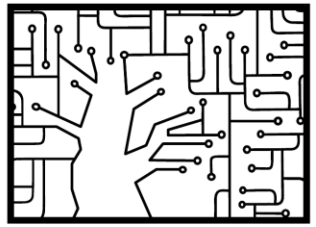
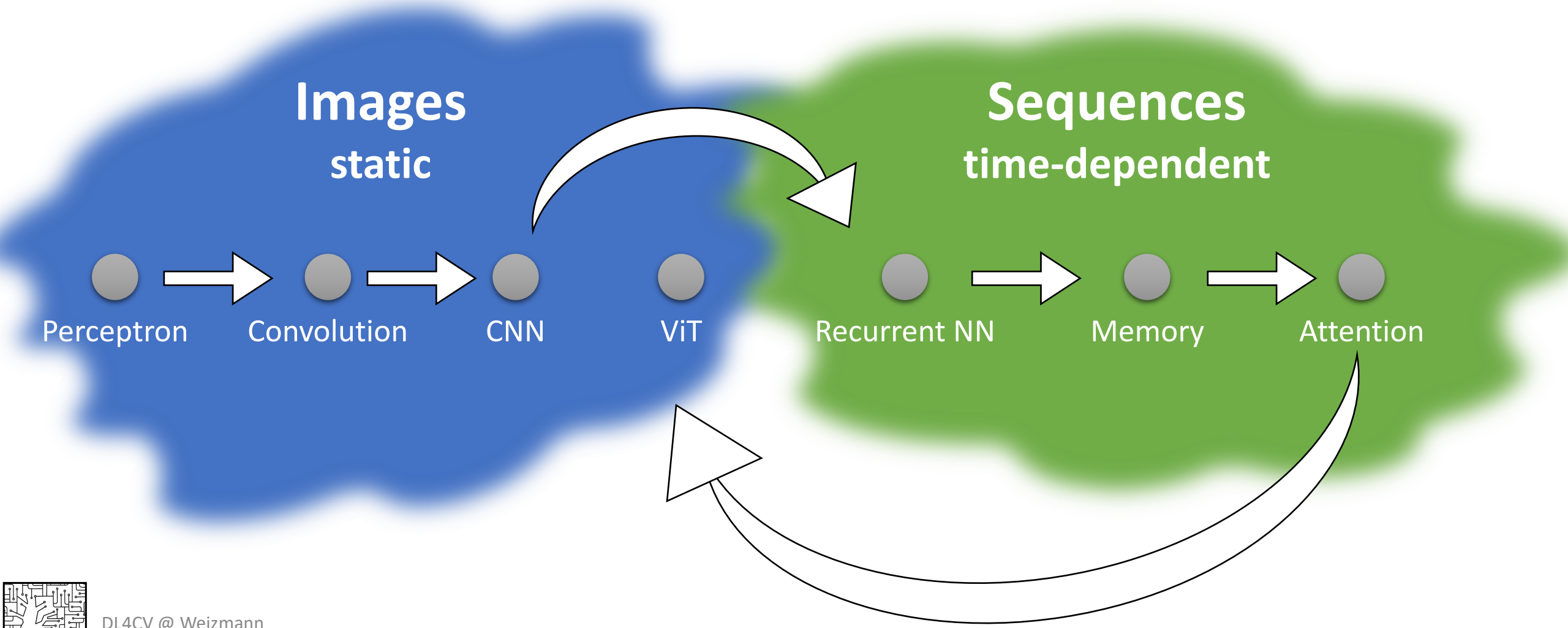
Deep Learning for Computer Vision:
Sequences and ViT

Shai Bagon



Agenda

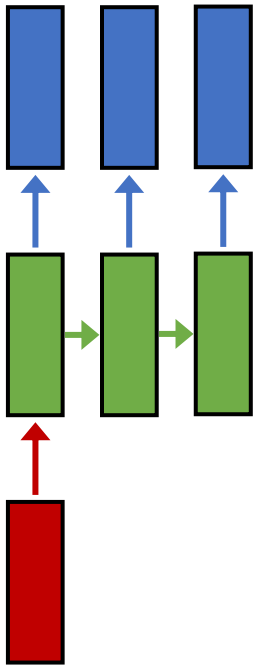

Images
static
Sequences
time-dependent
Perceptron
Convolution
CNN
ViT
Recurrent NN
Memory
Attention

Deep Learning for Sequences

One to one

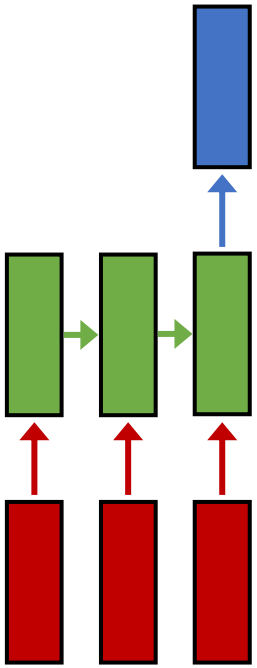
Feed-for
e.g., **classif**
image -> label

One to many



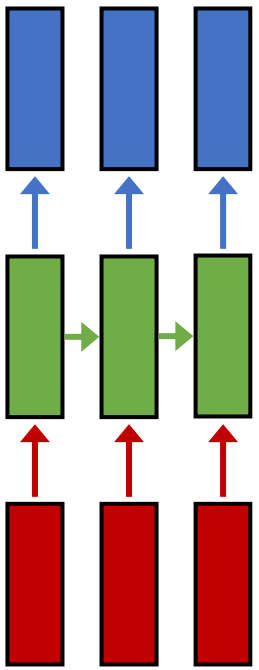
e.g., **image** ca
image -> sequenc

Many to one



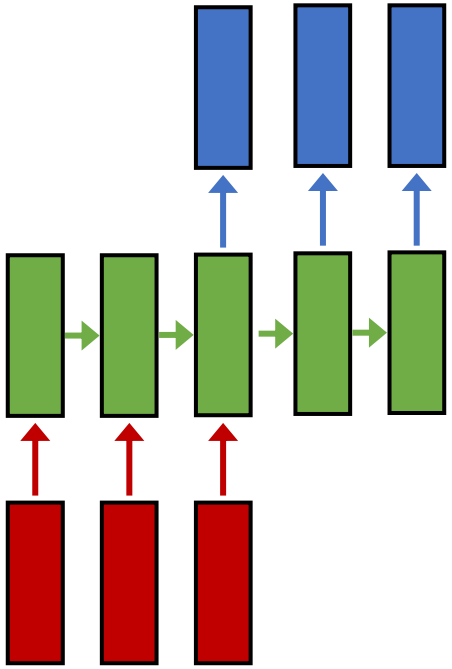
e.g., **video c**
sequence of f

Many to many



e.g., **video frames classi**
sequence of frames -> sec

Many to many



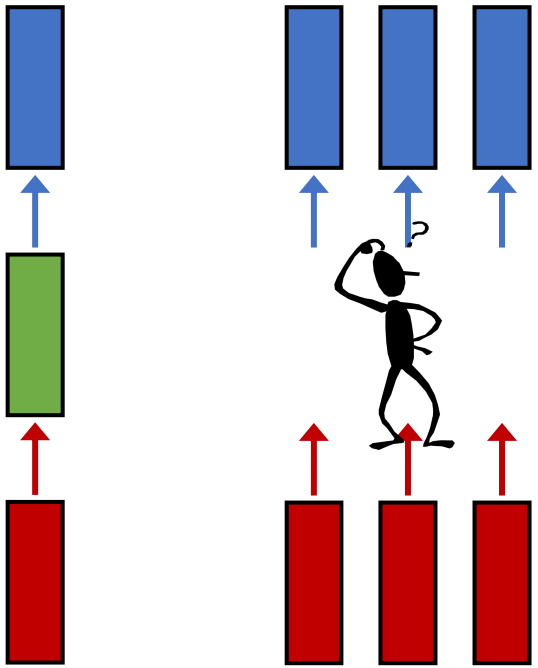
e.g., **Machine translation**
sequence of words -> seq. of words

Slide credit: Justin Johnson (EECS-498-007, UMich)

Recurrent Neural Networks

One to one

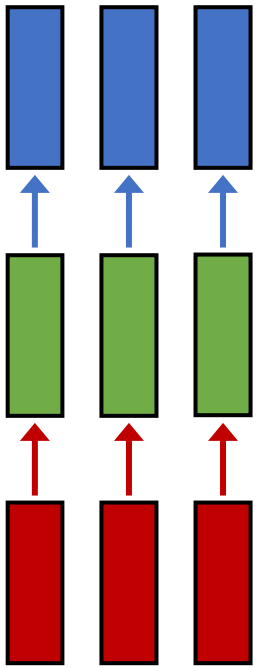
Many to many



Recurrent Neural Networks

One to one

Many to many



```python
class ManyToManyV0(nn.Module):
    def __init__(self, number_of_time_steps):
        super(ManyToMany, self).__init__()
        # SAME instance of SingleTimeStep for each time step
        self.time_steps = SingleTimeStep(...)

    def forward(self, in_seq):
        out_pred = []
        for t, x_t in enumerate(in_seq):
            p_t = self.time_steps(x_t)
            out_pred.append(p_t)
        return out_pred
```

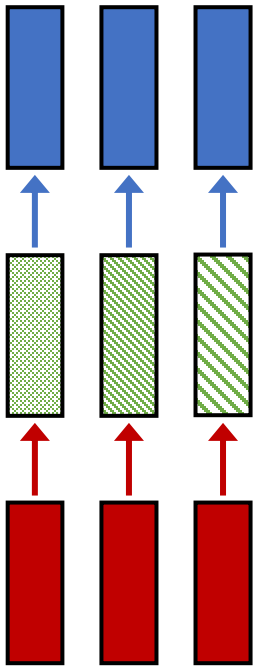
(+) Parameter efficient

(-) No temporal dependency

Recurrent Neural Networks

One to one

Many to many



```python
class ManyToManyV1(nn.Module):
    def __init__(self, number_of_time_steps):
        super(ManyToMany, self).__init__()
        # DIFFERENT instance of SingleTimeStep for each time step
        self.time_steps = nn.ModuleList([SingleTimeStep(...)
                                         for _ in range(number_of_time_steps)])

    def forward(self, in_seq):
        out_pred = []
        for t, x_t in enumerate(in_seq):
            p_t = self.time_steps[t](x_t)
            out_pred.append(p_t)
        return out_pred
```

(+?) Temporal dependency (via trained parameters)

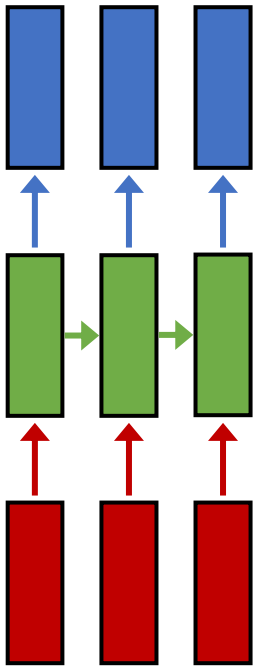
(-) Parameter inefficiency

(-) Fixed sequence length

Recurrent Neural Networks

One to one

Many to many



```python
class ManyToMany(nn.Module):
    def __init__(self):
        super(ManyToMany, self).__init__()
        # SHARE a single instance of SingleTimeStep
        self.time_step = SingleTimeStep(...)

    def forward(self, in_seq):
        out_pred = []
        state = self.init_state
        for t, x_t in enumerate(in_seq):
            p_t, state = self.time_step(x_t, state)
            out_pred.append(p_t)
        return out_pred
```

(+) Temporal dependency (via “hidden state”)

(+) Parameter efficiency

(+) Arbitrary sequence length

Recurrent Neural Networks

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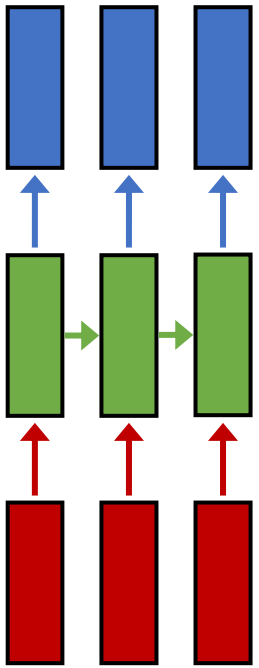
Many to many



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```

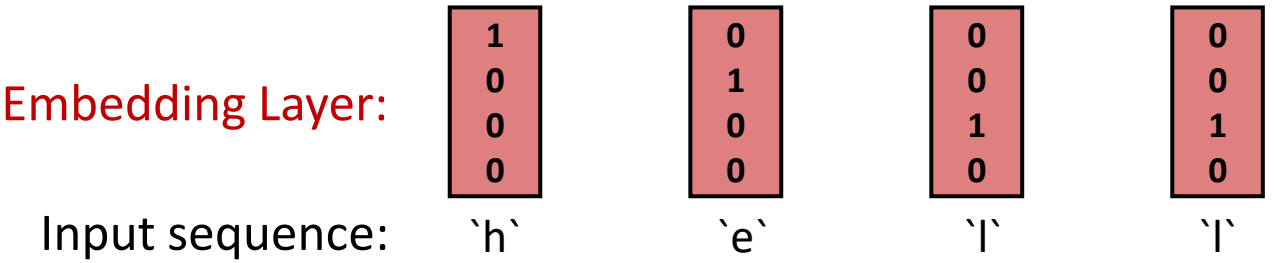
$$h_t = f(h_{t-1}, x_t; \boldsymbol{W})$$

Example: Language Modeling

Task:
Given characters $c_0, c_1, \ldots, c_{t-1}$
Predict c_t

Training sequence: “hello”

Vocabulary: [‘h’, ‘e’, ‘l’, ‘o’]



Slide credit: Justin Johnson (EECS-498-007, UMich)

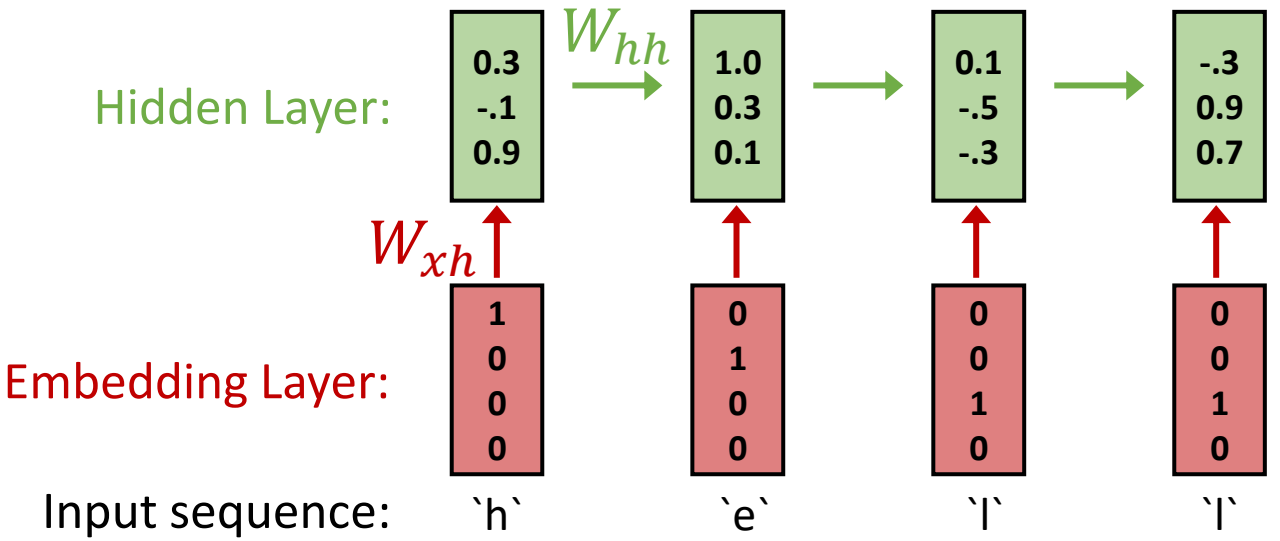
Example: Language Modeling

Task:
Given characters $c_0, c_1, \ldots, c_{t-1}$
Predict c_t

$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t)$$

Training sequence: “hello”

Vocabulary: [‘h’, ‘e’, ‘l’, ‘o’]



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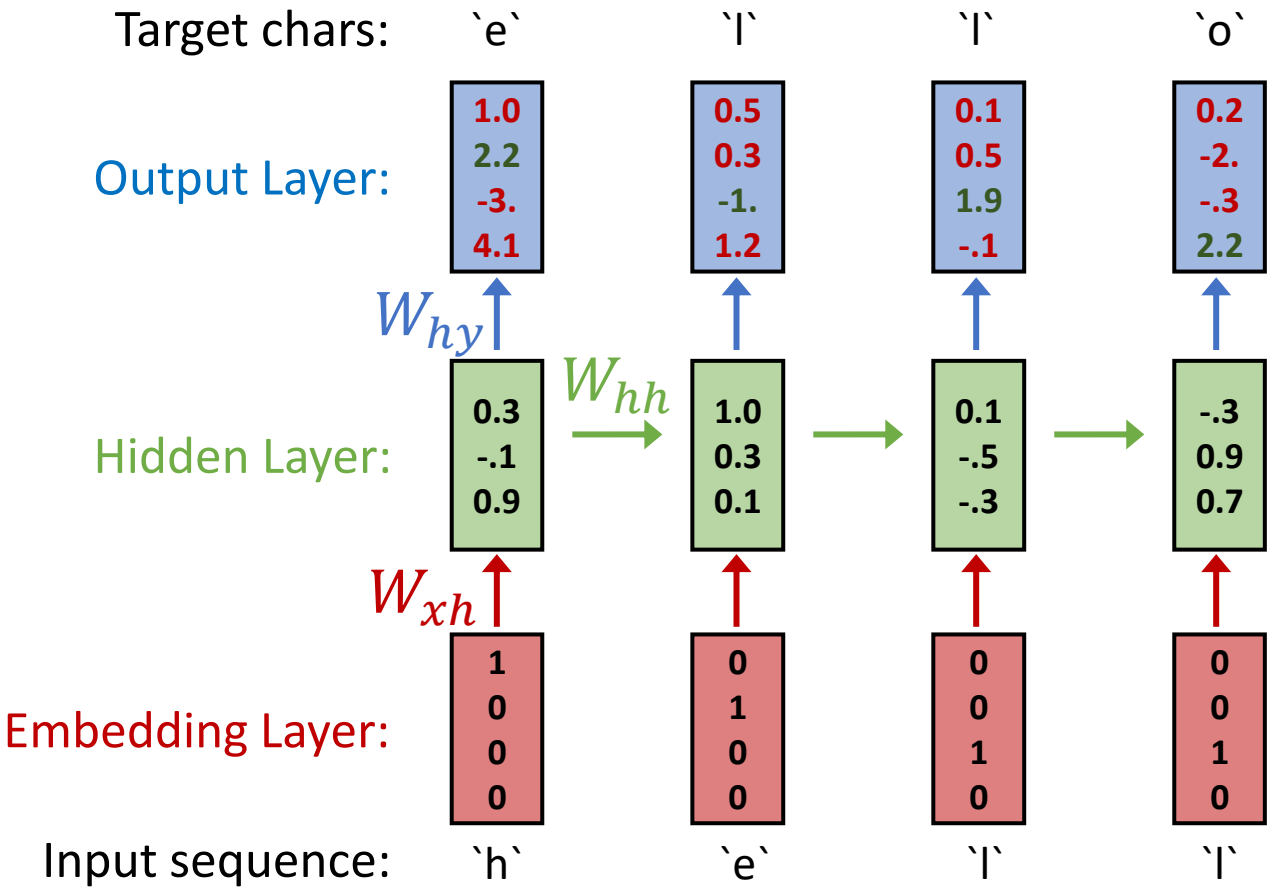

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Task:
Given characters $c_0, c_1, \ldots, c_{t-1}$
Predict c_t

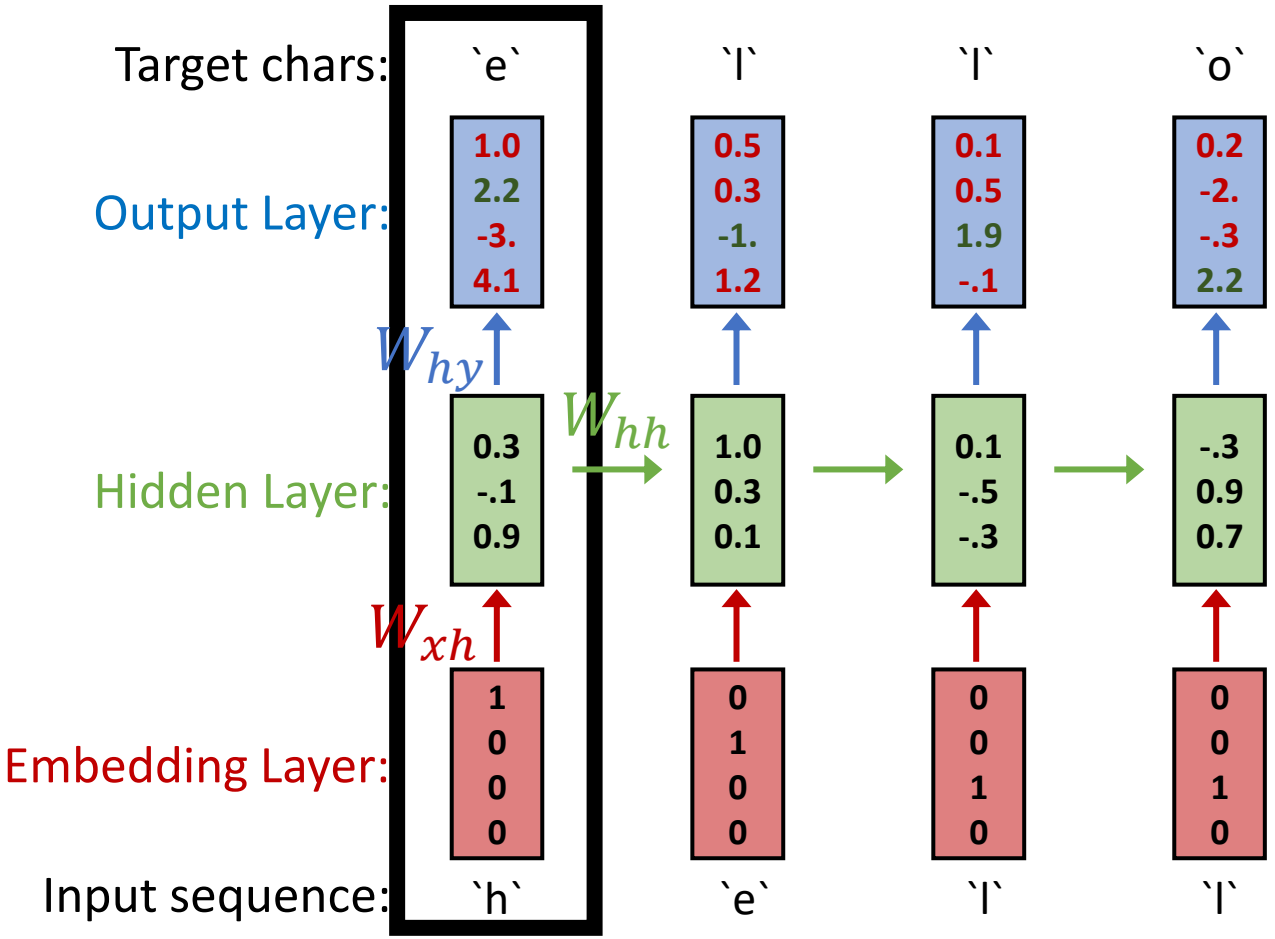
$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t)$$

$$y_t = W_{hy} h_t$$

Training sequence: “hello”

Vocabulary: [‘h’, ‘e’, ‘l’, ‘o’]

Given “h” predict “e”



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Example: Language Modeling

Task:
Given characters $c_0, c_1, \ldots, c_{t-1}$
Predict c_t

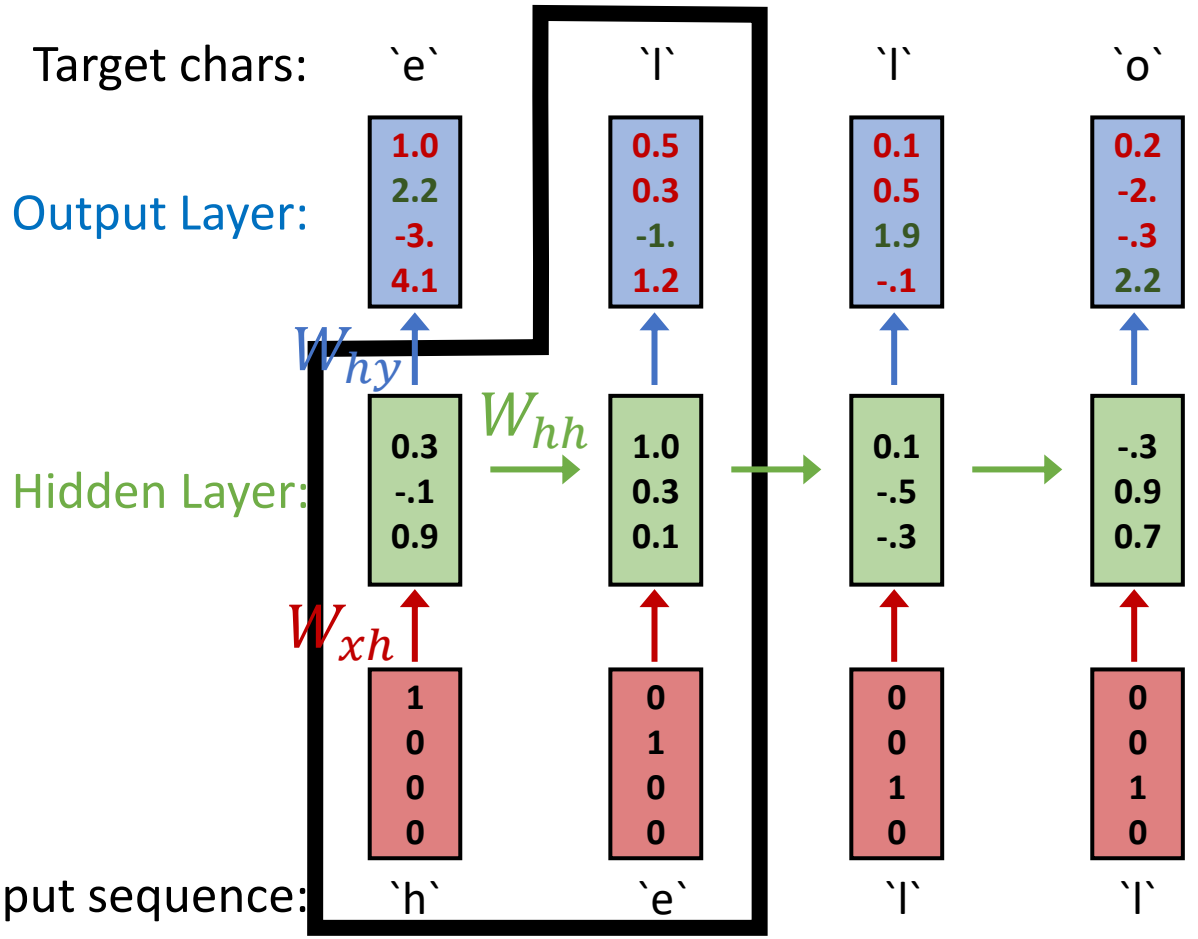
$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t)$$

$$y_t = W_{hy} h_t$$

Training sequence: “hello”

Vocabulary: [‘h’, ‘e’, ‘l’, ‘o’]

Given “he” predict “l”



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Example: Language Modeling

Task:
Given characters $c_0, c_1, \ldots, c_{t-1}$
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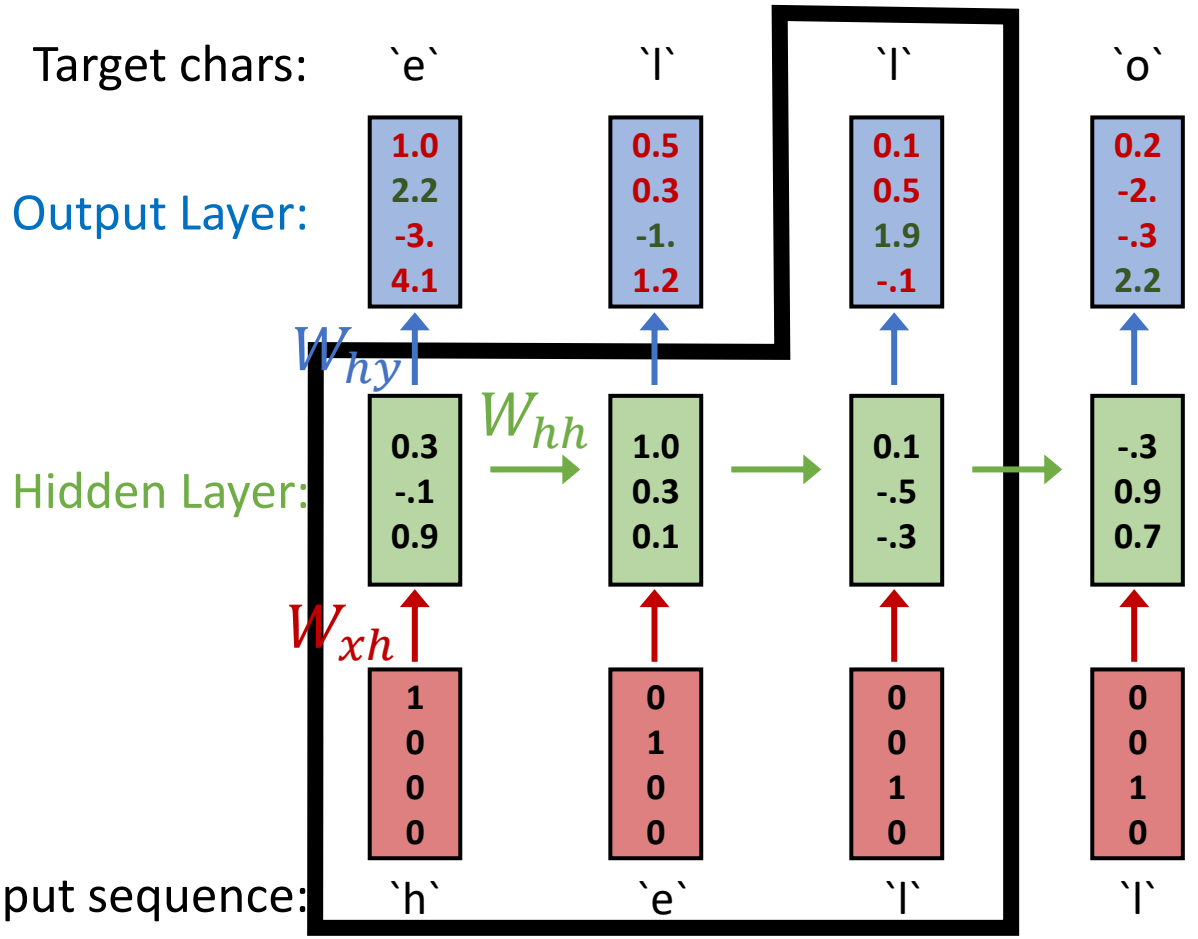
Training sequence: “hello”

Vocabulary: [‘h’, ‘e’, ‘l’, ‘o’]

Given “hel” predict “l”



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Example: Language Modeling

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Given characters $c_0, c_1, \ldots, c_{t-1}$
Predict c_t

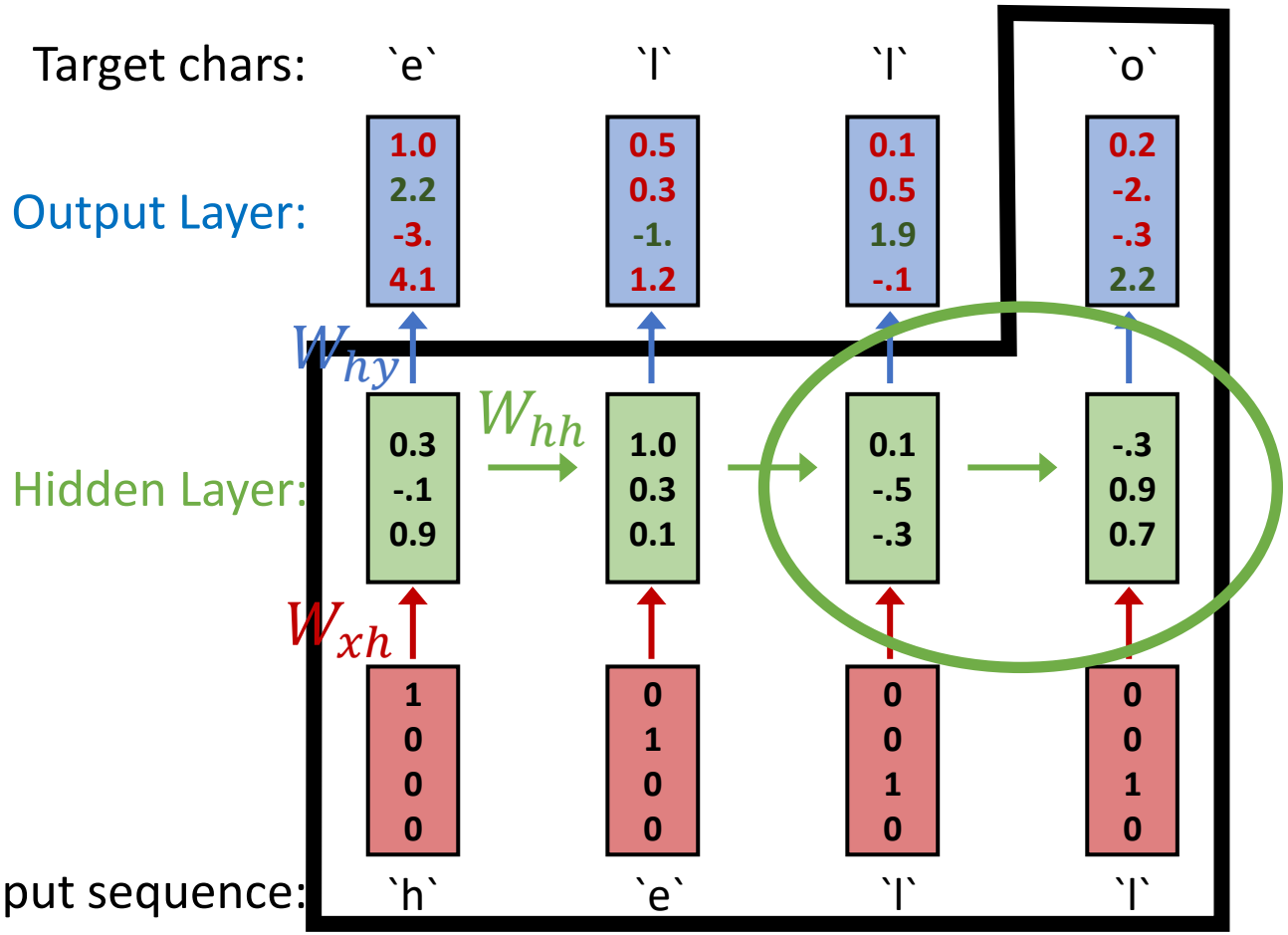
$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t)$$

$$y_t = W_{hy} h_t$$

Training sequence: “hello”

Vocabulary: [‘h’, ‘e’, ‘l’, ‘o’]

Given “hell” predict “o”



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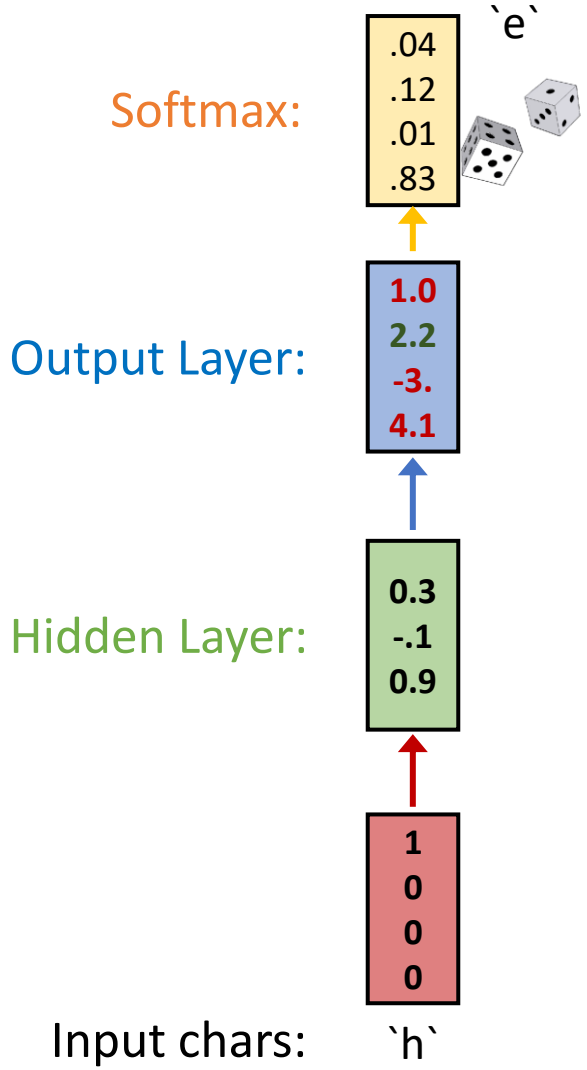
Example: Language Modeling

Task:
Given characters $c_0, c_1, \ldots, c_{t-1}$
Predict c_t

At test time: **generate** new text
Sample one char at a time

Training sequence: “hello”

Vocabulary: [‘h’, ‘e’, ‘l’, ‘o’]



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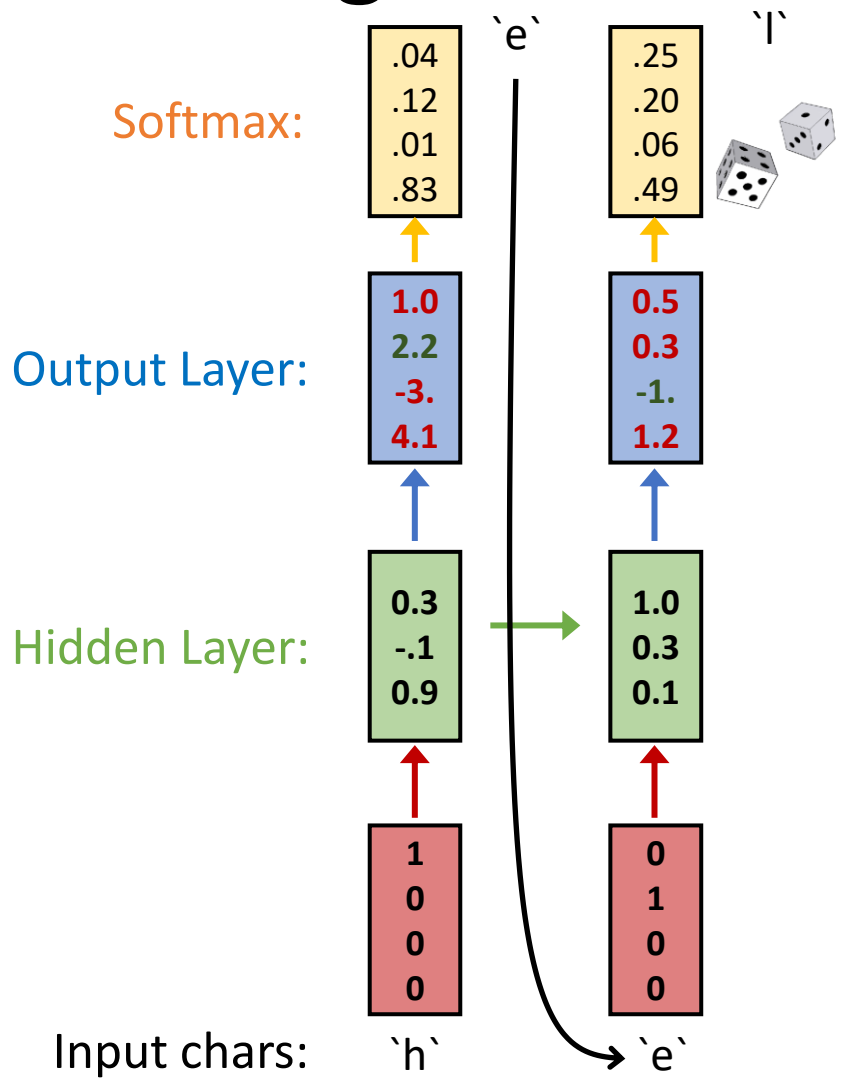

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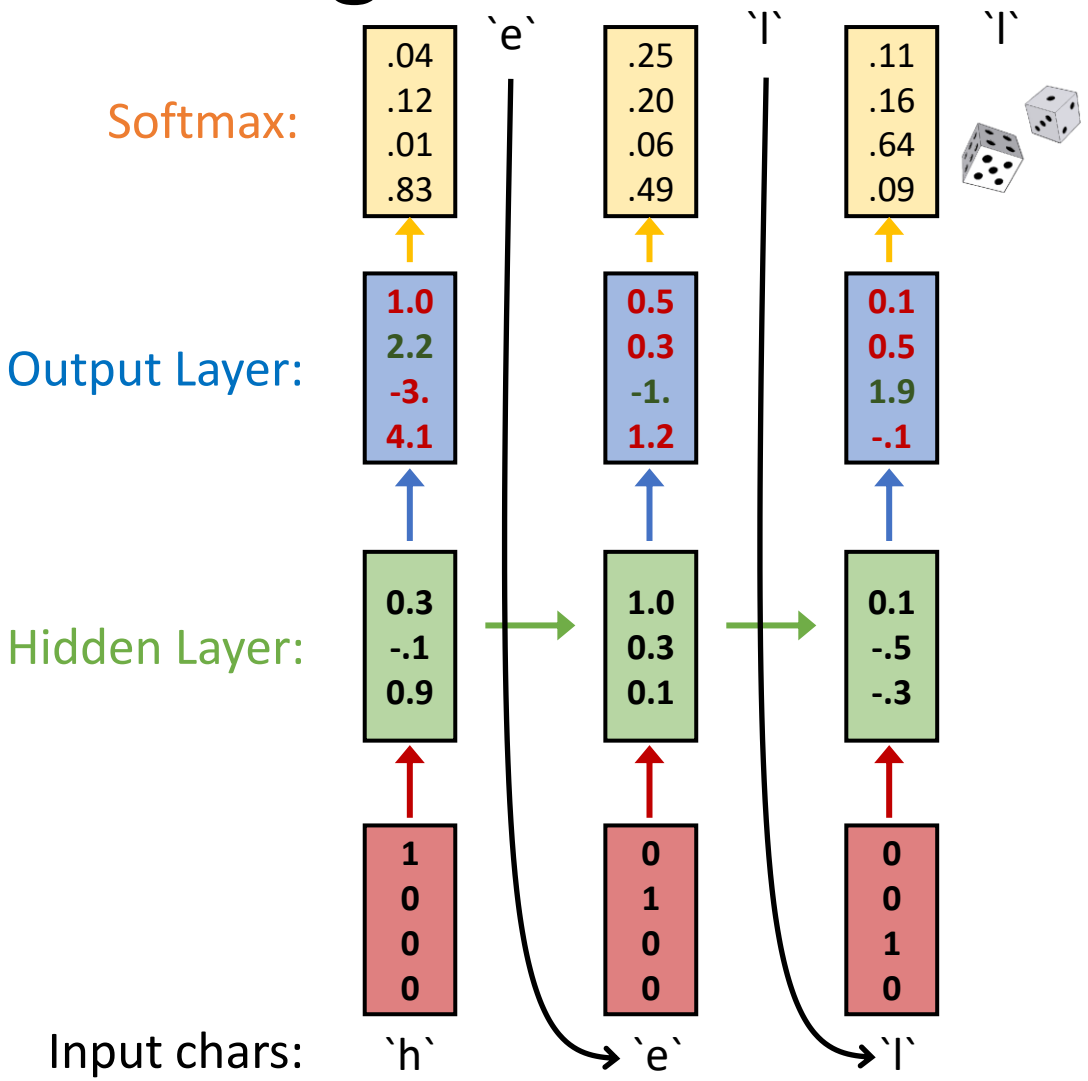

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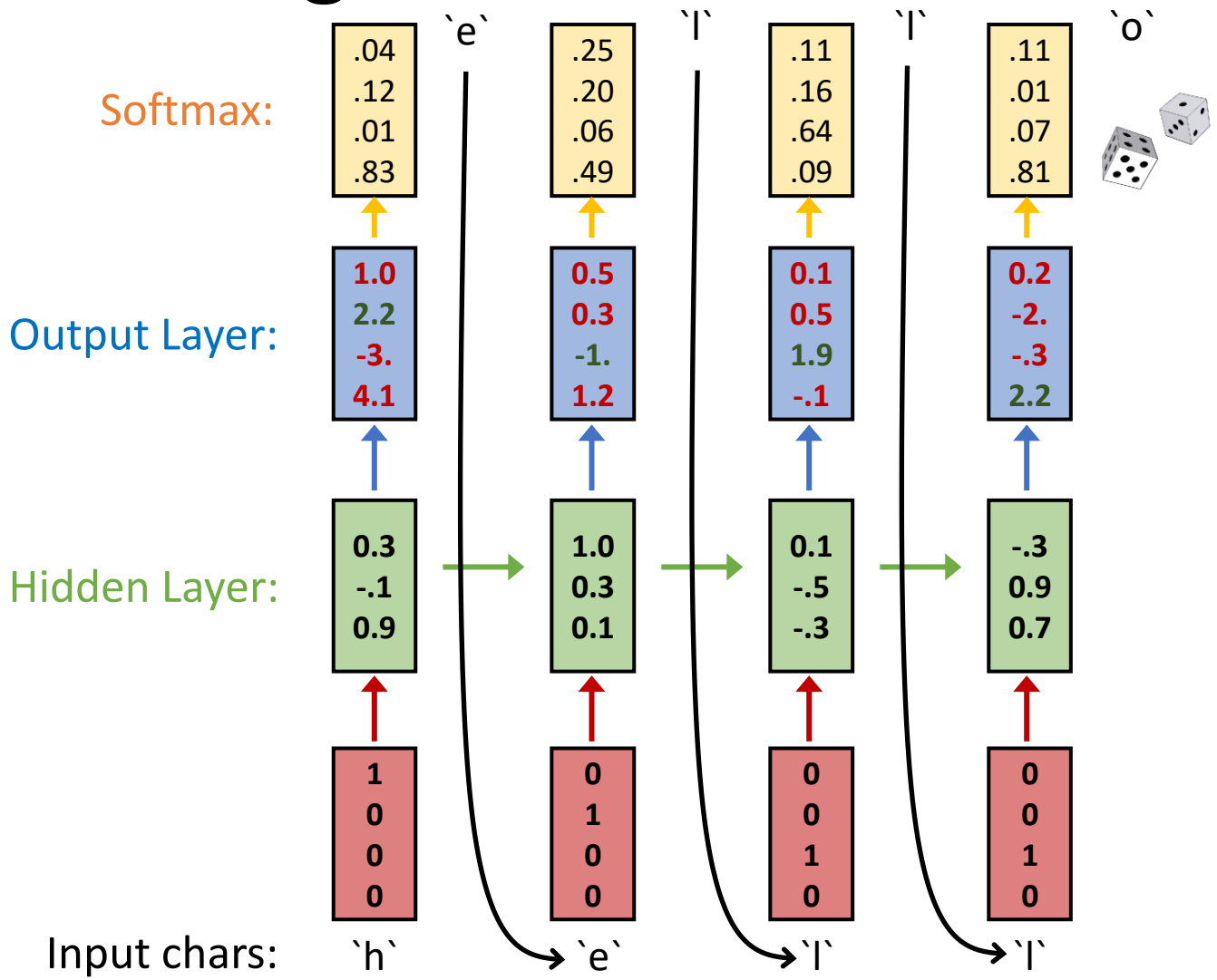

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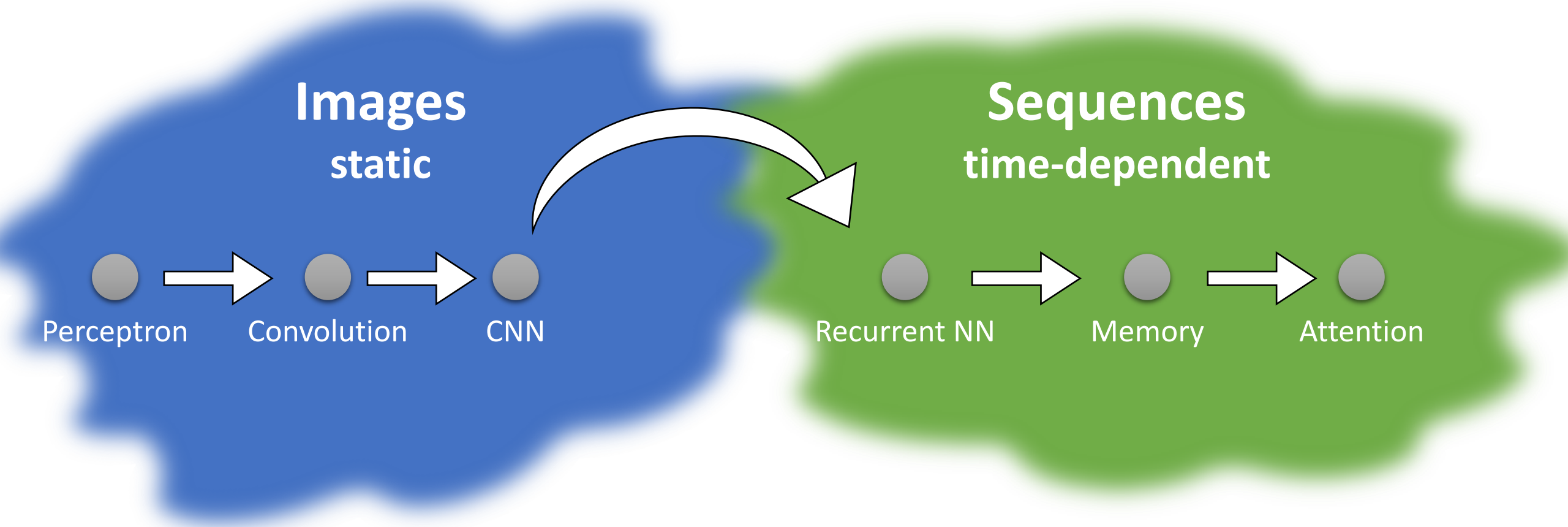
Agenda


Images
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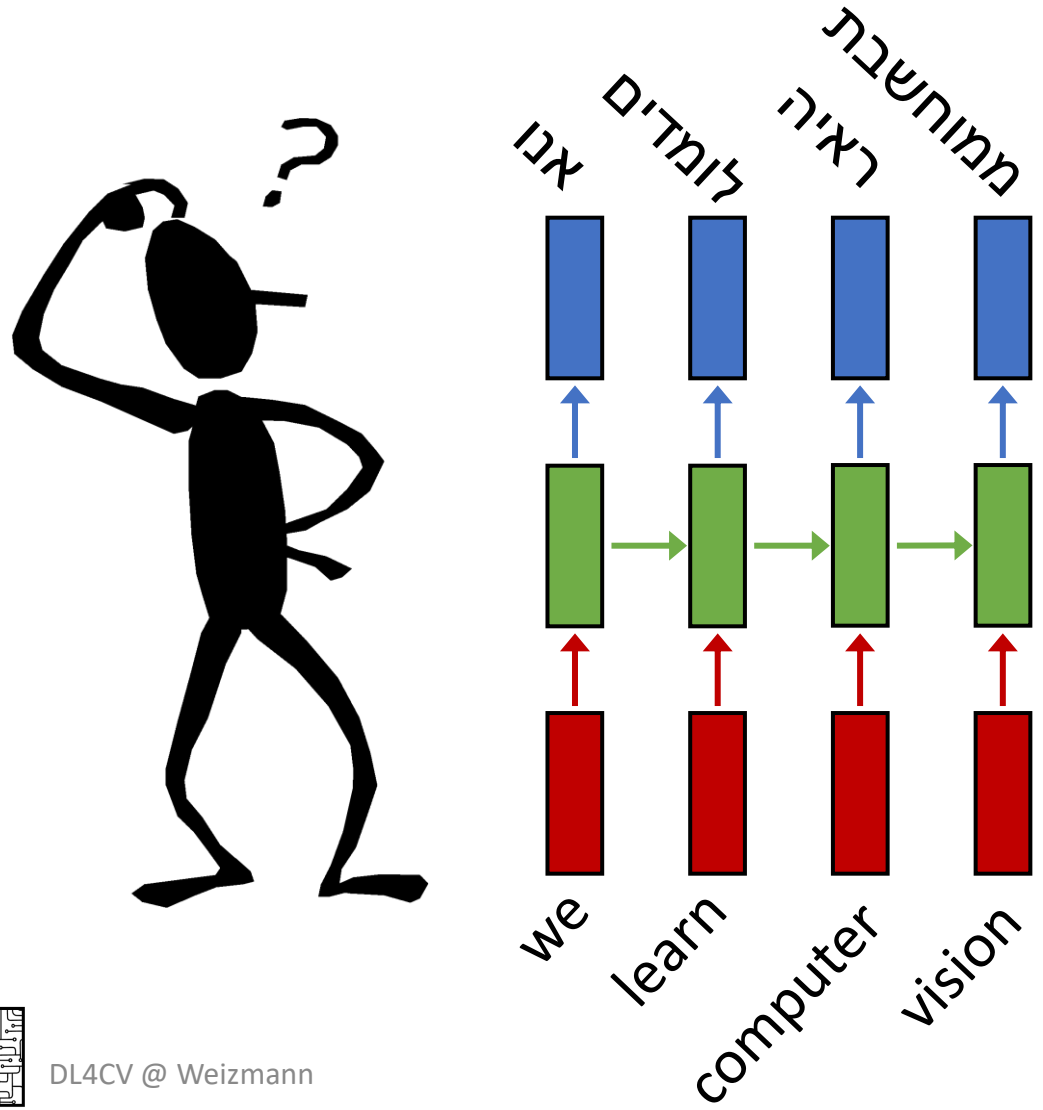
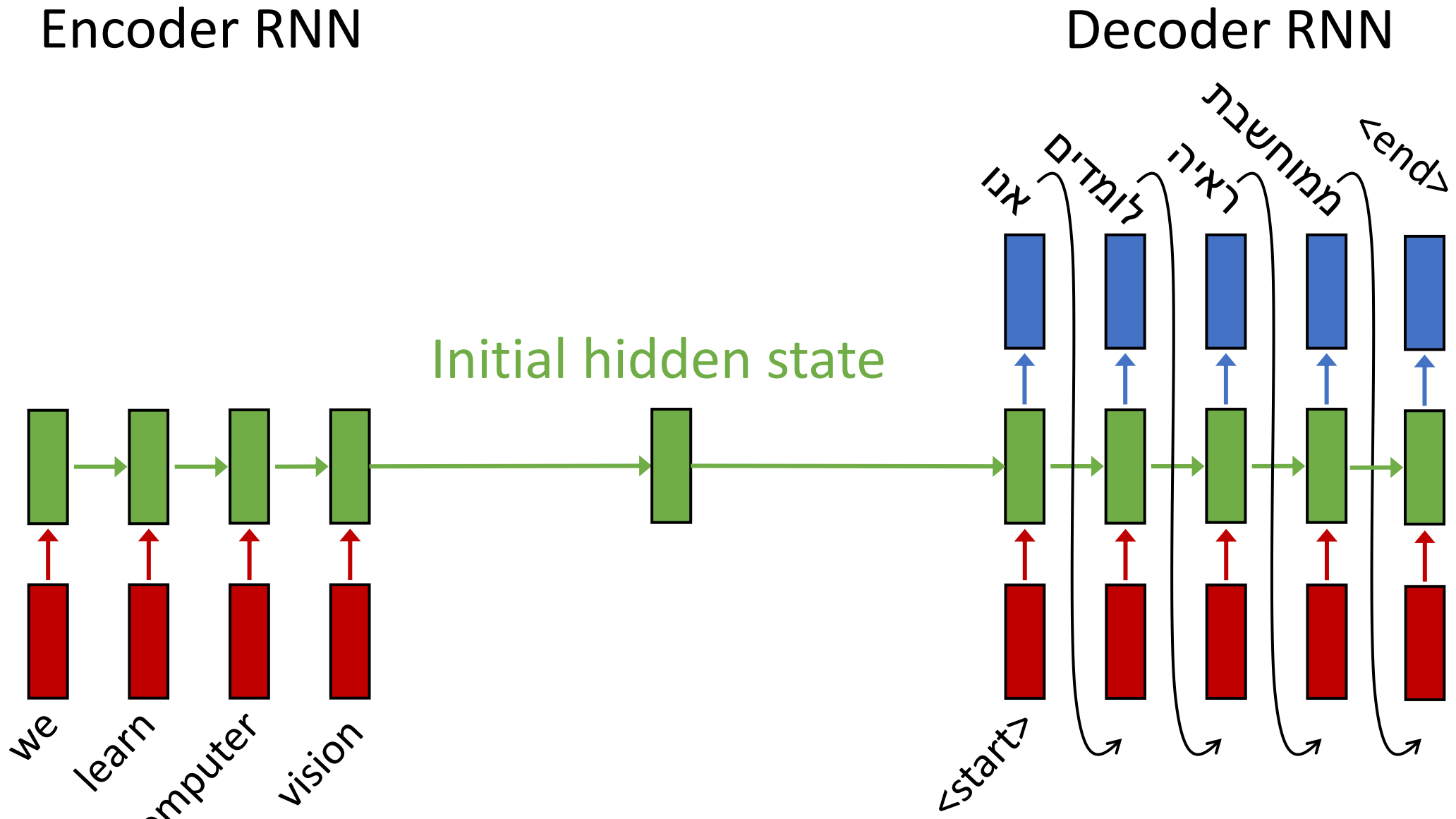
Sequence to Sequence



We	אנו (ANU)
Learn	לומדים (LOMDIM)
Computer	ממוחשבת (MEMUCHSHEVET)
Vision	ראיה (RE’EYA)

Sequence to Sequence: RNN



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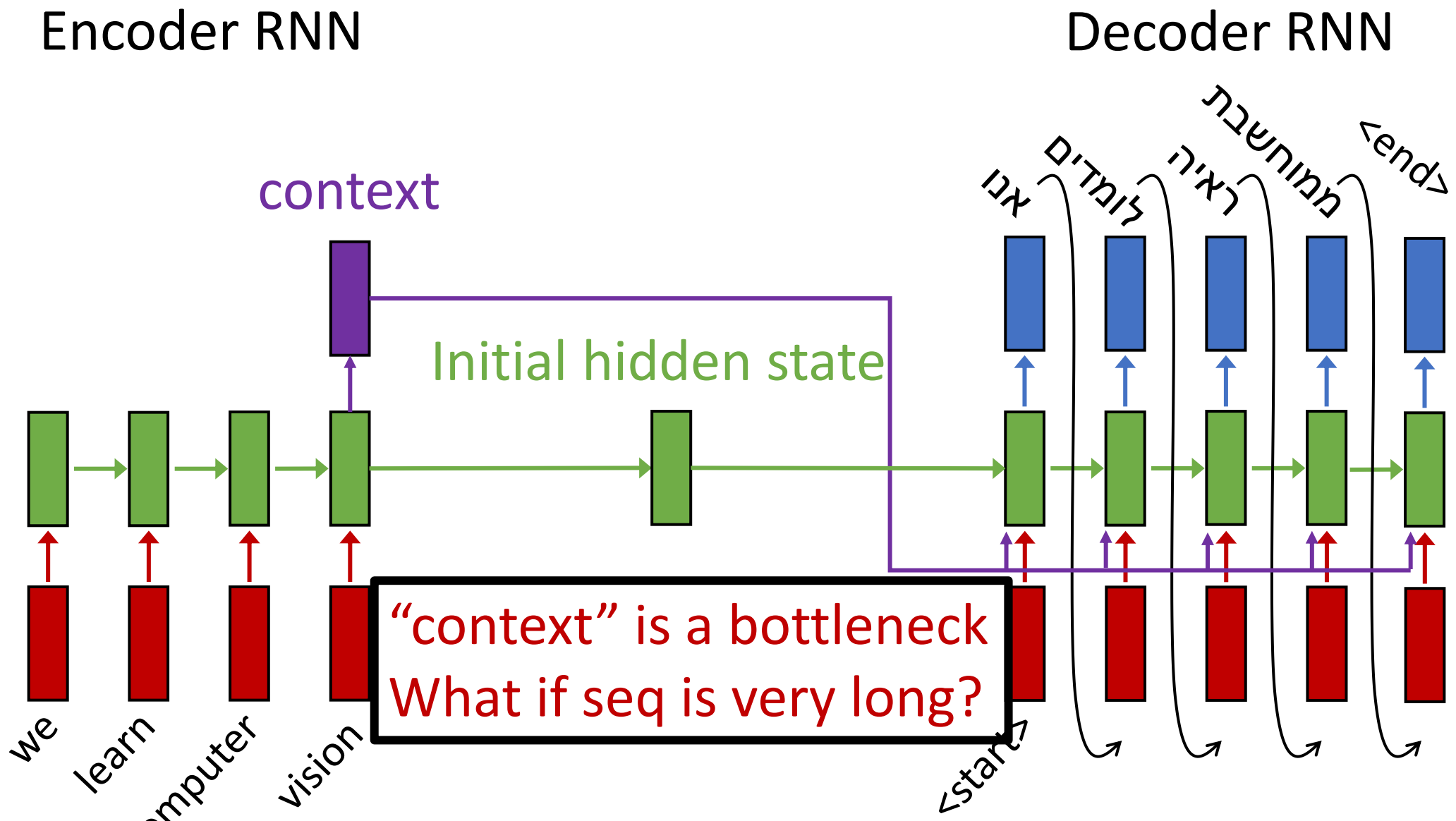

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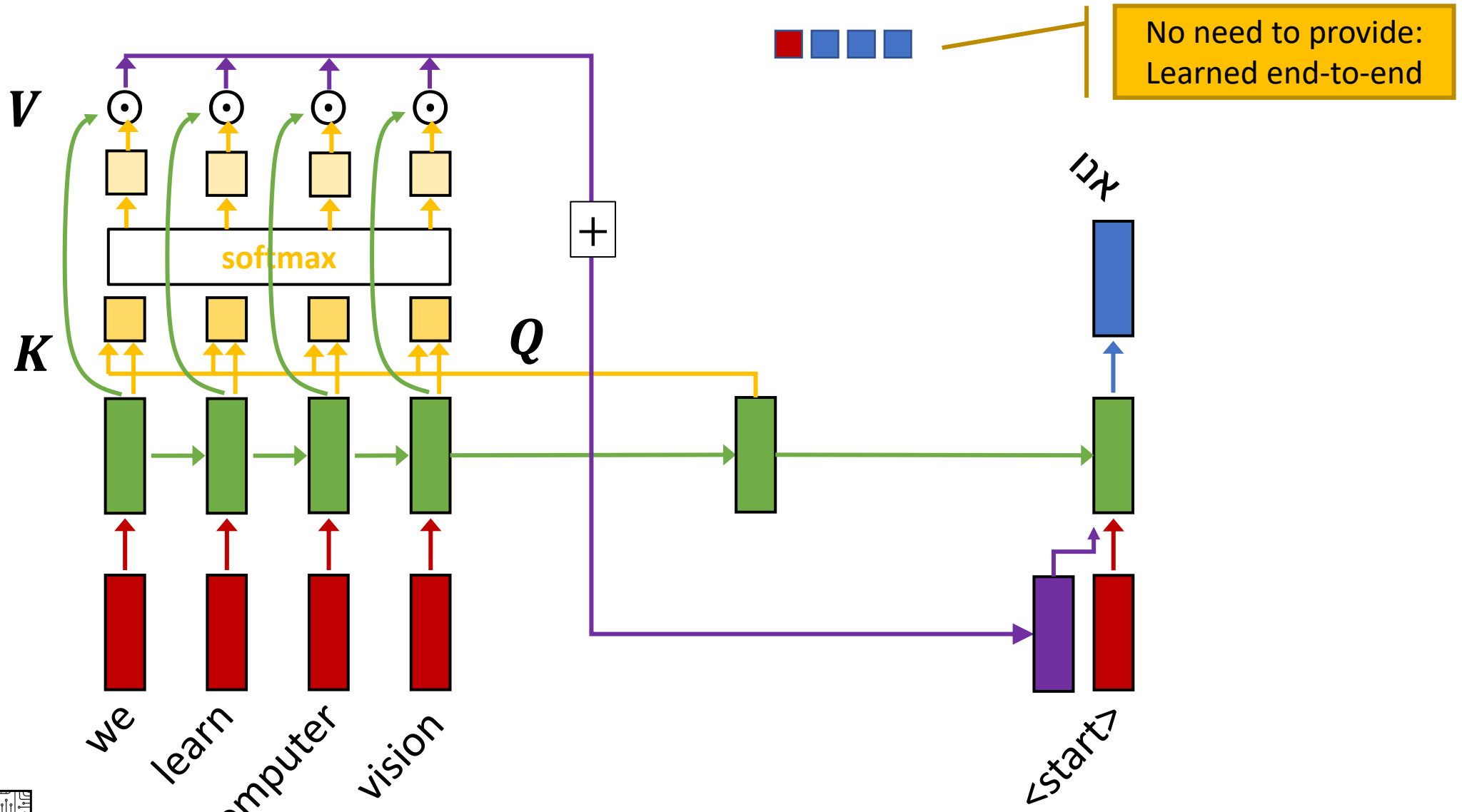
Sequence to Sequence: RNN & Attention



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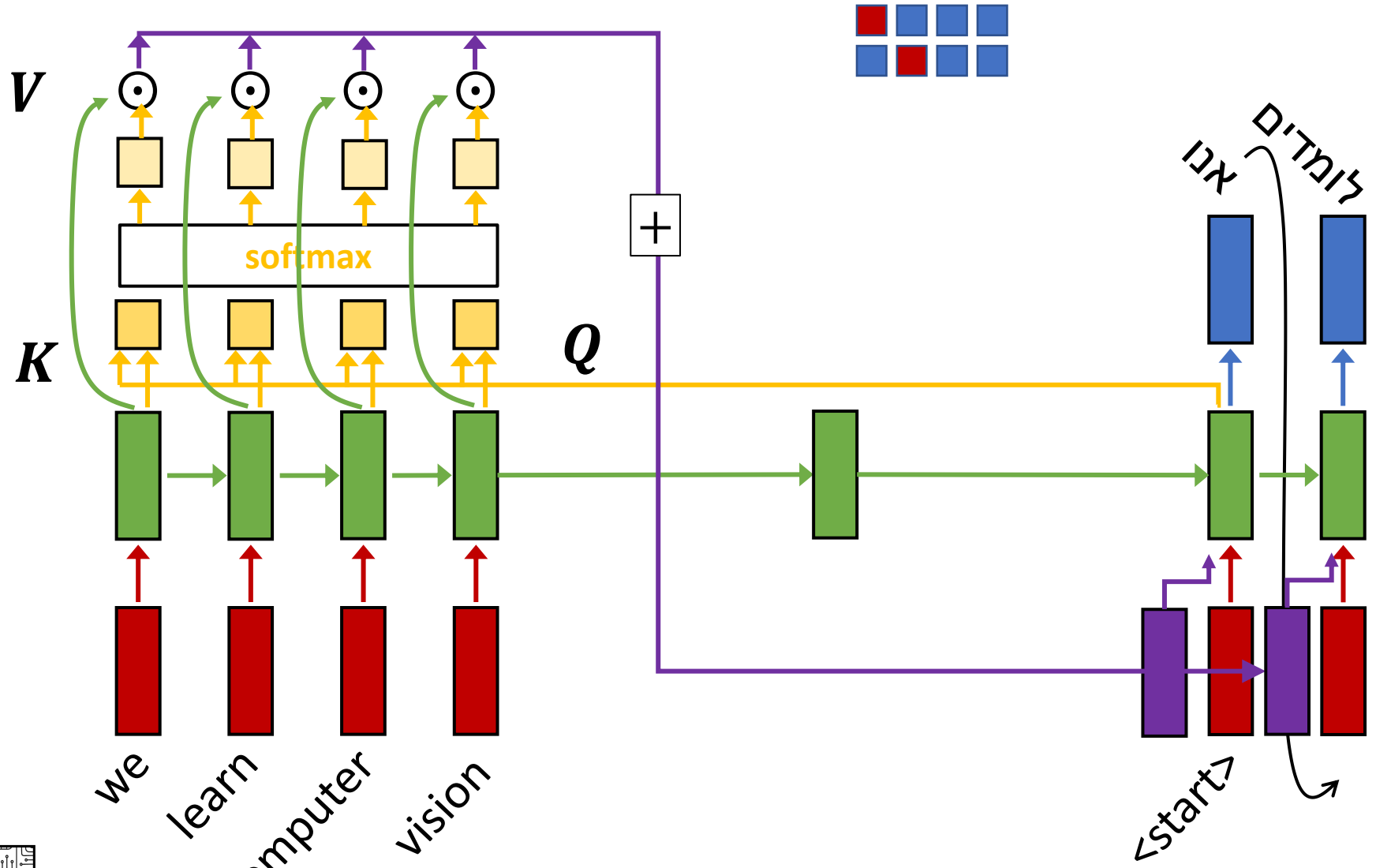

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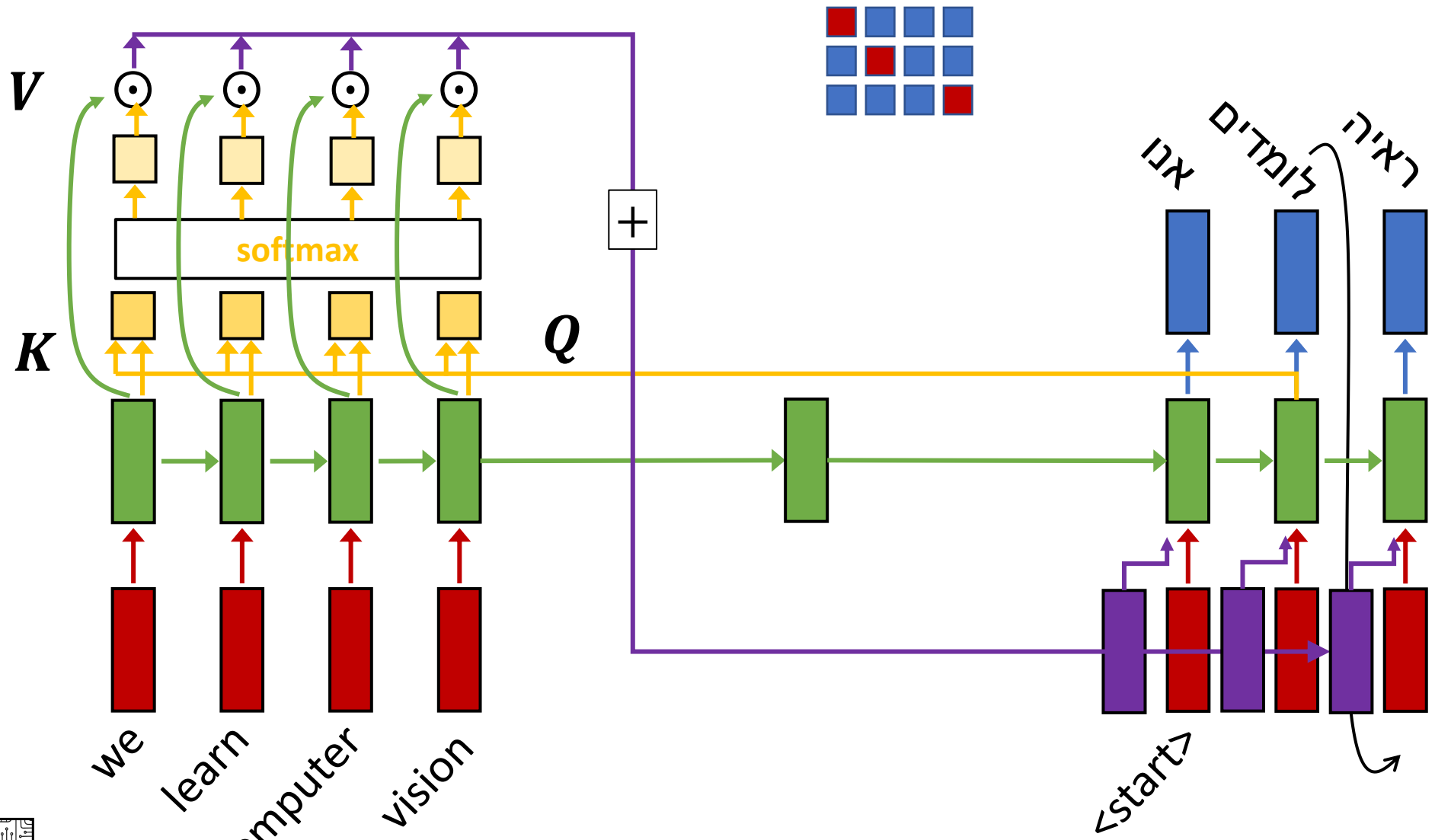

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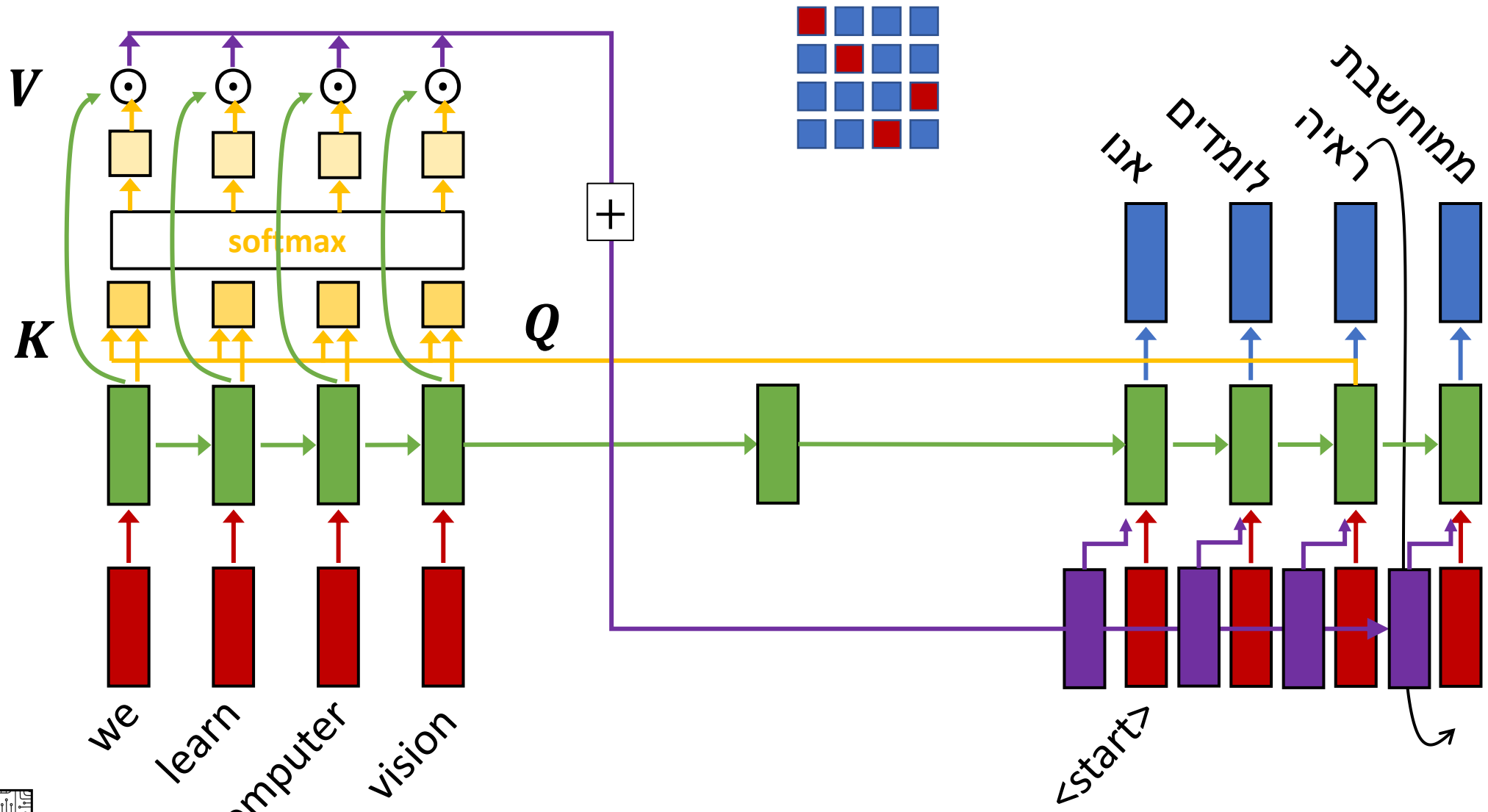

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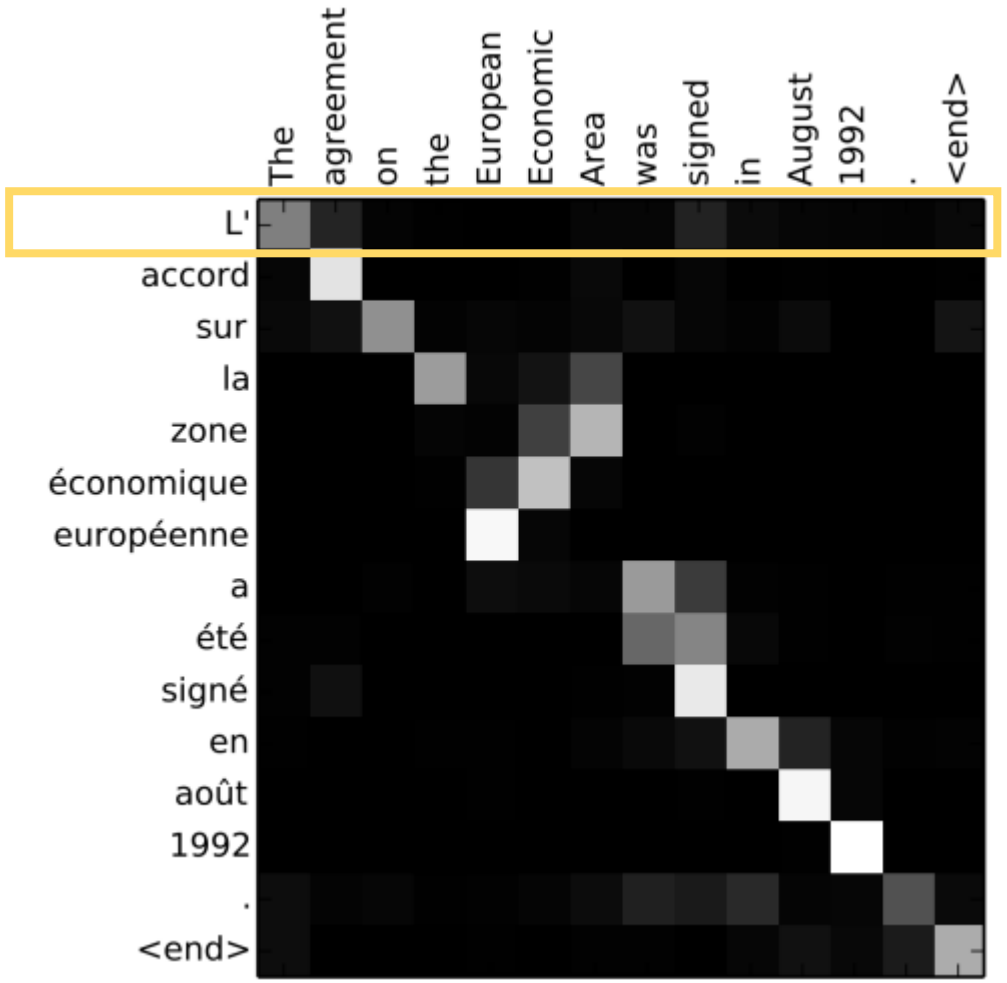
Sequence to Sequence: RNN & Attention

Example: English to French translation

Input (English):
The agreement on the European Economic Area was signed in August 1992.

Output (French):
L'accord sur la zone économique européenne a été signé en août 1992.



Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015
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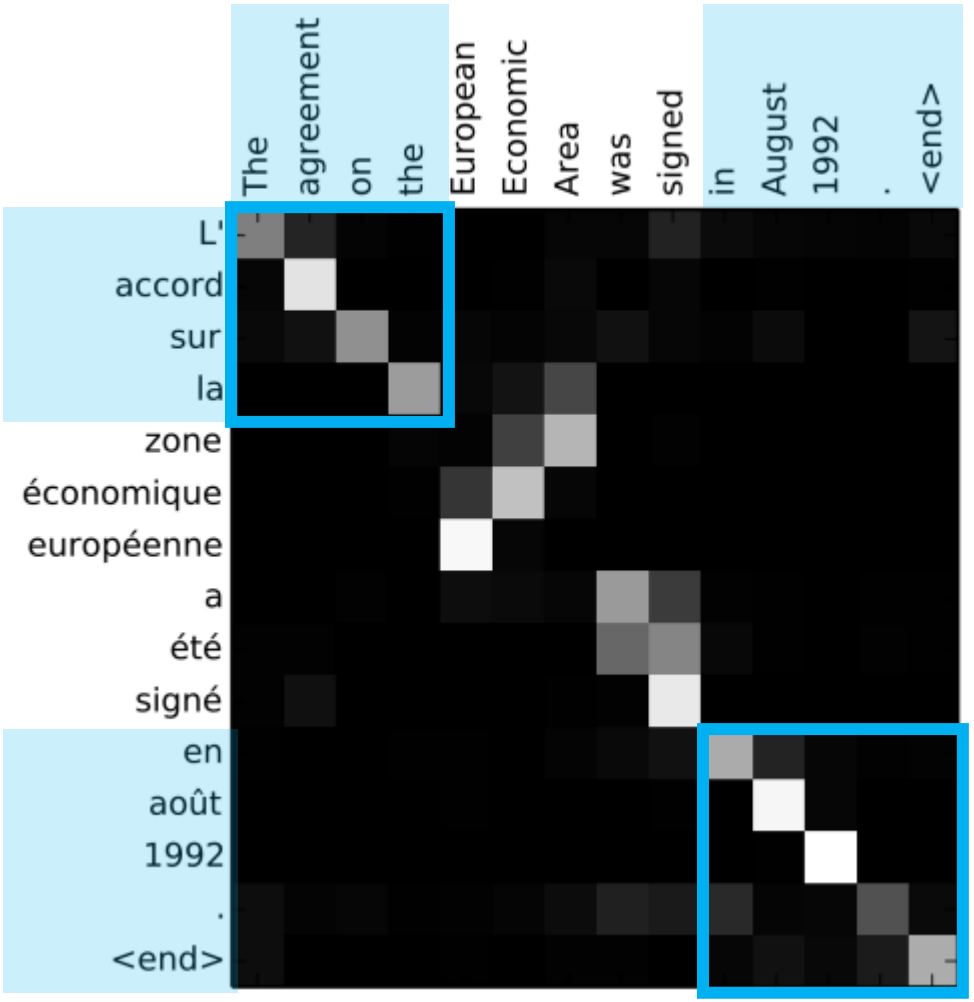

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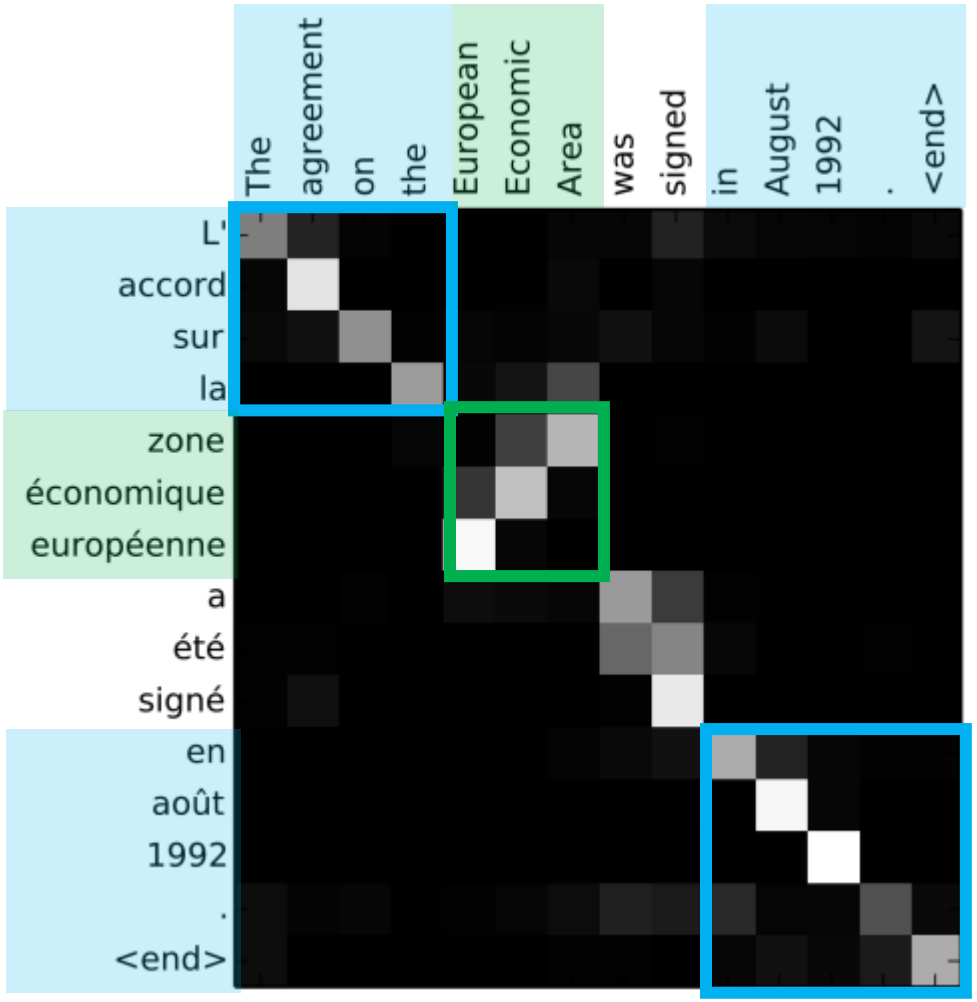

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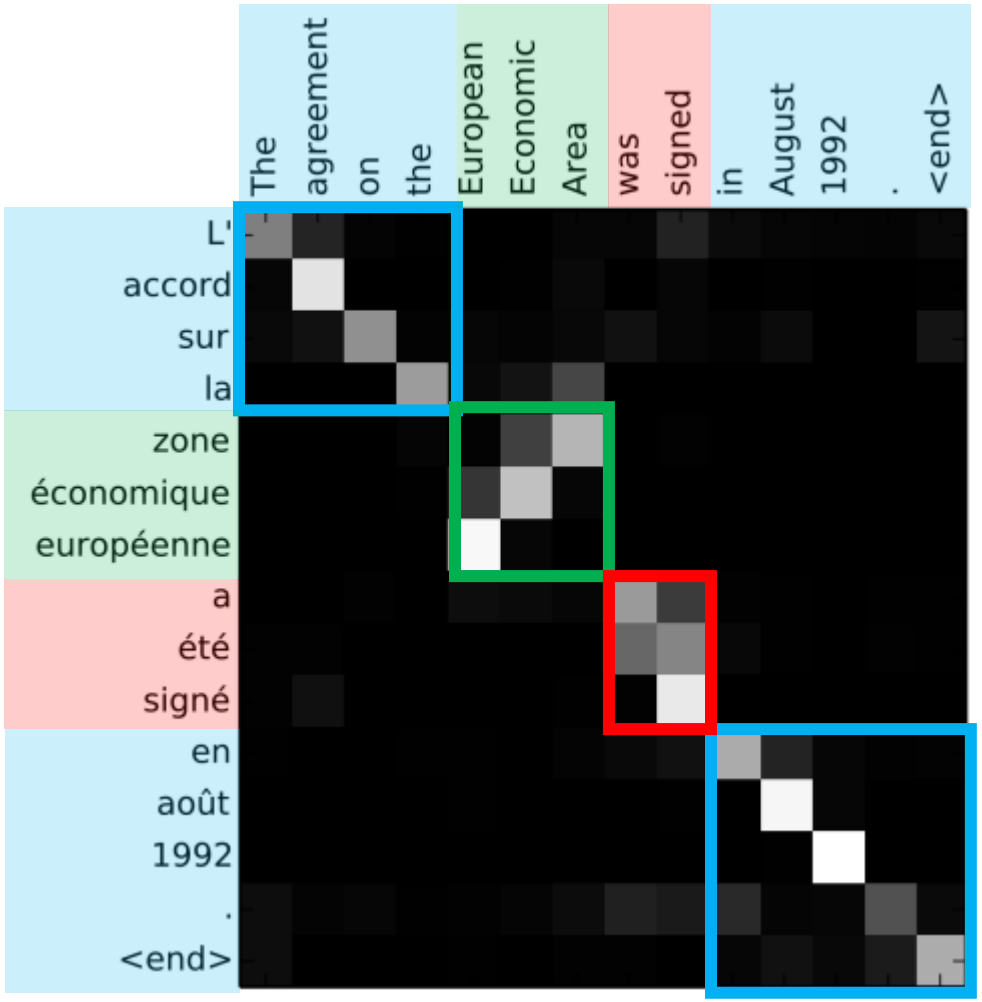

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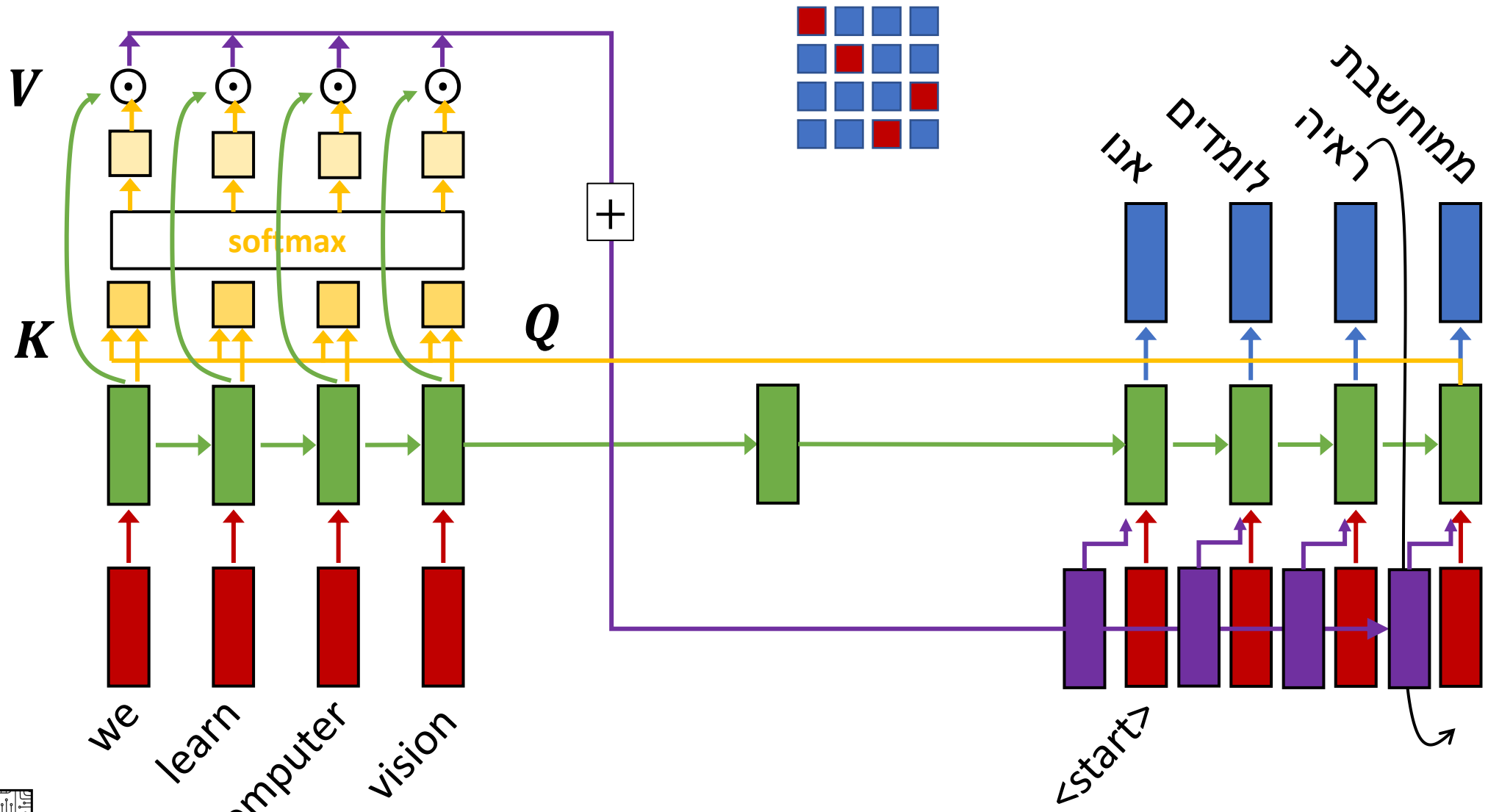
Attention Layer



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Attention Layer

Inputs:

Query: $\boldsymbol{Q}$ (shape: $N_q \times D_q$)

Input: $\boldsymbol{X}$ (shape: $N_x \times D_x$)

Layer's Parameters:

$\boldsymbol{X} \rightarrow \boldsymbol{K}$: W_k (shape: $D_x \times D_q$)

$\boldsymbol{X} \rightarrow \boldsymbol{V}$: W_v (shape: $D_x \times D_v$)

Compute:

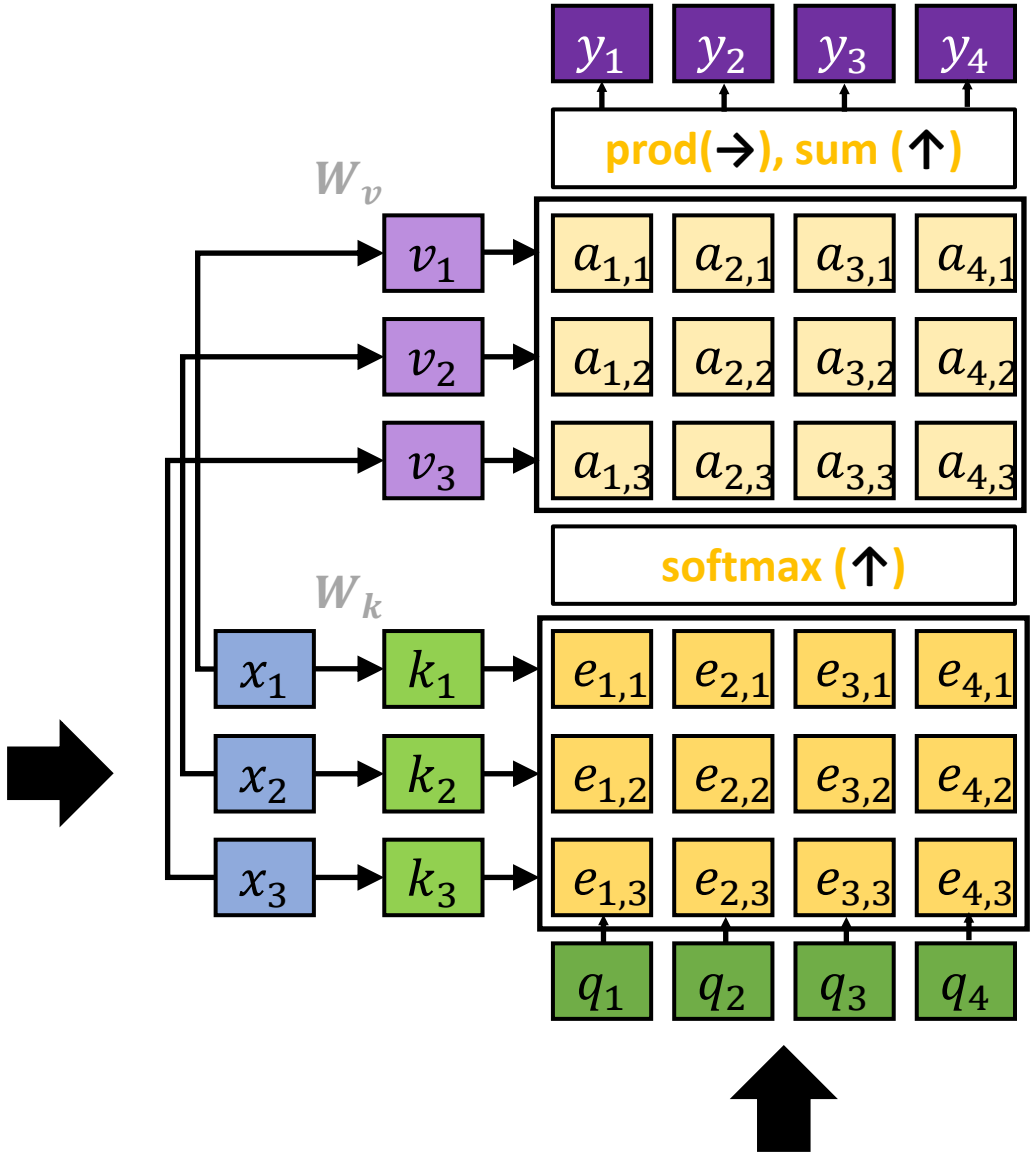
Keys: $\boldsymbol{K} = \boldsymbol{X}\boldsymbol{W_k}$ (shape: $N_x \times D_q$)

Values: $\mathbf{V} = \mathbf{X}\boldsymbol{W_v}$ (shape: $N_x \times D_v$)

Similarities: $\boldsymbol{E} = \boldsymbol{Q}\boldsymbol{K}^T / \sqrt{D_q}$ (shape: $N_q \times N_x$)

Attention: $\boldsymbol{A} = \mathrm{softmax}(\boldsymbol{E}; \uparrow)$ (shape: $N_q \times N_x$)

Outputs: $\mathbf{Y} = \mathbf{A}\mathbf{V}$ (shape: $N_q \times D_v$)



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Self-Attention Layer

Input:

Input: $\boldsymbol{X}$ (shape: $N_x \times D_x$)

Layer's Parameters:

$\boldsymbol{X} \rightarrow \boldsymbol{Q}$: W_q (shape: $D_x \times D_q$)

$\boldsymbol{X} \rightarrow \boldsymbol{K}$: W_k (shape: $D_x \times D_q$)

$\boldsymbol{X} \rightarrow \boldsymbol{V}$: W_v (shape: $D_x \times D_v$)

Compute:

Query: $\boldsymbol{Q} = \boldsymbol{X}\boldsymbol{W_q}$ (shape: $N_x \times D_q$)

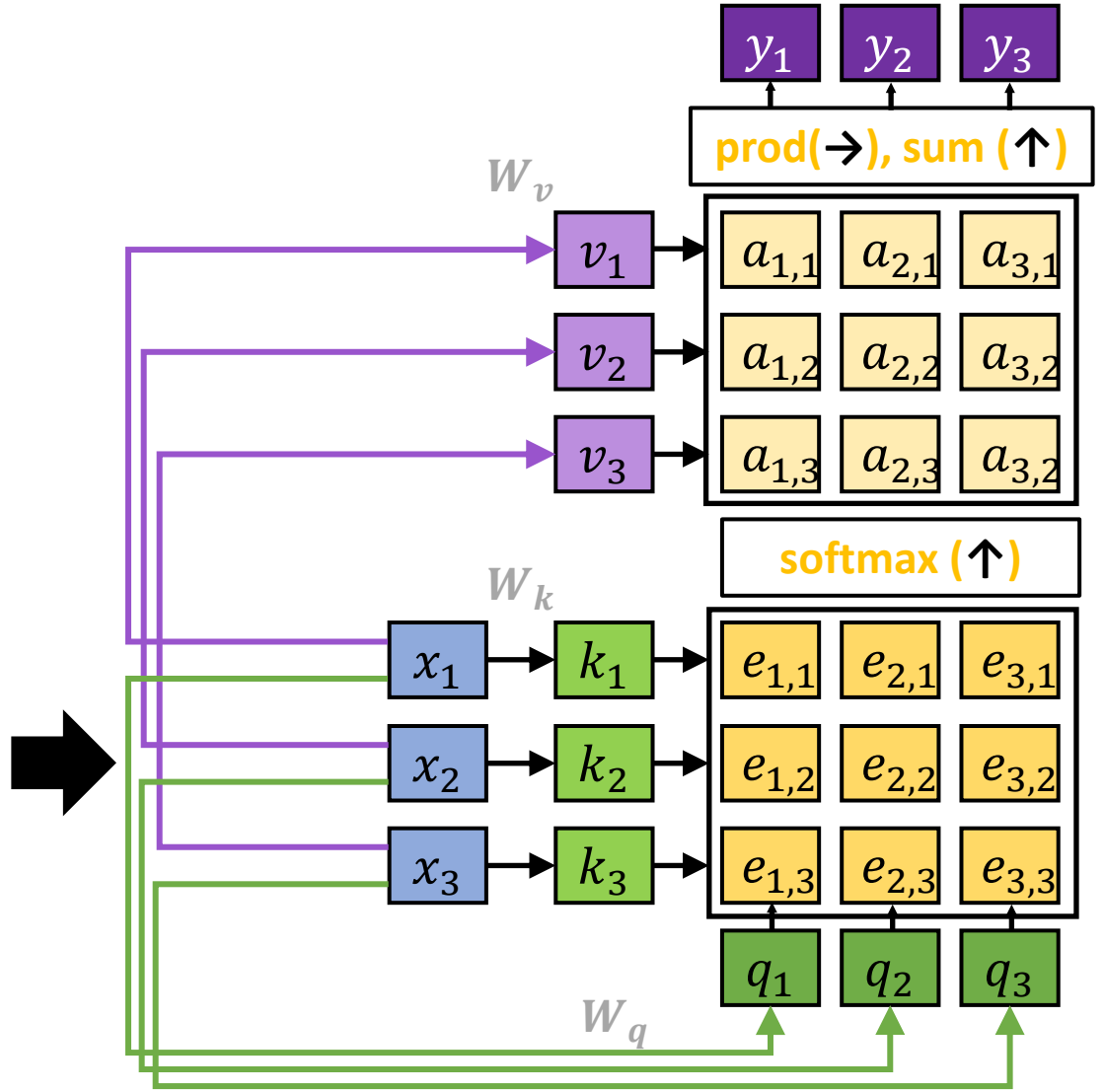
Keys: $\boldsymbol{K} = \boldsymbol{X}\boldsymbol{W_k}$ (shape: $N_x \times D_q$)

Values: $\mathbf{V} = \mathbf{X}\boldsymbol{W_v}$ (shape: $N_x \times D_v$)

Similarities: $\boldsymbol{E} = \boldsymbol{Q}\boldsymbol{K}^T / \sqrt{D_q}$ (shape: $N_q \times N_x$)

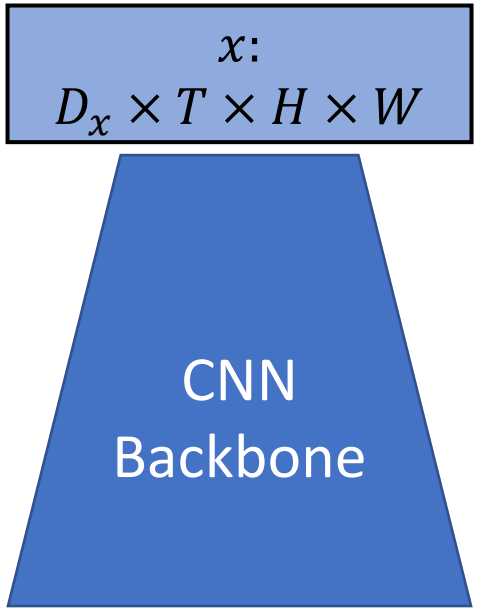
Attention: $\boldsymbol{A} = \mathrm{softmax}(\boldsymbol{E}; \uparrow)$ (shape: $N_q \times N_x$)

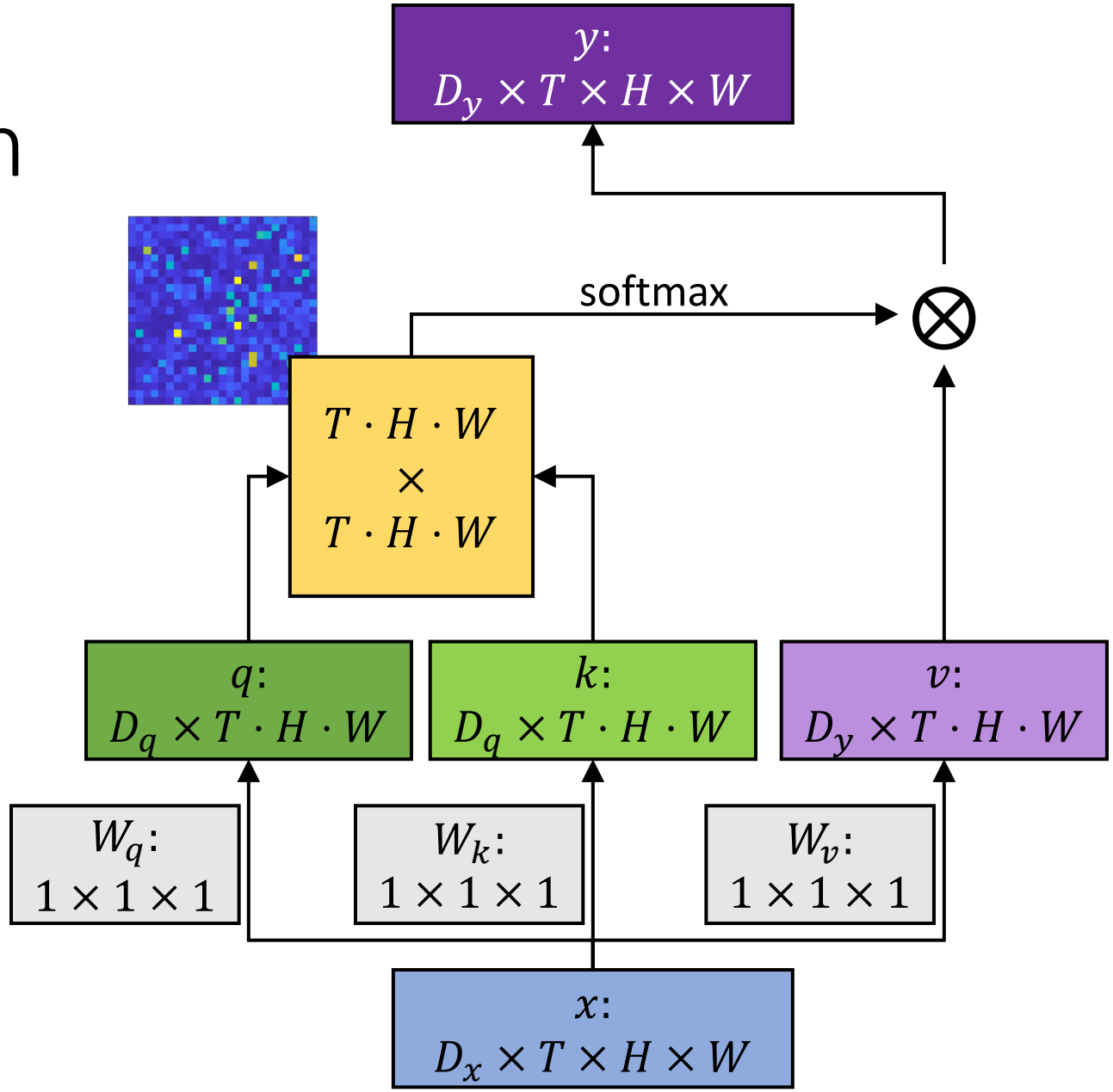
Outputs: $\mathbf{Y} = \mathbf{A}\mathbf{V}$ (shape: $N_q \times D_v$)



Slide credit: Justin Johnson (EECS-498-007, UMich)

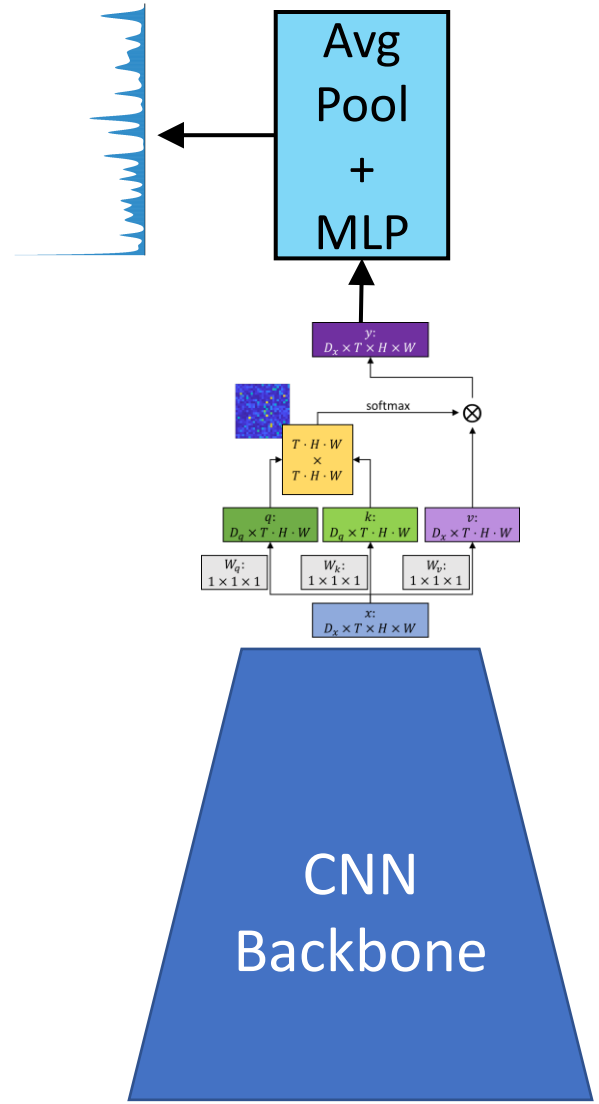
Self Attention in Vision





Wang, X., Girshick, R., Gupta, A. and He, K., "Non-local neural networks" CVPR (2018)

Self Attention in Vision



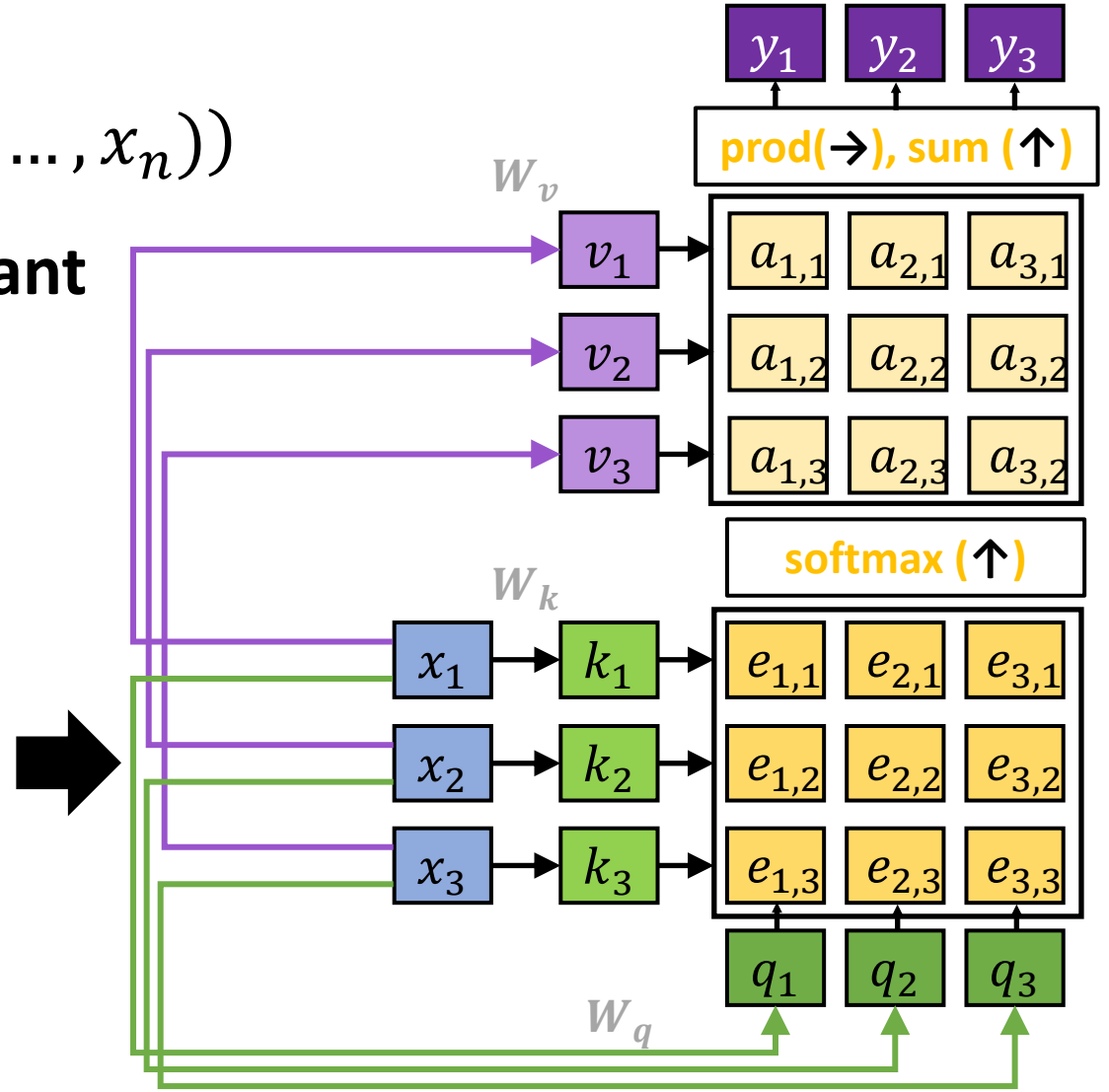
Wang, X., Girshick, R., Gupta, A. and He, K., "Non-local neural networks" CVPR (2018)

Self-Attention Layer: Properties

$$\text{SelfAtt}\big(\pi(x_1, \ldots, x_n)\big) = \pi(\text{SelfAtt}(x_1, \ldots, x_n))$$

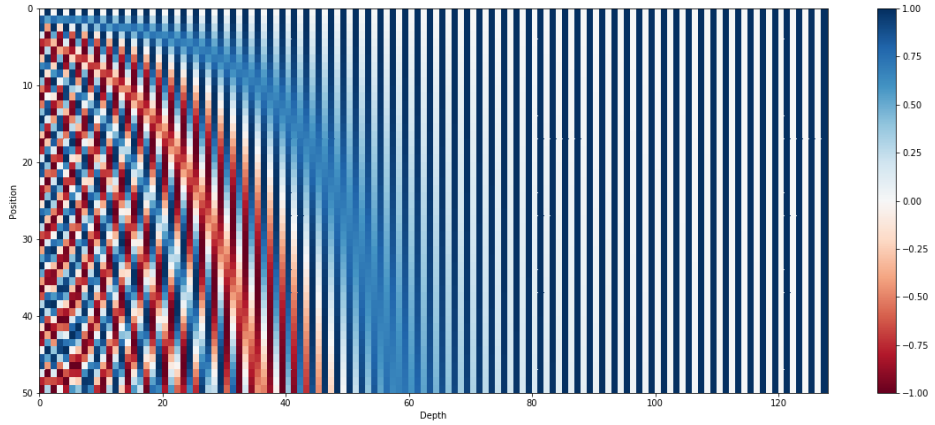
Self-Attention is **permutation equivariant**

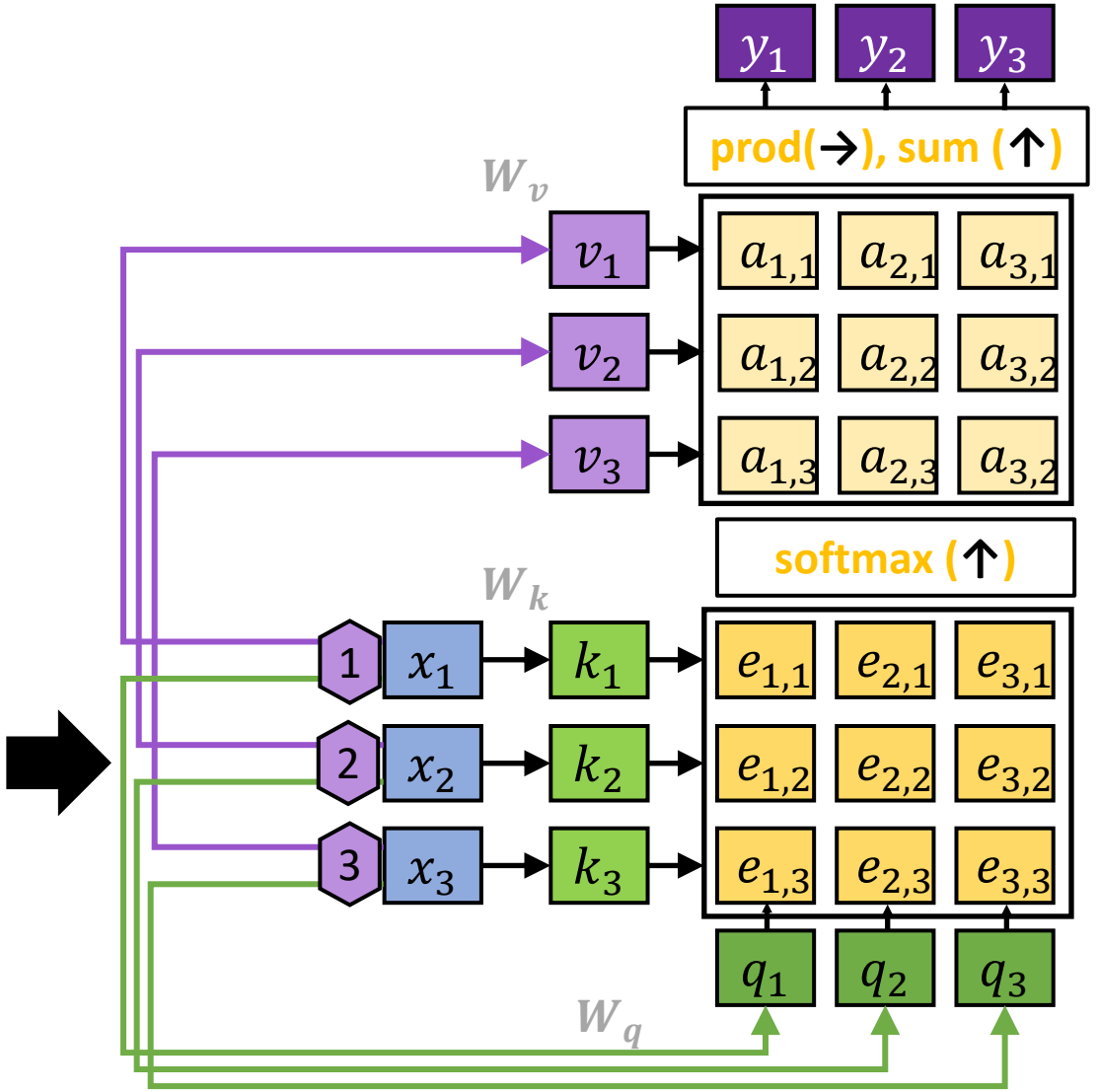
"I am studying" ? "Am I studying"



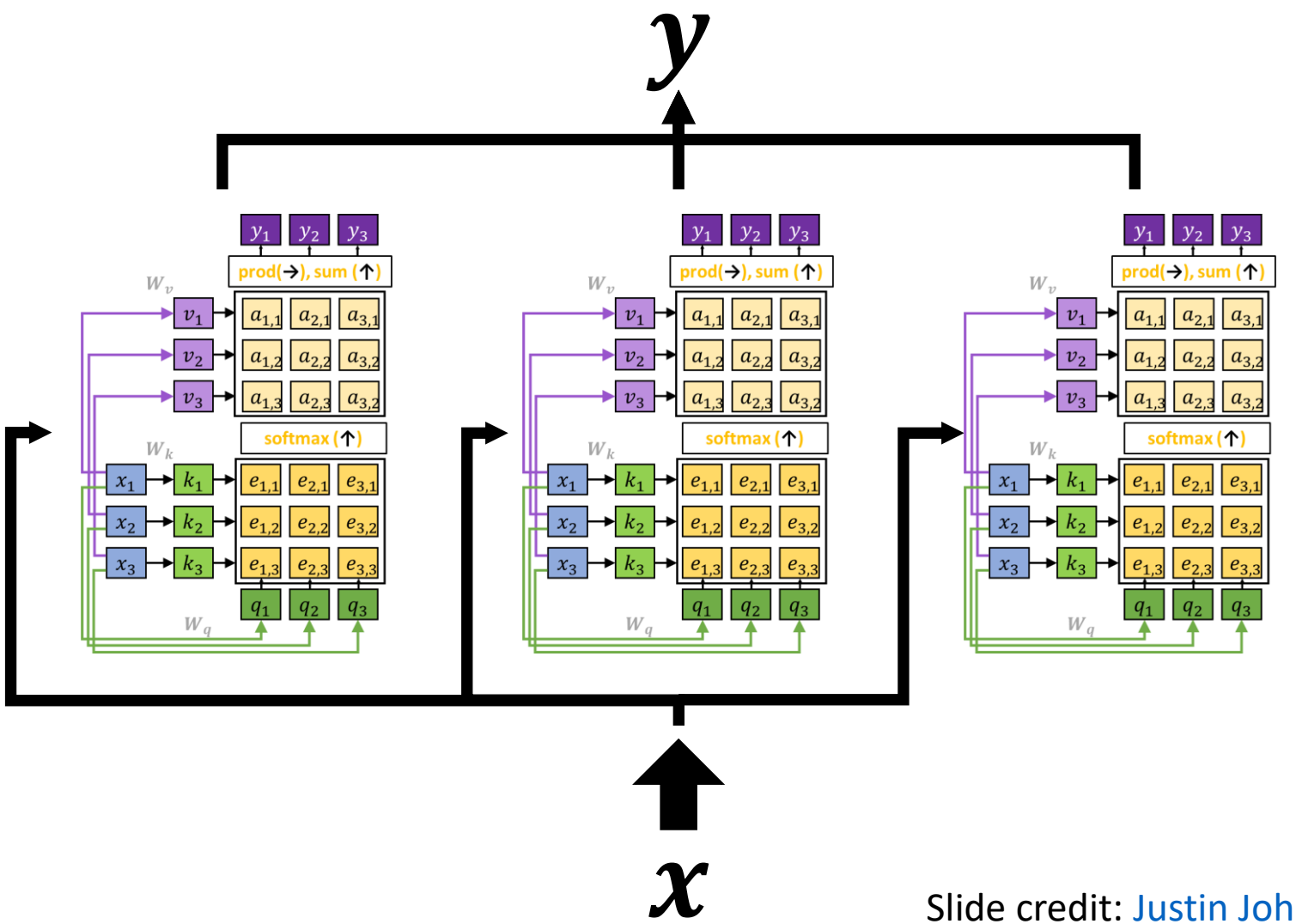
Self-Attention Layer: Properties

Positional Encoding





Multi-head Self-Attention



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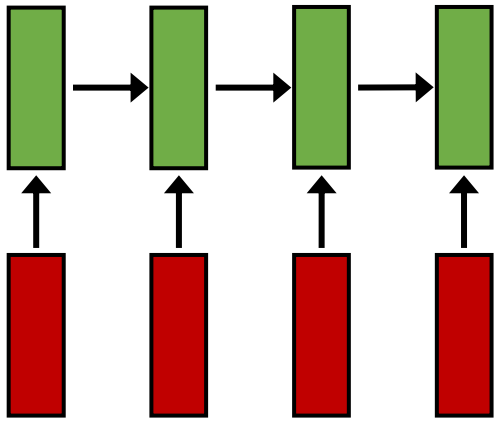
Three Ways of Processing Sequences

Recurrent Neural Network

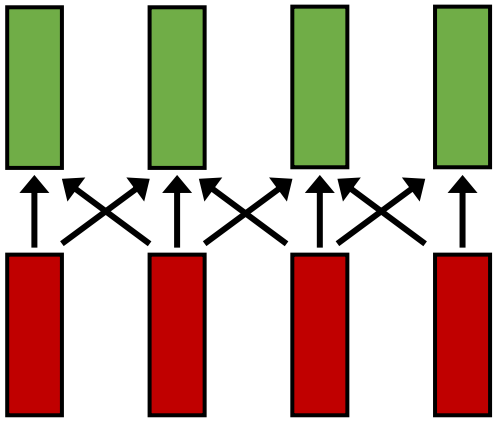


Works on **Ordered Sequences**

(+) large and adaptive receptive field via hidden state

(-) Not parallelizable: need to process states sequentially

1D Convolution

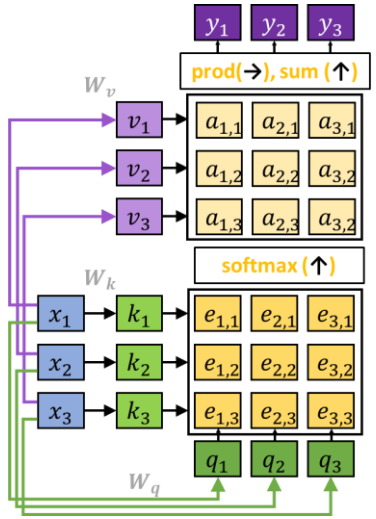


Works on **Multidimensional Grids**

(-) Fixed receptive field. Need to stack many layers to have a decent one

(+) Highly parallelizable

Self-Attention



Works on **Sets**

(+) receptive filed = entire sequence

(+) parallelizable

(-) Very memory intensive

Slide credit: [Justin Johnson (EECS-498-007, UMich)]

Three Ways of Processing Sequences

Attention Is All You Need

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Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

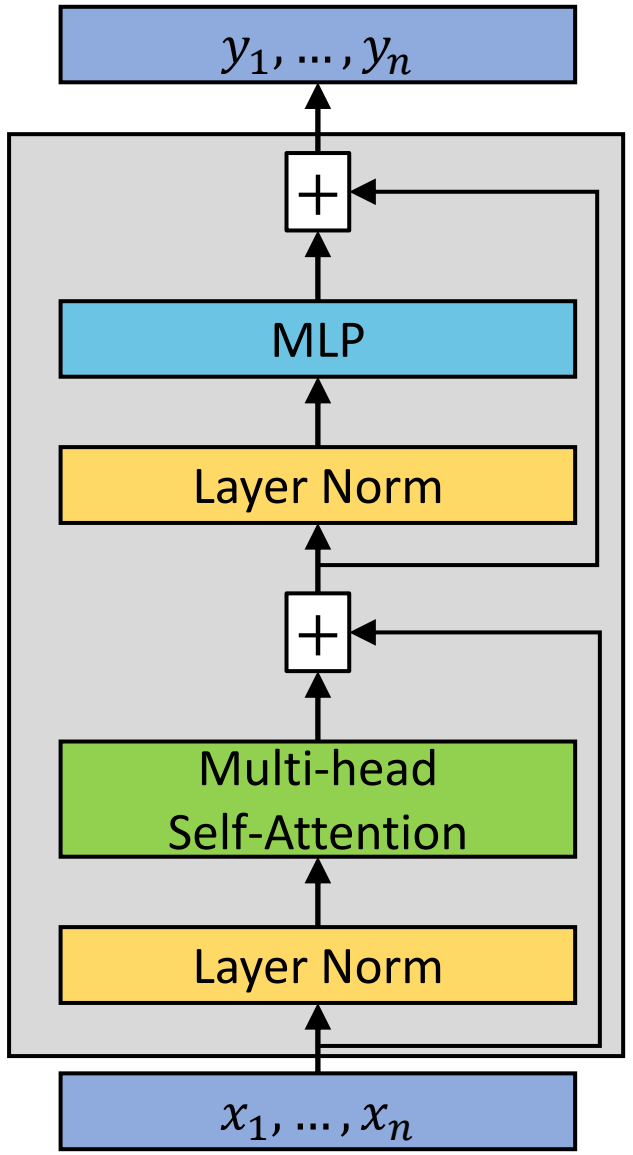
Slide credit: Justin Johnson (EECS-498-007, UMich)

Transformer Layer

Input: $x_1, \dots, x_n$ (n tokens in D dimensions)

Layer Norm:
γ, β: scale and shift parameters (D dimensions)

Compute:
$\mu_i = \sum_j x_{ij} / D$ (n scalars)
$\sigma_i = \sqrt{\sum_j (x_{ij} - \mu_i) / D}$ (n scalars)
output: $o_i = \gamma \cdot \frac{(x_i - \mu_i)}{\sigma_i} + \beta$



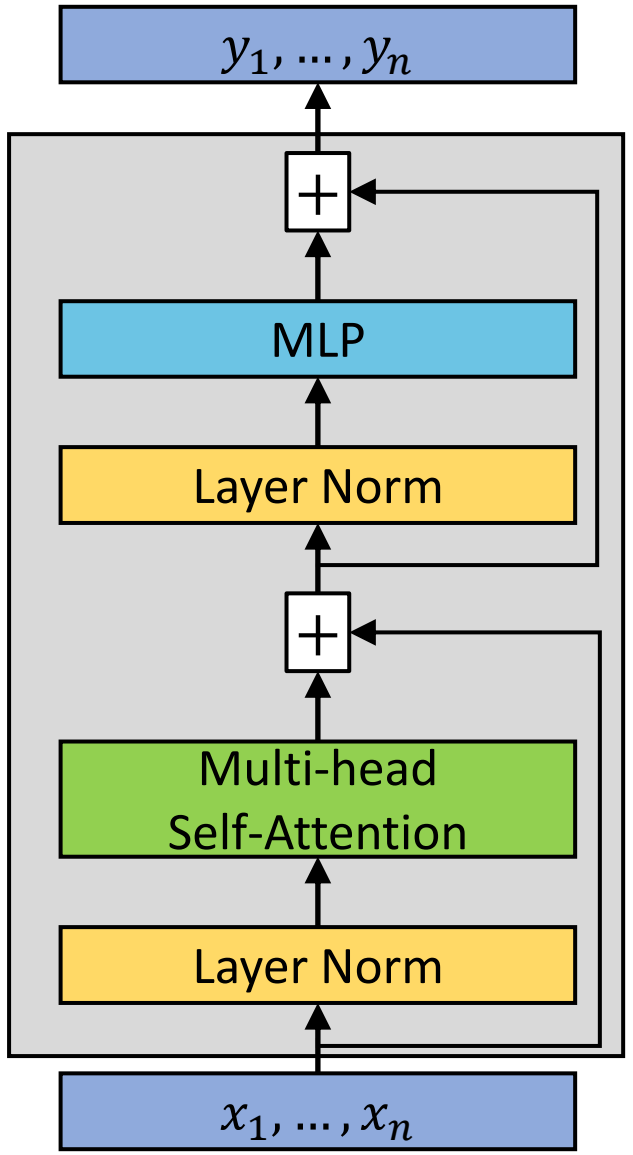
Slide credit: Justin Johnson (EECS-498-007, UMich)

Transformer Layer

Input: $x_1, \ldots, x_n$ (n tokens in D dimensions)
Output: $y_1, \ldots, y_n$ (n tokens in D dimensions)

Highly scalable

Highly parallelizable



Slide credit: Justin Johnson (EECS-498-007, UMich)

Transformers Network

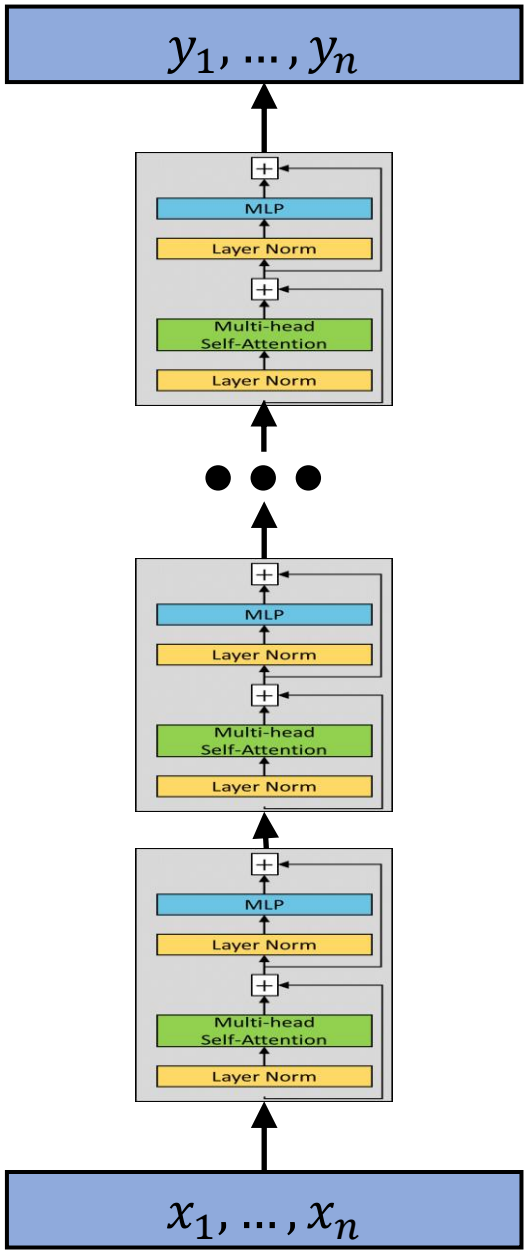
Pretraining:
Download a LOT of text from the internet

Train a transformers network using self-supervision

Finetuning:

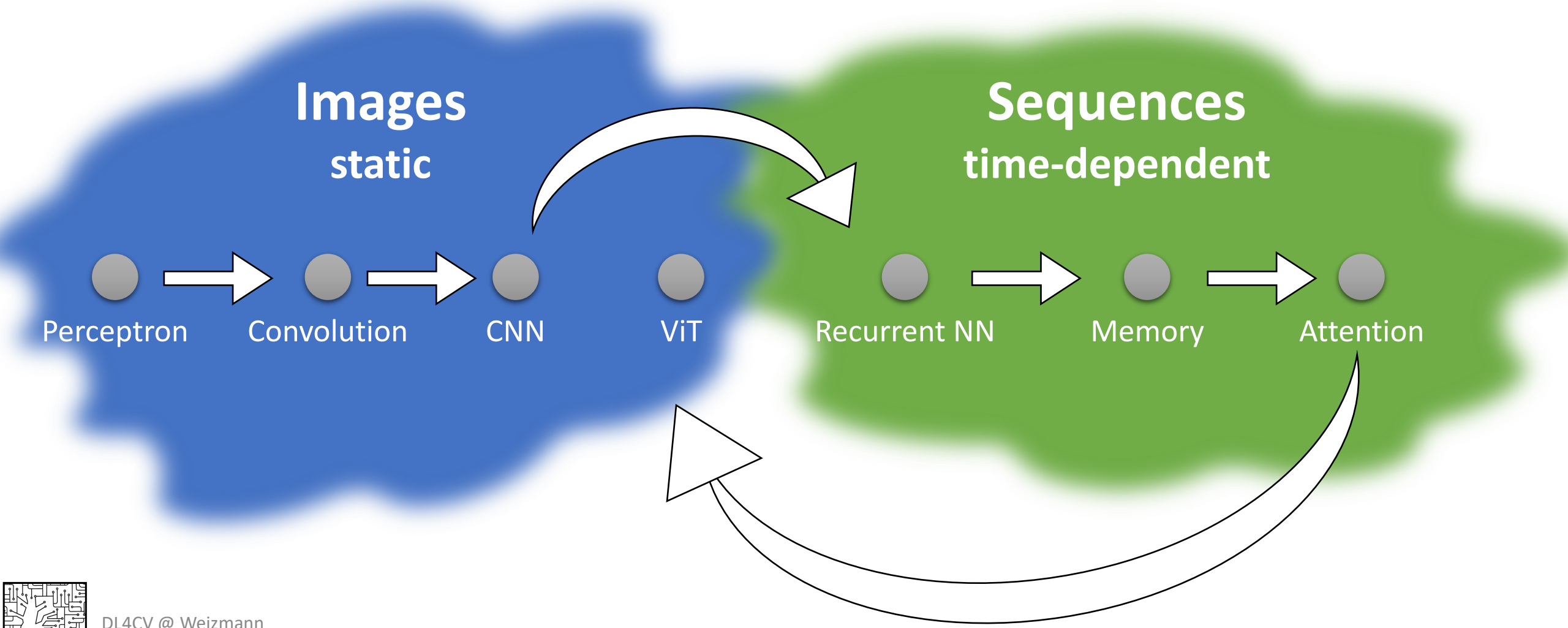
Fine-tune the transformer to specific NLP task at hand

Model	Layers	Width (D)	#Heads	#Params	Data
BERT-base	12	768	12	110M	13GB
BERT-large	24	1024	16	340M	13GB
GPT-2	48	1600	?	1.5B	40GB
GPT-3	96	12288	96	175B	694GB

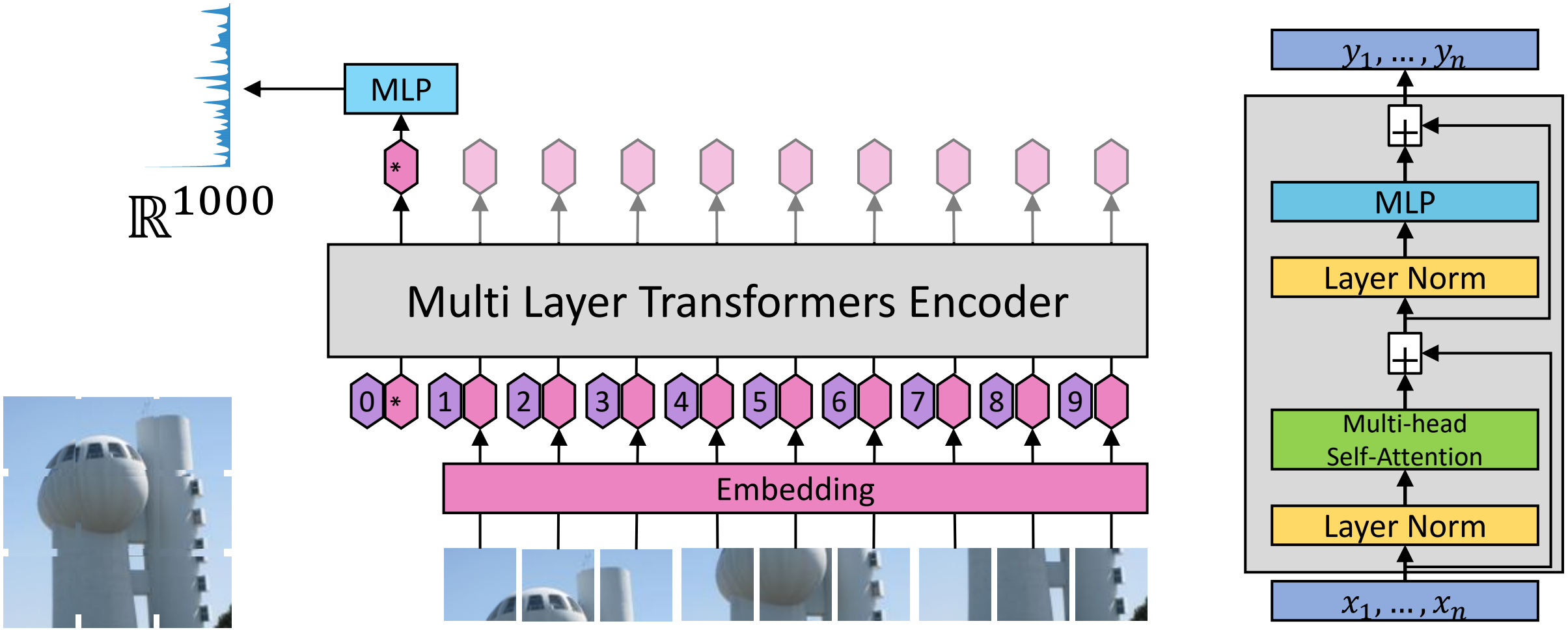


Example of GPT-3 generated text

Agenda


Images
static
Sequences
time-dependent
Perceptron
Convolution
CNN
ViT
Recurrent NN
Memory
Attention

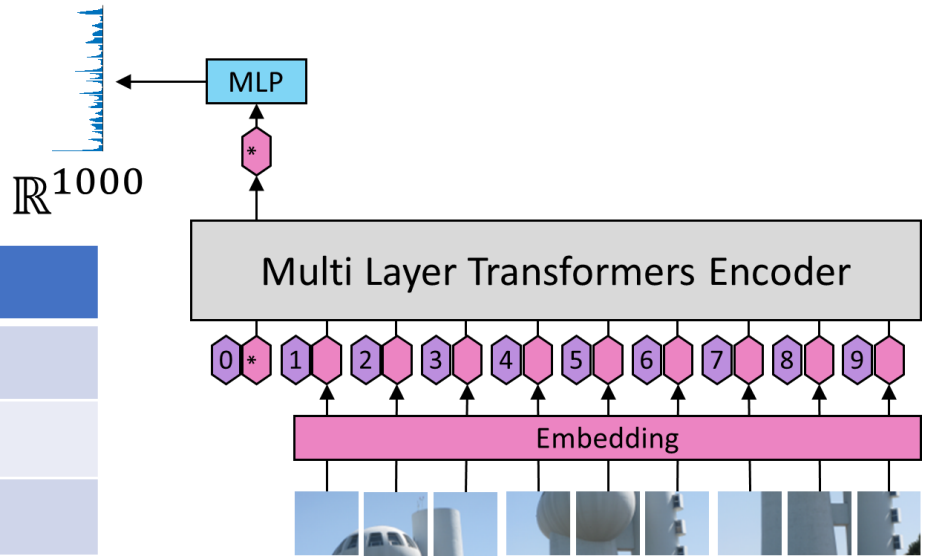
Vision Transformers (ViT)



Dosovitskiy A., Beyer L., Kolesnikov A., Weissenborn D., Zhai X., Unterthiner T., Dehghani M., Minderer M., Heigold G., Gelly S., Uszkoreit J. and Houlsby N. "**An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale**" (ICLR 2021)

Vision Transformers (ViT)

Model	Layers	Width (D)	#Heads	#Params
ViT-Base	12	768	12	86M
ViT-Large	24	1024	16	307M
ViT-Huge	32	1280	16	632M



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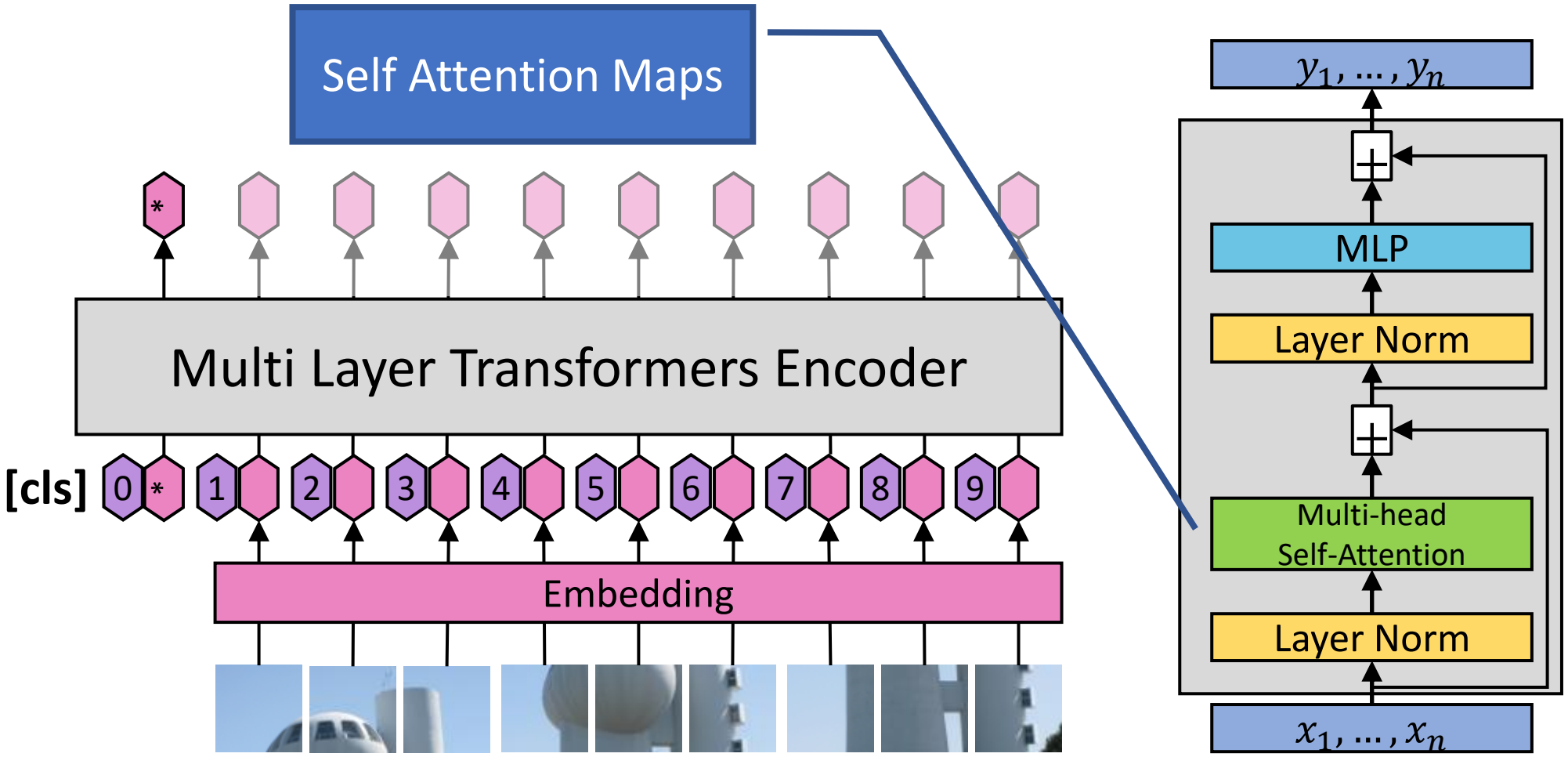
Vision Transformers (ViT)



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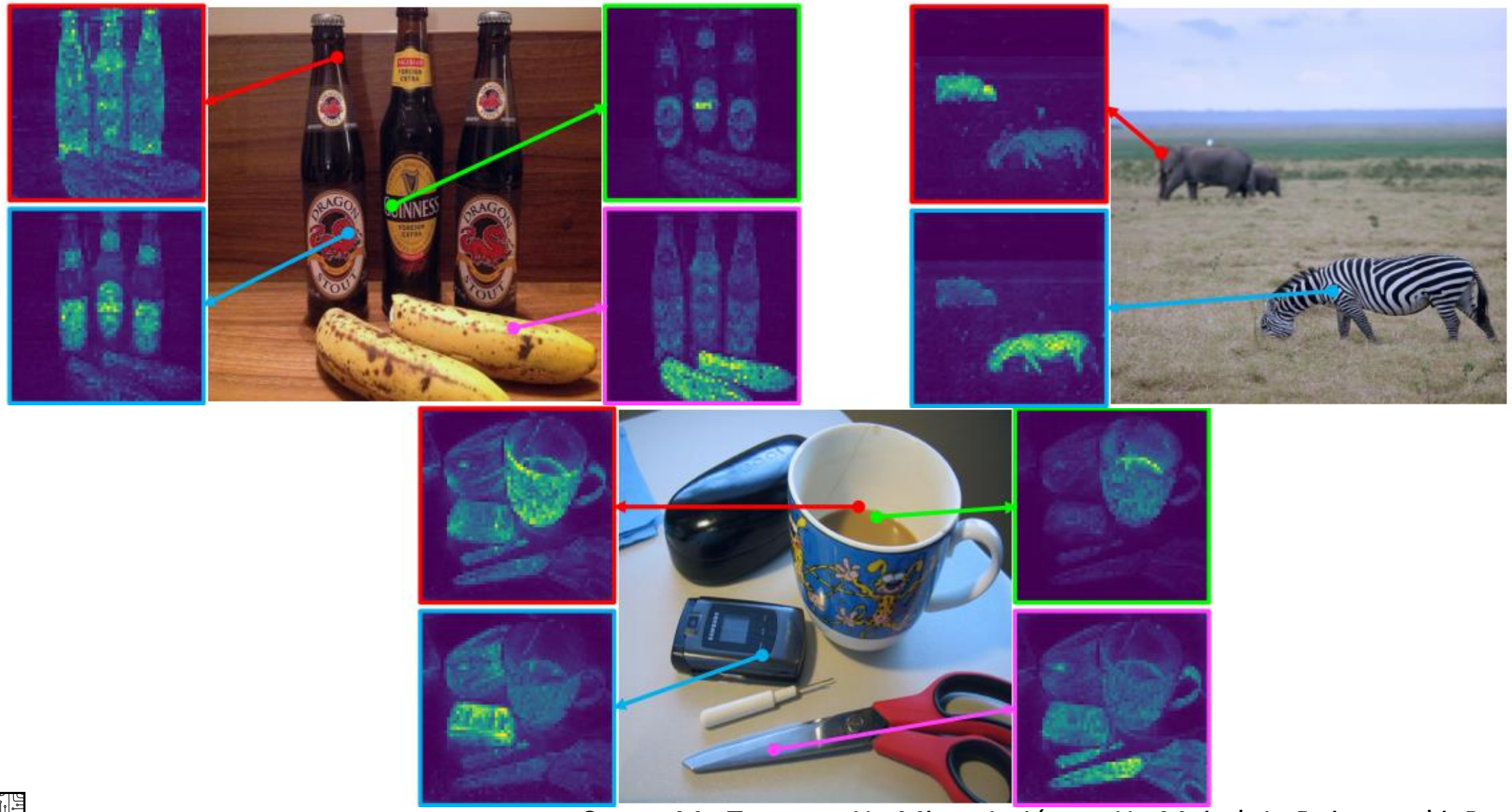
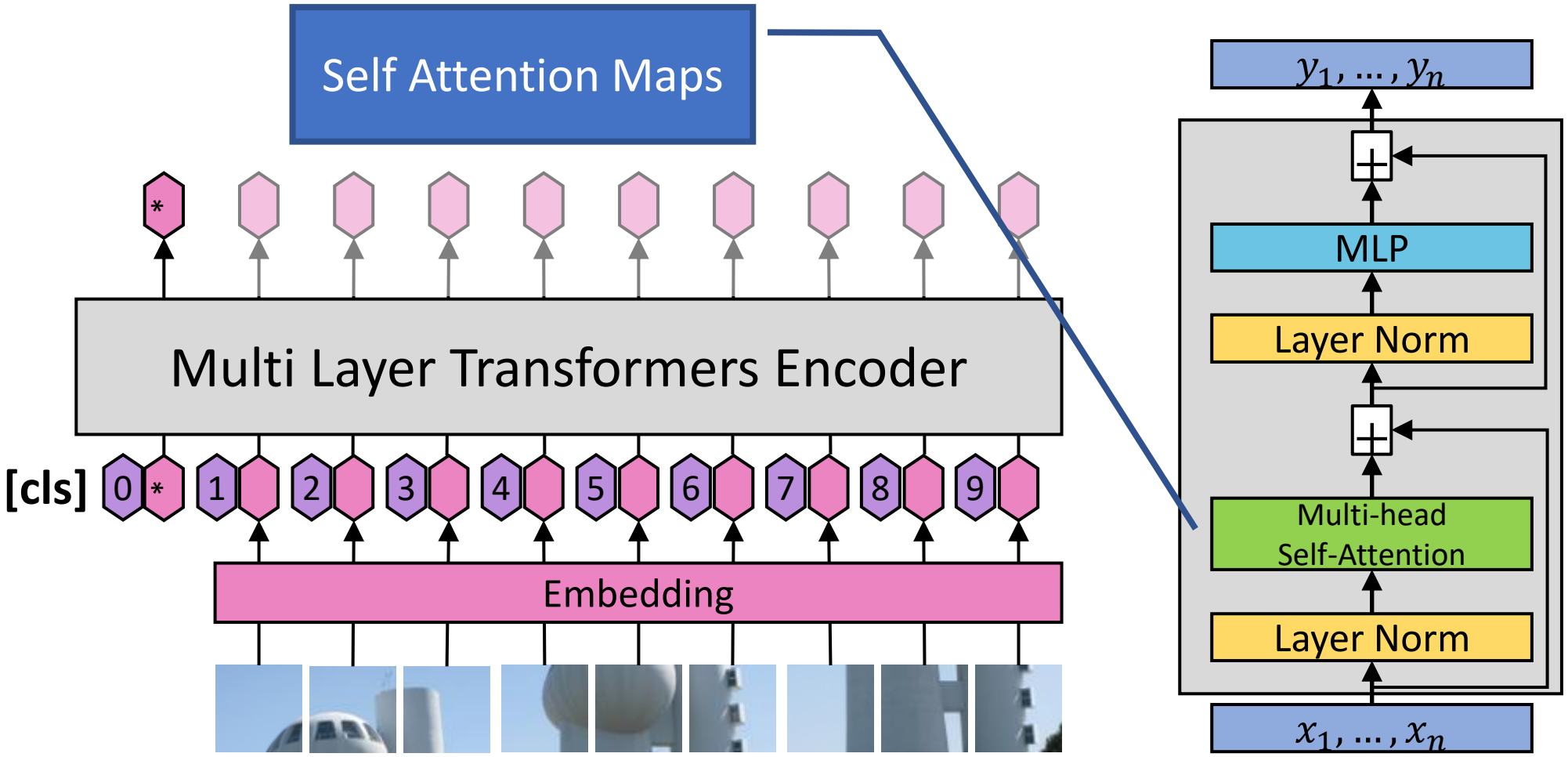


Caron, M., Touvron, H., Misra, I., Jégou, H., Mairal, J., Bojanowski, P. and Joulin, A., "Emerging Properties in Self-Supervised Vision Transformers". ICCV (2021)

Vision Transformers (ViT)



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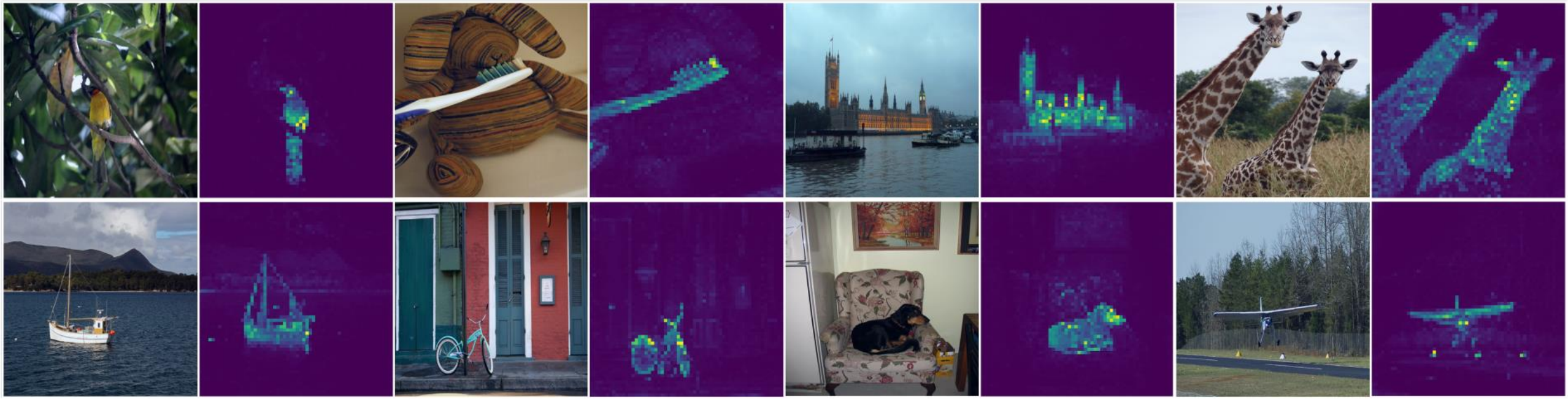

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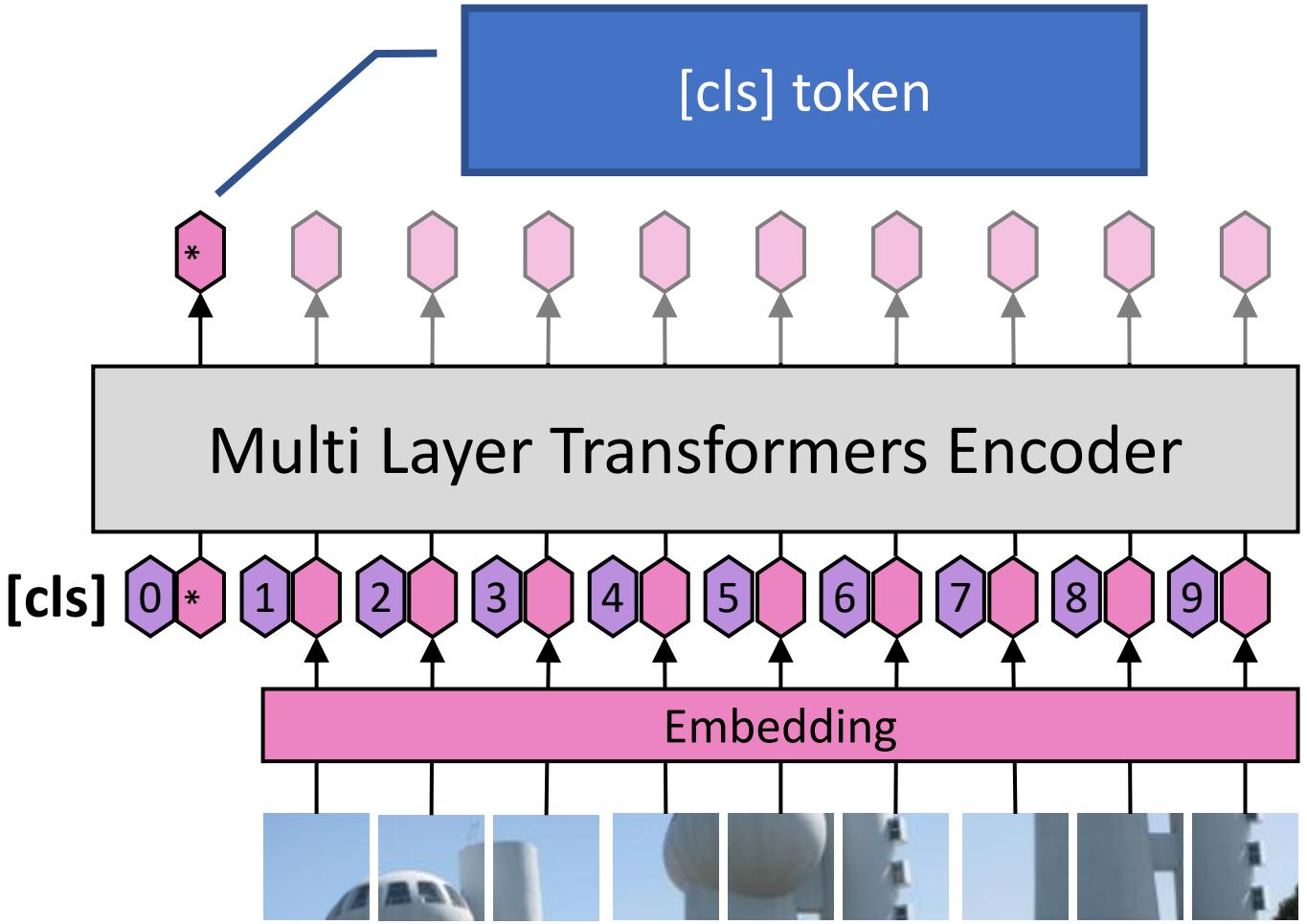

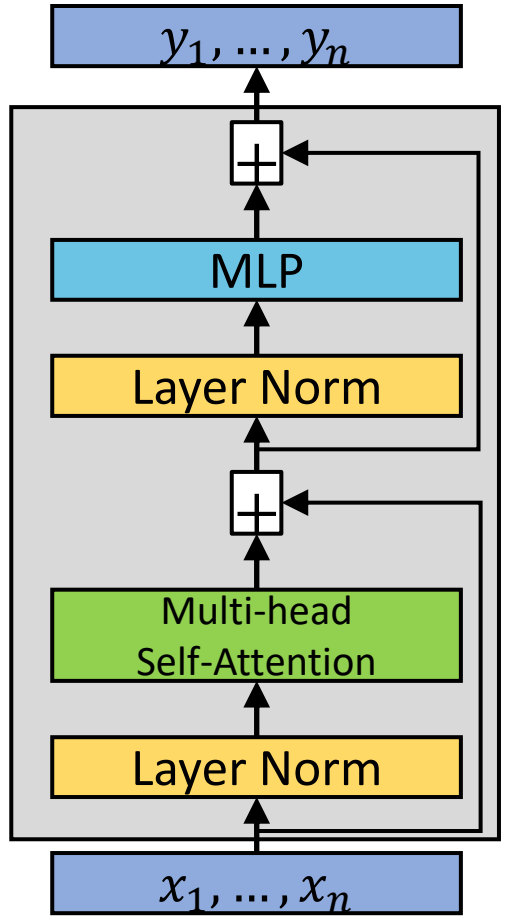

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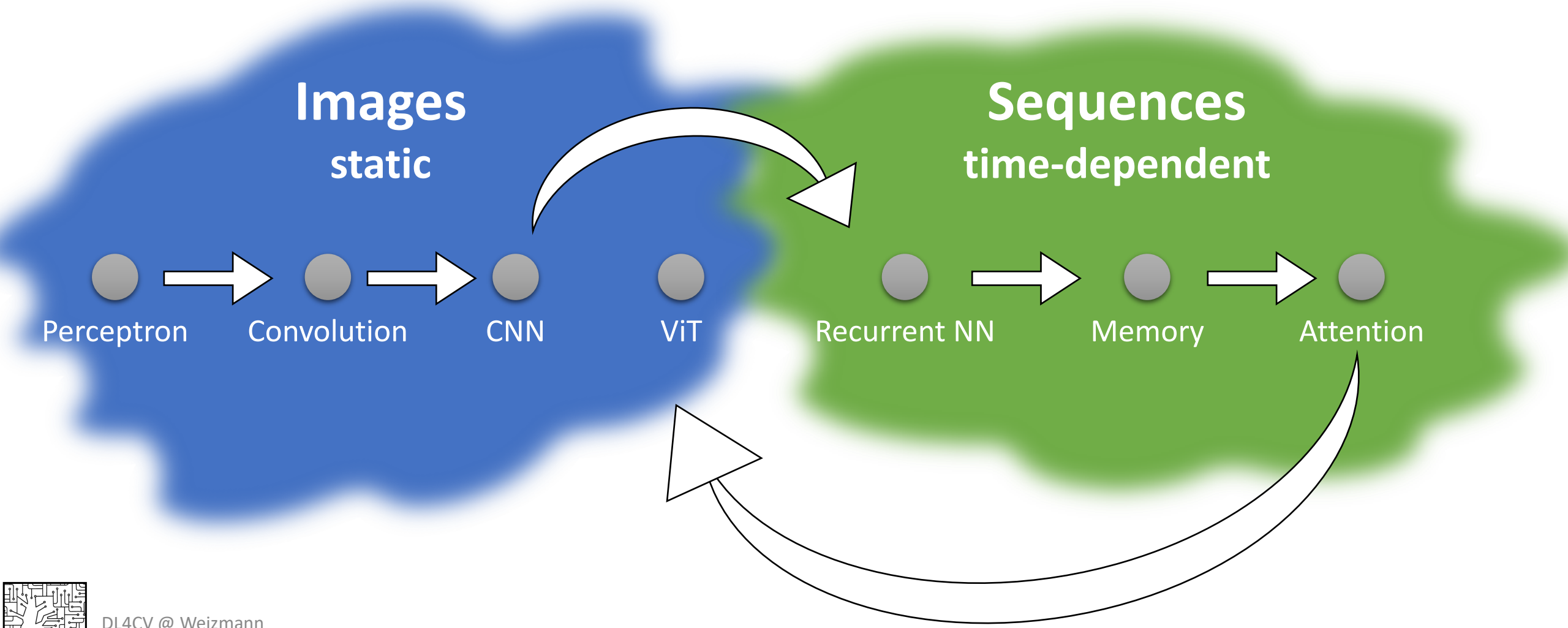
Vision Transformer (ViT)


Images
static
Sequences
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Recurrent NN
Memory
Attention

What's next?

Next tutorial:

Sequences and ViT (Shir)

Next lecture:

Detection and Segmentation (Shai)