Computer Vision – TP15
Attention

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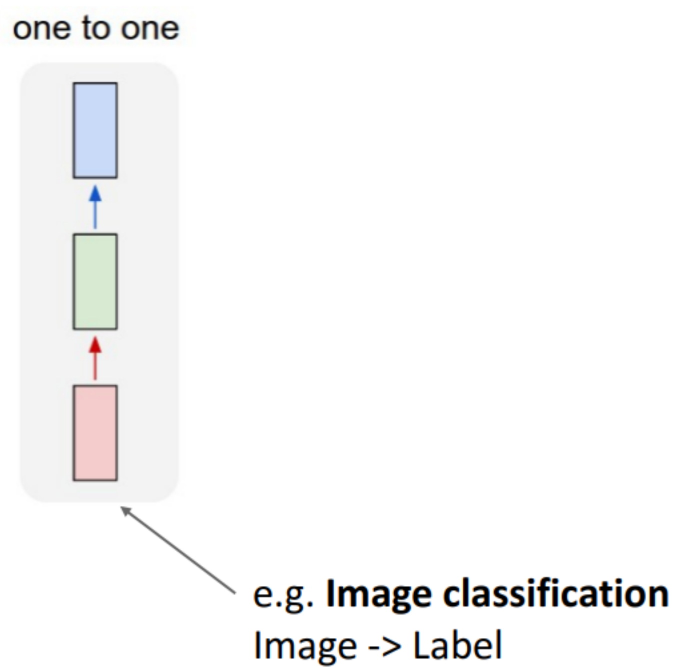
U.PORTO FC

Outline

- RNN
- Attention
- Transformers

Recurrent Neural Networks

- So far: “Feedforward” Neural Networks



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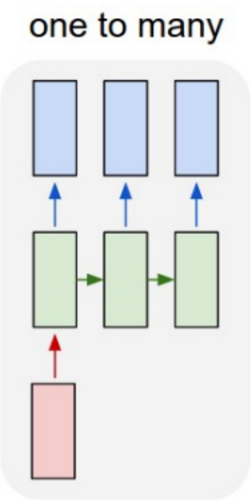
RNN: Examples



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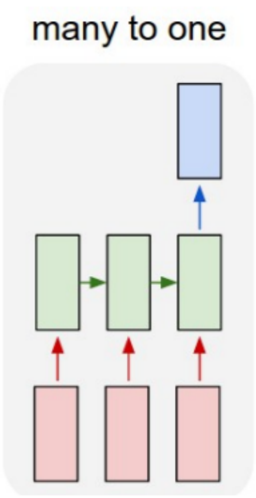
RNN: Examples



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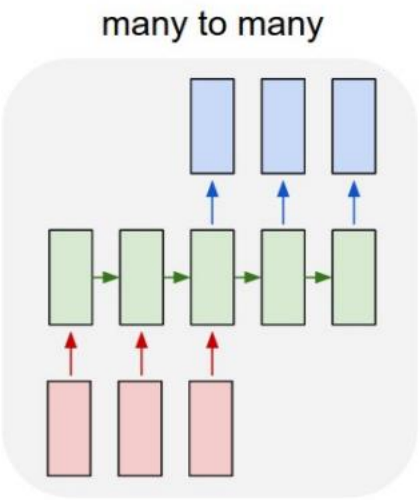
RNN: Examples



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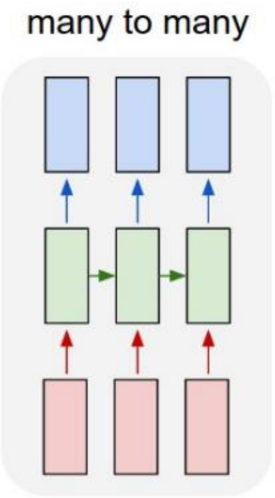
RNN: Examples



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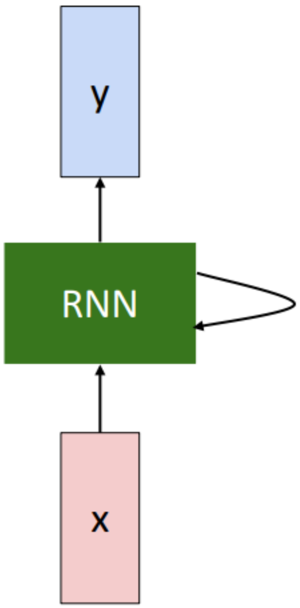
RNN: formulation



$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function
with parameters W

old state

input vector at
some time step

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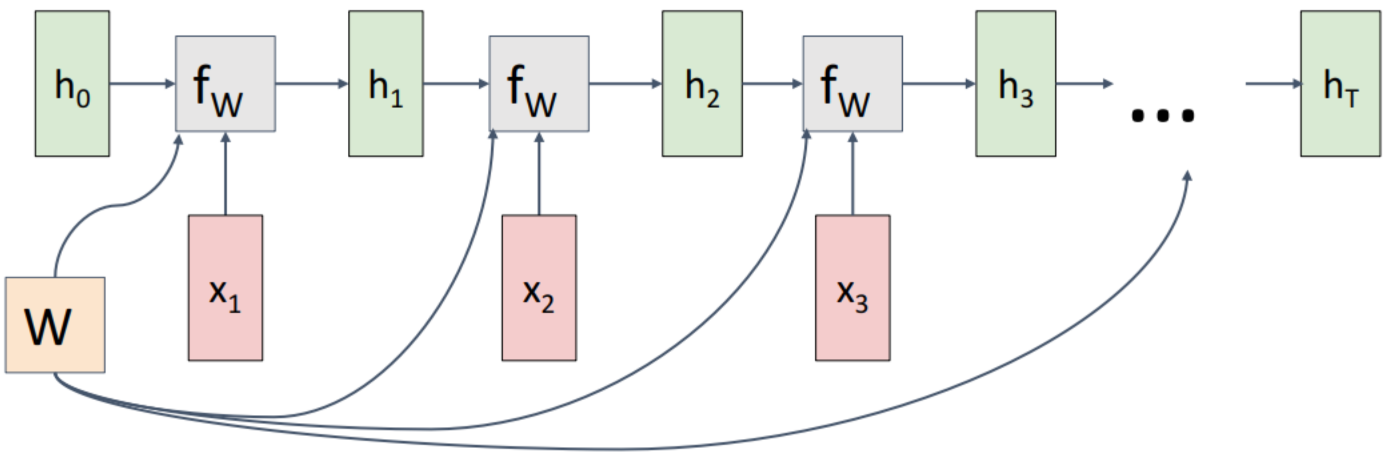
RNN: Computational Graph

- Re-use the same weight matrix at every time-step

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state
old state
input vector at some time step
some function with parameters W



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RNN: Computational Graph (many to many)

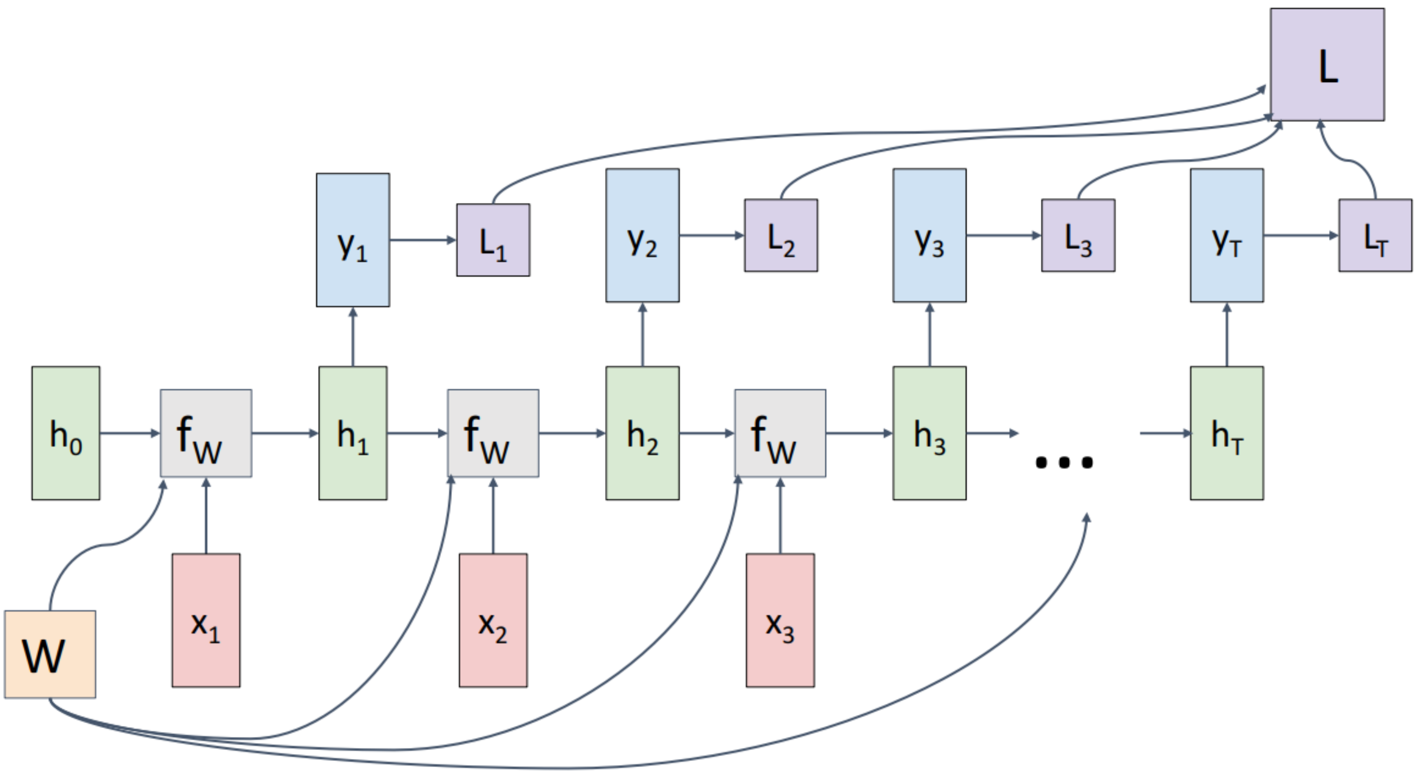
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

input vector at some time step

some function with parameters W



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RNN: Computational Graph (many to one)

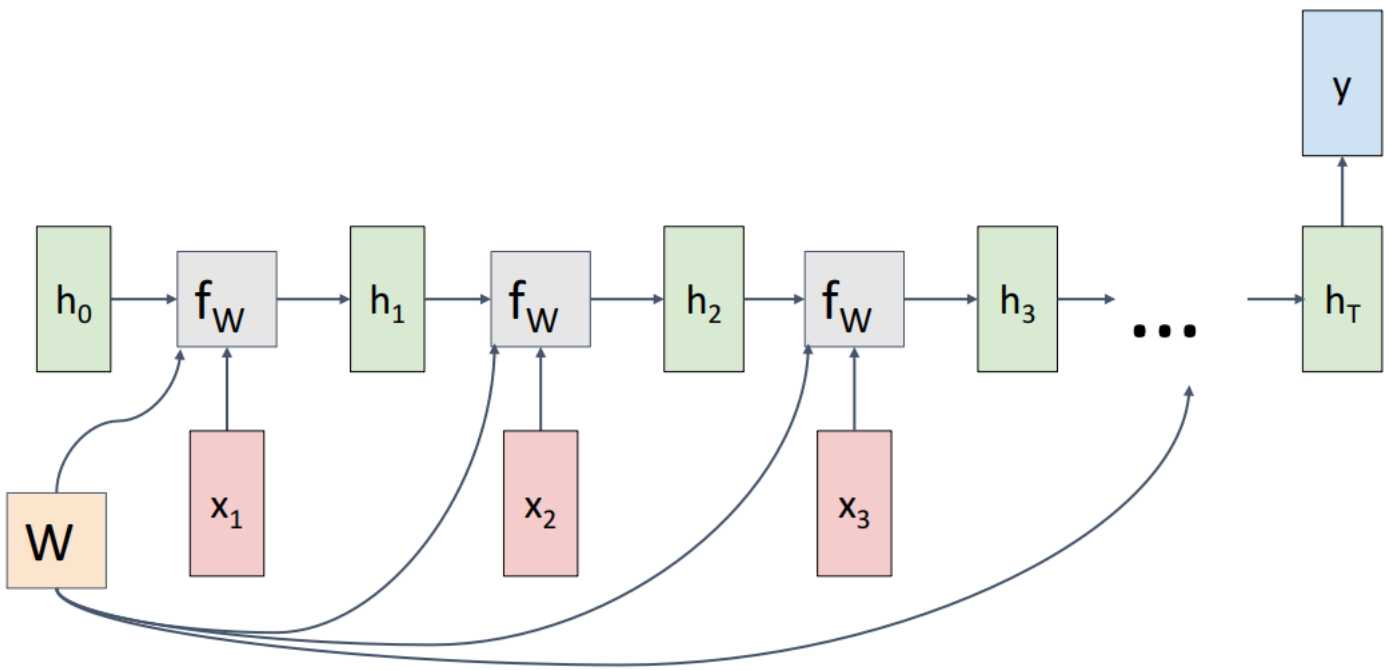
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

input vector at some time step

some function with parameters W



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RNN: Computational Graph (One to many)

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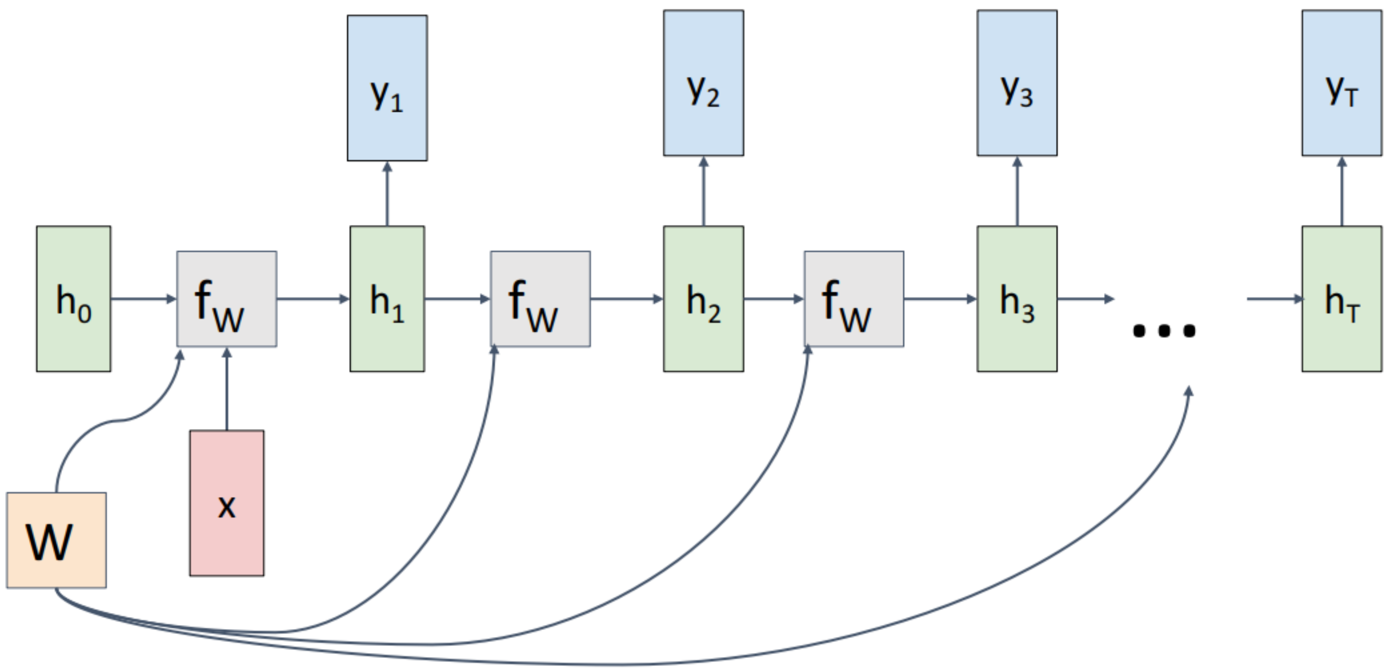
new state

old state

input vector at some time step

some function with parameters W



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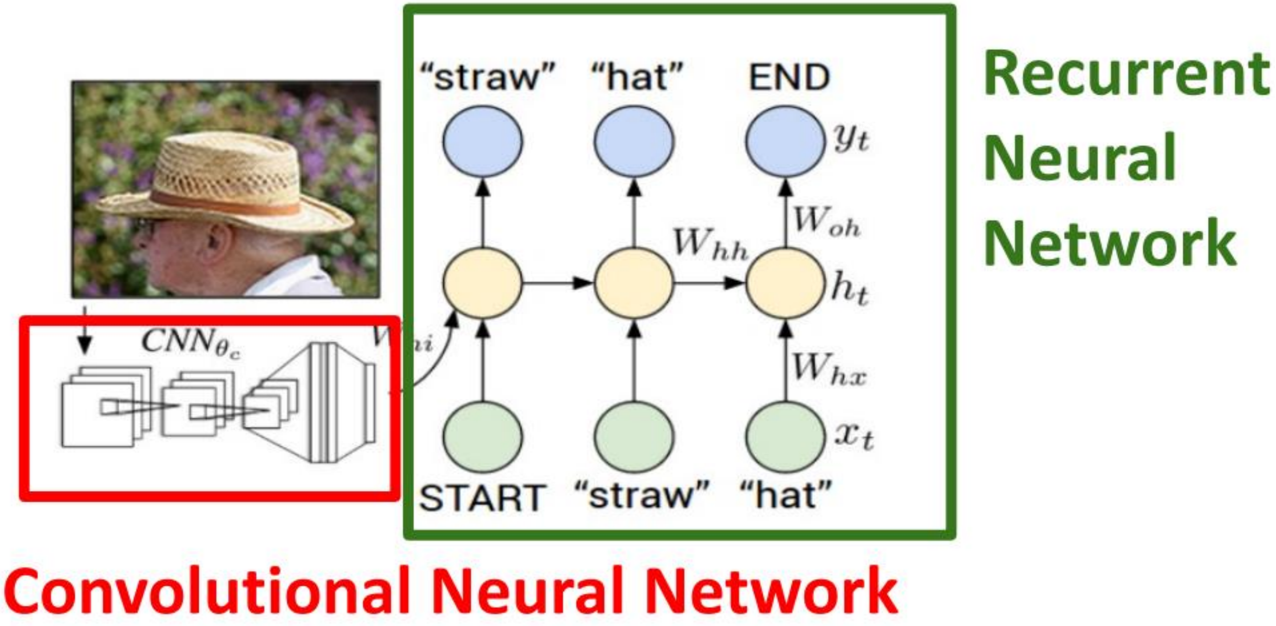
Examples: Image Captioning



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Examples: Image Captioning

A cat sitting on a suitcase on the floor

A cat is sitting on a tree branch

A dog is running in the grass with a frisbee

A white teddy bear sitting in the grass

Two people walking on the beach with surfboards

A tennis player in action on the court

Two giraffes standing in a grassy field

A man riding a dirt bike on a dirt track

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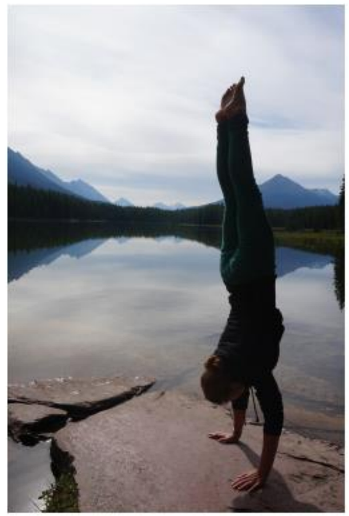
Examples: Image Captioning

A woman is holding a cat in her hand

A person holding a computer mouse on a desk



A woman standing on a beach holding a surfboard

A bird is perched on a tree branch

A man in a baseball uniform throwing a ball

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RNN: Sequence to Sequence

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

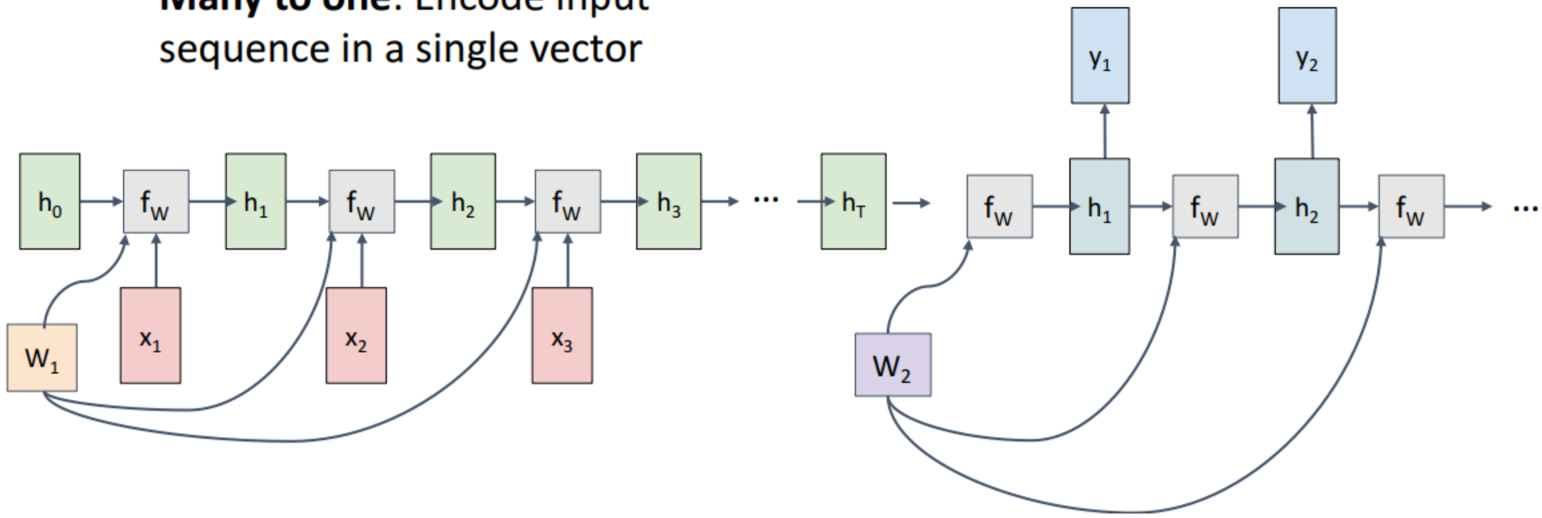
old state

input vector at some time step

some function with parameters W

One to many: Produce output sequence from single input vector

Many to one: Encode input sequence in a single vector



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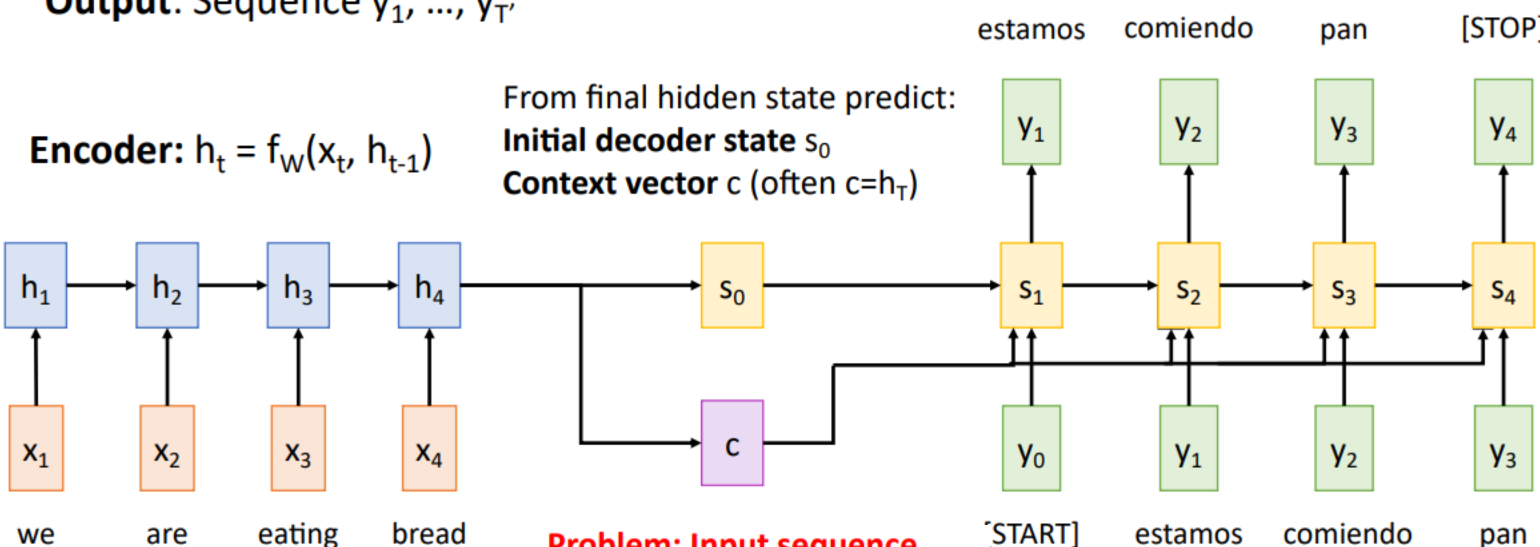
RNN: Sequence to Sequence

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

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

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?

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

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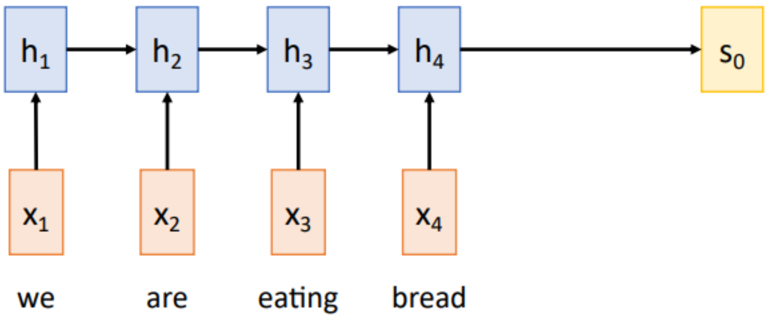
RNN: Sequence to Sequence and Attention

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



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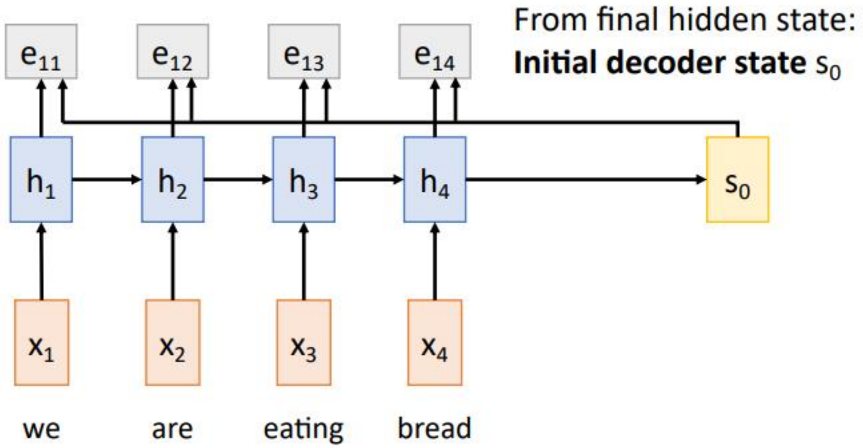
RNN: Sequence to Sequence and Attention

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



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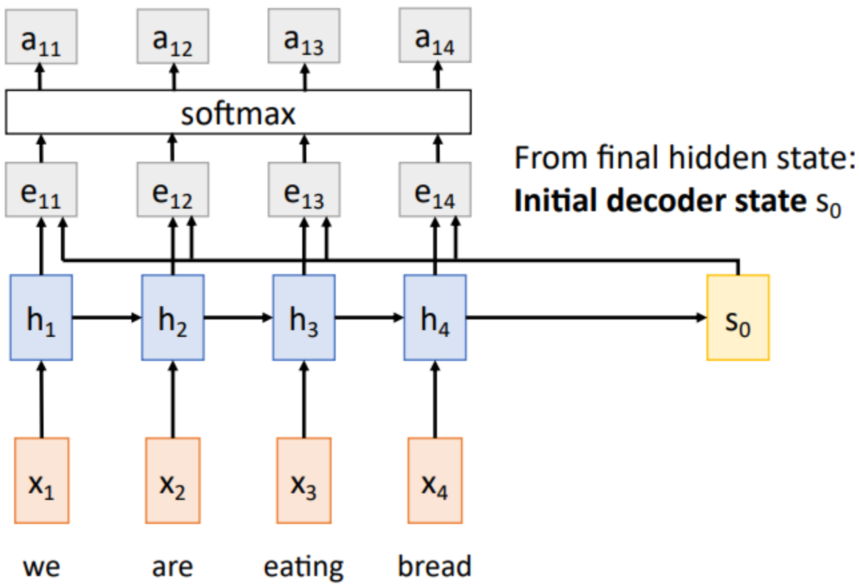
RNN: Sequence to Sequence and Attention



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**
$0 < a_{t,i} < 1$ $\sum_i a_{t,i} = 1$

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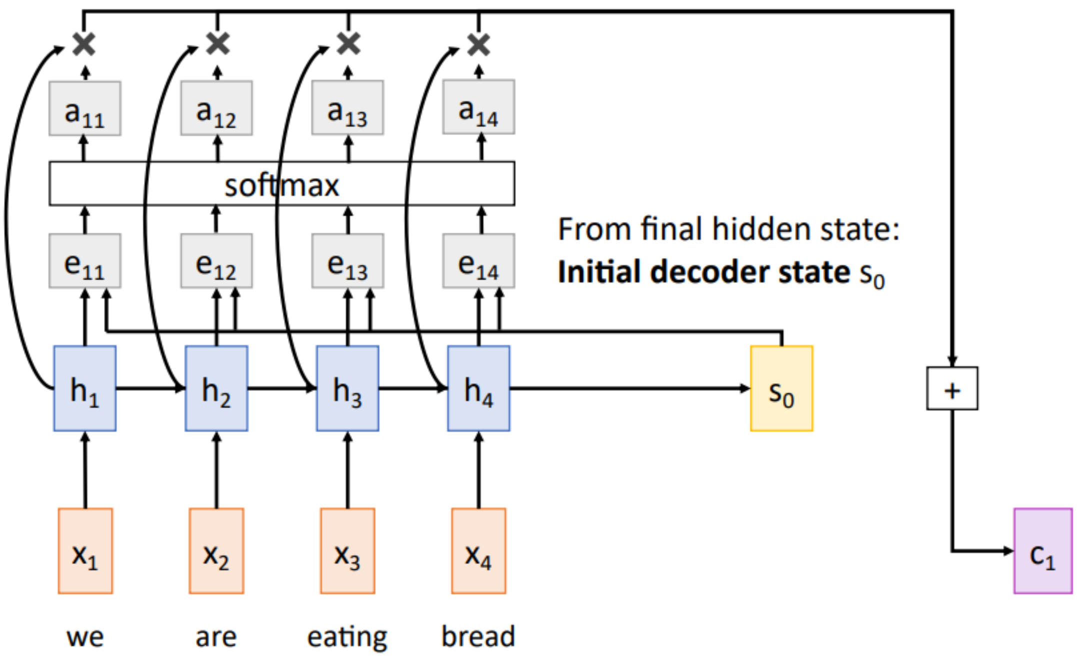
RNN: Sequence to Sequence and Attention



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Compute context vector as linear combination of hidden states
$c_t = \sum_i a_{t,i} h_i$

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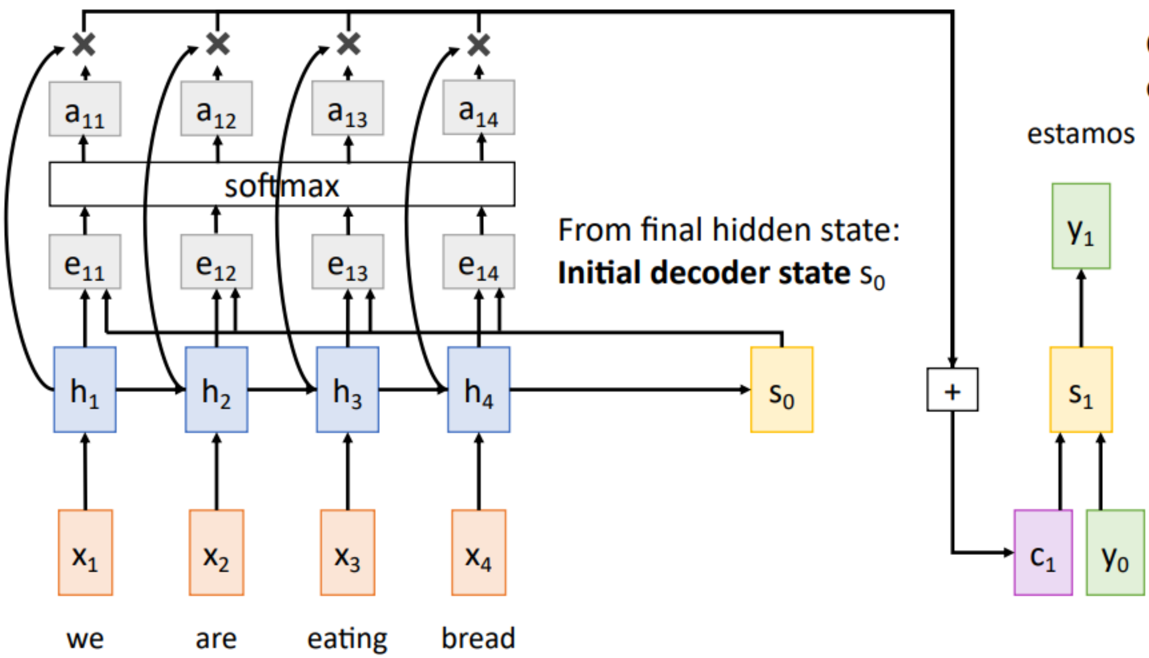
RNN: Sequence to Sequence and Attention



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Compute context vector as linear combination of hidden states
$c_t = \sum_i a_{t,i} h_i$

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

This is all differentiable! Do not supervise attention weights – backprop through everything

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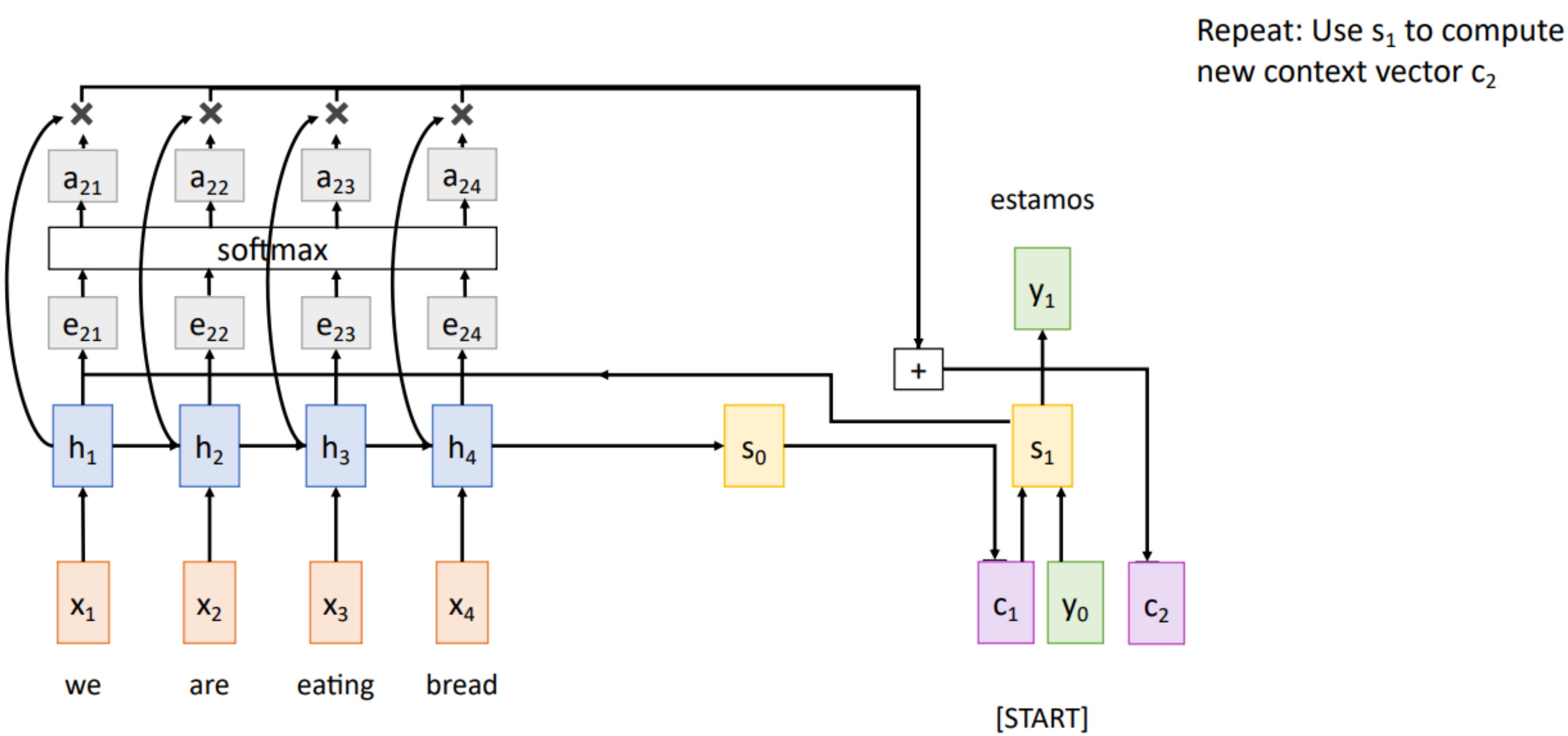
RNN: Sequence to Sequence and Attention



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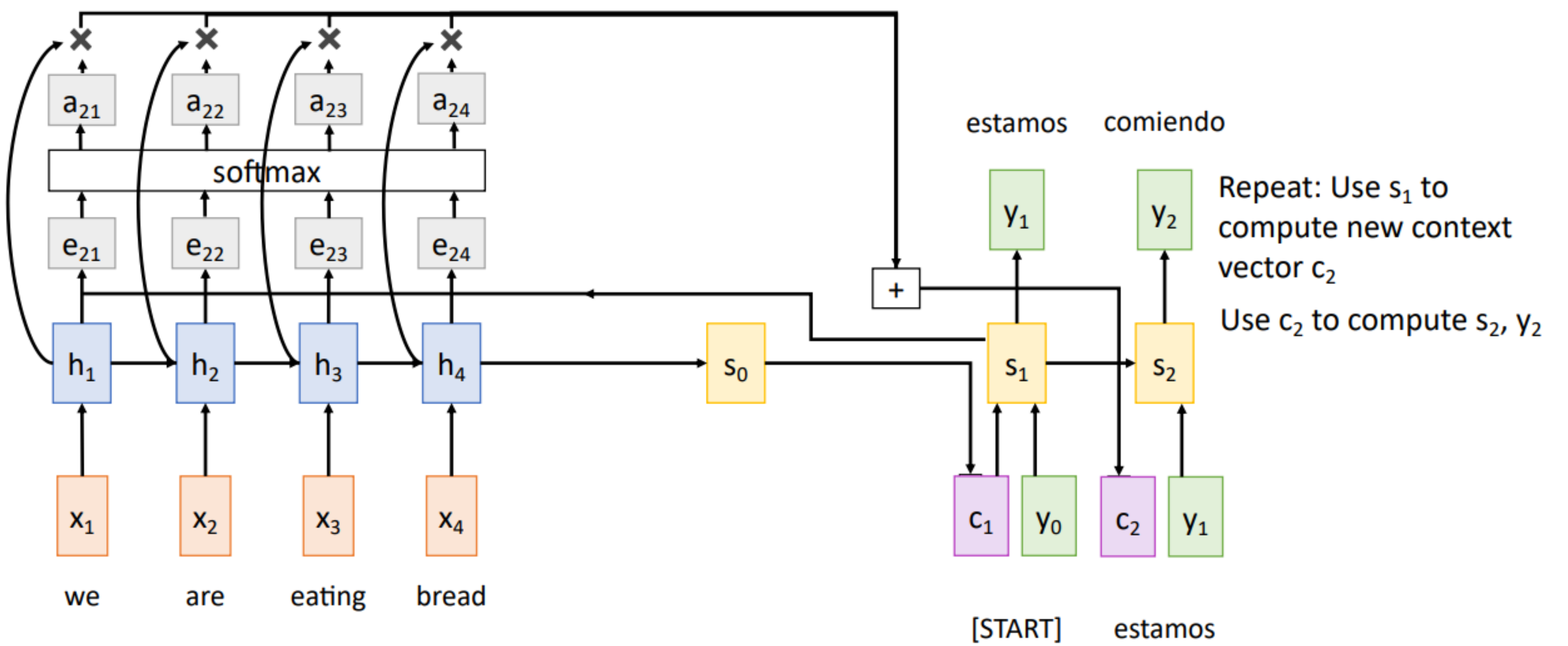

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RNN: Sequence to Sequence and Attention

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

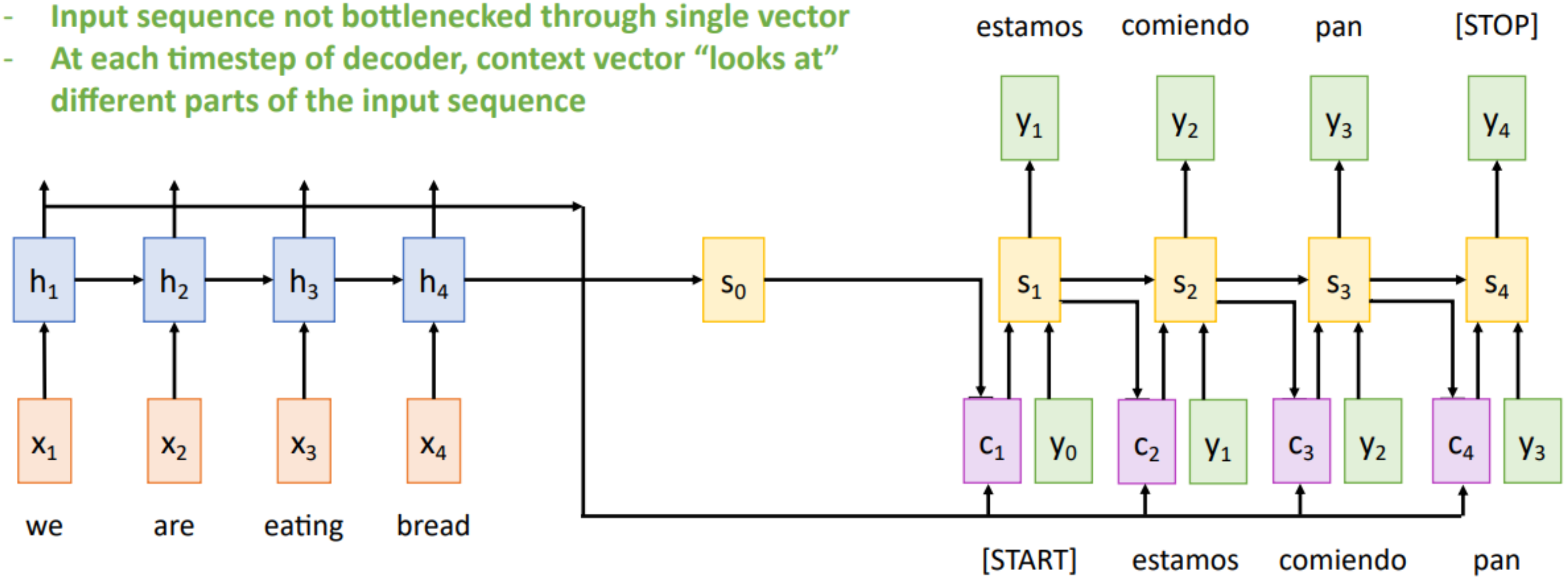

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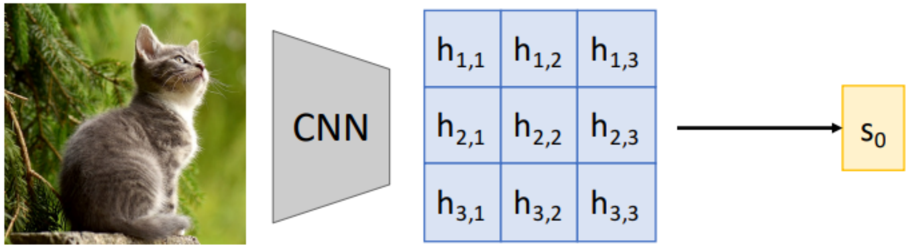
Image Captioning with RNNs and Attention



Use a CNN to compute a grid of features for an image

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Image Captioning with RNNs and Attention

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

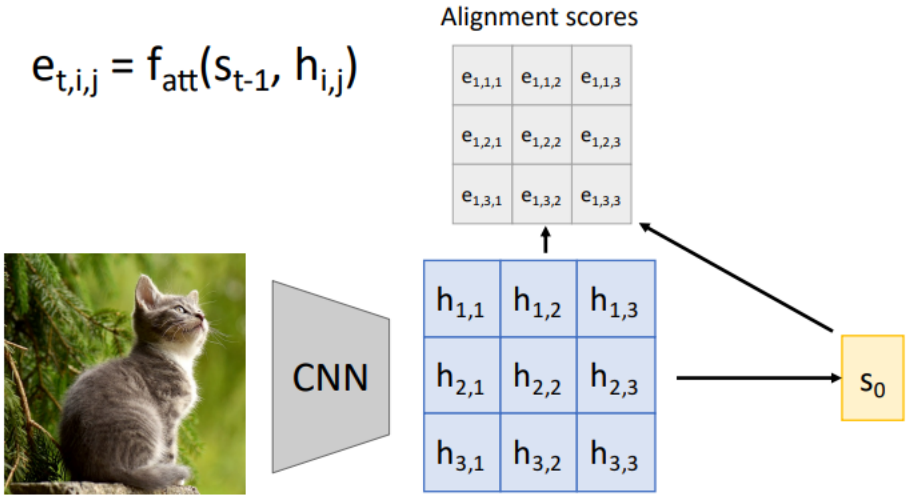

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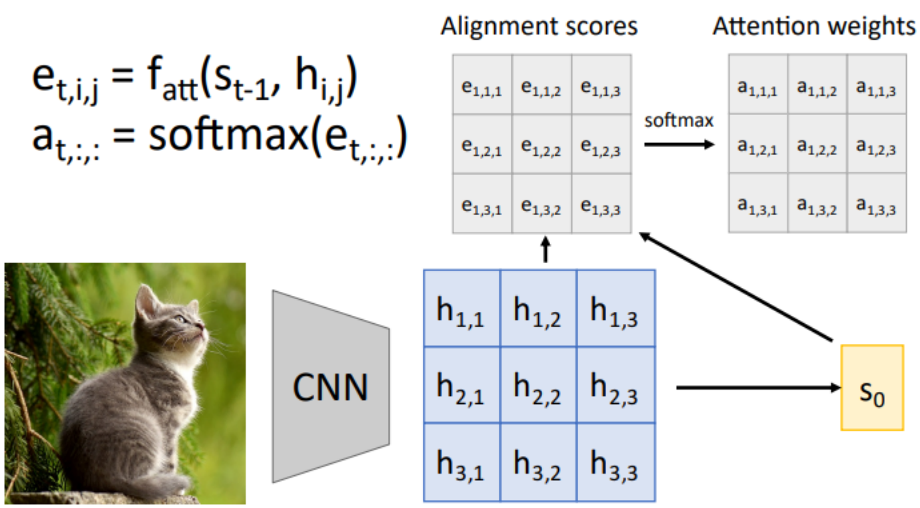
Image Captioning with RNNs and Attention

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



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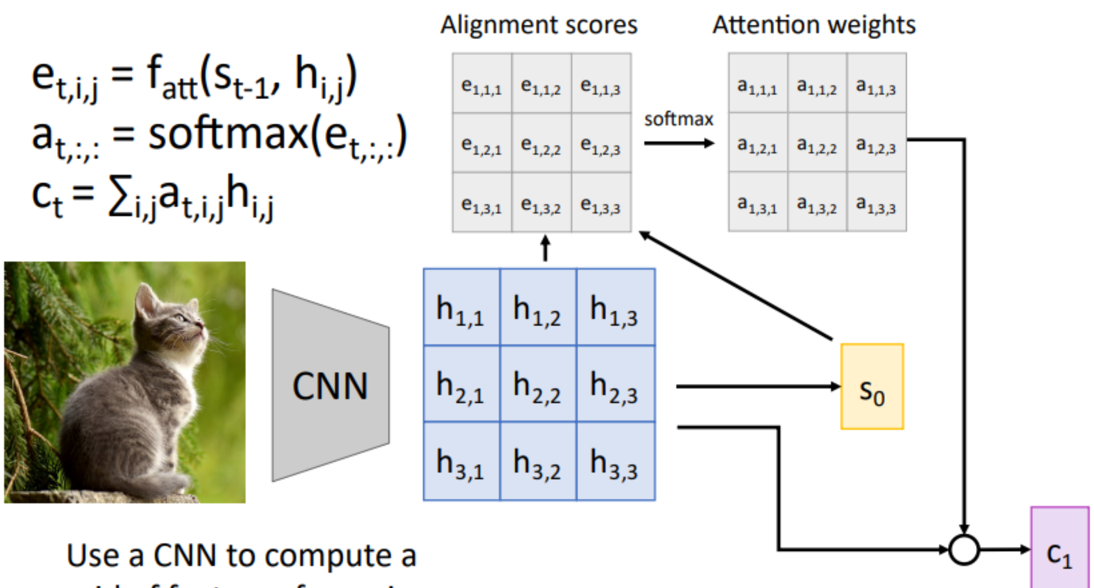

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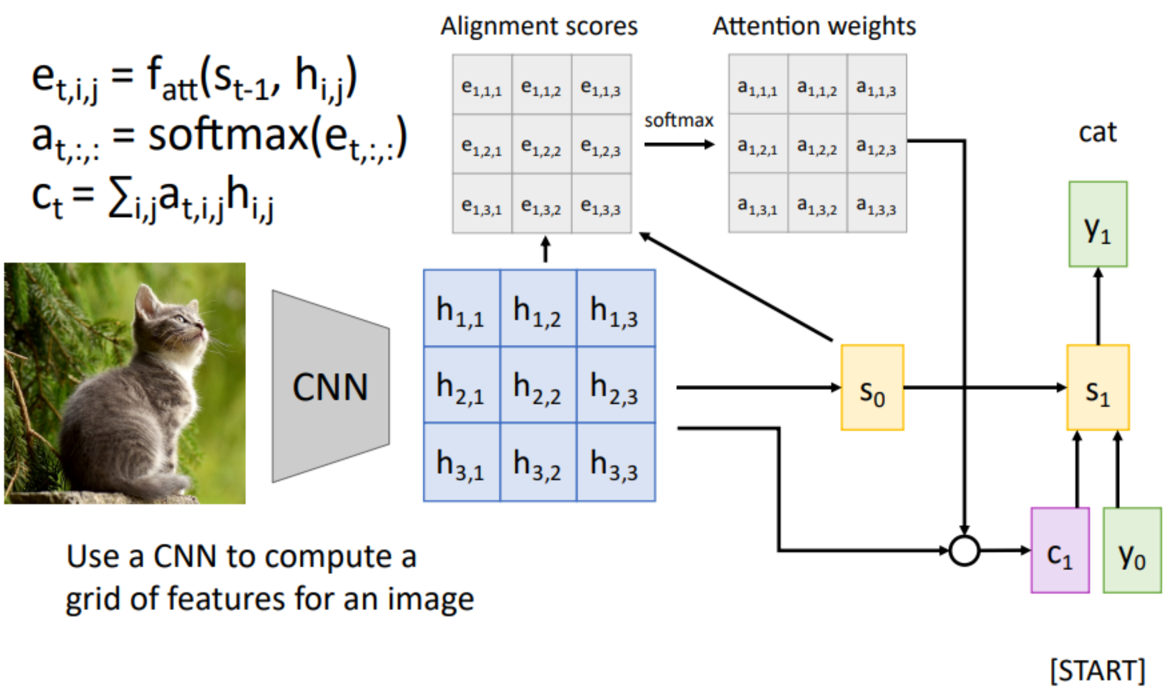

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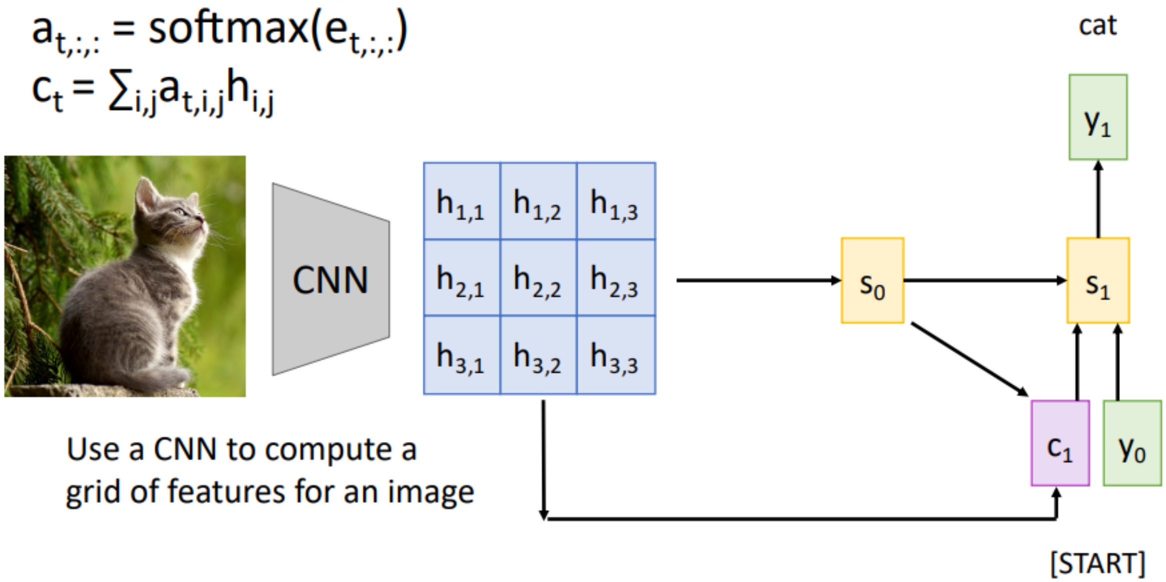

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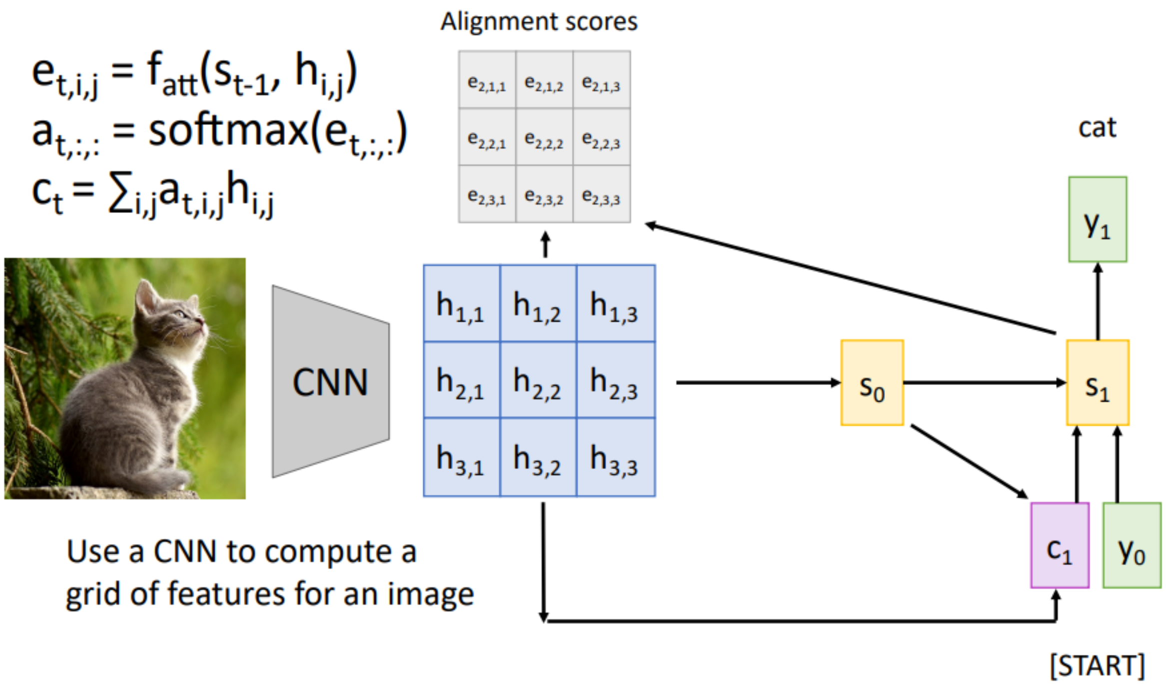

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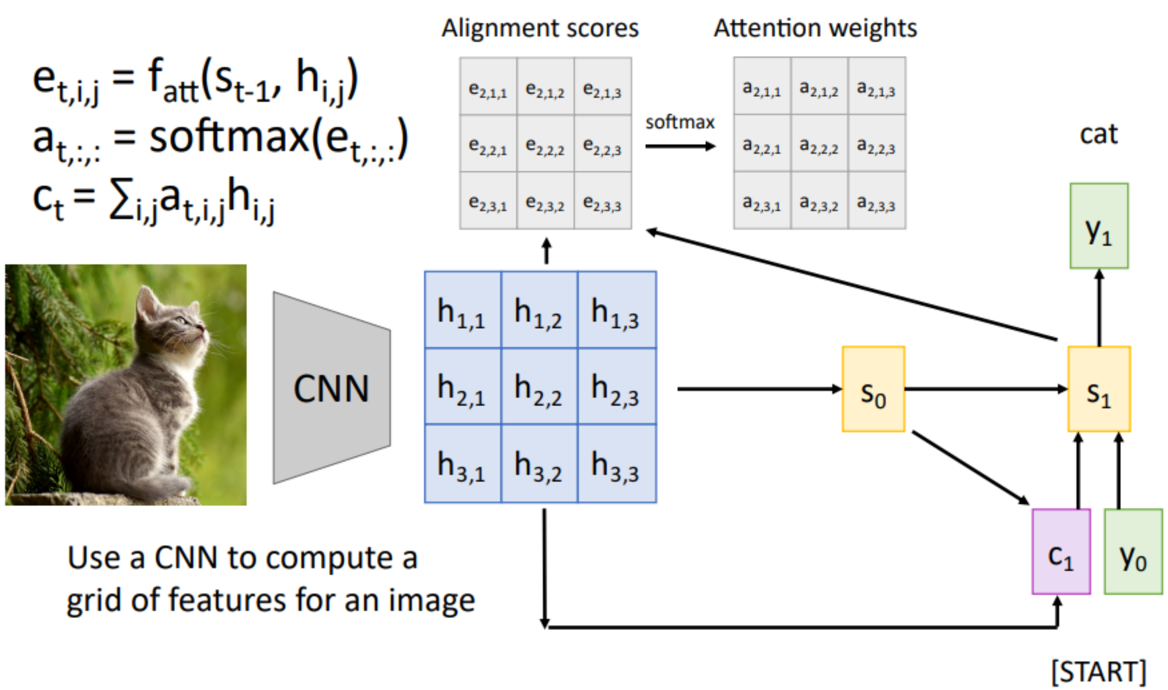

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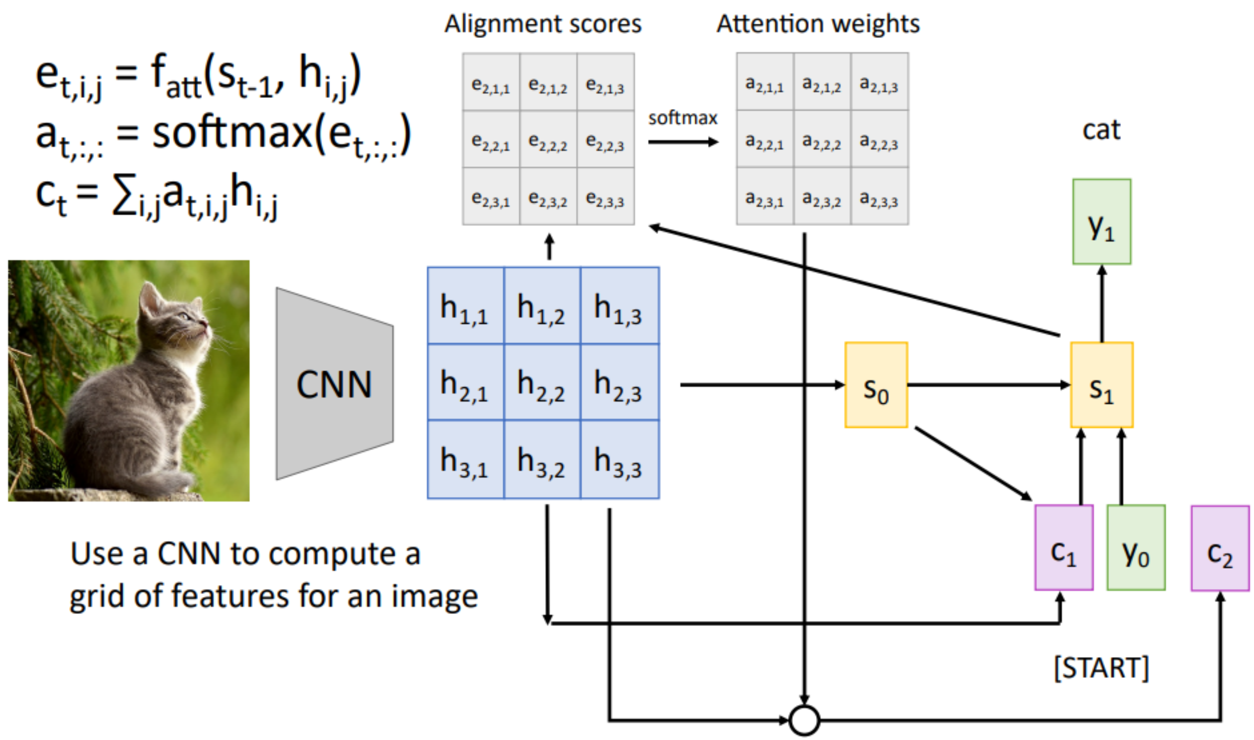

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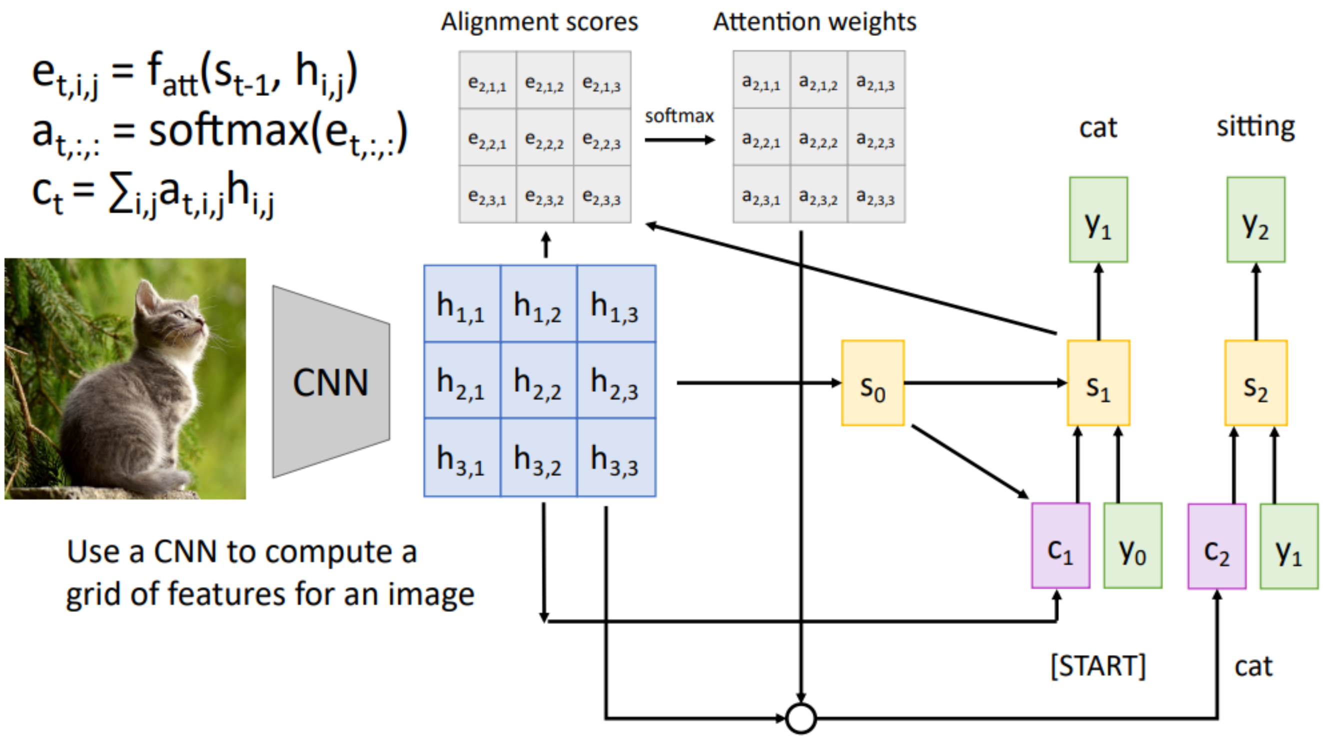

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$c_t = \sum_{i,j} a_{t,i,j} h_{i,j}$

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

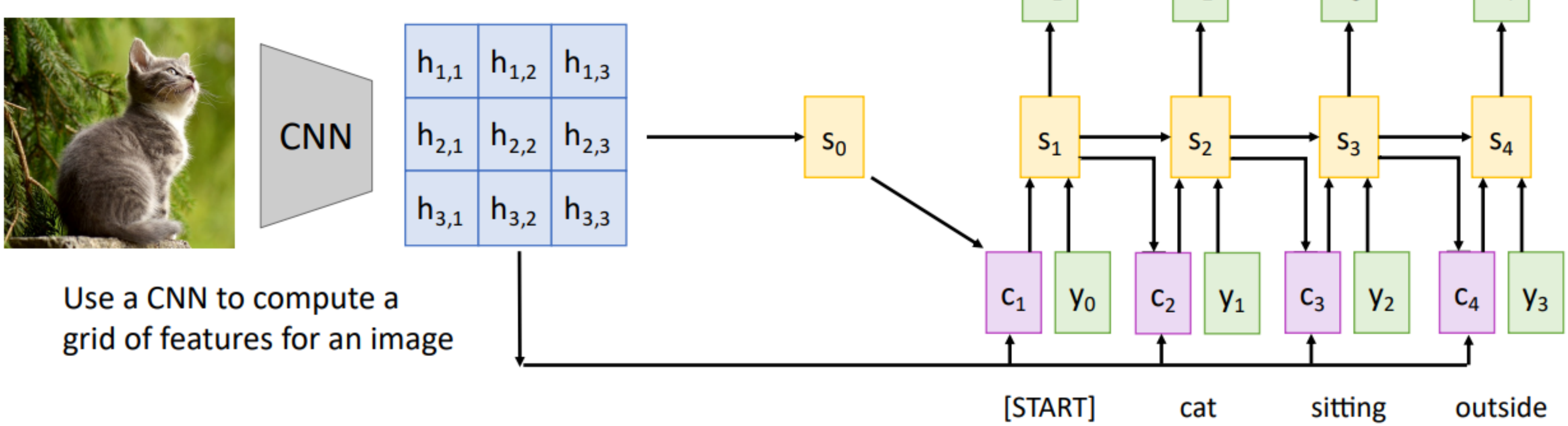

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Image Captioning with RNNs and Attention

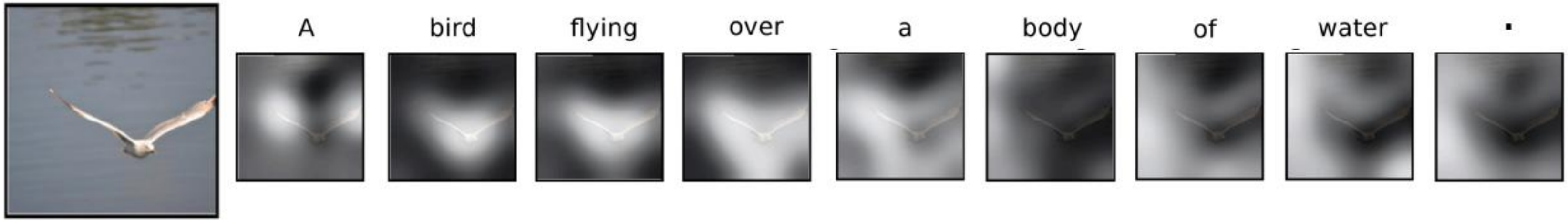

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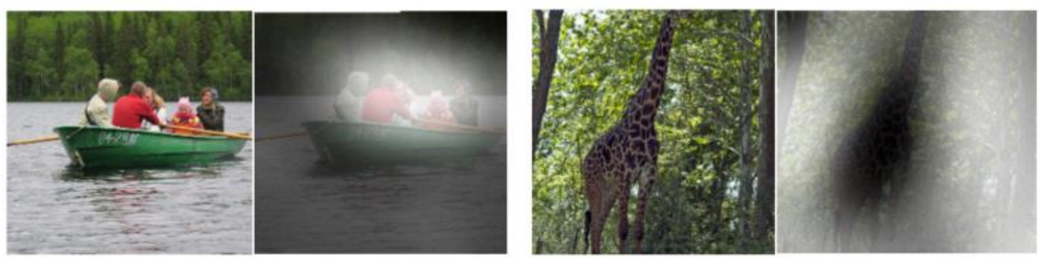
Image Captioning with RNNs and Attention

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.



A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

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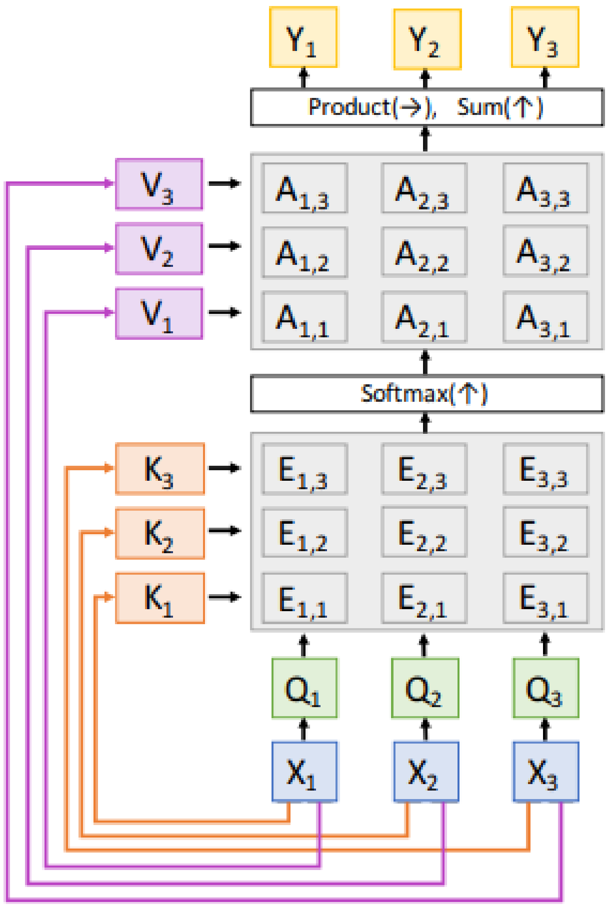
Self-Attention



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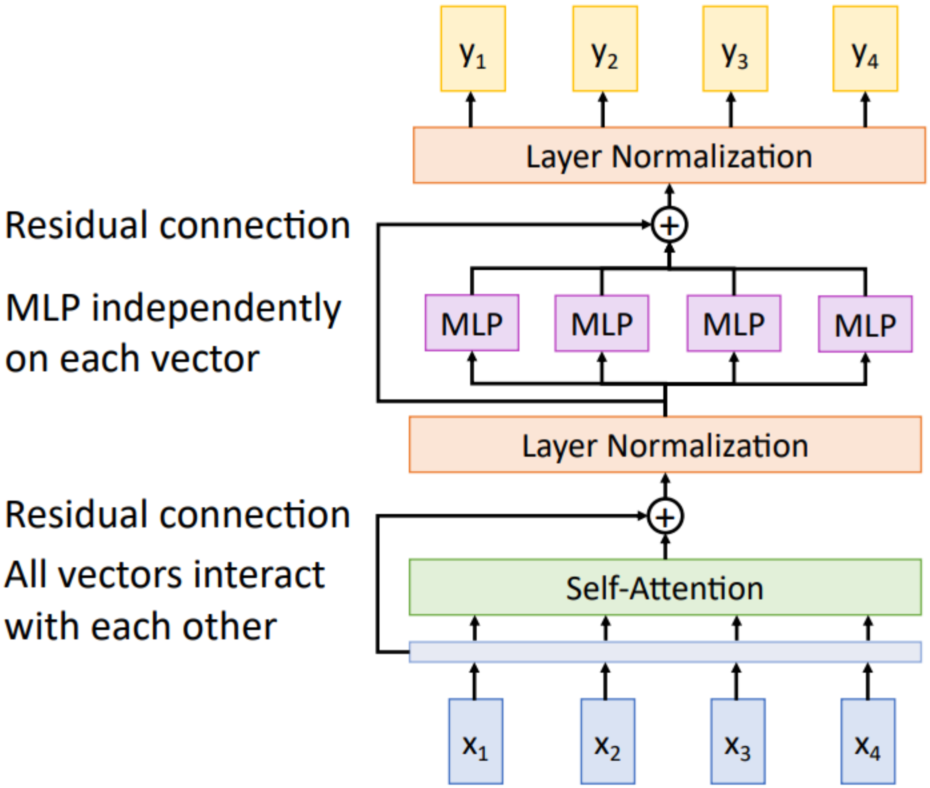
The Transformer



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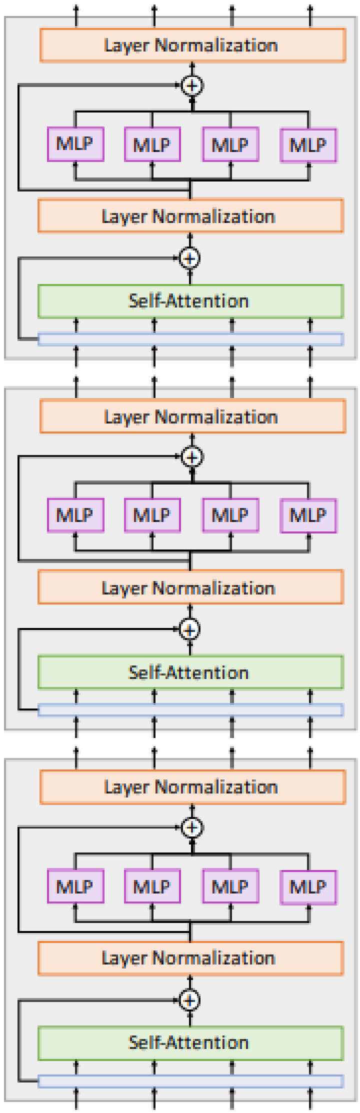
The Transformer

A Transformer is a sequence of transformer blocks



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Scaling up Transformers

Model	Layers	Width	Heads	Params	Data	Training
Transformer-Base	12	512	8	65M		8x P100 (12 hours)
Transformer-Large	12	1024	16	213M		8x P100 (3.5 days)
BERT-Base	12	768	12	110M	13 GB	
BERT-Large	24	1024	16	340M	13 GB	
XLNet-Large	24	1024	16	~340M	126 GB	512x TPU-v3 (2.5 days)
RoBERTa	24	1024	16	355M	160 GB	1024x V100 GPU (1 day)
GPT-2	12	768	?	117M	40 GB	
GPT-2	24	1024	?	345M	40 GB	
GPT-2	36	1280	?	762M	40 GB	
GPT-2	48	1600	?	1.5B	40 GB	
Megatron-LM	40	1536	16	1.2B	174 GB	64x V100 GPU
Megatron-LM	54	1920	20	2.5B	174 GB	128x V100 GPU
Megatron-LM	64	2304	24	4.2B	174 GB	256x V100 GPU (10 days)
Megatron-LM	72	3072	32	8.3B	174 GB	512x V100 GPU (9 days)

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Some Links

- Recurrent Networks (Michigan Online)
  - https://www.youtube.com/watch?v=dUzLD91Sj-o
- Attention (Michigan Online)
  - https://www.youtube.com/watch?v=YAgjfMR9R_M