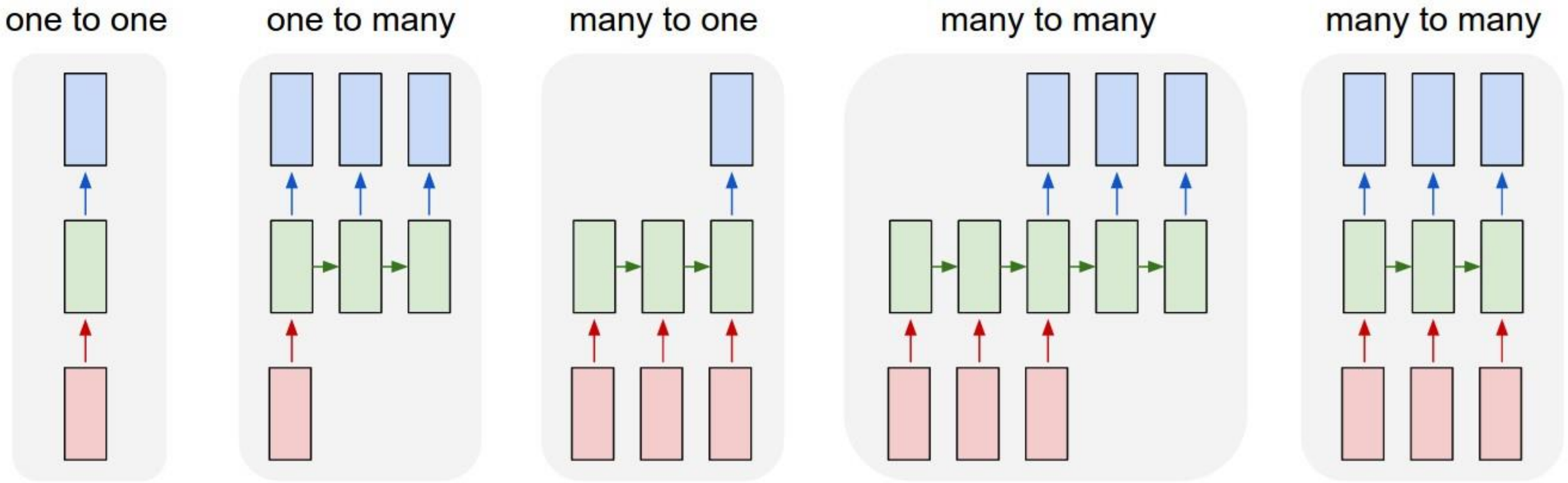
# Lecture 8: Attention and Transformers

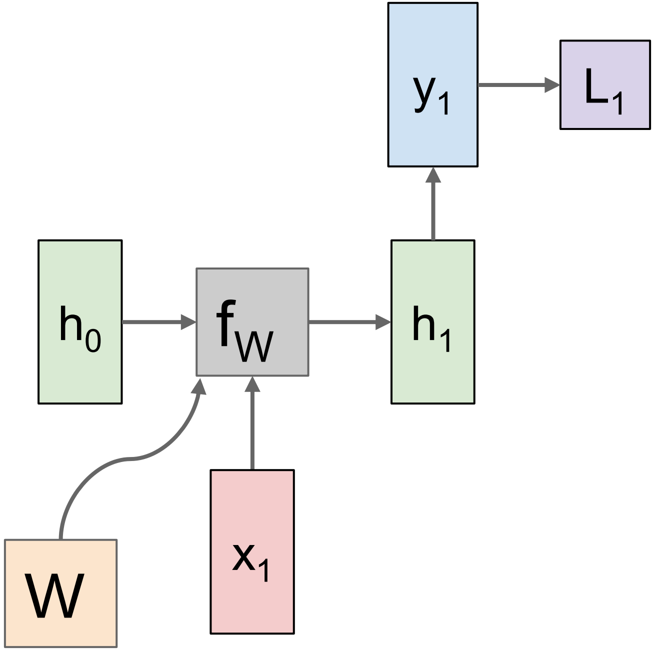
# Administrative

- Assignment 2 due **05/06**
- Discussion section **tomorrow**
  - Covering PyTorch, the main deep learning framework used by AI researchers + what we recommend for your projects!

# Last Time: Recurrent Neural Networks



# Last Time: Variable length computation graph with shared weights



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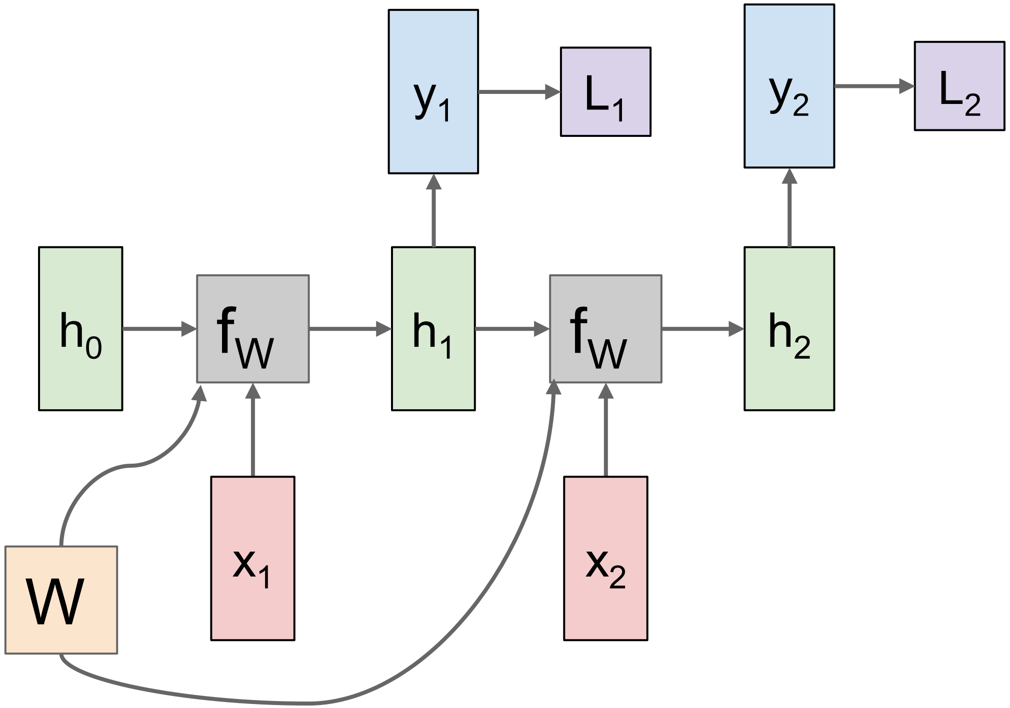
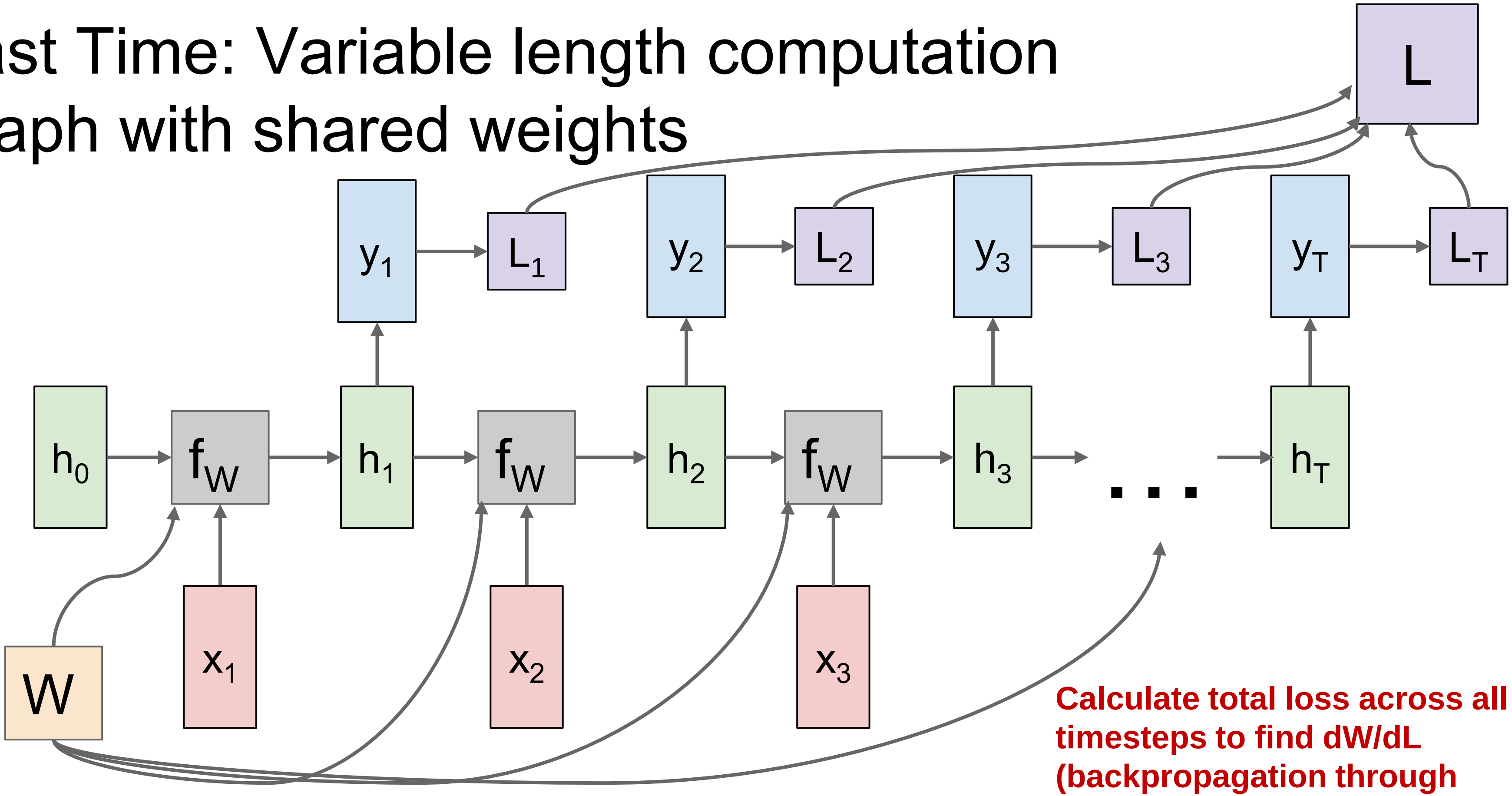



**W is reused (recurrently)!**

# Last Time: Variable length computation graph with shared weights



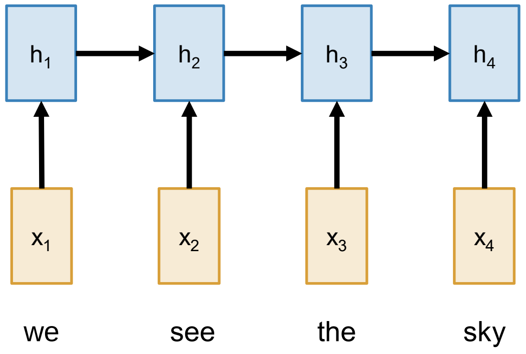

**Calculate total loss across all timesteps to find dW/dL (backpropagation through time)!**

# Sequence to Sequence with RNNs: Encoder - Decoder

**Input**: Sequence $x_1, \ldots x_T$
**Output**: Sequence $y_1, \ldots, y_{T'}$

**A motivating example for today's discussion – machine translation! English → Italian**

**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

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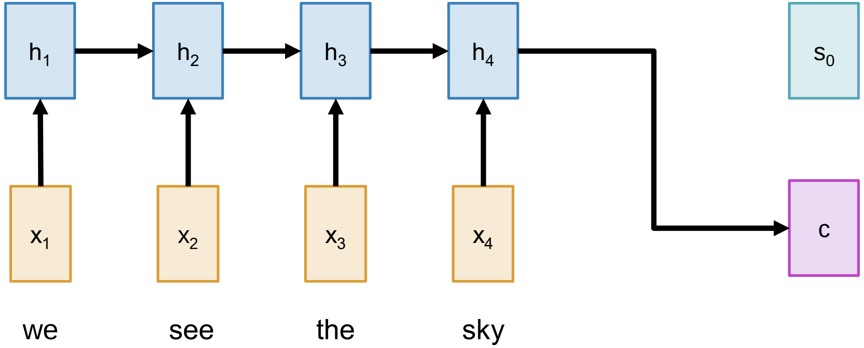
From final hidden state predict:
**Initial decoder state** $s_0$
**Context vector** c (often $c=h_T$)

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# Sequence to Sequence with RNNs

**Input**: Sequence $x_1, \ldots x_T$
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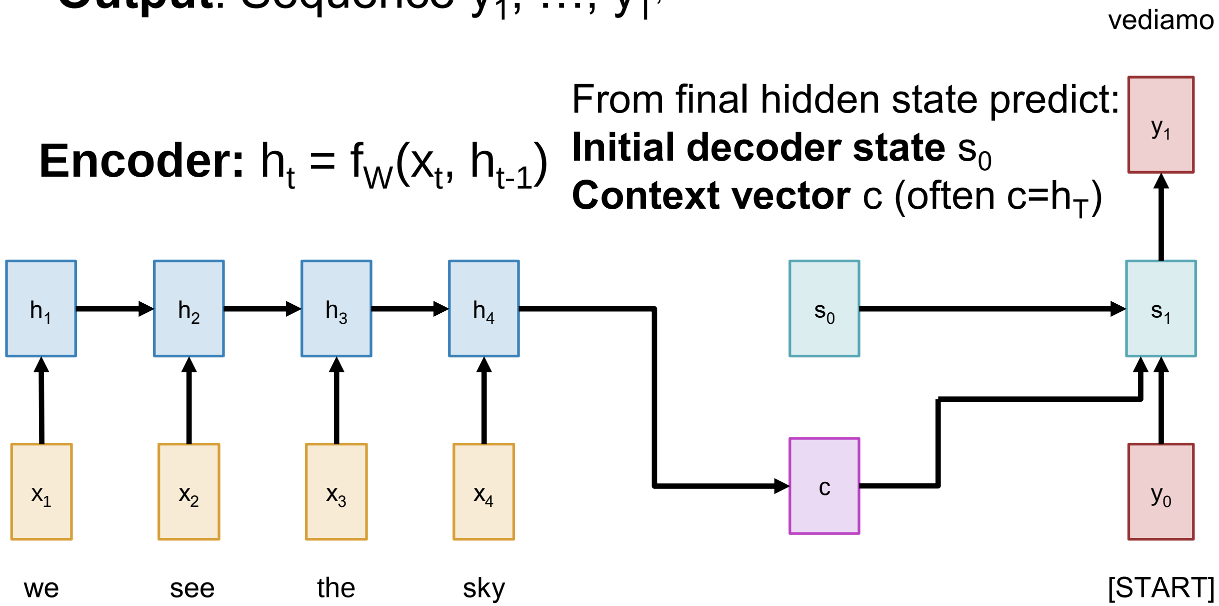


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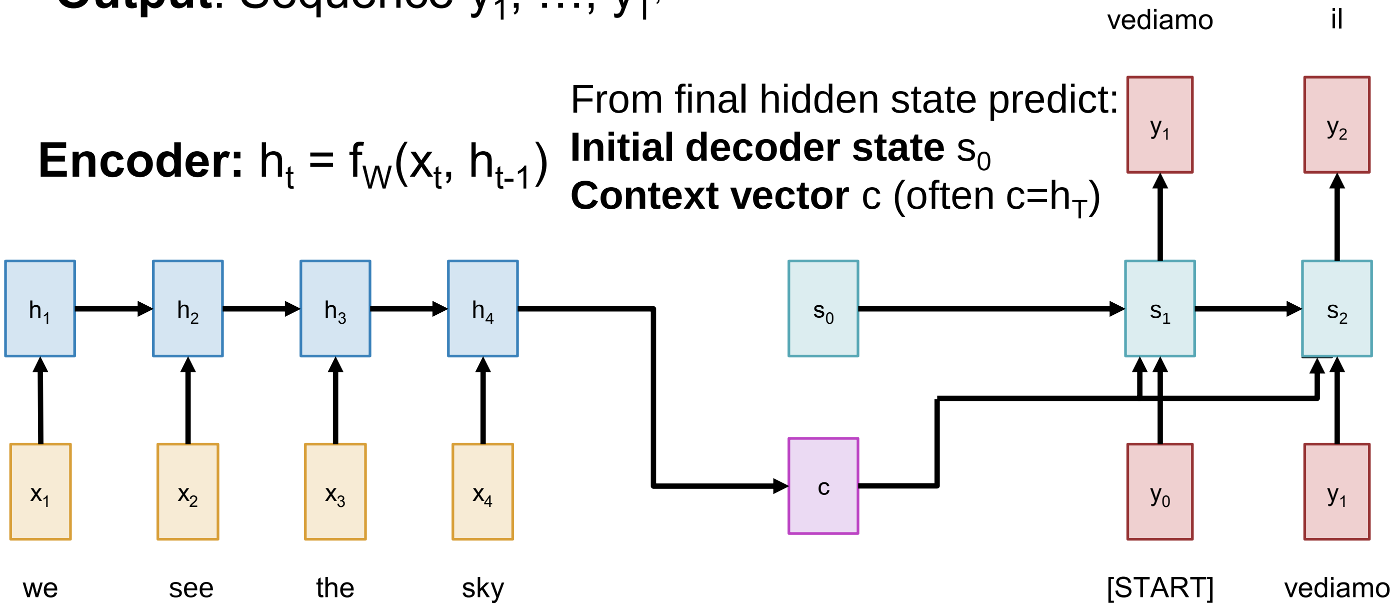


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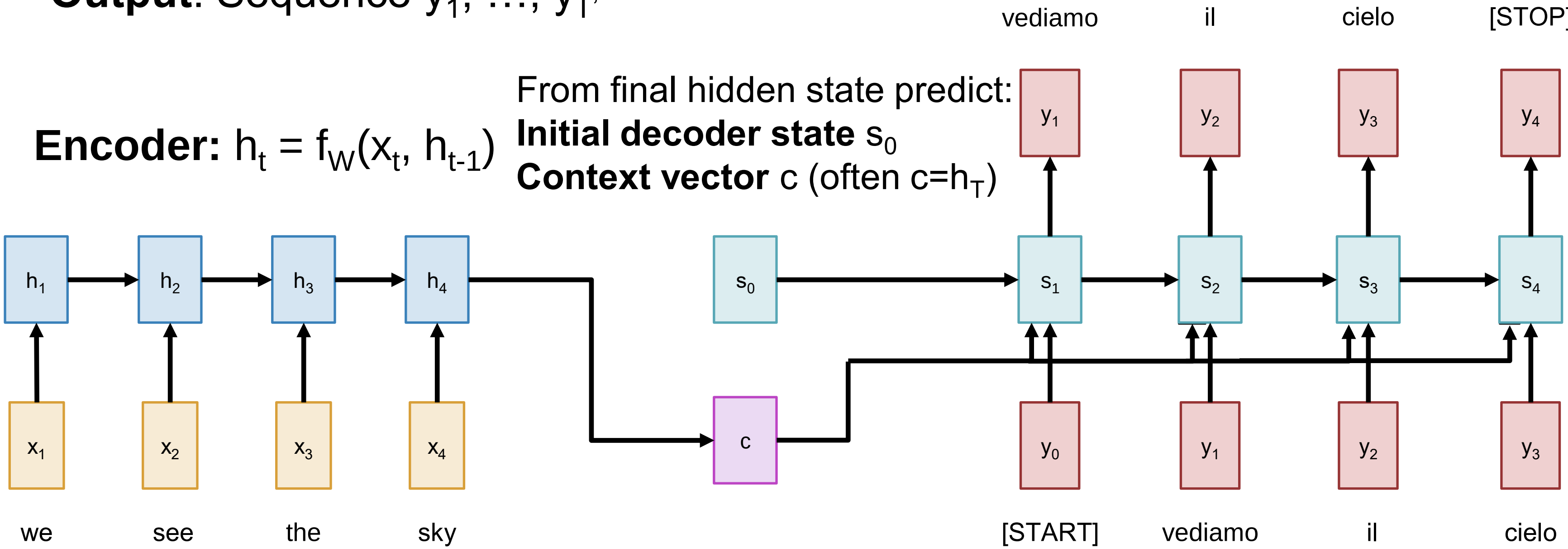


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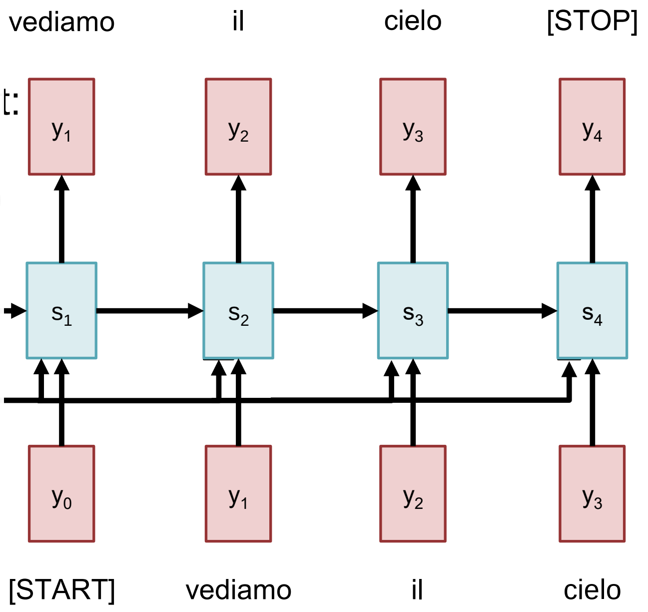
**Decoder:** $s_t = g_U(y_{t-1}, s_{t-1}, c)$

Remember:

**During Training:**
Often, we use the “correct” token even if the model is wrong. Called **teacher forcing**

**During Test-time:**
We sample from the model’s outputs until we sample [STOP]



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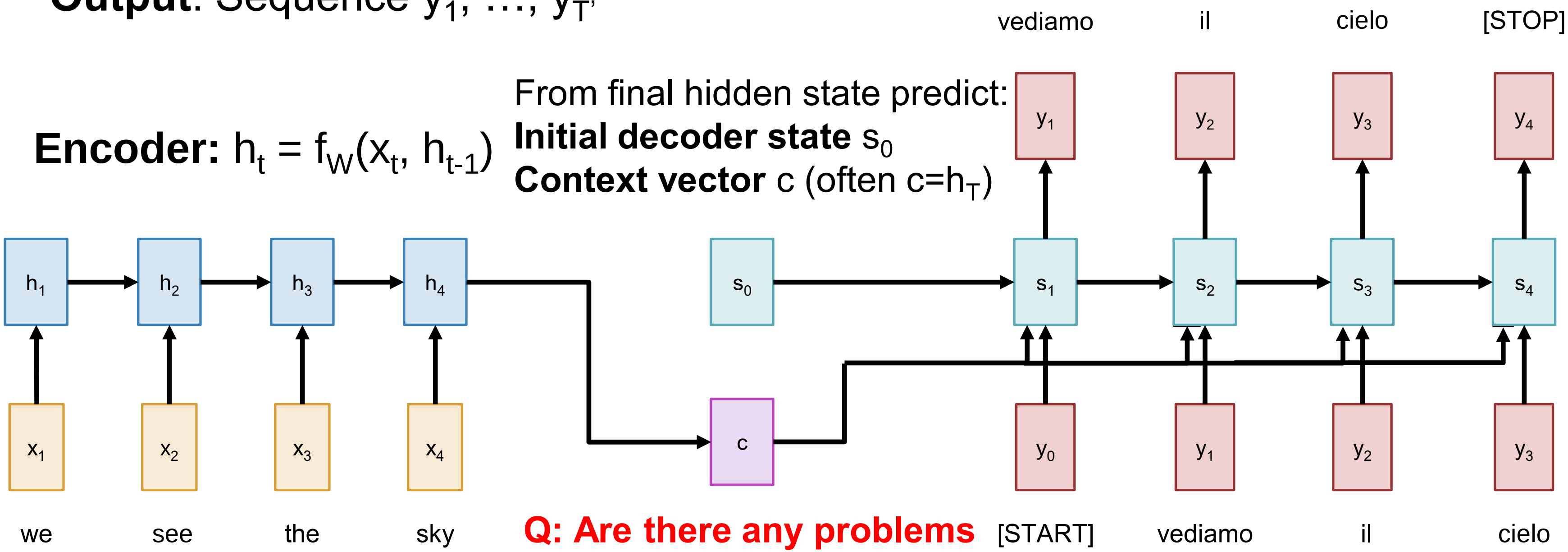


**Q: Are there any problems with using C like this??**

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

# Sequence to Sequence with RNNs

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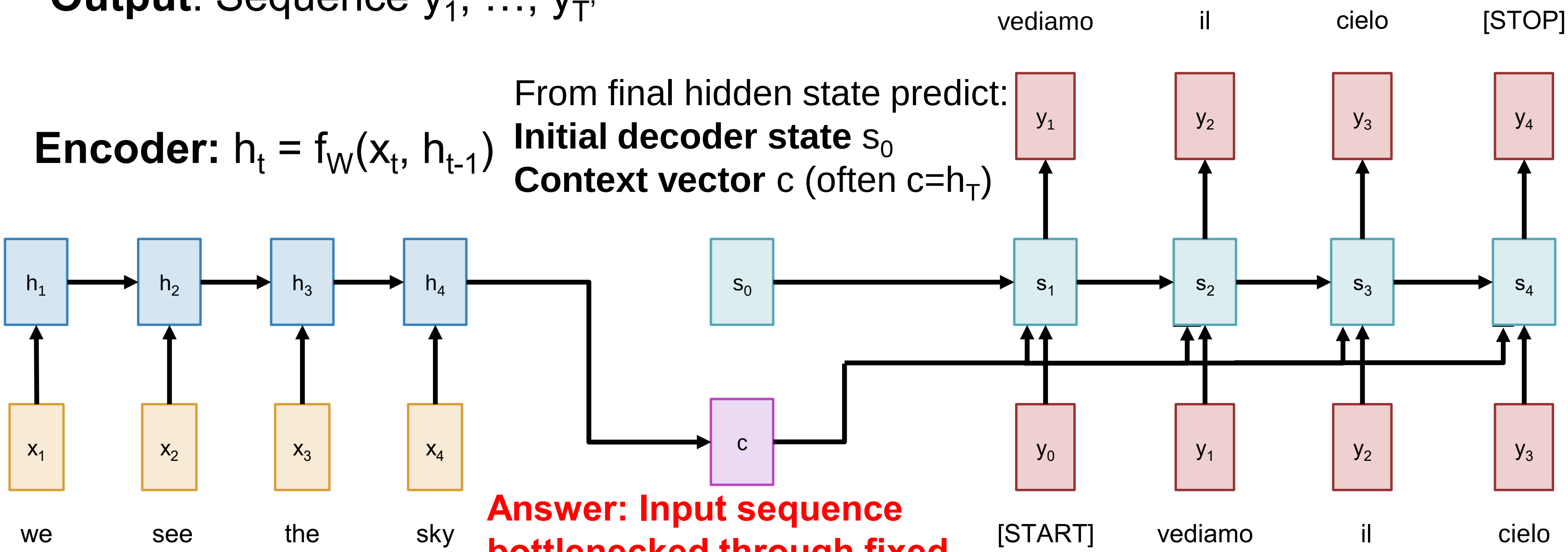


**Answer: Input sequence bottlenecked through fixed-sized vector. What if T=1000?**

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

# Sequence to Sequence with RNNs

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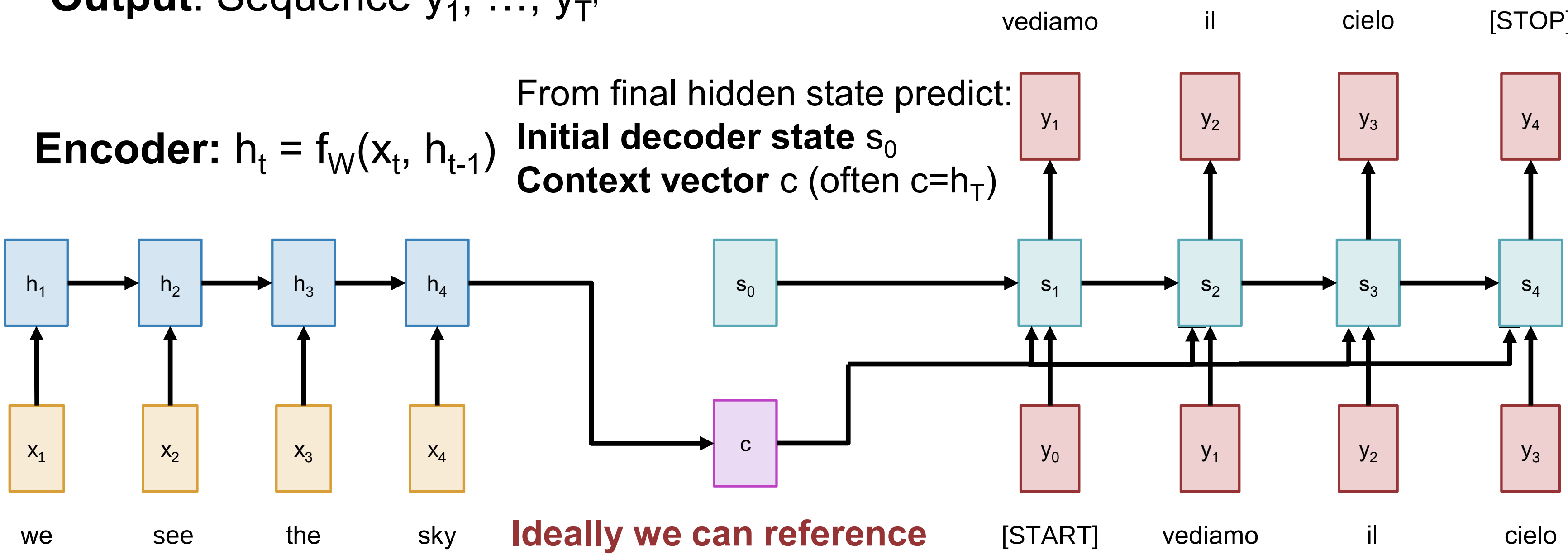


**Ideally we can reference the inputs as we decode…**

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

# Sequence to Sequence with RNNs and Attention

**Input**: Sequence $x_1, \ldots x_T$
**Output**: Sequence $y_1, \ldots, y_{T'}$

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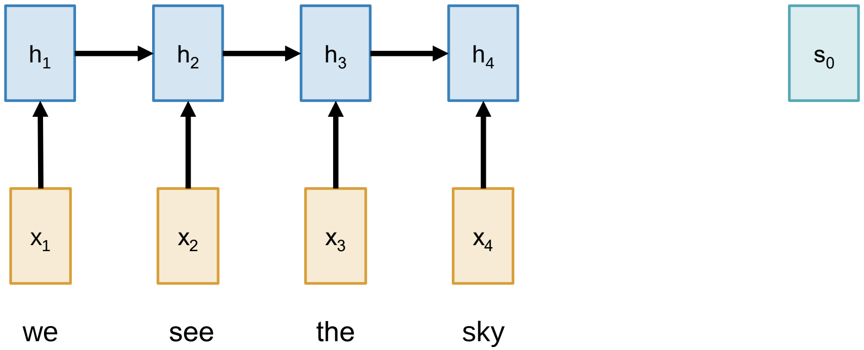
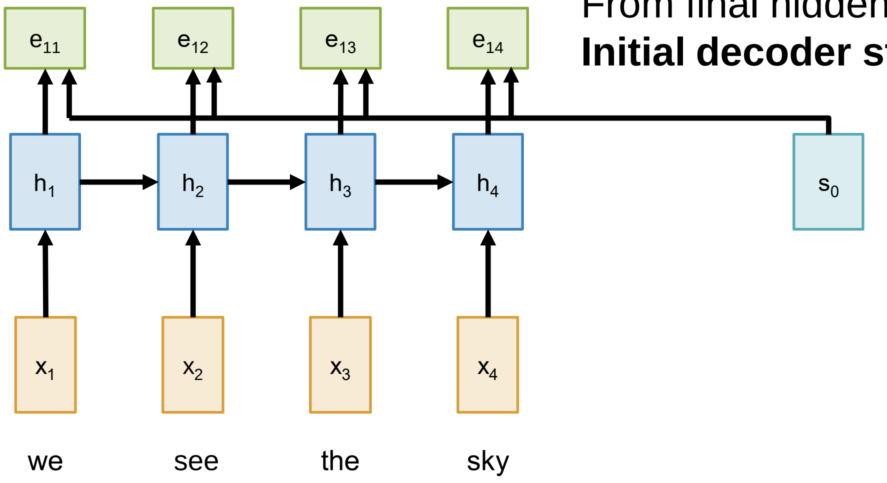



Bahdanau et al, “Neural machine translation by jointly learning to align and translate”, ICLR 2015

# Sequence to Sequence with RNNs and Attention

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

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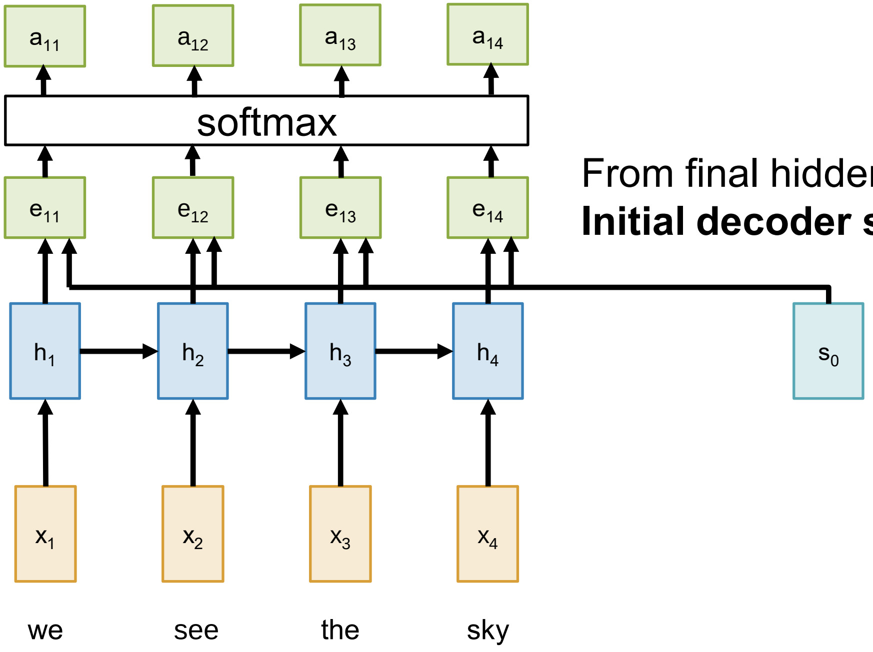


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Normalize alignment scores to get **attention weights**
$0 < a_{t,i} < 1$ $\sum_i a_{t,i} = 1$

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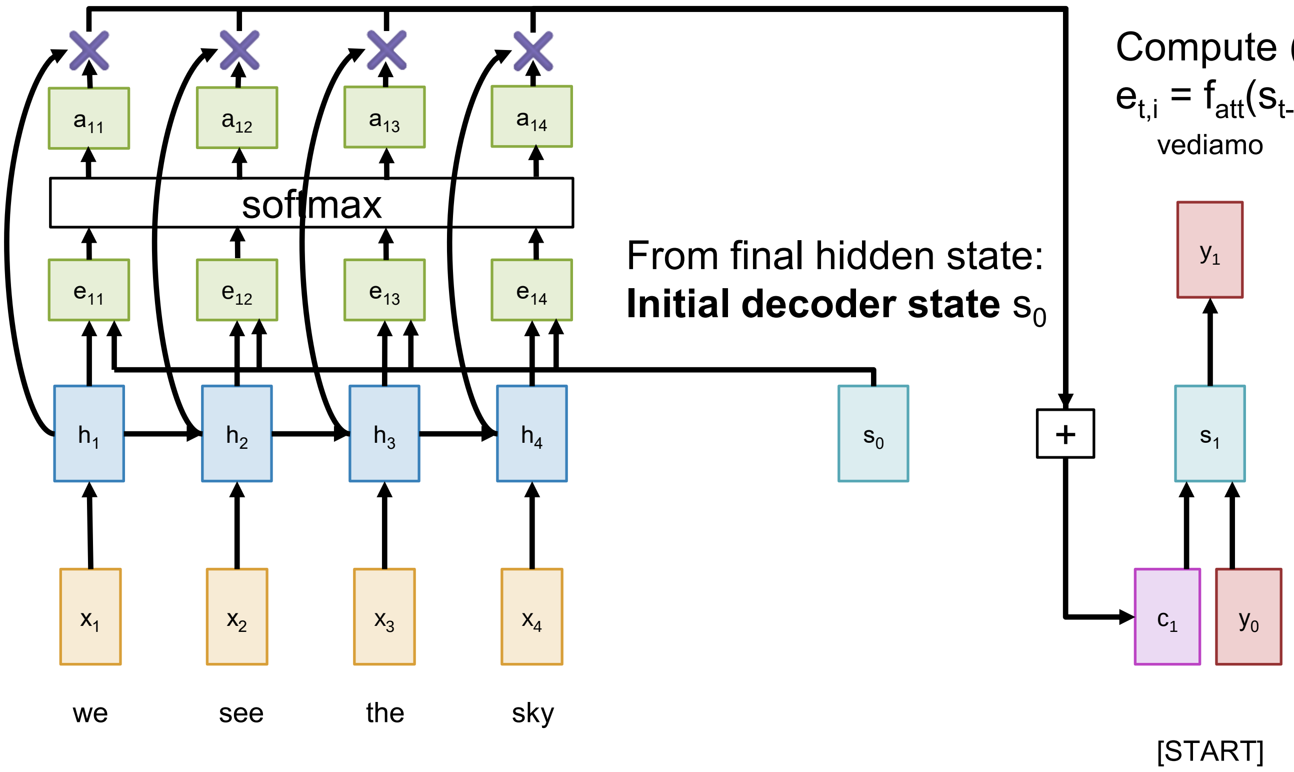
# Sequence to Sequence with RNNs and Attention




From final hidden state: **Initial decoder state $s_0$**

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Compute context vector as **weighted sum of hidden states**
$c_t = \sum_i a_{t,i} h_i$

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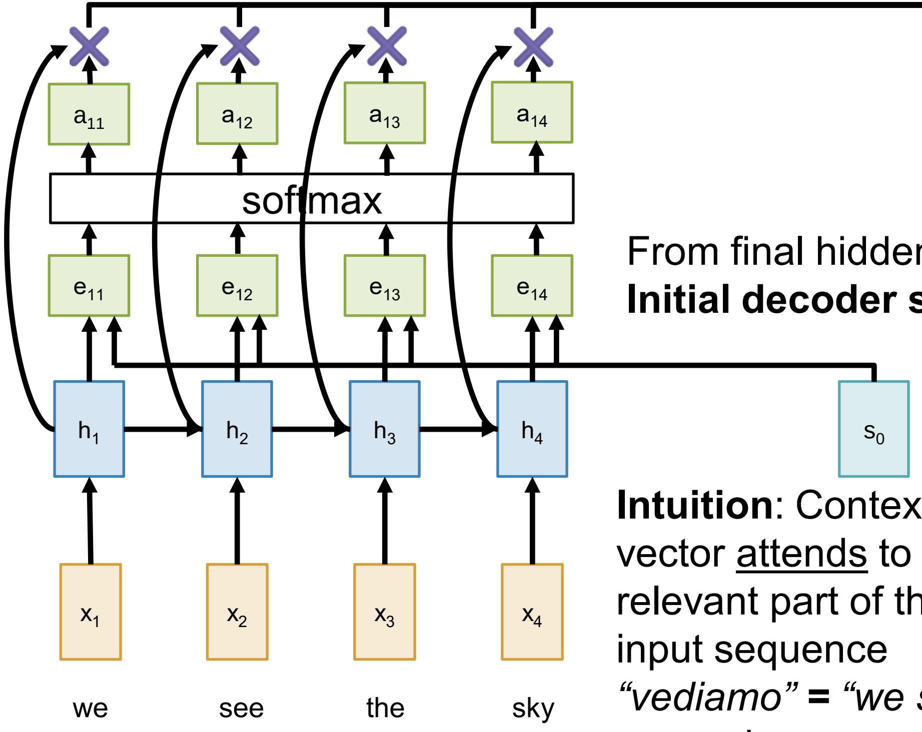
# Sequence to Sequence with RNNs and Attention

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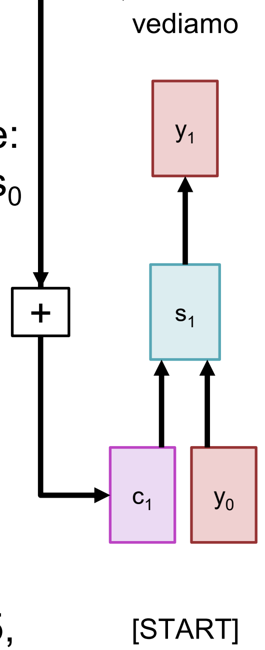


From final hidden state:
**Initial decoder state** $s_0$

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

Compute **context vector** as weighted sum of hidden states
$c_t = \sum_i a_{t,i} h_i$

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

**Intuition**: Context vector attends to the relevant part of the input sequence
*"vediamo"* **=** *"we see"*
so maybe $a_{11}=a_{12}=0.45$, $a_{13}=a_{14}=0.05$

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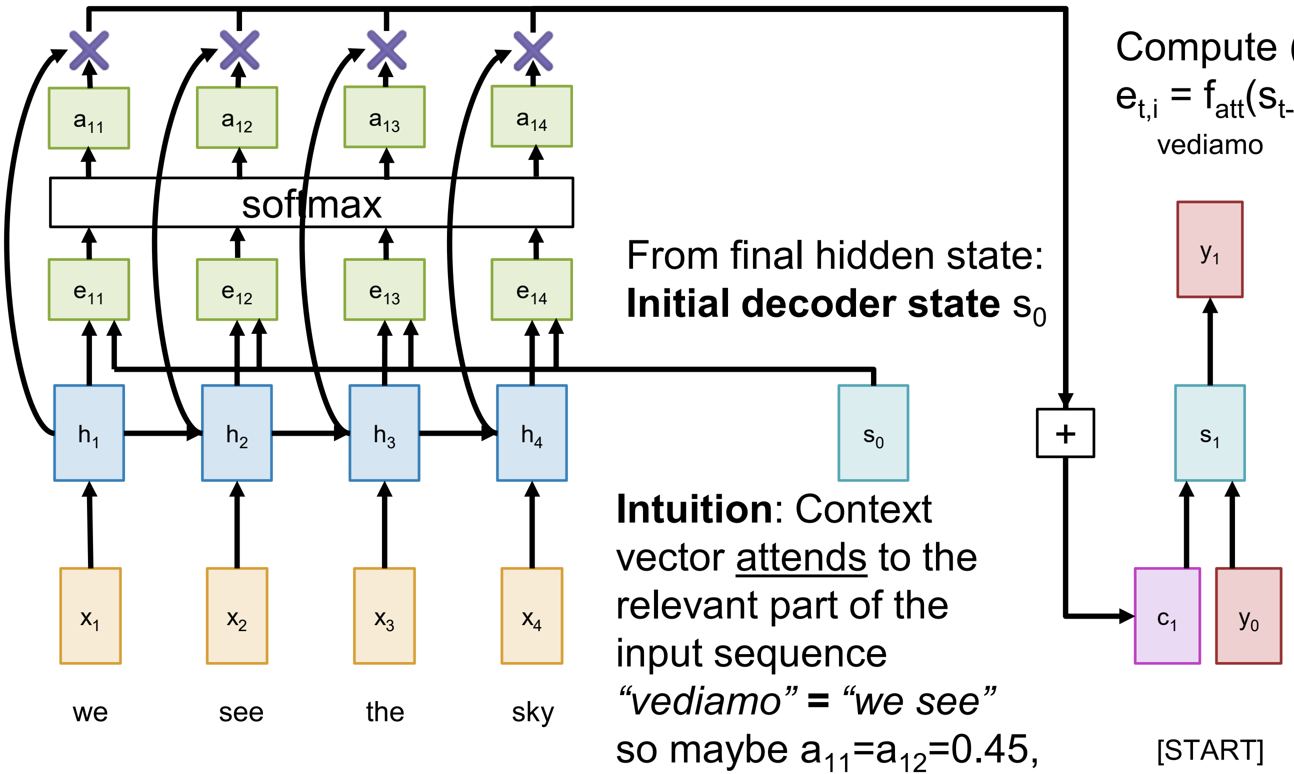
# Sequence to Sequence with RNNs and Attention

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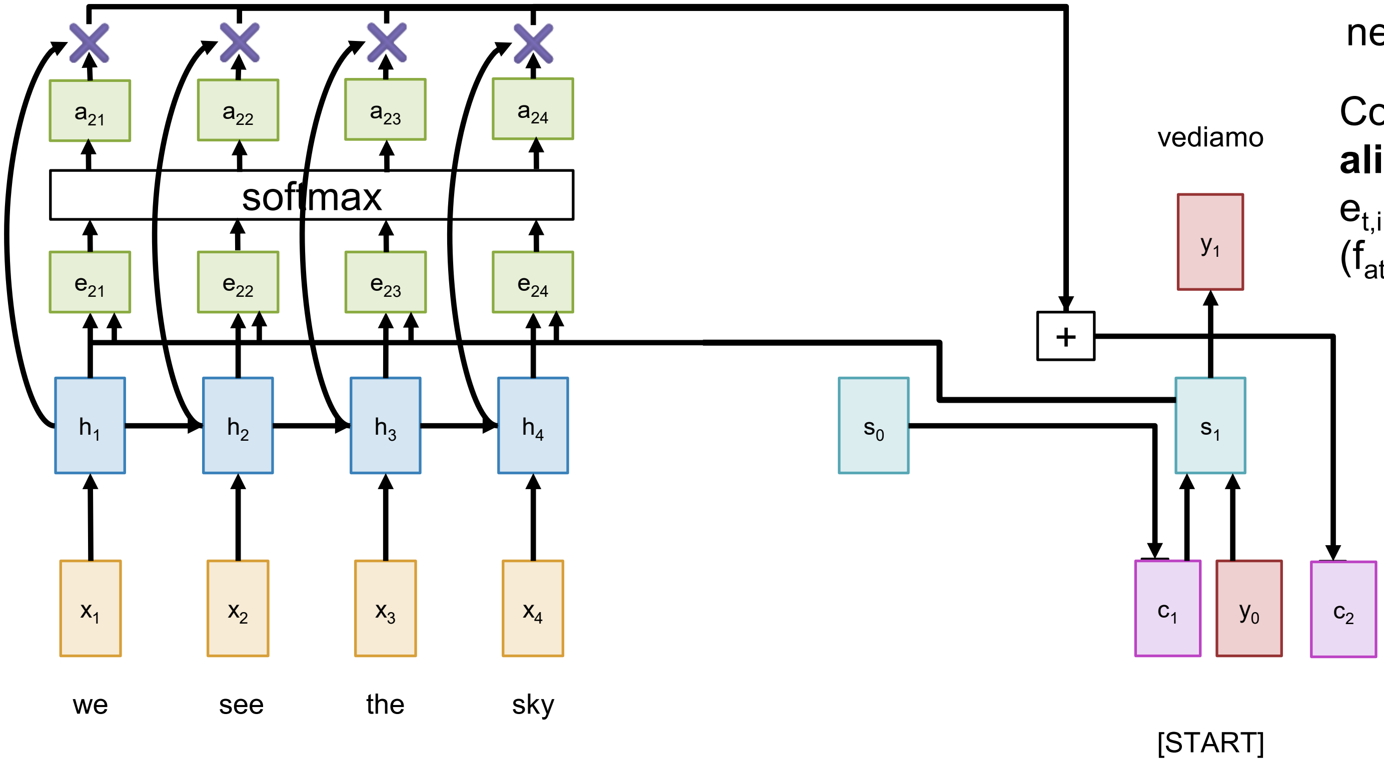
**This is all differentiable! No supervision on attention weights – backprop through everything**

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

# Sequence to Sequence with RNNs and Attention




Repeat: Use $s_1$ to compute new context vector $c_2$

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# Sequence to Sequence with RNNs and Attention

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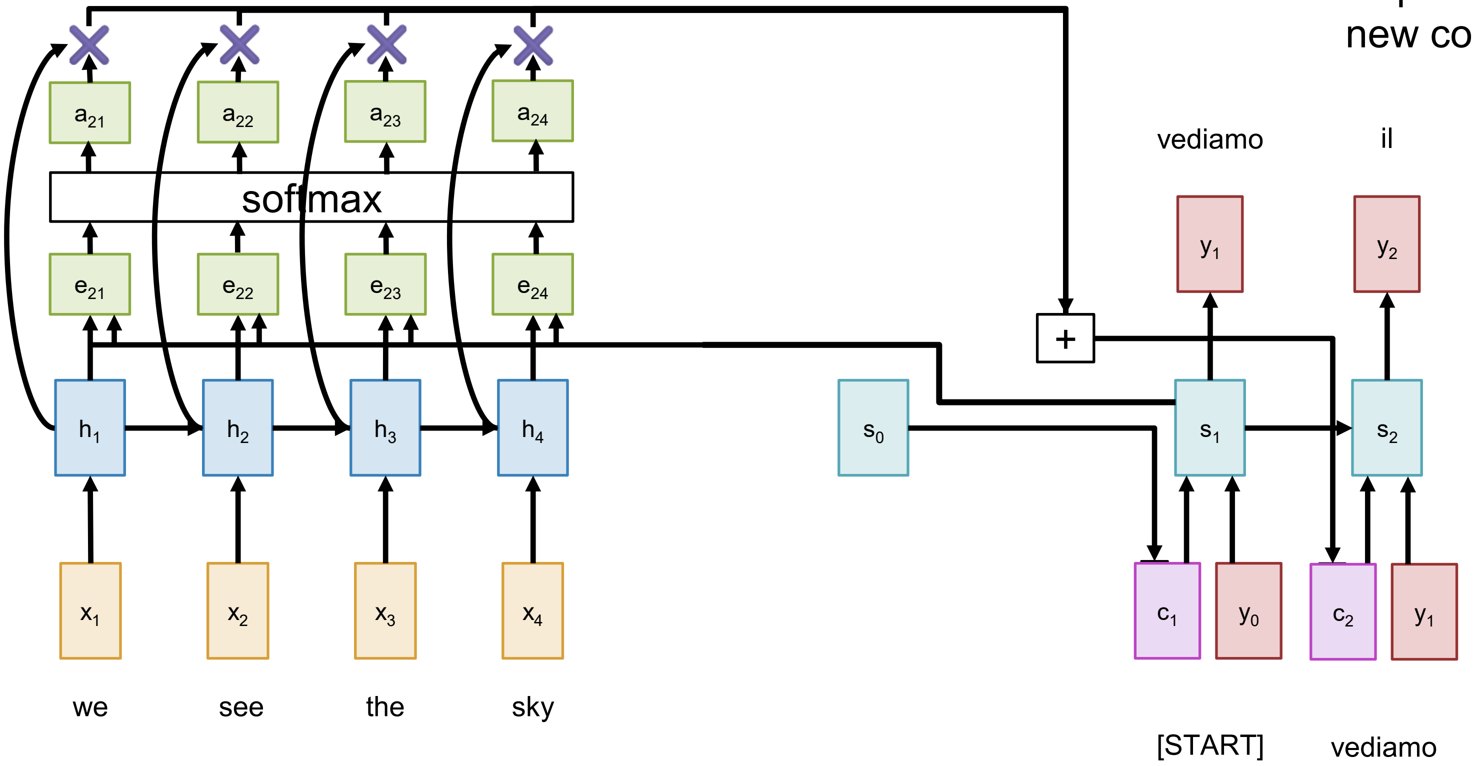


Use context vector in decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c_t)$

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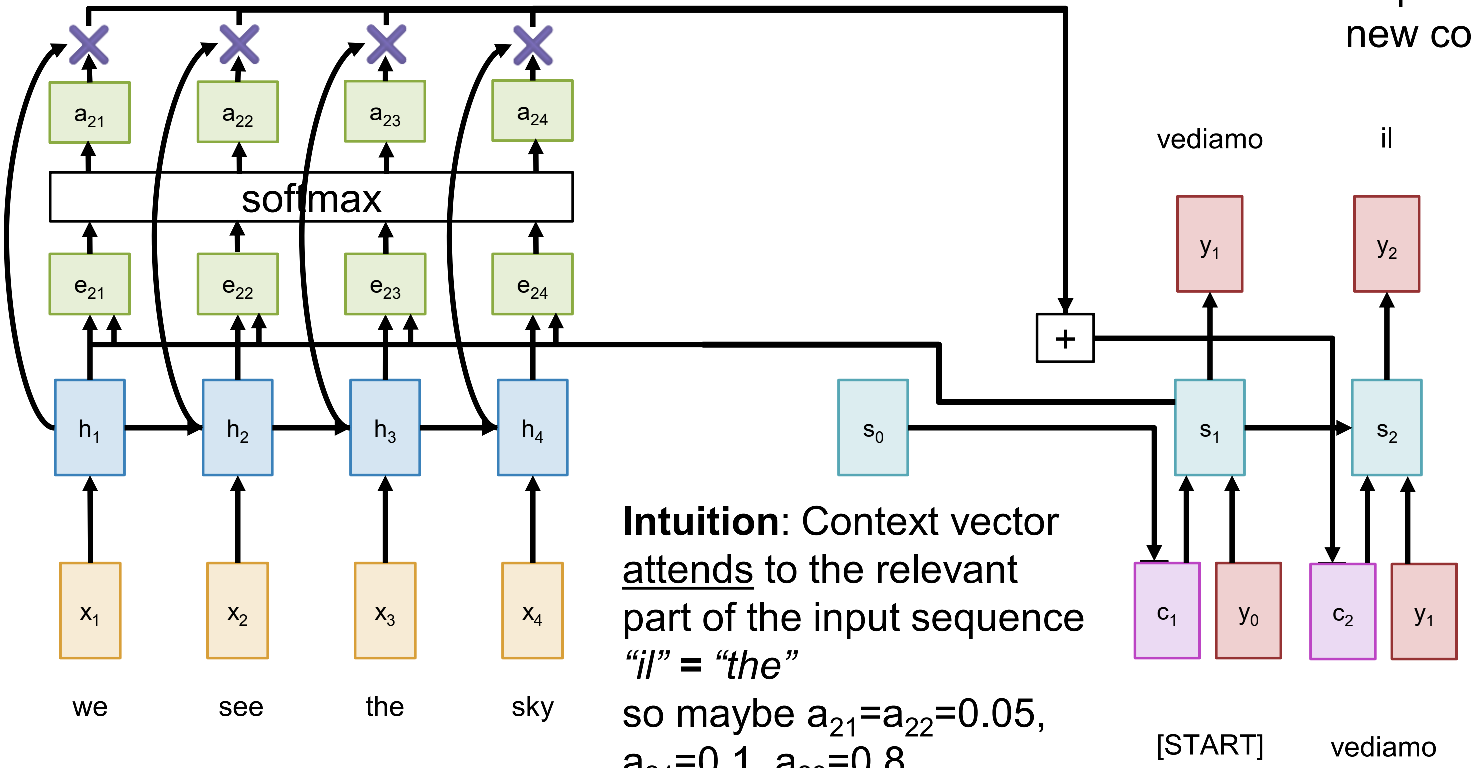
# Sequence to Sequence with RNNs and Attention




Repeat: Use $s_1$ to compute new context vector $c_2$

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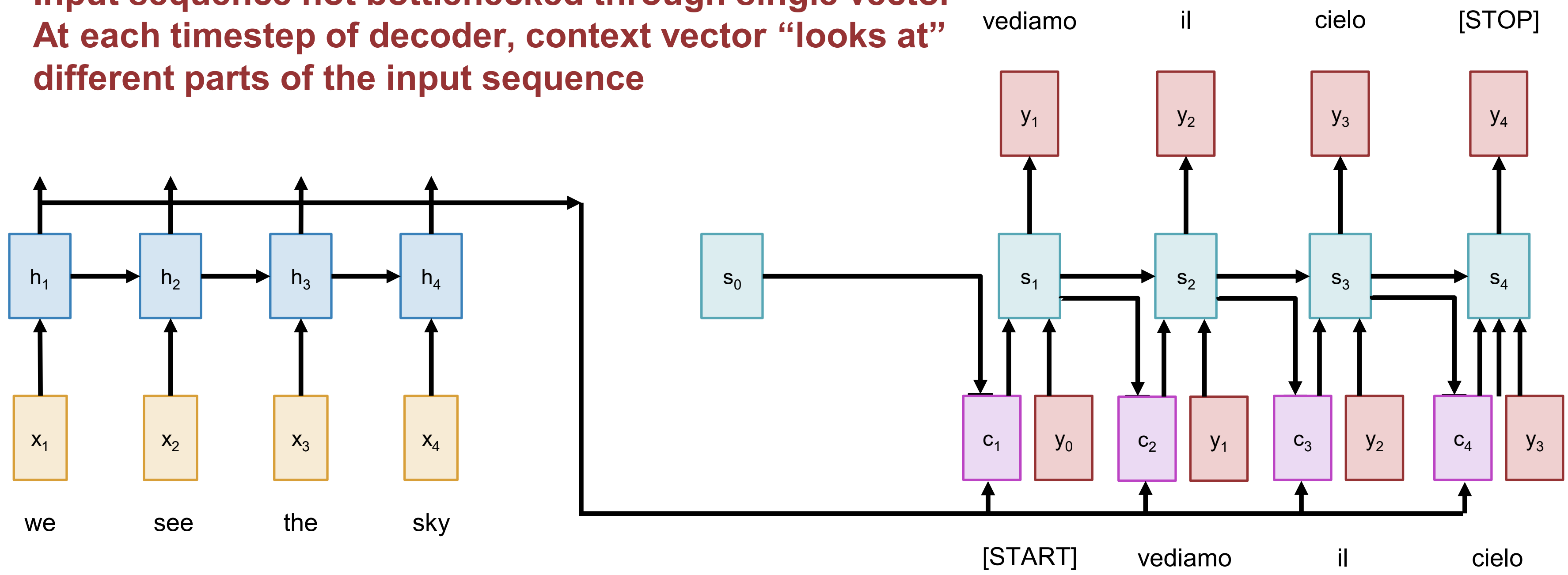
**Intuition**: Context vector attends to the relevant part of the input sequence
*"il"* = *"the"*
so maybe $a_{21}=a_{22}=0.05$, $a_{24}=0.1$, $a_{23}=0.8$

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

# 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**

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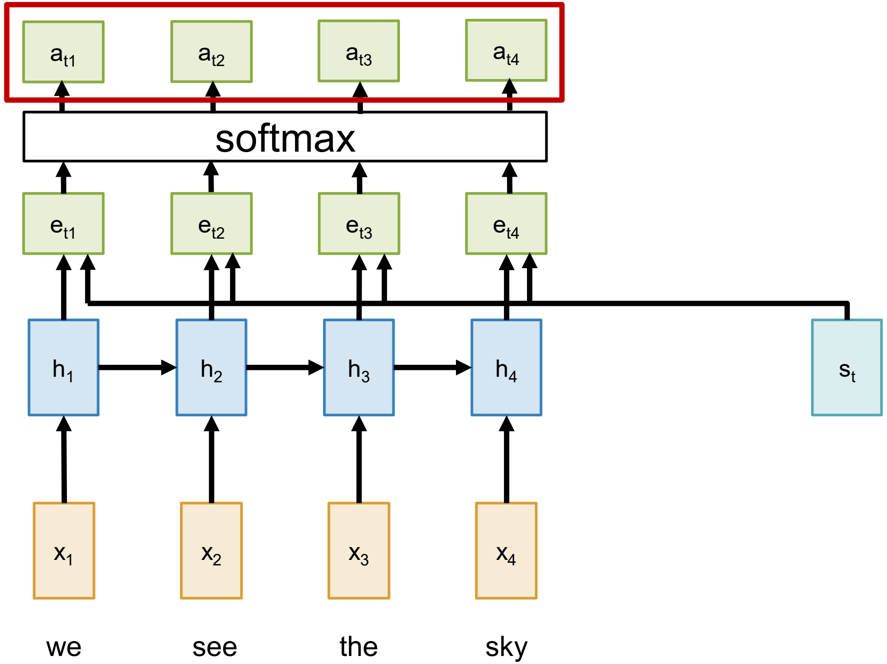
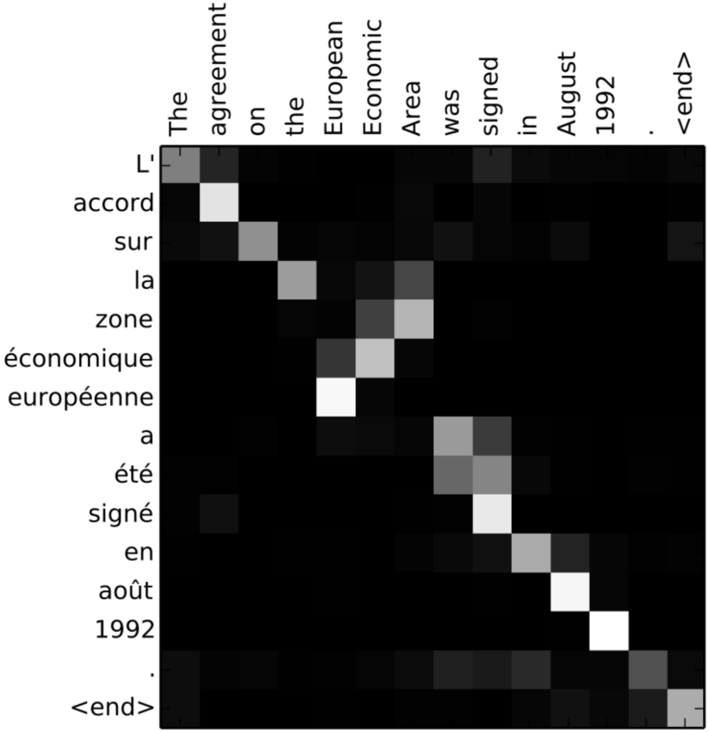
# Sequence to Sequence with RNNs and Attention

**Example**: English to French translation




Visualize attention weights $a_{t,i}$

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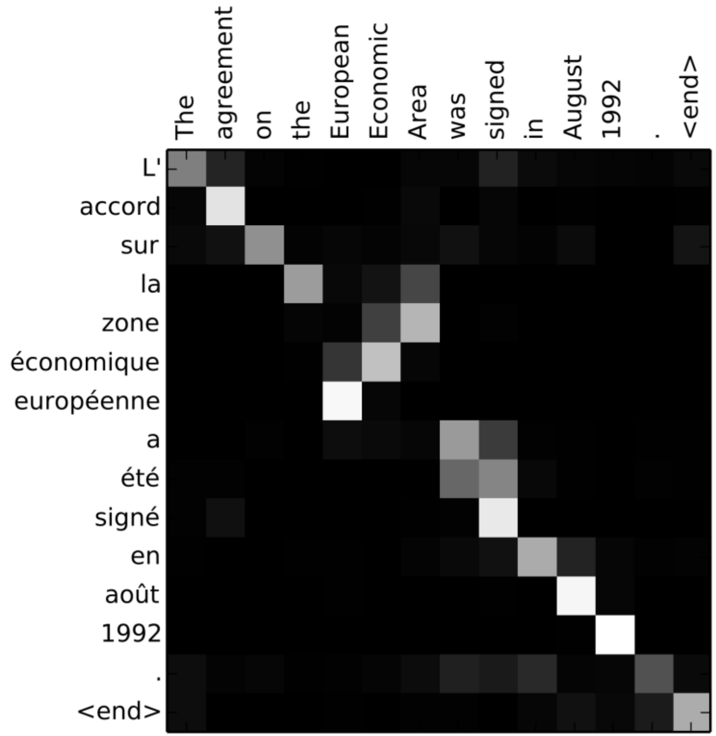


**Example**: English to French translation

**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."

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

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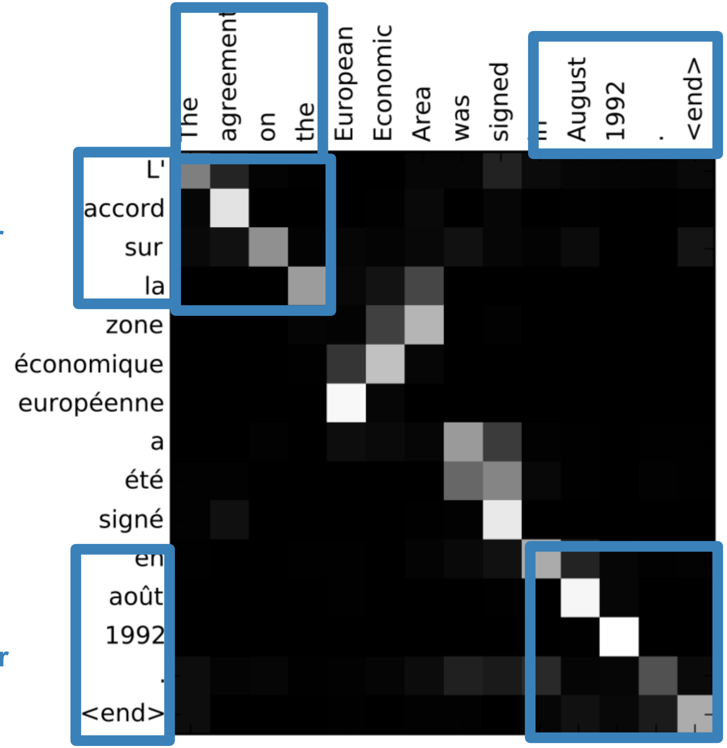


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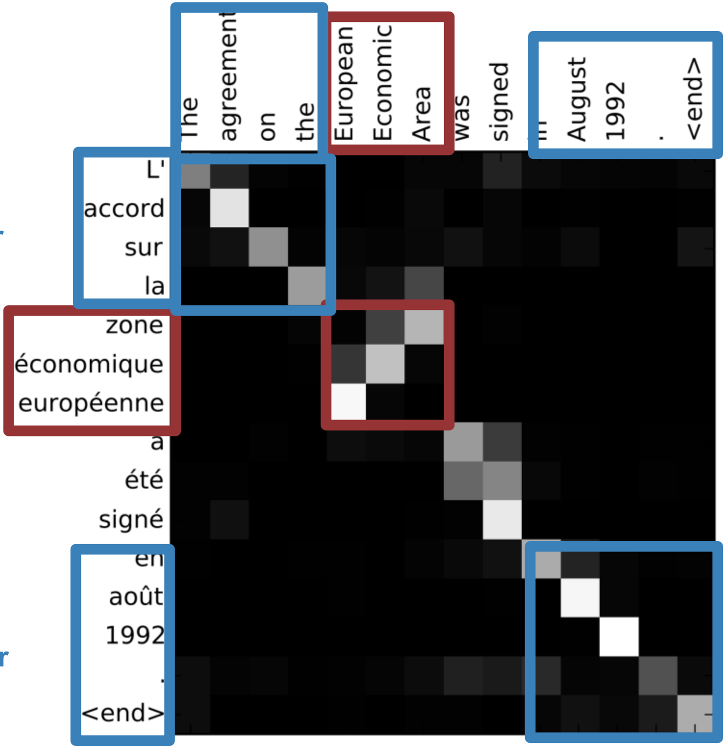
Visualize attention weights $a_{t,i}$

Diagonal attention means words correspond in order

Attention figures out different word orders

Diagonal attention means words correspond in order

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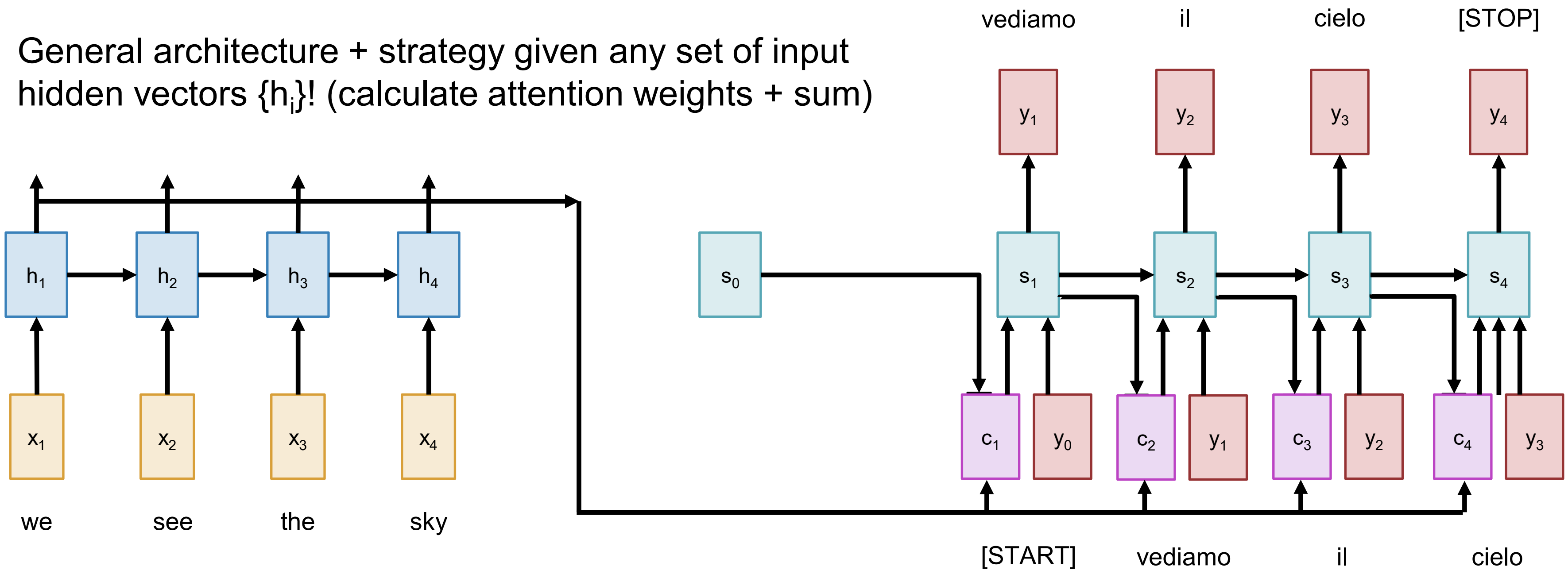
# Sequence to Sequence with RNNs and Attention

Context vectors don't use the fact that $h_i$ form an ordered sequence – it just treats them as an unordered set $\{h_i\}$

General architecture + strategy given any set of input hidden vectors $\{h_i\}$! (calculate attention weights + sum)

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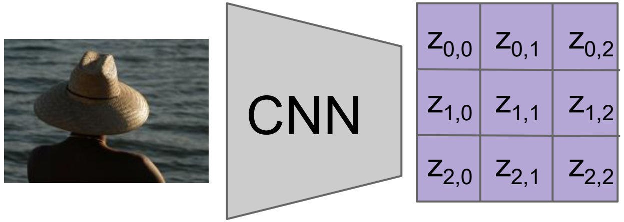
# Image Captioning using spatial features

**Input**: Image **I**
**Output:** Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$

An example network for image captioning **without attention**




Extract spatial features from a pretrained CNN

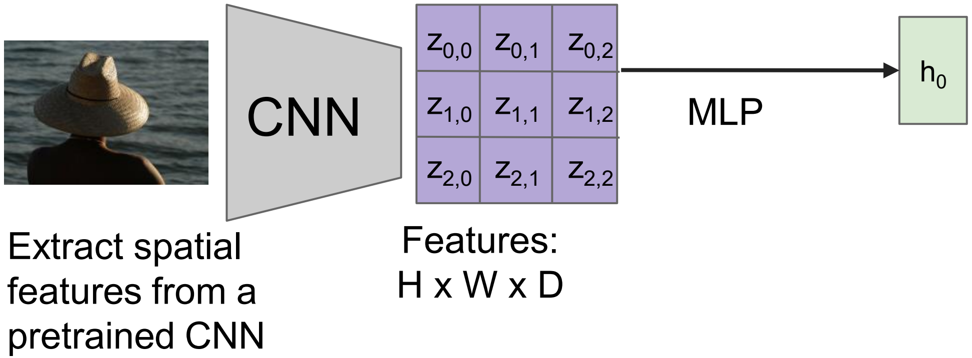
Features: H x W x D

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 $\mathbf{y} = y_1, y_2, \ldots, y_T$

**Encoder**: $h_0 = f_{\mathbf{W}}(\mathbf{z})$
where **z** is spatial CNN features
$f_{\mathbf{W}}(.)$ is an MLP

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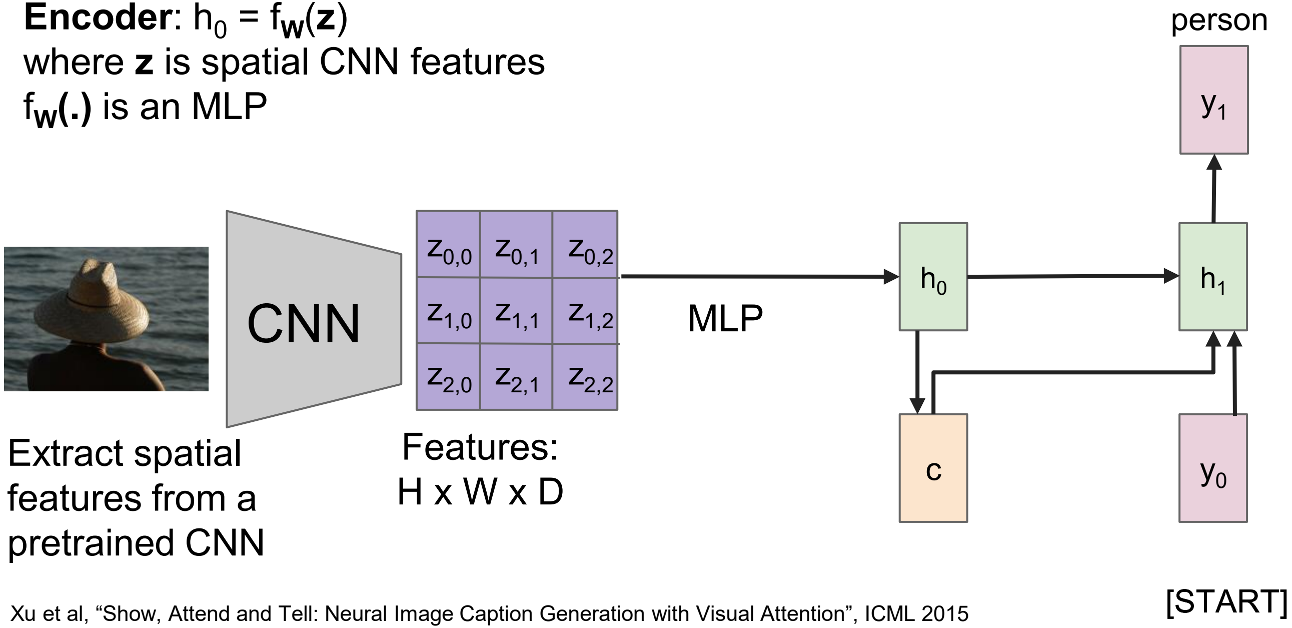
# Image Captioning using spatial features

**Input**: Image **I**
**Output:** Sequence **y** = $y_1, y_2, \ldots, y_T$

**Decoder**: $h_t = g_V(y_{t-1}, h_{t-1}, c)$
where context vector c is often $c = h_0$
and output $y_t = T(h_t)$

**Encoder**: $h_0 = f_W(\mathbf{z})$
where **z** is spatial CNN features
$f_W(.)$ is an MLP

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**Encoder**: $h_0 = f_\mathbf{W}(\mathbf{z})$
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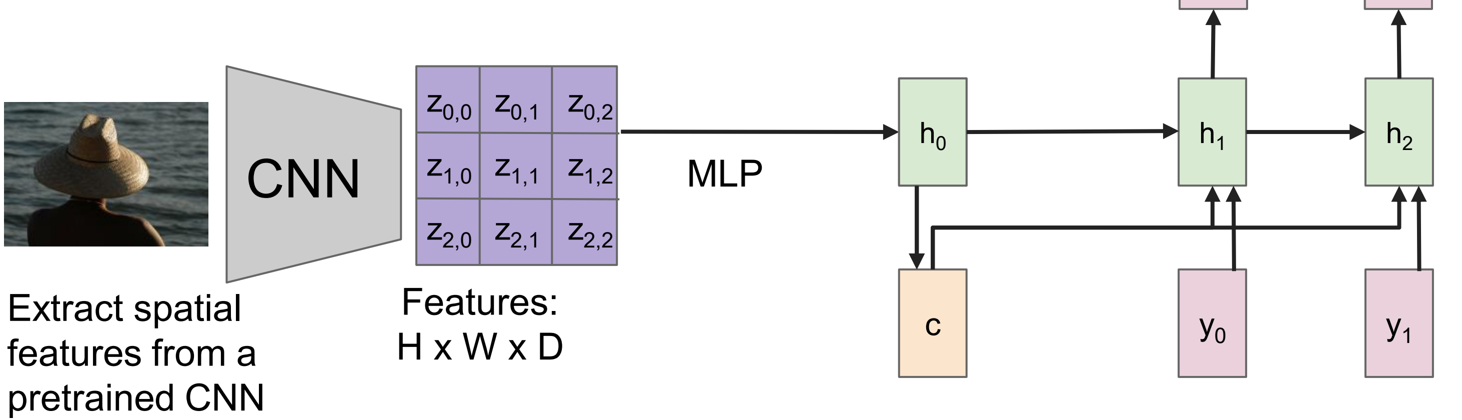
$f_\mathbf{W}(.)$ is an MLP

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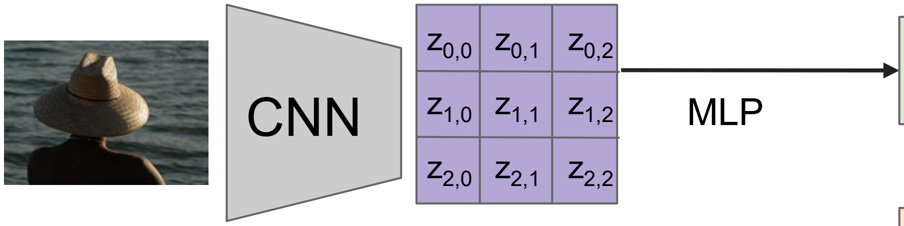
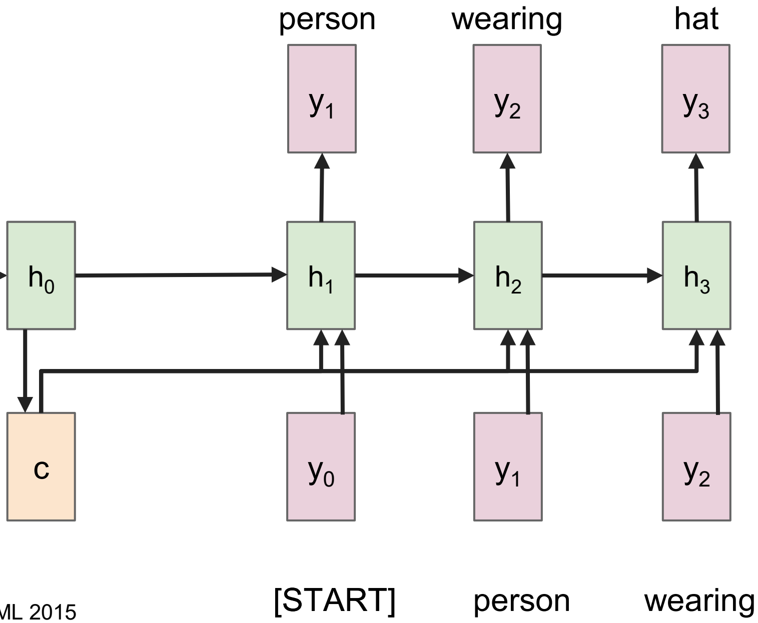



Extract spatial features from a pretrained CNN

Features: H x W x D

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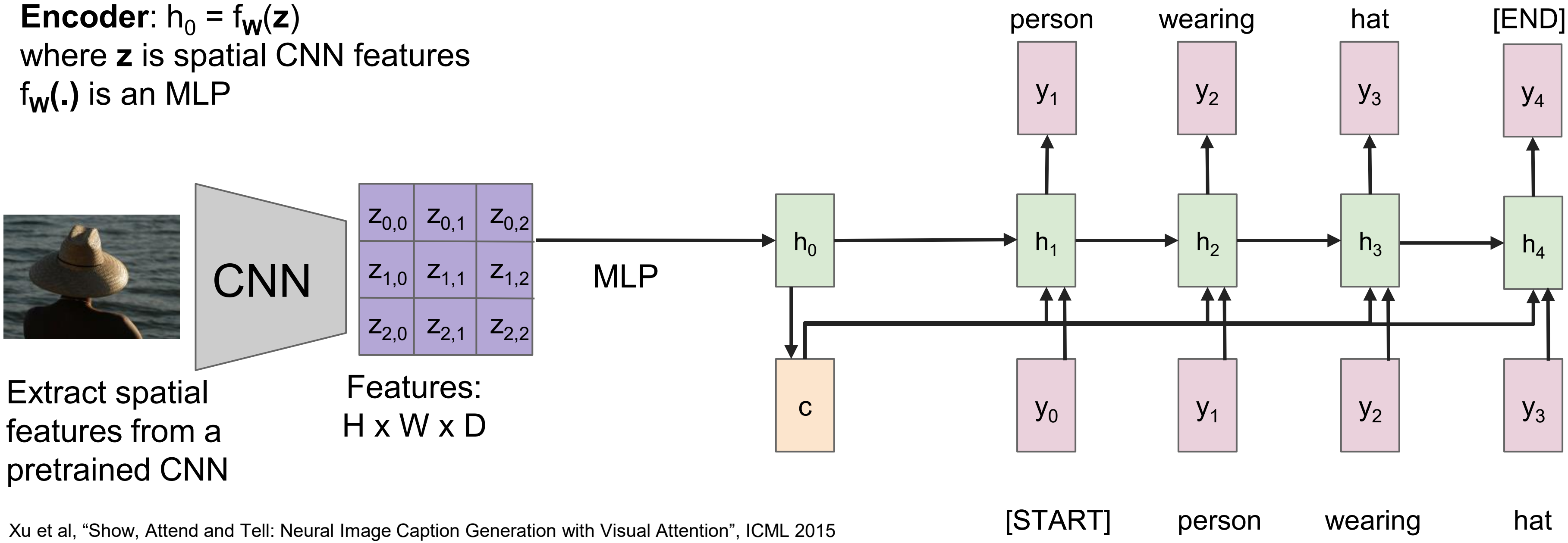
**Decoder**: $h_t = g_V(y_{t-1}, h_{t-1}, c)$
where context vector c is often $c = h_0$
and output $y_t = T(h_t)$

**Encoder**: $h_0 = f_W(\mathbf{z})$
where **z** is spatial CNN features
$f_W(.)$ is an MLP




Extract spatial features from a pretrained CNN

Features: H x W x D

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

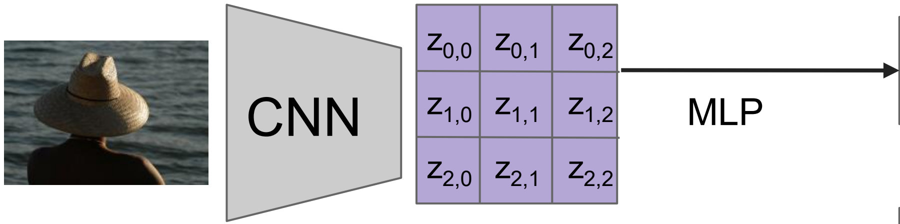
# Image Captioning using spatial features

**Input**: Image **I**
**Output:** Sequence **y** = $y_1, y_2, \ldots, y_T$

**Encoder**: $h_0 = f_{\mathbf{W}}(\mathbf{z})$
where **z** is spatial CNN features
$f_{\mathbf{W}}(.)$ is an MLP

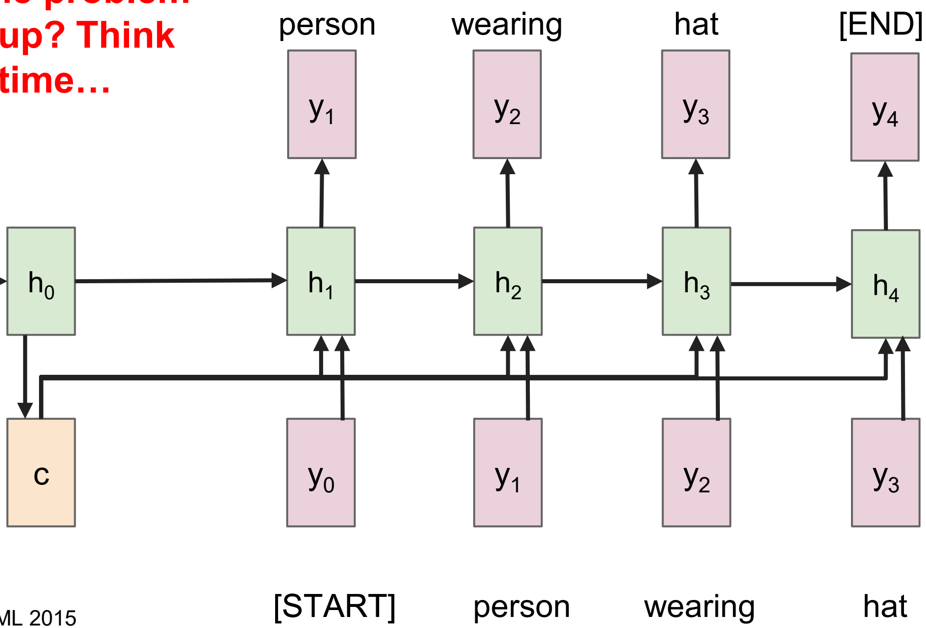
**Q: What is the problem with this setup? Think back to last time…**

**Decoder**: $h_t = g_{\mathbf{V}}(y_{t-1}, h_{t-1}, c)$
where context vector c is often $c = h_0$
and output $y_t = T(h_t)$




Extract spatial features from a pretrained CNN

Features: H x W x D



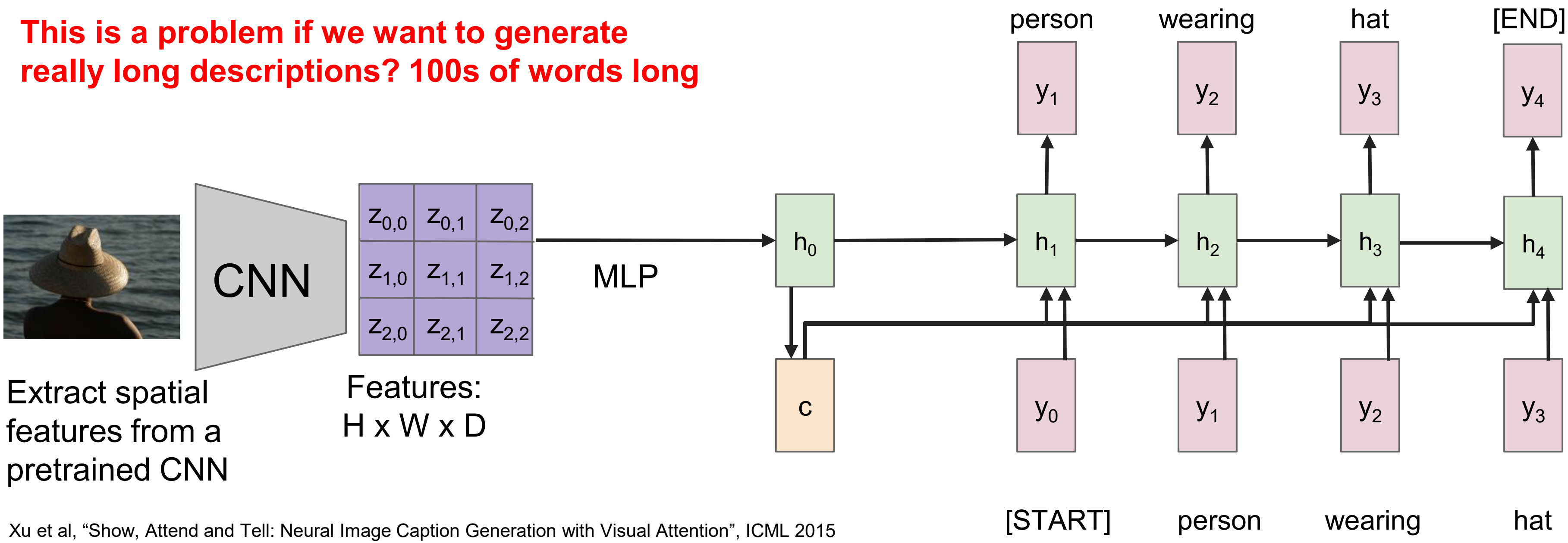

Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

# Image Captioning using spatial features

**Answer: 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**




Extract spatial features from a pretrained CNN

Features: H x W x D

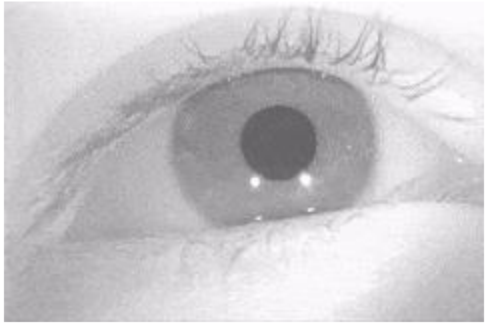
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

# Image Captioning with RNNs and Attention

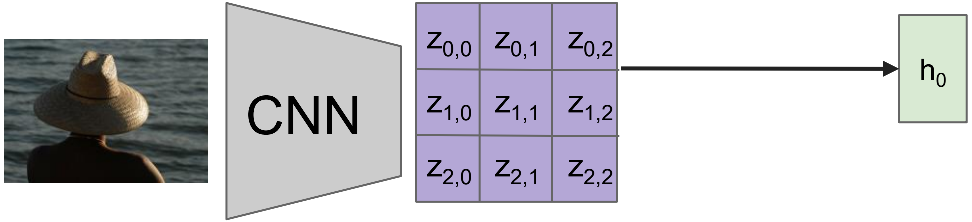
[gif source](#)

**Attention idea: New context vector at every time step.**

**Each context vector will attend to different image regions**



**Attention Saccades in humans**




Extract spatial features from a pretrained CNN

Features: H x W x D

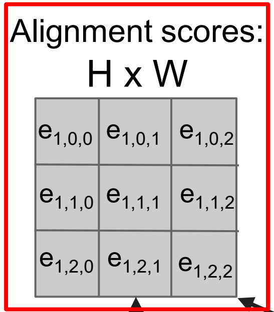
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

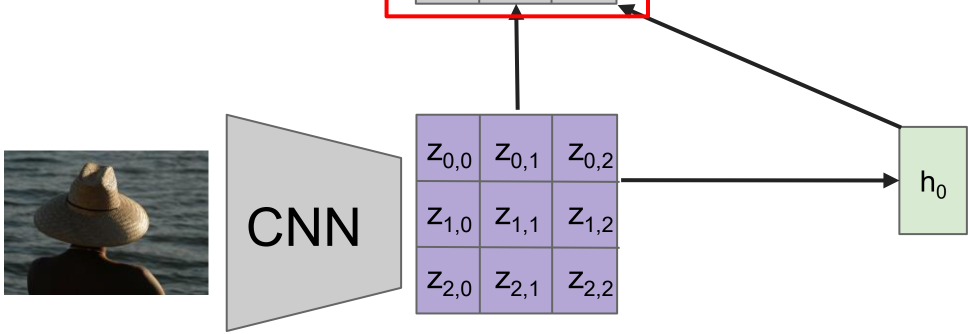
# Image Captioning with RNNs and Attention

Compute alignments scores (scalars):

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

$f_{att}(.)$ is an MLP




Extract spatial features from a pretrained CNN

Features:
H x W x D

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

# Image Captioning with RNNs and Attention

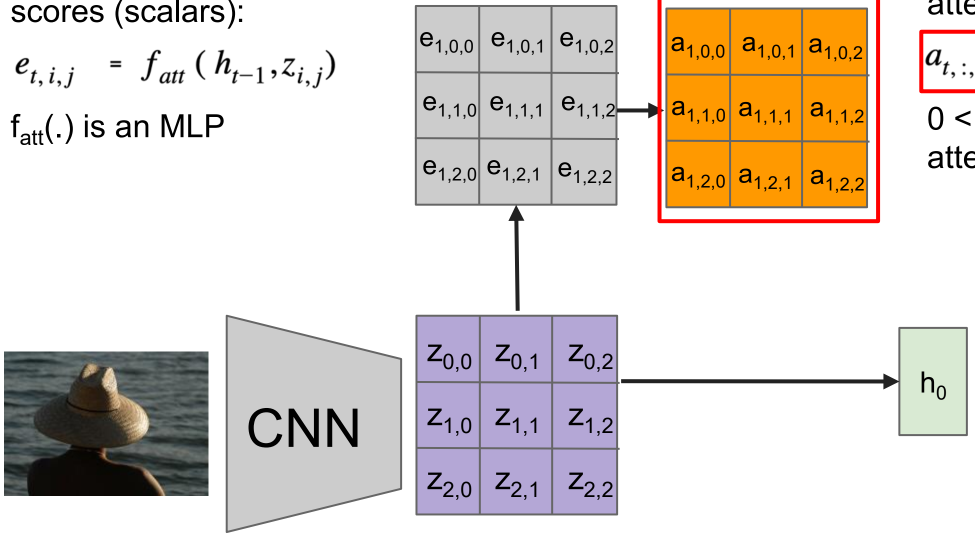
Compute alignments scores (scalars):

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

$f_{att}(.)$ is an MLP

Alignment scores: H x W

Attention: H x W




Normalize to get attention weights:

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

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

Extract spatial features from a pretrained CNN

Features: H x W x 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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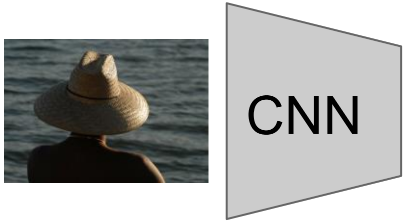
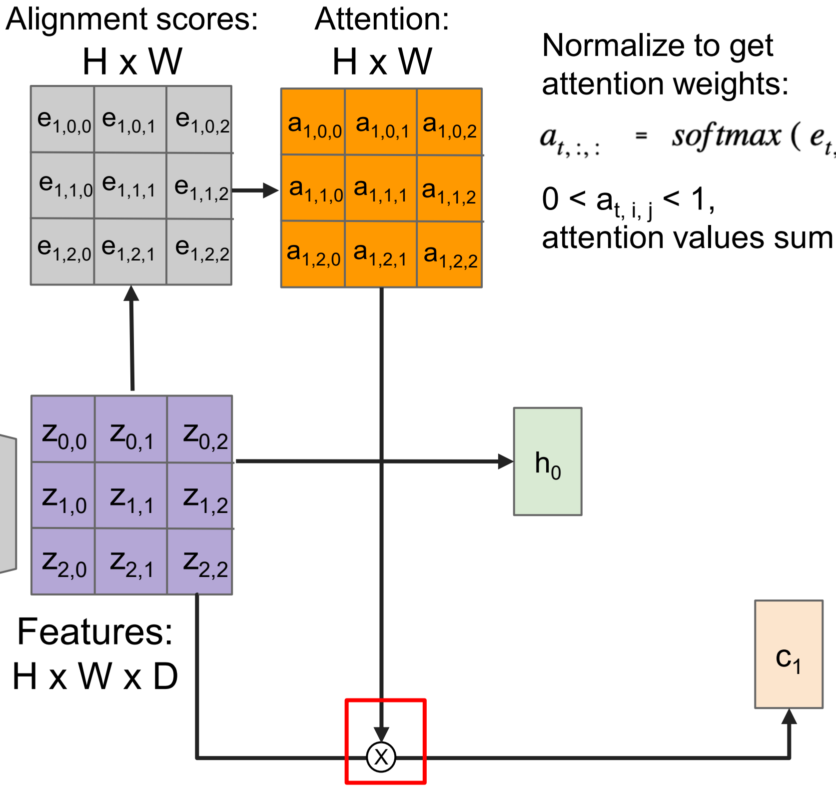



Extract spatial features from a pretrained CNN




Normalize to get attention weights:

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

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

Compute context vector:

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

**Q: How many context vectors are computed?**

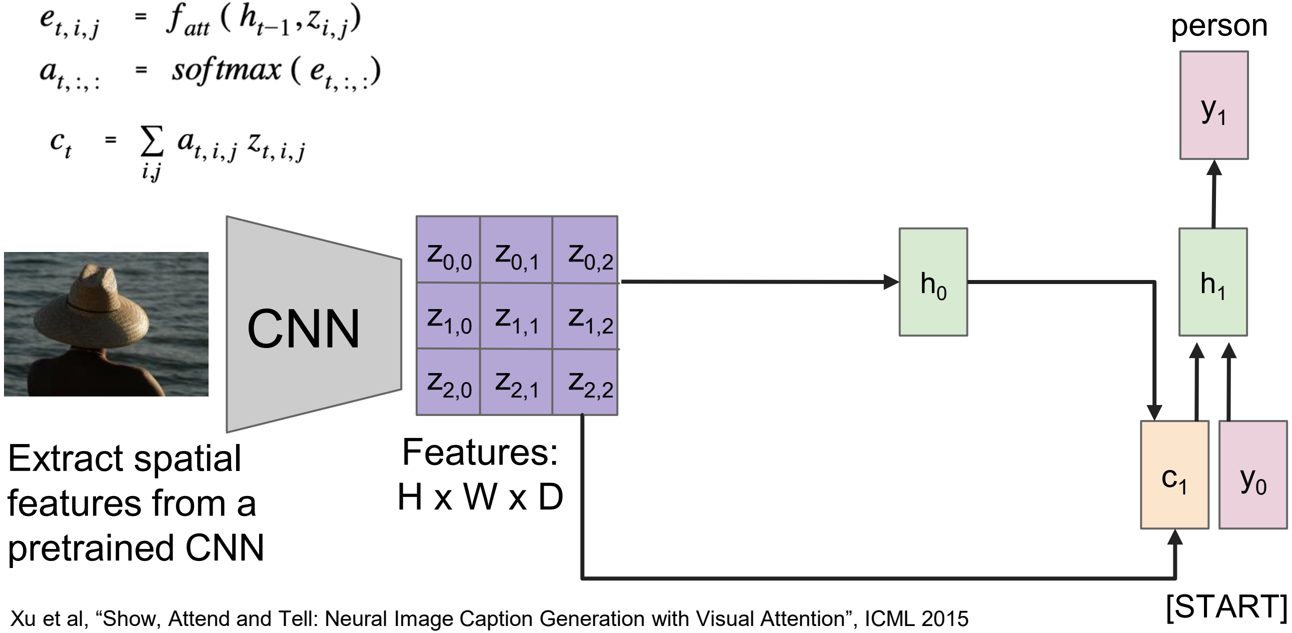
Xu et al, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML 2015

# Image Captioning with RNNs and Attention

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

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

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

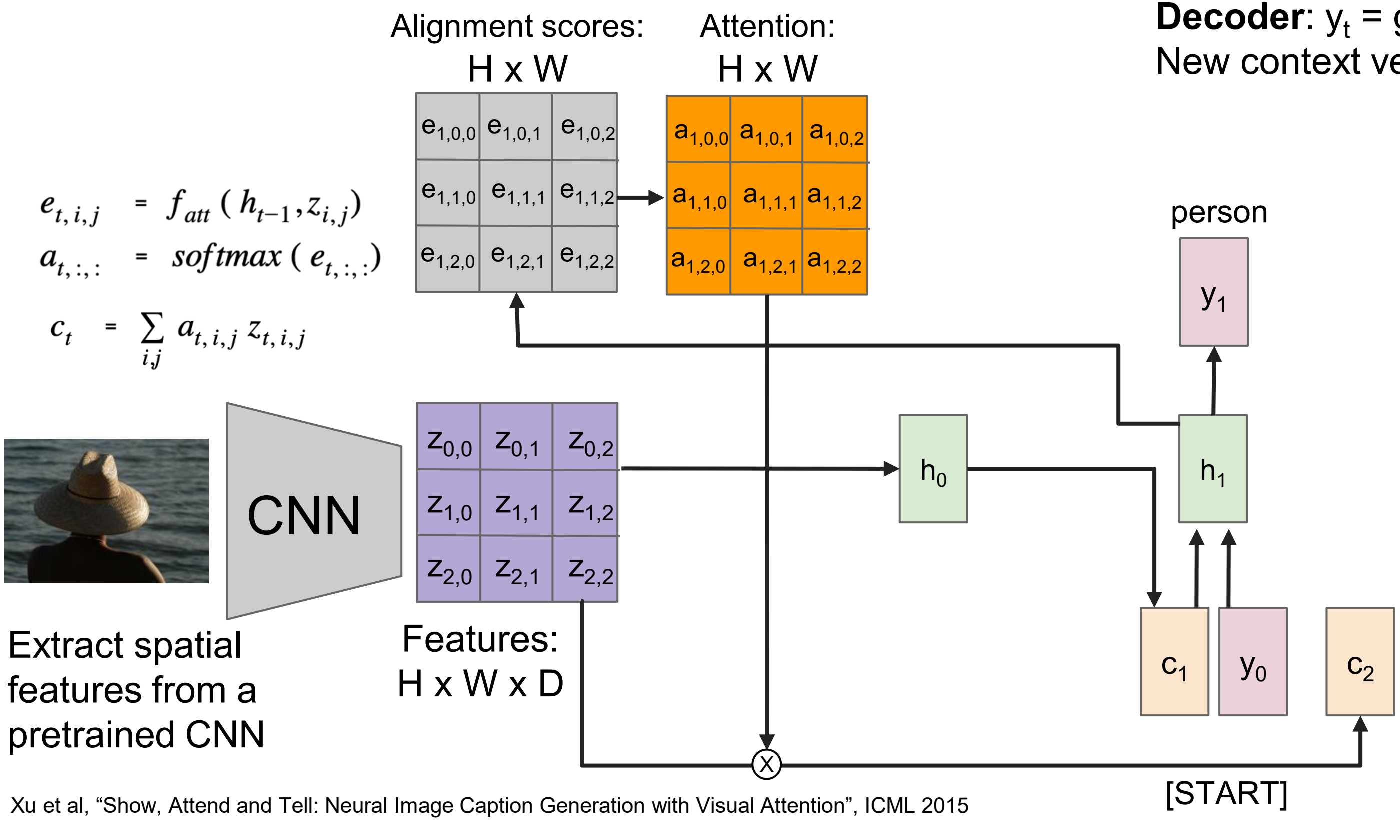



Xu et al, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML 2015

# Image Captioning with RNNs and Attention

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

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

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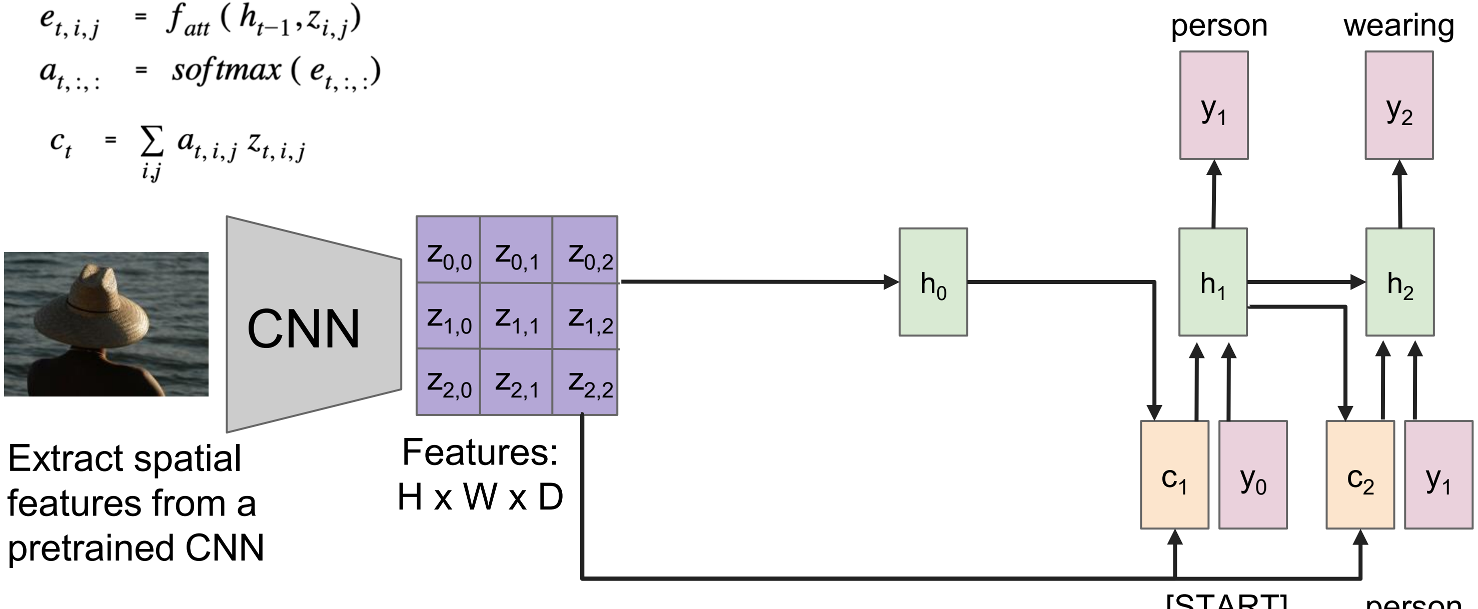


Extract spatial features from a pretrained CNN

Features: H x W x D

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

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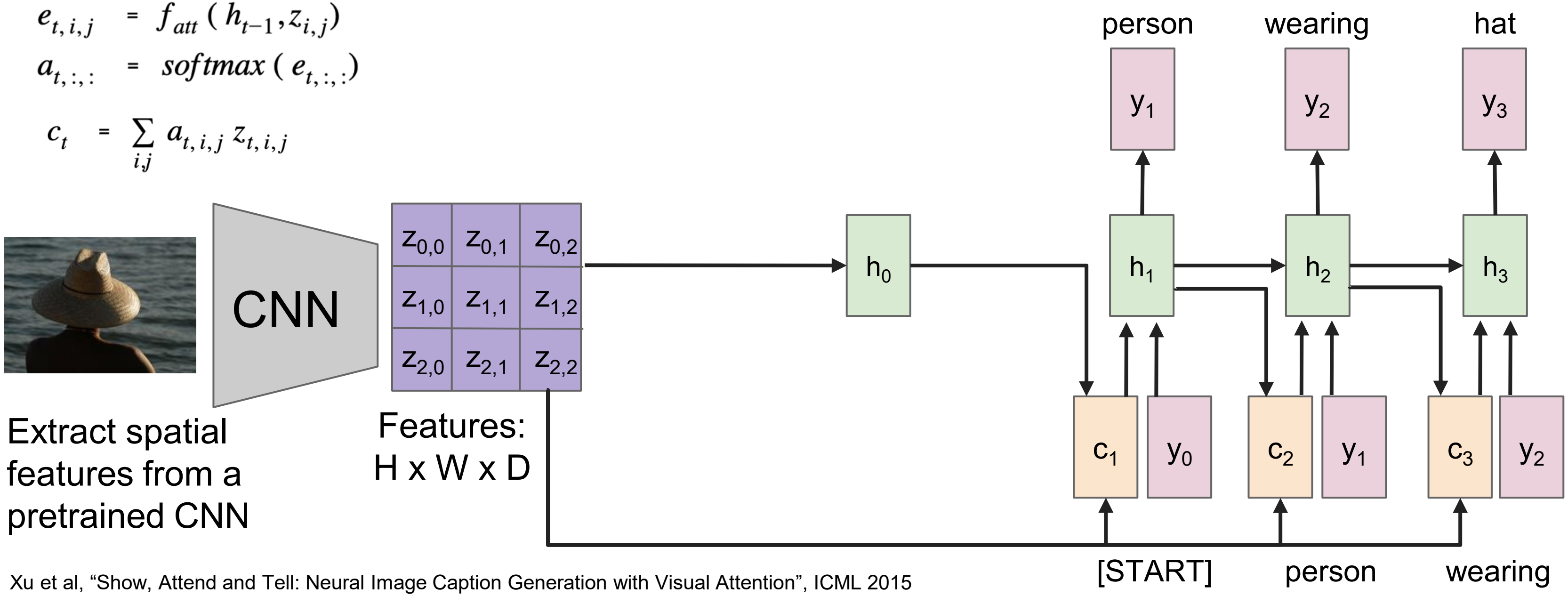


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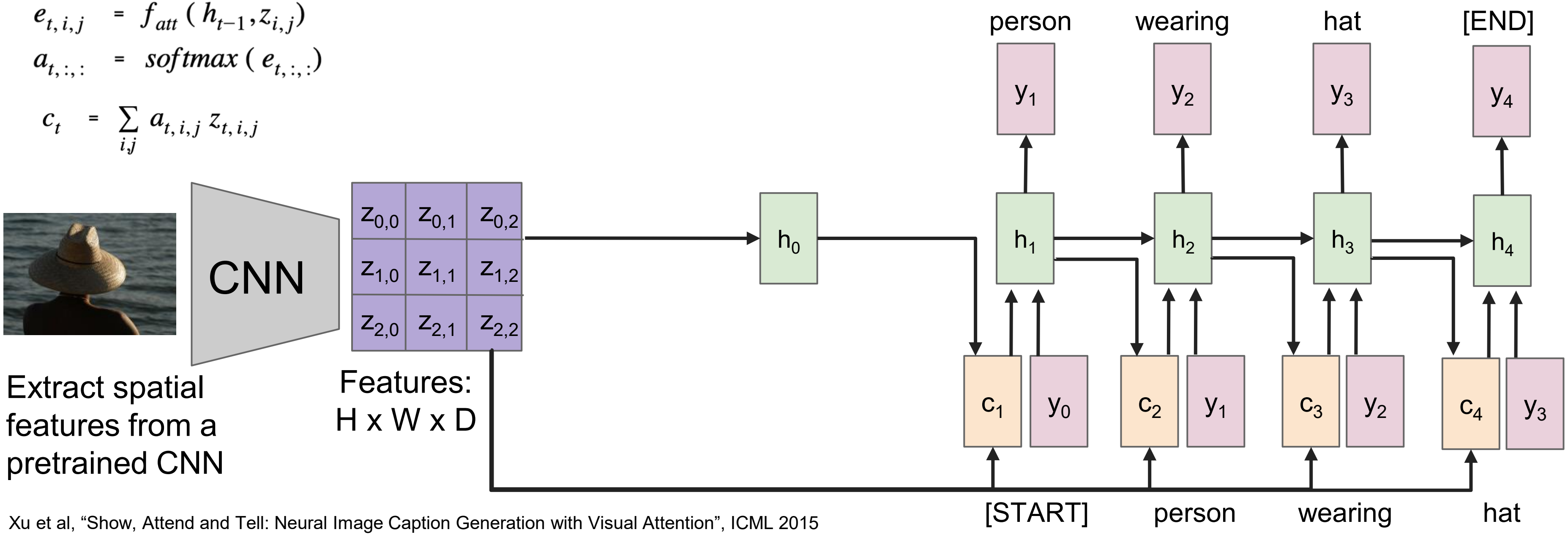


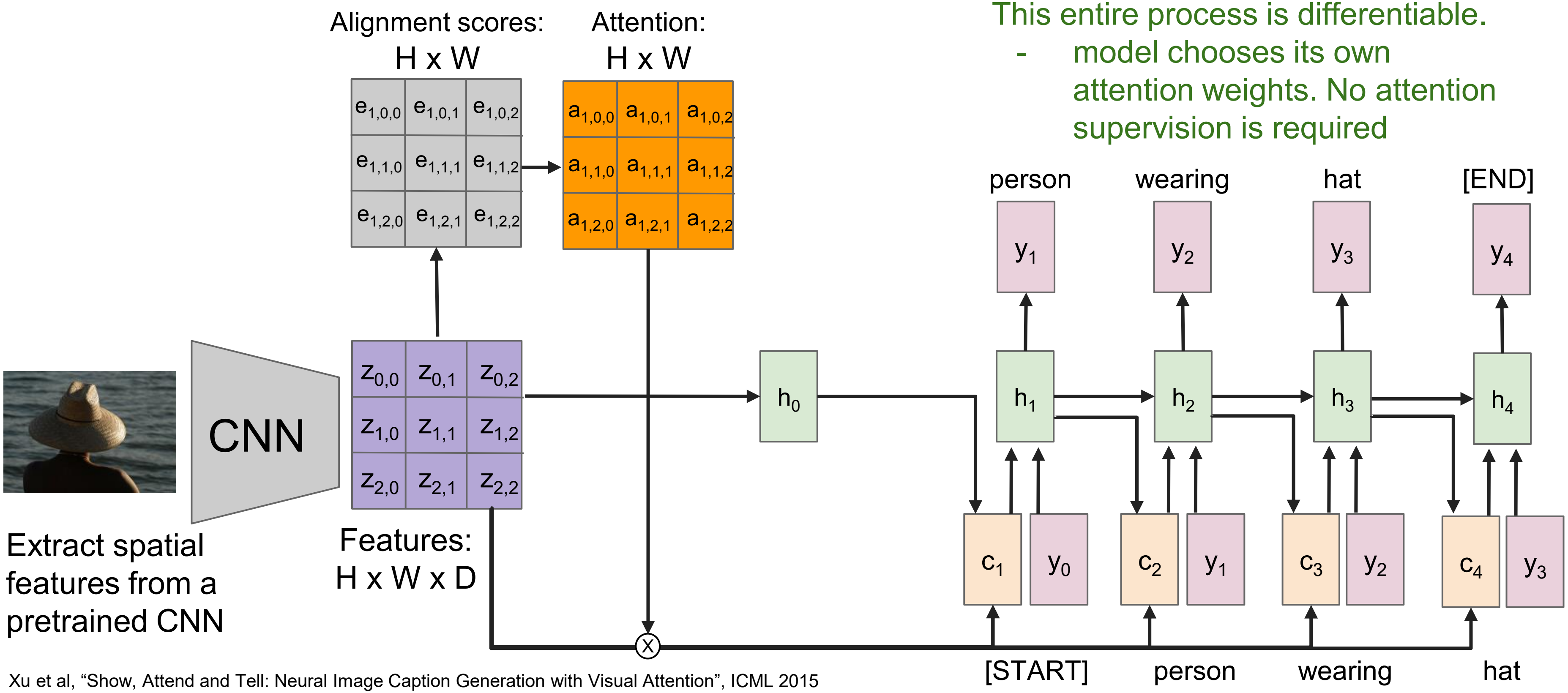

Extract spatial features from a pretrained CNN

Features: H x W x D

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

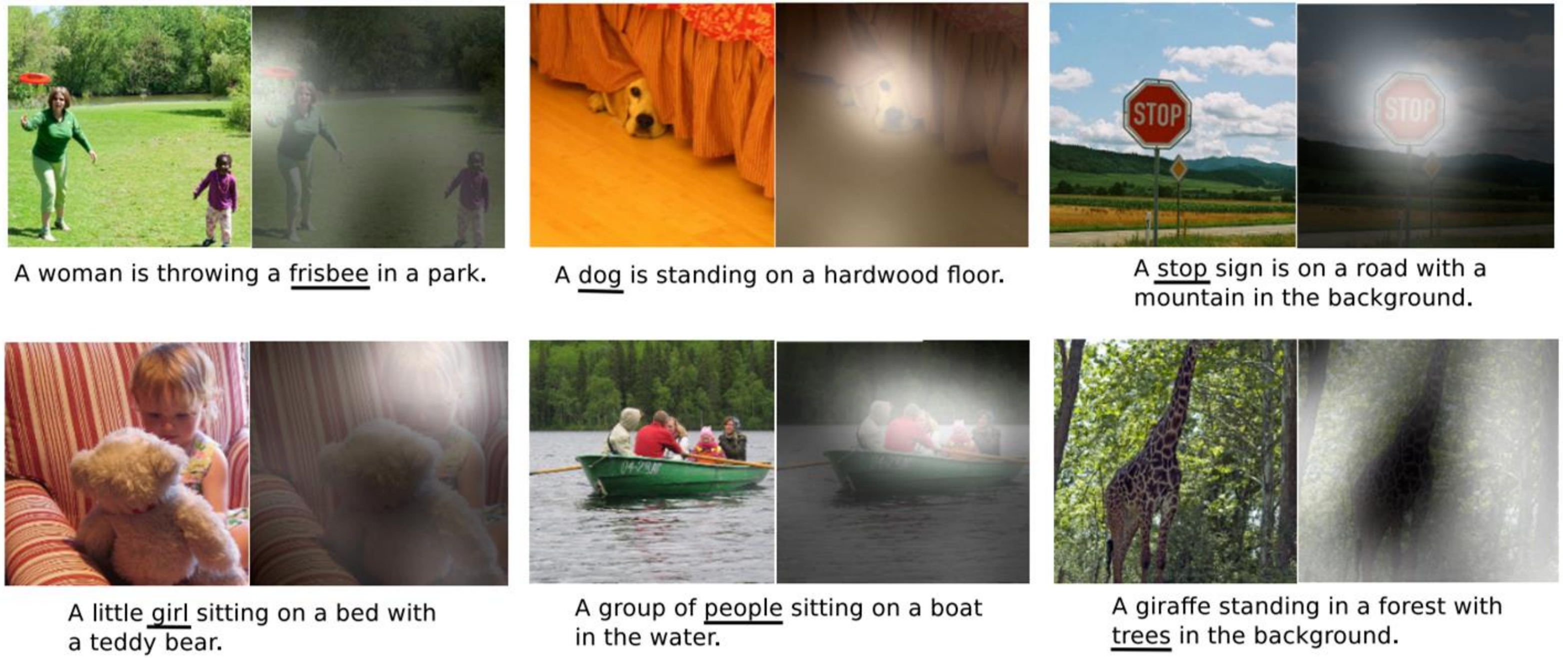
# Image Captioning with RNNs and Attention

This entire process is differentiable.
- model chooses its own attention weights. No attention supervision is required




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

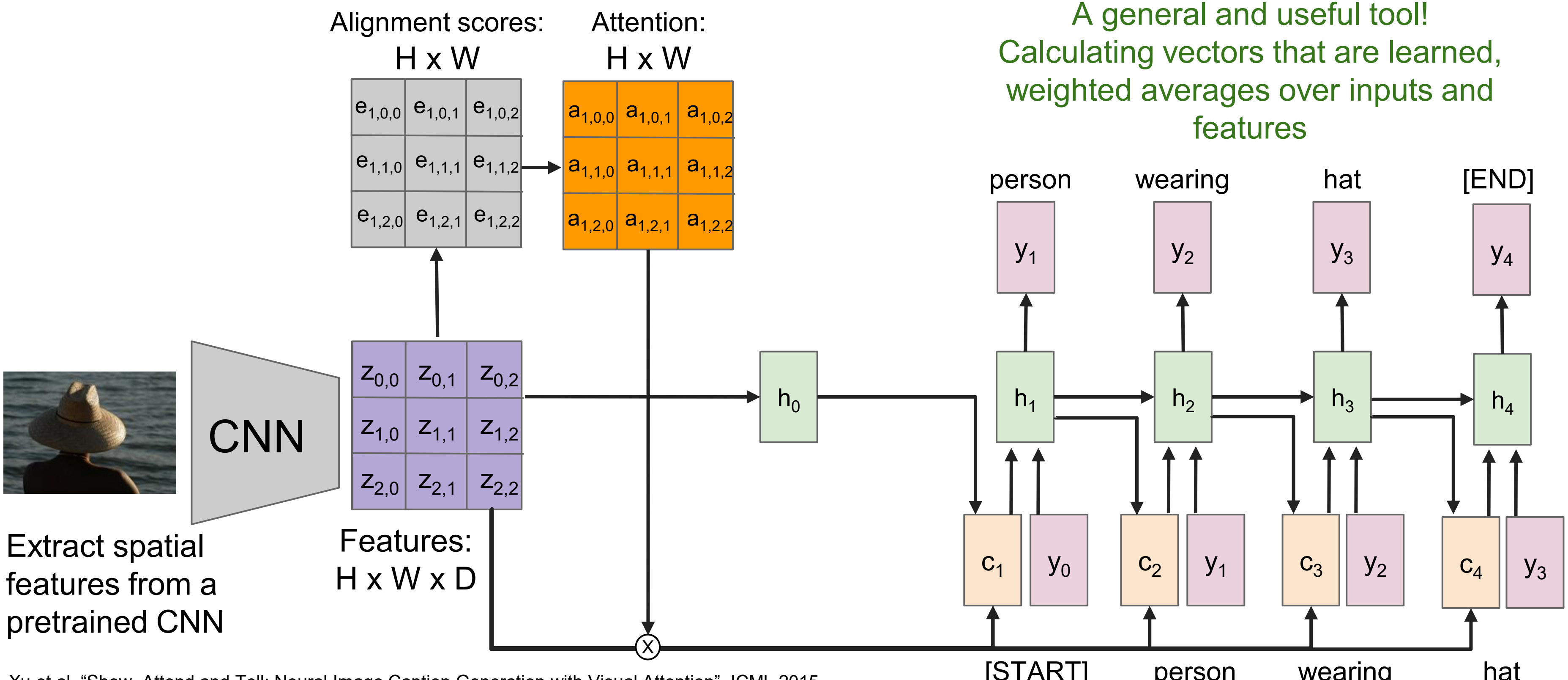
# Image Captioning with Attention




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

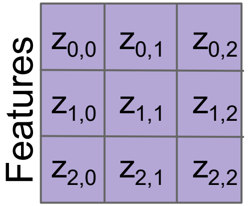
# Image Captioning with RNNs and Attention

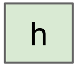
A general and useful tool!
Calculating vectors that are learned, weighted averages over inputs and features




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

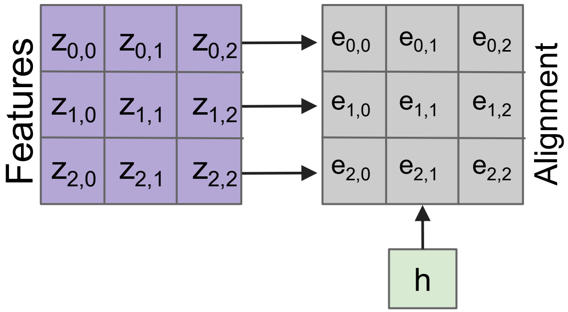
# Attention we just saw in image captioning




**Inputs**:
Features: **z** (shape: H x W x D)
Query: **h** (shape: D) ← "query" refers to a vector used to calculate a corresponding context vector.

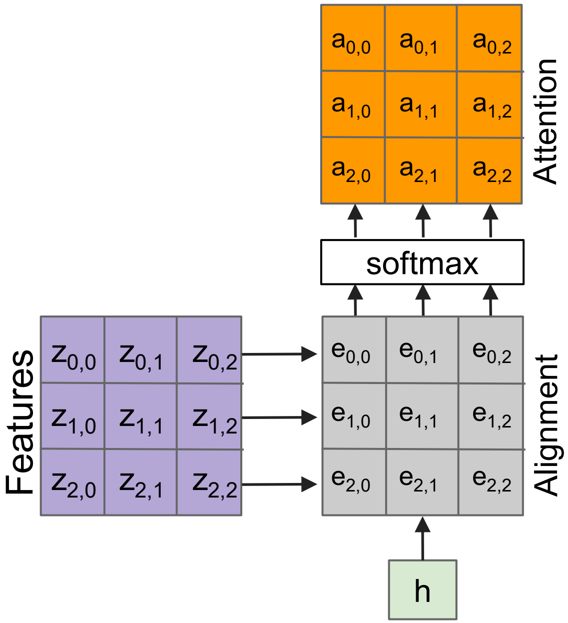
# Attention we just saw in image captioning




**Operations:**
Alignment: $e_{i,j} = f_{att}(h, z_{i,j})$

**Inputs**:
Features: **z** (shape: H x W x D)
Query: **h** (shape: D)

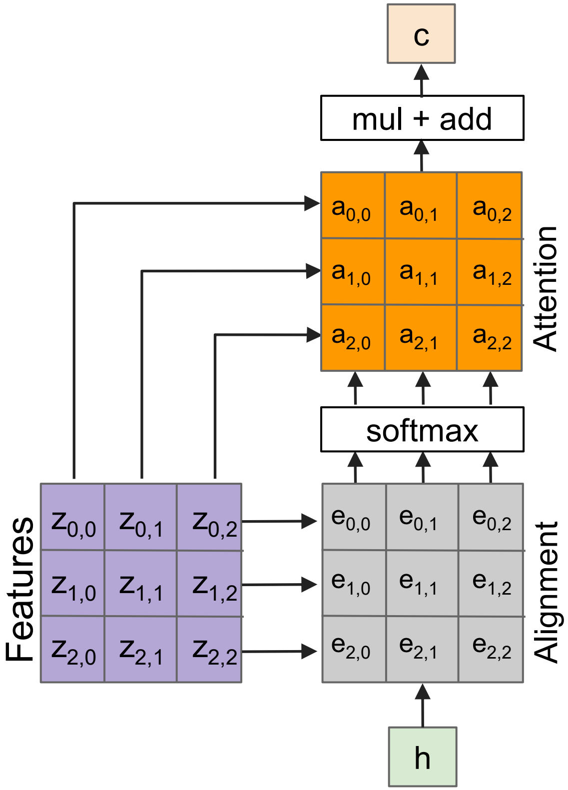
# Attention we just saw in image captioning




**Operations:**
Alignment: $e_{i,j} = f_{att}(h, z_{i,j})$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$

**Inputs**:
Features: $\mathbf{z}$ (shape: H x W x D)
Query: $\mathbf{h}$ (shape: D)

# Attention we just saw in image captioning

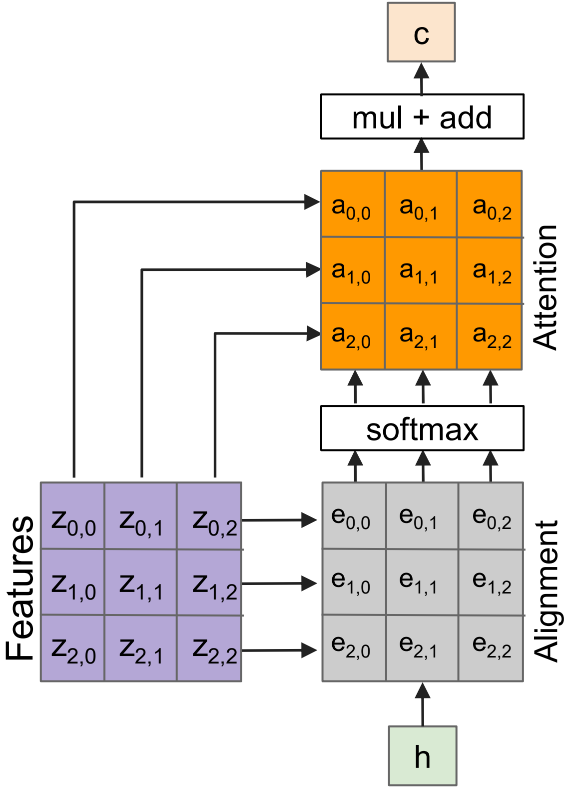



**Outputs:**
context vector: **c** (shape: D)

**Operations:**
Alignment: $e_{i,j} = f_{att}(h, z_{i,j})$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $\mathbf{c} = \sum_{i,j} a_{i,j} z_{i,j}$

**Inputs**:
Features: **z** (shape: H x W x D)
Query: **h** (shape: D)

# Attention we just saw in image captioning




**Outputs:**
context vector: **c** (shape: D)

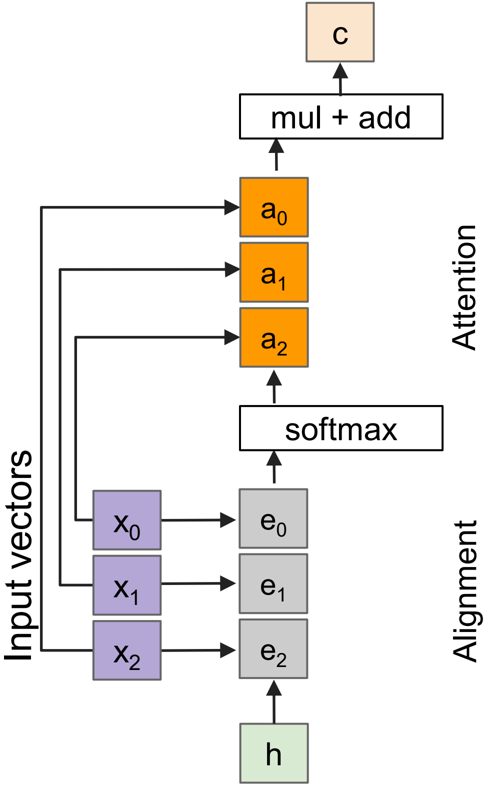
**Operations:**
Alignment: $e_{i,j} = f_{att}(h, z_{i,j})$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $\mathbf{c} = \sum_{i,j} a_{i,j} z_{i,j}$

**Inputs**:
Features: **z** (shape: H x W x D)
Query: **h** (shape: D)

**How is this different from the attention mechanism in transformers?**

**We'll go into that next, any questions?**

# General attention layer – used in LLMs + beyond



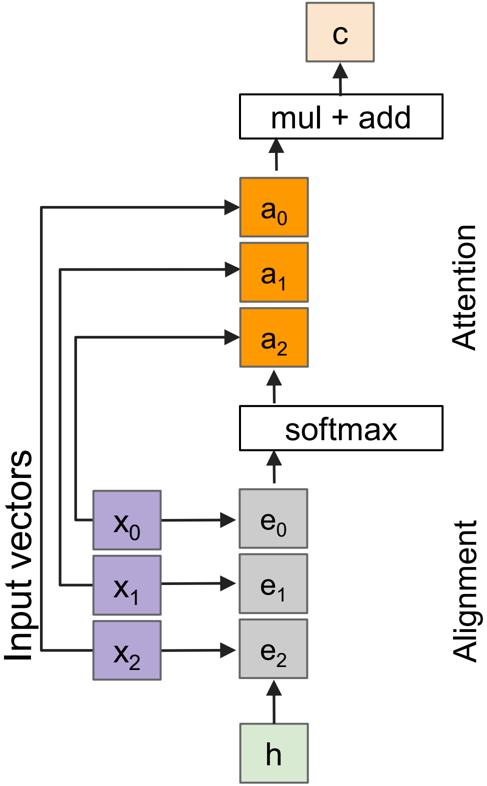

**Outputs:**
context vector: **c** (shape: D)

**Operations:**
Alignment: $e_i = f_{att}(h, x_i)$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $\mathbf{c} = \sum_i a_i x_i$

Attention operation is **permutation invariant.**
- Doesn't care about ordering of the features
- Stretch into **N = H x W** vectors

**Inputs**:
Input vectors: **x** (shape: N x D)
Query: **h** (shape: D)

# General attention layer



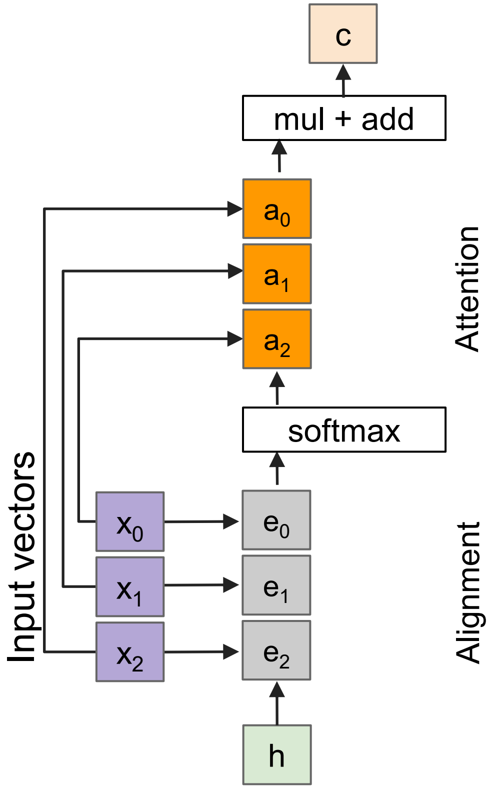

**Outputs:**
context vector: **c** (shape: D)

**Operations:**
$\boxed{\text{Alignment: } e_i = h \cdot x_i}$
Attention: **a** = softmax(**e**)
Output: **c** = $\sum_i a_i x_i$

Change $f_{att}(.)$ to a dot product, this actually can work well in practice, but a simple dot product can have some issues…

**Inputs**:
Input vectors: **x** (shape: N x D)
Query: **h** (shape: D)

# General attention layer




**Outputs:**
context vector: **c** (shape: D)

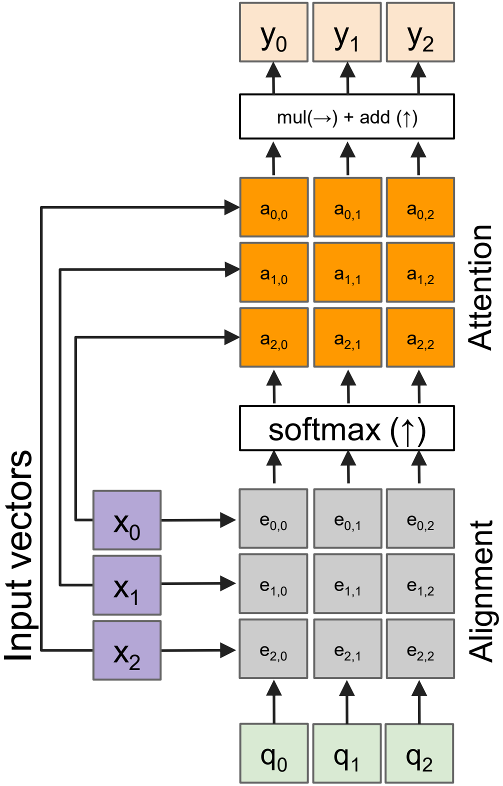
**Operations:**
$\boxed{\text{Alignment: } e_i = h \cdot x_i \,/\, \sqrt{D}}$
Attention: **a** = softmax(**e**)
Output: **c** = $\sum_i a_i x_i$

**Inputs**:
Input vectors: **x** (shape: N x D)
Query: **h** (shape: D)

Change $f_{att}(.)$ 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 √D to reduce effect of large magnitude vectors
- Similar to Xavier and Kaiming Initialization!

# General attention layer




**Outputs:**
context vectors: **y** (shape: D)

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

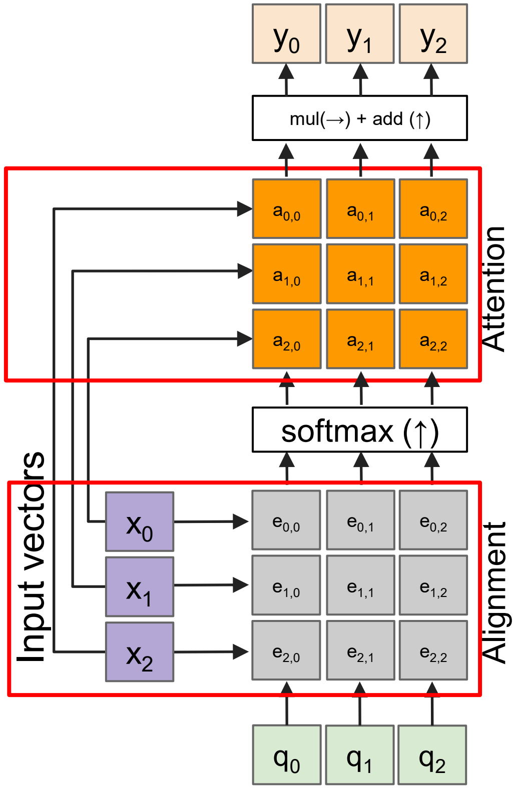
**Operations:**
Alignment: $e_{i,j} = q_j \cdot x_i / \sqrt{D}$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $y_j = \sum_i a_{i,j} x_i$

Allows us to compute multiple attention context vectors at once
Will go into more details in future slides, but this allows us to compute context vectors for multiple timesteps in parallel

Multiple query vectors

**Inputs**:
Input vectors: **x** (shape: N x D)
Queries: **q** (shape: M x D)

# General attention layer




**Outputs:**
context vectors: **y** (shape: D)

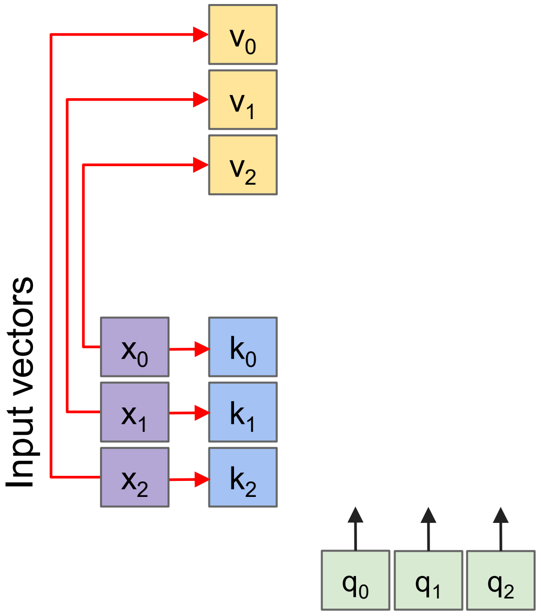
**Operations:**
Alignment: $e_{i,j} = q_j \cdot x_i / \sqrt{D}$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $y_j = \sum_i a_{i,j} x_i$

**Inputs**:
Input vectors: **x** (shape: N x D)
Queries: **q** (shape: M x D)

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



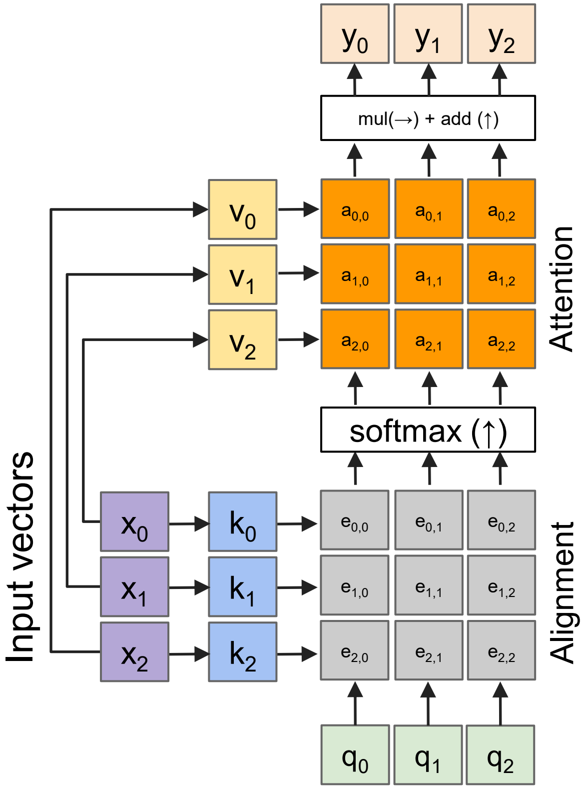

**Operations:**
Key vectors: $\mathbf{k} = \mathbf{x}\mathbf{W_k}$
Value vectors: $\mathbf{v} = \mathbf{x}\mathbf{W_v}$

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.

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

# General attention layer




**Outputs:**
context vectors: **y** (shape: $\boxed{D_v}$)

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

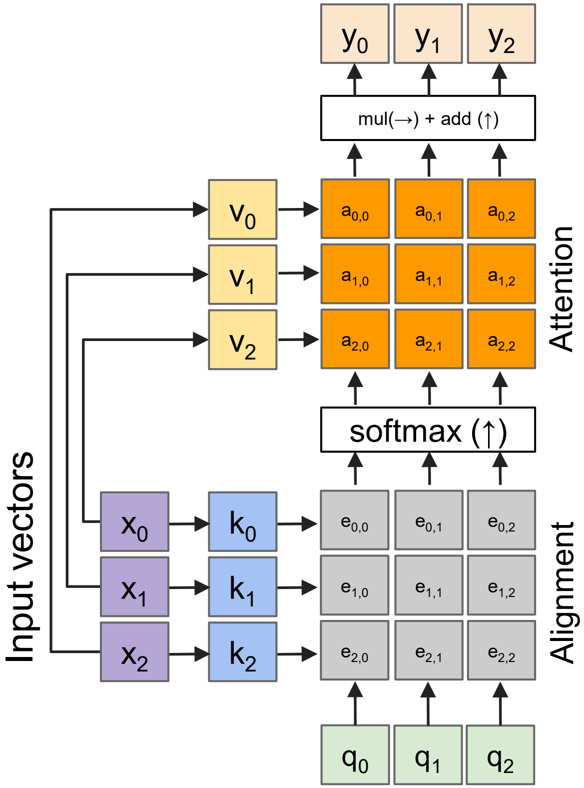
**Inputs**:
Input vectors: **x** (shape: N x D)
Queries: **q** (shape: M x $\boxed{D_k}$)

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

Since the alignment scores are just scalars, the value vectors can be any dimension we want

# General attention layer

**This is a working example of how we could use an attention layer + CNN encoder for image captioning**



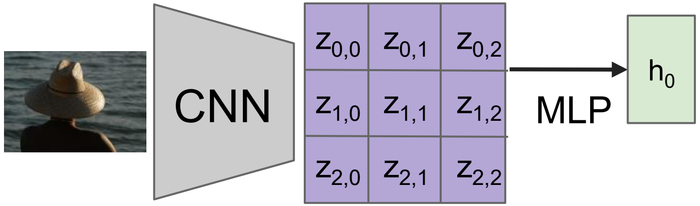

**Outputs:**
context vectors: **y** (shape: $D_v$)

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

**Inputs**:
Input vectors: **x** (shape: N x D)
Queries: **q** (shape: M x $D_k$)

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

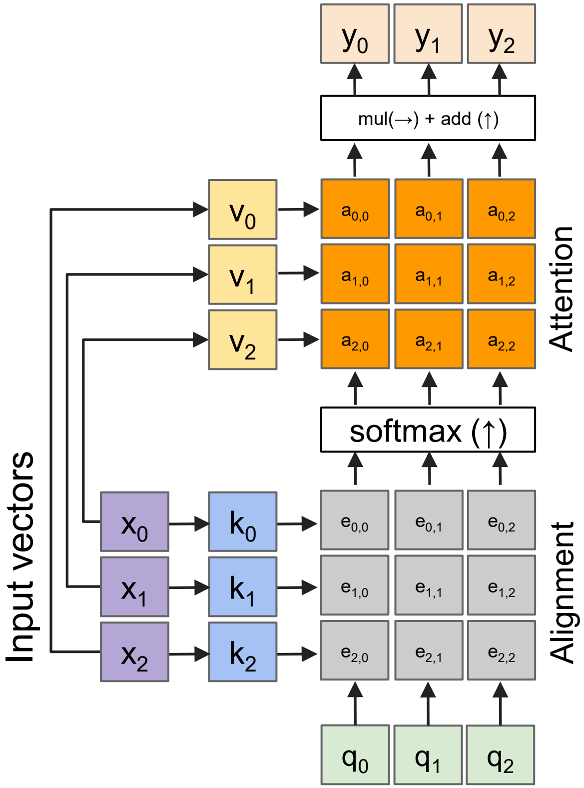
**Encoder**: $h_0 = f_W(\mathbf{z})$
where **z** is spatial CNN features
$f_W(.)$ is an MLP




We used $h_0$ as $q_0$ previously

# Lecture 8:
# Video Lecture Supplement
# Attention and Transformers

# Next: The Self-attention Layer




**Outputs:**
context vectors: **y** (shape: $D_v$)

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

**Inputs**:
Input vectors: **x** (shape: N x D)
Queries: **q** (shape: M x $D_k$)

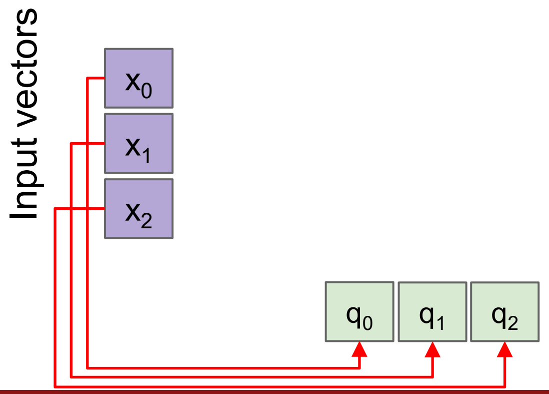
**Idea: leverages the strengths of attention layers without the need for separate query vectors.**

# Self attention layer

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

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

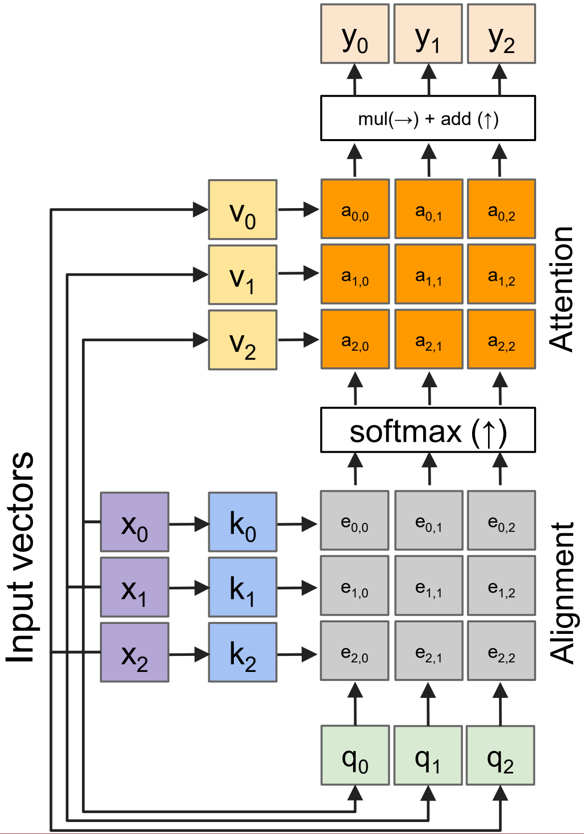
Instead, query vectors are calculated using a FC layer.




No input query vectors anymore

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

# Self attention layer

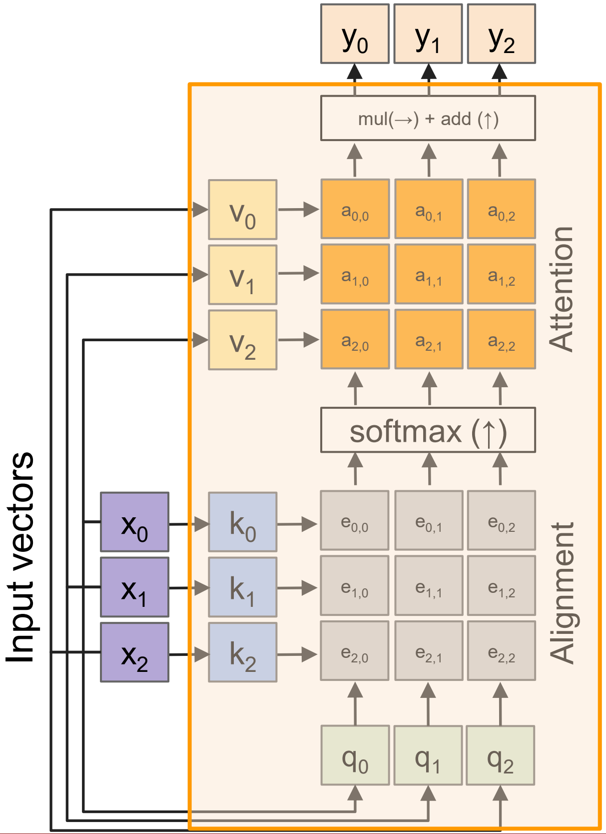



**Outputs:**
context vectors: **y** (shape: $D_v$)

**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: $e_{i,j} = q_j \cdot k_i / \sqrt{D}$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $y_j = \sum_i a_{i,j} v_i$

**Inputs**:
Input vectors: **x** (shape: N x D)

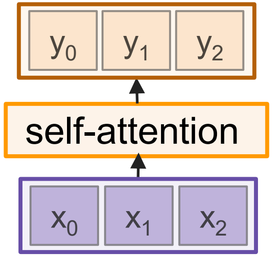
# Self attention layer - attends over sets of inputs



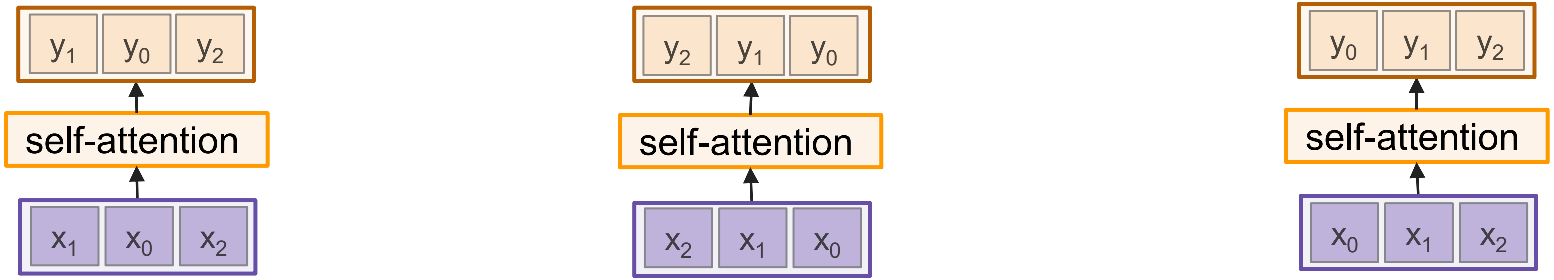

**Outputs:**
context vectors: **y** (shape: $D_v$)

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

**Inputs**:
Input vectors: **x** (shape: N x D)



# Self attention layer - attends over sets of inputs

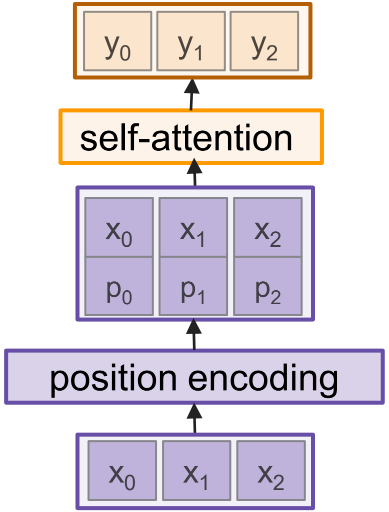



Permutation equivariant

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 or **add** special positional encoding $p_j$ to each input vector $x_j$

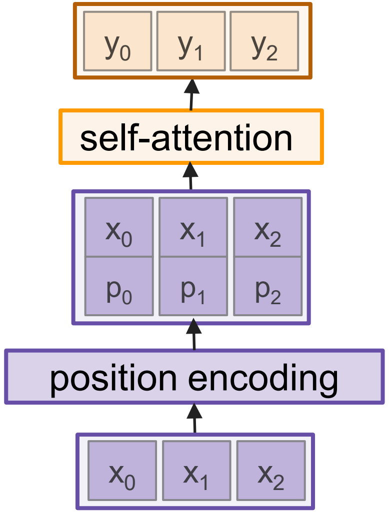
We use a function *pos*: $N \rightarrow R^d$ to process the position j of the vector into a d-dimensional vector

So, $p_j = pos(j)$

Possible desirable properties of *pos*(.) :

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*: $N \rightarrow R^d$ to process the position $j$ of the vector into a d-dimensional vector

So, $p_j$ = *pos*(j)

Options for *pos*(.)

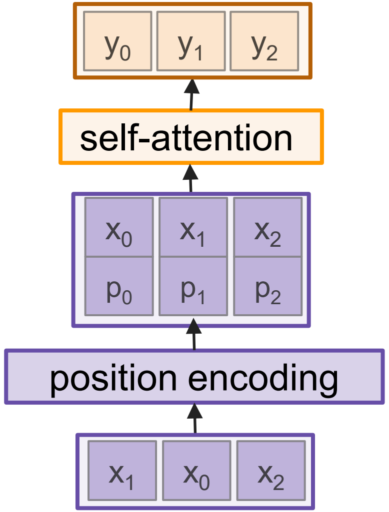
1. Learn a lookup table:
   - Learn parameters to use for *pos*(t) for $t \in [0, T)$
   - Lookup table contains T x d parameters.

Possible desirable properties of *pos*(.) :

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**.

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*: $N \rightarrow R^d$ to process the position $j$ of the vector into a d-dimensional vector

So, $p_j = pos(j)$

Options for *pos*(.)

1. Learn a lookup table:
   - Learn parameters to use for *pos*(t) for t ε [0, T)
   - Lookup table contains T x d parameters.

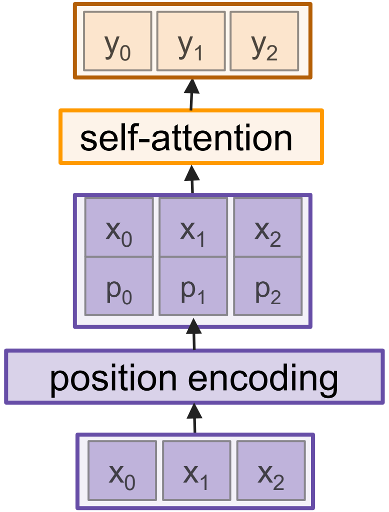
2. Design a fixed function with the desired properties

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

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*: $N \rightarrow R^d$ to process the position $j$ of the vector into a d-dimensional vector

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Options for *pos*(.)

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

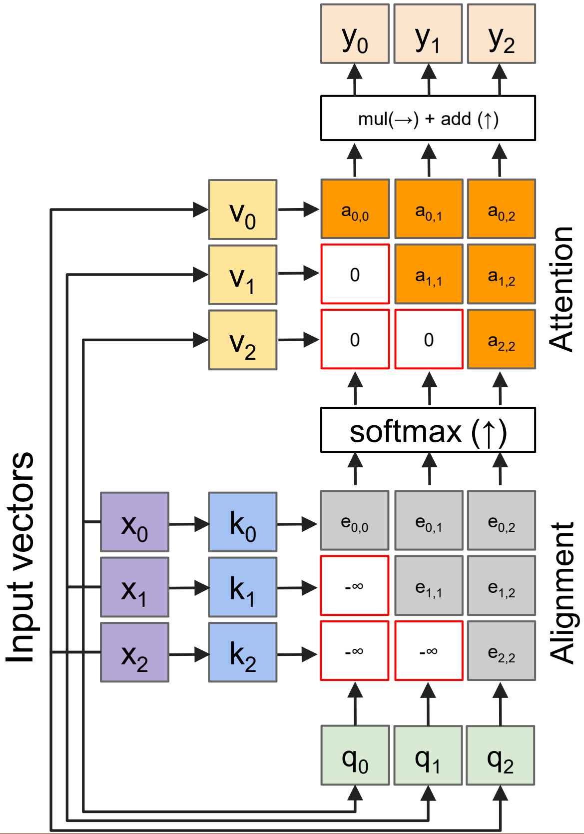
Intuition:

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 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 |

image source

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

# Masked self-attention layer




**Outputs:**
context vectors: **y** (shape: $D_v$)

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

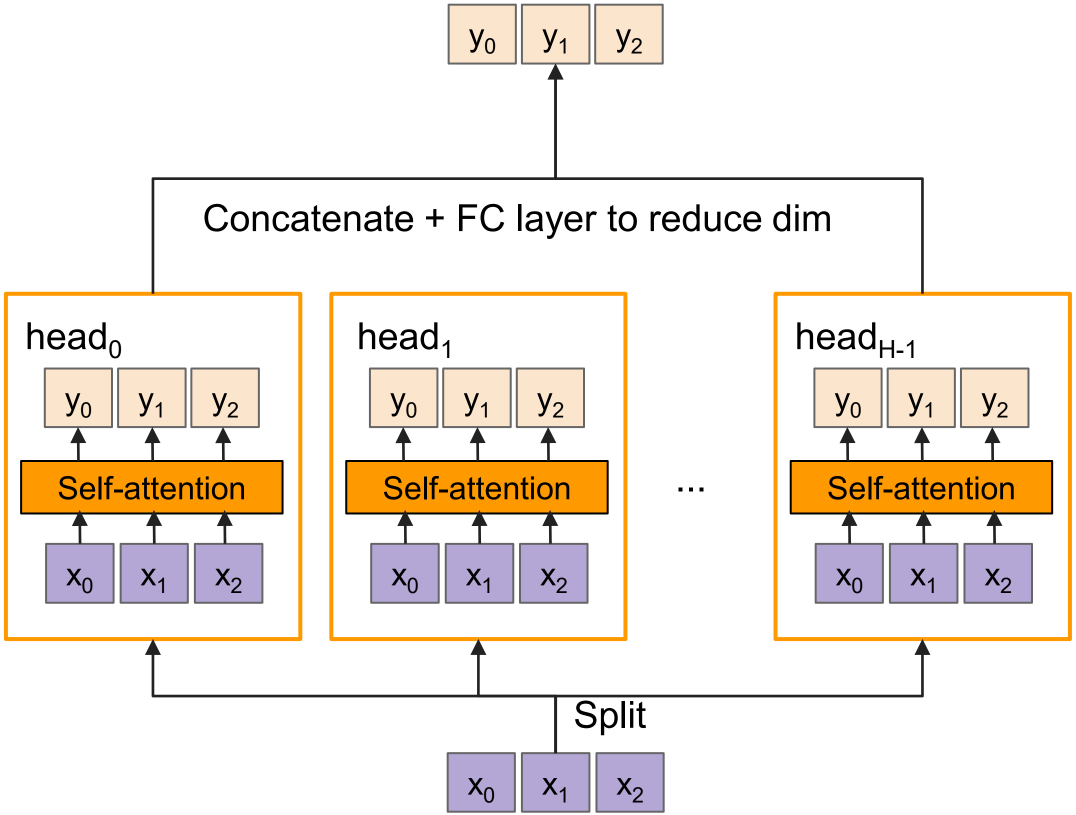
**Inputs**:
Input vectors: **x** (shape: N x D)

- Allows us to parallelize attention across time
- Don't need to calculate the context vectors from the previous timestep first!

- Prevent vectors from looking at future vectors.
- Manually set alignment scores to –infinity (-nan)

# Multi-head self-attention layer

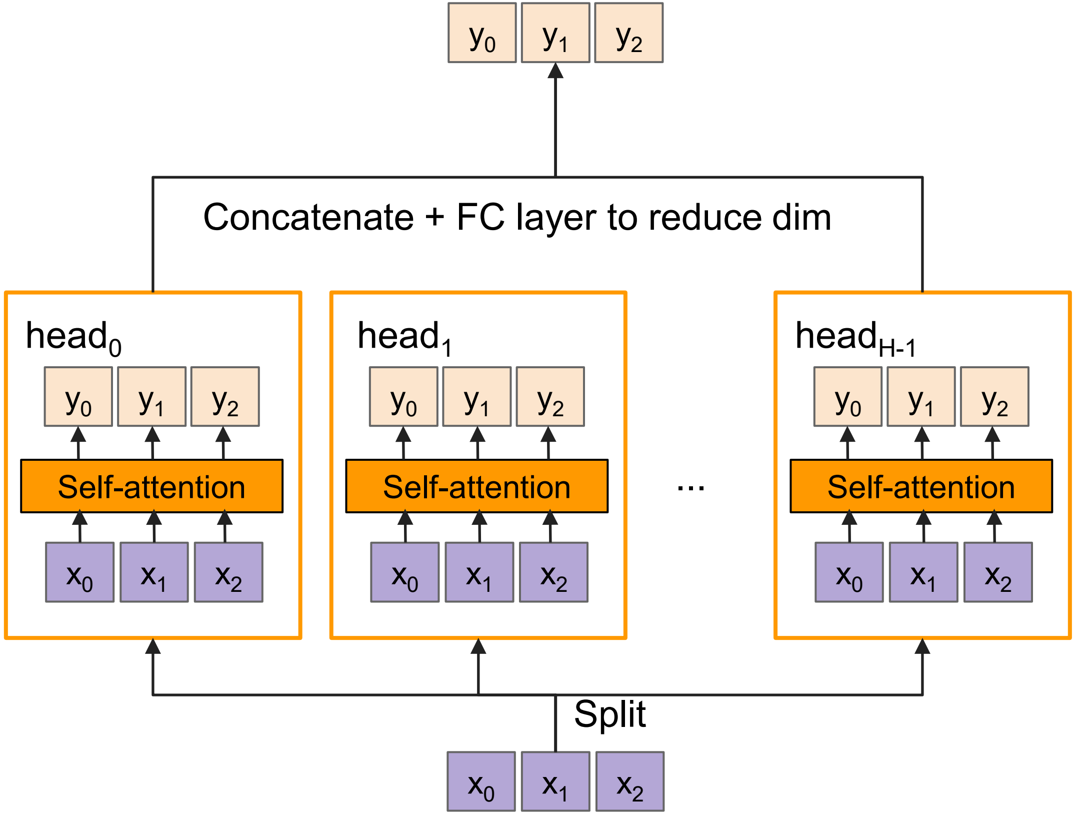
- Multiple self-attention “heads” in parallel




**Q: Why do this?**

# Multi-head self-attention layer

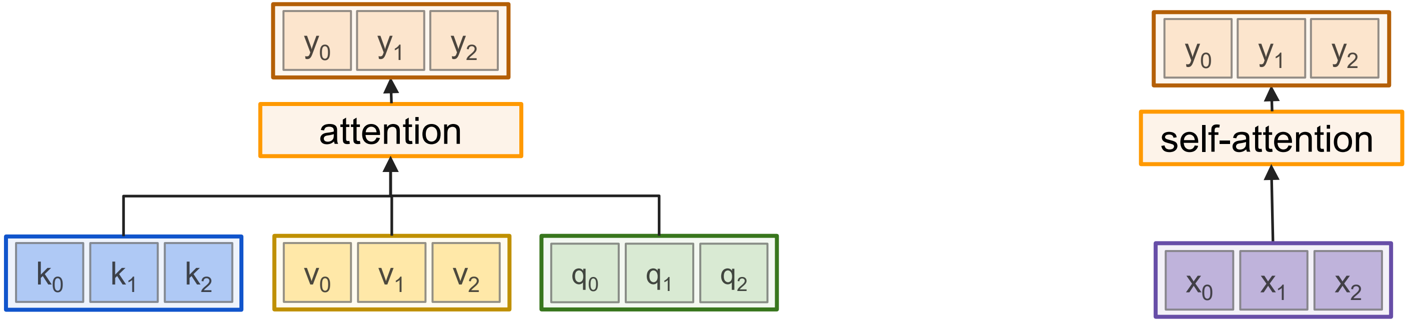
- Multiple self-attention “heads” in parallel




A: We may want to have multiple sets of queries/keys/values calculated in the layer. This is a similar idea to having multiple conv filters learned in a layer

# General attention versus self-attention

Transformer models rely on many, stacked self-attention layers



# 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 x M alignment and attention scalers need to be calculated and stored for a single self-attention head. (but GPUs are getting bigger and better)

# Attention Is All You Need

**Ashish Vaswani*** Google Brain avaswani@google.com

**Noam Shazeer*** Google Brain noam@google.com

**Niki Parmar*** Google Research nikip@google.com

**Jakob Uszkoreit*** Google Research usz@google.com

**Llion Jones*** Google Research llion@google.com

**Aidan N. Gomez*** † University of Toronto aidan@cs.toronto.edu

**Łukasz Kaiser*** Google Brain lukaszkaiser@google.com

**Illia Polosukhin*** ‡ illia.polosukhin@gmail.com

"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

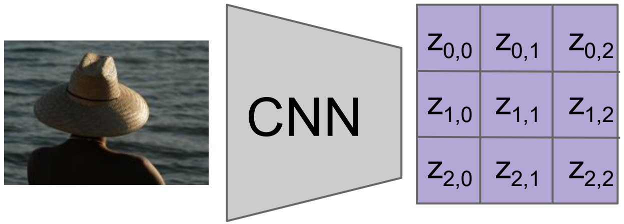
# On the Opportunities and Risks of Foundation Models

Rishi Bommasani* Drew A. Hudson Ehsan Adeli Russ Altman Simran Arora
Sydney von Arx Michael S. Bernstein Jeannette Bohg Antoine Bosselut Emma Brunskill
Erik Brynjolfsson Shyamal Buch Dallas Card Rodrigo Castellon Niladri Chatterji
Annie Chen Kathleen Creel Jared Quincy Davis Dorottya Demszky Chris Donahue
Moussa Doumbouya Esin Durmus Stefano Ermon John Etchemendy Kawin Ethayarajh
Li Fei-Fei Chelsea Finn Trevor Gale Lauren Gillespie Karan Goel Noah Goodman
Shelby Grossman Neel Guha Tatsunori Hashimoto Peter Henderson John Hewitt
Daniel E. Ho Jenny Hong Kyle Hsu Jing Huang Thomas Icard Saahil Jain
Dan Jurafsky Pratyusha Kalluri Siddharth Karamcheti Geoff Keeling Fereshte Khani
Omar Khattab Pang Wei Koh Mark Krass Ranjay Krishna Rohith Kuditipudi
Ananya Kumar Faisal Ladhak Mina Lee Tony Lee Jure Leskovec Isabelle Levent
Xiang Lisa Li Xuechen Li Tengyu Ma Ali Malik Christopher D. Manning
Suvir Mirchandani Eric Mitchell Zanele Munyikwa Suraj Nair Avanika Narayan
Deepak Narayanan Ben Newman Allen Nie Juan Carlos Niebles Hamed Nilforoshan
Julian Nyarko Giray Ogut Laurel Orr Isabel Papadimitriou Joon Sung Park Chris Piech
Eva Portelance Christopher Potts Aditi Raghunathan Rob Reich Hongyu Ren
Frieda Rong Yusuf Roohani Camilo Ruiz Jack Ryan Christopher Ré Dorsa Sadigh
Shiori Sagawa Keshav Santhanam Andy Shih Krishnan Srinivasan Alex Tamkin
Rohan Taori Armin W. Thomas Florian Tramèr Rose E. Wang William Wang Bohan Wu
Jiajun Wu Yuhuai Wu Sang Michael Xie Michihiro Yasunaga Jiaxuan You Matei Zaharia
Michael Zhang Tianyi Zhang Xikun Zhang Yuhui Zhang Lucia Zheng Kaitlyn Zhou
Percy Liang*[1]

Center for Research on Foundation Models (CRFM)
Stanford Institute for Human-Centered Artificial Intelligence (HAI)
Stanford University

# Image Captioning using Transformers

**Input**: Image **I**
**Output:** Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$



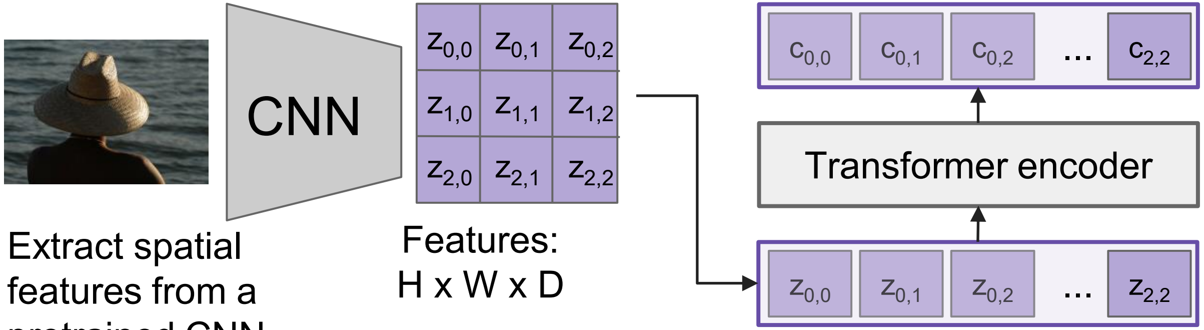

Extract spatial features from a pretrained CNN

Features: H x W x D

# Image Captioning using Transformers

**Input**: Image **I**
**Output:** Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$

**Encoder**: $\mathbf{c} = T_W(\mathbf{z})$
where $\mathbf{z}$ is spatial CNN features
$T_W(.)$ is the transformer encoder




Extract spatial features from a pretrained CNN

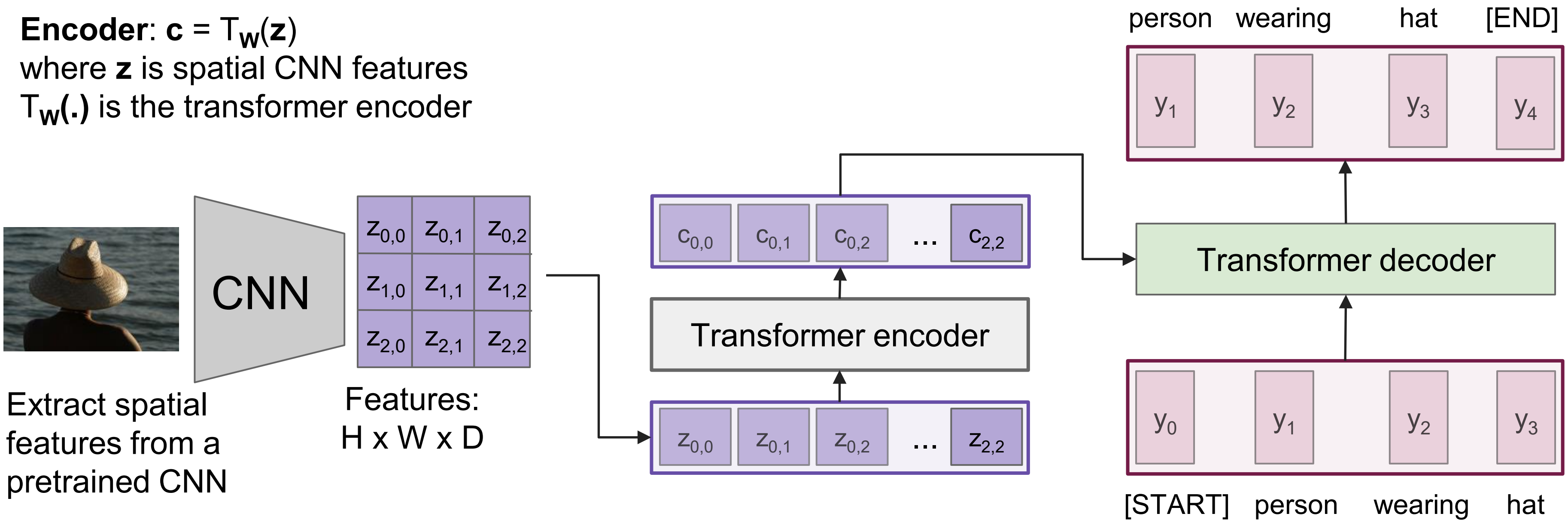
Features: H x W x D

# Image Captioning using Transformers

**Input**: Image **I**
**Output:** Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$

**Decoder**: $y_t = T_D(\mathbf{y}_{0:t-1}, \mathbf{c})$
where $T_D(.)$ is the transformer decoder

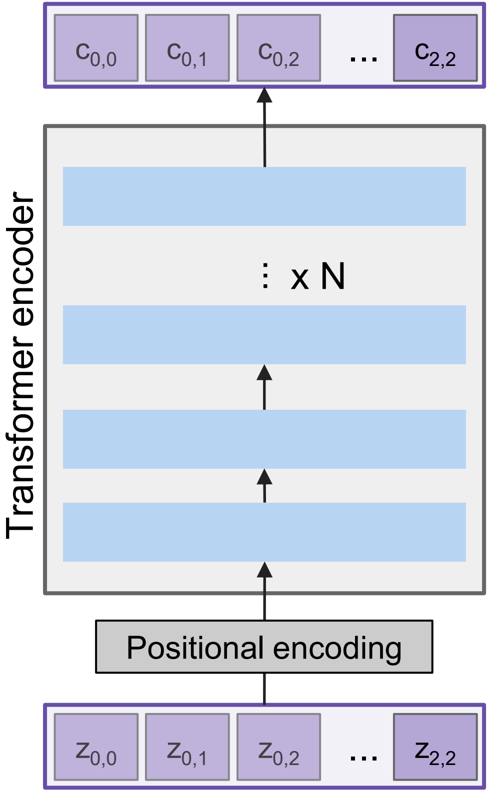
**Encoder**: $\mathbf{c} = T_W(\mathbf{z})$
where **z** is spatial CNN features
$T_W(.)$ is the transformer encoder




Extract spatial features from a pretrained CNN

Features: H x W x D

# The Transformer encoder block

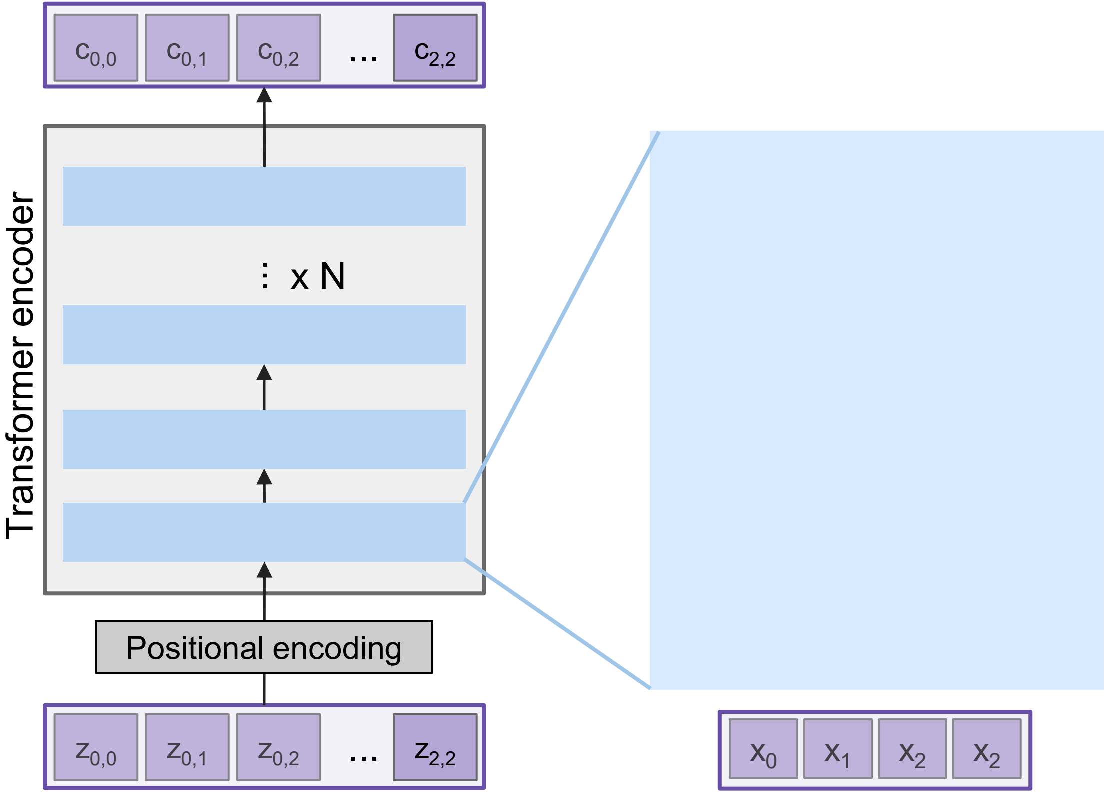



Made up of N encoder blocks.

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

Vaswani et al, “Attention is all you need”, NeurIPS 2017

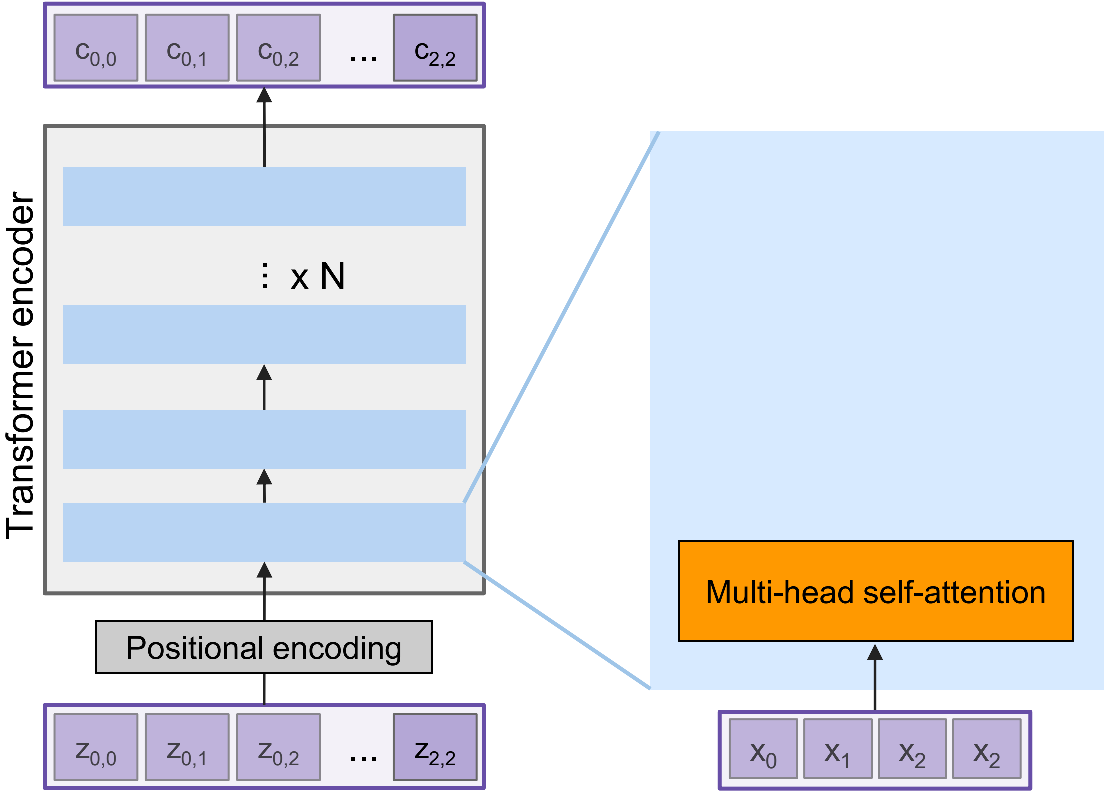
# The Transformer encoder block




Let's dive into one encoder block

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

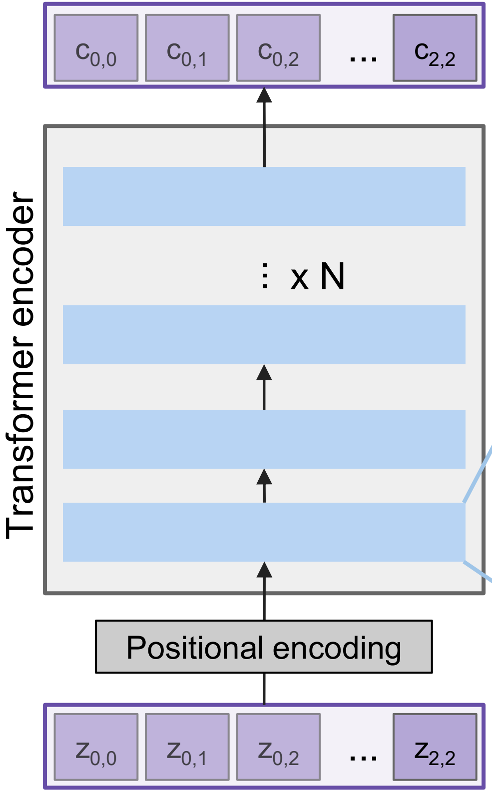
# The Transformer encoder block

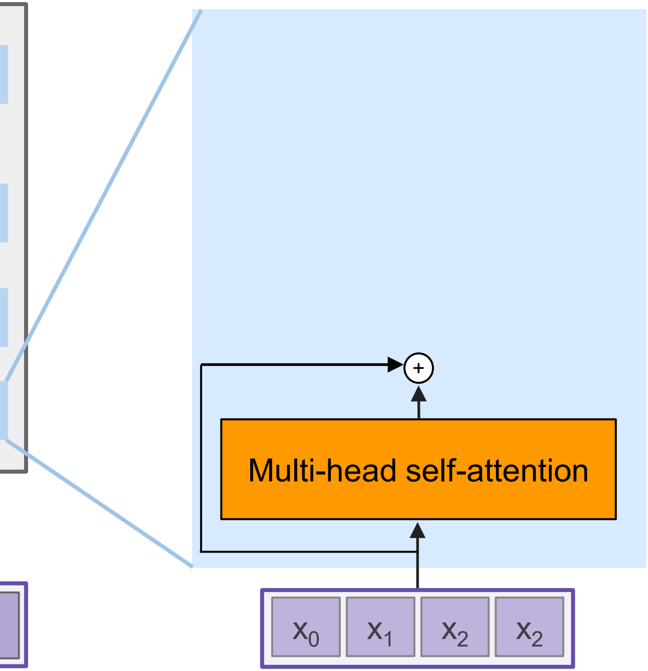



Attention attends over all the vectors

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

# The Transformer encoder block



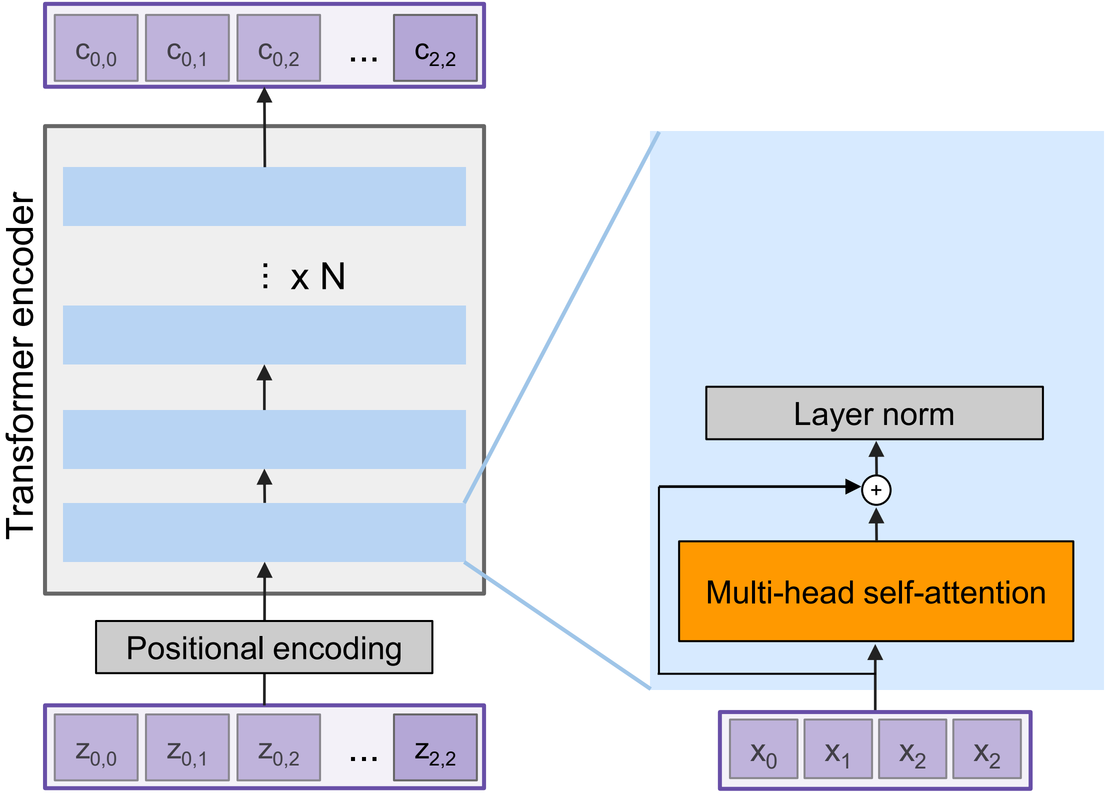




Residual connection

Attention attends over all the vectors

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

# The Transformer encoder block



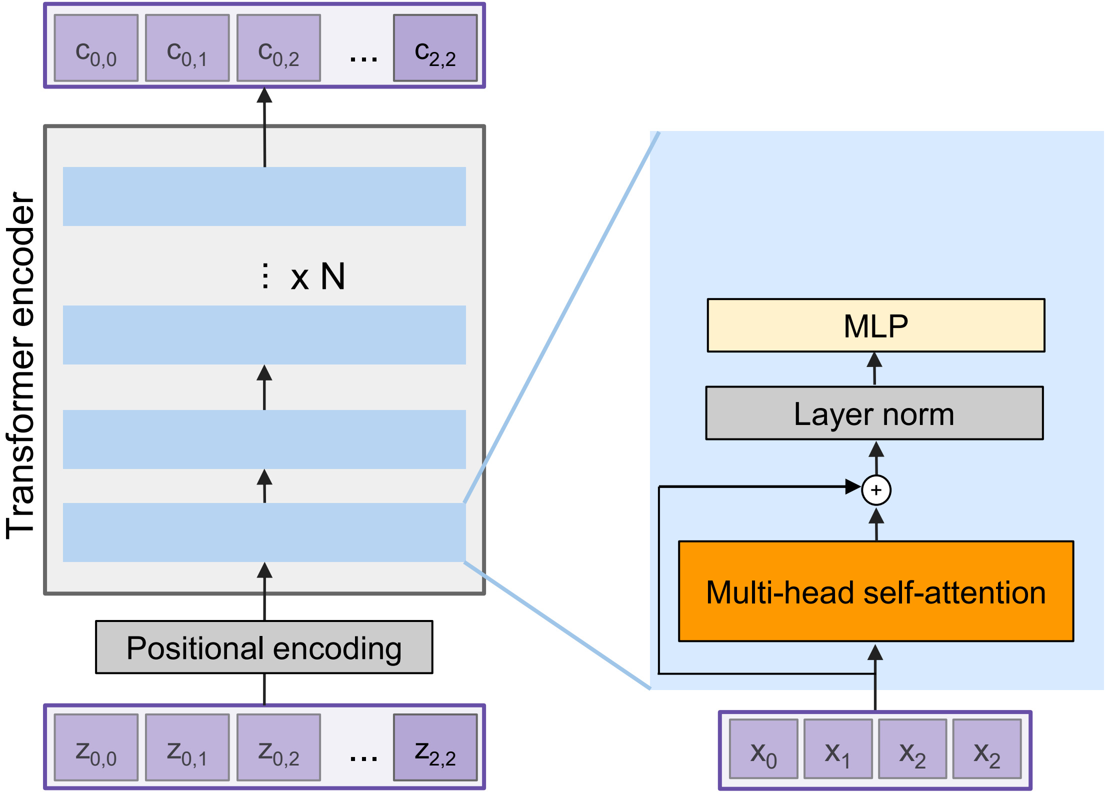

LayerNorm over each vector individually

Residual connection

Attention attends over all the vectors

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

# The Transformer encoder block




MLP over each vector individually

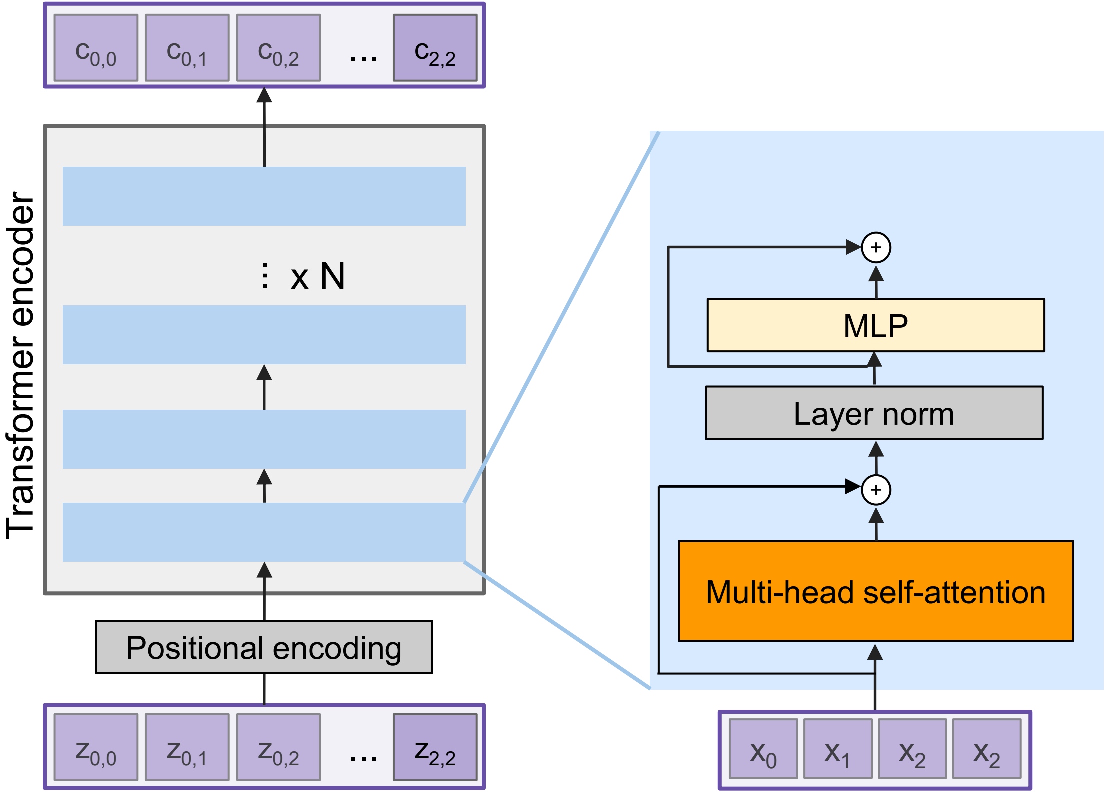
LayerNorm over each vector individually

Residual connection

Attention attends over all the vectors

Vaswani et al, “Attention is all you need”, NeurIPS 2017

# The Transformer encoder block




Residual connection

MLP over each vector individually

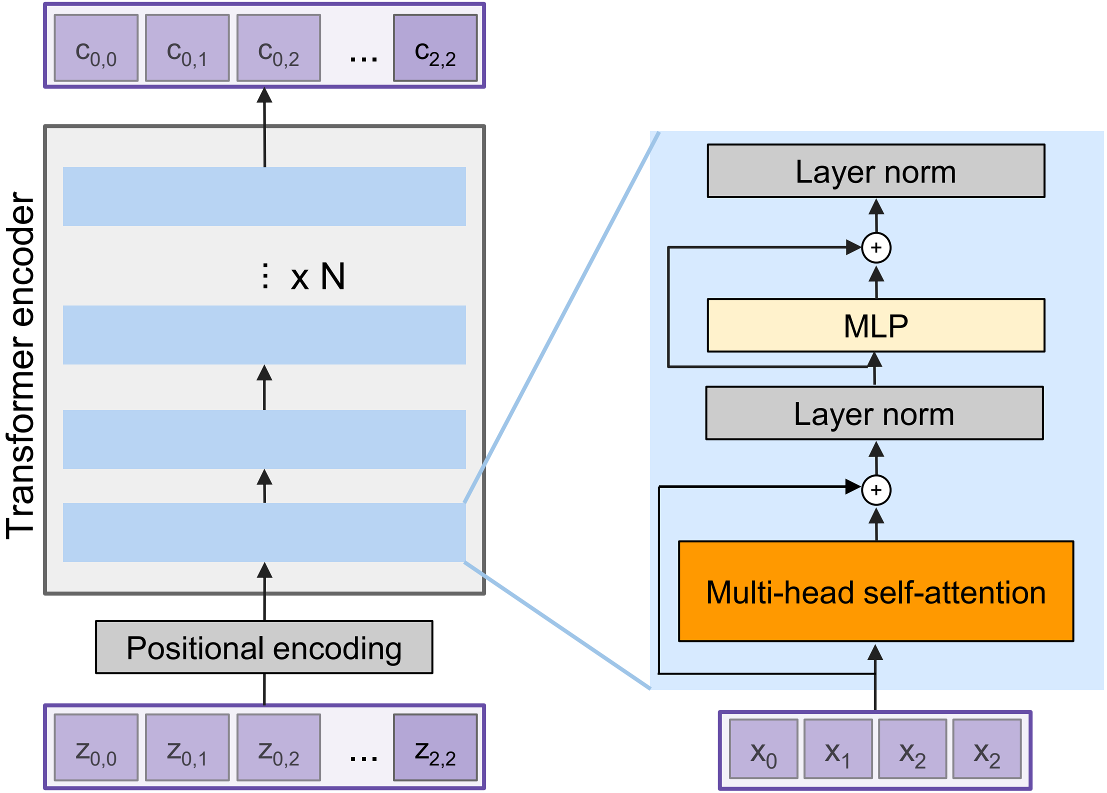
LayerNorm over each vector individually

Residual connection

Attention attends over all the vectors

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

# The Transformer encoder block




LayerNorm over each vector individually

Residual connection

MLP over each vector individually

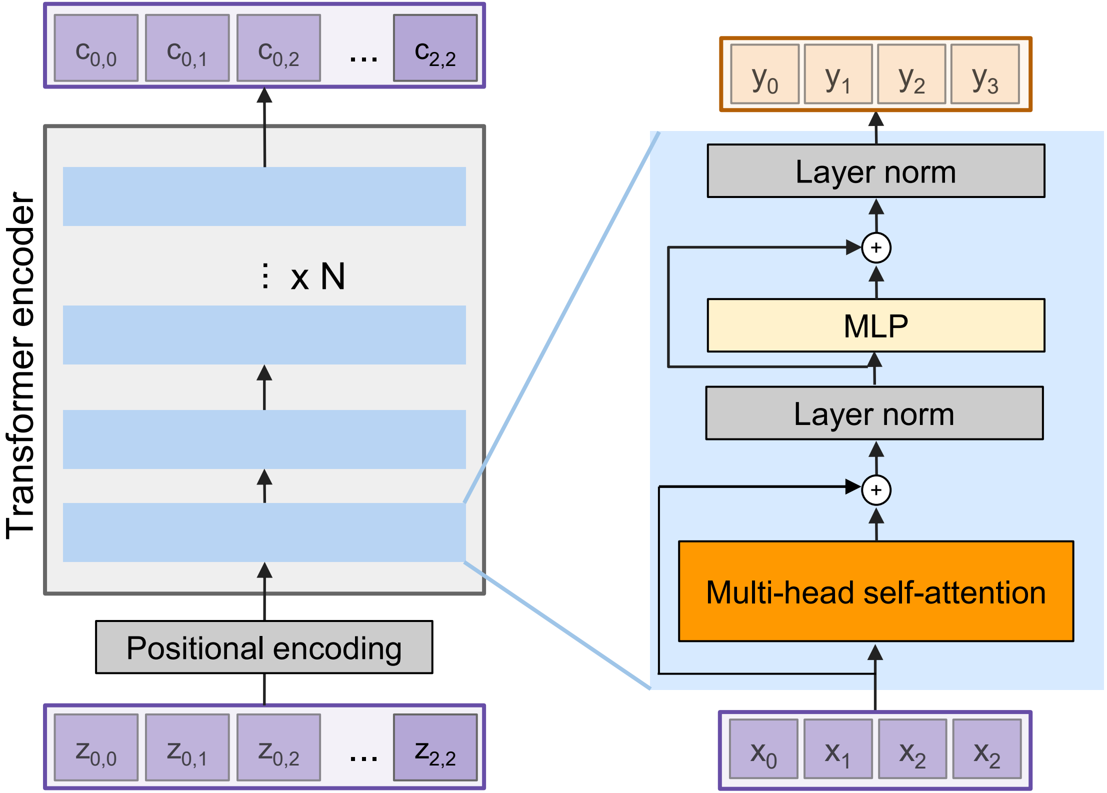
LayerNorm over each vector individually

Residual connection

Attention attends over all the vectors

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**

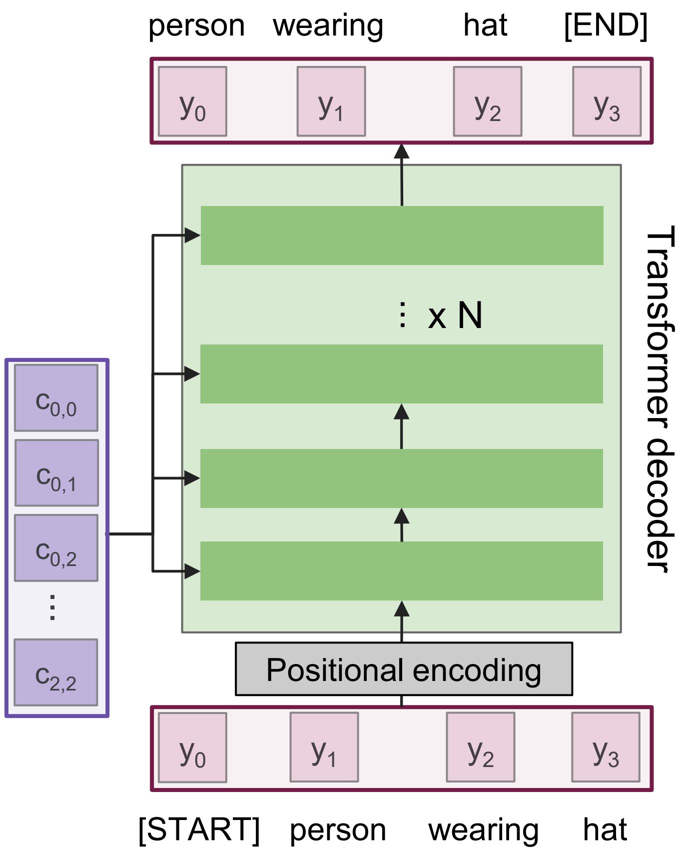
Self-attention is the only interaction between vectors.

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

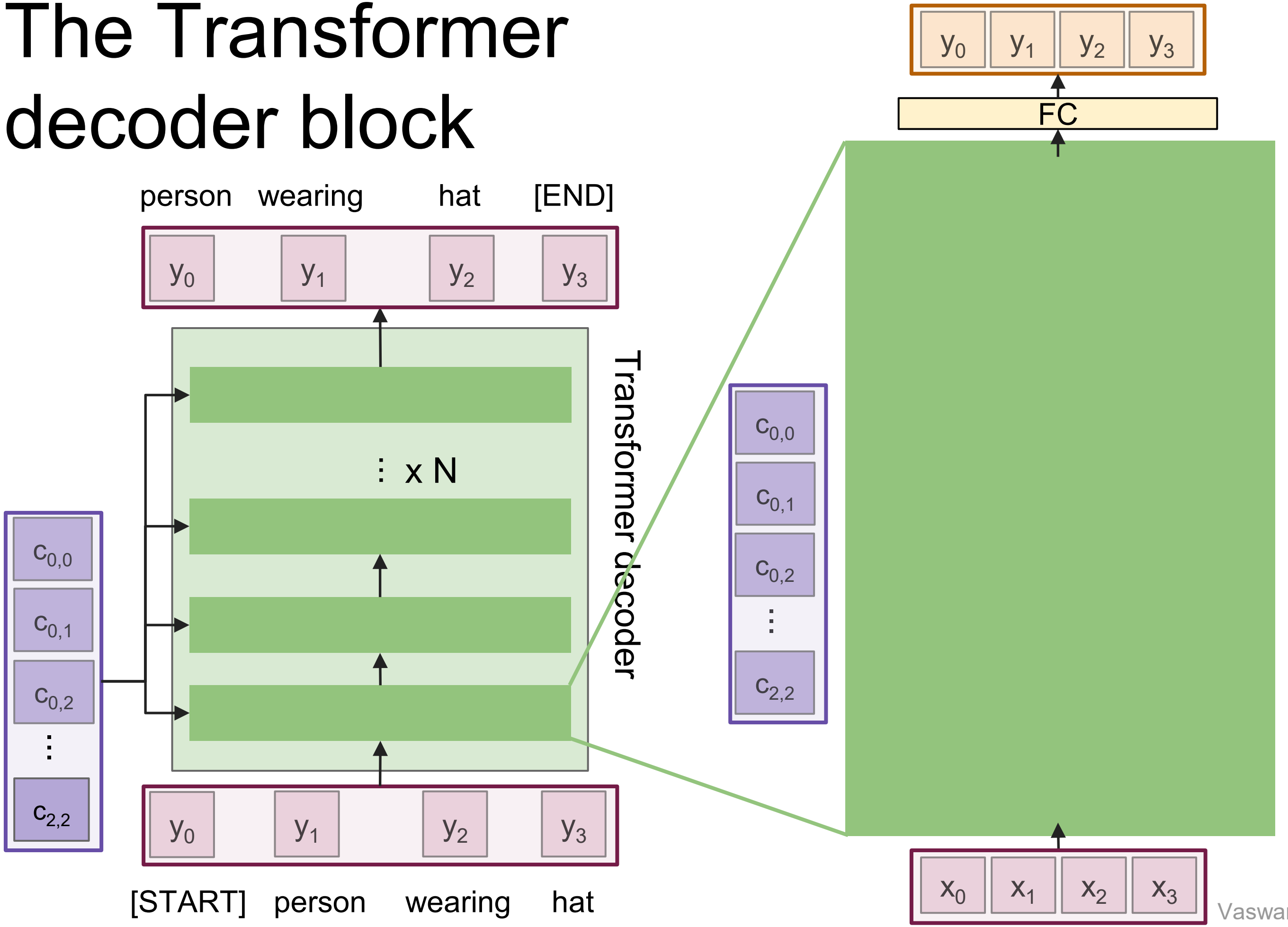



Made up of N decoder blocks.

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

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

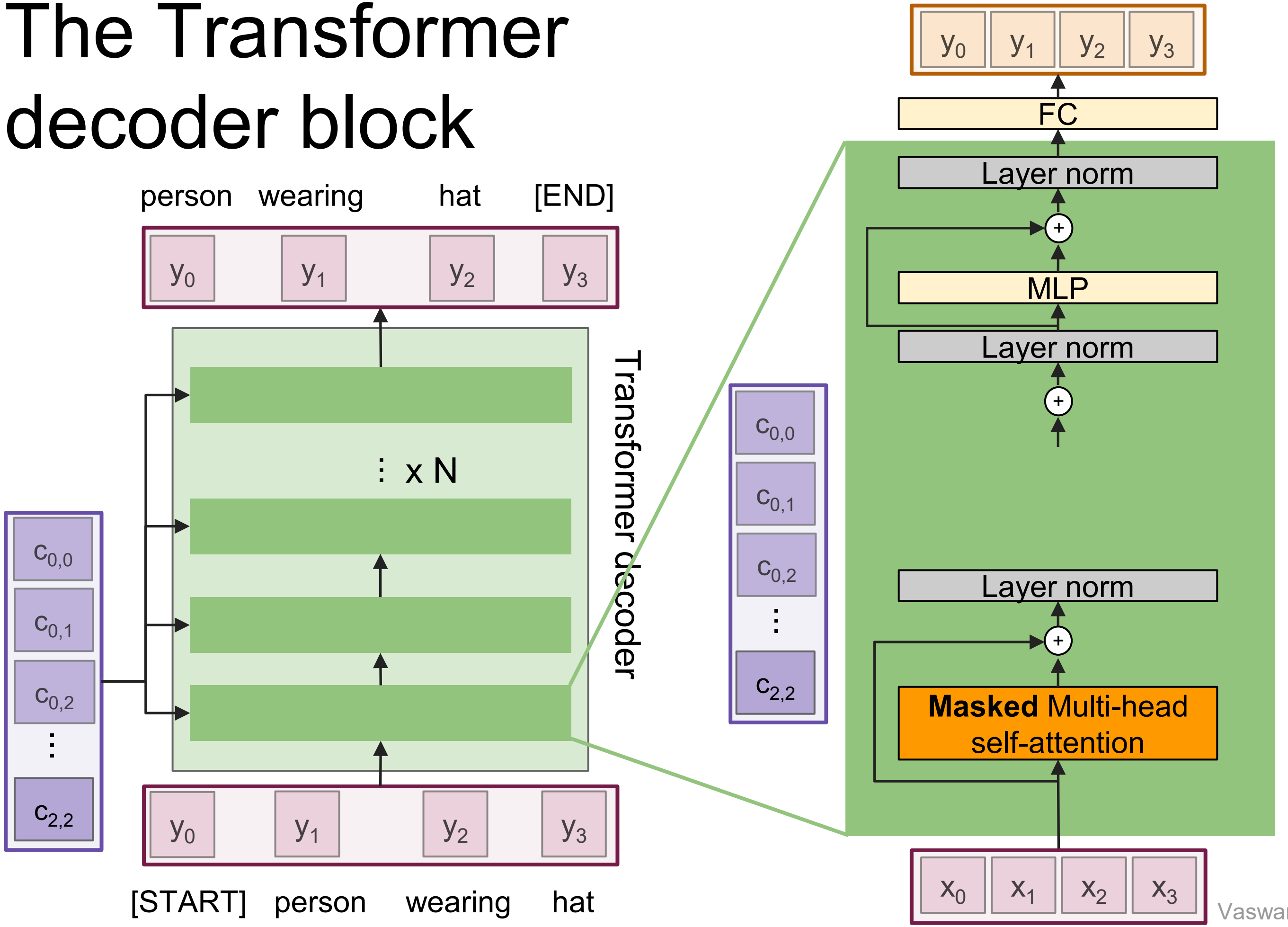
# The Transformer decoder block




Let's dive into the transformer decoder block

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

# The Transformer decoder block

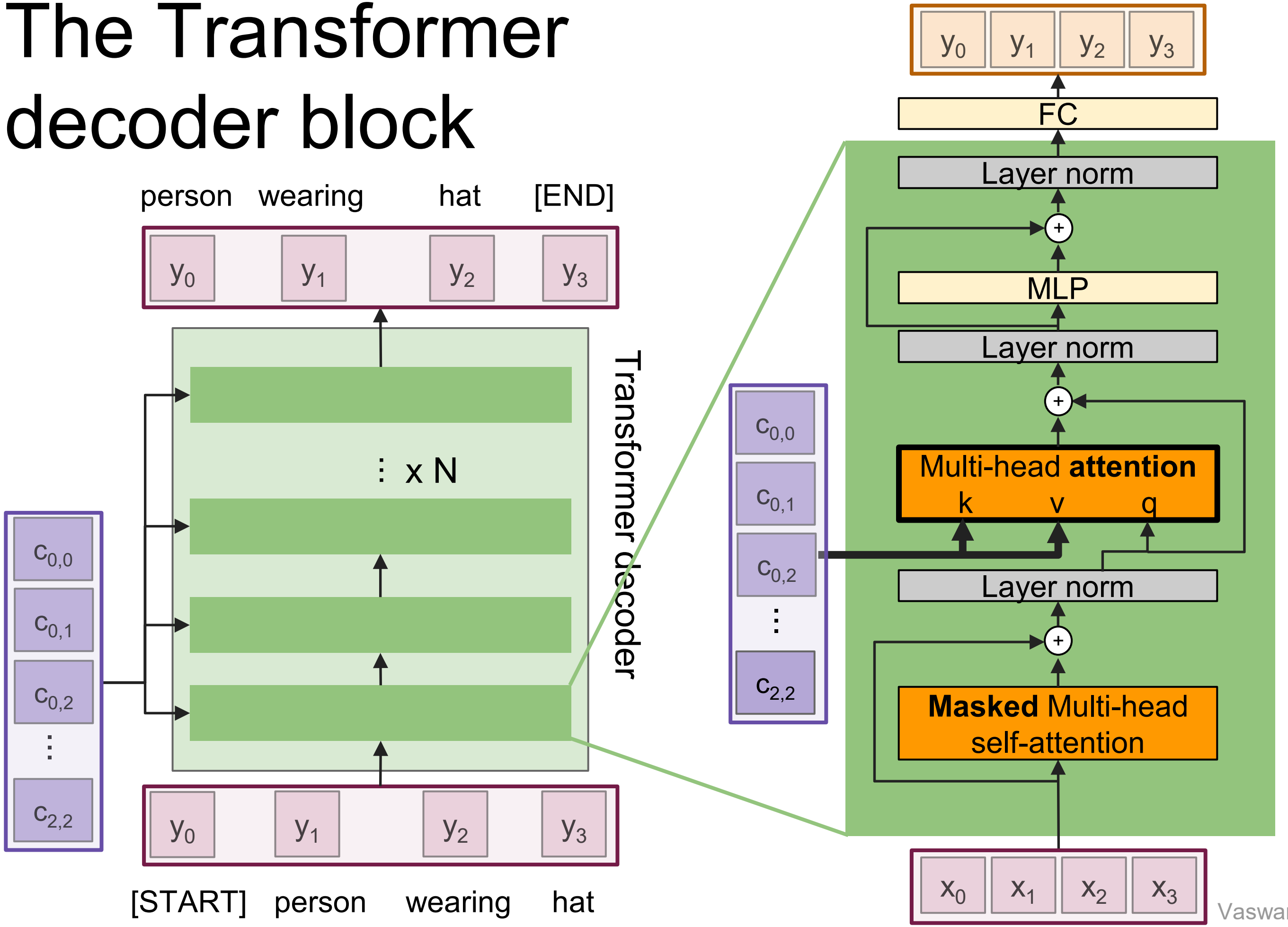



Most of the network is the same the transformer encoder.

Ensures we only look at the previous tokens (teacher forcing during training)

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

# The Transformer decoder block

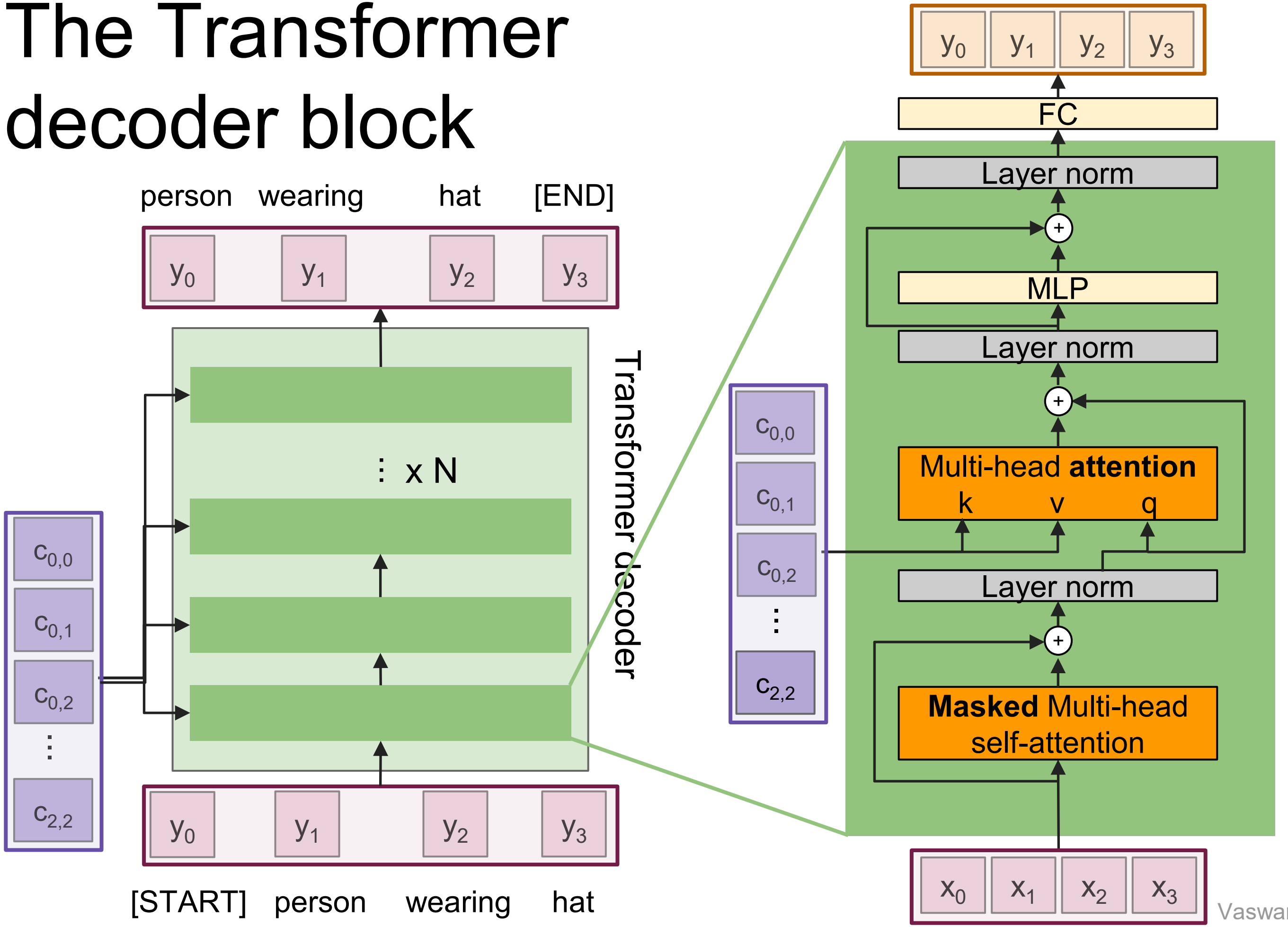



Multi-head attention block attends over the transformer encoder outputs.

For image captioning, this is how we inject image features into the decoder.

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

# The Transformer decoder block




**Transformer Decoder Block:**

**Inputs**: Set of vectors **x** and Set of context vectors **c.**
**Outputs**: Set of vectors **y.**

Masked Self-attention only interacts with past inputs.

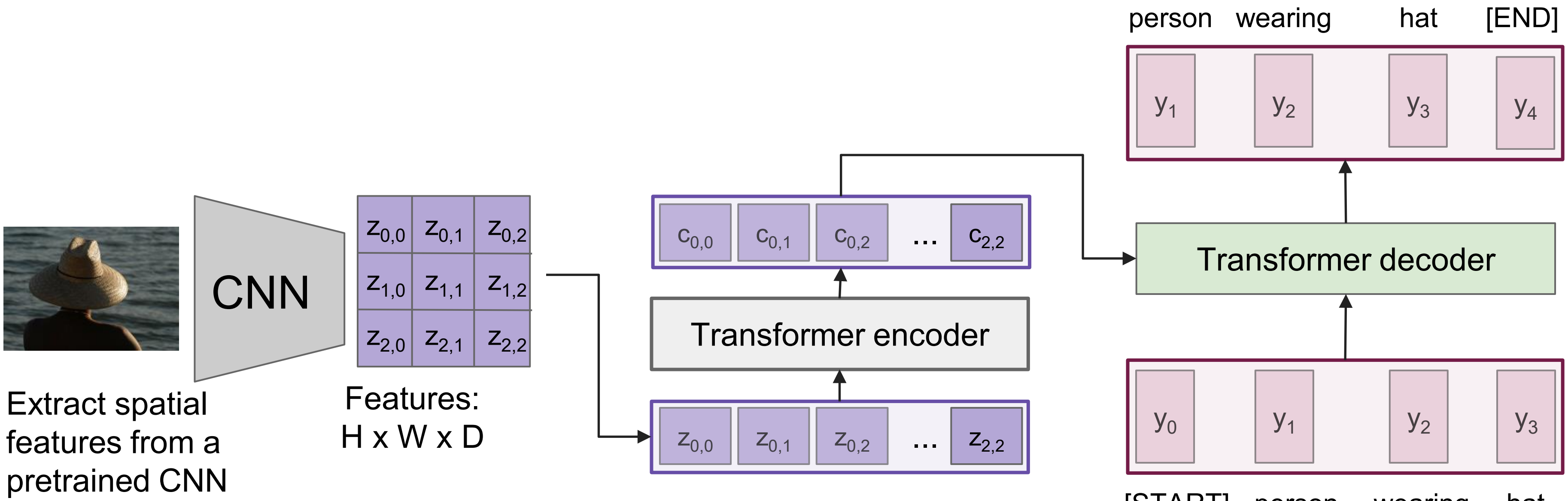
Multi-head attention block is NOT self-attention. It attends over encoder outputs.

Highly scalable, highly parallelizable, but high memory usage.

Vaswani et al, “Attention is all you need”, NeurIPS 2017

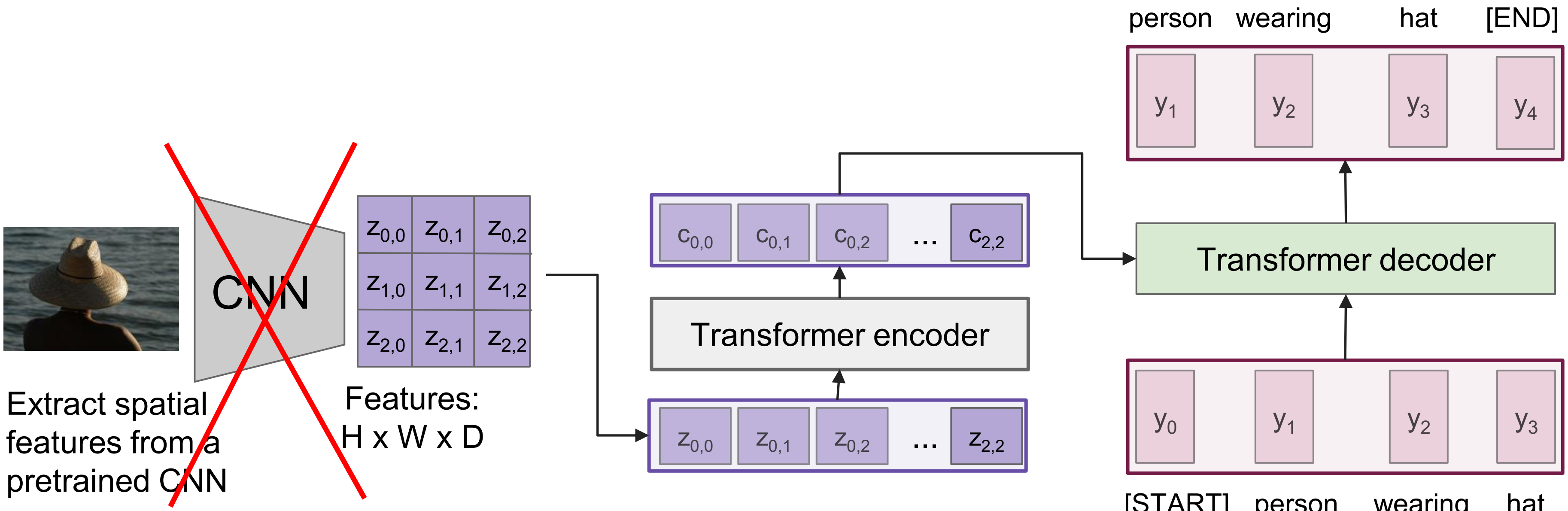
# Image Captioning using transformers

- **No recurrence at all**



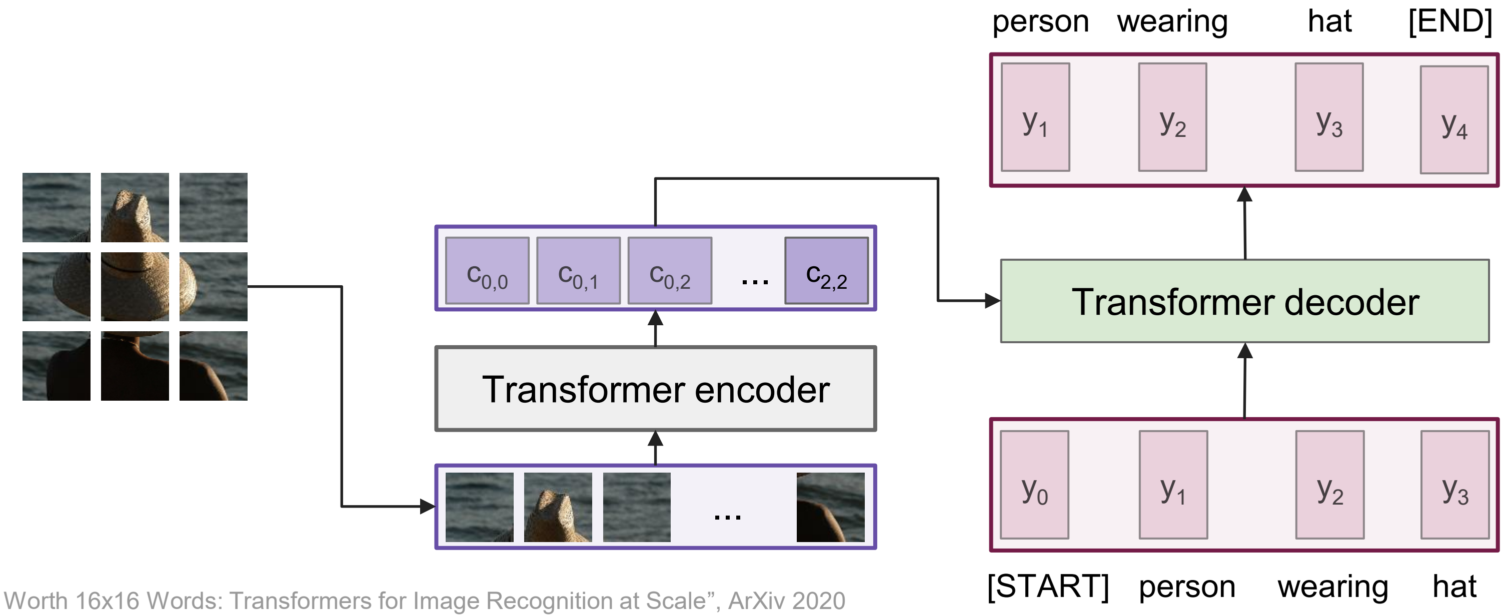
# Image Captioning using transformers

- **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

# ViTs – Vision Transformers

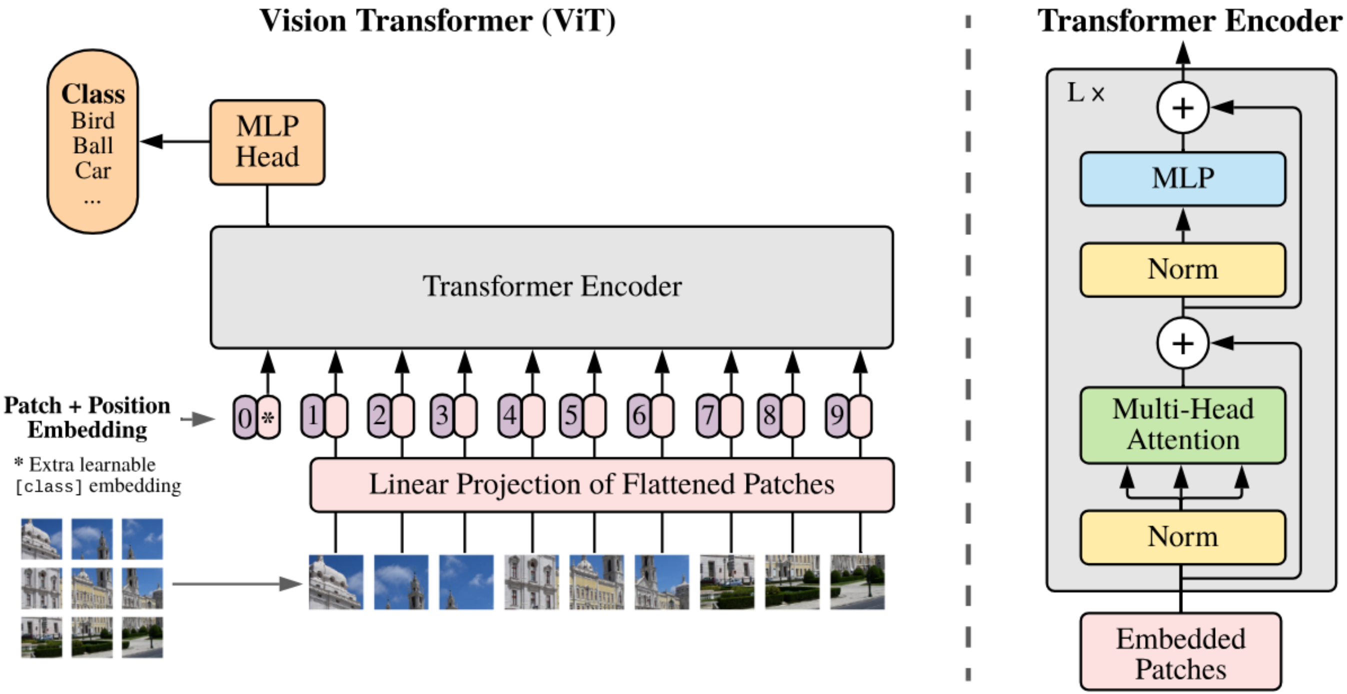



Figure from:
Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ArXiv 2020

# Vision Transformers vs. ResNets

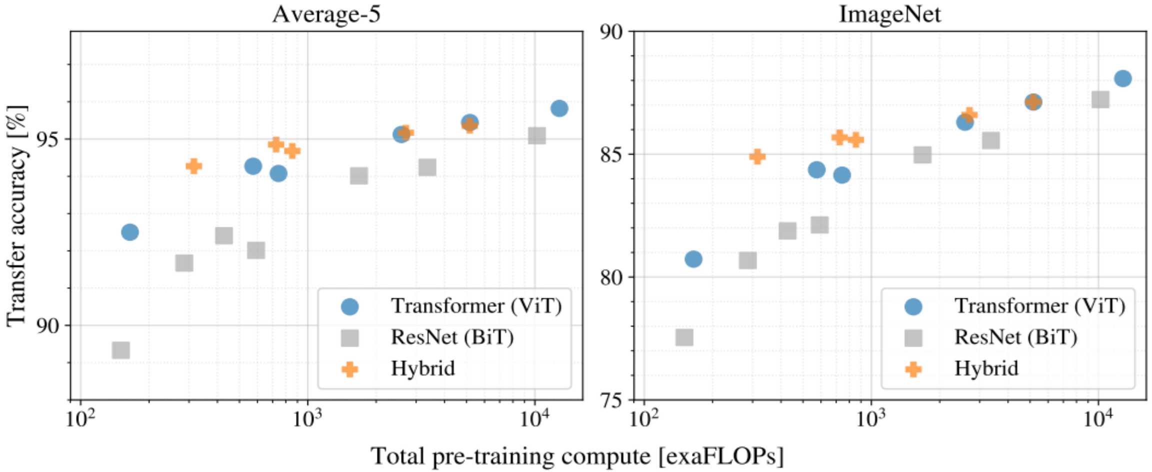
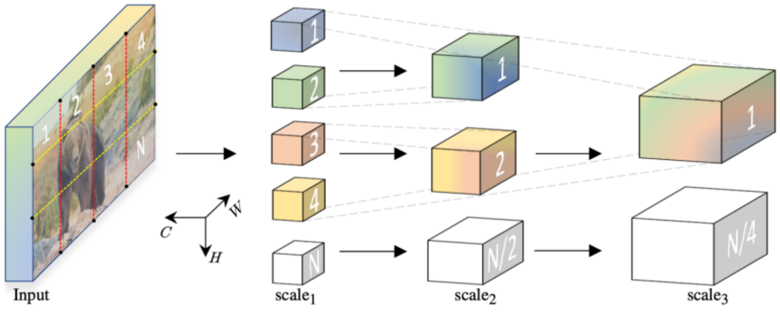



Figure 5: Performance versus cost for different architectures: Vision Transformers, ResNets, and hybrids. Vision Transformers generally outperform ResNets with the same computational budget. Hybrids improve upon pure Transformers for smaller model sizes, but the gap vanishes for larger models.

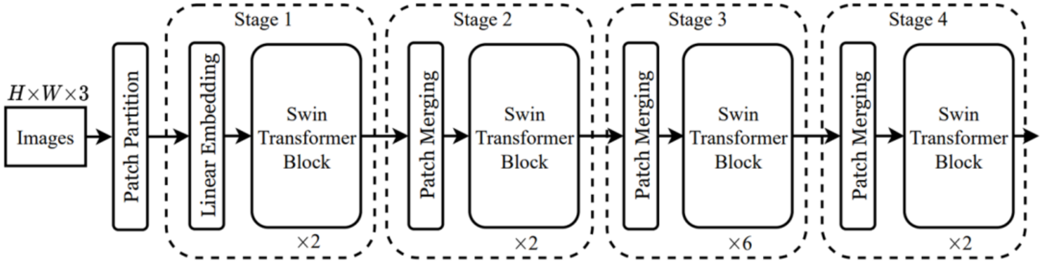
Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ArXiv 2020

Colab link to an implementation of vision transformers

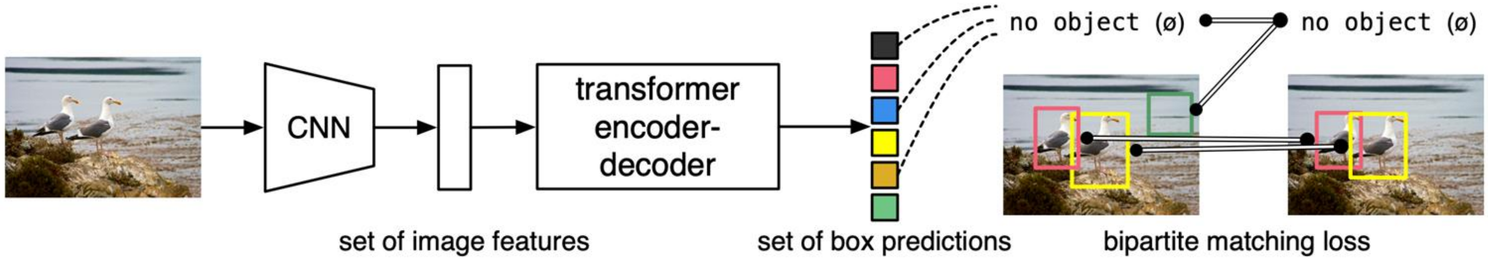
# Vision Transformers




Fan et al, “Multiscale Vision Transformers”, ICCV 2021

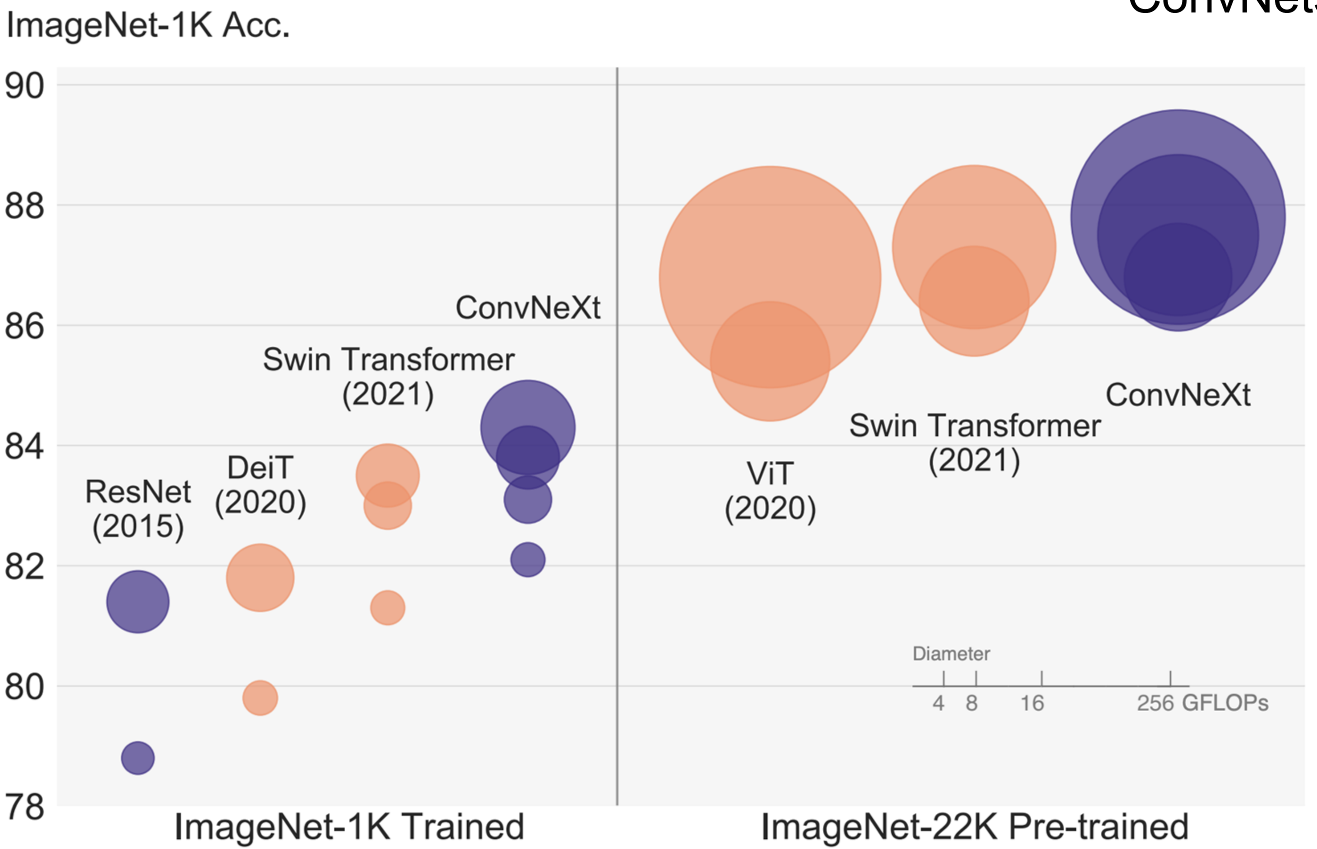



Liu et al, “Swin Transformer: Hierarchical Vision Transformer using Shifted Windows”, CVPR 2021




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

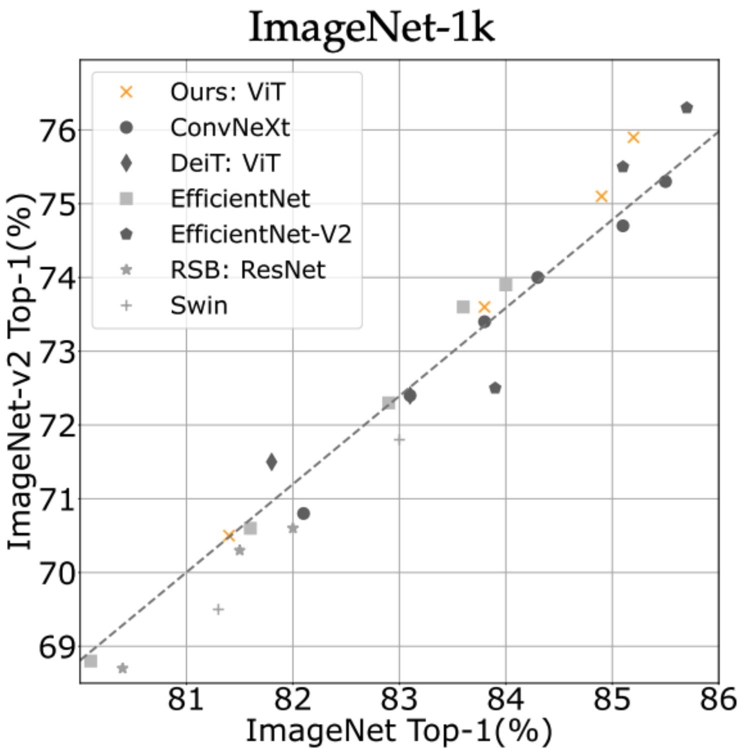
ConvNets strike back!

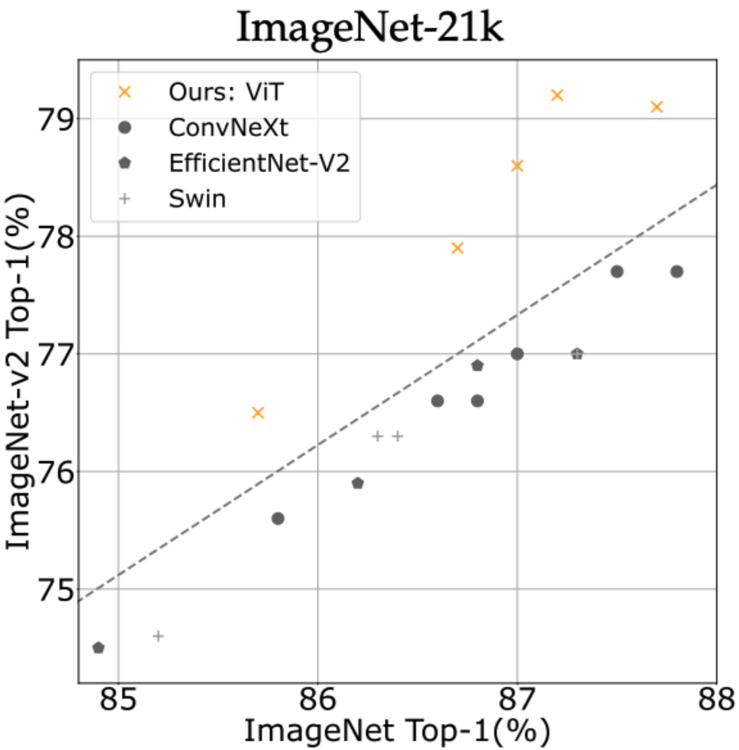



A ConvNet for the 2020s. Liu et al. CVPR 2022

# DeiT III: Revenge of the ViT

Hugo Touvron[*,†] Matthieu Cord[†] Hervé Jégou[*]



# 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.
  - It is highly **scalable** and highly **parallelizable**
  - **Faster** training, **larger** models, **better** performance across vision and language tasks
  - They are quickly replacing RNNs, LSTMs, and may(?) even replace convolutions.

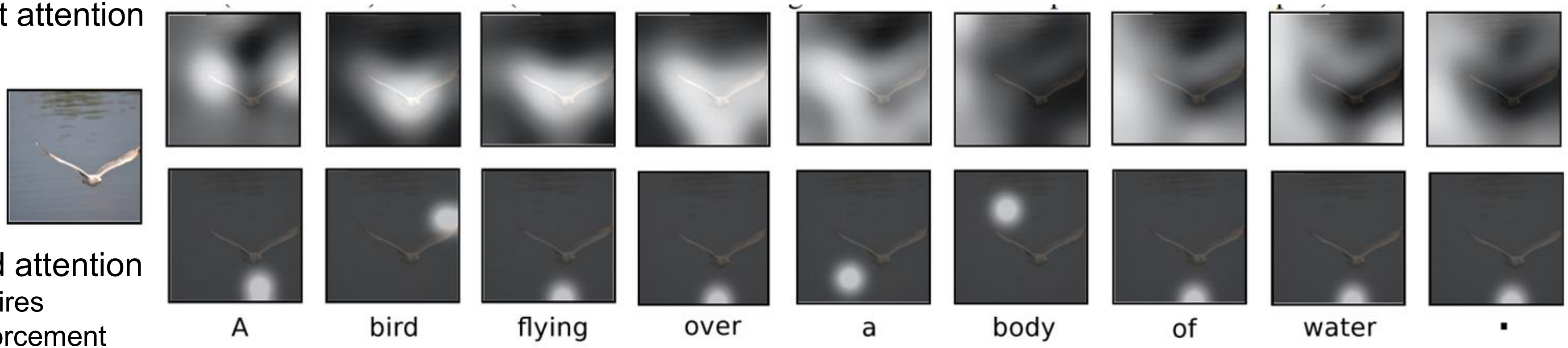
Next time: Object Detection + Segmentation

Appendix Slides from Previous Years

# Image Captioning with Attention

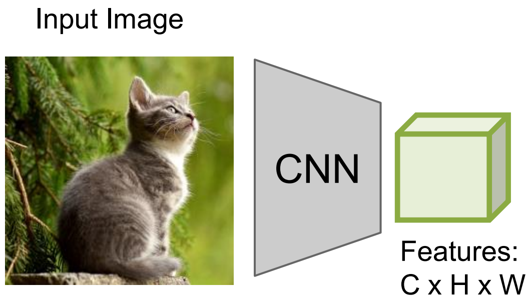
Soft attention

Hard attention
(requires
reinforcement
learning)




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

# Example: CNN with Self-Attention

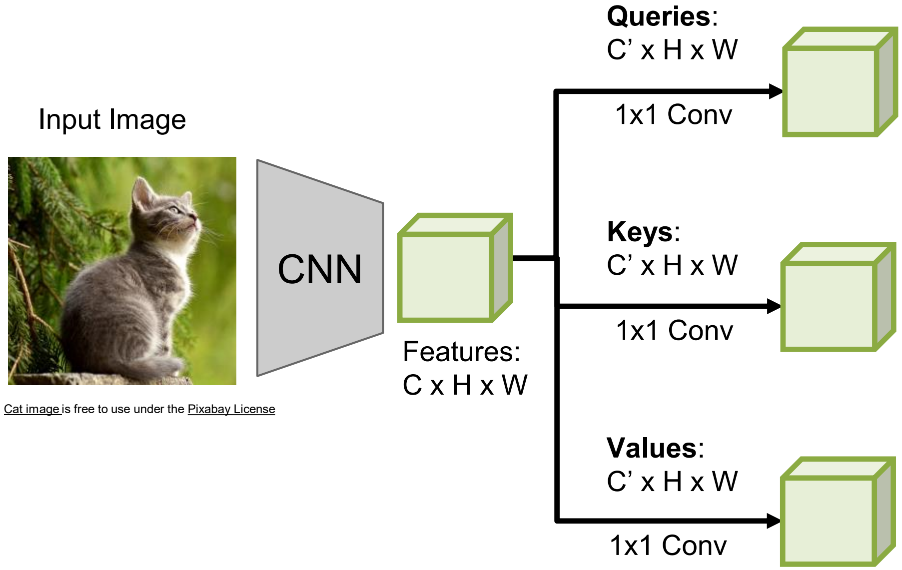





Zhang et al, “Self-Attention Generative Adversarial Networks”, ICML 2018

Slide credit: Justin Johnson

# Example: CNN with Self-Attention

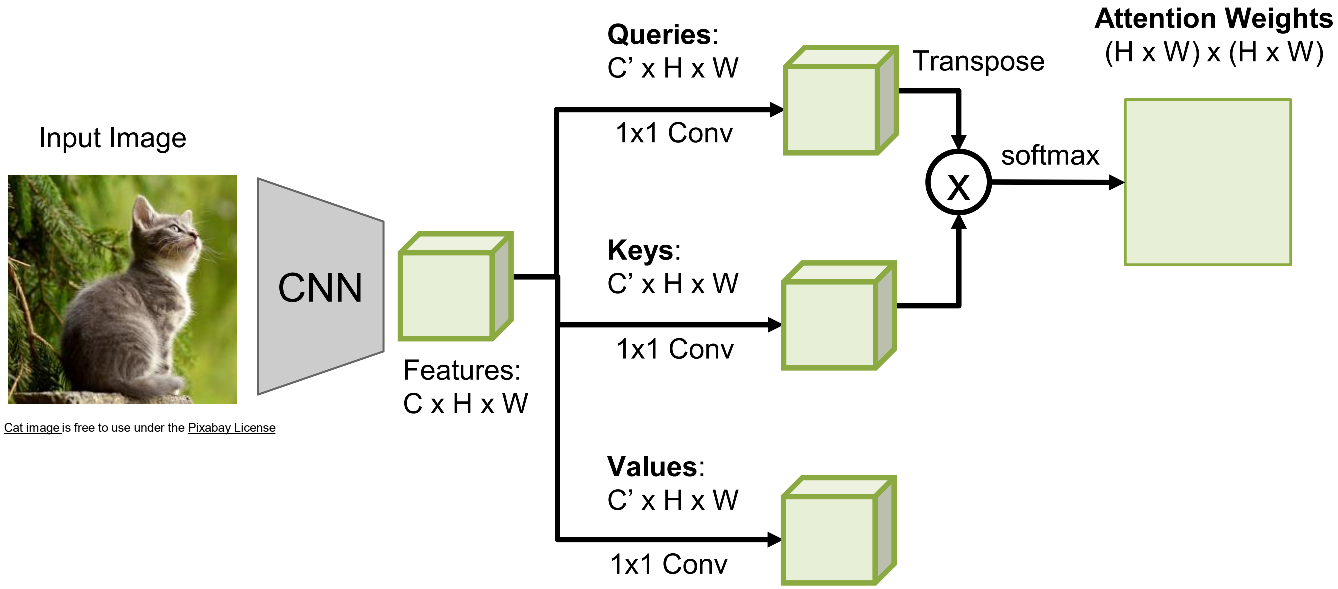





Zhang et al, "Self-Attention Generative Adversarial Networks", ICML 2018

Slide credit: Justin Johnson

# Example: CNN with Self-Attention

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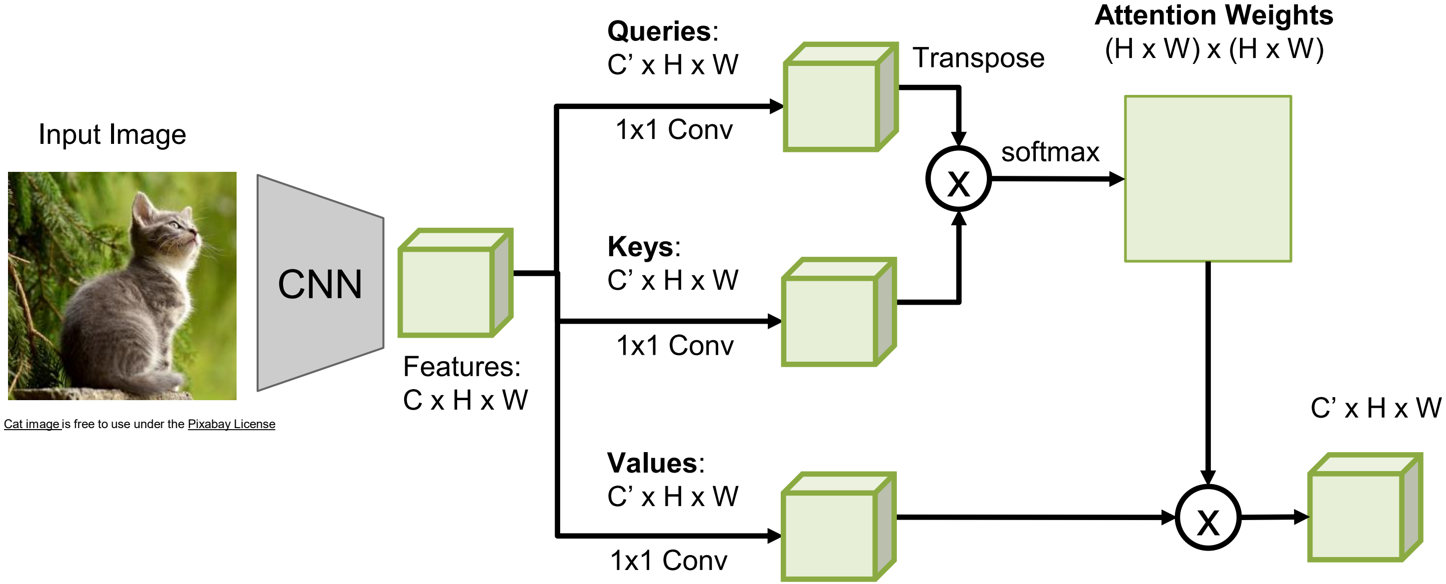
Zhang et al, "Self-Attention Generative Adversarial Networks", ICML 2018

Slide credit: Justin Johnson

# Example: CNN with Self-Attention

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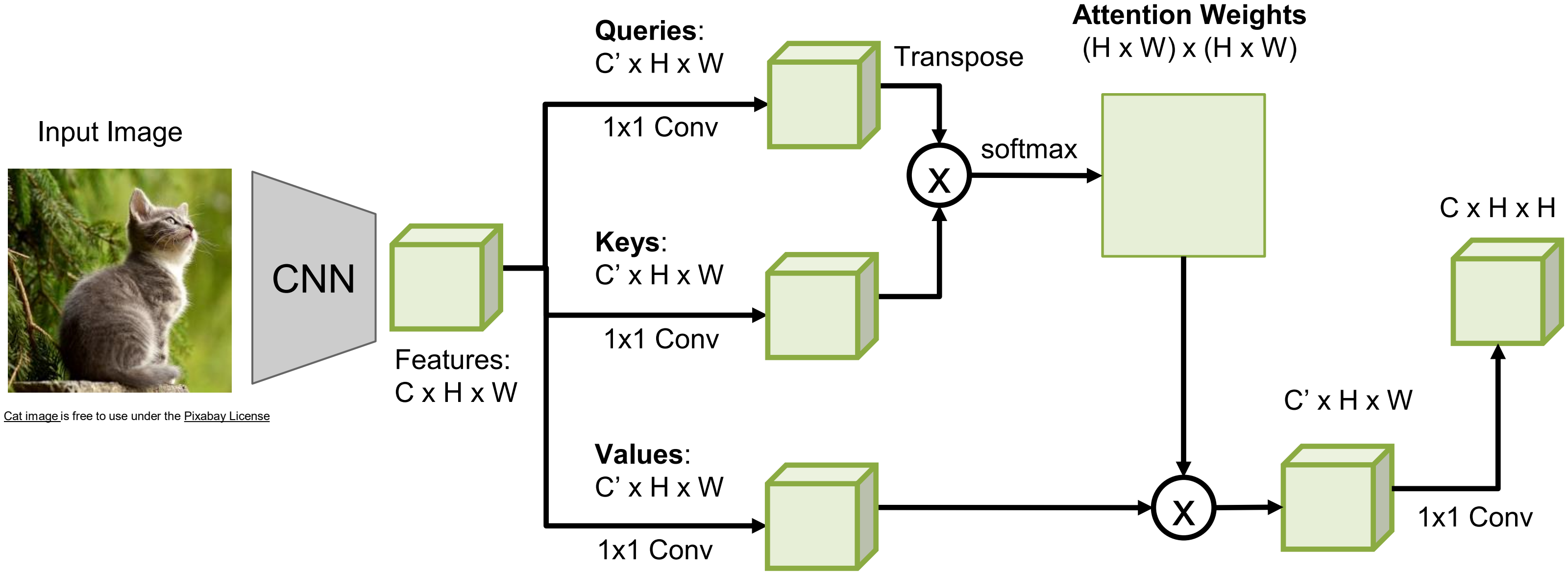
Slide credit: Justin Johnson

# Example: CNN with Self-Attention






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

Slide credit: Justin Johnson

# Example: CNN with Self-Attention

Input Image

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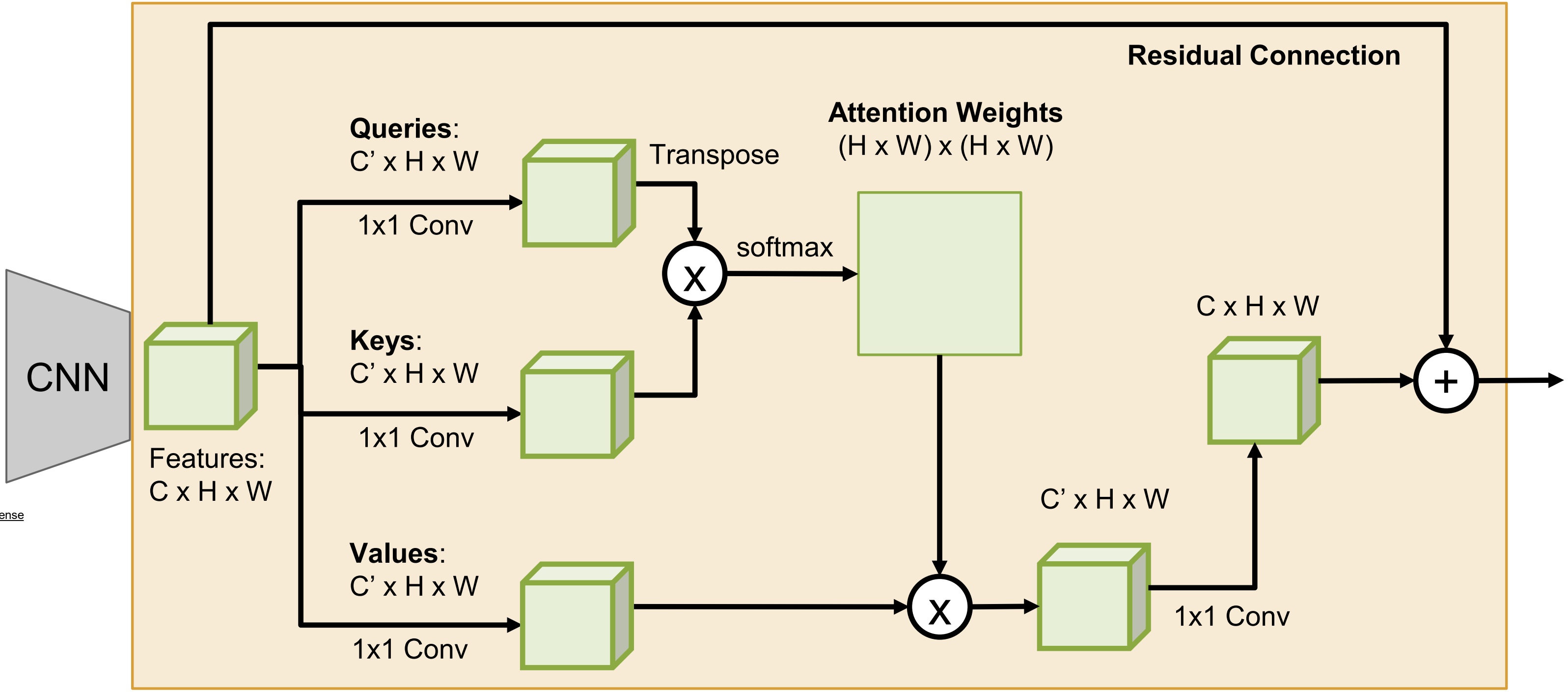


Self-Attention Module

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

Slide credit: Justin Johnson