CS 446/ECE 449: Machine Learning

Shenlong Wang

University of Illinois at Urbana-Champaign, 2024

Attention and Transformers

Goals of this lecture

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- Getting to know attention mechanisms

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- Getting to know attention mechanisms
- Learning about transformers

Recap: Sequence data

More flexibility regarding inputs and outputs:

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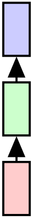

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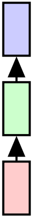

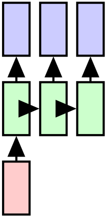

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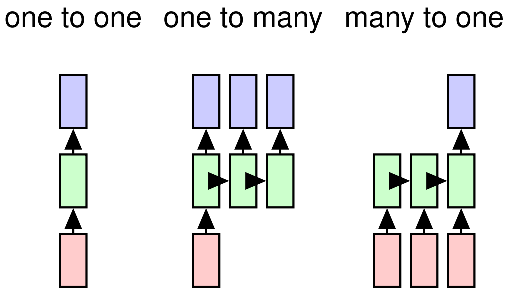

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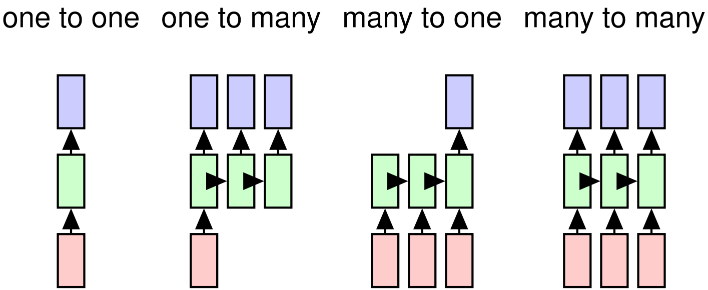

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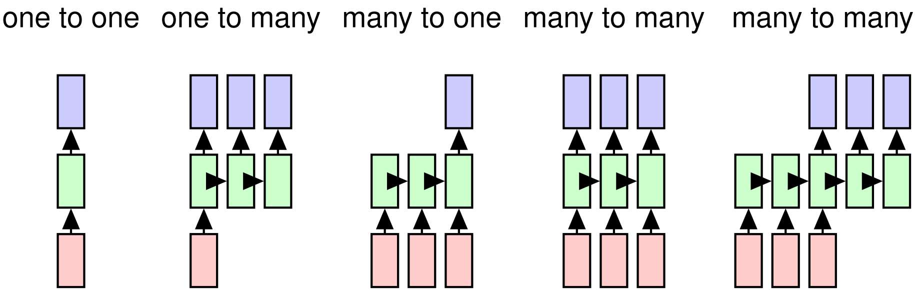

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- Recurrent Neural Net (RNNs)
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- Gated recurrent unit (GRU)

What else:

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Attention mechanisms and Transformers

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Why:

- RNNs, LSTMs, GRUs are not parallelizable (process data sequentially)

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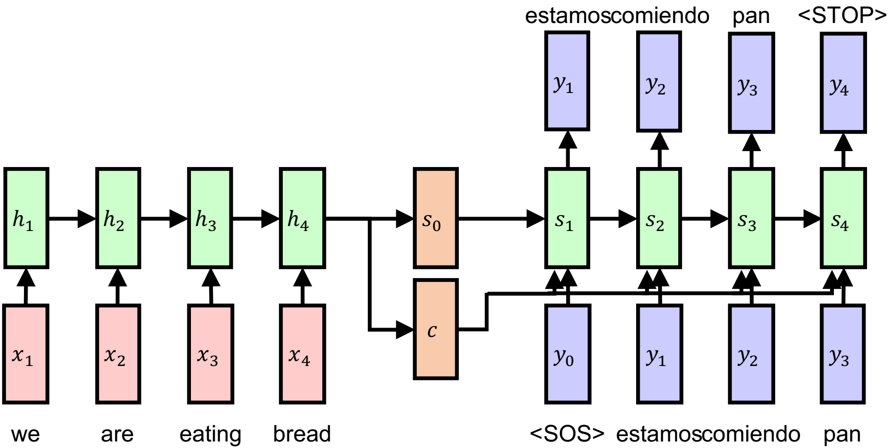
Attention mechanisms and Transformers

Why:

- RNNs, LSTMs, GRUs are not parallelizable (process data sequentially)
- Still bottleneck for very long sequences

Let's consider an example:



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- Input: $(x_1, x_2, \ldots)$

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Problem:

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Problem: What if sequence very long?

Fix:

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Problem: What if sequence very long?

Fix: Use a new context vector for every output.

What is a good context vector for each element?

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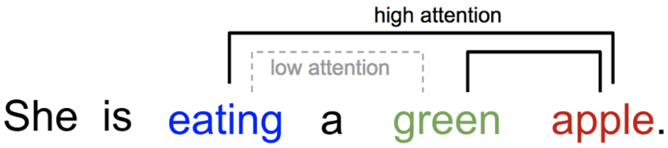

What is a good context vector for each element?

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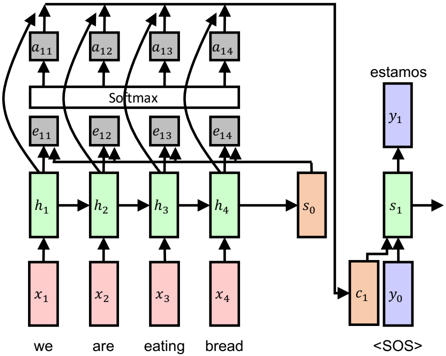
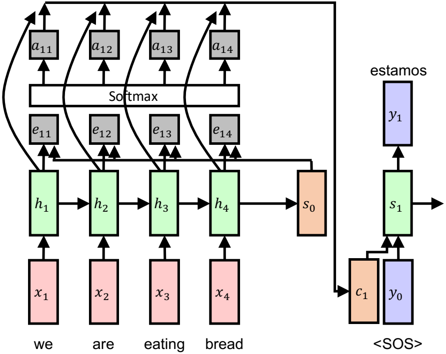


a_{11}
a_{12}
a_{13}
a_{14}
Softmax
e_{11}
e_{12}
e_{13}
e_{14}
estamos
y_1
h_1
h_2
h_3
h_4
s_0
s_1
x_1
x_2
x_3
x_4
c_1
y_0
we
are
eating
bread
<SOS>

How?

- Alignment scores:
  $e_{t,i} = f_{\text{att}}(s_{t-1}, h_i) \in \mathbb{R}$
  f_{att} is an MLP



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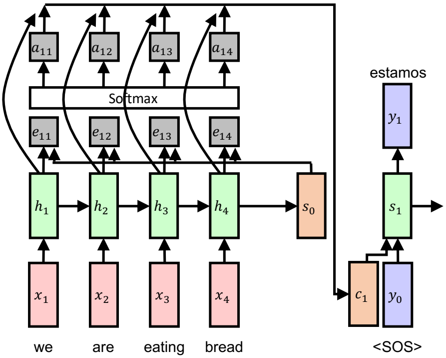
- Normalize via softmax to obtain **attention** weights $0 \leq a_{t,i} \leq 1$ $(\sum_i a_{t,i} = 1)$



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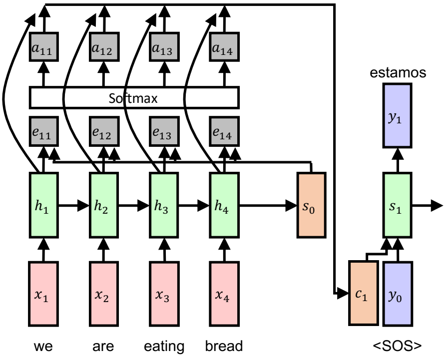
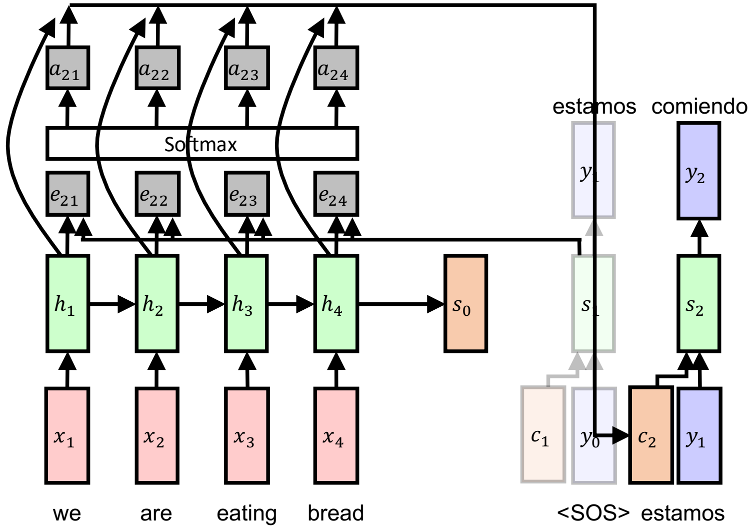
- Normalize via softmax to obtain **attention** weights
  $0 \leq a_{t,i} \leq 1$ $(\sum_i a_{t,i} = 1)$
- Compute attended representation via linear combination:
  $c_t = \sum_i a_{t,i} h_i$



Next time step:



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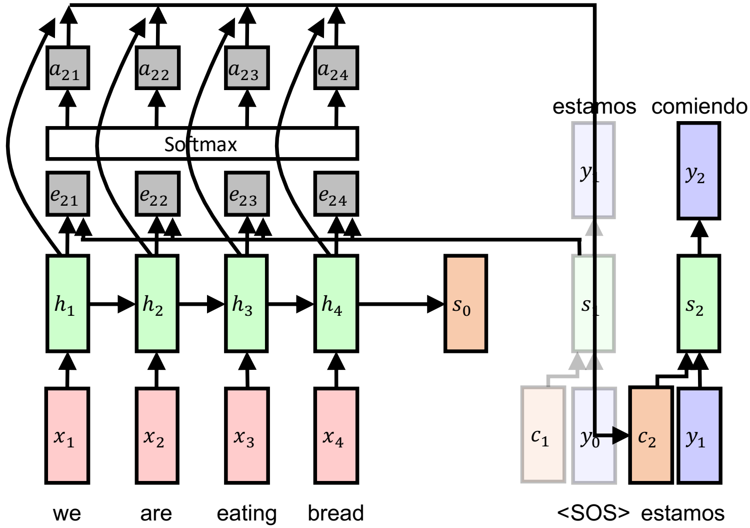

All differentiable. Don't supervise. Backprop through entire net.

Observation:

By re-computing context vectors c_t at every decoding step we avoid the bottleneck obtained when using a single vector for the input data.

At every decoding step the context vector “looks at” different parts of the input sequence. The attention weight $a_{t,i}$ determines the strength.

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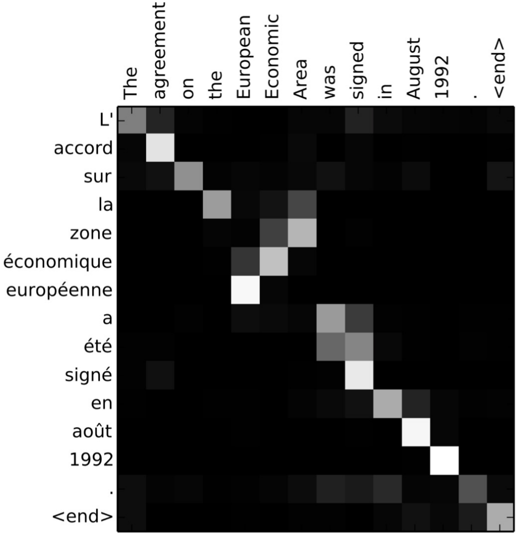

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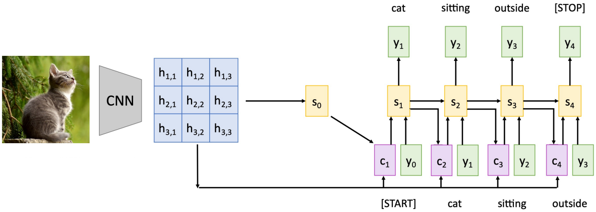

A dog is standing on a hardwood floor.

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.

Generalizing: **Towards the Attention Layer**

We started with

Inputs:

- Query vector: q
- Input vectors: X
- Similarity function: f_{att}

Computations:

- Scores: $e_i = f_{\text{att}}(q, X_i)$
- Attention: $a = \text{softmax}(e)$
- Attended representation: $y = \sum_i a_i X_i$

The Attention Layer

Inputs:

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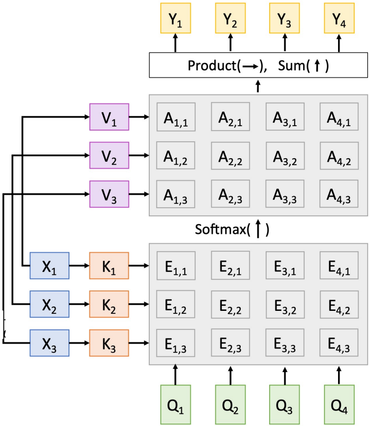

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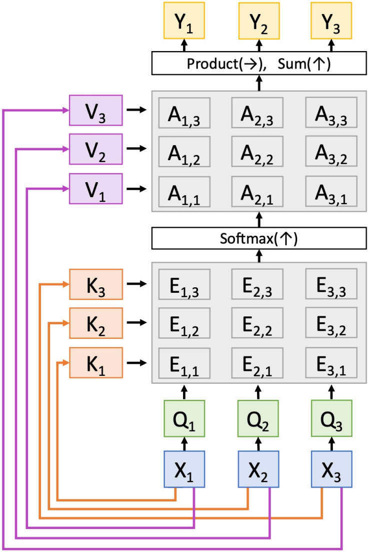

Why a **Self-**Attention Layer?

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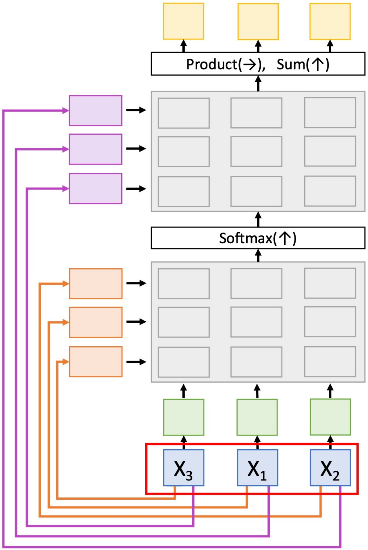

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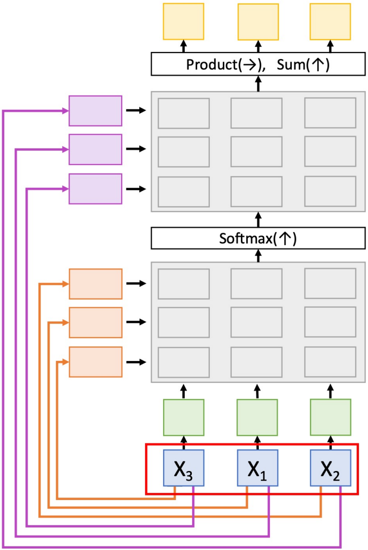

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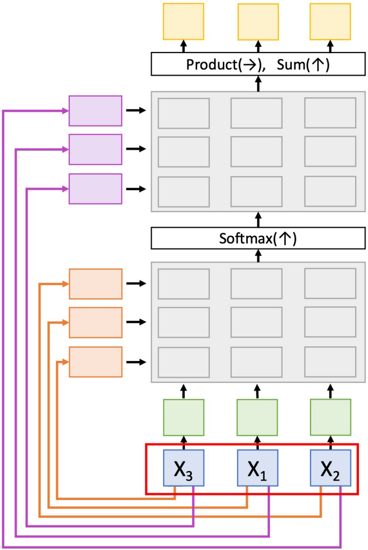

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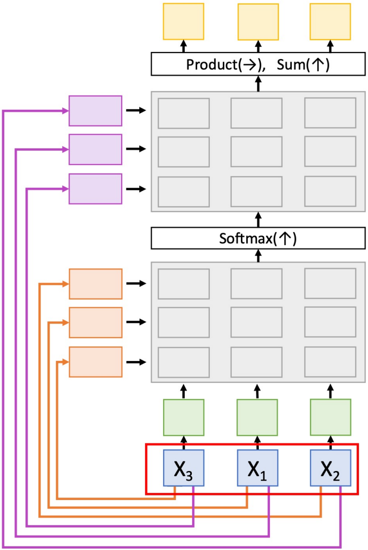

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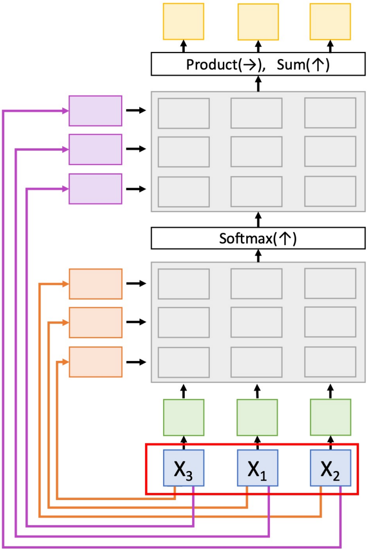

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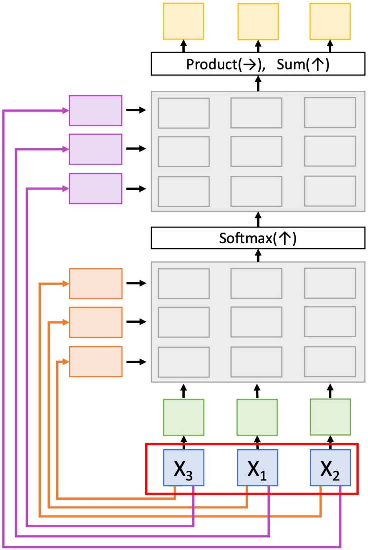

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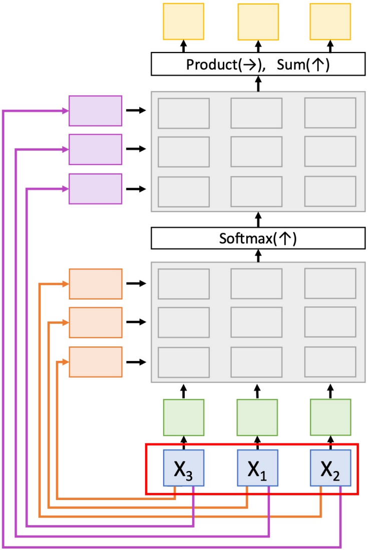

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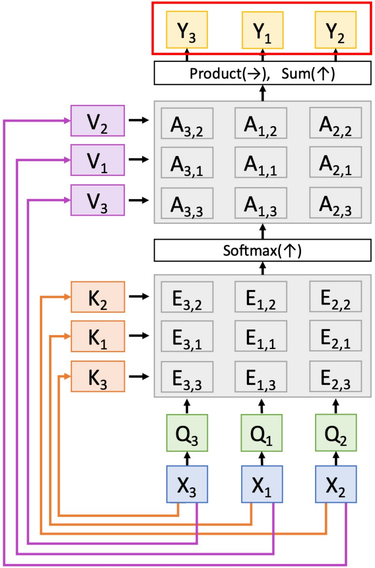

Self-Attention Layer:

- Permuting inputs results in permuted outputs
- Self-attention layer is **permutation equivariant** $f(s(x)) = s(f(x))$
- Self-attention layer operates on sets of vectors

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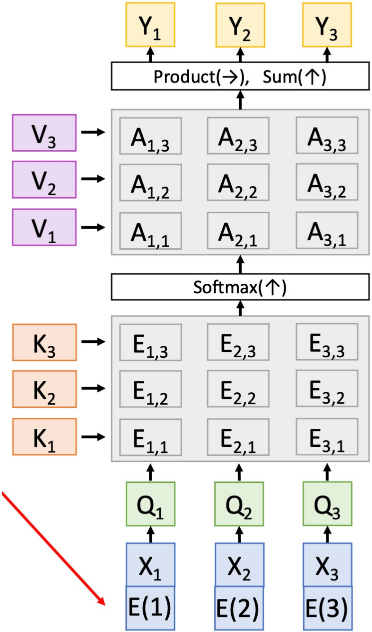

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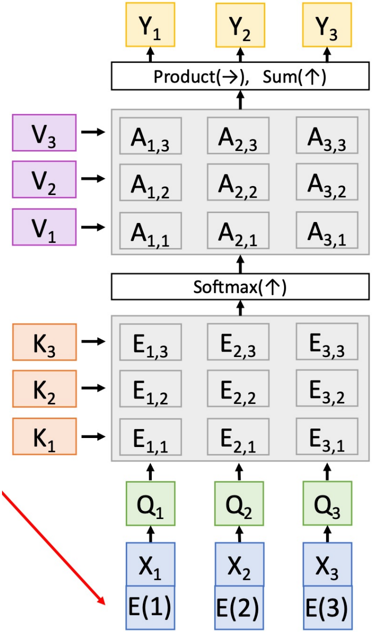

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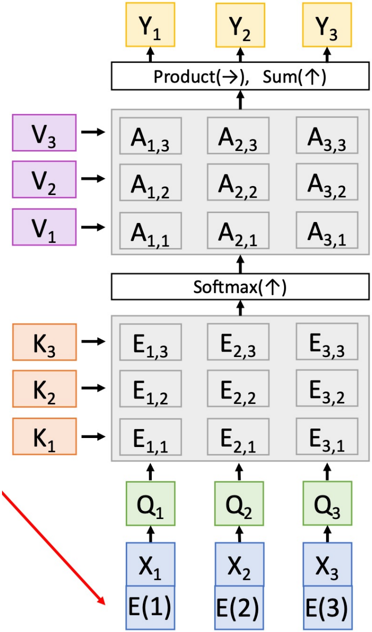
Use positional encoding E



Problem: How to use this to encode text where we shouldn't look ahead?

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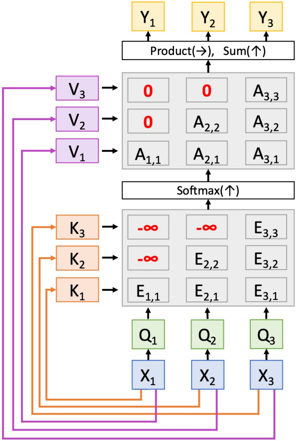

Multihead Self-Attention Layer

Use a set of independent attention heads

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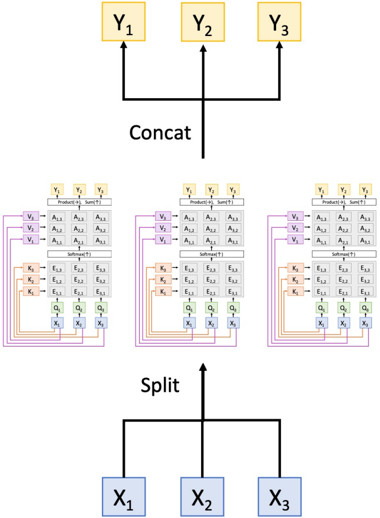

Ways to process sequence data:

Classical RNNs

(+) Reasonably good at long sequences

(-) Not parallelizable

1D Convolutions

(-) Bad at long sequences

(+) Trivially parallelizable

Self-Attention

(+) Good at long sequences

(+) Trivially parallelizable

(-) Memory intensive

Transformer

Transformer block:

- Input: set of vectors
- Output: set of vectors
- Computation:

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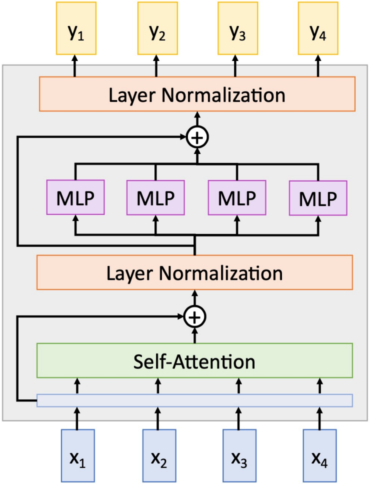
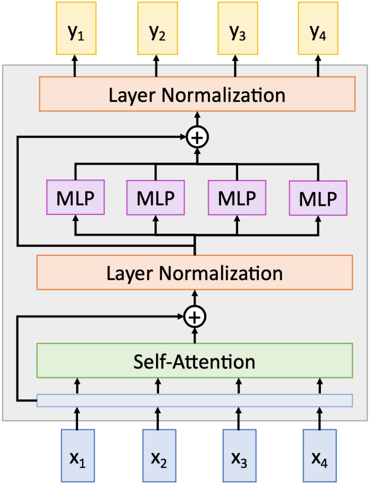


Transformer

Transformer block:

- Input: set of vectors
- Output: set of vectors
- Computation:
  - self-interaction is the only interaction between vectors
  - normalization and MLP operate independently
  - position of normalization may change



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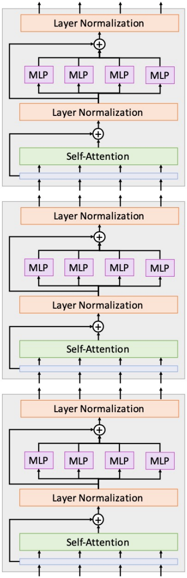

Transformer

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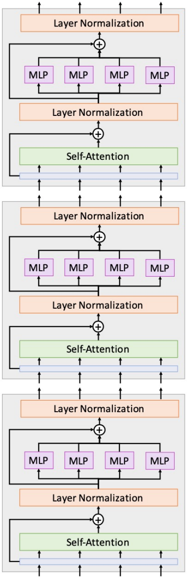
Revolutionized (?) natural language processing:

- Download a lot of text
- Train a giant transformer model
- Fine-tune on desired task with little data

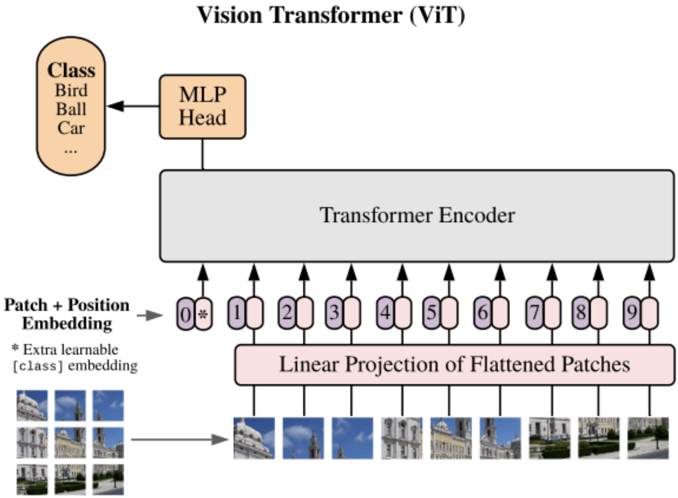


Scaling Natural Language Processing:

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	48	1600	?	1.5B	40 GB	
Megatron-LM	72	3072	32	8.3B	174 GB	512x V100 GPU (9 days)
Turing-NLG	78	4256	28	17B	?	256x V100 GPU
GPT-3	96	12288	96	175B	694GB	?

Plenty of website demos: ChatGPT, GPT4, Llama2, etc.

Improving Computer Vision:



VIT, MaskFormer, MaskGIT, etc.

Quiz:

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- What is attention?

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- Properties of self-attention?

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- What is attention?
- Properties of self-attention?
- What is a transformer?

Important topics of this lecture

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- Getting to know different attention mechanisms

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- Getting to know different attention mechanisms
- Understanding the transformer layer