# CSE 190 – Intro to Deep RL
# 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 $\eta$
- 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

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

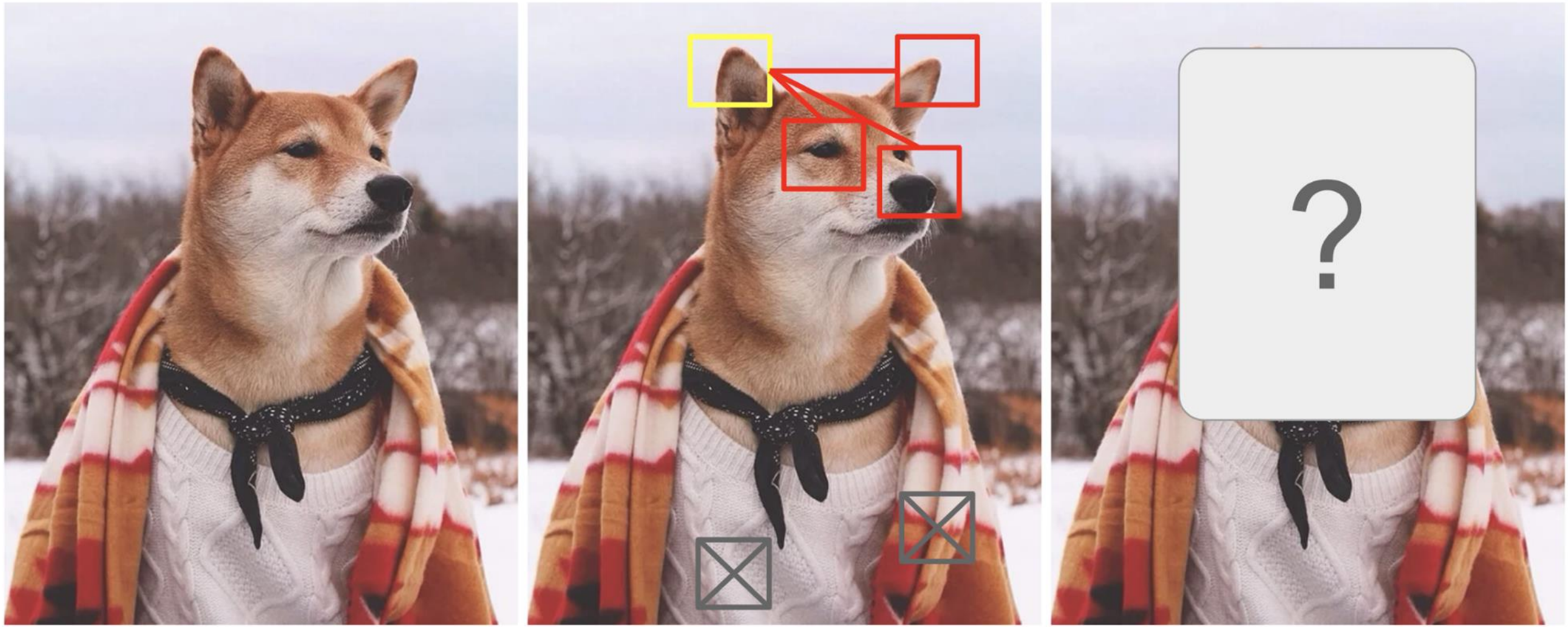
# Pros and Cons of MBRL

- 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

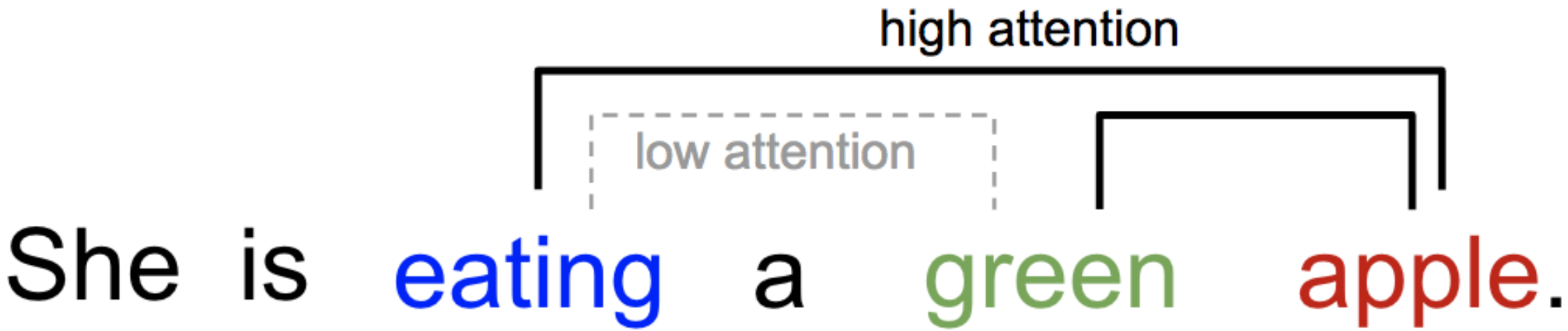
# Simultaneous Bottlenecks of Deep RL

- 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

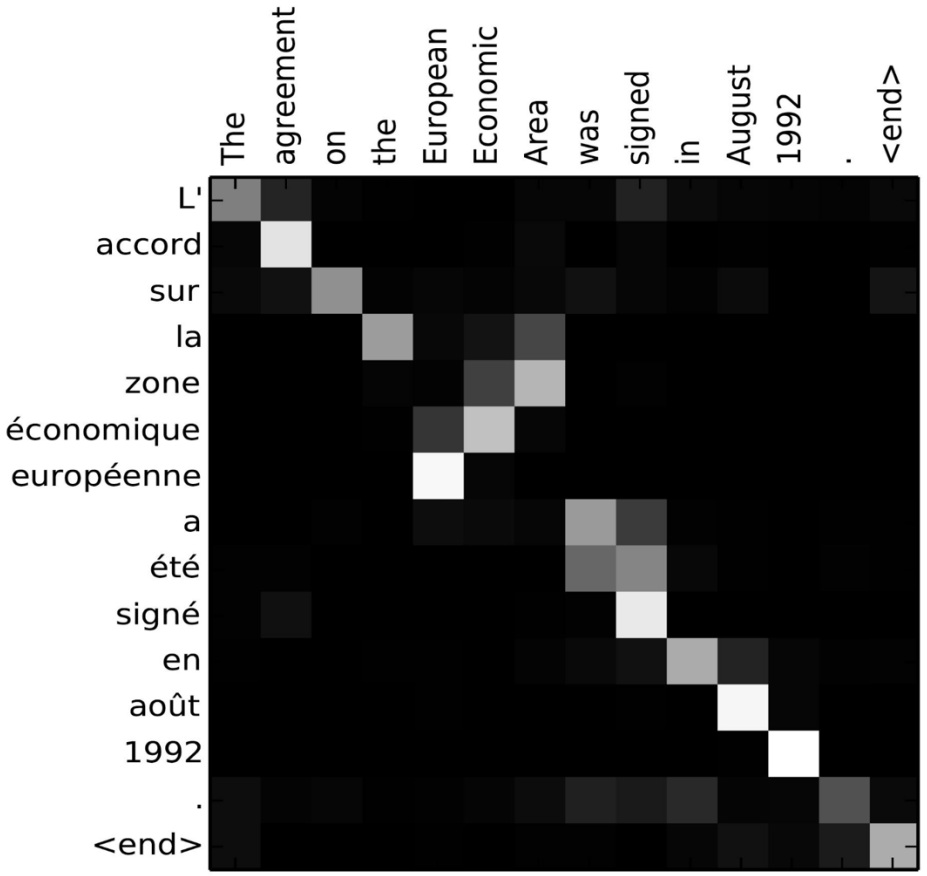


# Pay Attention to your Words



# Deep Learning Attention

- A vector of importance weights over an input sequence



# Attention Alignment

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

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

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

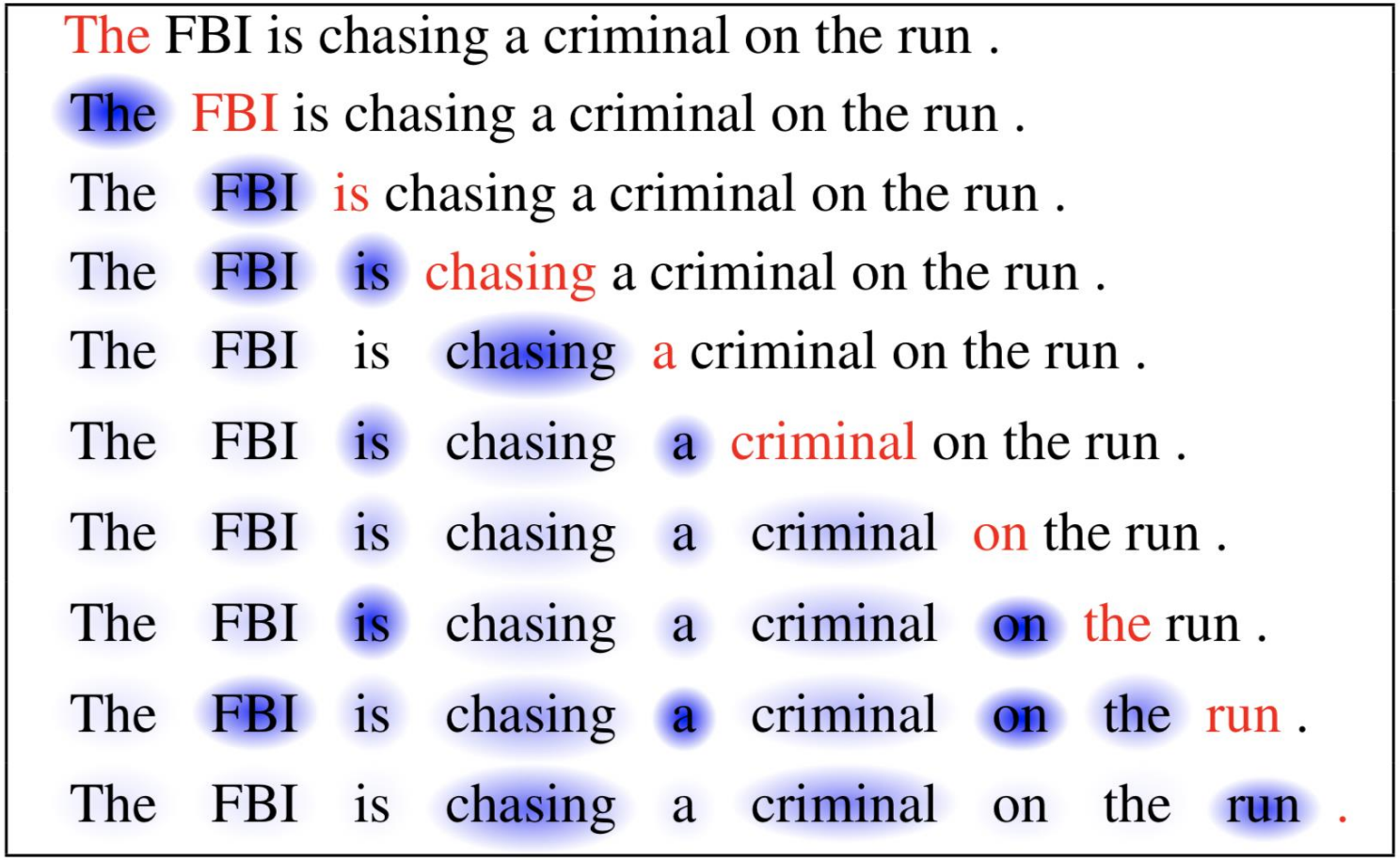
$$= \frac{\exp(\text{score}(\boldsymbol{s}_{t-1}, \boldsymbol{h}_i))}{\sum_{i'=1}^{n} \exp(\text{score}(\boldsymbol{s}_{t-1}, \boldsymbol{h}_{i'}))} \quad ; \text{Softmax of some predefined alignment score..}$$

# Types of Attention (pre Vaswani)

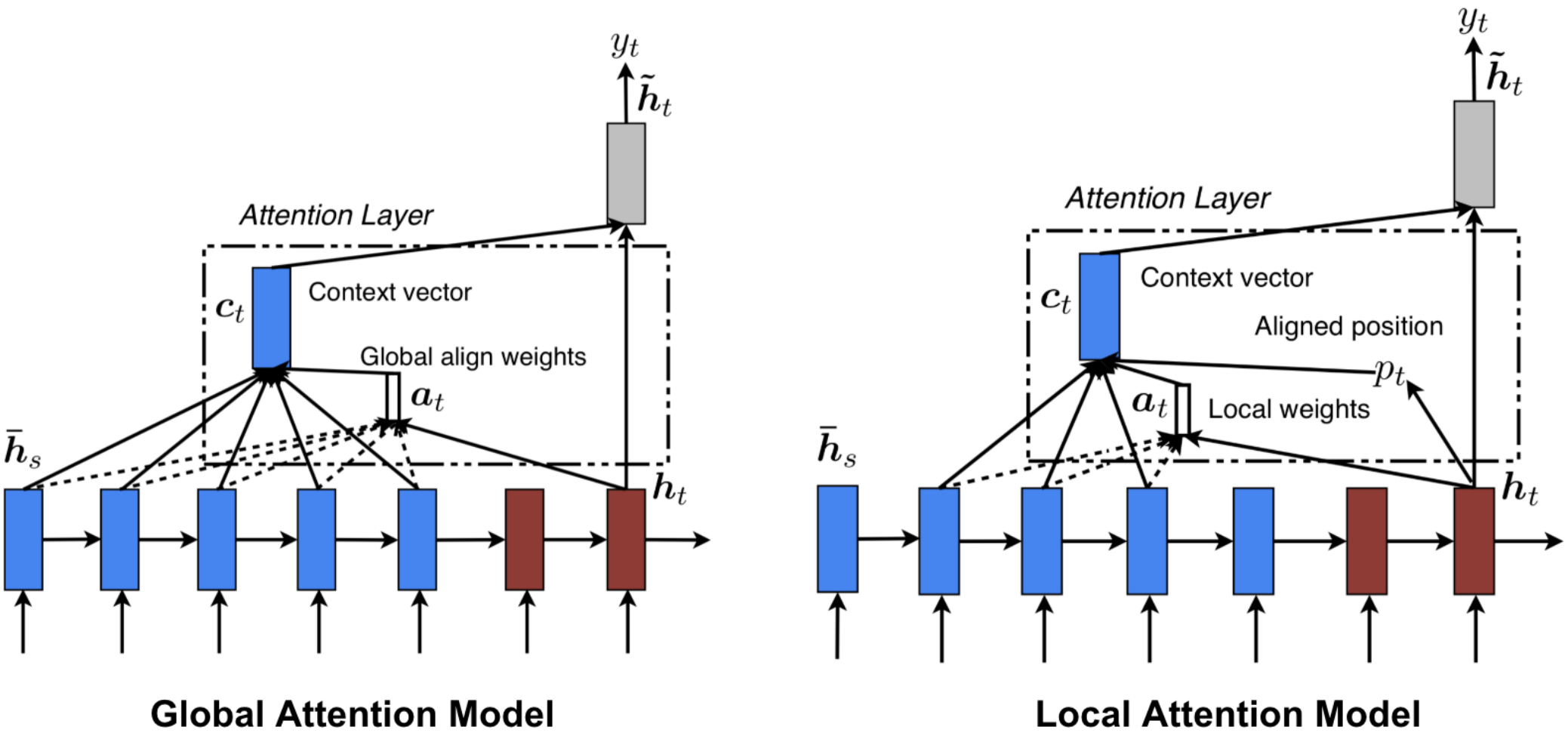
| Name | Alignment score function | Citation |
|---|---|---|
| Content-base attention | $\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \text{cosine}[\boldsymbol{s}_t, \boldsymbol{h}_i]$ | Graves2014 |
| Additive(*) | $\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \mathbf{v}_a^\top \tanh(\mathbf{W}_a[\boldsymbol{s}_{t-1}; \boldsymbol{h}_i])$ | Bahdanau2015 |
| Location-Base | $\alpha_{t,i} = \text{softmax}(\mathbf{W}_a \boldsymbol{s}_t)$<br>Note: This simplifies the softmax alignment to only depend on the target position. | Luong2015 |
| General | $\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \mathbf{W}_a \boldsymbol{h}_i$<br>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(^) | $\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \frac{\boldsymbol{s}_t^\top \boldsymbol{h}_i}{\sqrt{n}}$<br>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

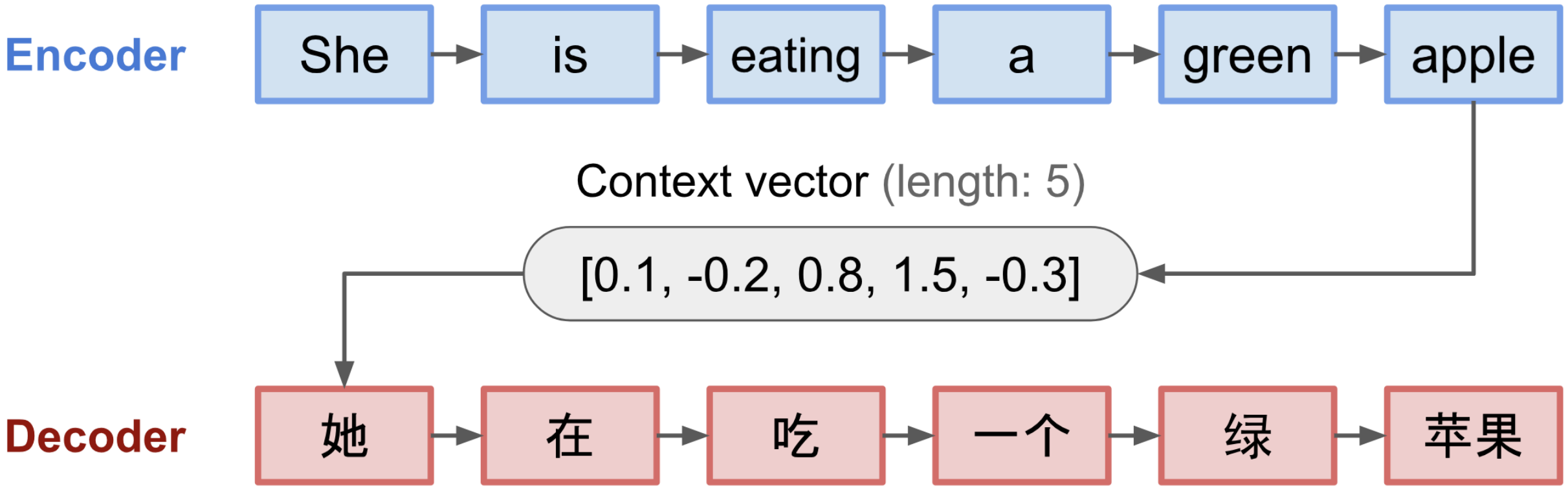
- Different parts of the same sequence attend to each other
- Previously it was all one sequence to another
- Proposed by Cheng et al 2016

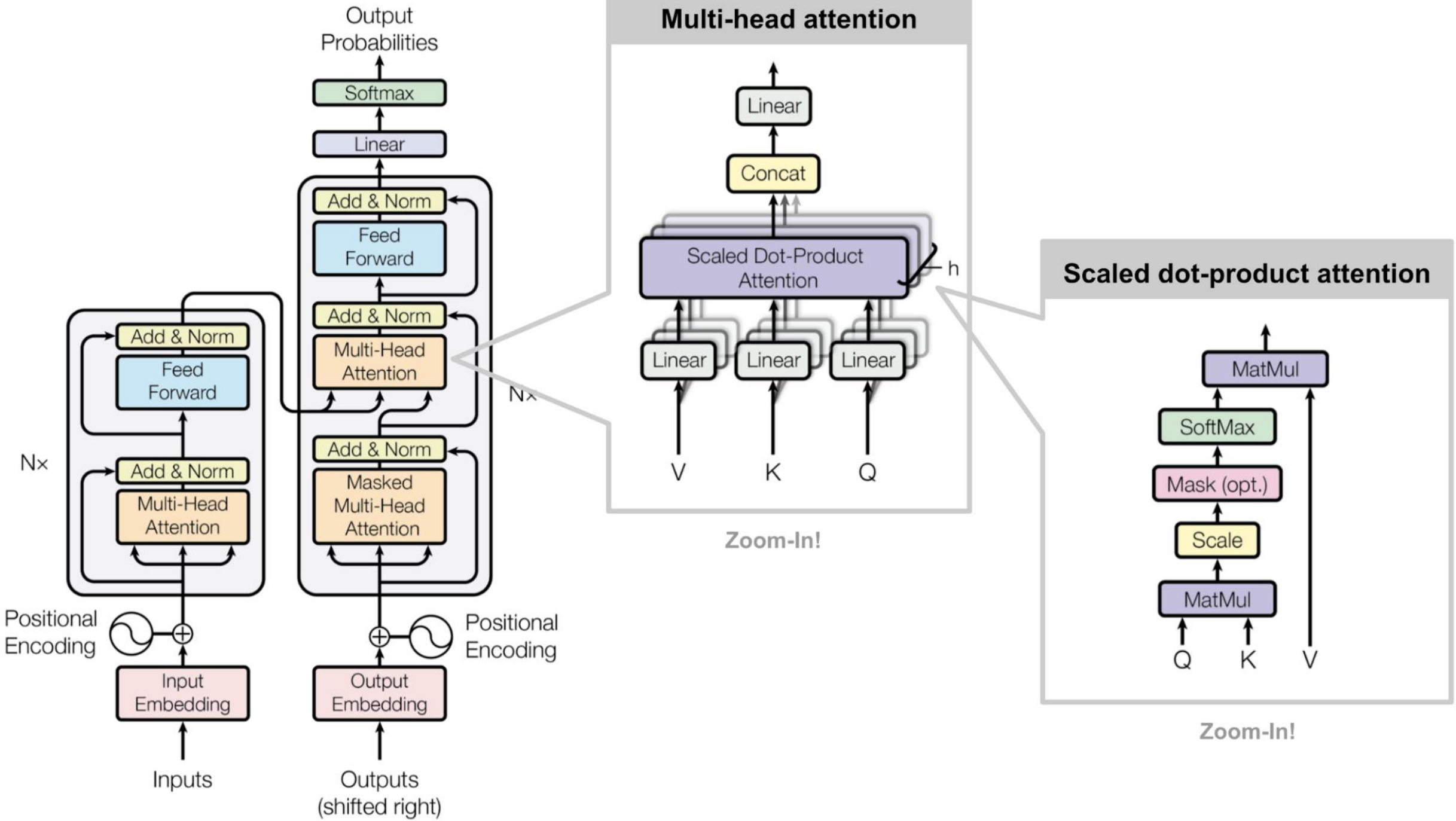


# Global vs Local Attention (Luong et al. 2015)



# Encoder Decoder RNN Failures

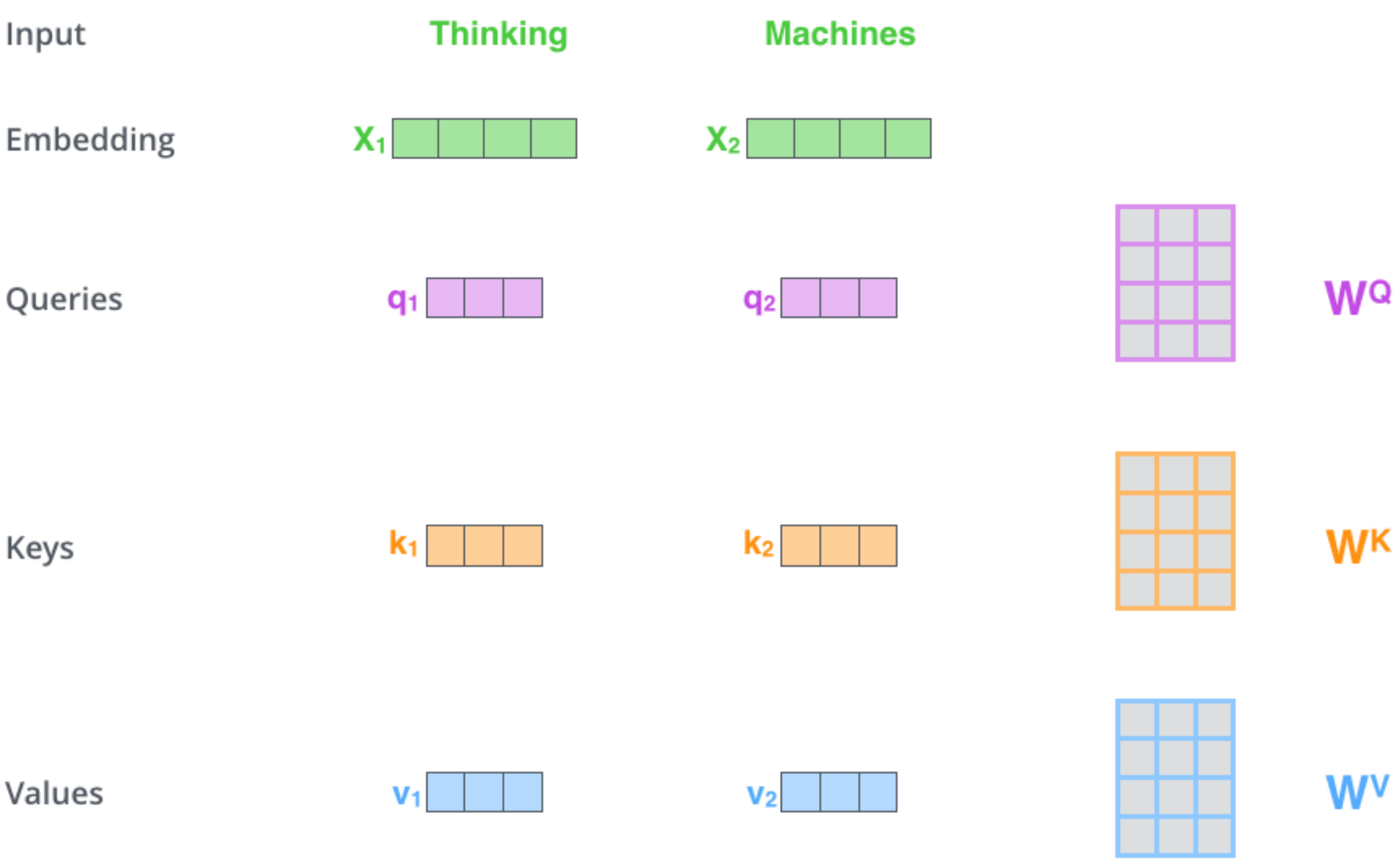


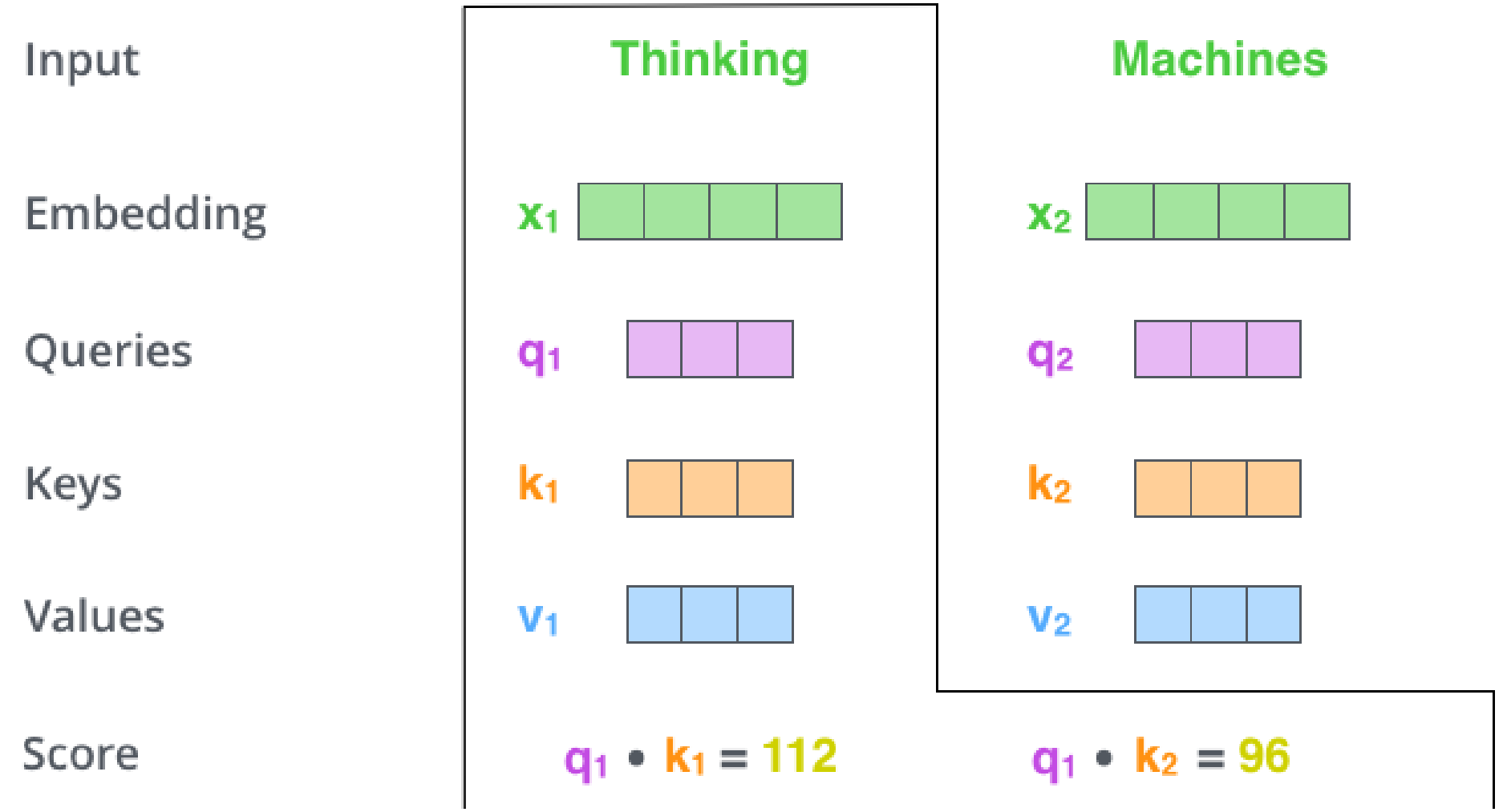

Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)
Multi-head 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!

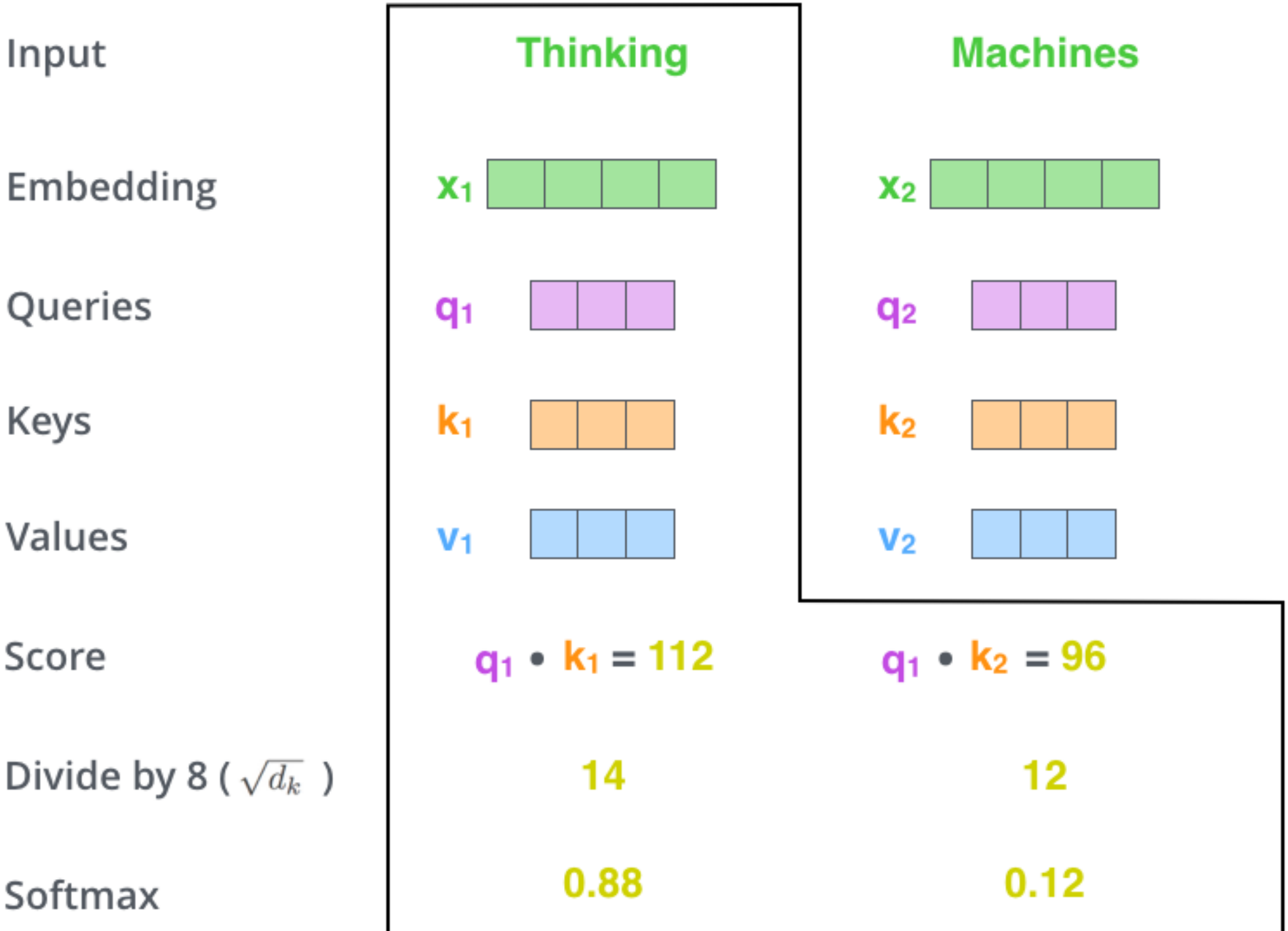
# Scaled Dot Product Attention

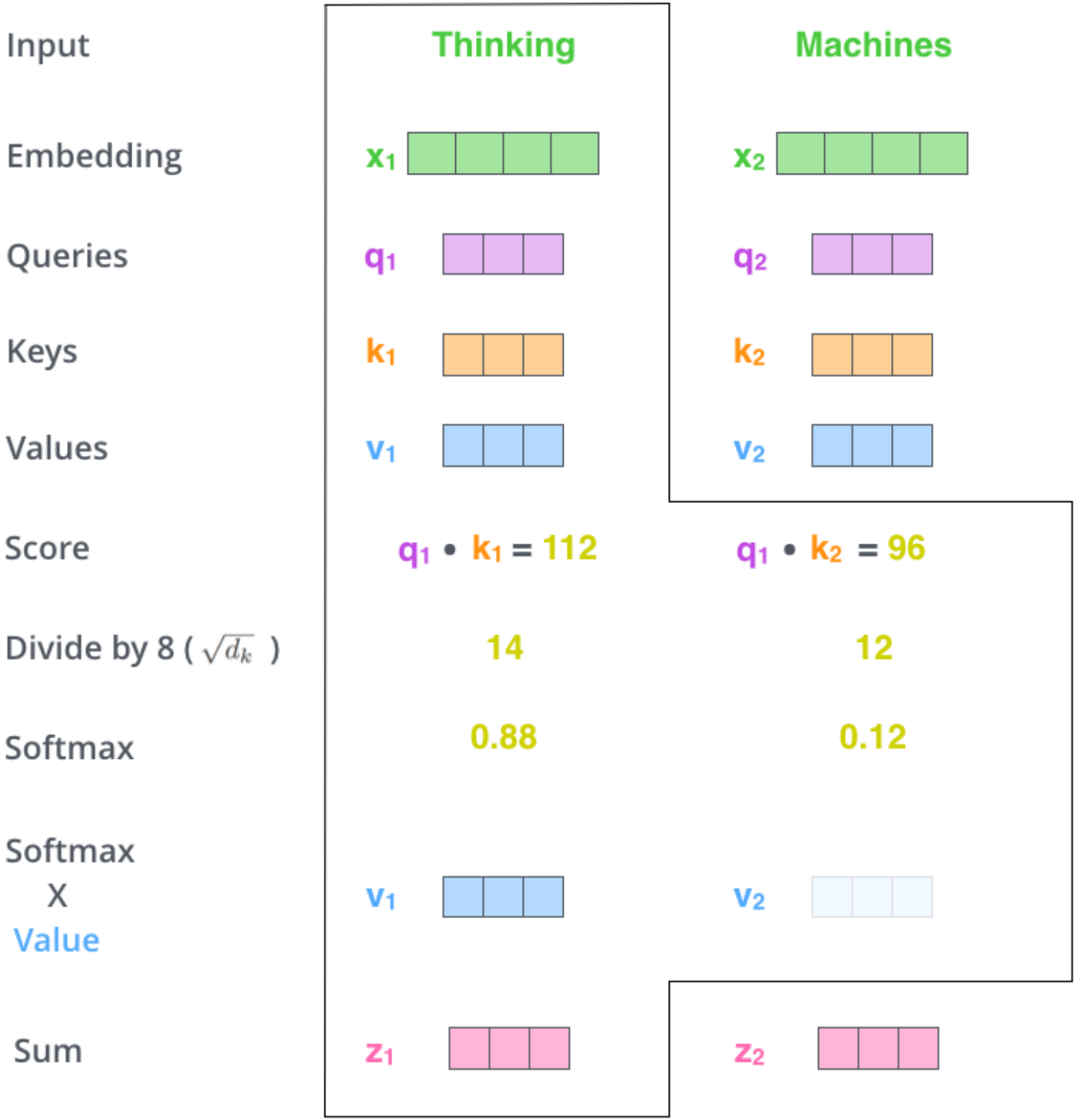
For each input word we create a query, key, value vector

- 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?

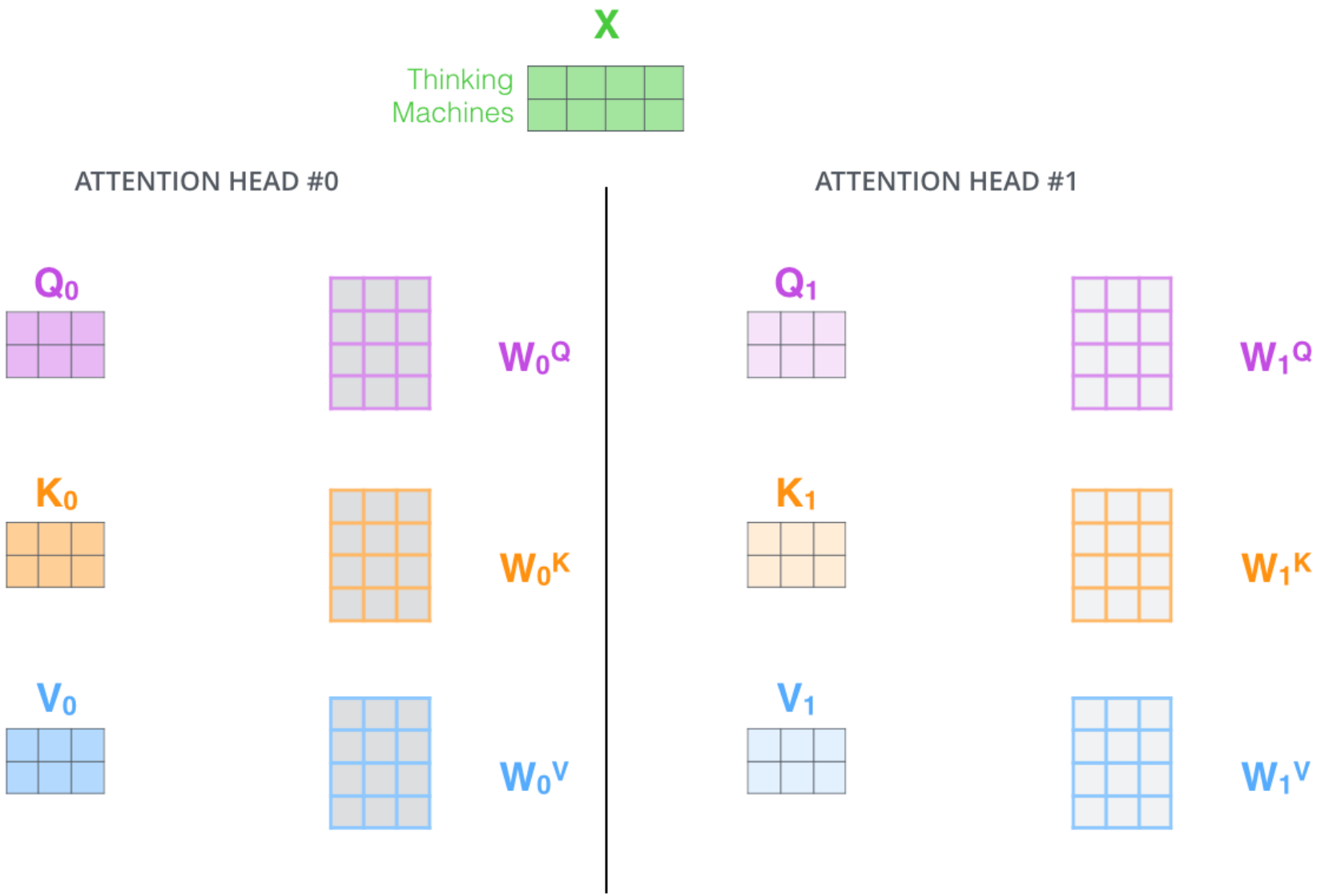

Input
Thinking
Machines
Embedding
$X_1$
$X_2$
Queries
$q_1$
$q_2$
$W^Q$
Keys
$k_1$
$k_2$
$W^K$
Values
$v_1$
$v_2$
$W^V$


Input
Thinking
Machines
Embedding
$x_1$
$x_2$
Queries
$q_1$
$q_2$
Keys
$k_1$
$k_2$
Values
$v_1$
$v_2$
Score
$q_1 \cdot k_1 = 112$
$q_1 \cdot k_2 = 96$


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 ( √dk )
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 ( √dk )
14
12
Softmax
0.88
0.12
Softmax
X
Value
v1
v2
Sum
z1
z2

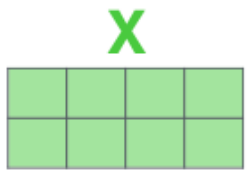
# Multi-Head Attention



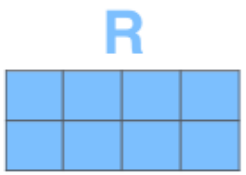
1) This is our input sentence*

Thinking Machines

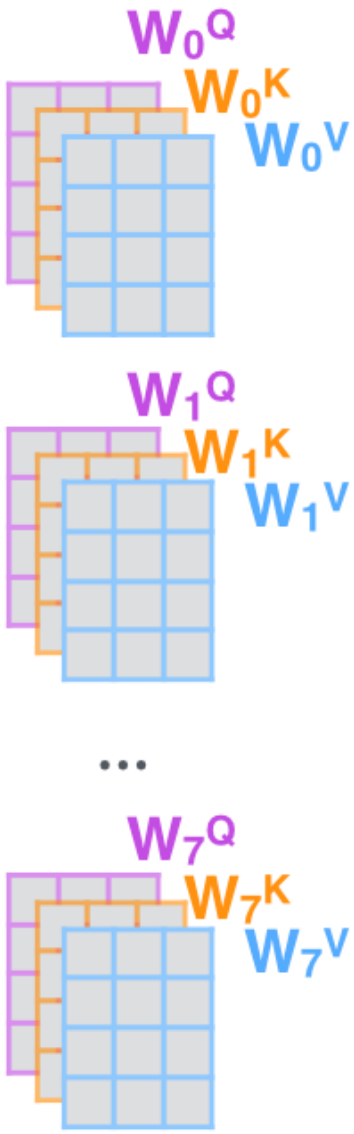
2) We embed each word*



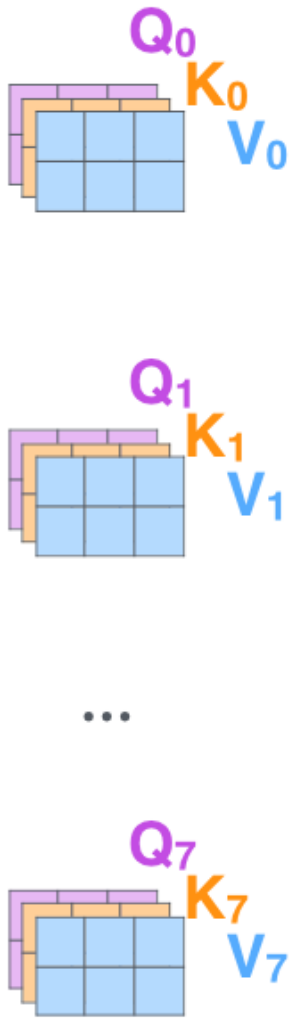

* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one



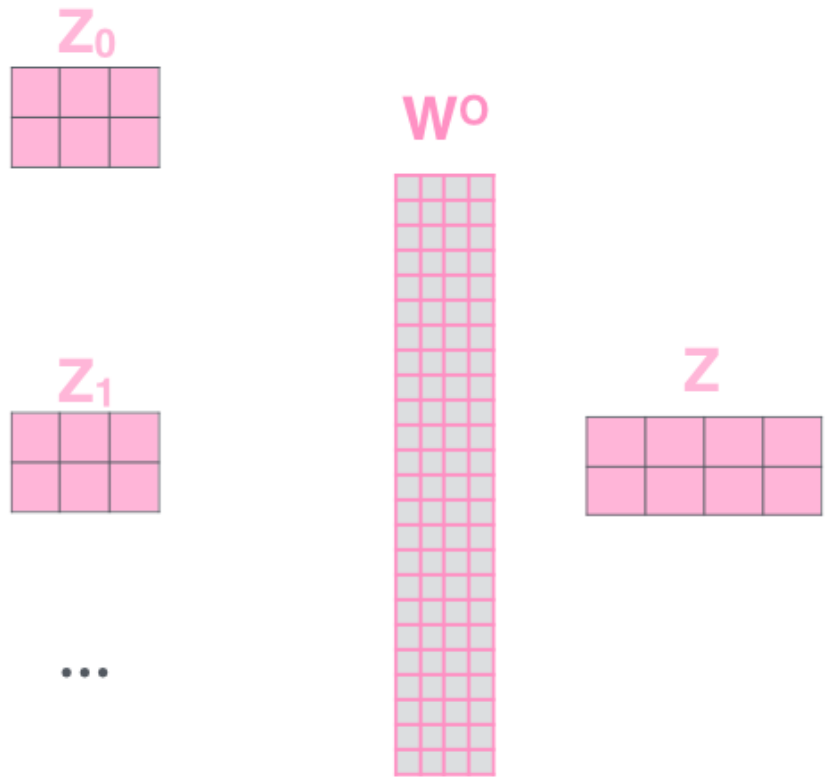

3) Split into 8 heads. We multiply X or R with weight matrices




4) Calculate attention using the resulting Q/K/V matrices



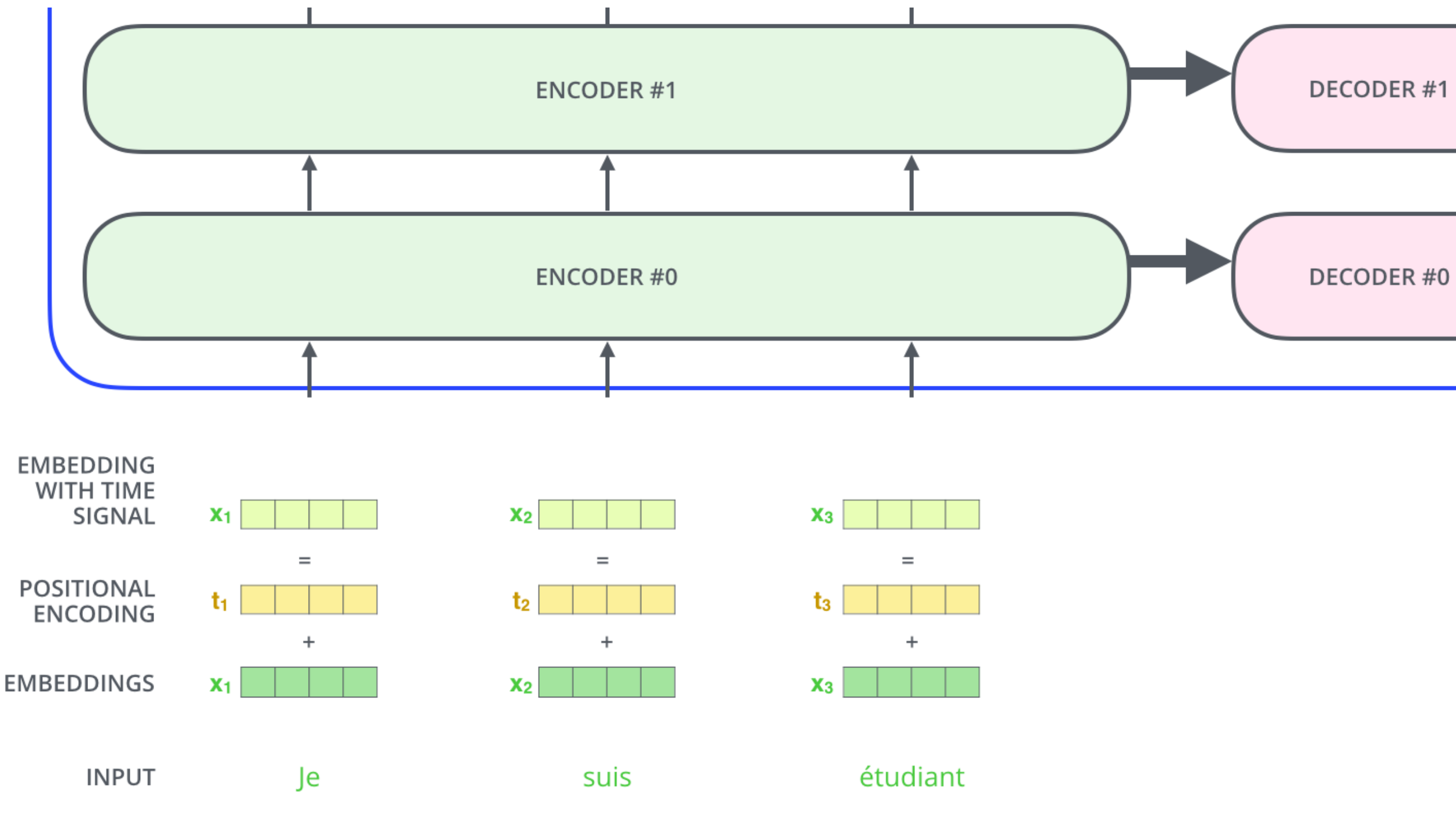

5) Concatenate the resulting Z matrices, then multiply with weight matrix $W^O$ to produce the output of the layer

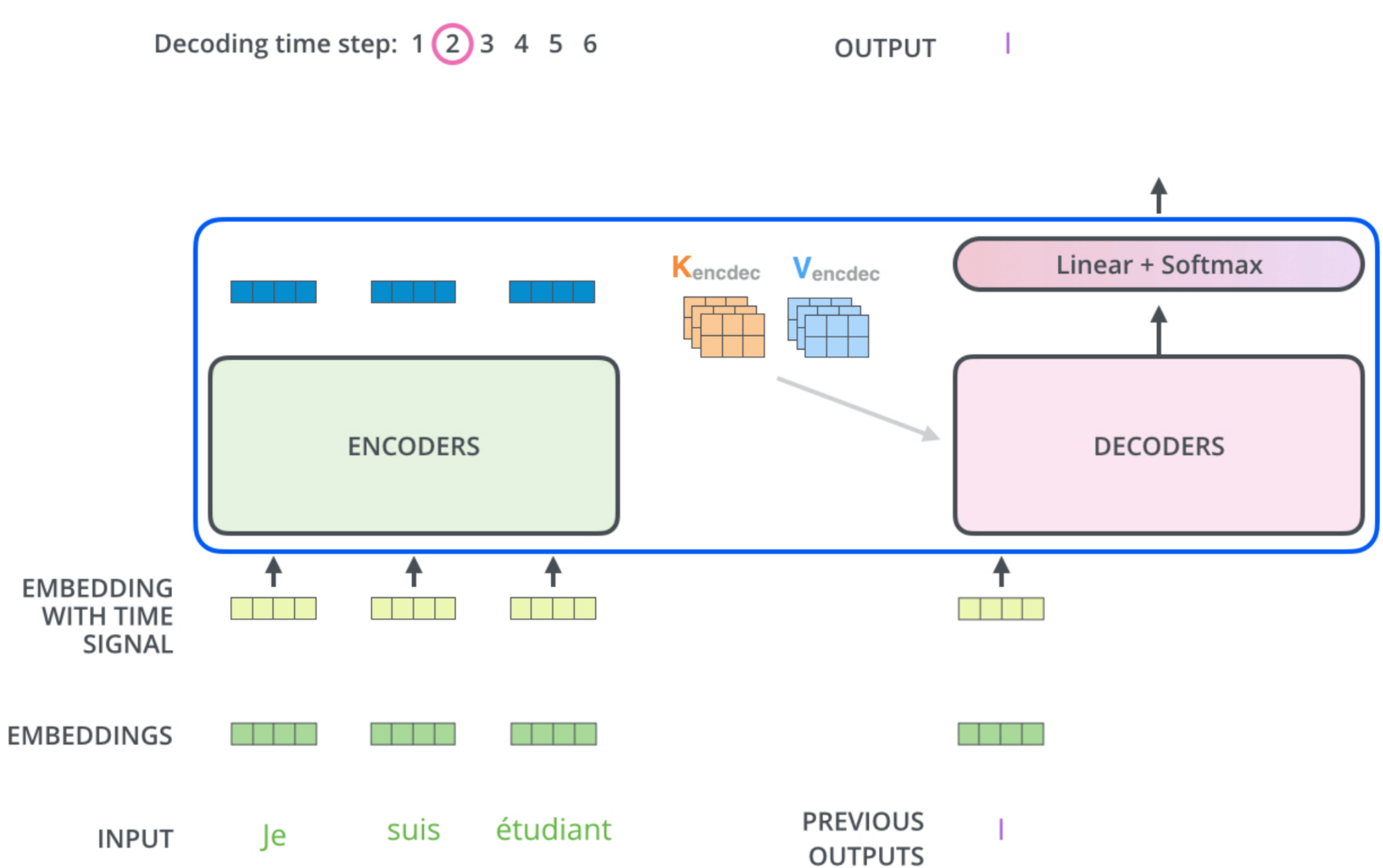


# Position Encoding and Tokenizers

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
POSITIONAL ENCODING
EMBEDDINGS
INPUT
x1
x2
x3
=
t1
t2
t3
+
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**


Softmax

**logits**


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


Correct and desired output


a am I thanks student <eos>

# 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

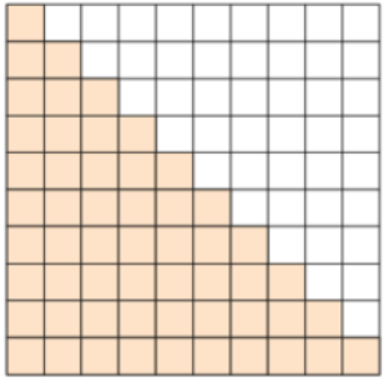
# Generating from the logits

- Top-k: select from k most likely tokens each time (k=1 for greedy)
- Sample: pick each token proportional to their probability
- Top-p (aka nucleus sampling): sample from smallest set of tokens that add up to a certain probability mass

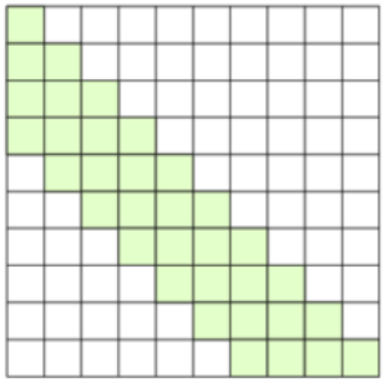
# What does this mean for Deep RL?

- 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



a) Causal Attention



b) Sliding Window Attention

https://github.com/karpathy/minGPT

Pt 1: using mingpt/bpe.py find two *strategies* to generate sequences that look the same to the human eye but return two different BPE tokenid sequences

Pt 2: using mingpt/model.py find how to calculate total trainable parameters as a closed form equation for GPT-2 architecture. What inputs do you need? What changes for other architectures?

Pt 3: [TRY WITHOUT LLM] Rewrite the CausalSelfAttention's forward() to use a Sliding Attention Window of width w (accessed as self.w) (2 line code change). What is the Big O of this re computational complexity given full self attention is $O(n^2)$

(Bonus) Pt 4: Add "top-p" sampling to generate(), explain why it can be better than top-k/greedy (p accessed as self.p)

Submit a txt of answers + model.py