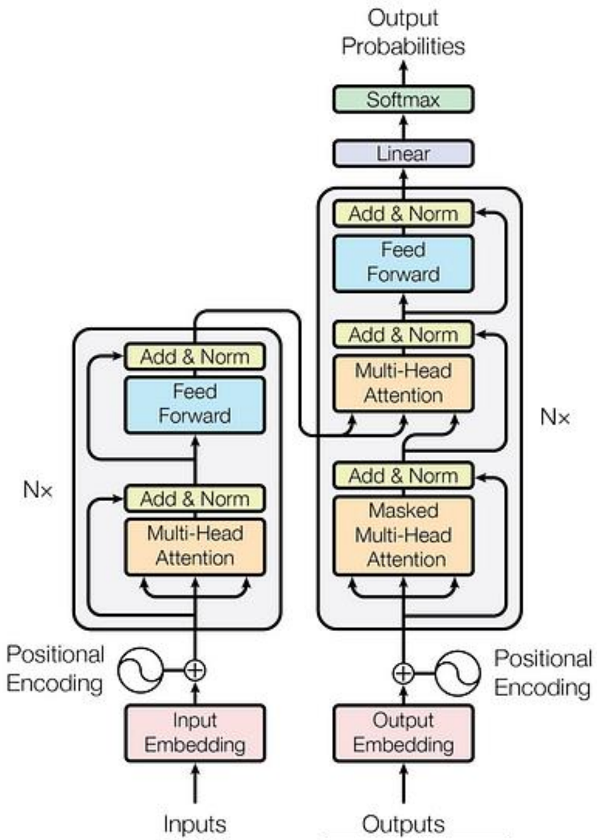
Transformers

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

BERT

Encoder

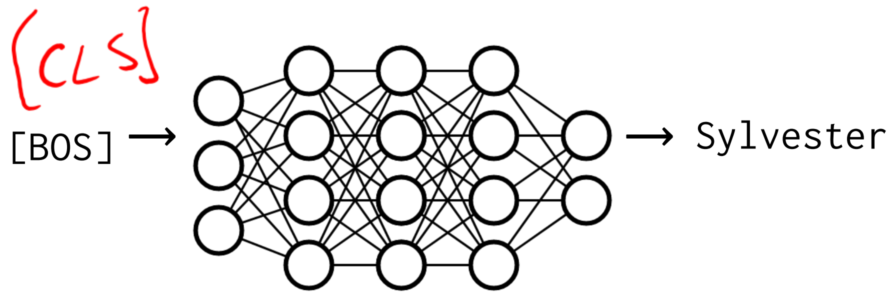
CVAE



GPT

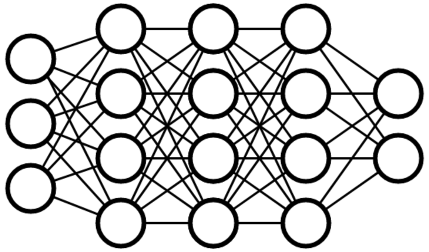
Decoder

Neural language modeling



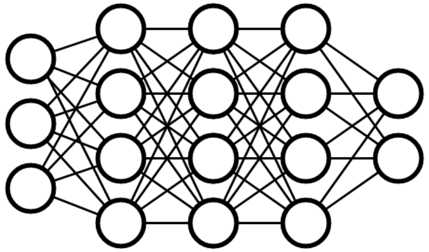
Neural language modeling

[BOS] Sylvester →

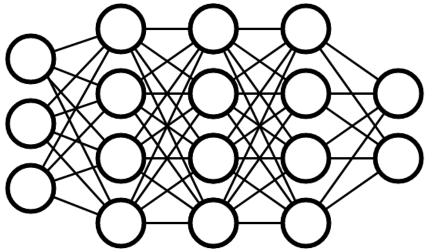


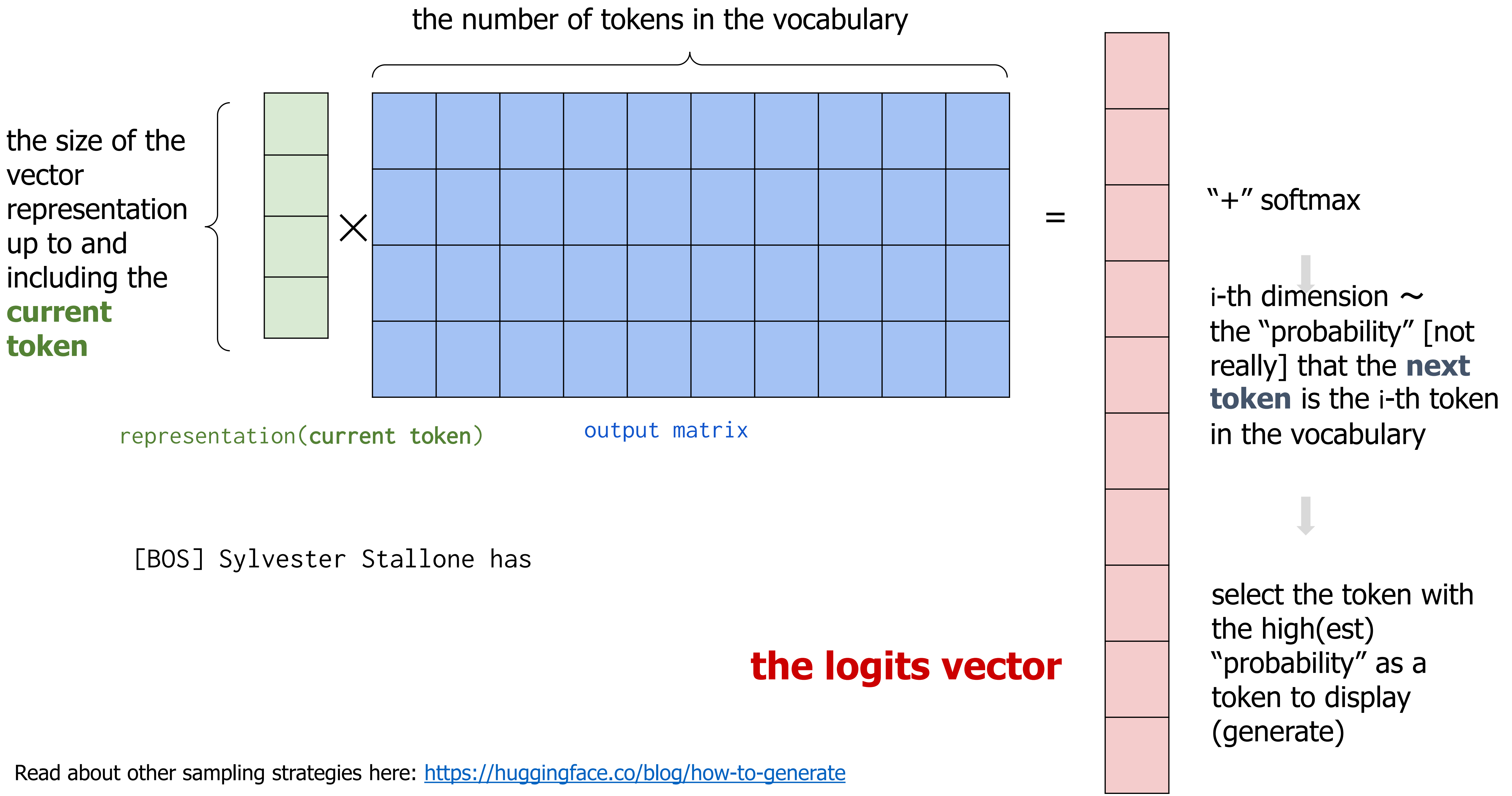
→ Stallone

Neural language modeling

[BOS] Sylvester Stallone →  → has

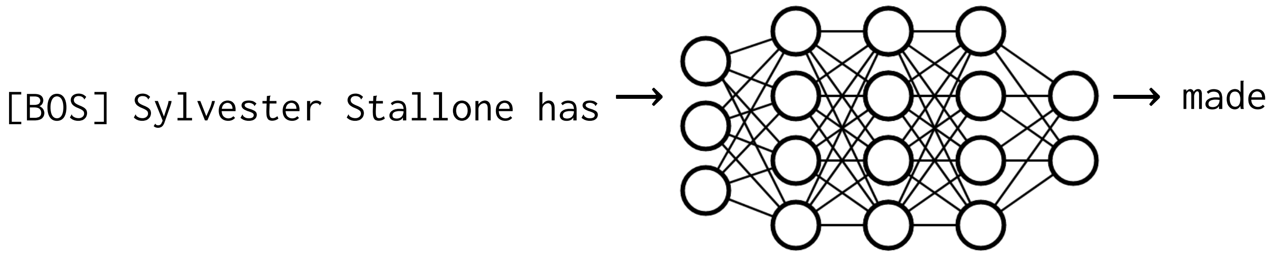
Neural language modeling

[BOS] Sylvester Stallone has →  → made



Read about other sampling strategies here: https://huggingface.co/blog/how-to-generate

Neural sequence modeling

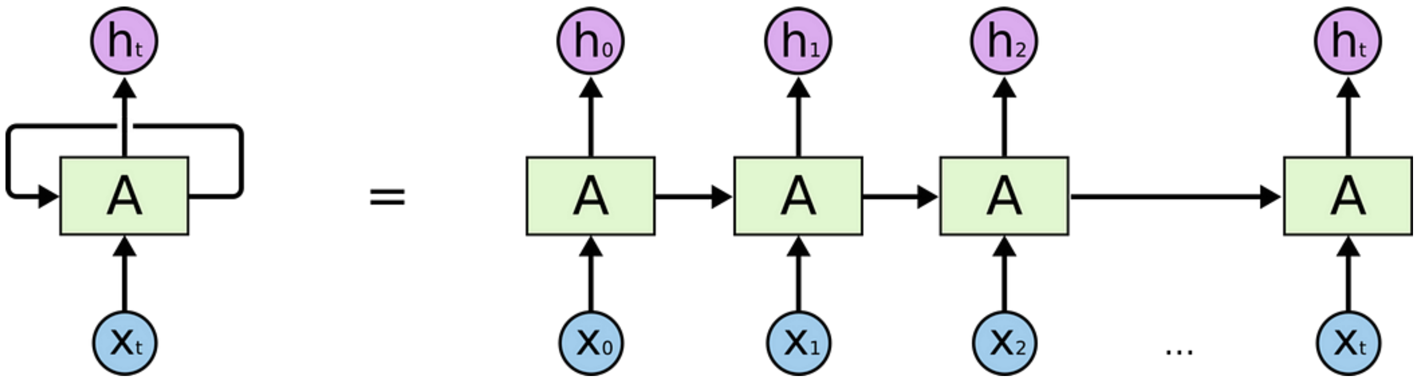


Problems:

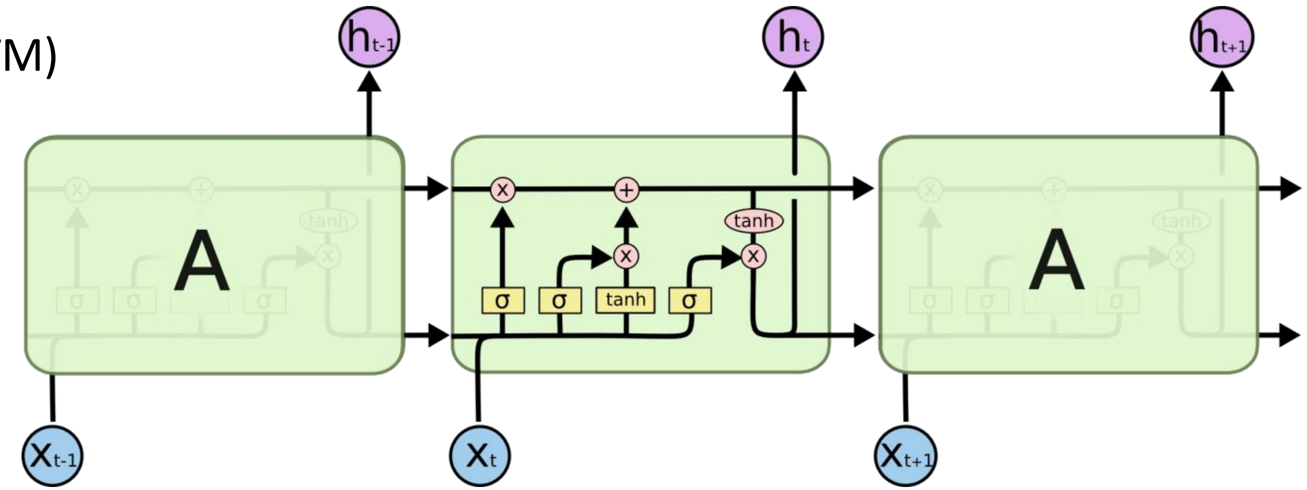
- How do we deal with different length inputs?
- How do we model long-range dependencies?

Recurrent Neural Networks

- Standard RNN

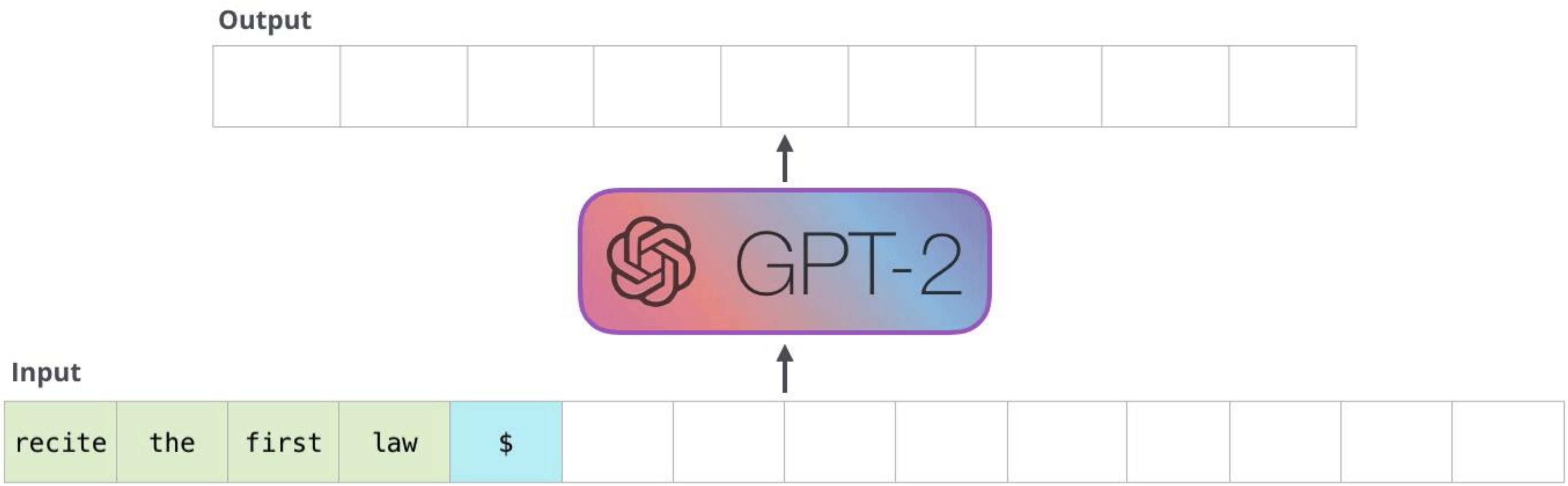


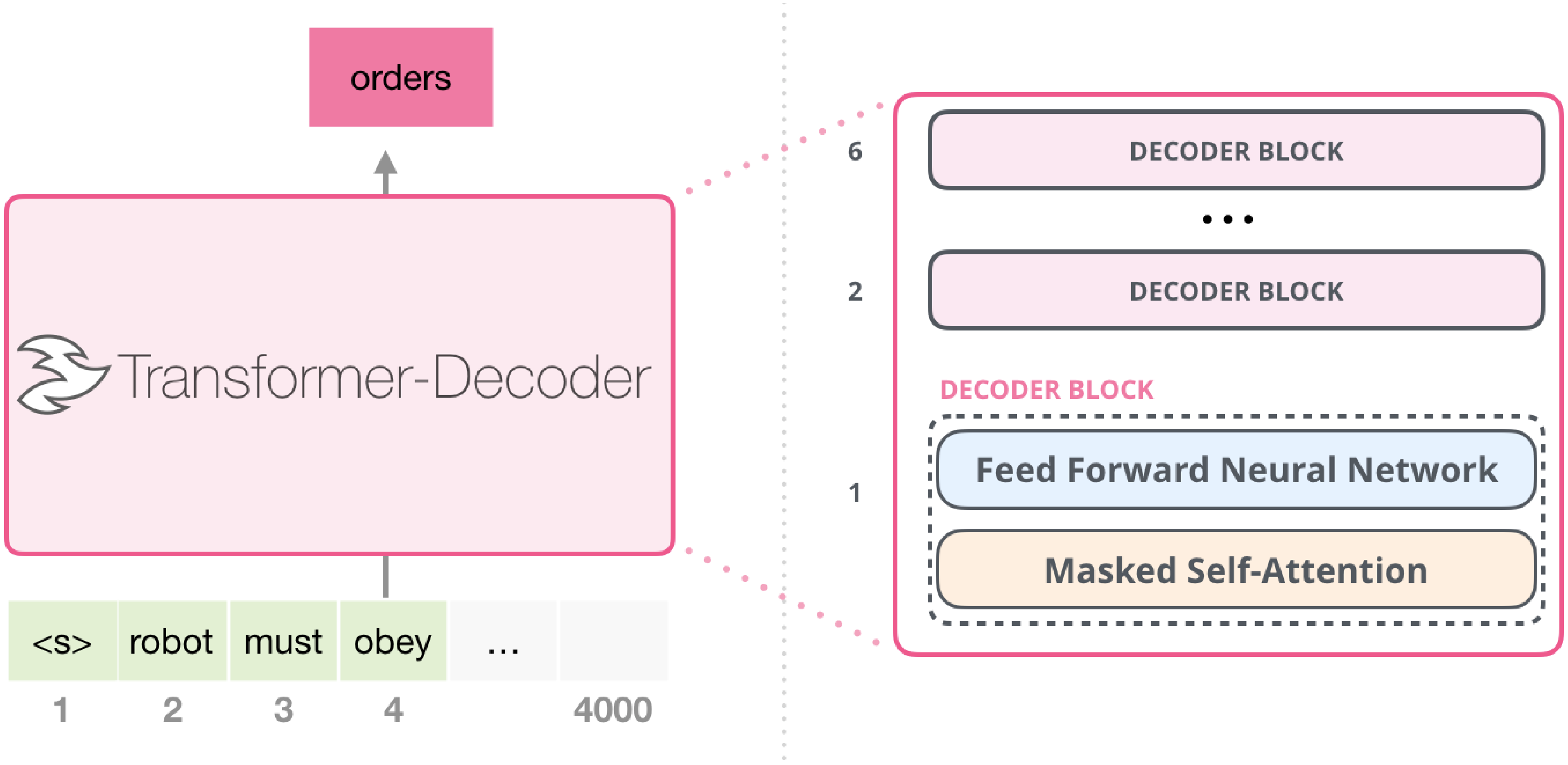
- Long short-term memory (LSTM)

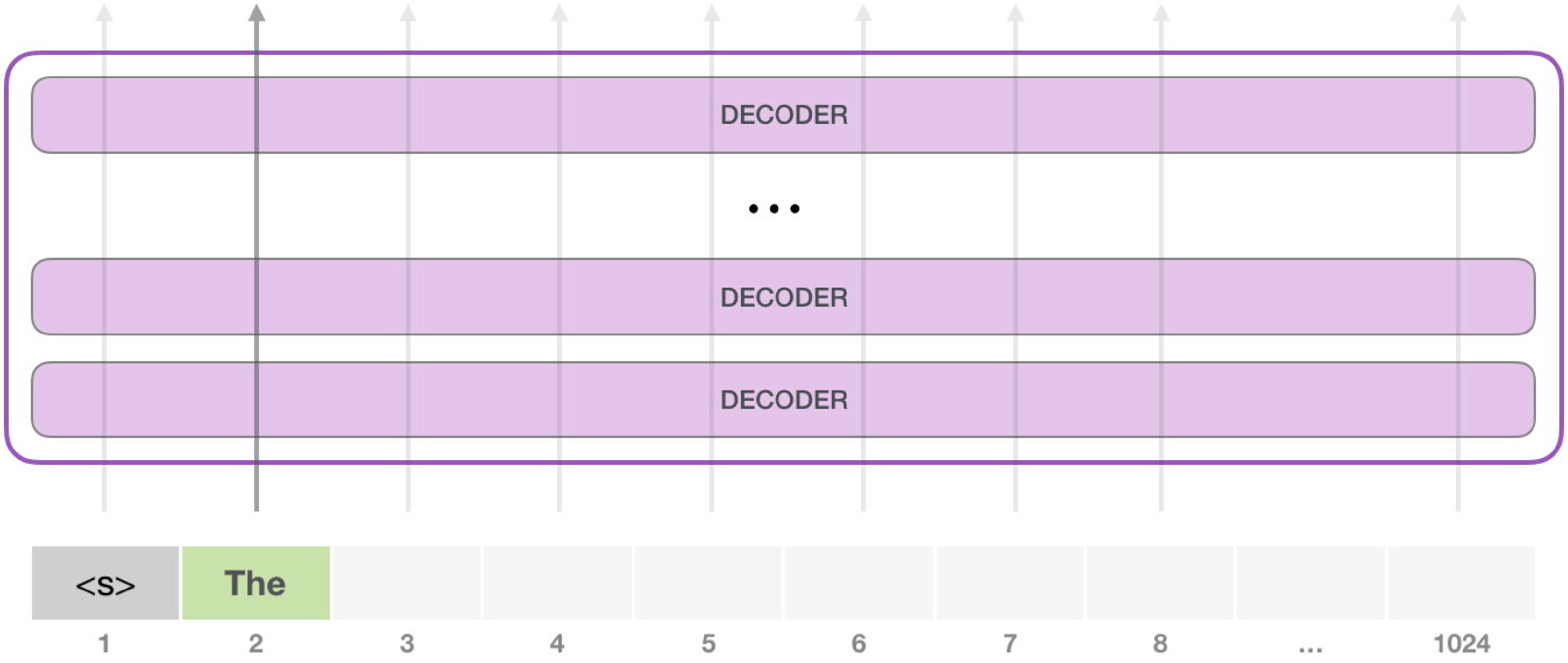


https://colah.github.io/posts/2015-08-Understanding-LSTMs/

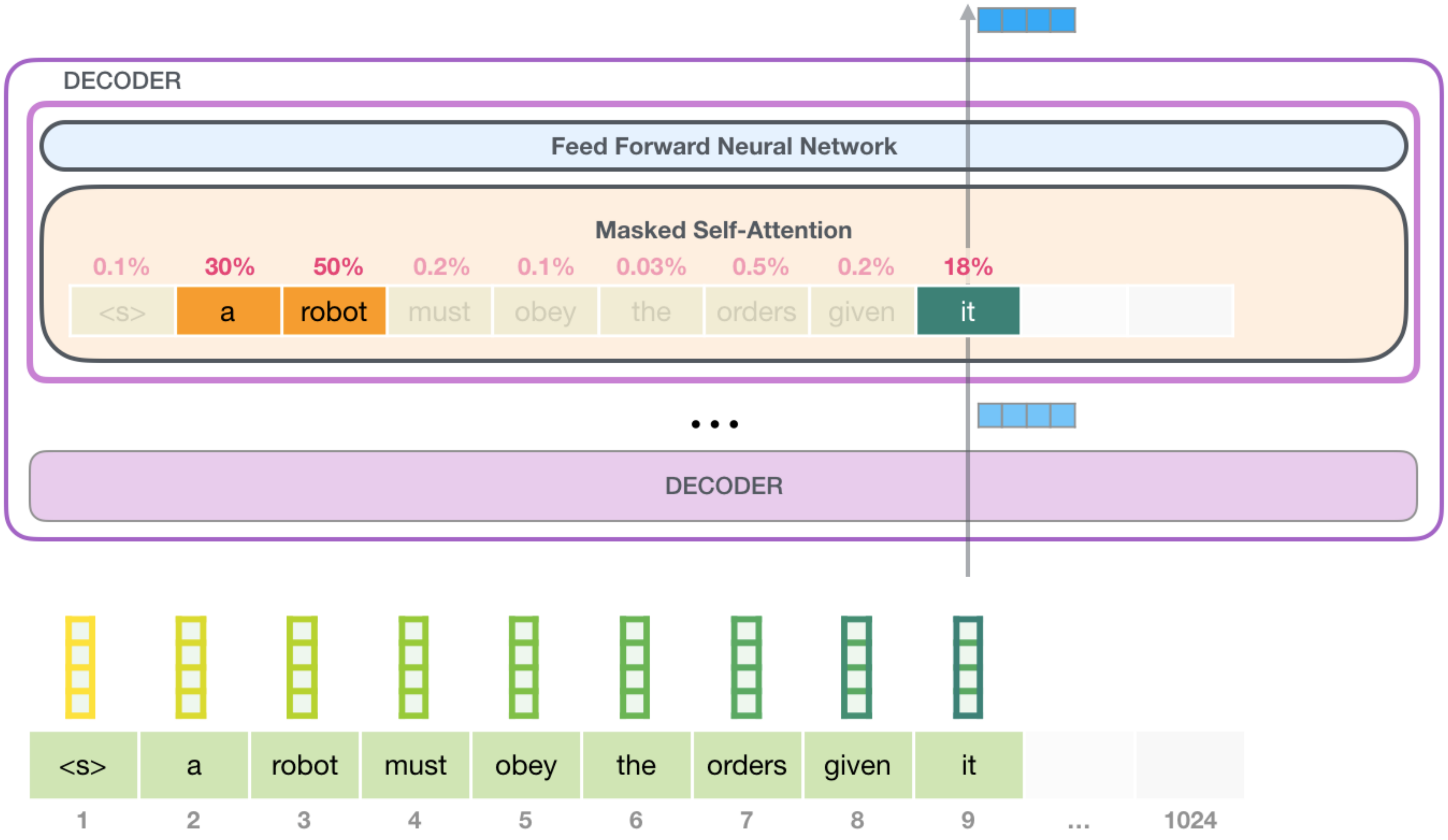
Large Language Models



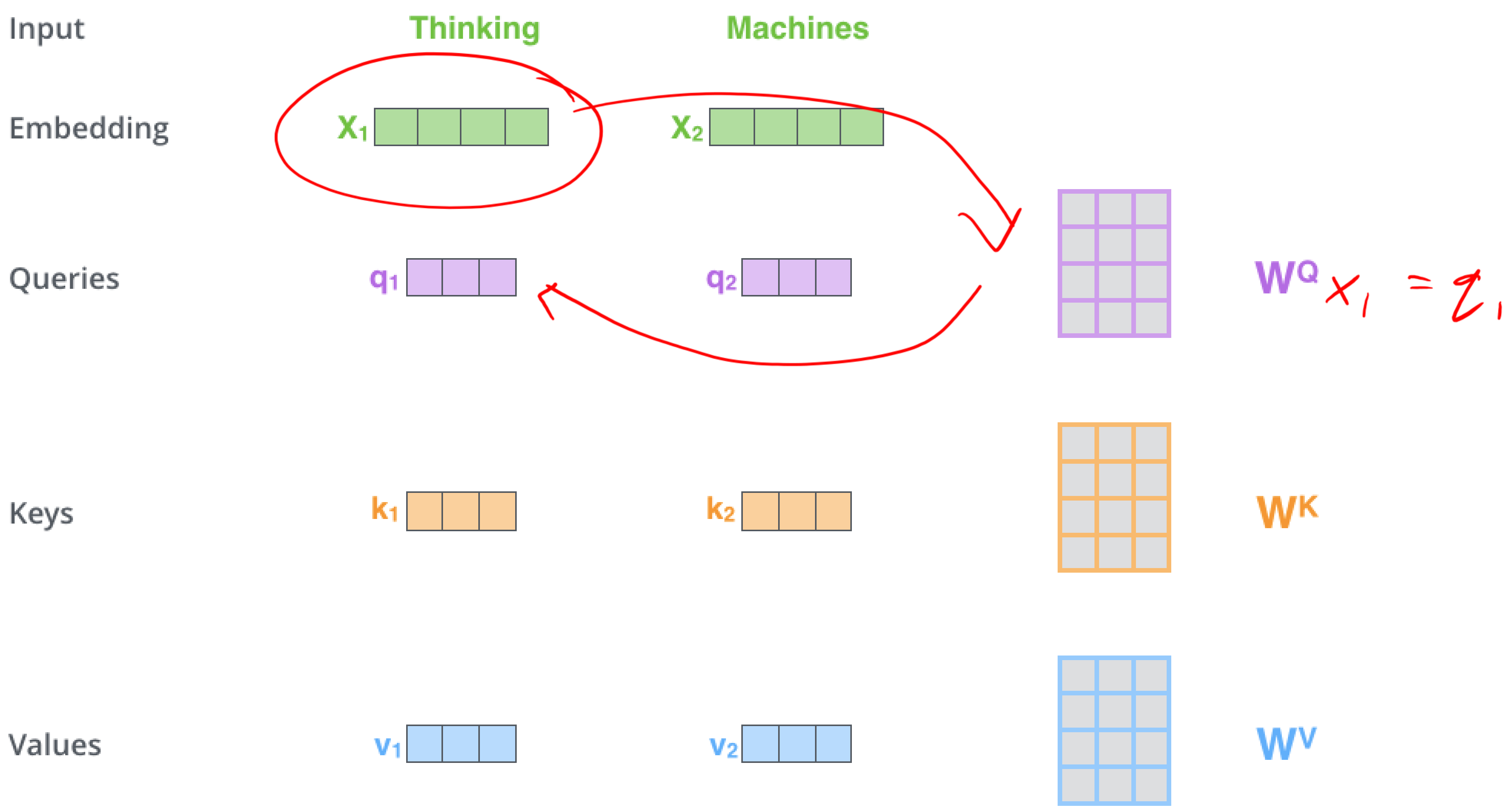

orders
Transformer-Decoder
<s>
robot
must
obey
...
1
2
3
4
4000
6
DECODER BLOCK
2
DECODER BLOCK
DECODER BLOCK
1
Feed Forward Neural Network
Masked Self-Attention


DECODER
DECODER
DECODER
<s>
The
1
2
3
4
5
6
7
8
...
1024


DECODER
DECODER
Positional encoding for token #1
Token embedding of <s>
<s>
1
2
...
1024
Token Embeddings
Positional Encodings

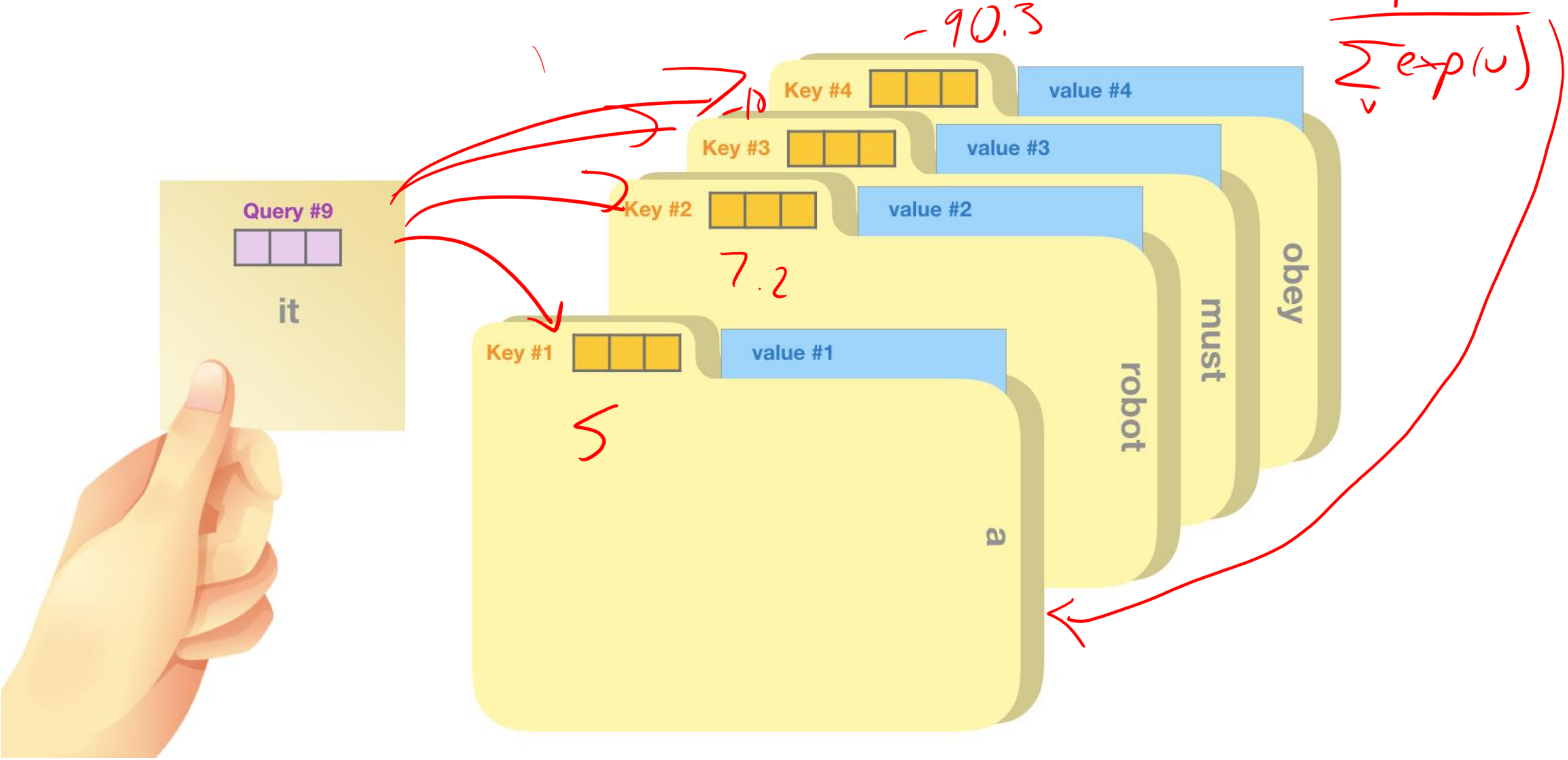


DECODER
Feed Forward Neural Network
Masked Self-Attention
0.1%
30%
50%
0.2%
0.1%
0.03%
0.5%
0.2%
18%
<s>
a
robot
must
obey
the
orders
given
it
• • •
DECODER
<s>
a
robot
must
obey
the
orders
given
it
1
2
3
4
5
6
7
8
9
...
1024

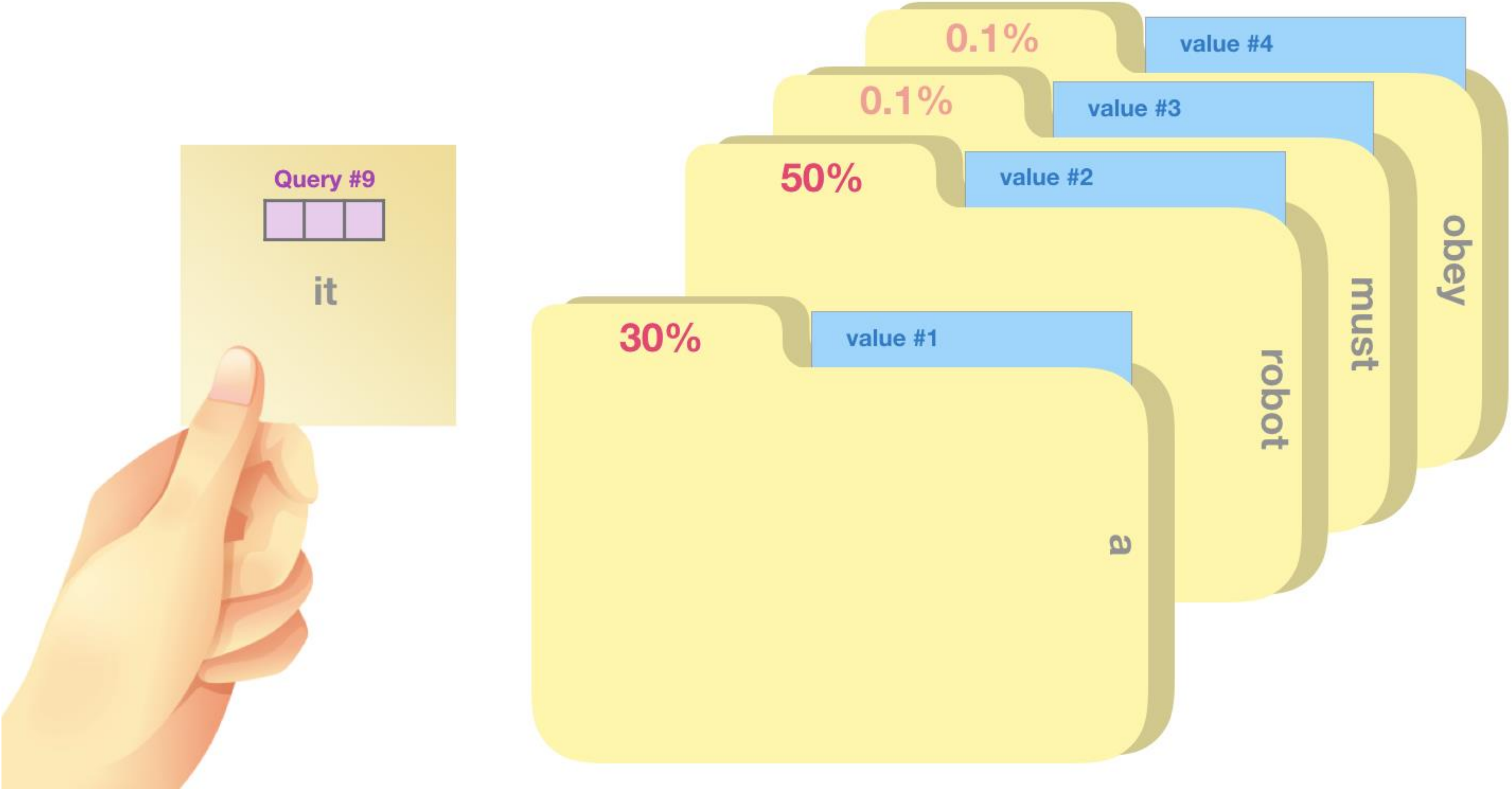


Input
Thinking
Machines
Embedding
X1
X2
Queries
q1
q2
WQ
Keys
k1
k2
WK
Values
v1
v2
WV

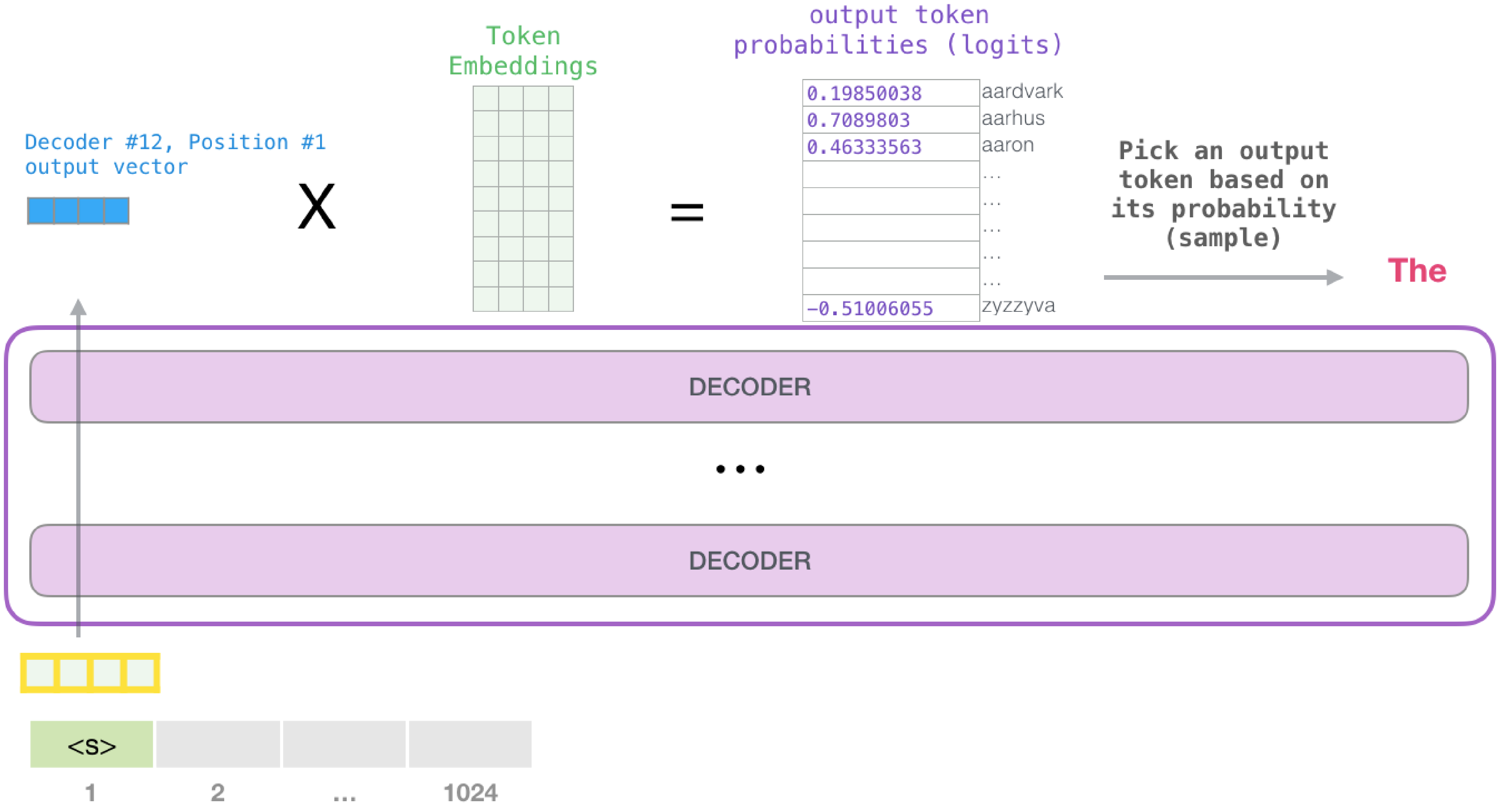
Perform dot product between query and all keys to get a raw score for each previous word (including current word).

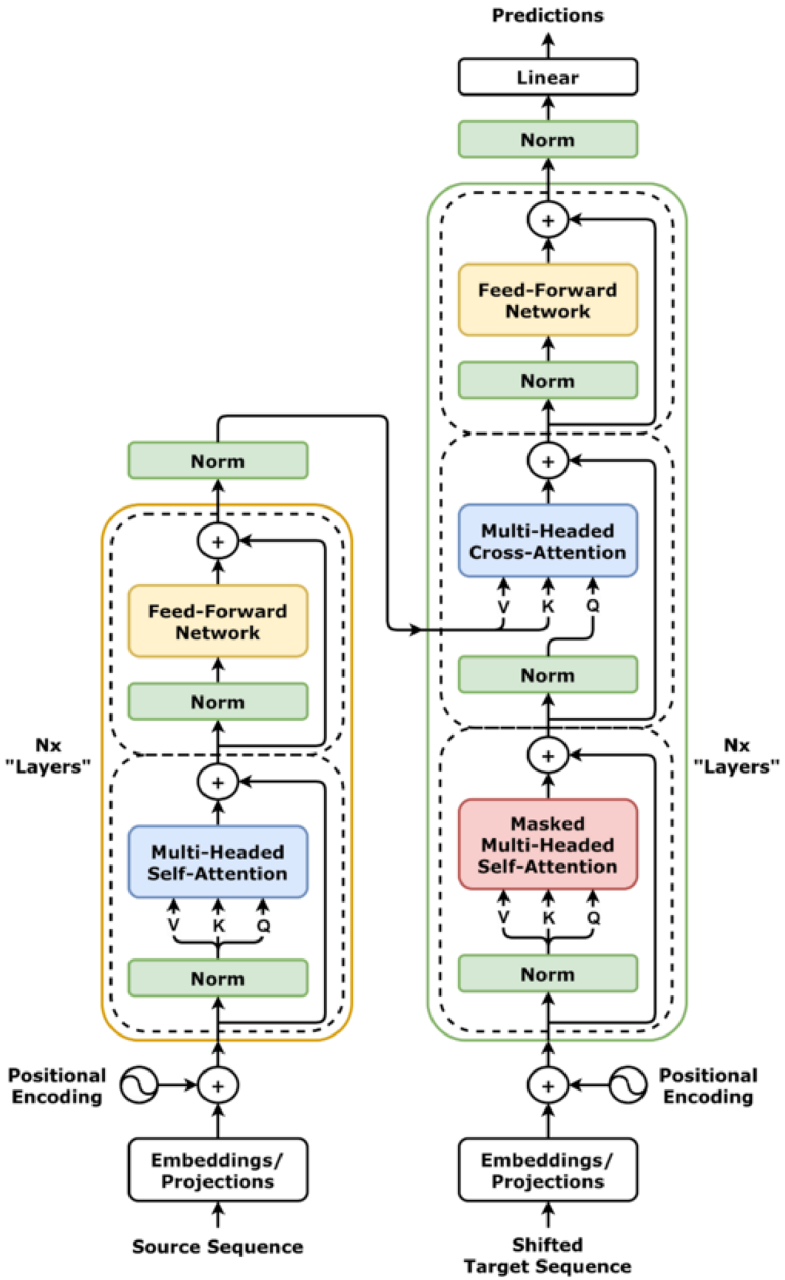


Normalize these scores via a softmax to get a probability distribution. Then return a weighted sum of the values.



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:	


Decoder #12, Position #1
output vector
X
Token
Embeddings
=
output token
probabilities (logits)
0.19850038 aardvark
0.7089803 aarhus
0.46333563 aaron
...
...
...
...
...
-0.51006055 zyzzyva
Pick an output
token based on
its probability
(sample)
The
DECODER
DECODER
<s>
1
2
...
1024


Predictions
Linear
Norm
Feed-Forward Network
Norm
Multi-Headed Cross-Attention
V K Q
Norm
Masked Multi-Headed Self-Attention
V K Q
Norm
Nx "Layers"
Positional Encoding
Embeddings/ Projections
Shifted Target Sequence
Norm
Feed-Forward Network
Norm
Multi-Headed Self-Attention
V K Q
Norm
Nx "Layers"
Positional Encoding
Embeddings/ Projections
Source Sequence

Diffusion Policy

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

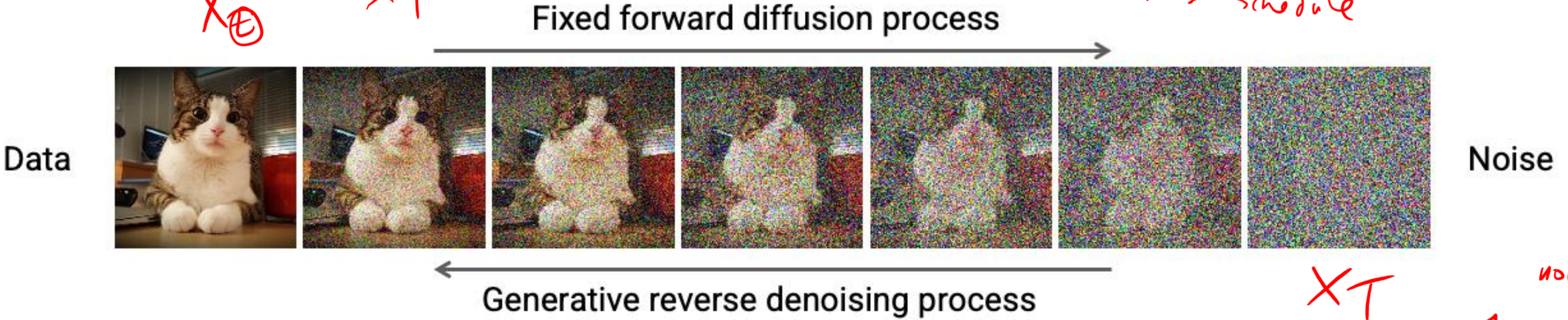
Denoising Diffusion (high-level)

$\alpha_t = 0 \rightarrow \mathcal{N}(0, I)$

$P(x_{t+1} | x_t) = \mathcal{N}(x_t | \sqrt{\alpha_t}\, x_t, (1-\alpha_t) I)$

↑ noise schedule

x_0 x_1



x_T noise

$x_{T-1} = x_T - \hat{\epsilon}_T + \gamma$

Gradient descent

$t \rightarrow \square \rightarrow \hat{\epsilon}$

$x_t \rightarrow$

t ϵ_t

$MSE = \min_\theta || \hat{\epsilon}_\theta(t, x_t) - \epsilon_t ||^2$