

ITCS 6156/8156 Fall 2024

Machine Learning

Attention & Transformers

Instructor: Hongfei Xue

Email: hongfei.xue@charlotte.edu

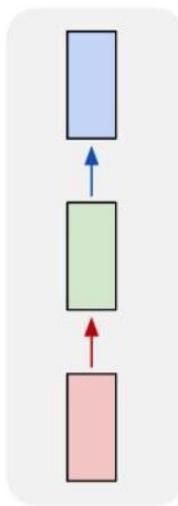
Class Meeting: Tue & Thu, 4:00 PM – 5:15 PM, WWH 130



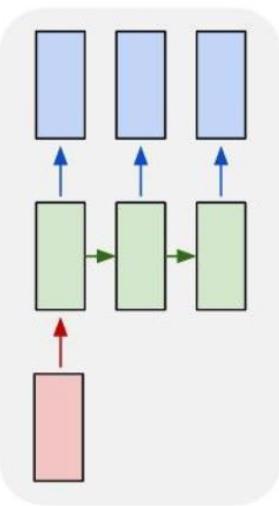
Some content in the slides is based on Dr. Ruohan Gao's lectures

Recurrent Neural Networks

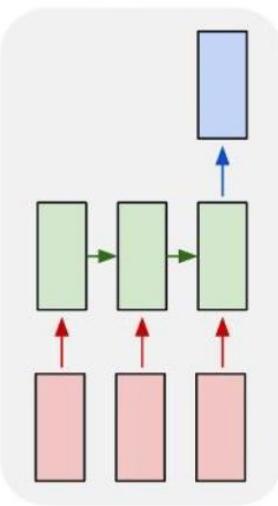
one to one



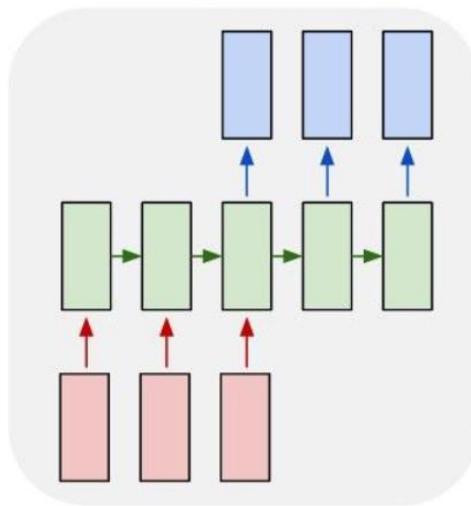
one to many



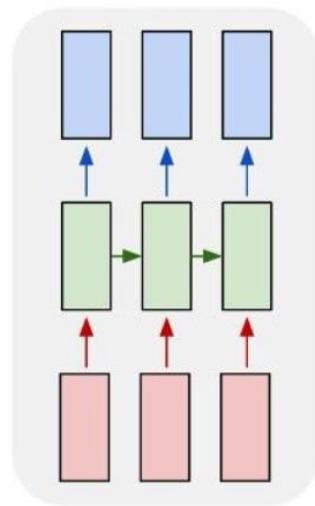
many to one



many to many



many to many

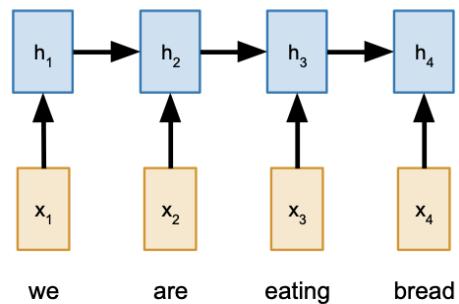


Sequence to Sequence with RNNs

Input: Sequence x_1, \dots, x_T

Output: Sequence y_1, \dots, y_T

Encoder: $h_t = f_W(x_t, h_{t-1})$



Sutskever et al, "Sequence to sequence learning with neural networks", NeurIPS 2014

Sequence to Sequence with RNNs

Input: Sequence x_1, \dots, x_T

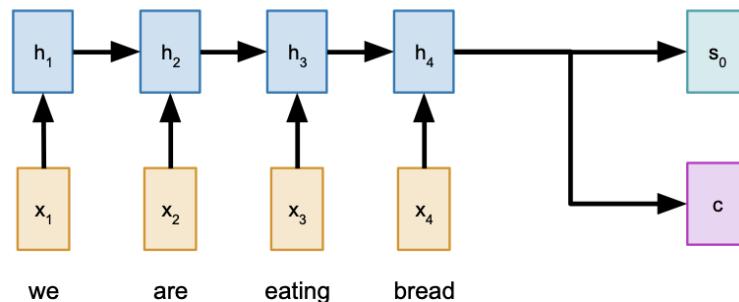
Output: Sequence y_1, \dots, y_T

Encoder: $h_t = f_W(x_t, h_{t-1})$

From final hidden state predict:

Initial decoder state s_0

Context vector c (often $c=h_T$)



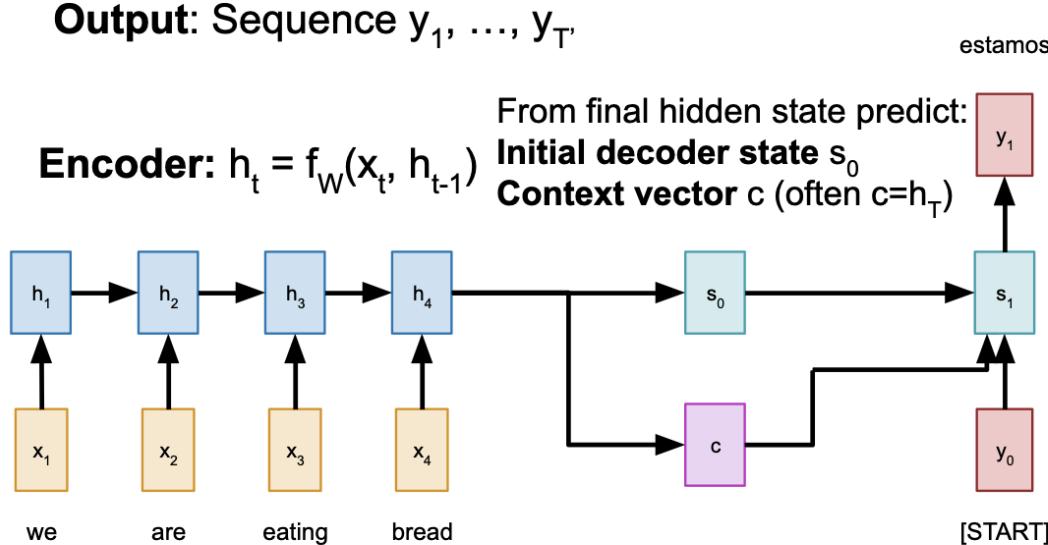
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Sequence to Sequence with RNNs

Input: Sequence x_1, \dots, x_T

Output: Sequence y_1, \dots, y_T

Decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c)$



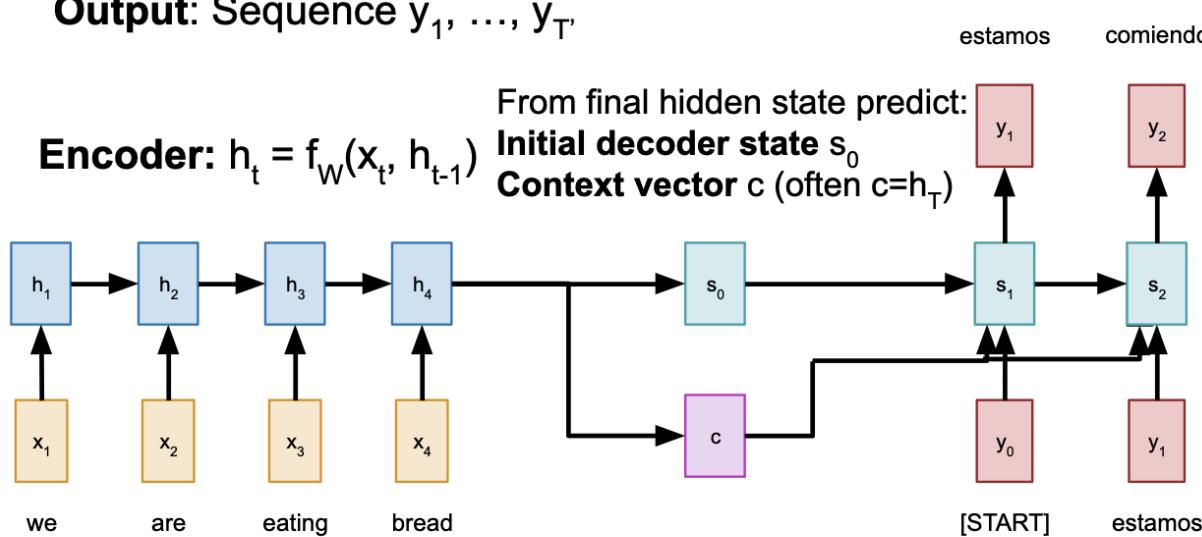
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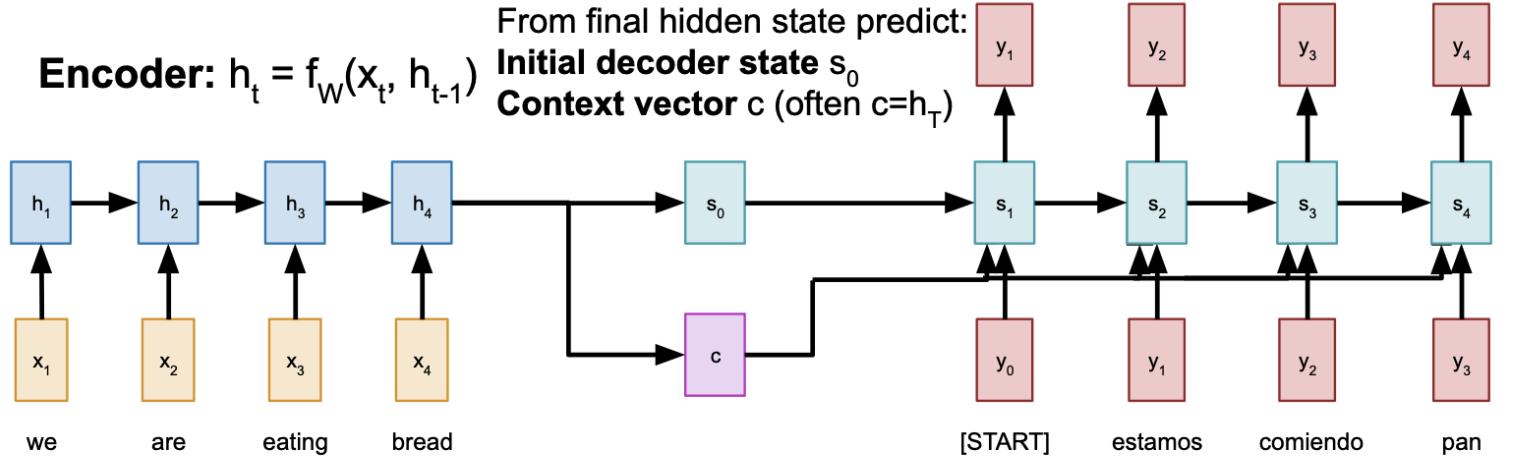
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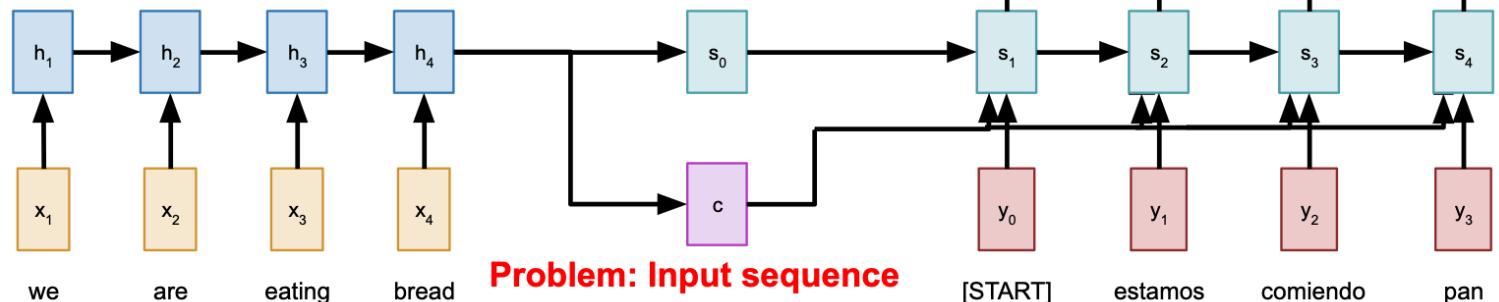
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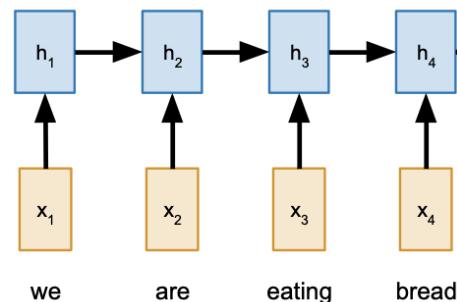
Problem: Input sequence
bottlenecked through
fixed-sized vector. What if
 $T=1000$?

Sequence to Sequence with RNNs

Input: Sequence x_1, \dots, x_T

Output: Sequence y_1, \dots, y_T

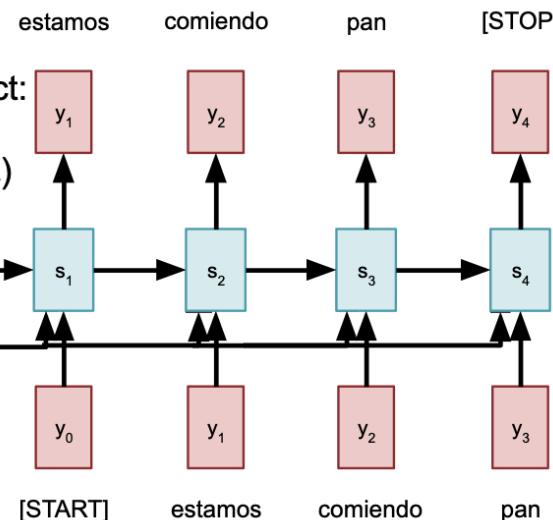
Encoder: $h_t = f_W(x_t, h_{t-1})$



From final hidden state predict:
Initial decoder state s_0
Context vector c (often $c=h_T$)

**Problem: Input sequence
bottlenecked through
fixed-sized vector. What if
 $T=1000$?**

Decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c)$



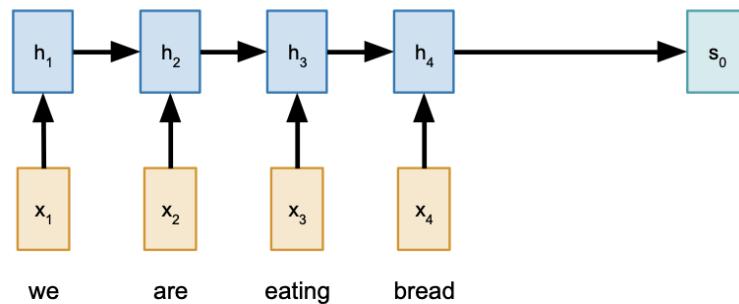
**Idea: use new context vector
at each step of decoder!**

Sequence to Sequence with RNNs and Attention

Input: Sequence x_1, \dots, x_T

Output: Sequence y_1, \dots, y_T

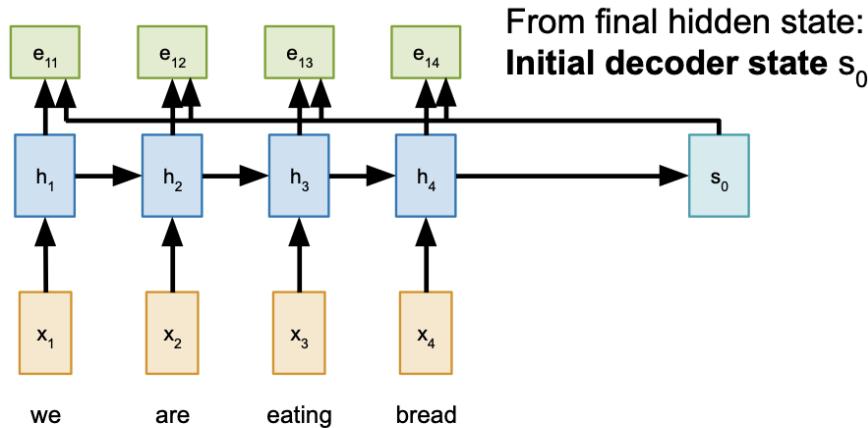
Encoder: $h_t = f_W(x_t, h_{t-1})$ From final hidden state:
Initial decoder state s_0



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

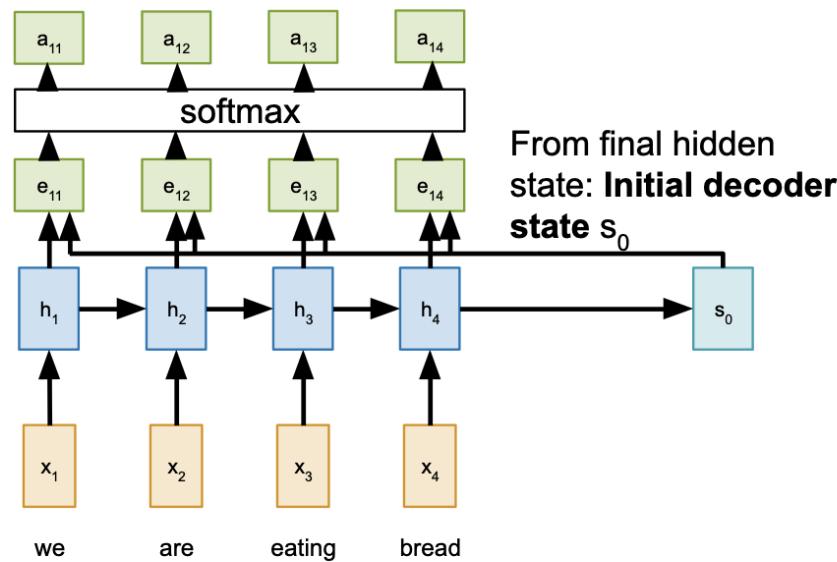
Sequence to Sequence with RNNs and Attention

Compute (scalar) **alignment scores**
 $e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)



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

Sequence to Sequence with RNNs and Attention

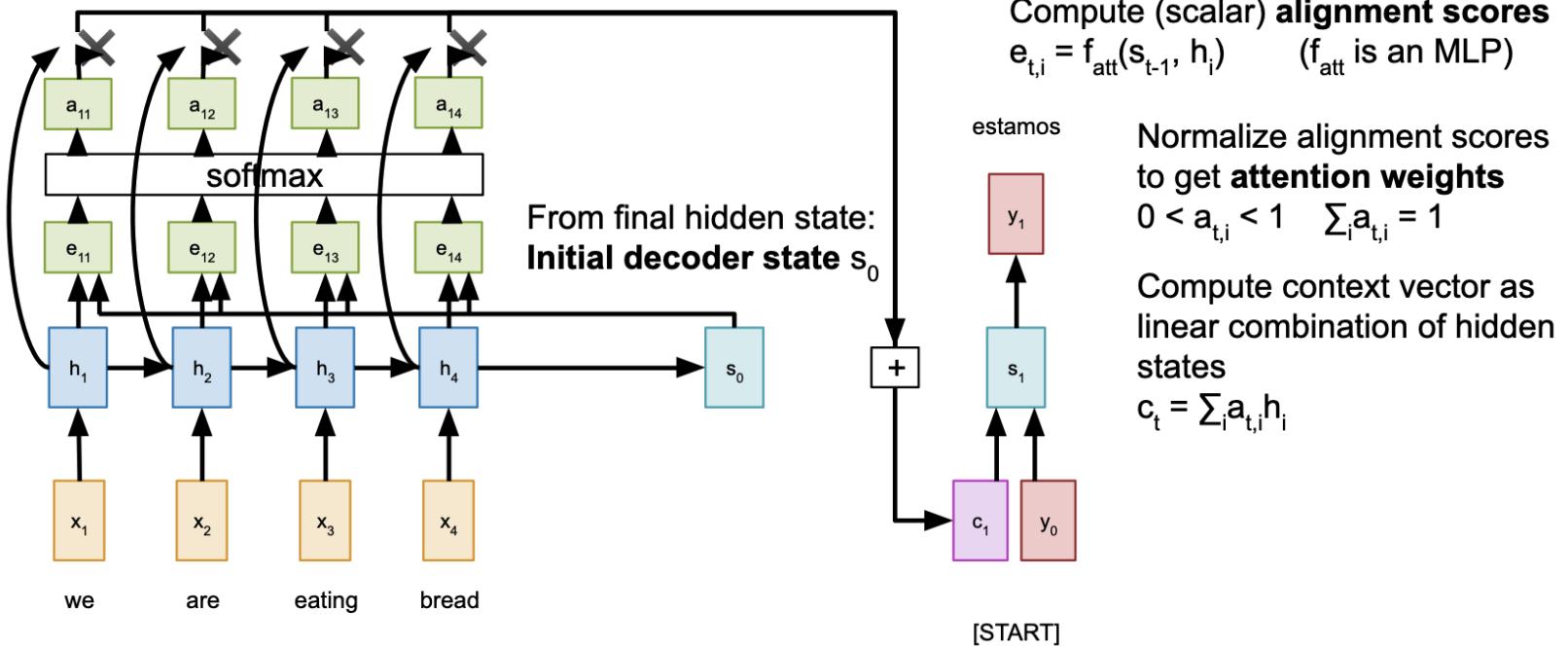


Compute (scalar) **alignment scores**
 $e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)

Normalize alignment scores
to get **attention weights**
 $0 < a_{t,i} < 1 \quad \sum_i a_{t,i} = 1$

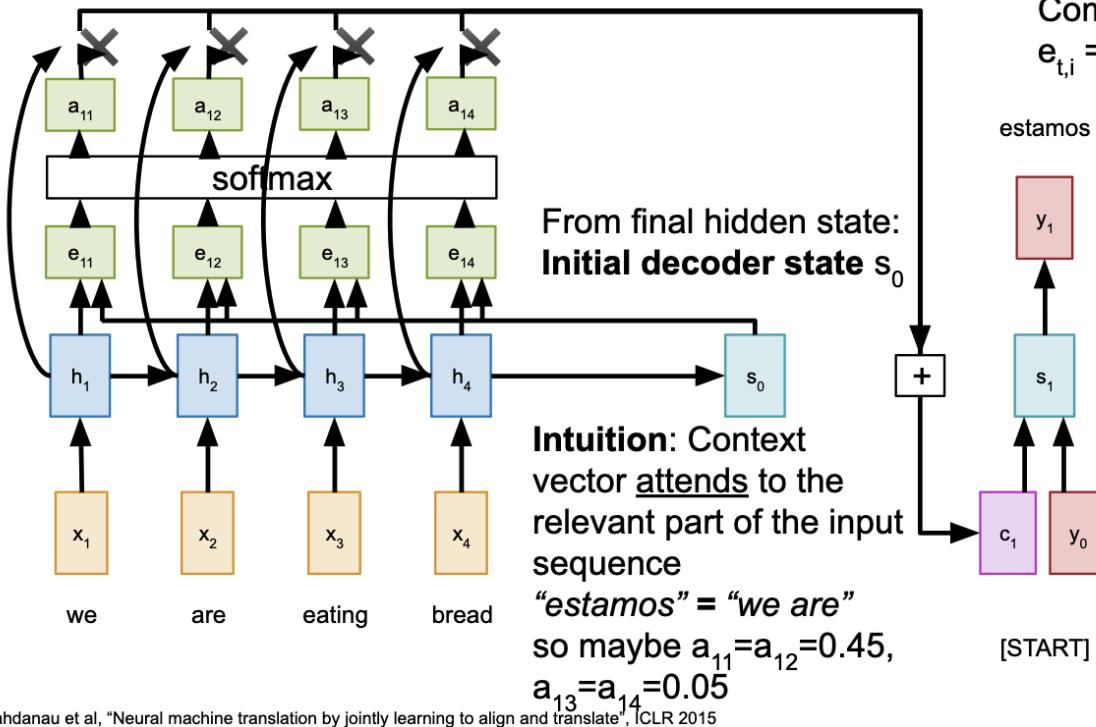
Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



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

Sequence to Sequence with RNNs and Attention



Compute (scalar) **alignment scores**
 $e_{t,i} = f_{\text{att}}(s_{t-1}, h_i)$ (f_{att} is an MLP)

estamos

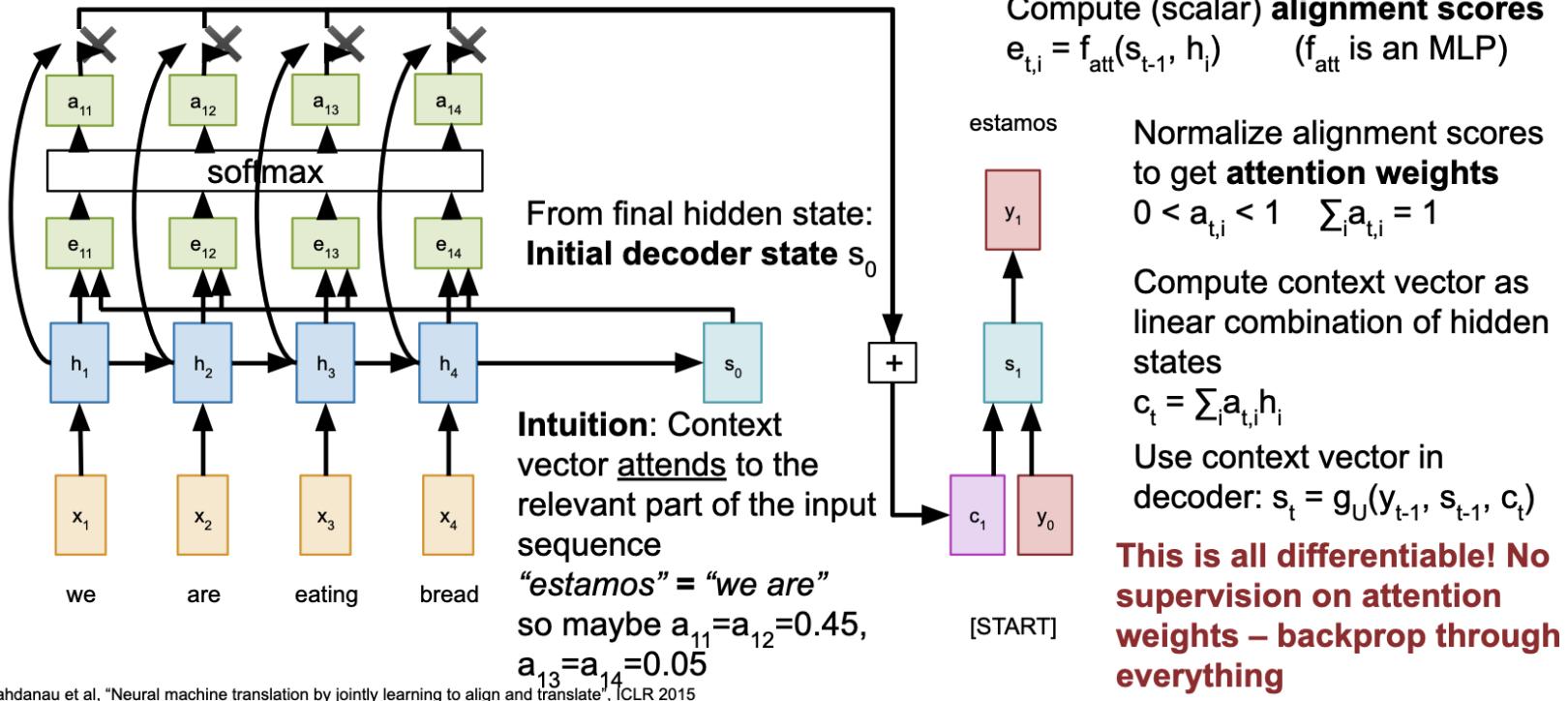
Normalize alignment scores to get **attention weights**
 $0 < a_{t,i} < 1 \quad \sum_i a_{t,i} = 1$

Compute context vector as linear combination of hidden states

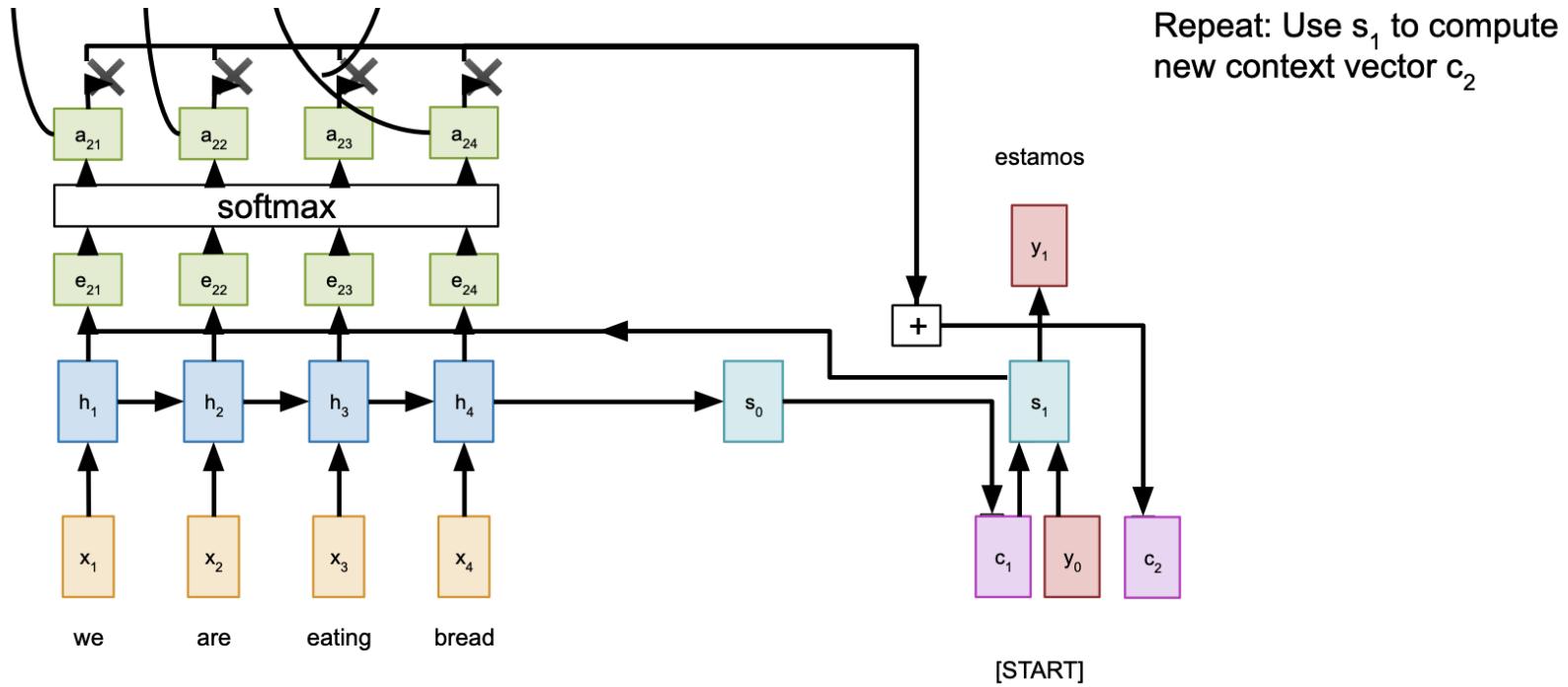
$$c_t = \sum_i a_{t,i} h_i$$

Use context vector in decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c_t)$

Sequence to Sequence with RNNs and Attention

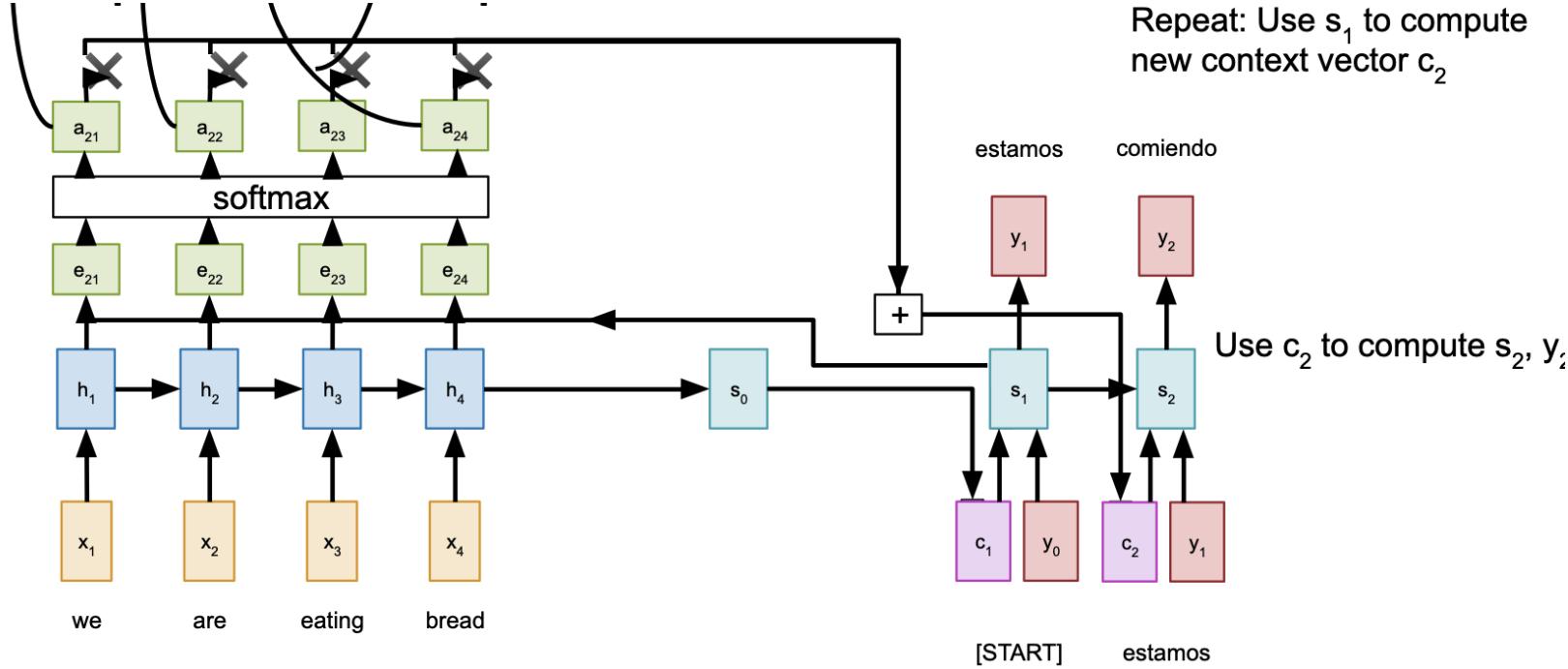


Sequence to Sequence with RNNs and Attention



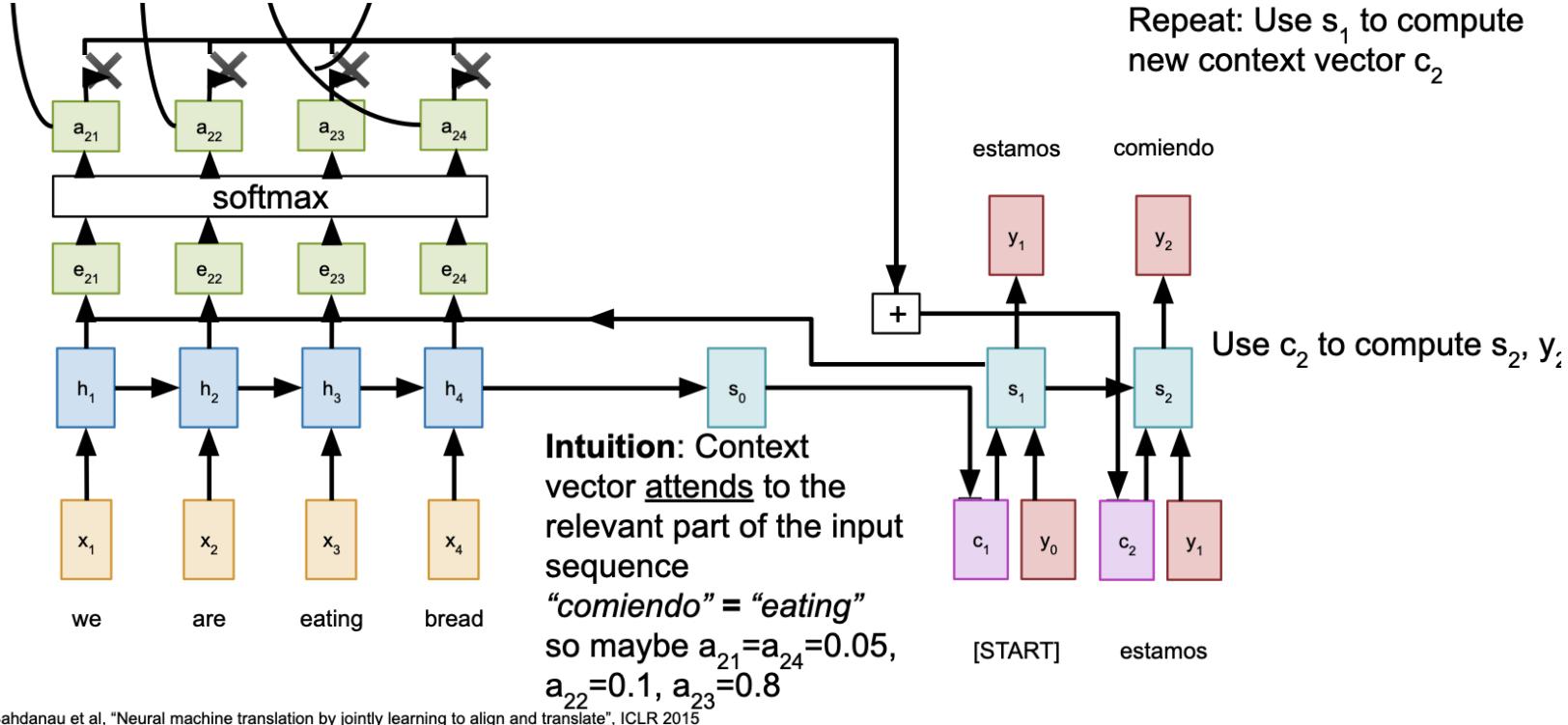
Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



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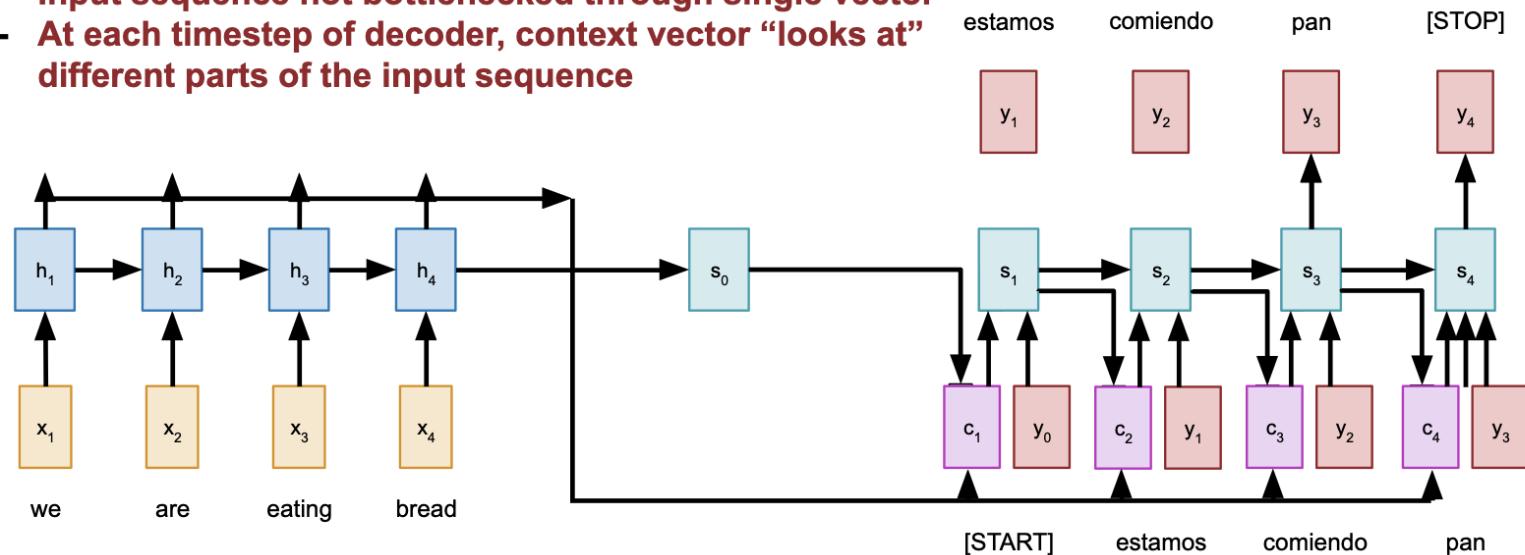
Sequence to Sequence with RNNs and Attention



Sequence to Sequence with RNNs and Attention

Use a different context vector in each timestep of decoder

- Input sequence not bottlenecked through single vector
- At each timestep of decoder, context vector “looks at” different parts of the input sequence



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

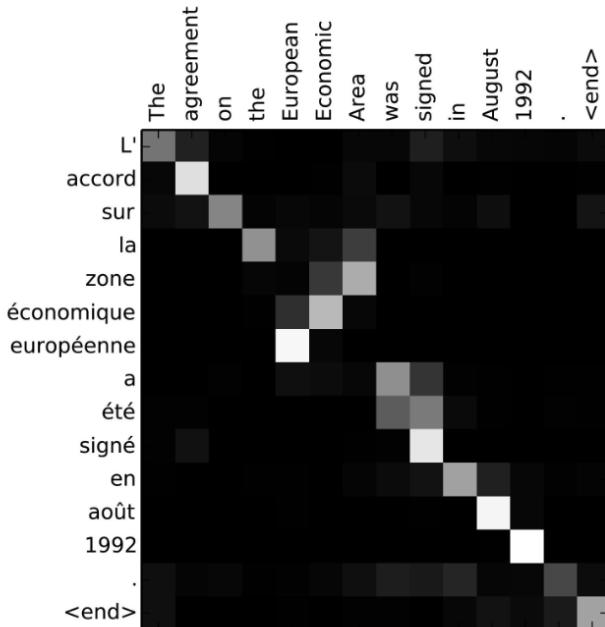
Sequence to Sequence with RNNs and Attention

Example: English to French translation

Input: “The agreement on the European Economic Area was signed in August 1992.”

Output: “L'accord sur la zone économique européenne a été signé en août 1992.”

Visualize attention weights $a_{t,i}$



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

Sequence to Sequence with RNNs and Attention

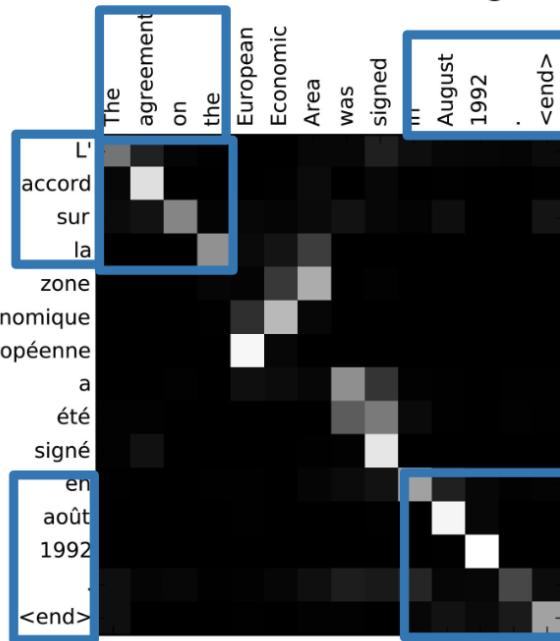
Example: English to French translation

Input: “**The agreement on the European Economic Area was signed in August 1992.**”

Output: “**L'accord sur la zone économique européenne a été signé en août 1992.**”

Diagonal attention means words correspond in order

Visualize attention weights $a_{t,i}$



Diagonal attention means words correspond in order

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

Sequence to Sequence with RNNs and Attention

Example: English to French translation

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Output: “L'accord sur la zone économique européenne a été signé en août 1992.”

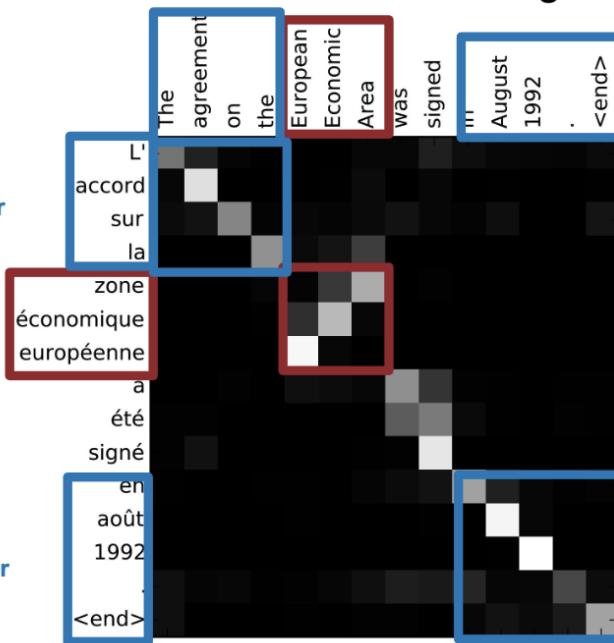
Bahdanau et al, “Neural machine translation by jointly learning to align and translate”, ICLR 2015

Diagonal attention means words correspond in order

Attention figures out different word orders

Diagonal attention means words correspond in order

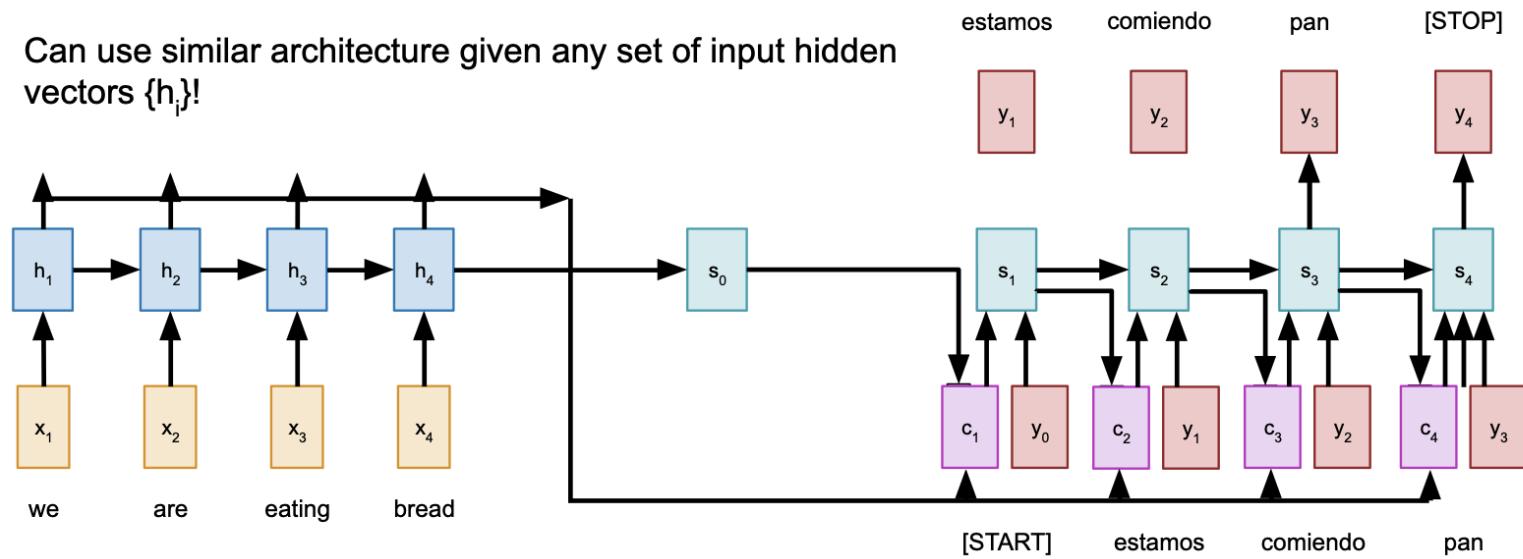
Visualize attention weights $a_{t,i}$



Sequence to Sequence with RNNs and Attention

The decoder doesn't use the fact that h_i form an ordered sequence – it just treats them as an unordered set $\{h_i\}$

Can use similar architecture given any set of input hidden vectors $\{h_i\}$!

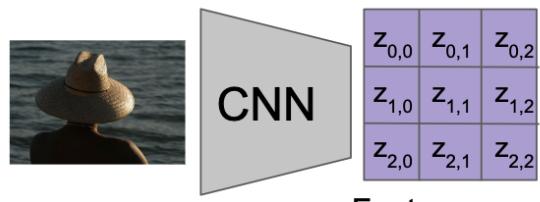


Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Image Captioning using spatial features

Input: Image I

Output: Sequence $\mathbf{y} = y_1, y_2, \dots, y_T$



Extract spatial
features from a
pretrained CNN

Features:
 $H \times W \times D$

Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning using spatial features

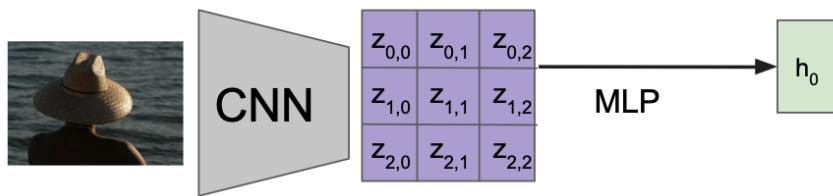
Input: Image I

Output: Sequence $\mathbf{y} = y_1, y_2, \dots, y_T$

Encoder: $h_0 = f_w(\mathbf{z})$

where \mathbf{z} is spatial CNN features

$f_w(\cdot)$ is an MLP



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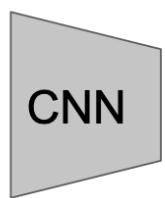
Decoder: $y_t = g_v(y_{t-1}, h_{t-1}, c)$

where context vector c is often $c = h_0$

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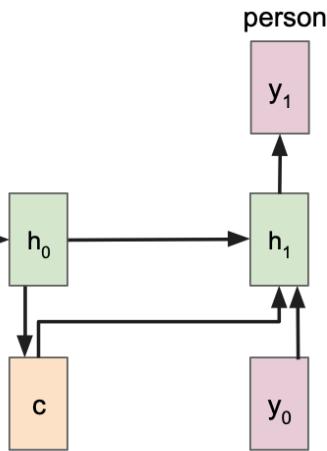


$z_{0,0}$	$z_{0,1}$	$z_{0,2}$
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$z_{2,0}$	$z_{2,1}$	$z_{2,2}$

MLP

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 $H \times W \times D$



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

[START]

Image Captioning using spatial features

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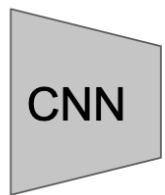
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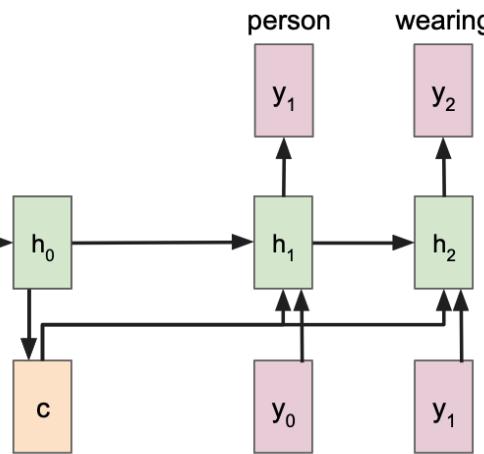


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[START] person

Image Captioning using spatial features

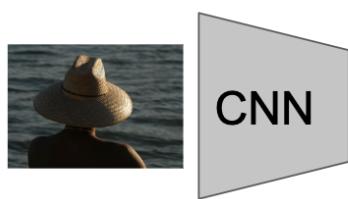
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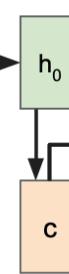
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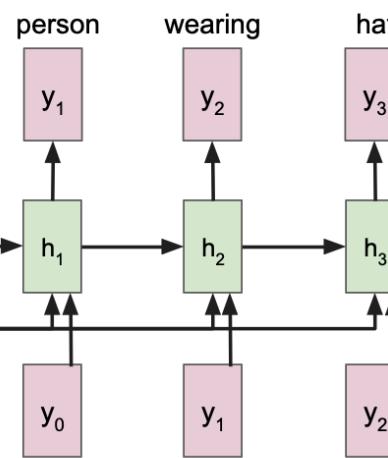
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MLP



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Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

[START] person wearing

Image Captioning using spatial features

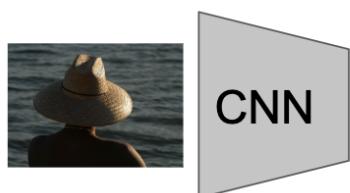
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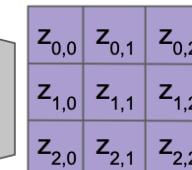
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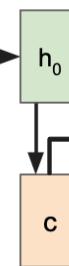


Extract spatial
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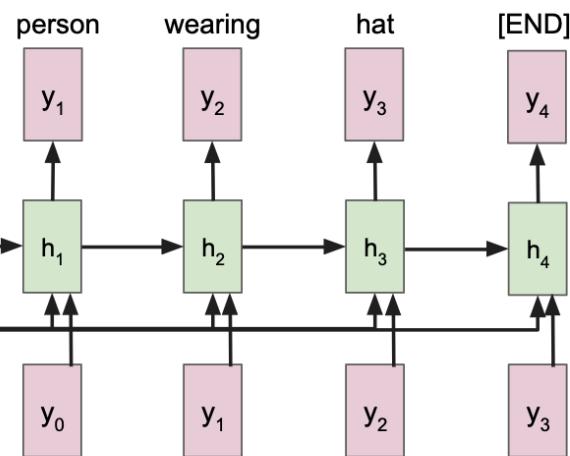
Features:
 $H \times W \times D$

MLP



c

Decoder: $y_t = g_v(y_{t-1}, h_{t-1}, c)$
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Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

[START] person wearing hat

Image Captioning using spatial features

Problem: Input is "bottlenecked" through c

- Model needs to encode everything it wants to say within c

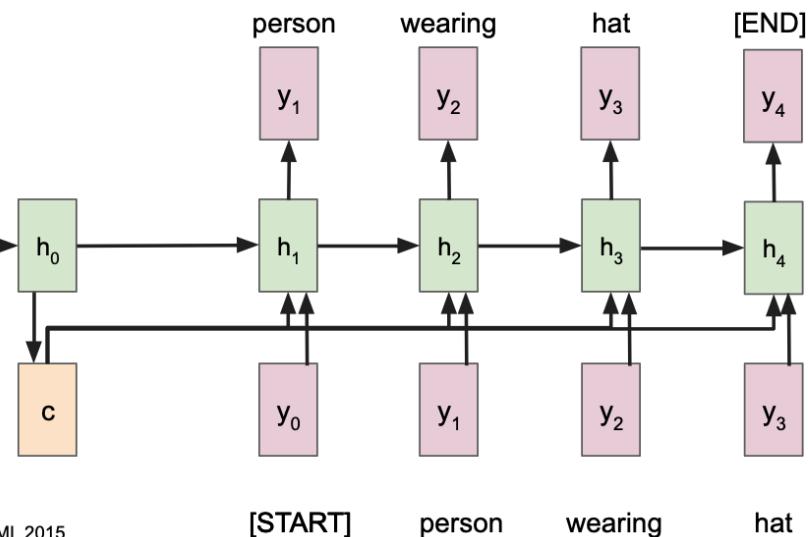
This is a problem if we want to generate really long descriptions? 100s of words long



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MLP



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

[START]

person

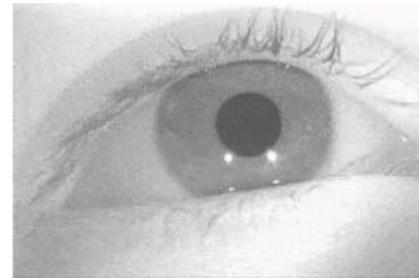
wearing

hat

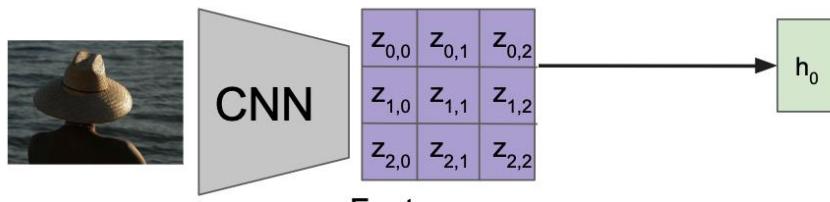
Image Captioning with RNNs and Attention

Attention idea: New context vector at every time step.

Each context vector will attend to different image regions



Attention Saccades in humans



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with RNNs and Attention

Compute alignments scores (scalars):

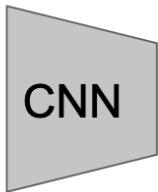
$$e_{t,i,j} = f_{att}(h_{t-1}, z_{i,j})$$

$f_{att}(\cdot)$ is an MLP

Alignment scores:

$H \times W$

$e_{1,0,0}$	$e_{1,0,1}$	$e_{1,0,2}$
$e_{1,1,0}$	$e_{1,1,1}$	$e_{1,1,2}$
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Extract spatial features from a pretrained CNN

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$z_{2,0}$	$z_{2,1}$	$z_{2,2}$

Features:
 $H \times W \times D$



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with RNNs and Attention

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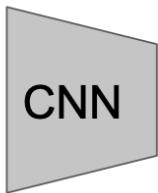
Attention:
 $H \times W$

$a_{1,0,0}$	$a_{1,0,1}$	$a_{1,0,2}$
$a_{1,1,0}$	$a_{1,1,1}$	$a_{1,1,2}$
$a_{1,2,0}$	$a_{1,2,1}$	$a_{1,2,2}$

Normalize to get attention weights:

$$a_{t,:,:} = \text{softmax}(e_{t,:,:})$$

$0 < a_{t,i,j} < 1$,
attention values sum to 1



Extract spatial features from a pretrained CNN

Features:
 $H \times W \times D$

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$z_{1,0}$	$z_{1,1}$	$z_{1,2}$
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Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

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 $H \times W$

$e_{1,0,0}$	$e_{1,0,1}$	$e_{1,0,2}$
$e_{1,1,0}$	$e_{1,1,1}$	$e_{1,1,2}$
$e_{1,2,0}$	$e_{1,2,1}$	$e_{1,2,2}$

Attention:
 $H \times W$

$a_{1,0,0}$	$a_{1,0,1}$	$a_{1,0,2}$
$a_{1,1,0}$	$a_{1,1,1}$	$a_{1,1,2}$
$a_{1,2,0}$	$a_{1,2,1}$	$a_{1,2,2}$

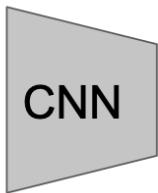
Normalize to get attention weights:

$$a_{t,:,:} = \text{softmax}(e_{t,:,:})$$

$0 < a_{t,i,j} < 1$,
attention values sum to 1

Compute context vector:

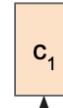
$$c_t = \sum_{i,j} a_{t,i,j} z_{t,i,j}$$



Extract spatial features from a pretrained CNN

Features:
 $H \times W \times D$

$z_{0,0}$	$z_{0,1}$	$z_{0,2}$
$z_{1,0}$	$z_{1,1}$	$z_{1,2}$
$z_{2,0}$	$z_{2,1}$	$z_{2,2}$



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

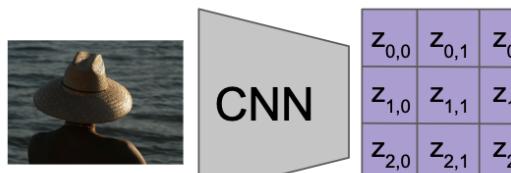
Image Captioning with RNNs and Attention

Each timestep of decoder uses a different context vector that looks at different parts of the input image

$$e_{t,i,j} = f_{att}(h_{t-1}, z_{i,j})$$

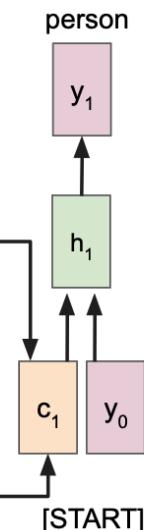
$$a_{t,:,:} = \text{softmax}(e_{t,:,:})$$

$$c_t = \sum_{i,j} a_{t,i,j} z_{t,i,j}$$



Extract spatial features from a pretrained CNN

Decoder: $y_t = g_v(y_{t-1}, h_{t-1}, c_t)$
New context vector at every time step



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with RNNs and Attention

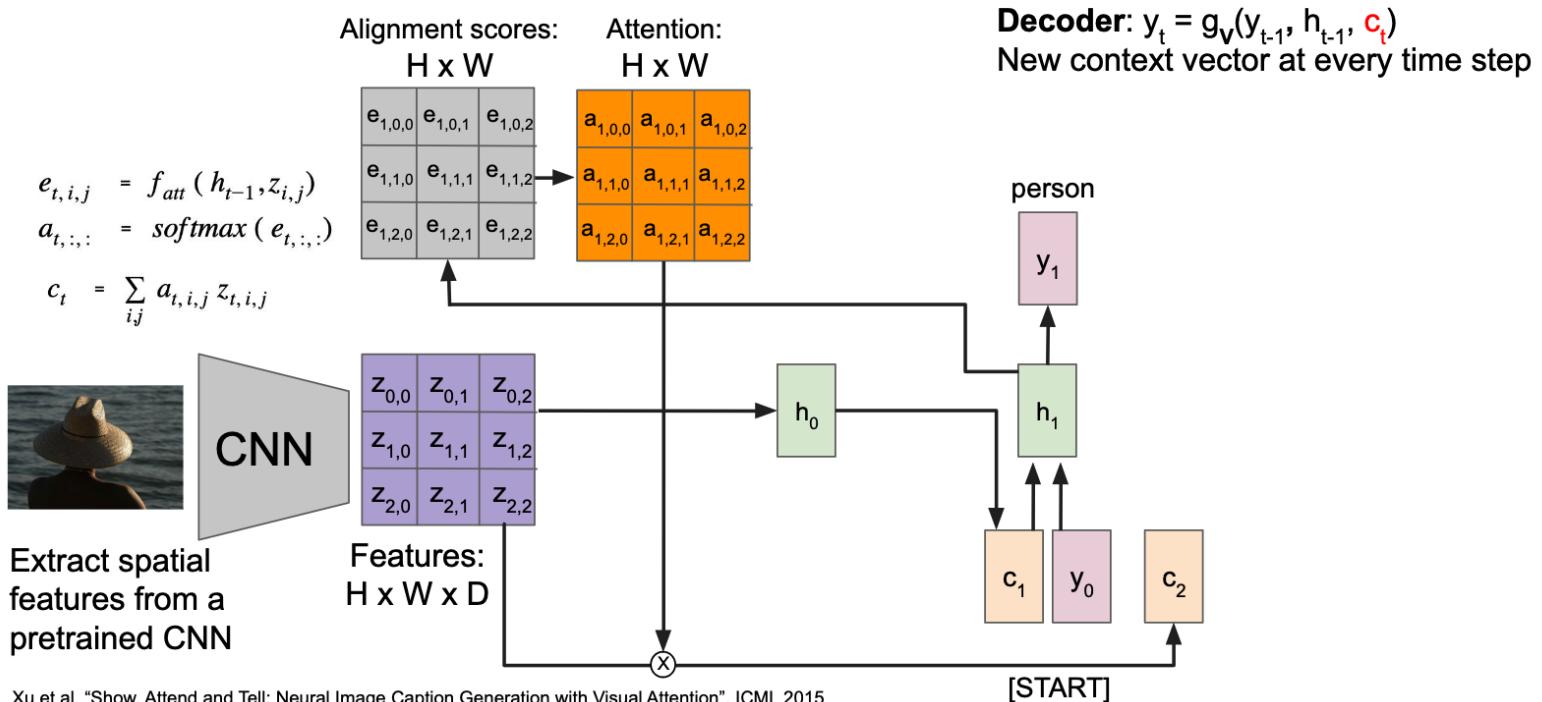
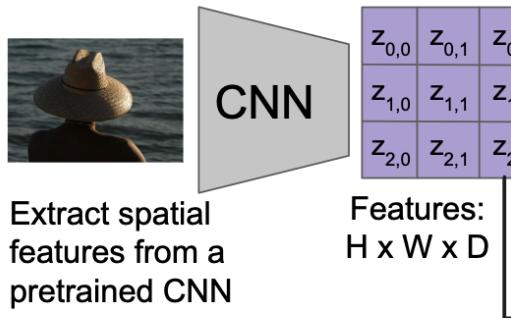


Image Captioning with RNNs and Attention

Each timestep of decoder uses a different context vector that looks at different parts of the input image

$$e_{t,i,j} = f_{att}(h_{t-1}, z_{i,j})$$
$$a_{t,:,:} = \text{softmax}(e_{t,:,:})$$

$$c_t = \sum_{i,j} a_{t,i,j} z_{t,i,j}$$



Extract spatial
features from a
pretrained CNN

Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Decoder: $y_t = g_v(y_{t-1}, h_{t-1}, c_t)$
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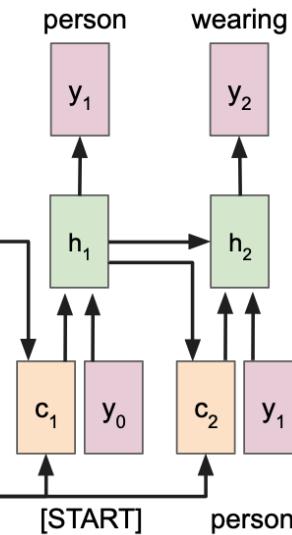
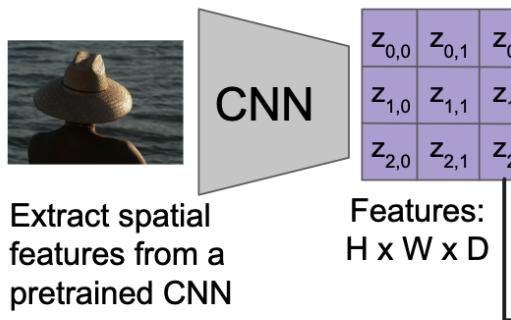


Image Captioning with RNNs and Attention

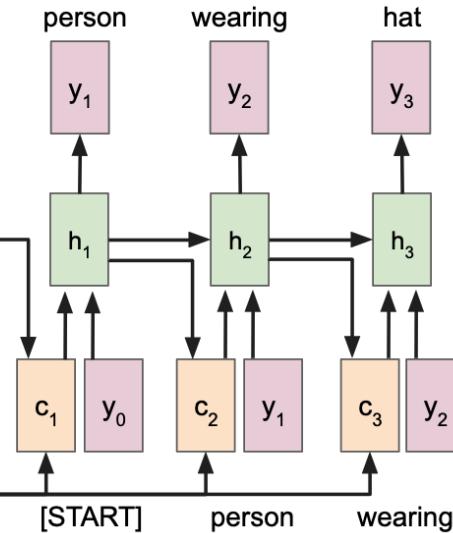
Each timestep of decoder uses a different context vector that looks at different parts of the input image

$$\begin{aligned} e_{t,i,j} &= f_{att}(h_{t-1}, z_{i,j}) \\ a_{t,:,:} &= \text{softmax}(e_{t,:,:}) \\ c_t &= \sum_{i,j} a_{t,i,j} z_{t,i,j} \end{aligned}$$



Extract spatial
features from a
pretrained CNN

Decoder: $y_t = g_v(y_{t-1}, h_{t-1}, c_t)$
New context vector at every time step



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

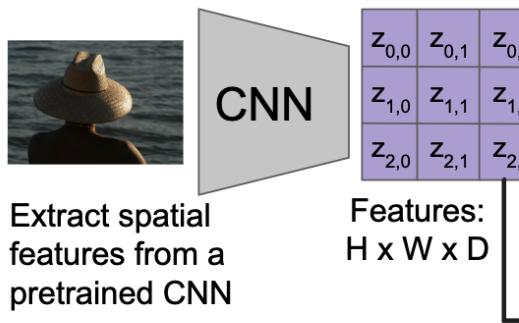
Image Captioning with RNNs and Attention

Each timestep of decoder uses a different context vector that looks at different parts of the input image

$$e_{t,i,j} = f_{att}(h_{t-1}, z_{i,j})$$

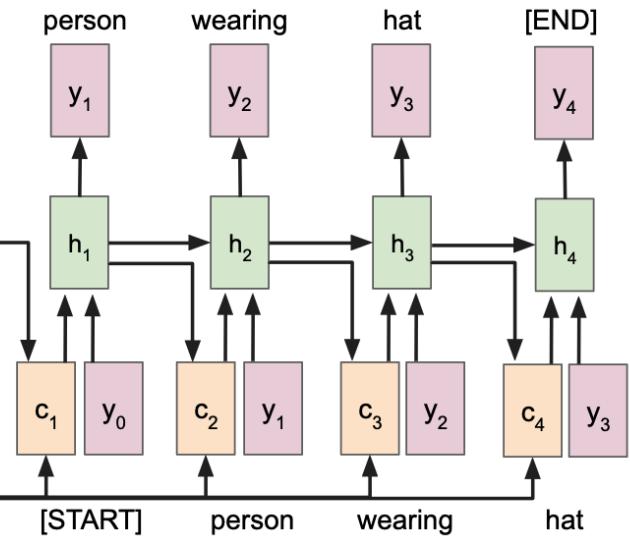
$$a_{t,:,:} = \text{softmax}(e_{t,:,:})$$

$$c_t = \sum_{i,j} a_{t,i,j} z_{t,i,j}$$



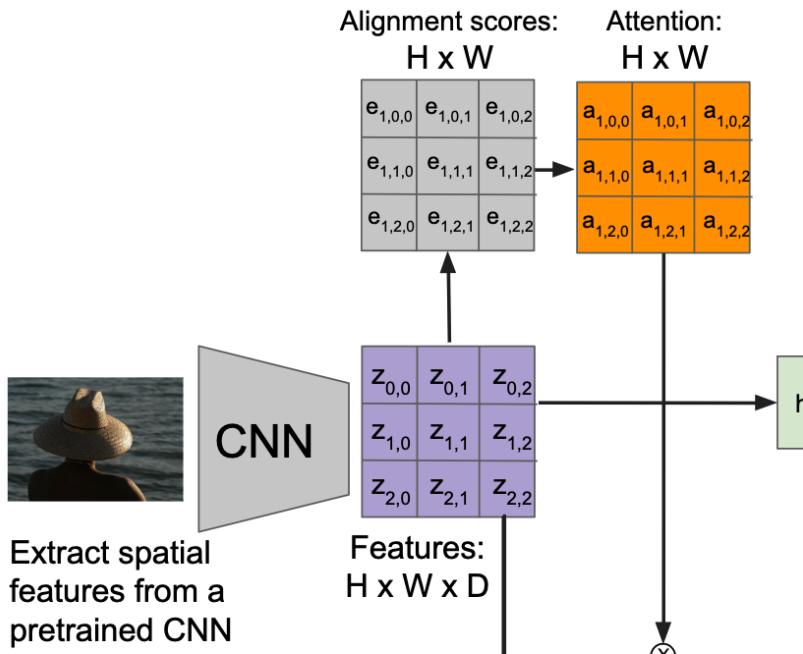
Extract spatial
features from a
pretrained CNN

Decoder: $y_t = g_v(y_{t-1}, h_{t-1}, c_t)$
New context vector at every time step



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

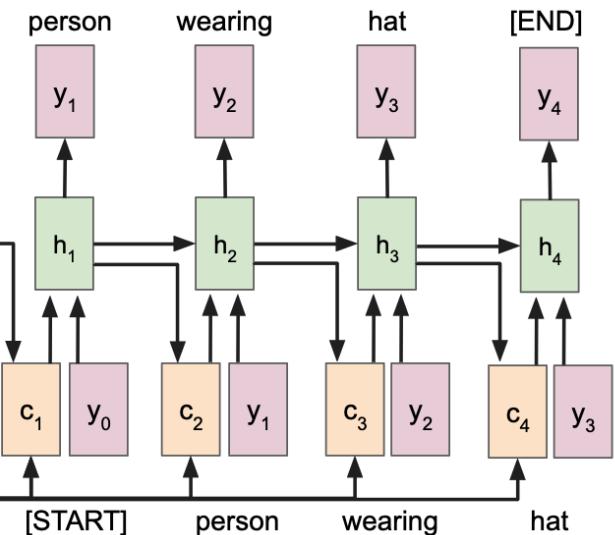
Image Captioning with RNNs and Attention



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

This entire process is differentiable.

- model chooses its own attention weights. No attention supervision is required



Attention we just saw in image captioning

Features	$z_{0,0}$	$z_{0,1}$	$z_{0,2}$
	$z_{1,0}$	$z_{1,1}$	$z_{1,2}$
	$z_{2,0}$	$z_{2,1}$	$z_{2,2}$

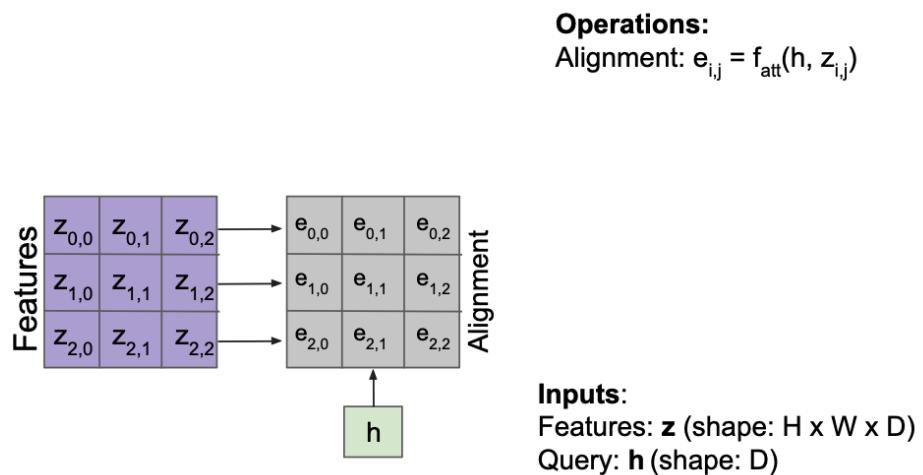
h

Inputs:

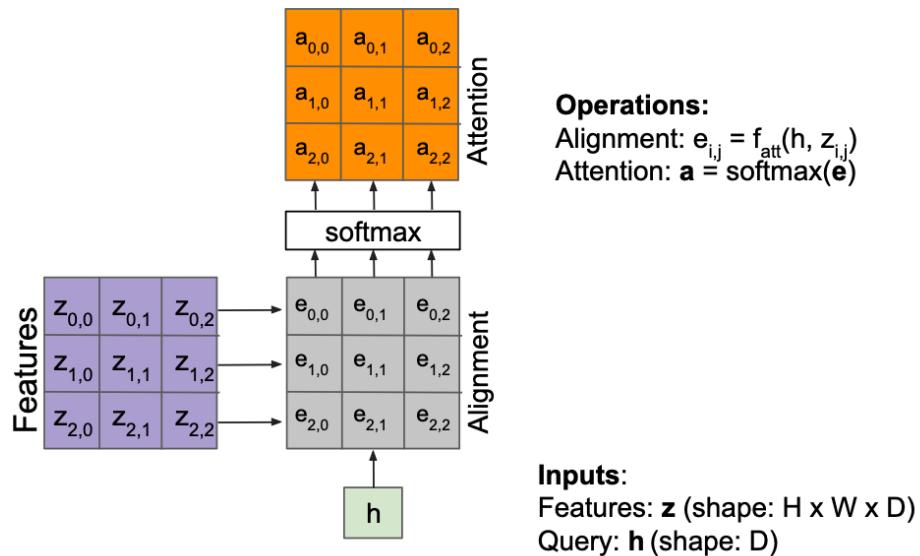
Features: \mathbf{z} (shape: $H \times W \times D$)

Query: \mathbf{h} (shape: D)

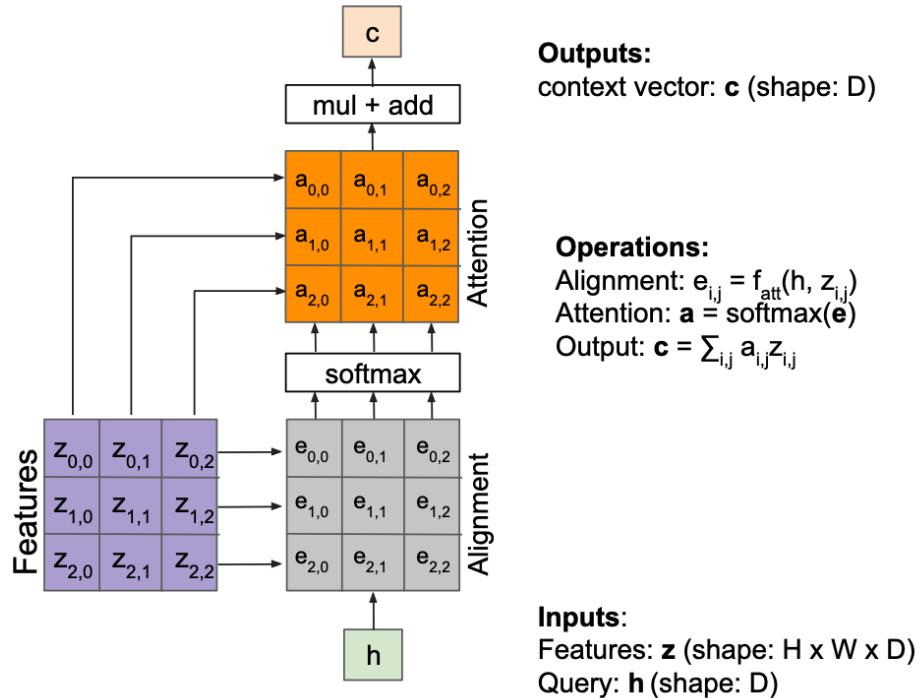
Attention we just saw in image captioning



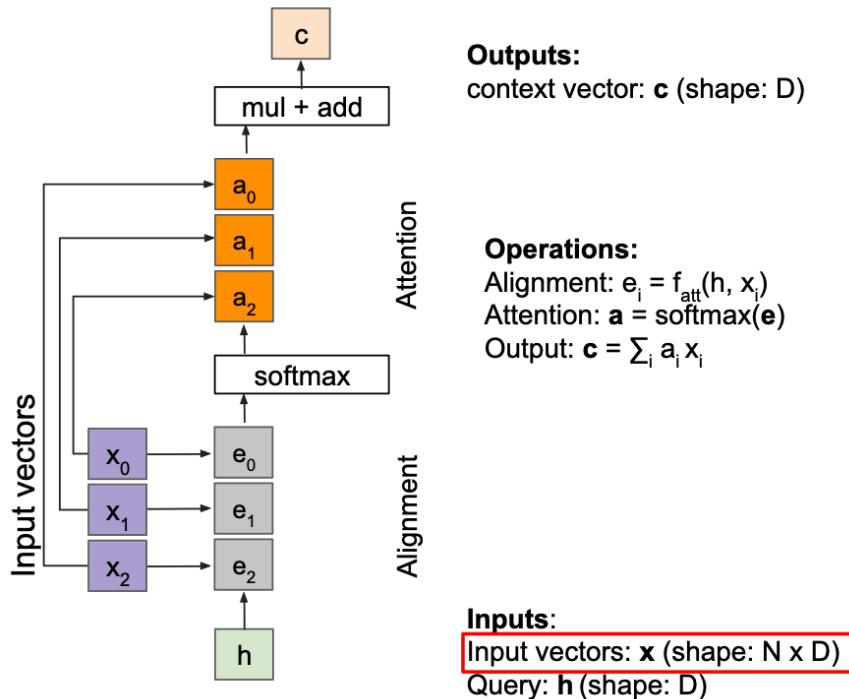
Attention we just saw in image captioning



Attention we just saw in image captioning



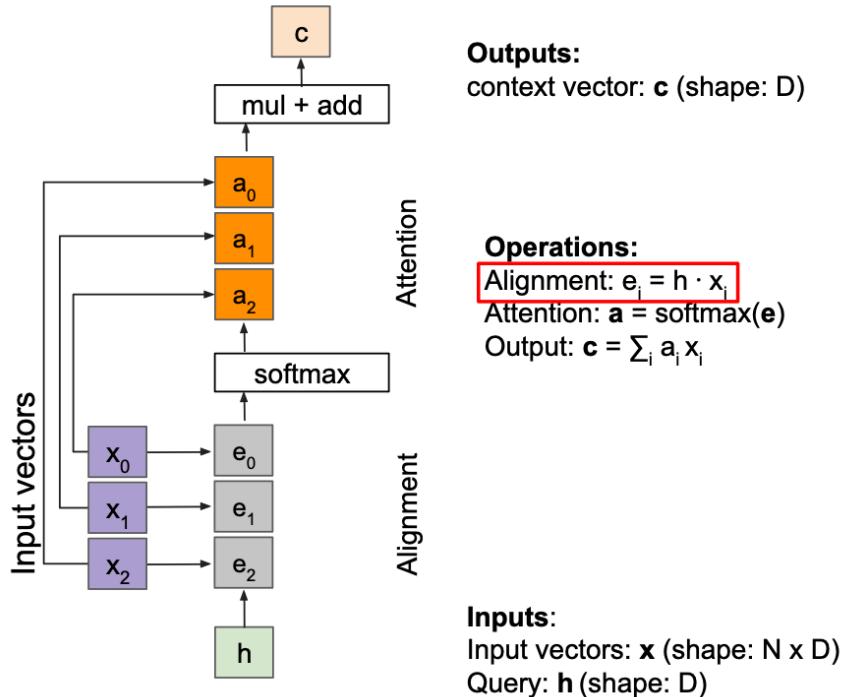
General Attention Layer



Attention operation is **permutation invariant**.

- Doesn't care about ordering of the features
- Stretch $H \times W = N$ into N vectors

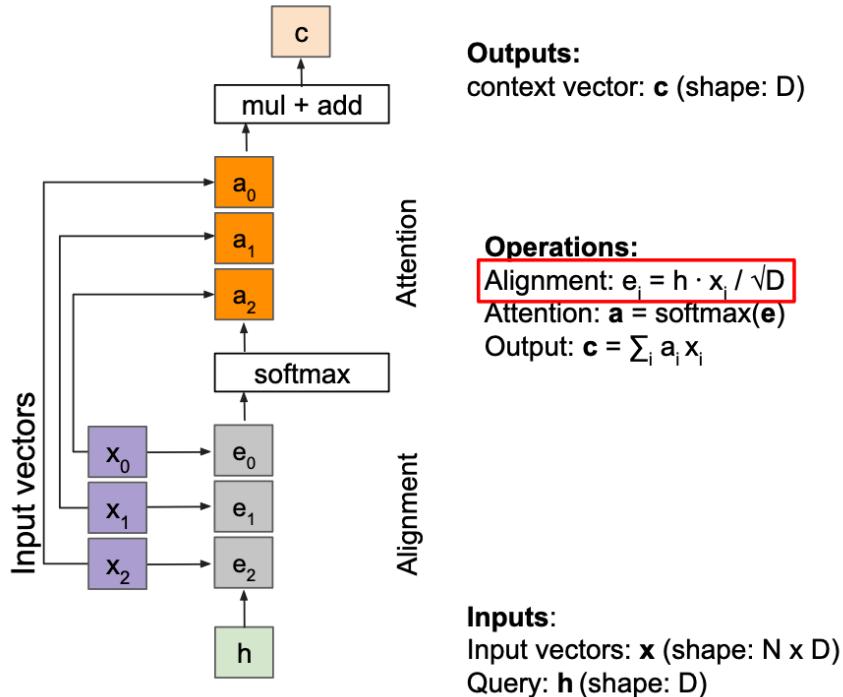
General Attention Layer



Change $f_{att}(.)$ to a simple dot product

- only works well with key & value transformation trick (will mention in a few slides)

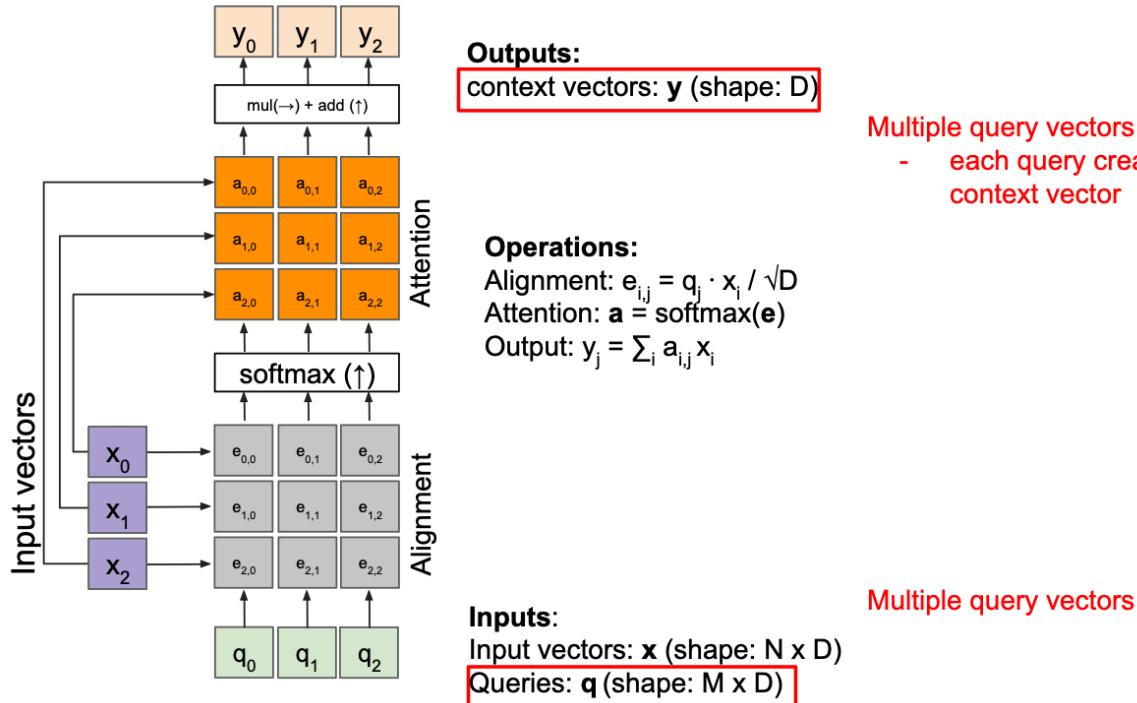
General Attention Layer



Change $f_{\text{att}}(\cdot)$ to a **scaled** simple dot product

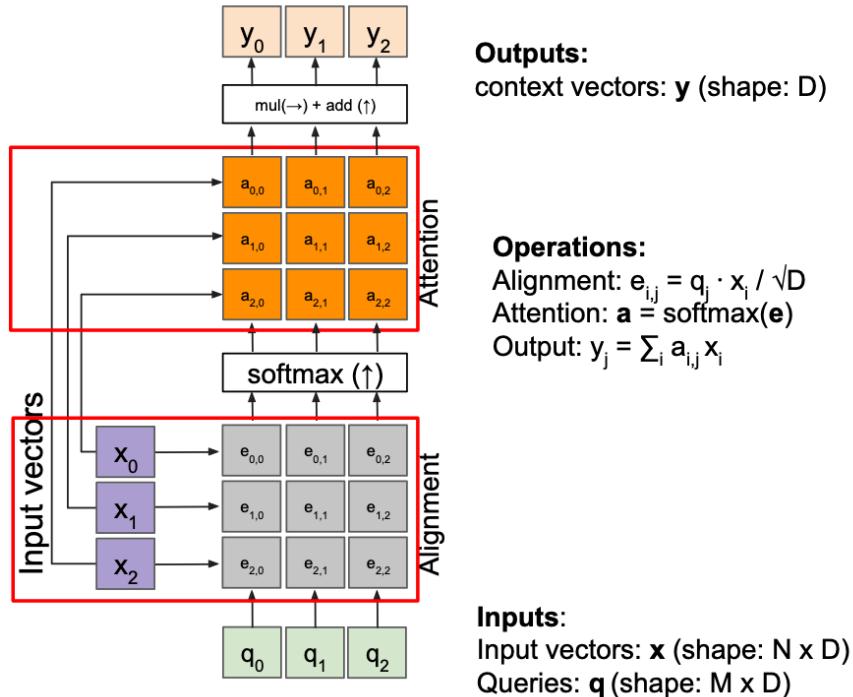
- Larger dimensions means more terms in the dot product sum.
- So, the variance of the logits is higher. Large magnitude vectors will produce much higher logits.
- So, the post-softmax distribution has lower-entropy, assuming logits are IID.
- Ultimately, these large magnitude vectors will cause softmax to peak and assign very little weight to all others
- Divide by \sqrt{D} to reduce effect of large magnitude vectors

General Attention Layer



Multiple query vectors
- each query creates a new output context vector

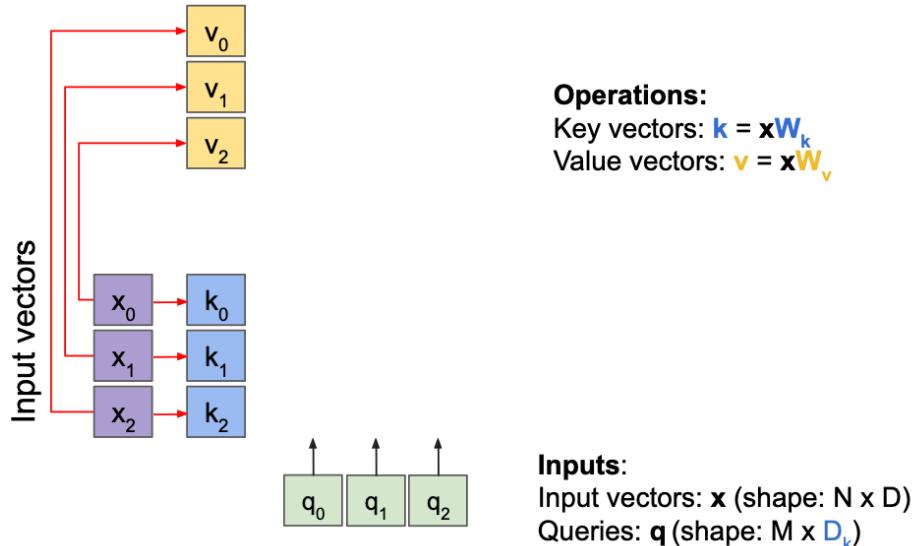
General Attention Layer



Notice that the input vectors are used for both the alignment as well as the attention calculations.

- We can add more expressivity to the layer by adding a different FC layer before each of the two steps.

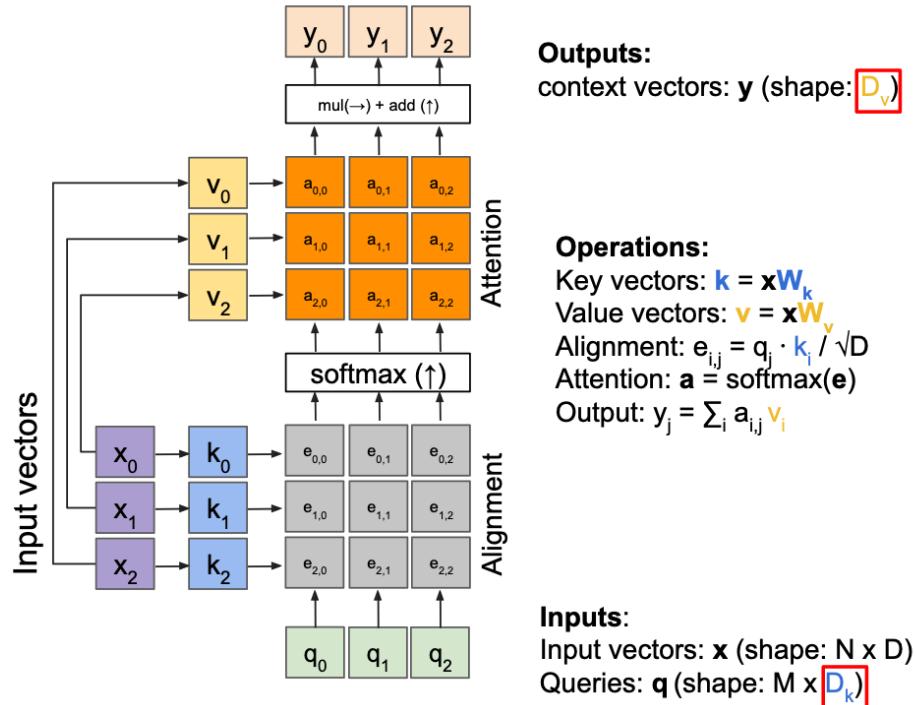
General Attention Layer



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General Attention Layer

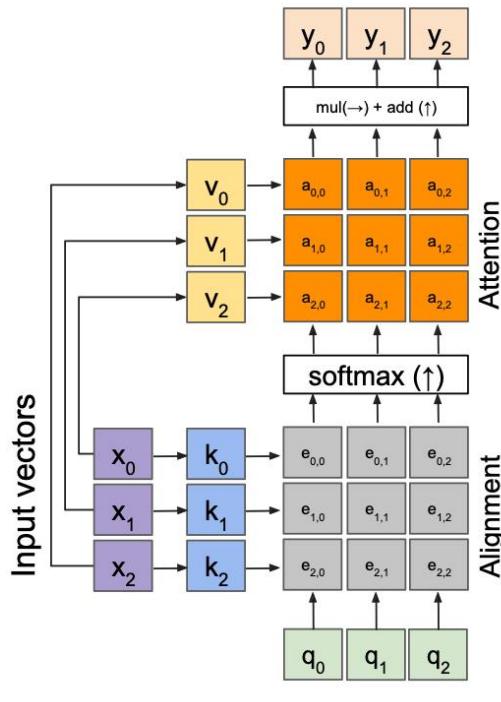


The input and output dimensions can now change depending on the key and value FC layers

Notice that the input vectors are used for both the alignment as well as the attention calculations.

- We can add more expressivity to the layer by adding a different FC layer before each of the two steps.

General Attention Layer



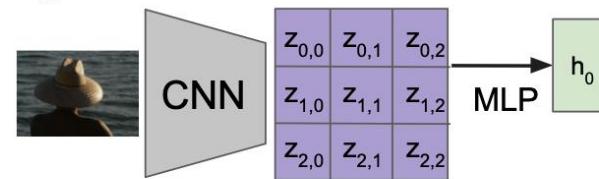
Outputs:
context vectors: \mathbf{y} (shape: D_v)

Operations:
Key vectors: $\mathbf{k} = \mathbf{x}W_k$
Value vectors: $\mathbf{v} = \mathbf{x}W_v$
Alignment: $e_{i,j} = q_j \cdot k_i / \sqrt{D}$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $y_j = \sum_i a_{i,j} \mathbf{v}_i$

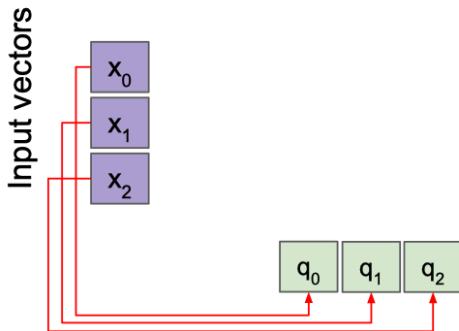
Inputs:
Input vectors: \mathbf{x} (shape: $N \times D$)
Queries: \mathbf{q} (shape: $M \times D_k$)

Recall that the query vector was a function of the input vectors

Encoder: $h_0 = f_w(\mathbf{z})$
where \mathbf{z} is spatial CNN features
 $f_w(\cdot)$ is an MLP



Self Attention Layer



Operations:

Key vectors: $k = xW_k$
Value vectors: $v = xW_v$
Query vectors: $q = xW_q$
Alignment: $e_{i,j} = q_i \cdot k_j / \sqrt{D}$
Attention: $a = \text{softmax}(e)$
Output: $y_j = \sum_i a_{i,j} v_i$

We can calculate the query vectors from the input vectors, therefore, defining a "self-attention" layer.

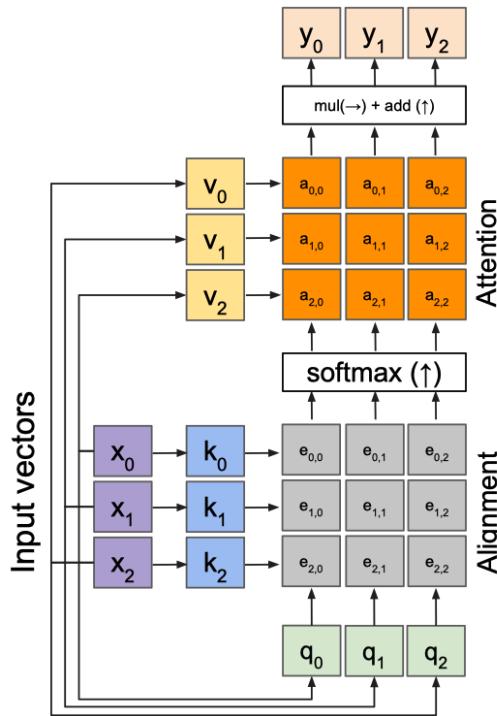
Instead, query vectors are calculated using a FC layer.

Inputs:

Input vectors: x (shape: $N \times D$)
Queries: q (shape: $M \times D_q$)

No input query vectors anymore

Self Attention Layer

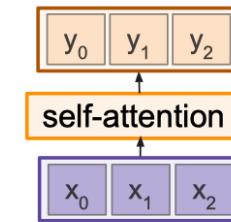
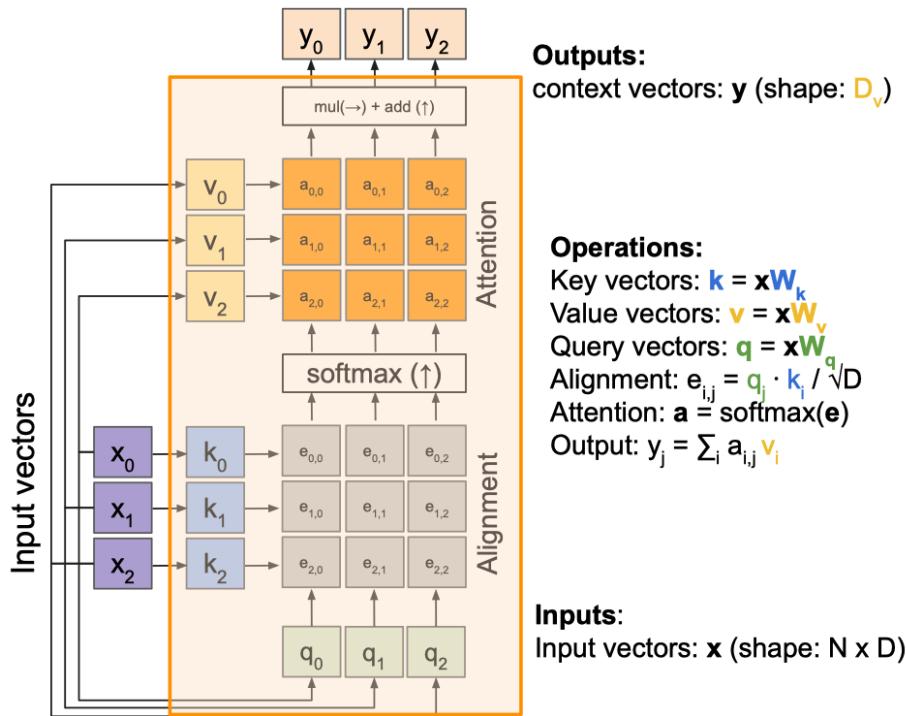


Outputs:
context vectors: \mathbf{y} (shape: D_v)

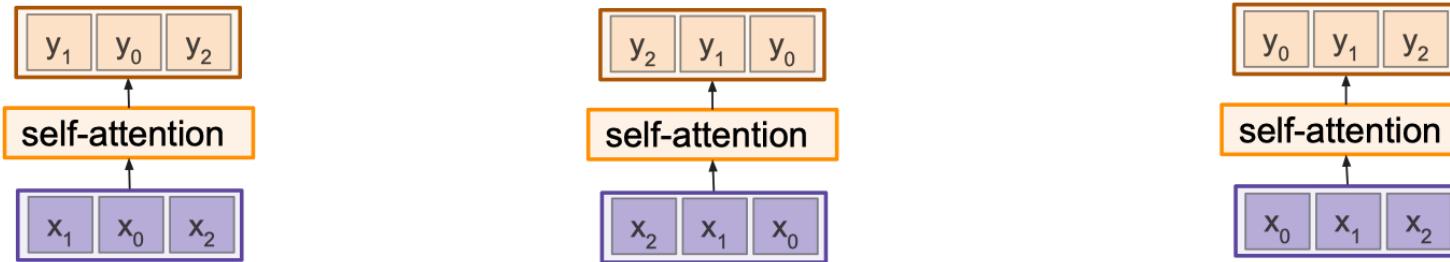
Operations:
Key vectors: $\mathbf{k} = \mathbf{x}W_k$
Value vectors: $\mathbf{v} = \mathbf{x}W_v$
Query vectors: $\mathbf{q} = \mathbf{x}W_q$
Alignment: $e_{i,j} = \mathbf{q}_j \cdot \mathbf{k}_i / \sqrt{D}$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $\mathbf{y}_j = \sum_i a_{i,j} \mathbf{v}_i$

Inputs:
Input vectors: \mathbf{x} (shape: $N \times D$)

Self Attention Layer – Attends Over Sets of Inputs



Self Attention Layer – Attends Over Sets of Inputs

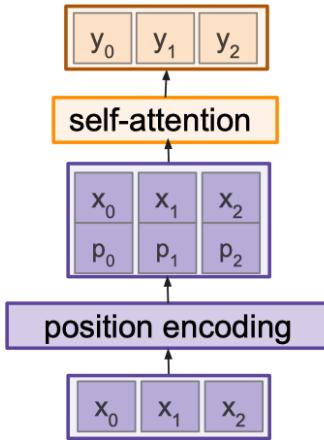


Permutation equivariant

Self-attention layer doesn't care about the orders of the inputs!

Problem: How can we encode ordered sequences like language or spatially ordered image features?

Positional Encoding



Concatenate/add special positional encoding p_j to each input vector x_j

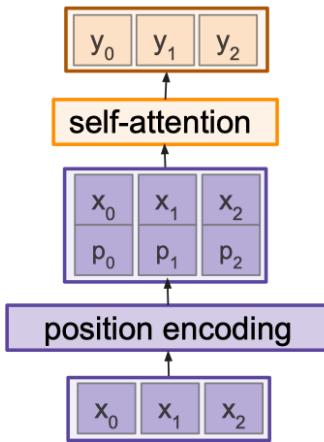
We use a function $pos: N \rightarrow \mathbb{R}^d$ to process the position j of the vector into a d -dimensional vector

So, $p_j = pos(j)$

Desiderata of $pos(\cdot)$:

1. It should output a **unique** encoding for each time-step (word's position in a sentence)
2. **Distance** between any two time-steps should be consistent across sentences with different lengths.
3. Our model should generalize to **longer** sentences without any efforts. Its values should be bounded.
4. It must be **deterministic**.

Positional Encoding



Concatenate special positional encoding p_j to each input vector x_j

We use a function $pos: N \rightarrow \mathbb{R}^d$ to process the position j of the vector into a d -dimensional vector

So, $p_j = pos(j)$

Options for $pos(\cdot)$

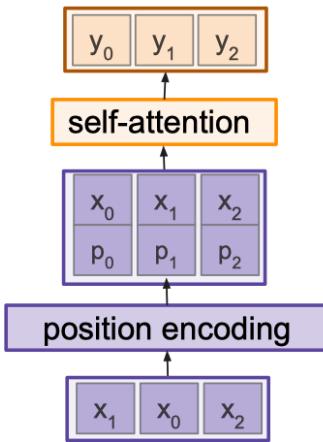
1. Learn a lookup table:
 - o Learn parameters to use for $pos(t)$ for $t \in [0, T]$
 - o Lookup table contains $T \times d$ parameters.

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Vaswani et al, "Attention is all you need", NeurIPS 2017

Positional Encoding



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Options for $pos(\cdot)$

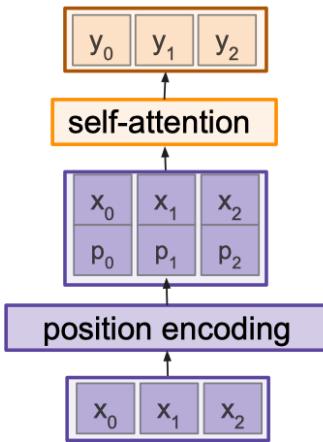
1. Learn a lookup table:
 - o Learn parameters to use for $pos(t)$ for $t \in [0, T]$
 - o Lookup table contains $T \times d$ parameters.
2. Design a fixed function with the desiderata

$$p(t) = \begin{bmatrix} \sin(\omega_1 \cdot t) \\ \cos(\omega_1 \cdot t) \\ \sin(\omega_2 \cdot t) \\ \cos(\omega_2 \cdot t) \\ \vdots \\ \sin(\omega_{d/2} \cdot t) \\ \cos(\omega_{d/2} \cdot t) \end{bmatrix}_d$$

where $\omega_k = \frac{1}{10000^{2k/d}}$

Vaswani et al, "Attention is all you need", NeurIPS 2017

Positional Encoding



Concatenate special positional encoding p_j to each input vector x_j

We use a function $pos: N \rightarrow \mathbb{R}^d$ to process the position j of the vector into a d -dimensional vector

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Intuition:

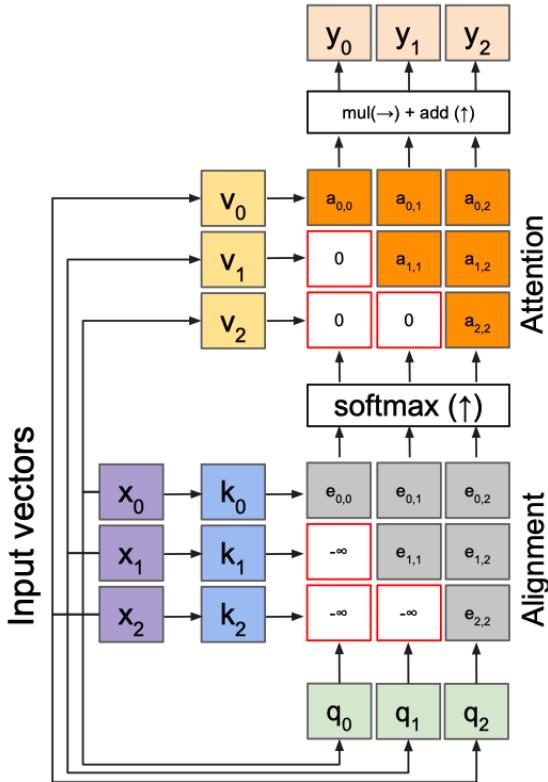
0 :	0 0 0 0	8 :	1 0 0 0
1 :	0 0 0 1	9 :	1 0 0 1
2 :	0 0 1 0	10 :	1 0 1 0
3 :	0 0 1 1	11 :	1 0 1 1
4 :	0 1 0 0	12 :	1 1 0 0
5 :	0 1 0 1	13 :	1 1 0 1
6 :	0 1 1 0	14 :	1 1 1 0
7 :	0 1 1 1	15 :	1 1 1 1

where $\omega_k = \frac{1}{10000^{2k/d}}$

[image source](#)

Vaswani et al, "Attention is all you need", NeurIPS 2017

Masked Self-attention Layer



Outputs:

context vectors: \mathbf{y} (shape: D_v)

Operations:

Key vectors: $\mathbf{k} = \mathbf{x}\mathbf{W}_k$

Value vectors: $\mathbf{v} = \mathbf{x}\mathbf{W}_v$

Query vectors: $\mathbf{q} = \mathbf{x}\mathbf{W}_q$

Alignment: $\mathbf{e}_{i,j} = \mathbf{q}_j \cdot \mathbf{k}_i / \sqrt{D}$

Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$

Output: $\mathbf{y}_j = \sum_i \mathbf{a}_{i,j} \mathbf{v}_i$

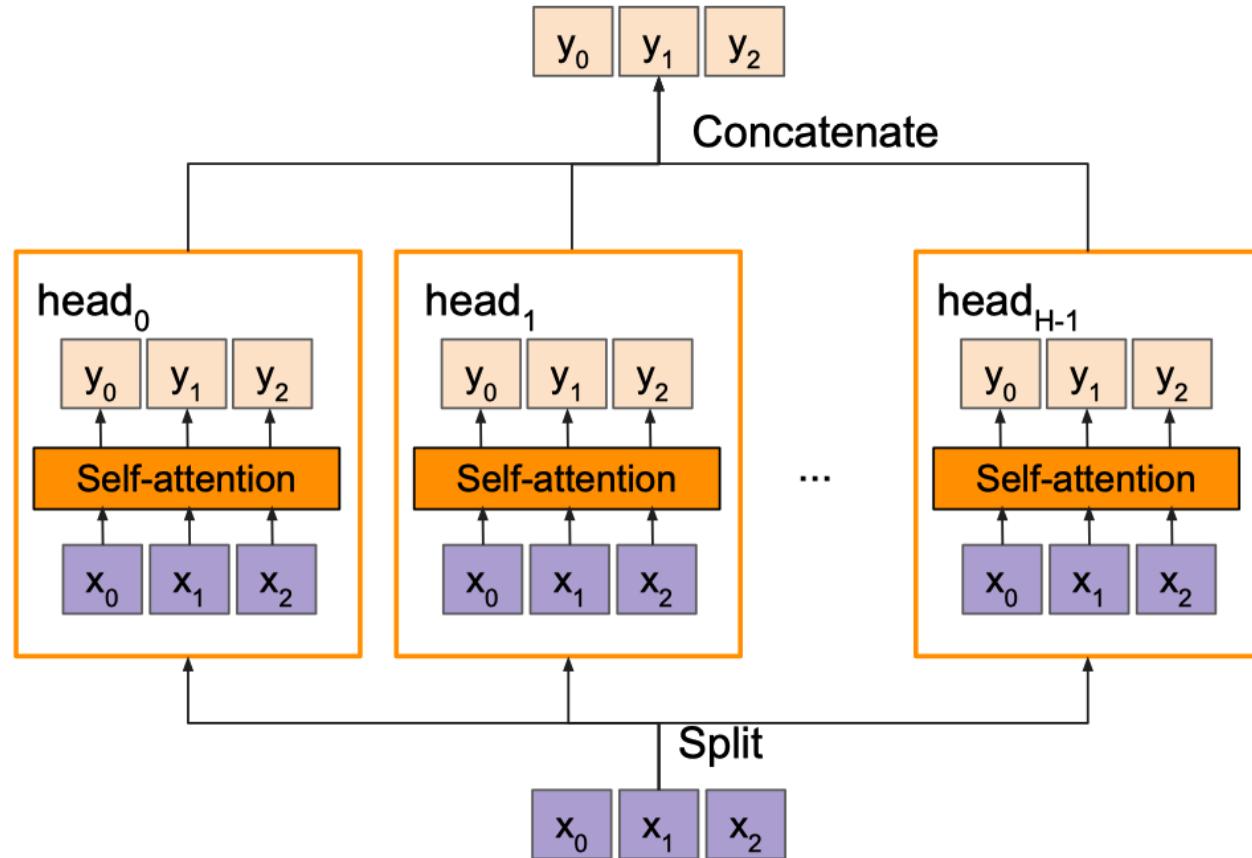
- Prevent vectors from looking at future vectors.
- Manually set alignment scores to $-\infty$

Inputs:

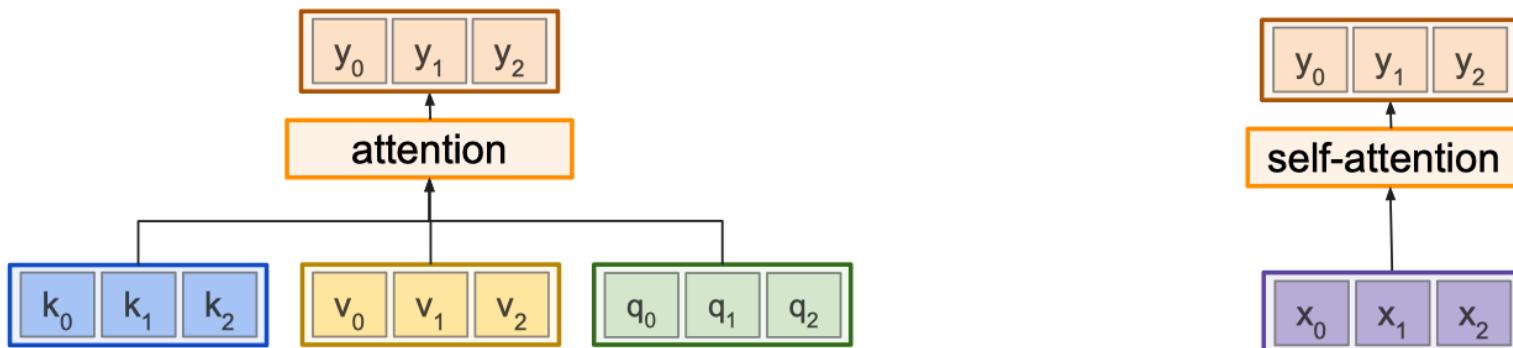
Input vectors: \mathbf{x} (shape: $N \times D$)

Multi-head Self-attention Layer

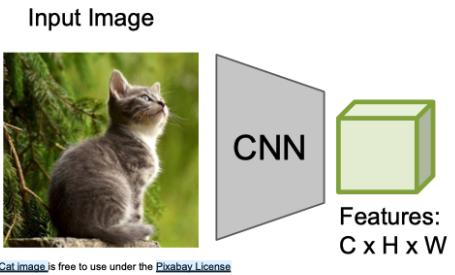
- Multiple self-attention heads in parallel



General Attention Versus Self-attention



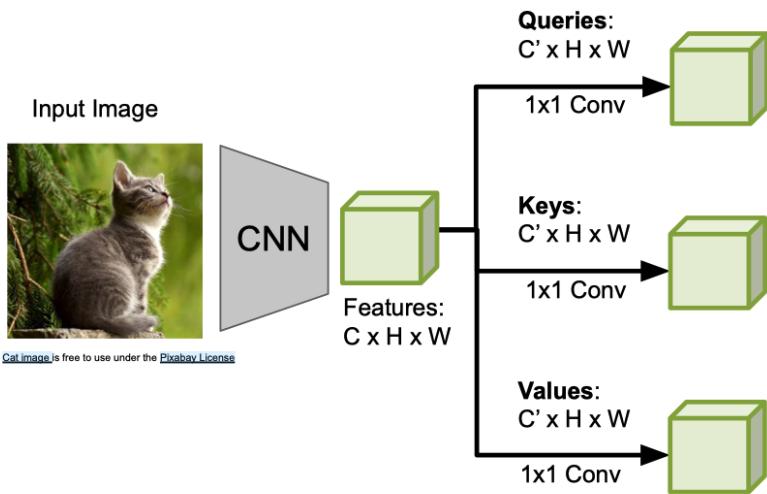
Example: CNN with Self-Attention



Zhang et al, "Self-Attention Generative Adversarial Networks", ICML 2018

Slide credit: Justin Johnson

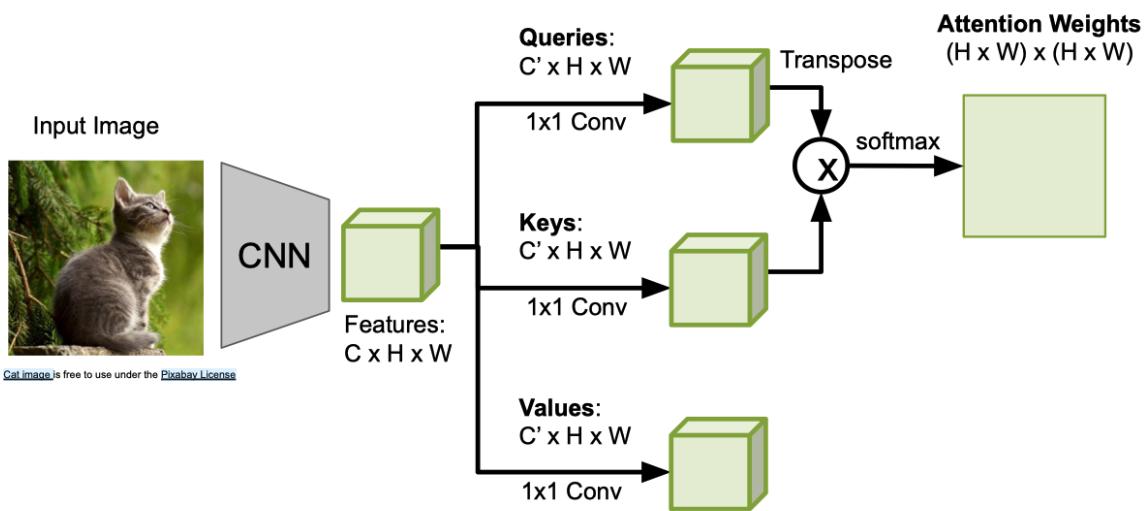
Example: CNN with Self-Attention



Zhang et al, "Self-Attention Generative Adversarial Networks", ICML 2018

Slide credit: Justin Johnson

Example: CNN with Self-Attention

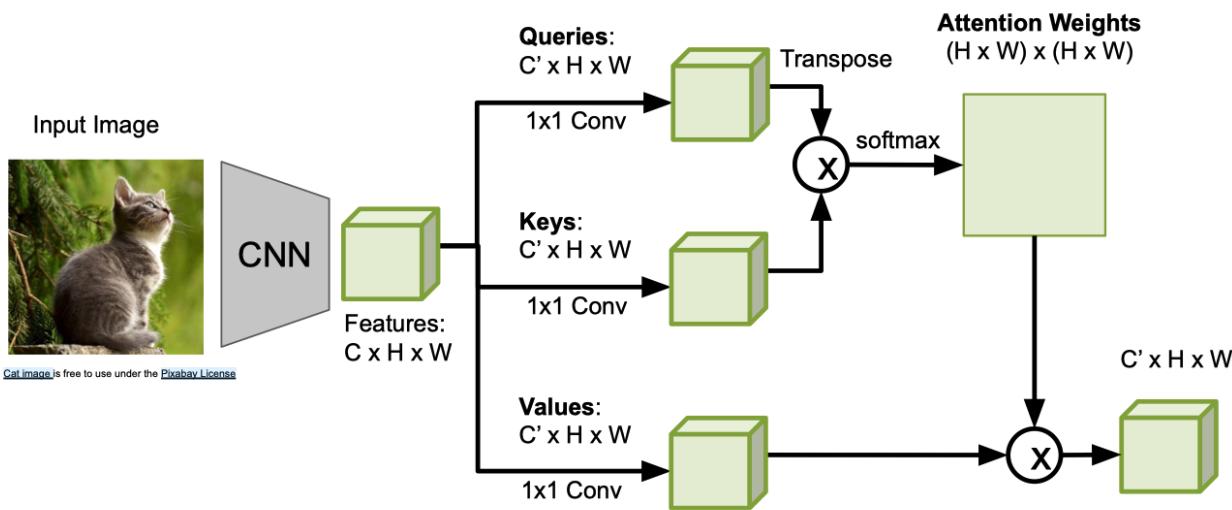


Cat image is free to use under the Pixabay License

Zhang et al, "Self-Attention Generative Adversarial Networks", ICML 2018

Slide credit: Justin Johnson

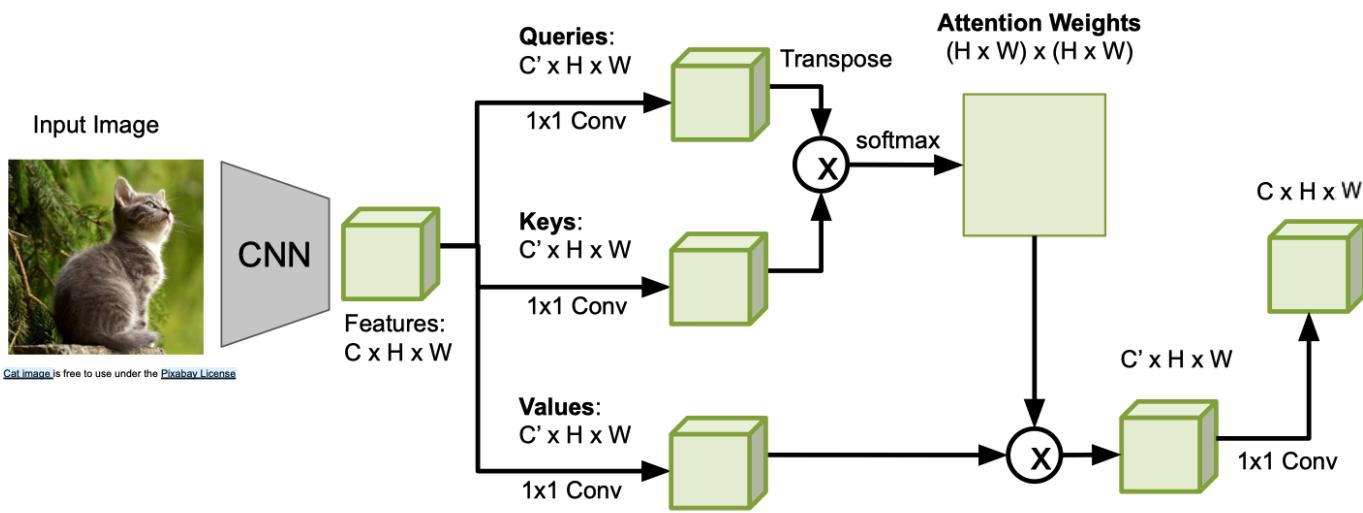
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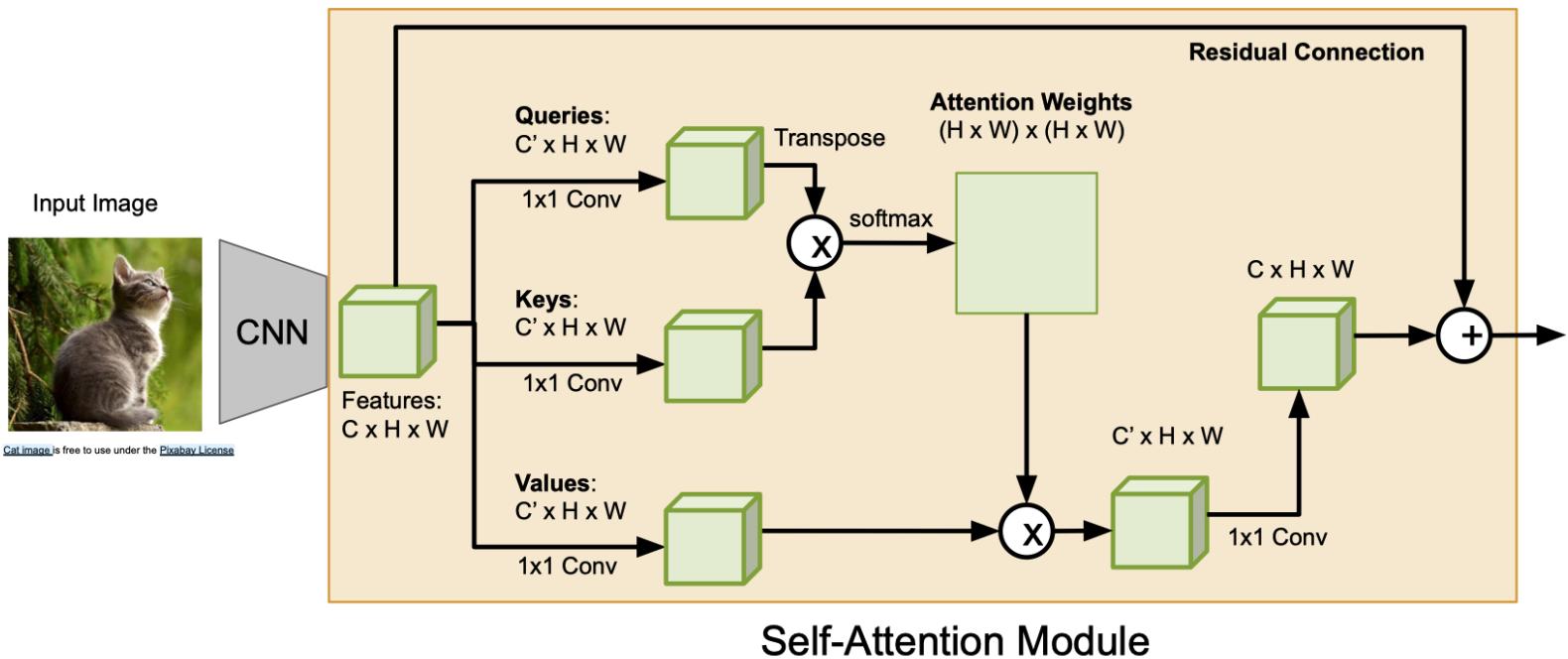
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Slide credit: Justin Johnson

Transformer

Attention Is All You Need

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"ImageNet Moment for Natural Language Processing"

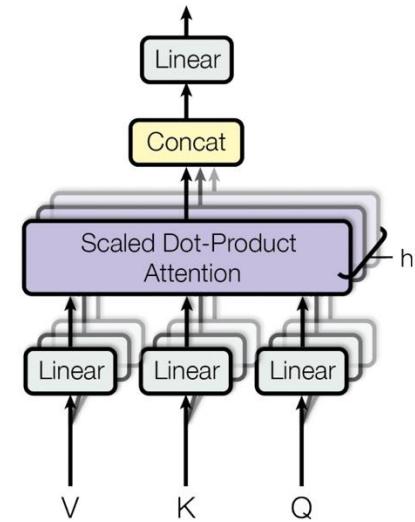
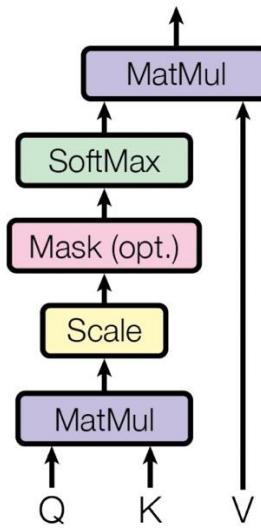
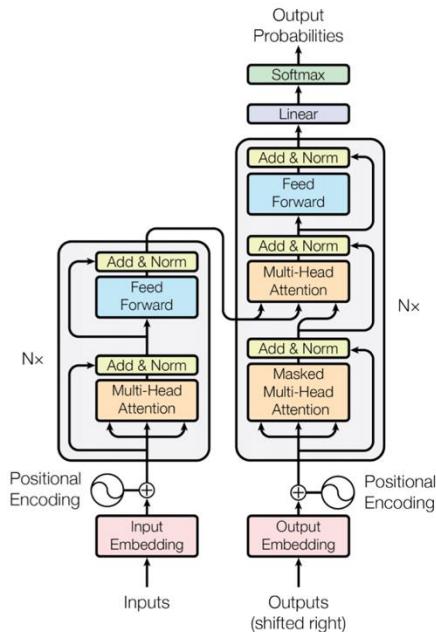
Pretraining:

Download a lot of text from the internet

Train a giant Transformer model for language modeling

Finetuning:

Fine-tune the Transformer on your own NLP task



Comparing RNNs to Transformer

RNNs

(+) LSTMs work reasonably well for long sequences.

(-) Expects an ordered sequences of inputs

(-) Sequential computation: subsequent hidden states can only be computed after the previous ones are done.

Transformer:

(+) Good at long sequences. Each attention calculation looks at all inputs.

(+) Can operate over unordered sets or ordered sequences with positional encodings.

(+) Parallel computation: All alignment and attention scores for all inputs can be done in parallel.

(-) Requires a lot of memory: $N \times M$ alignment and attention scalers need to be calculated and stored for a single self-attention head. (but GPUs are getting bigger and better)

Image Captioning using Transformers

Input: Image I

Output: Sequence $\mathbf{y} = y_1, y_2, \dots, y_T$

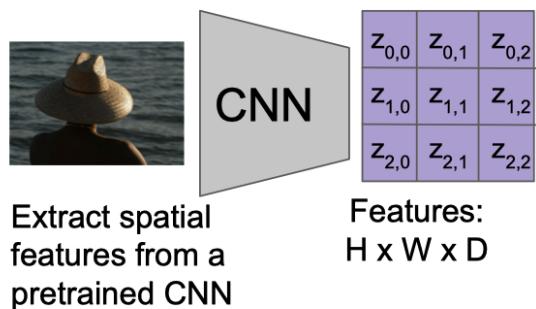


Image Captioning using Transformers

Input: Image I

Output: Sequence $\mathbf{y} = y_1, y_2, \dots, y_T$

Encoder: $\mathbf{c} = T_w(\mathbf{z})$

where \mathbf{z} is spatial CNN features

$T_w(\cdot)$ is the transformer encoder

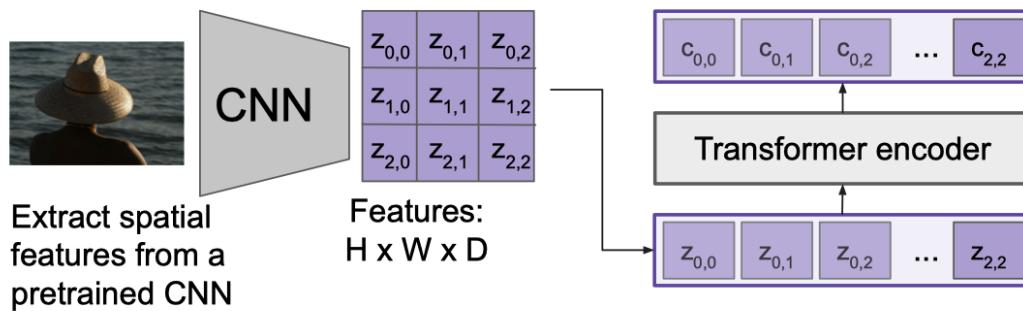


Image Captioning using Transformers

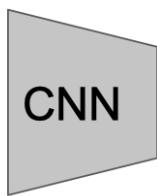
Input: Image I

Output: Sequence $\mathbf{y} = y_1, y_2, \dots, y_T$

Encoder: $\mathbf{c} = T_w(\mathbf{z})$

where \mathbf{z} is spatial CNN features

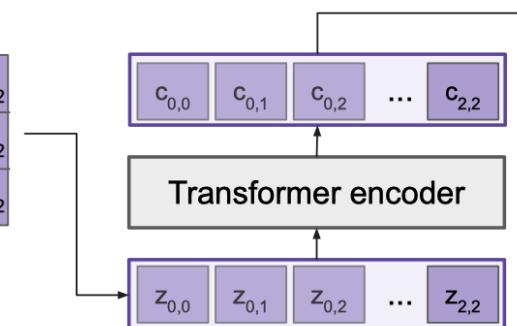
$T_w(\cdot)$ is the transformer encoder



$z_{0,0}$	$z_{0,1}$	$z_{0,2}$
$z_{1,0}$	$z_{1,1}$	$z_{1,2}$
$z_{2,0}$	$z_{2,1}$	$z_{2,2}$

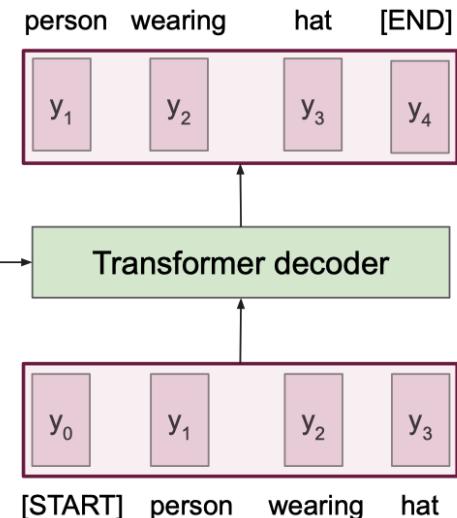
Features:
 $H \times W \times D$

Extract spatial
features from a
pretrained CNN

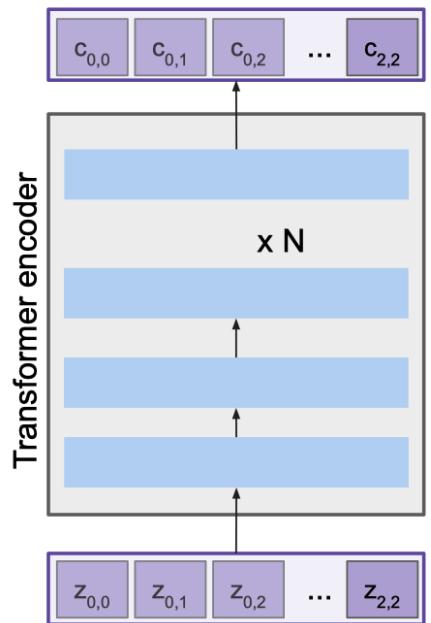


Decoder: $y_t = T_D(y_{0:t-1}, \mathbf{c})$

where $T_D(\cdot)$ is the transformer decoder



The Transformer Encoder Block

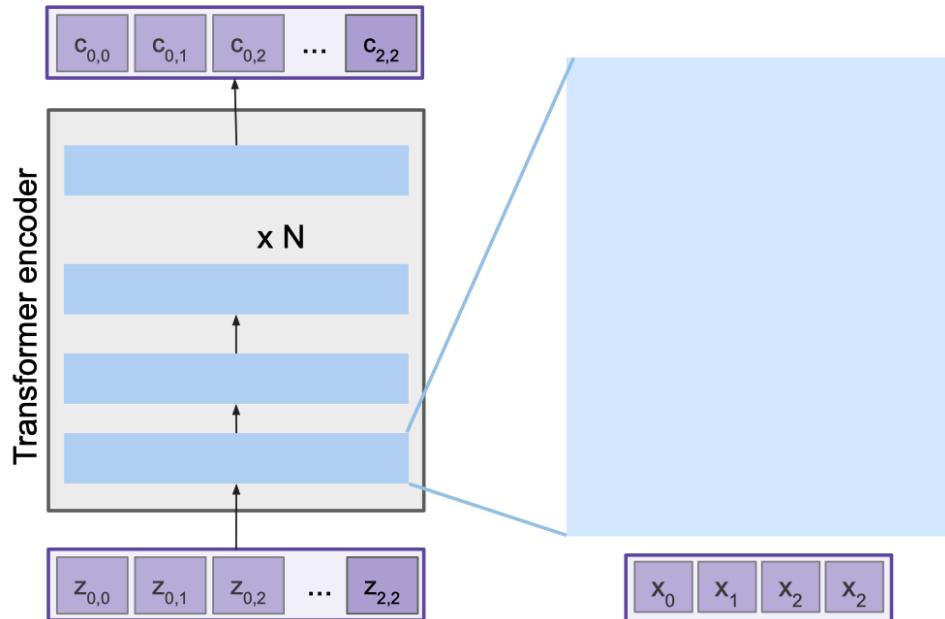


Made up of N encoder blocks.

In vaswani et al. $N = 6$, $D_q = 512$

Vaswani et al, "Attention is all you need", NeurIPS 2017

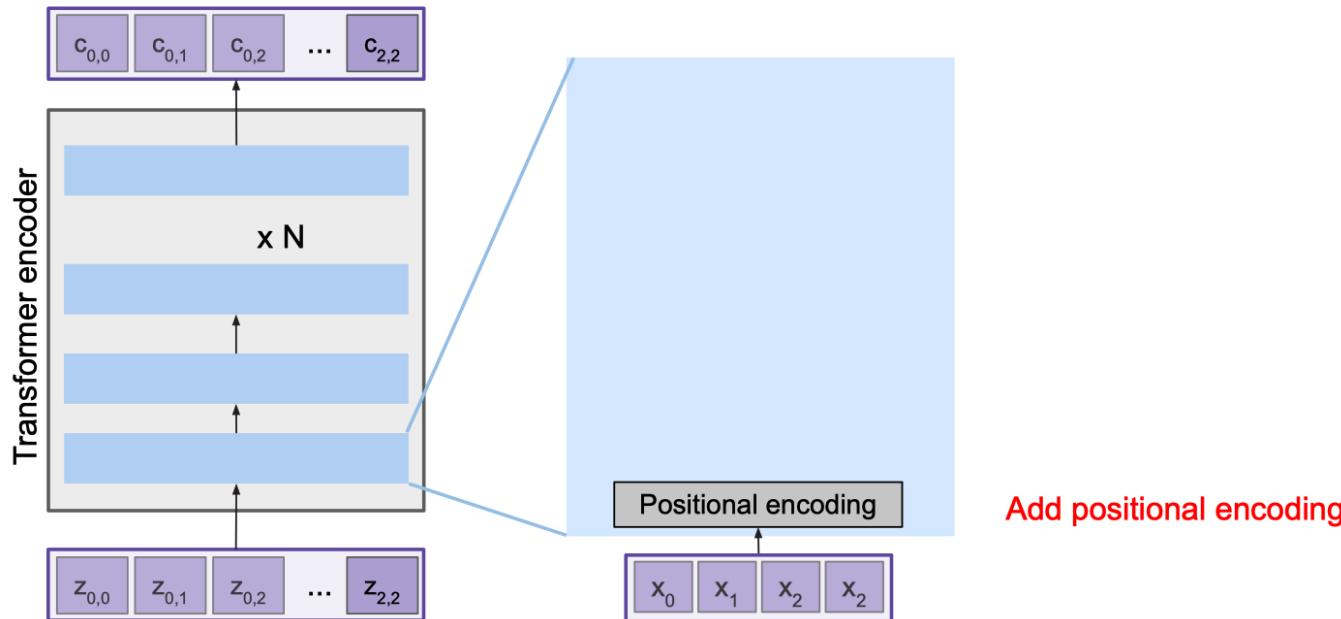
The Transformer Encoder Block



Let's dive into one encoder block

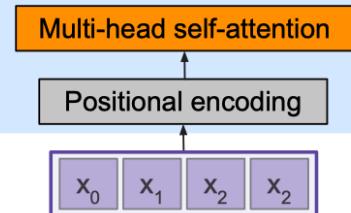
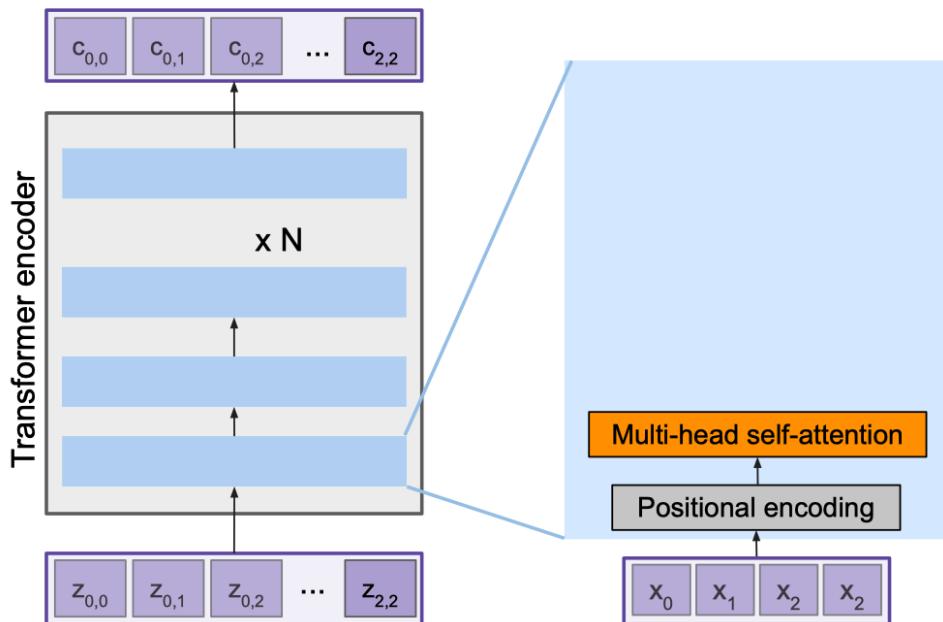
Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Encoder Block



Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Encoder Block

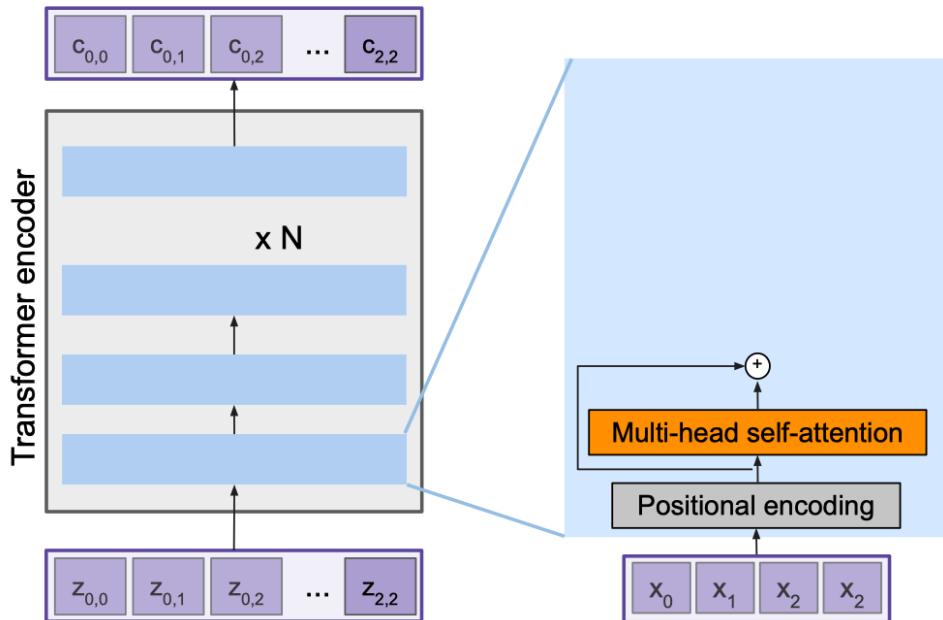


Attention attends over all the vectors

Add positional encoding

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Encoder Block



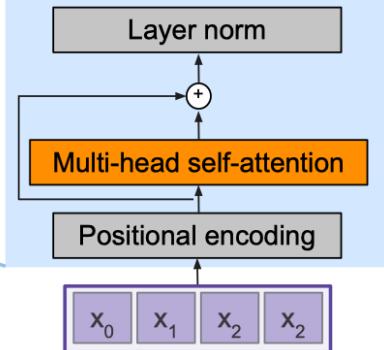
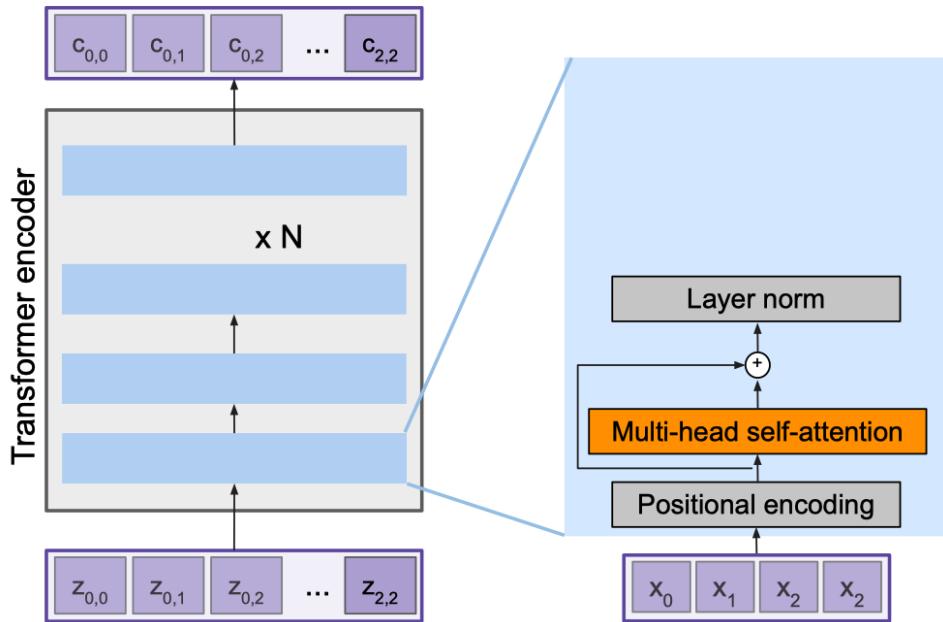
Residual connection

Attention attends over all the vectors

Add positional encoding

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Encoder Block



LayerNorm over each vector individually

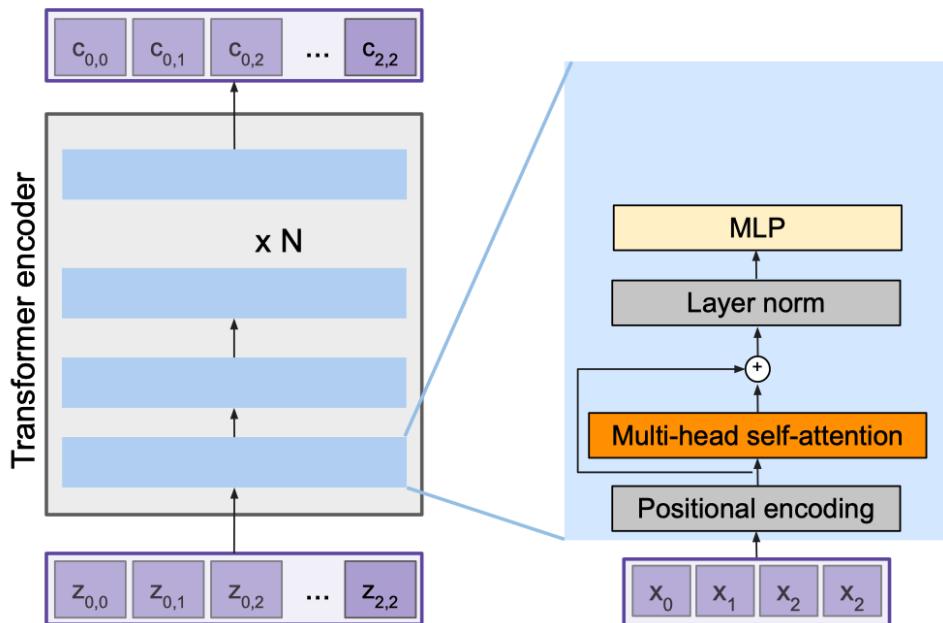
Residual connection

Attention attends over all the vectors

Add positional encoding

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Encoder Block



MLP over each vector individually

LayerNorm over each vector individually

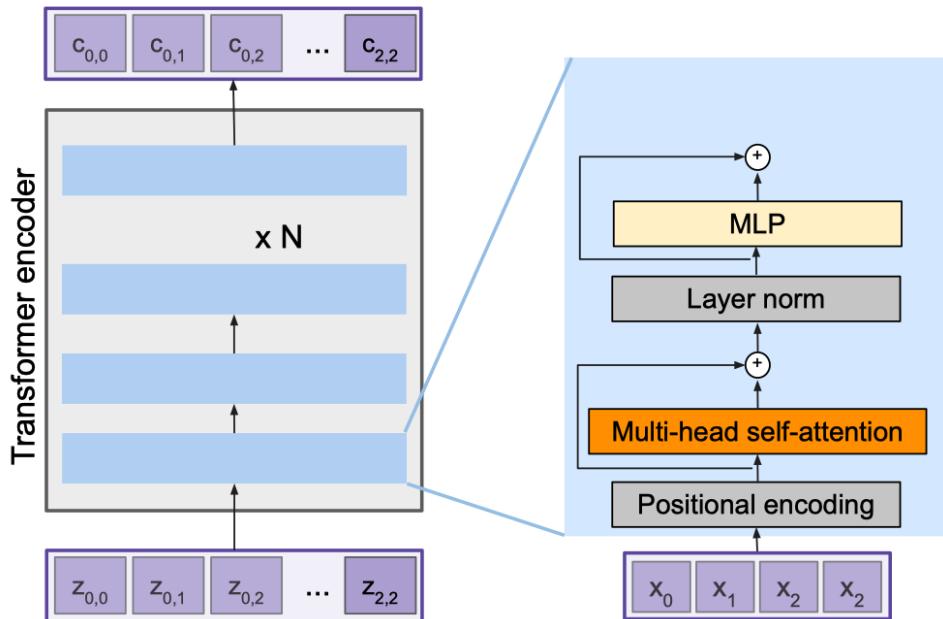
Residual connection

Attention attends over all the vectors

Add positional encoding

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Encoder Block



Residual connection

MLP over each vector individually

LayerNorm over each vector individually

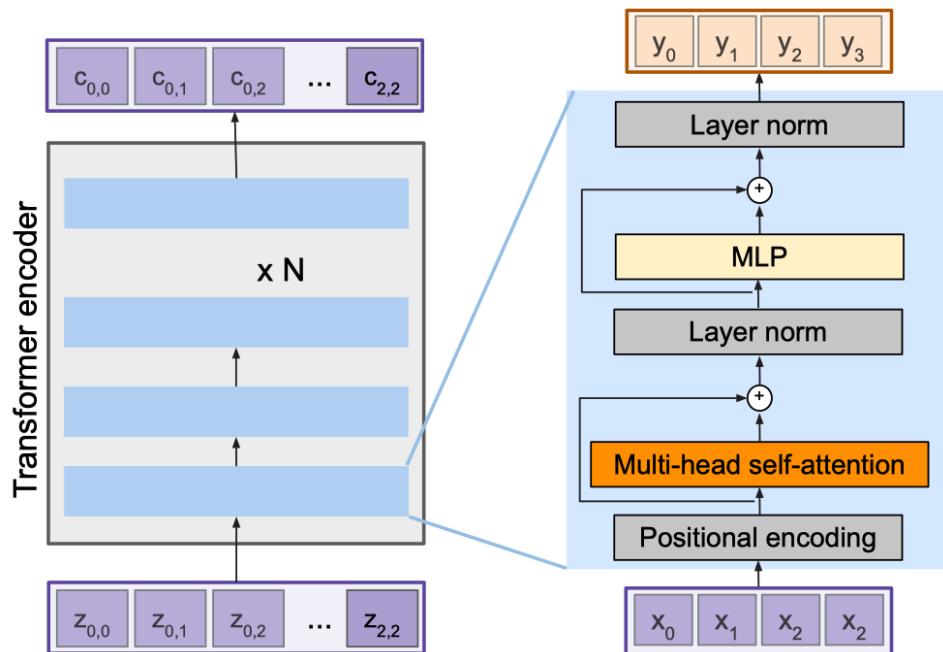
Residual connection

Attention attends over all the vectors

Add positional encoding

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Encoder Block



Transformer Encoder Block:

Inputs: Set of vectors x

Outputs: Set of vectors y

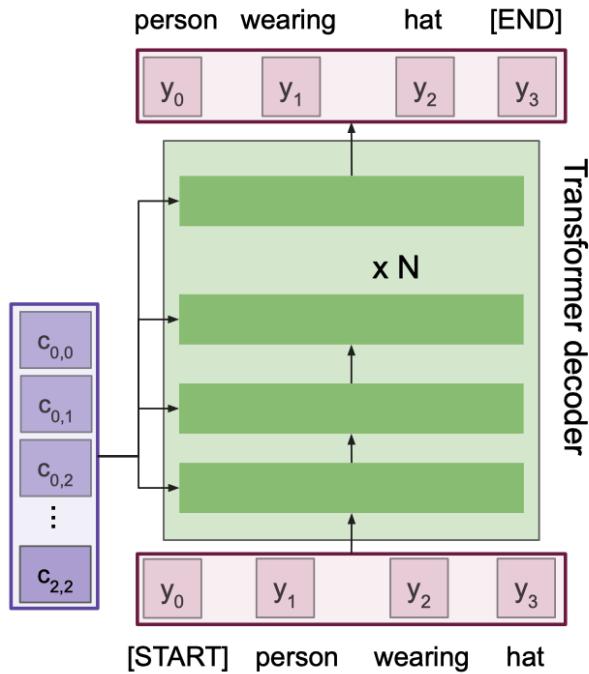
Self-attention is the only interaction between vectors.

Layer norm and MLP operate independently per vector.

Highly scalable, highly parallelizable, but high memory usage.

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Decoder Block

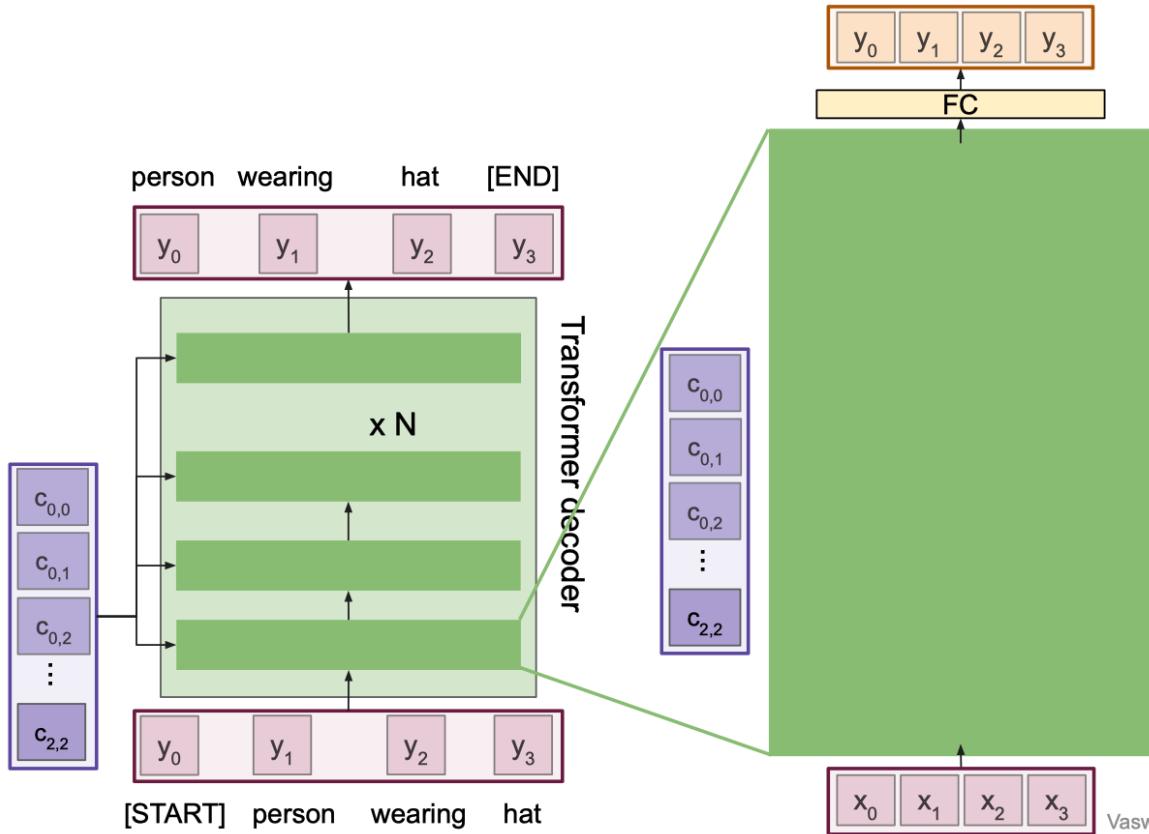


Made up of N decoder blocks.

In vaswani et al. $N = 6, D_q = 512$

Vaswani et al., "Attention is all you need", NeurIPS 2017

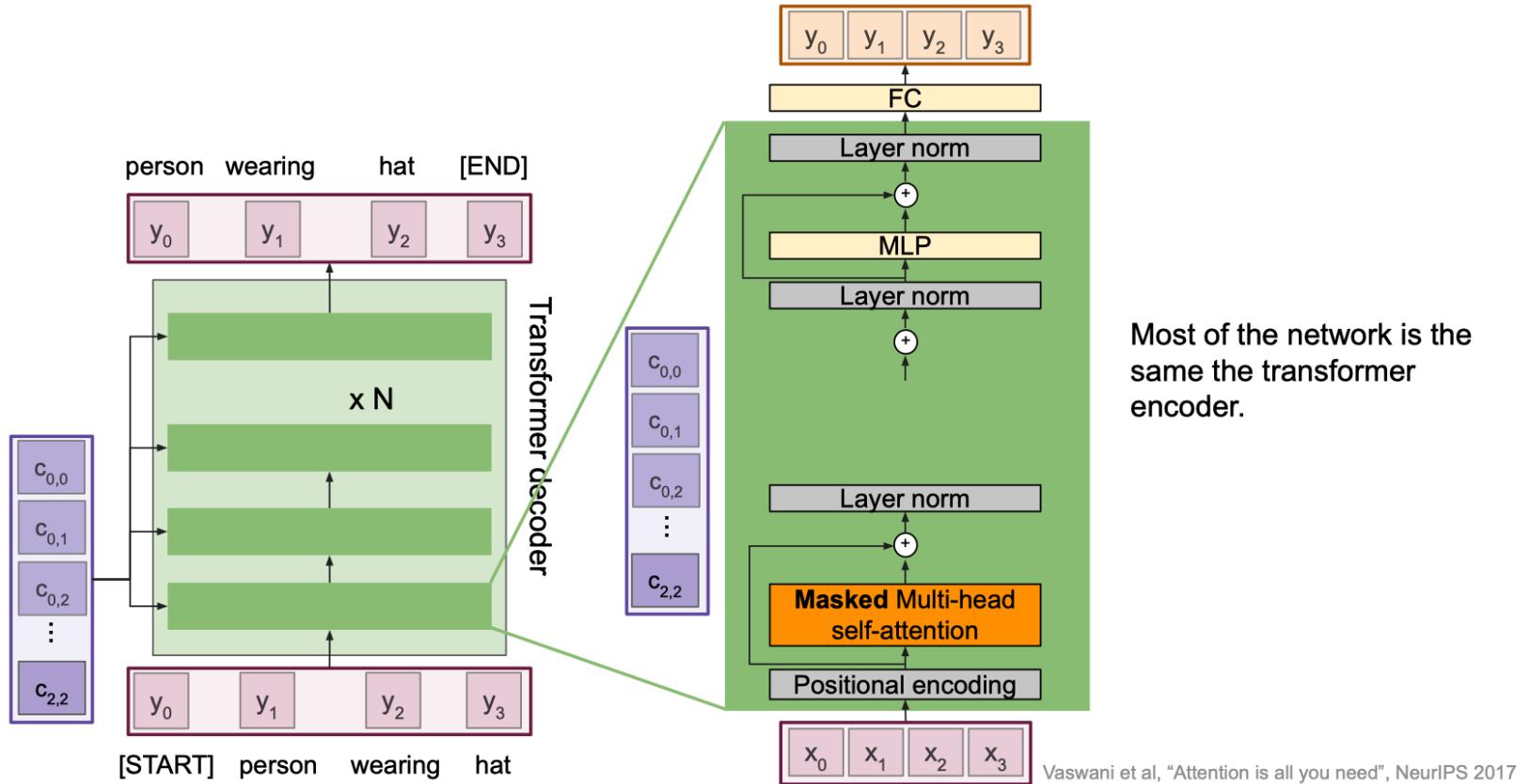
The Transformer Decoder Block



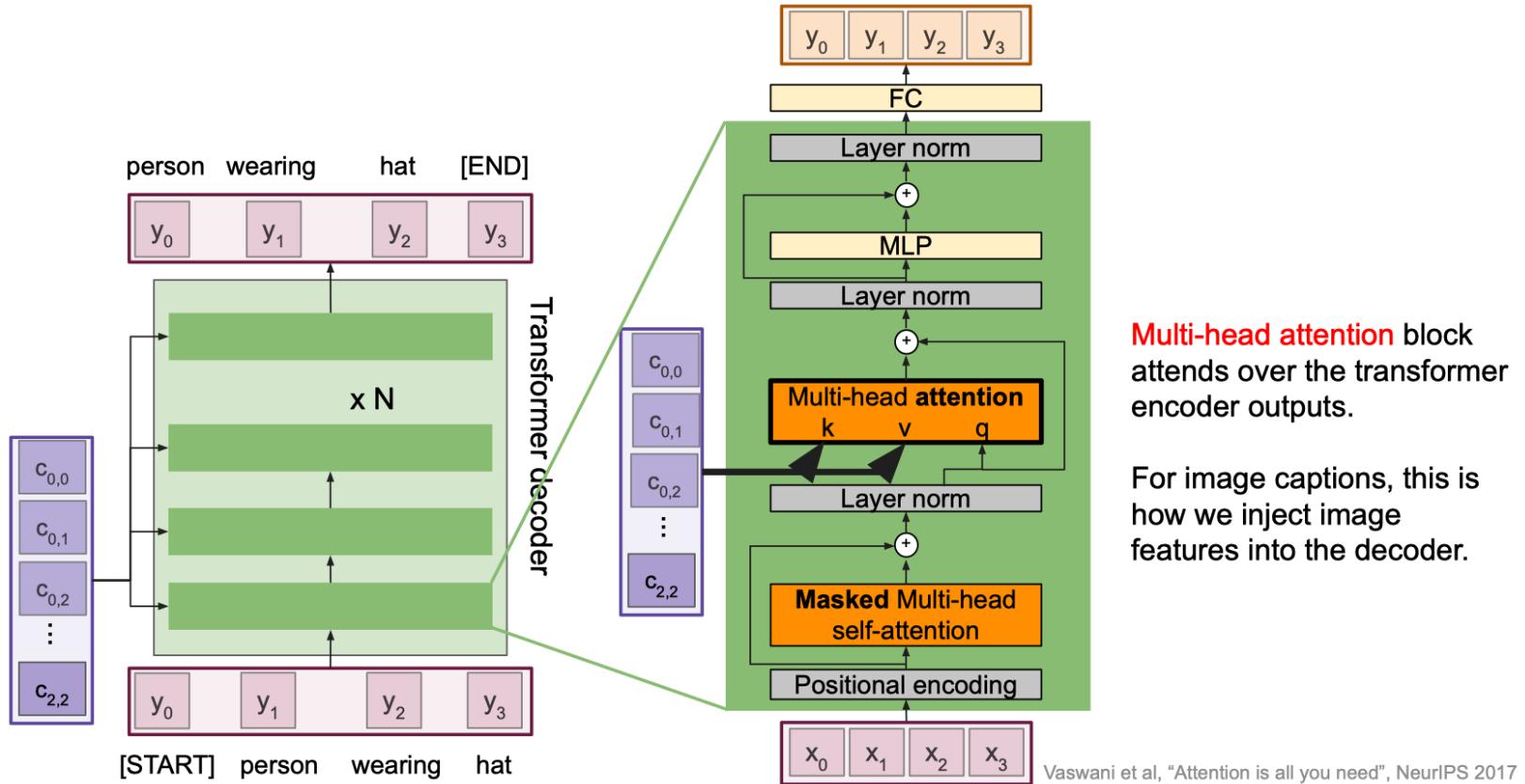
Let's dive into the
transformer decoder block

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer Decoder Block



The Transformer Decoder Block



The Transformer Decoder Block

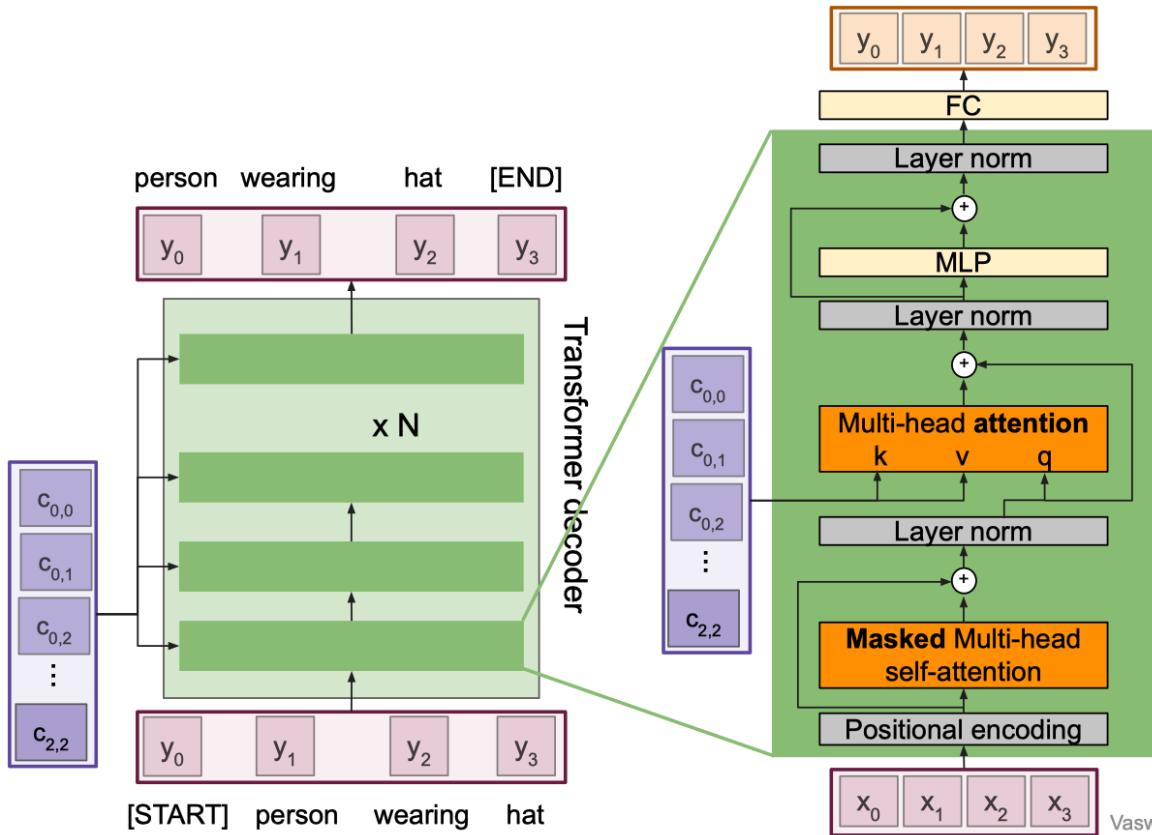


Image Captioning using Transformers

- No recurrence at all

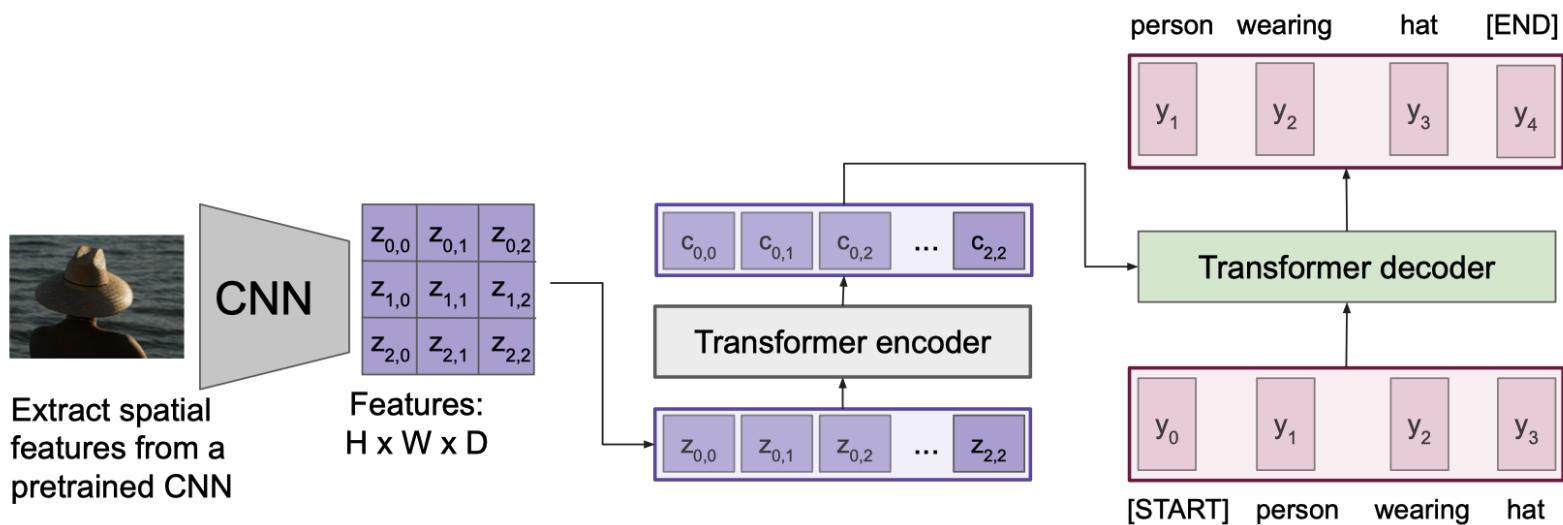


Image Captioning using Transformers

- Perhaps we don't need convolutions at all?

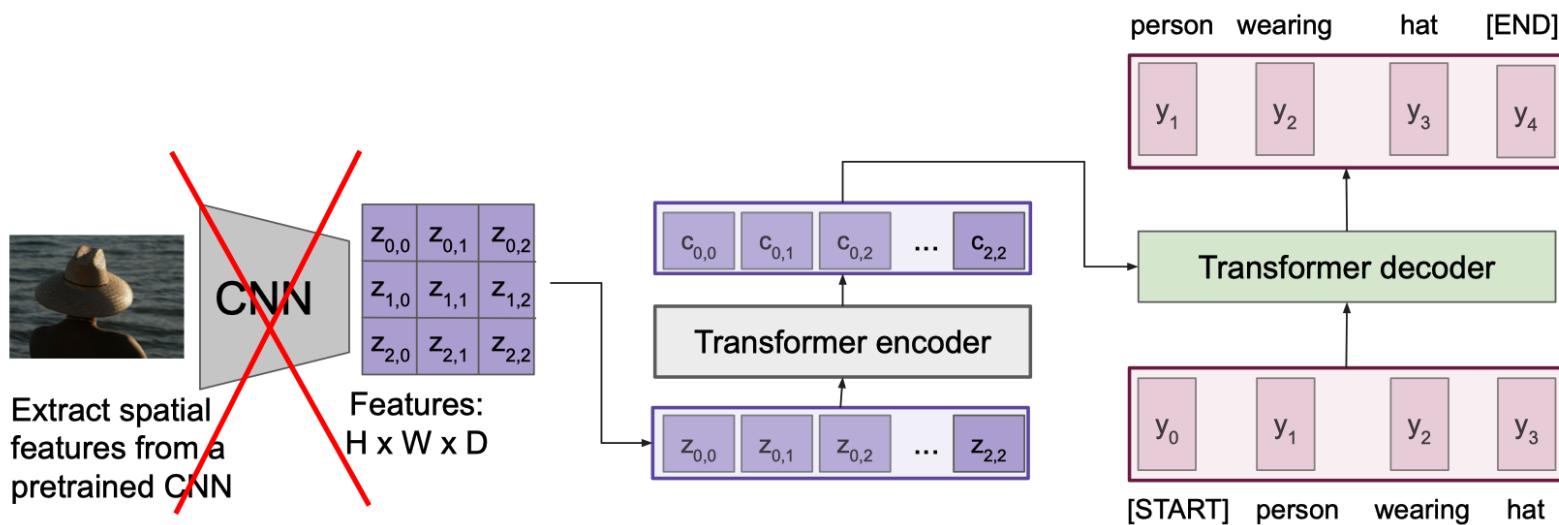
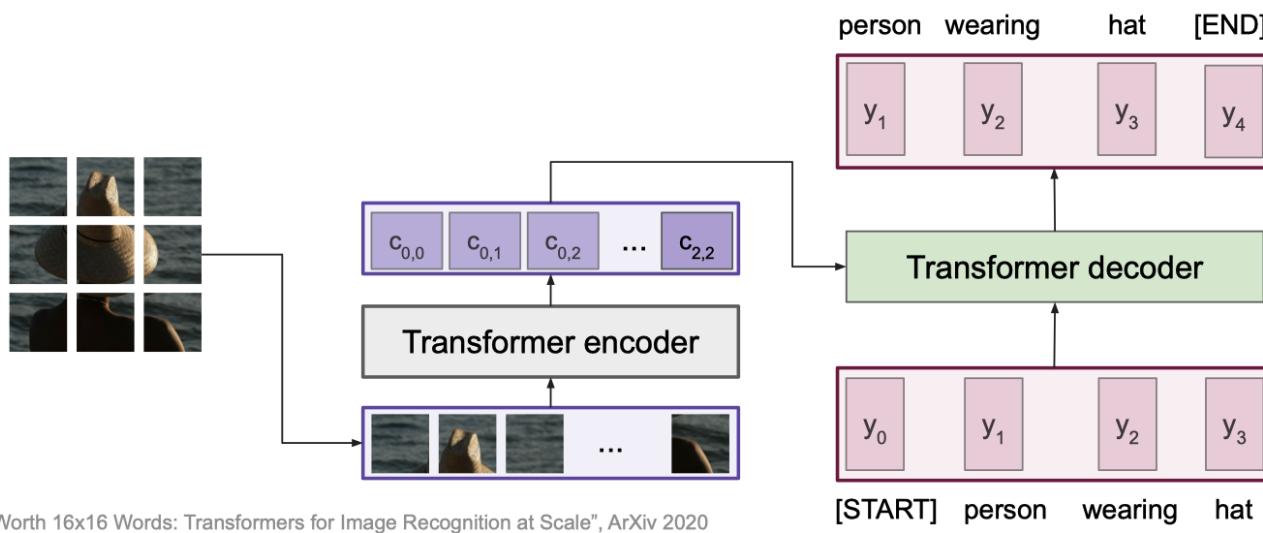


Image Captioning using ONLY Transformers

- **Transformers from pixels to language**



Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ArXiv 2020
[Colab link](#) to an implementation of vision transformers

Vision Transformers vs. ResNets

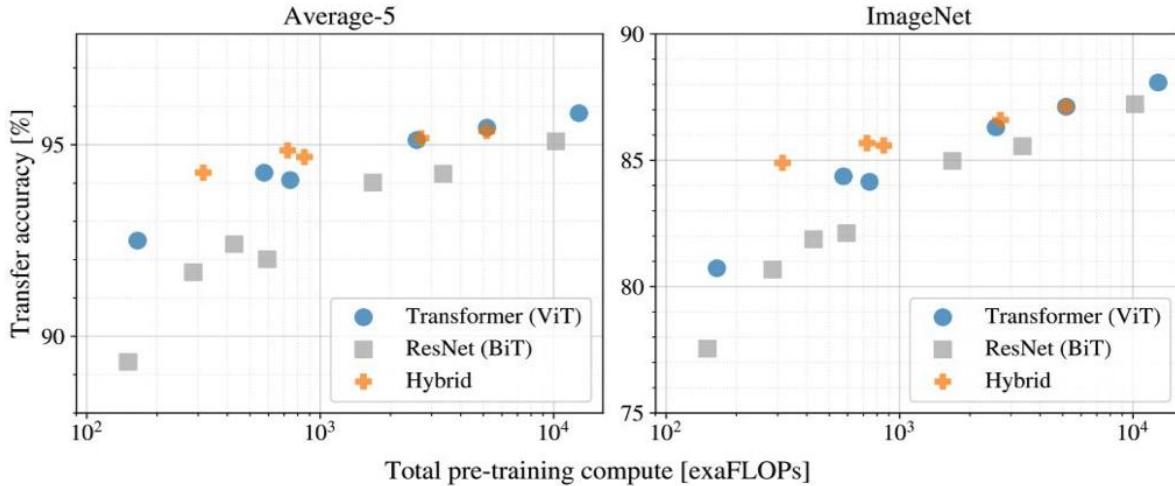
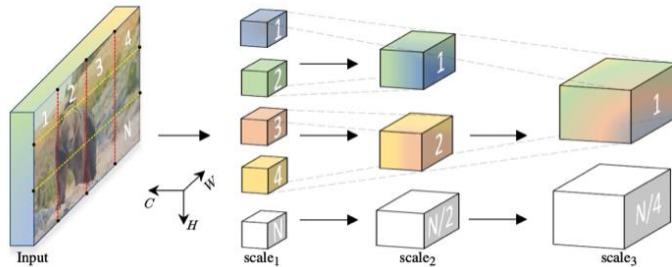


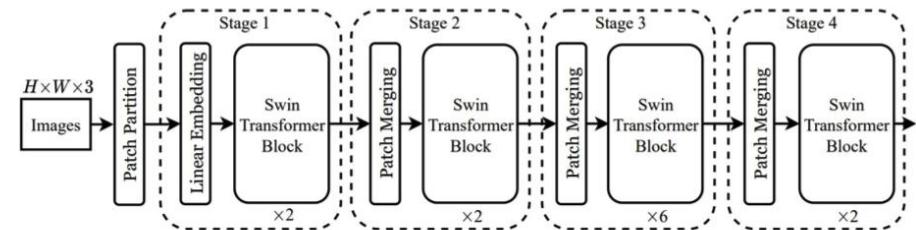
Figure 5: Performance versus cost for different architectures: Vision Transformers, ResNets, and hybrids. Vision Transformers generally outperform ResNets with the same computational budget. Hybrids improve upon pure Transformers for smaller model sizes, but the gap vanishes for larger models.

Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ArXiv 2020
[Colab link](#) to an implementation of vision transformers

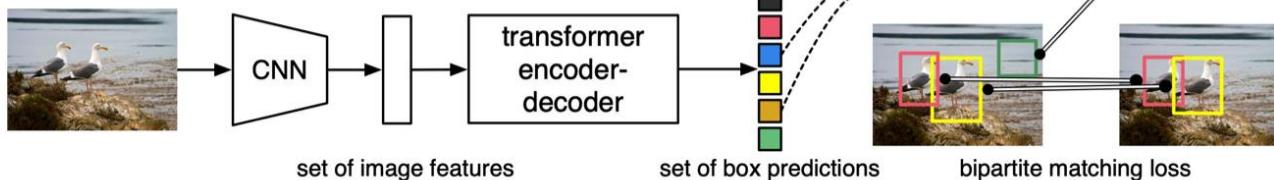
Vision Transformers



Fan et al, "Multiscale Vision Transformers", ICCV 2021



Liu et al, "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows", CVPR 2021



Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

Summary

- Adding **attention** to RNNs allows them to "attend" to different parts of the input at every time step
- The **general attention layer** is a new type of layer that can be used to design new neural network architectures
- **Transformers** are a type of layer that uses **self-attention** and layer norm.
 - o It is highly **scalable** and highly **parallelizable**
 - o **Faster** training, **larger** models, **better** performance across vision and language tasks
 - o They are quickly replacing RNNs, LSTMs, and may(?) even replace convolutions.

Questions?