CSE 291 – AI Agents
2/11 – Attention and Language Modeling

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Thanks to Lillian Weng, Abby Morgan, Jay Alamar, and Brandon Amos.
Some slides were adapted form their courses / blogs.

Model Free vs Model Based RL

- Model-Free RL
  - No model
  - Learn value function (and/or policy) from experience
- Model-Based RL
  - Learn a model from experience
  - Plan value function (and/or policy) from model

Sample Based Planning

- A simple but powerful approach to planning
- Use the model only to generate samples
- Sample experience from model

  $S_{t+1} \sim T_\eta(S_{t+1} \mid S_t , A_t)$

  $R_{t+1} = R_\eta(R_{t+1} \mid S_t , A_t)$

- Apply model-free RL to samples, e.g.: Monte-Carlo control Sarsa Q-learning
- Sample-based planning methods are often more efficient

What is a Model?

- A model M is a representation of an MDP <S, A,T, R>, parametrized by η
- We will assume state space S and action space A are known
- So a model $M = <T_\eta, R_\eta>$ represents state transitions $T_\eta \approx T$ and rewards $R\eta \approx R$

$$S_{t+1} \sim P\eta(S_{t+1} \mid S_t , A_t)$$

$$R_{t+1} = R\eta(R_{t+1} \mid S_t , A_t)$$

- Typically assume conditional independence between state transitions and rewards

$$P\, [S_{t+1}, R_{t+1} \mid S_t , A_t] = P[S_{t+1} \mid S_t , A_t]\, P[R_{t+1} \mid S_t , A_t]$$

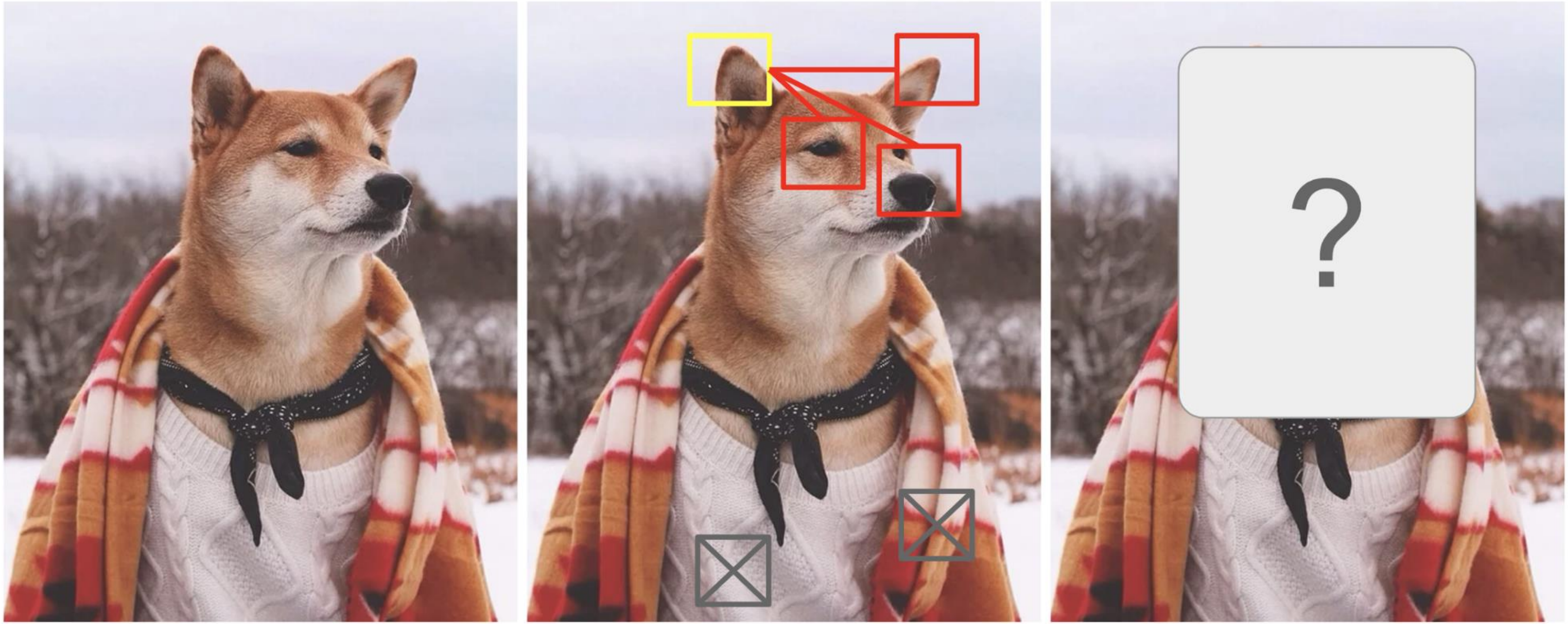
Pros and Cons of MBRL

- Pros
  - Can do all the (self, un) supervised learning tricks to learn from large scale data
  - Can reason about uncertainty
- Cons
  - Need model of T first
  - Will build estimate of value from that
  - Two(+) sources of error

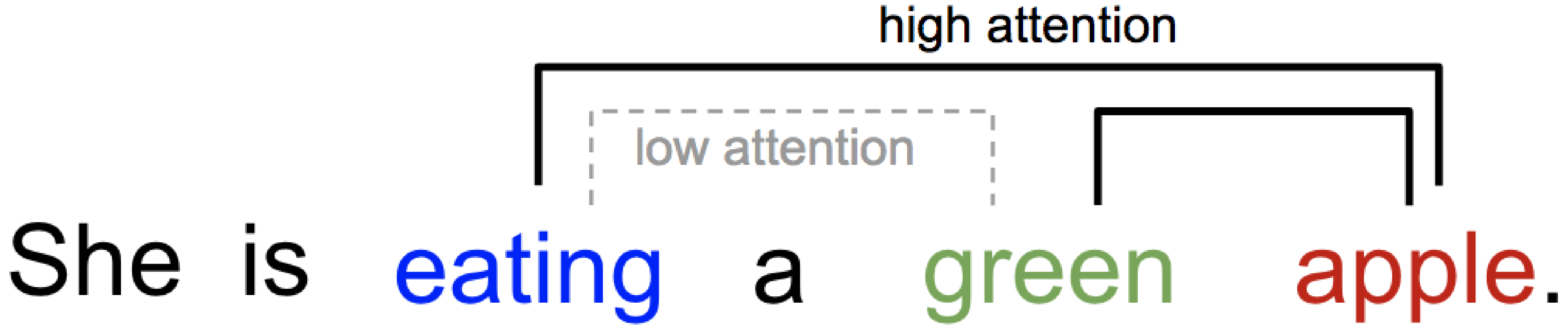
Simultaneous Bottlenecks of Deep RL

- The function approximator needs to be “good” for the task
- CNNs were great for Atari and then Go
- Why did they never work for language?

Pay Attention

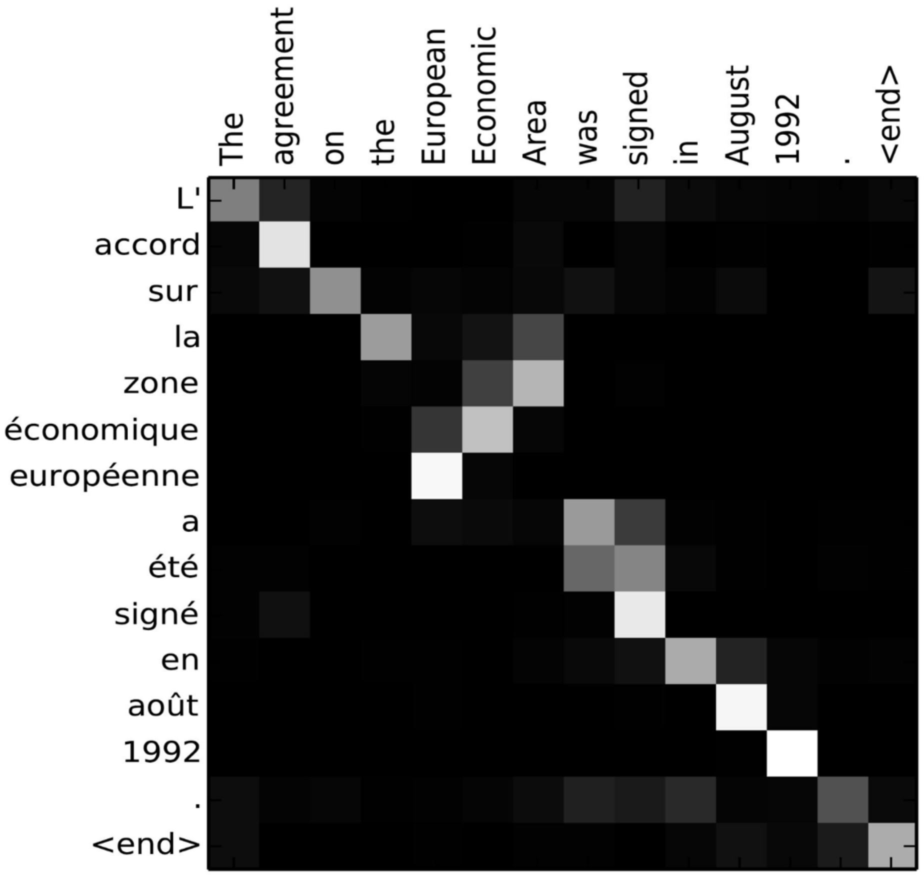


Pay Attention to your Words



Deep Learning Attention

- A vector of importance weights over an input sequence



Attention Alignment

$$\mathbf{x} = [x_1, x_2, \ldots, x_n]$$
$$\mathbf{y} = [y_1, y_2, \ldots, y_m]$$

$$\mathbf{c}_t = \sum_{i=1}^{n} \alpha_{t,i} \boldsymbol{h}_i \qquad \text{; Context vector for output } y_t$$

$$\alpha_{t,i} = \text{align}(y_t, x_i) \qquad \text{; How well two words } y_t \text{ and } x_i \text{ are aligned.}$$

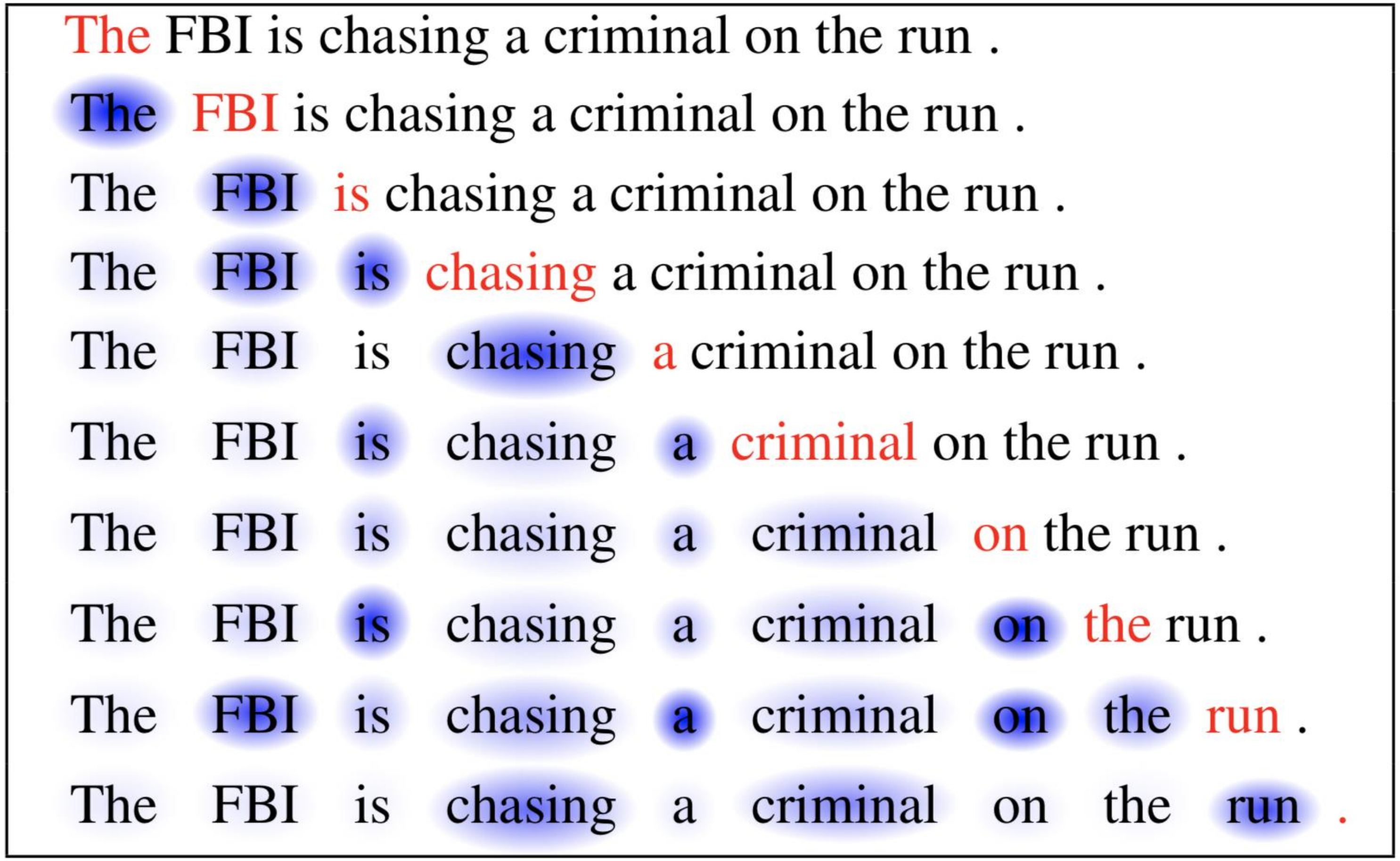
$$= \frac{\exp(\text{score}(\boldsymbol{s}_{t-1}, \boldsymbol{h}_i))}{\sum_{i'=1}^{n} \exp(\text{score}(\boldsymbol{s}_{t-1}, \boldsymbol{h}_{i'}))} \qquad \text{; Softmax of some predefined alignment score..}$$

Types of Attention (pre Vaswani)

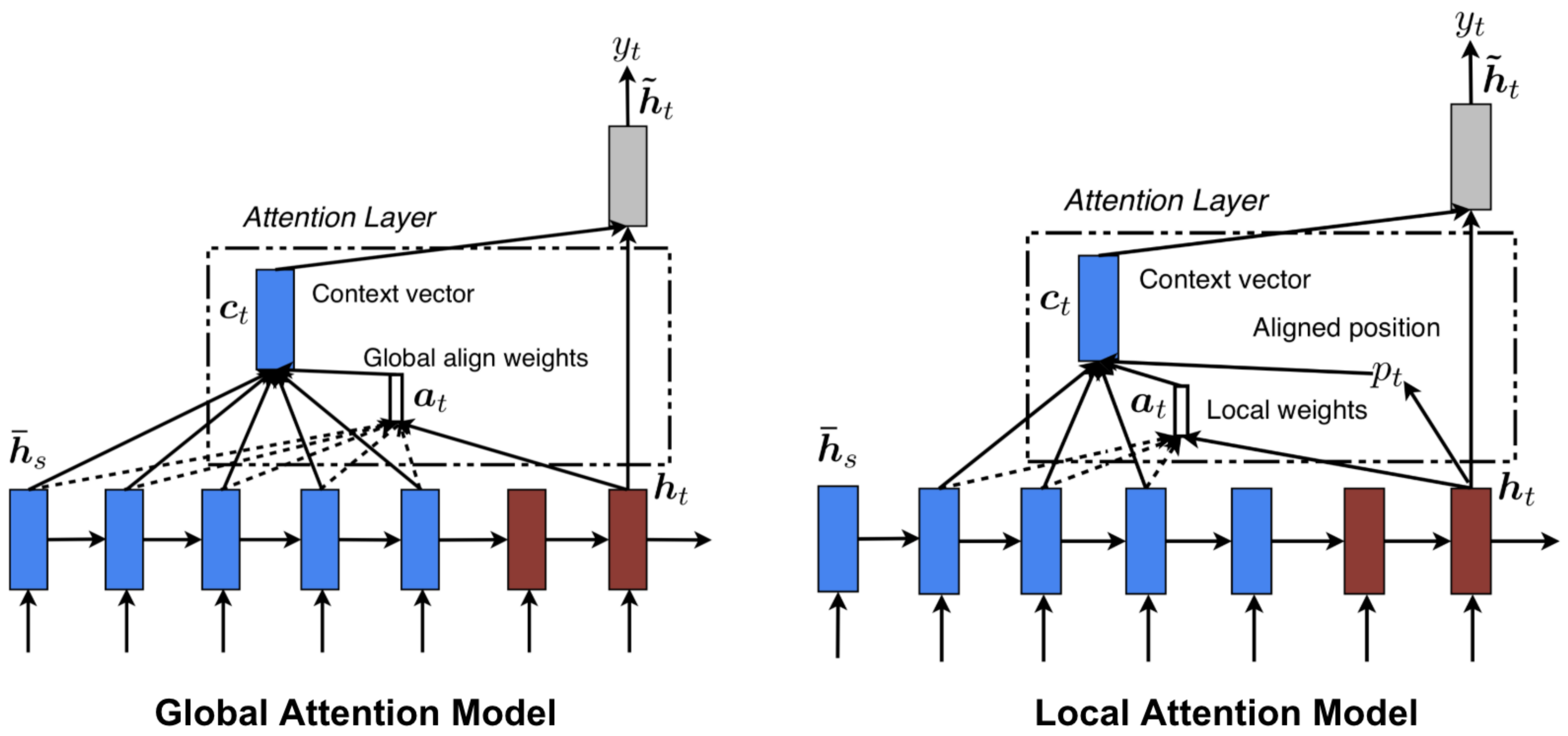
Name	Alignment score function	Citation
Content-base attention	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \text{cosine}[\boldsymbol{s}_t, \boldsymbol{h}_i]$	Graves2014
Additive(*)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \mathbf{v}_a^\top \tanh(\mathbf{W}_a[\boldsymbol{s}_{t-1}; \boldsymbol{h}_i])$	Bahdanau2015
Location-Base	$\alpha_{t,i} = \text{softmax}(\mathbf{W}_a \boldsymbol{s}_t)$ Note: This simplifies the softmax alignment to only depend on the target position.	Luong2015
General	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \mathbf{W}_a \boldsymbol{h}_i$ where $\mathbf{W}_a$ is a trainable weight matrix in the attention layer.	Luong2015
Dot-Product	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \boldsymbol{h}_i$	Luong2015
Scaled Dot-Product(^)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \frac{\boldsymbol{s}_t^\top \boldsymbol{h}_i}{\sqrt{n}}$ Note: very similar to the dot-product attention except for a scaling factor; where n is the dimension of the source hidden state.	Vaswani2017

Self Attention

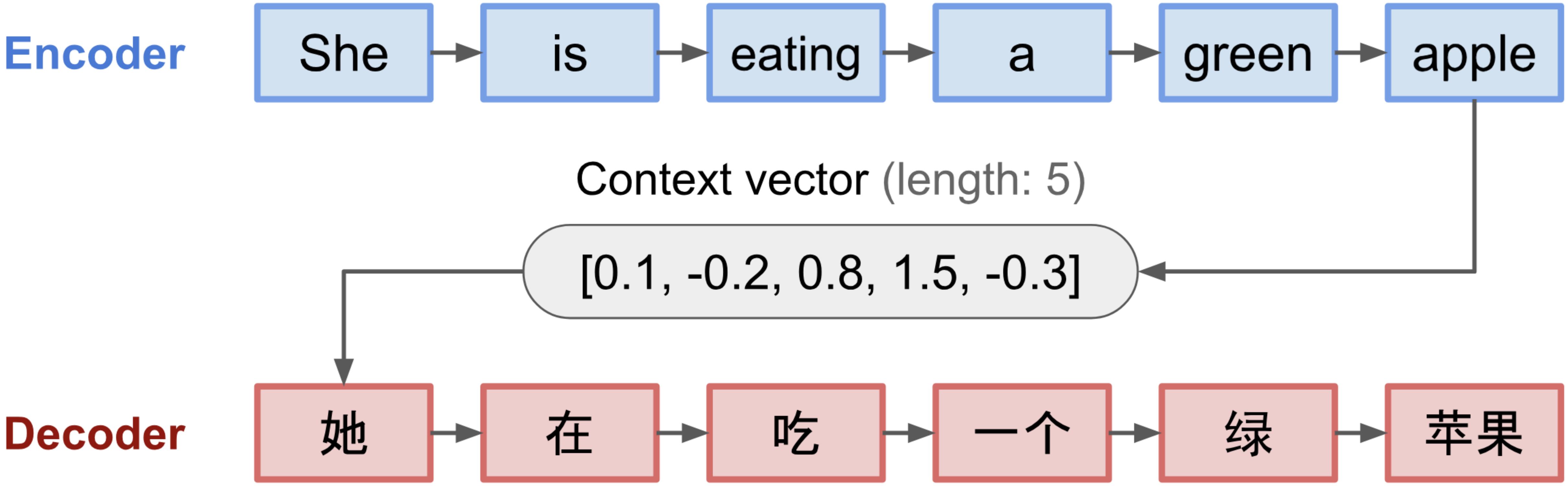
- Different parts of the same sequence attend to each other
- Previously it was all one sequence to another
- Proposed by Cheng et al 2016

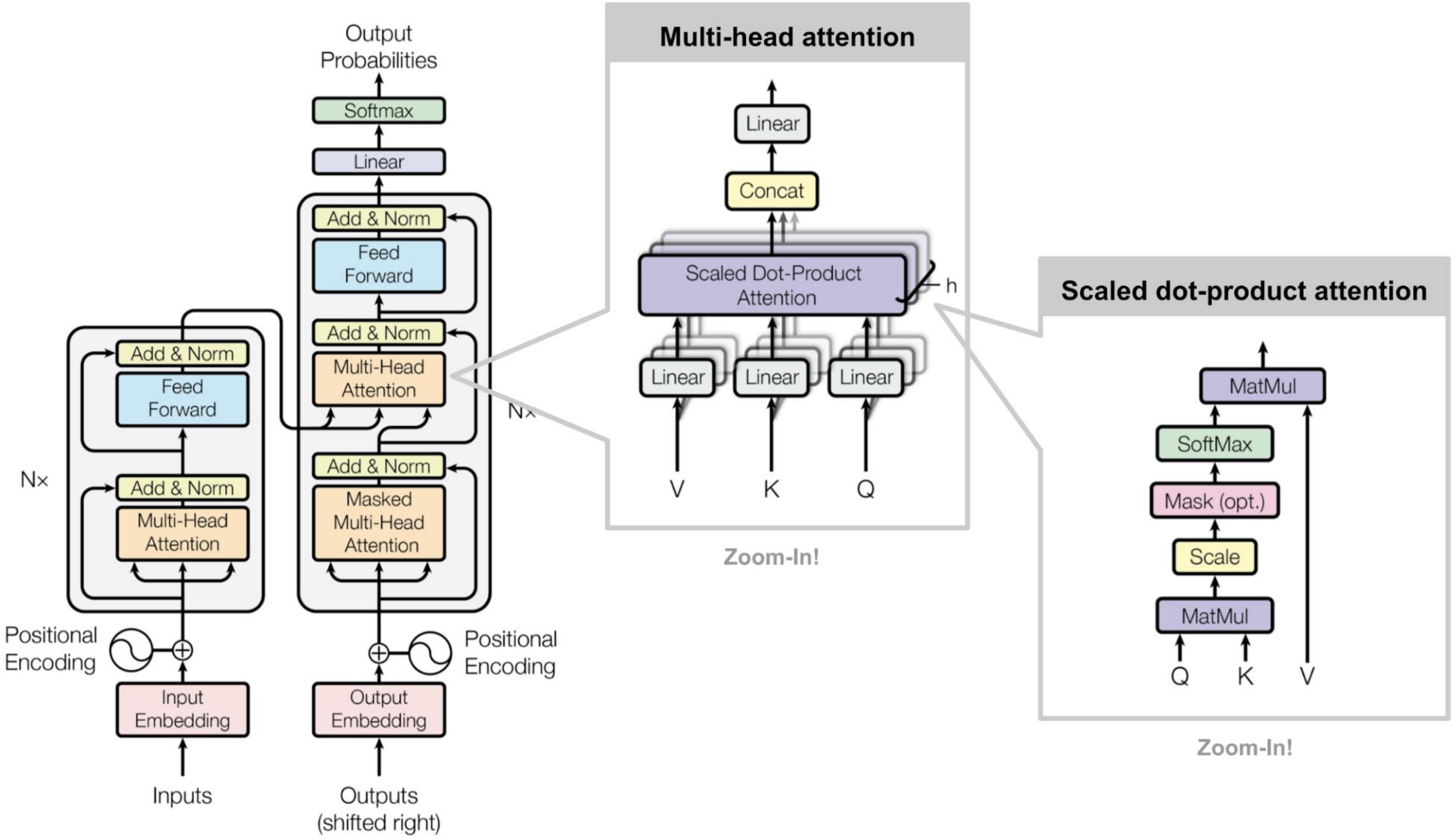


Global vs Local Attention (Luong et al. 2015)



Encoder Decoder RNN Failures

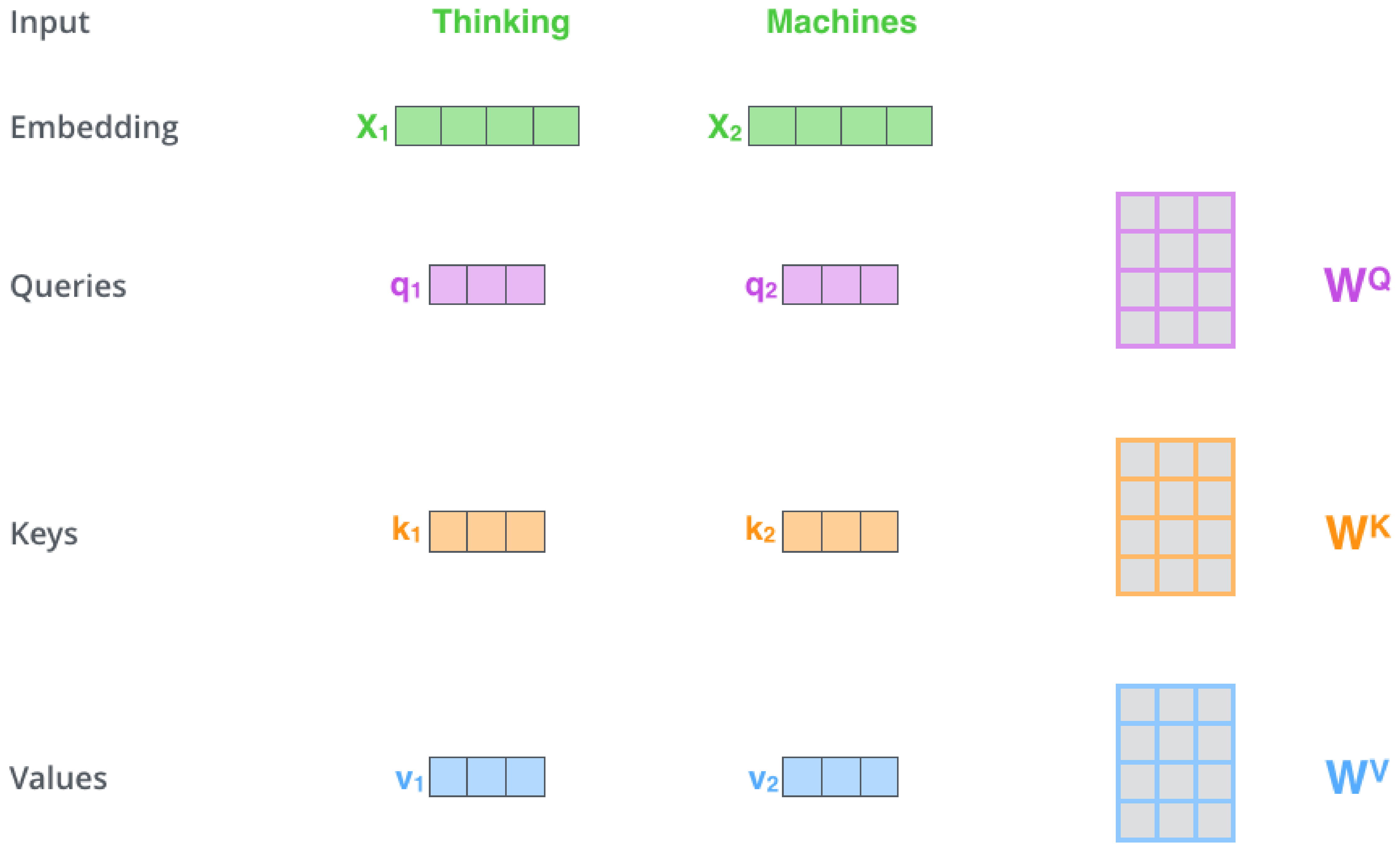


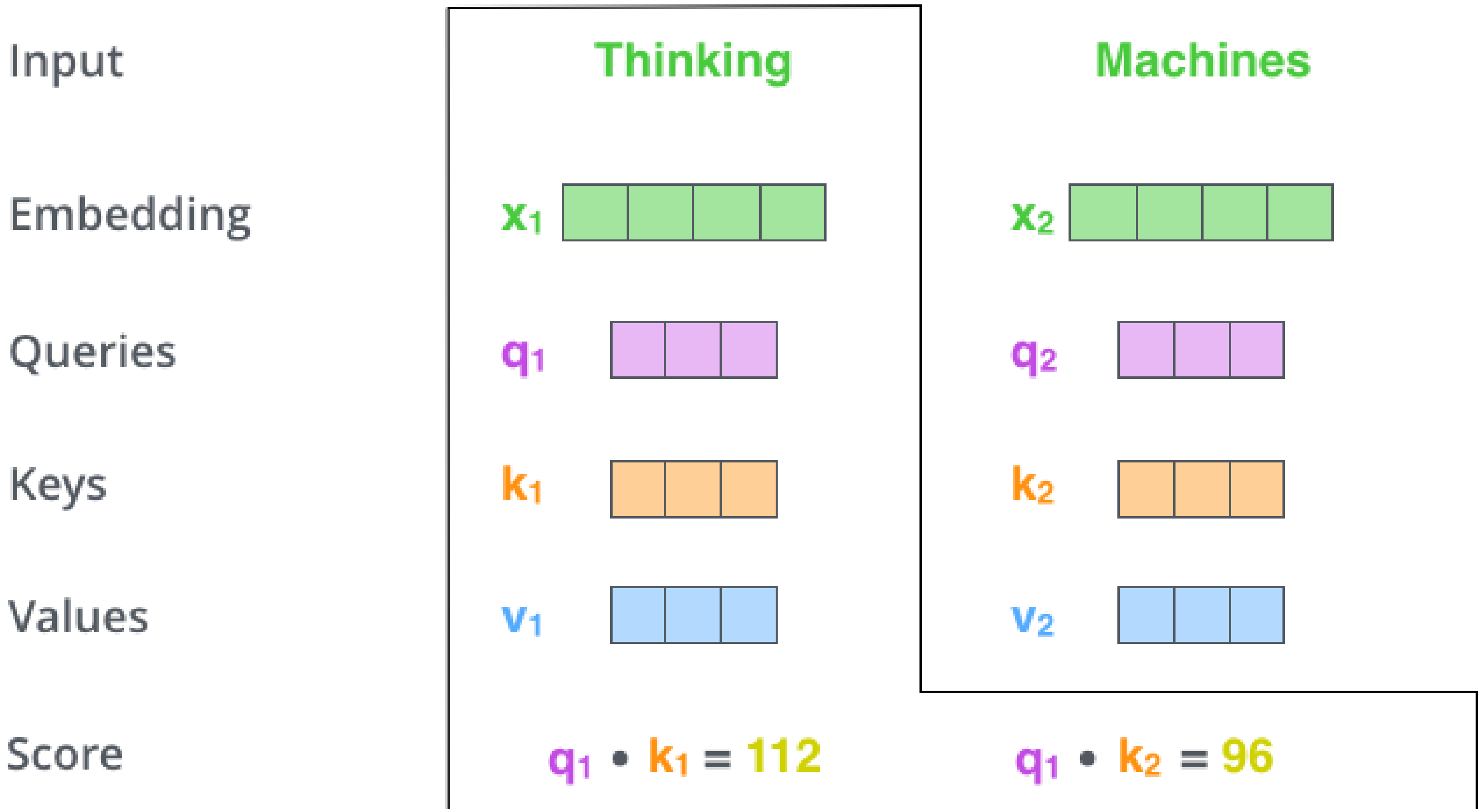

Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)
Multi-head attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
V
K
Q
Zoom-In!
Scaled dot-product attention
MatMul
SoftMax
Mask (opt.)
Scale
MatMul
Q
K
V
Zoom-In!

Scaled Dot Product Attention

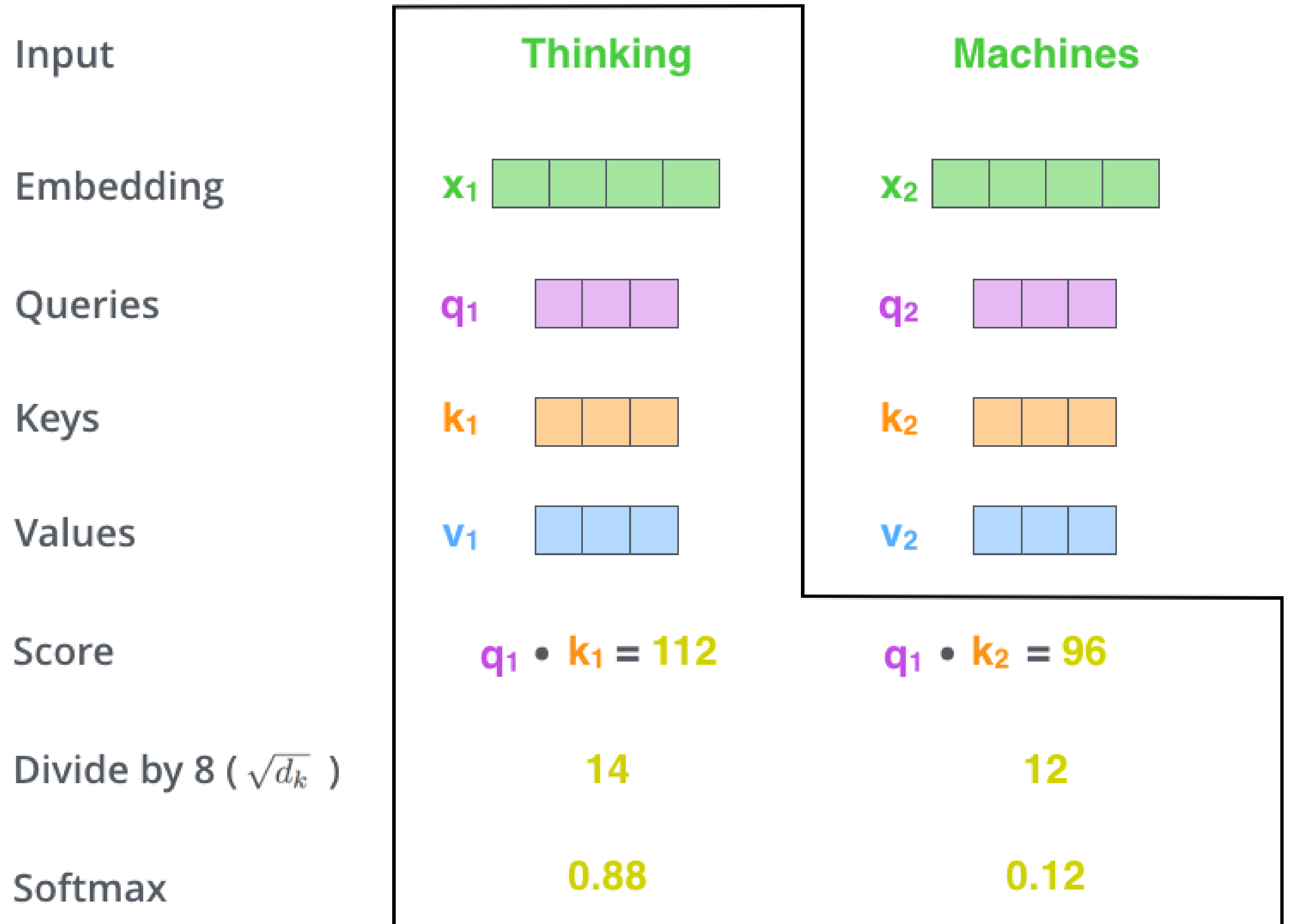
For each input word we create a query, key, value vector

- Query: What are the things I am looking for?
- Key: What are the things that I have?
- Value: What are the things that I will communicate?

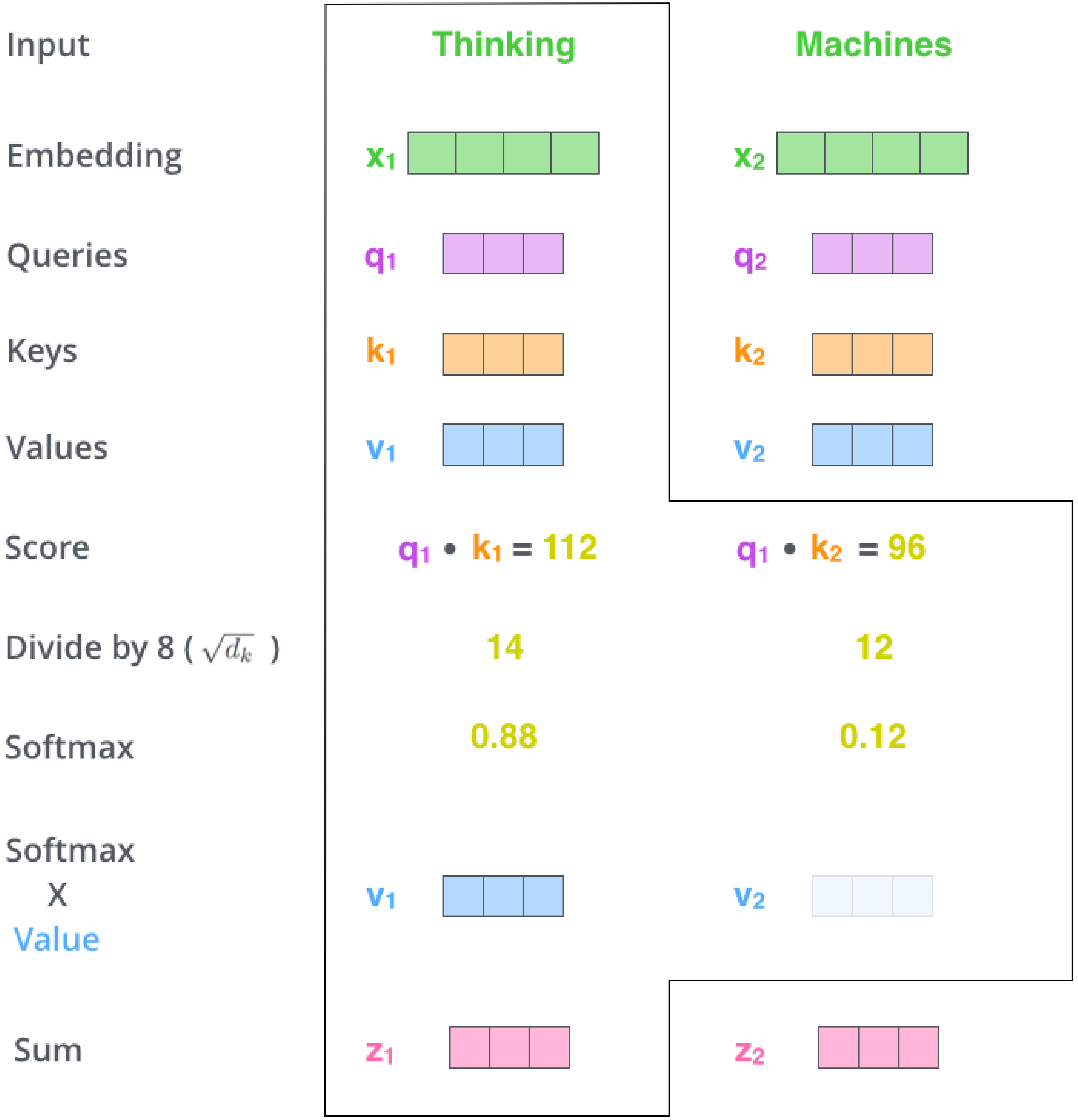

Input
Thinking
Machines
Embedding
X_1
X_2
Queries
q_1
q_2
W^Q
Keys
k_1
k_2
W^K
Values
v_1
v_2
W^V



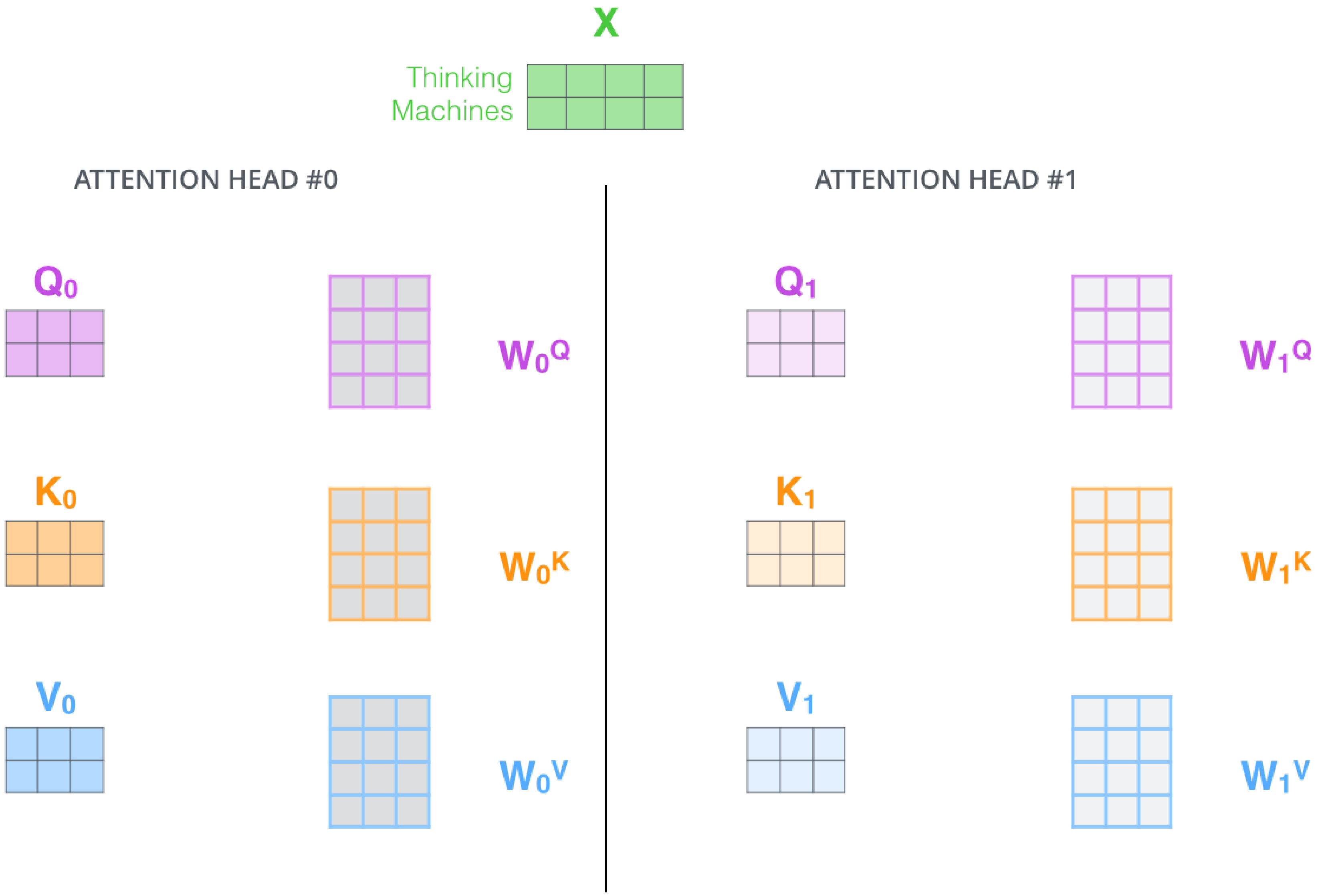
Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96

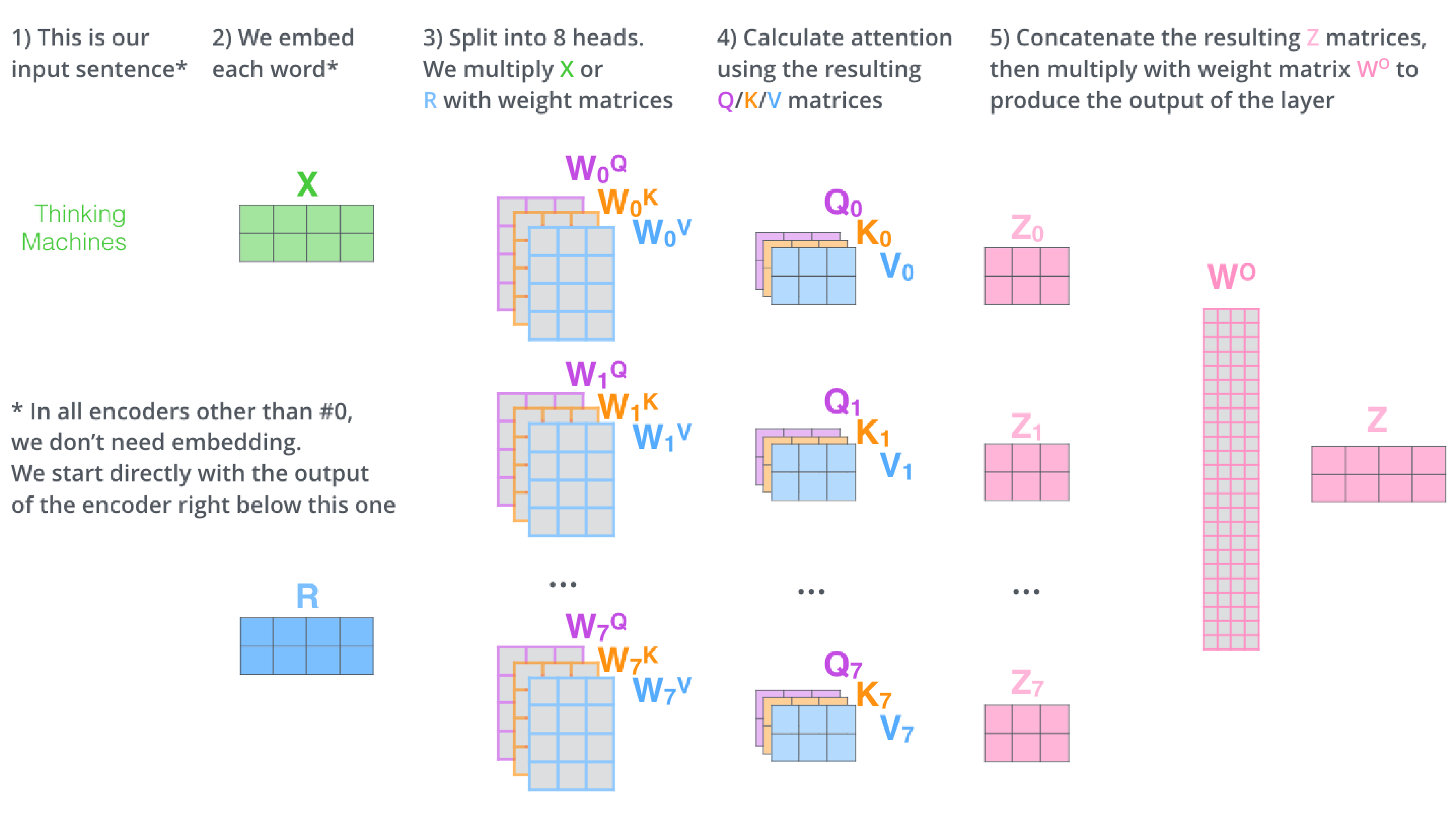


Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12


Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12
Softmax
X
Value
v1
v2
Sum
z1
z2

Multi-Head Attention

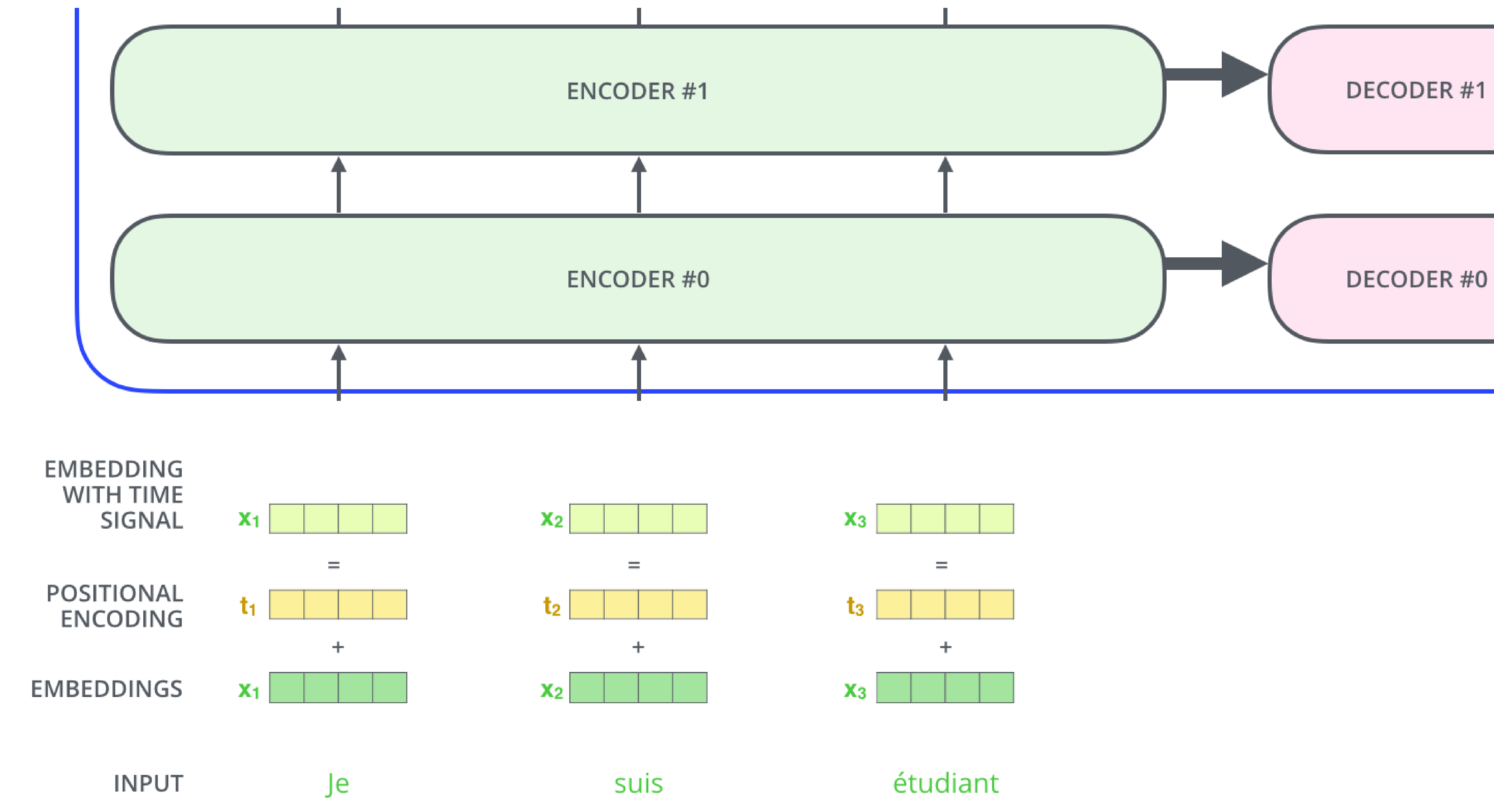


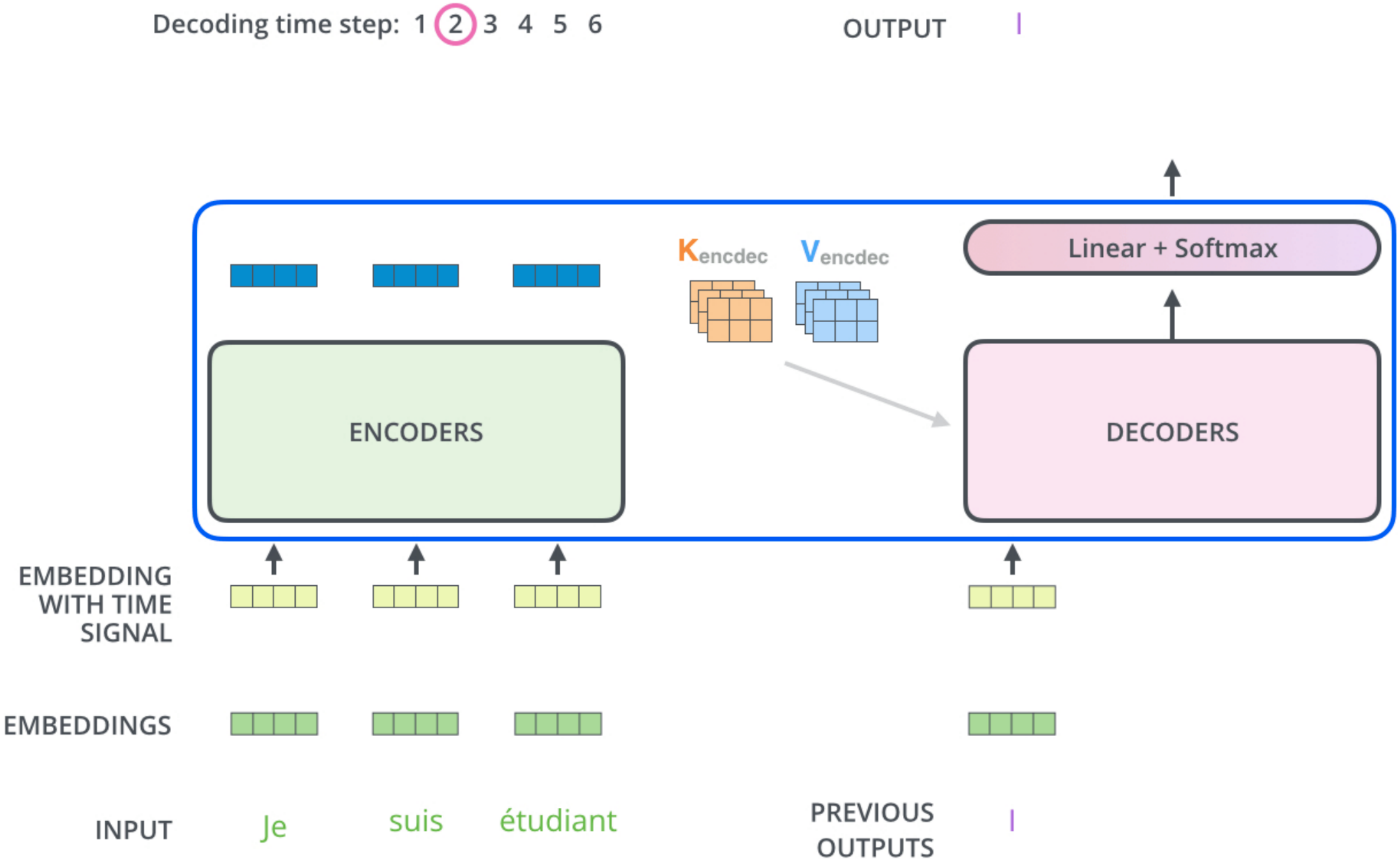

1) This is our input sentence*
2) We embed each word*
3) Split into 8 heads. We multiply X or R with weight matrices
4) Calculate attention using the resulting Q/K/V matrices
5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer
Thinking Machines
X
R
* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one
W0Q
W0K
W0V
W1Q
W1K
W1V
W7Q
W7K
W7V
Q0
K0
V0
Q1
K1
V1
Q7
K7
V7
Z0
Z1
Z7
WO
Z

Position Encoding and Tokenizers

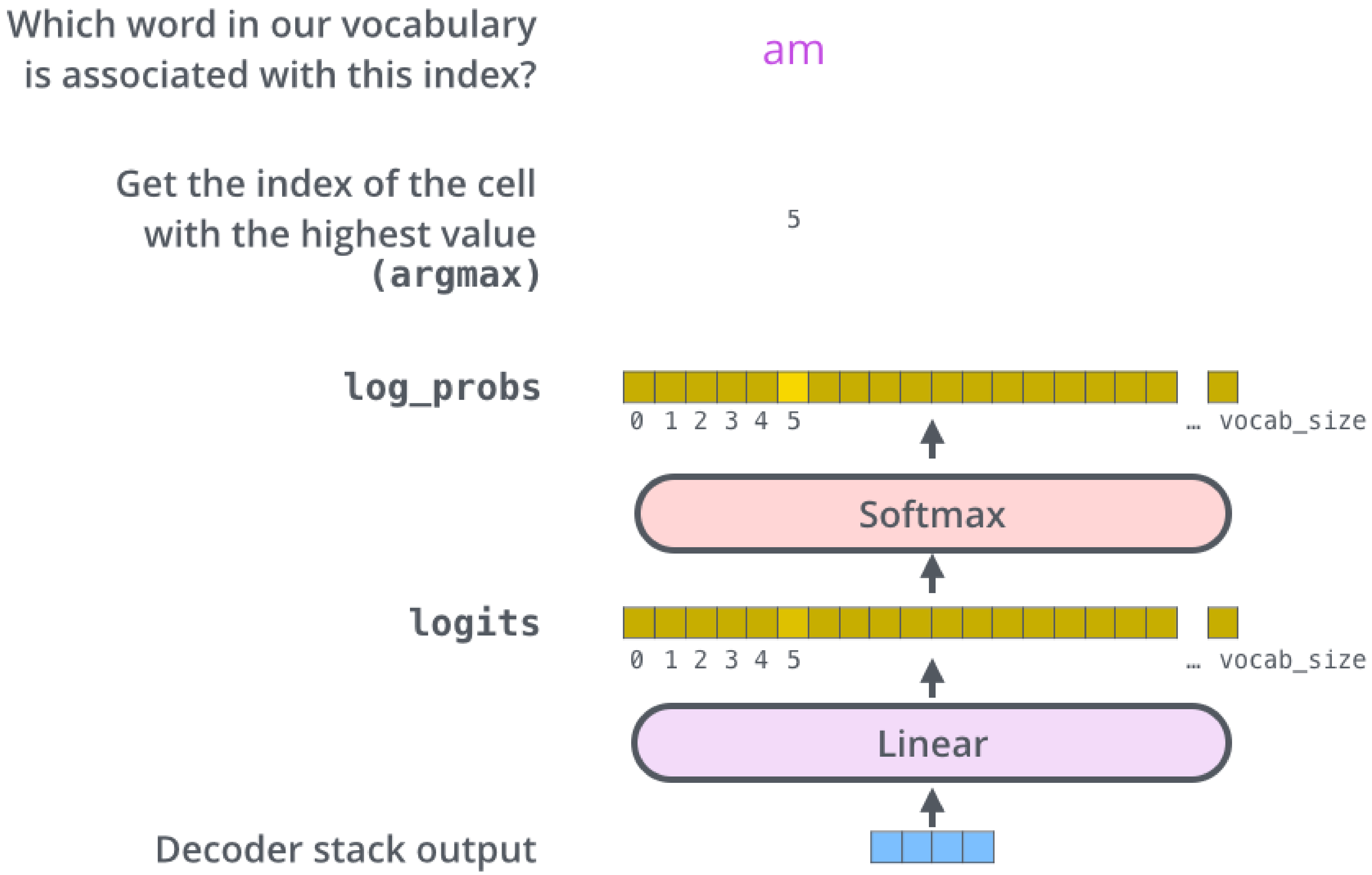
Transformer attention as seen so far is position invariant

- Position of a word in a sentence matters, how to encode this?
- How to deal with out of vocabulary words? i.e. how to split the input sequence


ENCODER #1
DECODER #1
ENCODER #0
DECODER #0
EMBEDDING WITH TIME SIGNAL
x1
x2
x3
=
POSITIONAL ENCODING
t1
t2
t3
+
EMBEDDINGS
x1
x2
x3
INPUT
Je
suis
étudiant



Decoding time step: 1 2 3 4 5 6
OUTPUT
I
Linear + Softmax
K_{encdec}
V_{encdec}
ENCODERS
DECODERS
EMBEDDING WITH TIME SIGNAL
EMBEDDINGS
INPUT
Je
suis
étudiant
PREVIOUS OUTPUTS
I



Which word in our vocabulary
is associated with this index?
am
Get the index of the cell
with the highest value
(argmax)
5
log_probs
0 1 2 3 4 5
… vocab_size
Softmax
logits
0 1 2 3 4 5
… vocab_size
Linear
Decoder stack output

Tokenization

Word Level

Deep Learning → Deep Learning

Character Level

Deep Learning → D e e p L e a r n i n g

Subword Level

Deep Learning → De ep Learn ##ing

Tokenization

- Subword (Tiktoken Byte Pair Encoding BPE) is the industry standard
- Learned from a representative subset of data

Tokenization (the bane of my existence)

- Many problems you think are LLM limitations are actually (partially) tokenizer issues
- E.g. Is 9.9 greater than 9.11?

    9 . 9 and 9 . 11

    compare initial 9

    compare .

    compare 9 and 11, wait 11 is greater than 9

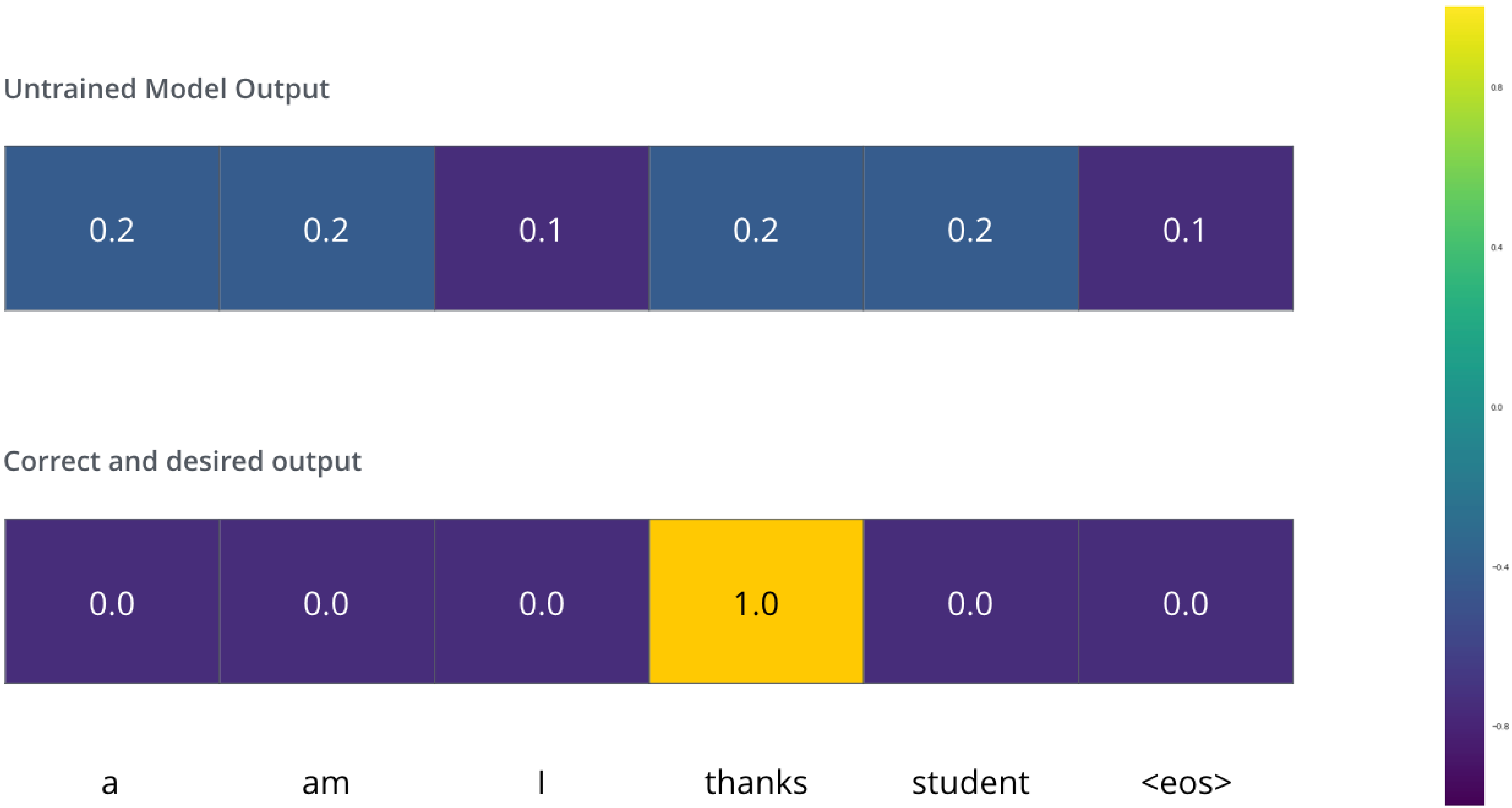
    so 9.9 is not greater than 9.11

How to train this network?

- Language Modeling! Looong history, will not cover here
- Many different forms of objectives

Two popular ones:

- Infill (used for BERT): This is the AI [MASK] Course.
- Next token Prediction (used for GPT): This is the AI Agents ____


Untrained Model Output
0.2
0.2
0.1
0.2
0.2
0.1
Correct and desired output
0.0
0.0
0.0
1.0
0.0
0.0
a
am
I
thanks
student
<eos>
0.8
0.4
0.0
-0.4
-0.8

Transformers

ENCODER ONLY

aka

auto-encoding models

TASKS

- Sentence classification
- Named entity recognition
- Extractive question-answering
- Masked language modeling

EXAMPLES

BERT, RoBERTa, distilBERT

DECODER ONLY

aka

auto-regressive models

TASKS

- Text generation
- Causal language modeling

EXAMPLES

GPT-2, GPT Neo, GPT-3

ENCODER-DECODER

aka

sequence-to-sequence models

TASKS

- Tran
- Summ on
- Gene stion-ans g

EXAMPLES

BART, T5, Marian

What does this mean for Deep RL?

- We have a neural net architecture that works well on language!
- We can probably use this as a function approximator for MDPs with language-based state-action spaces
- But how? What even is a language MDP?

In Class Activity

https://github.com/karpathy/nanoGPT