Trustworthy AI Systems

-- Pretrained Foundation Model

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Last Lecture

Voice Conversion

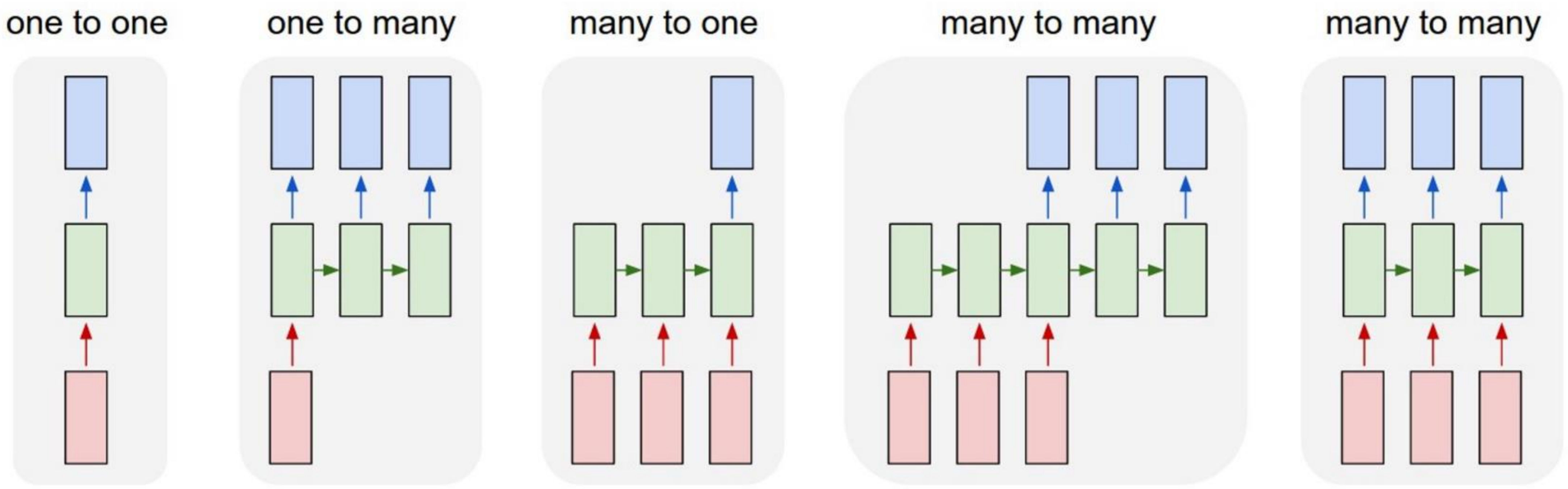
- Non-disentangle-based method

- Disentangle-based method
  - Instance normalization
  - Quantization

This Lecture

- Recurrent Neural Network
- Attention
- Transformers
- Pretrained Foundation Model

Recurrent Neural Network



Vanilla Neural Networks

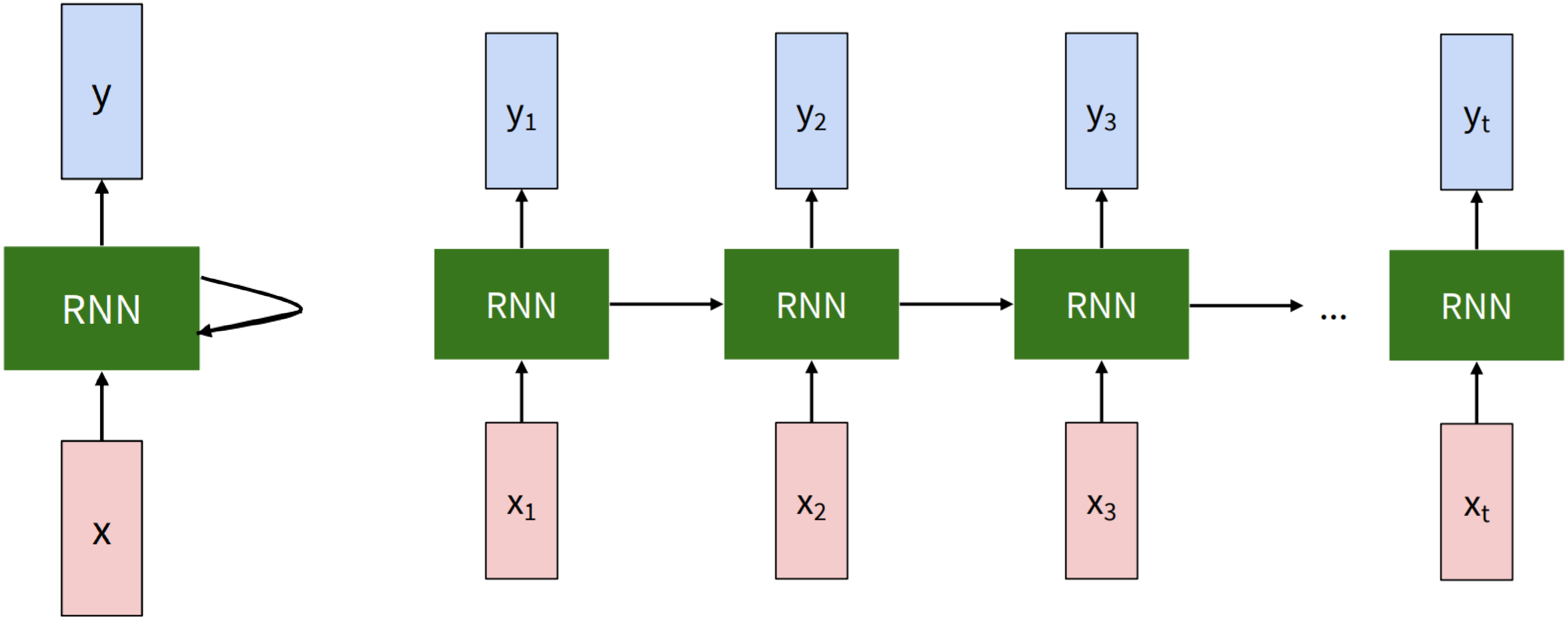
Image Captioning

Action Prediction

Video Captioning

Video classification on frame level

Recurrent Neural Network



RNN Hidden State Update

We can process a sequence of vectors x by applying a recurrence formula at every time step:

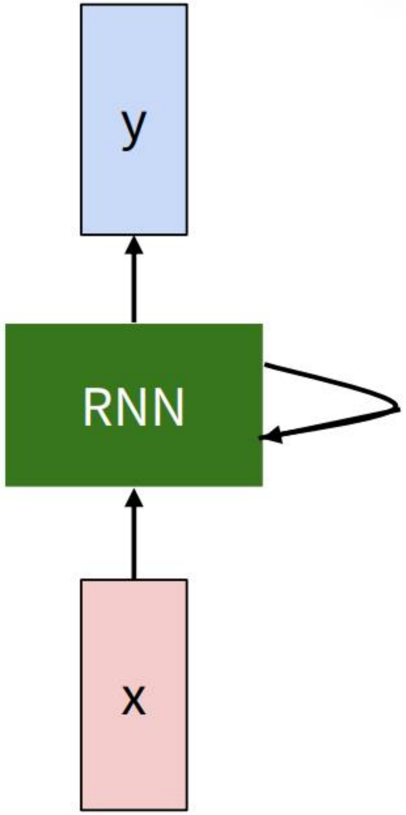
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

input vector at some time step

some function with parameters W



RNN Output Generation

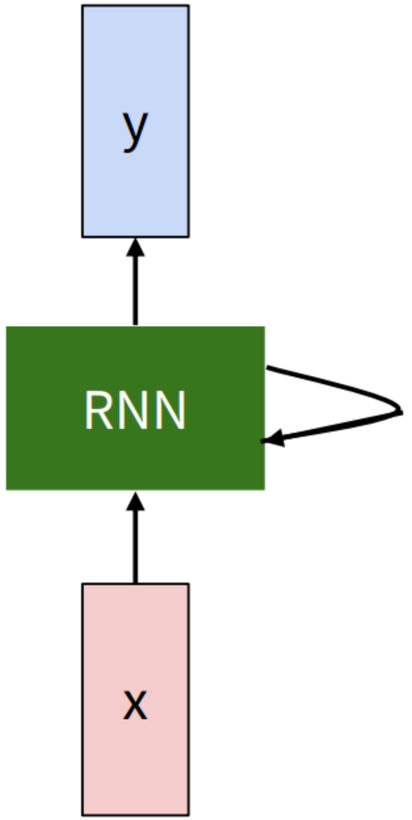
We can process a sequence of vectors x by applying a recurrence formula at every time step:

$$\boxed{y_t} = \boxed{f_{W_{hy}}}(\boxed{h_t})$$

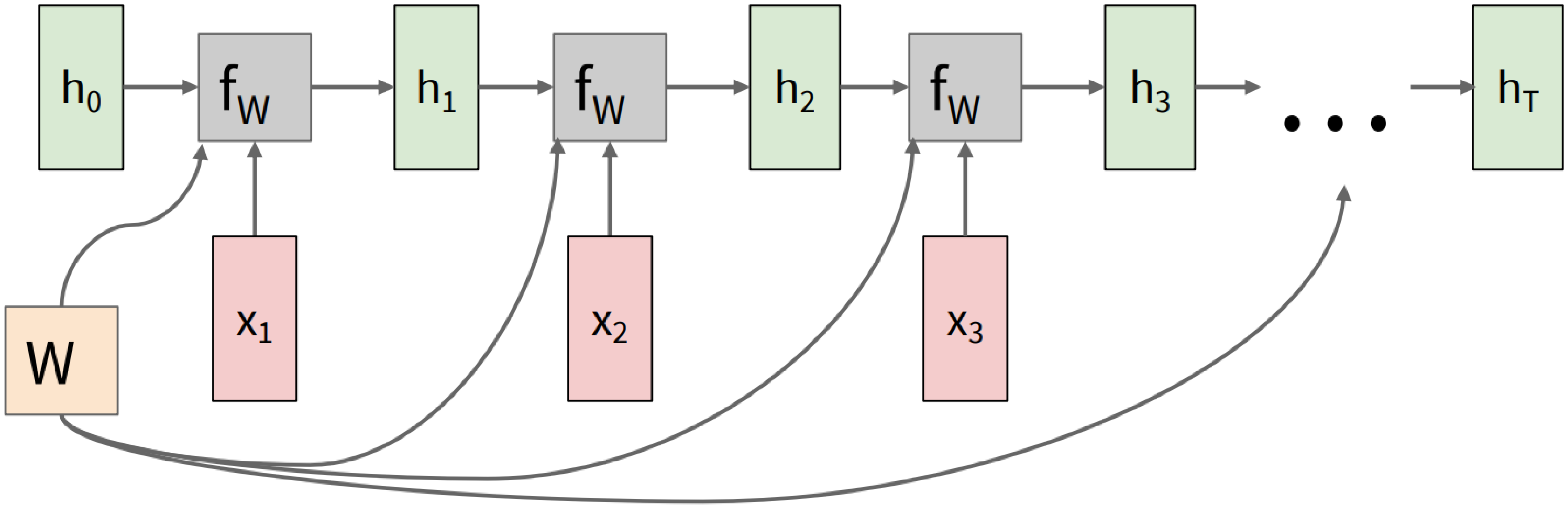
output

new state

another function
with parameters W_{hy}



RNN: Computational Graph



Notice: the same function and the same set of parameters (same weight matrix) are used at every time step.

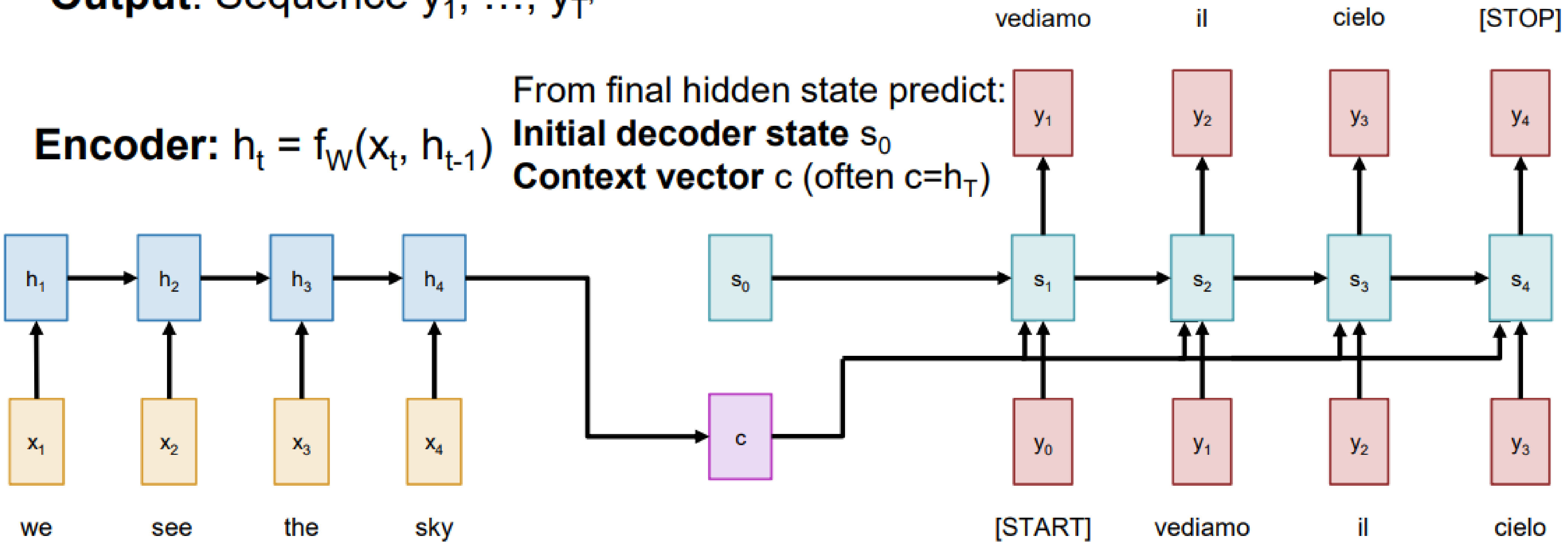
Sequence to Sequence with RNNs

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

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

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

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



During training, we use the “correct” token even if the model is wrong.

RNN Tradeoffs

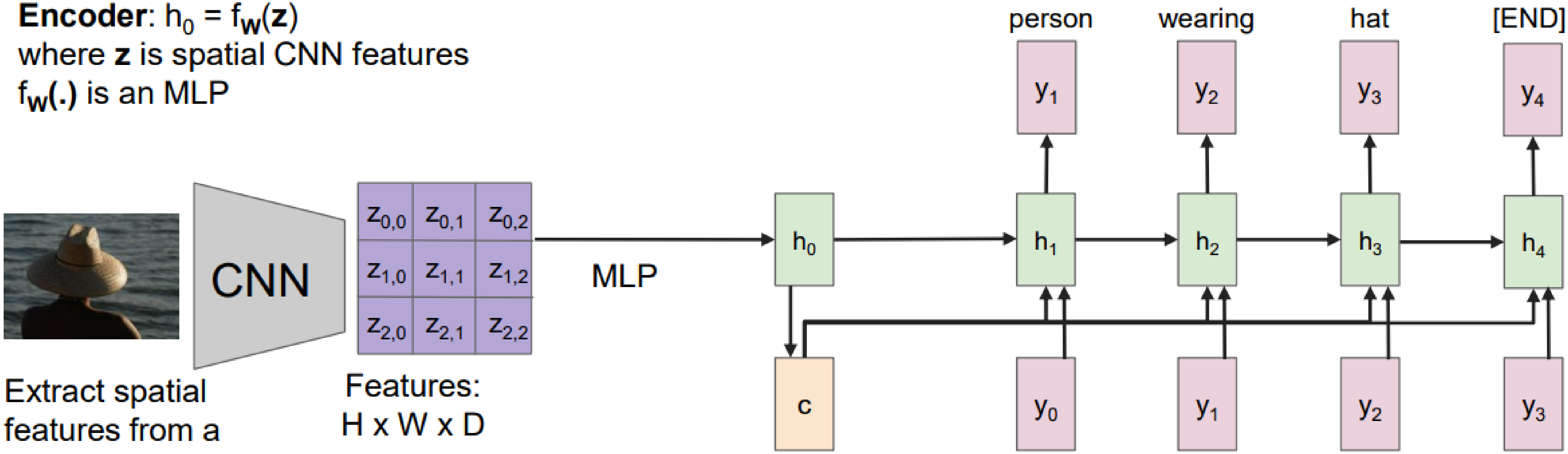
- RNN Advantages:
  - Can process any length of the input
  - Computation for step t can (in theory) use information from many steps back
  - Model size does not increase for longer input
  - The same weights are applied on every timestep, so there is symmetry in how inputs are processed.
- RNN Disadvantages:
  - Recurrent computation is slow
  - In practice, difficult to access information from many steps back

Image Captioning using Spatial Features

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

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

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



Extract spatial features from a pretrained CNN

Features: H x W x D

This Lecture

- Recurrent Neural Network
- Attention: the relative importance of each component in a sequence
- Transformers
- Pretrained Foundation Model

Image Captioning with RNNs and Attention

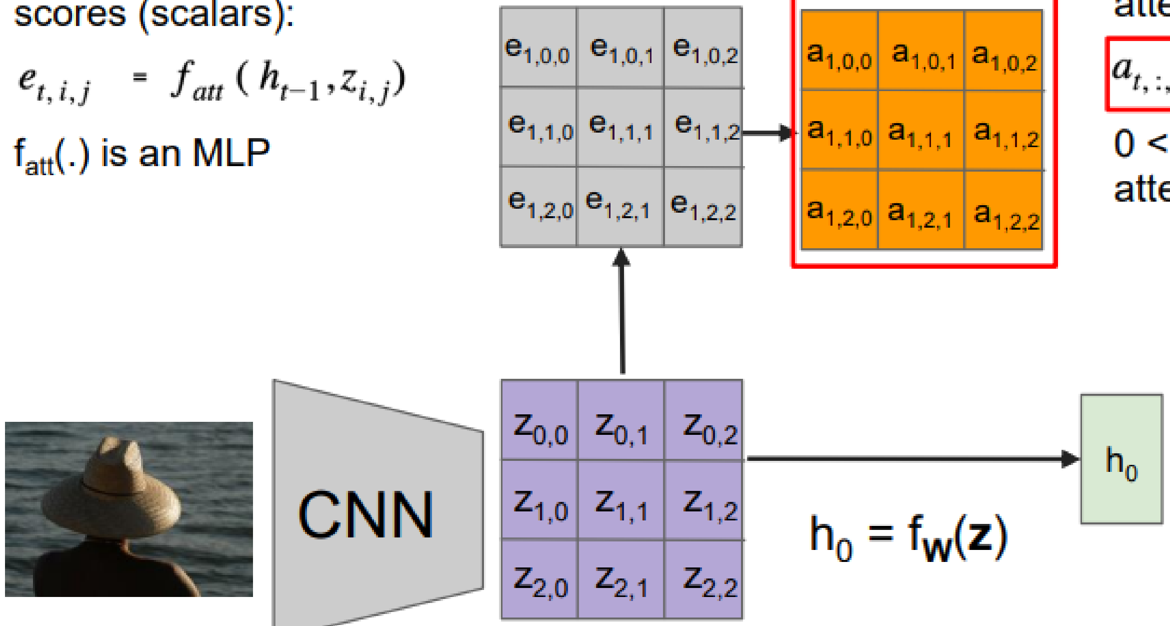
Compute alignments scores (scalars):

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

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

Alignment scores: H x W

Attention: H x W



Normalize to get attention weights:

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

$0 < a_{t,i,j} < 1$,
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 x W x D

Image Captioning with RNNs and Attention

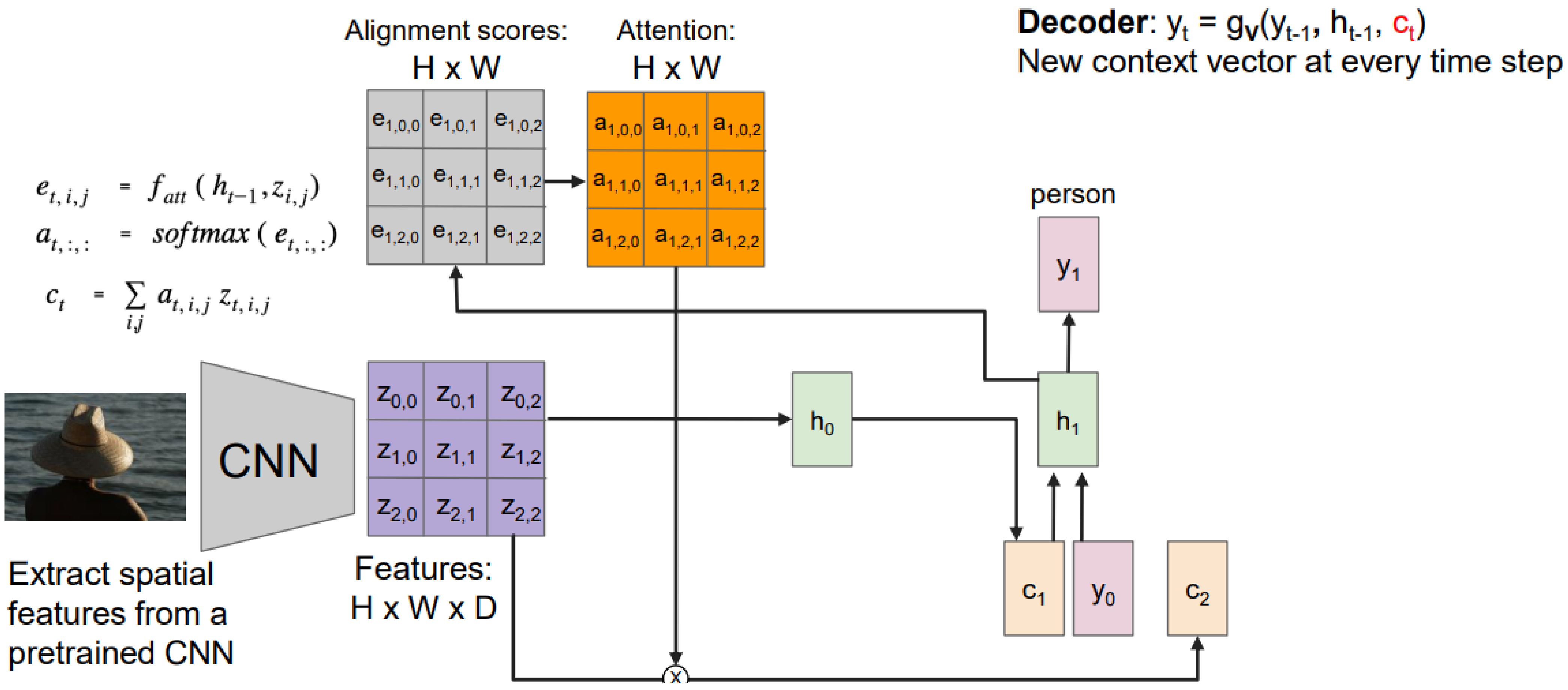
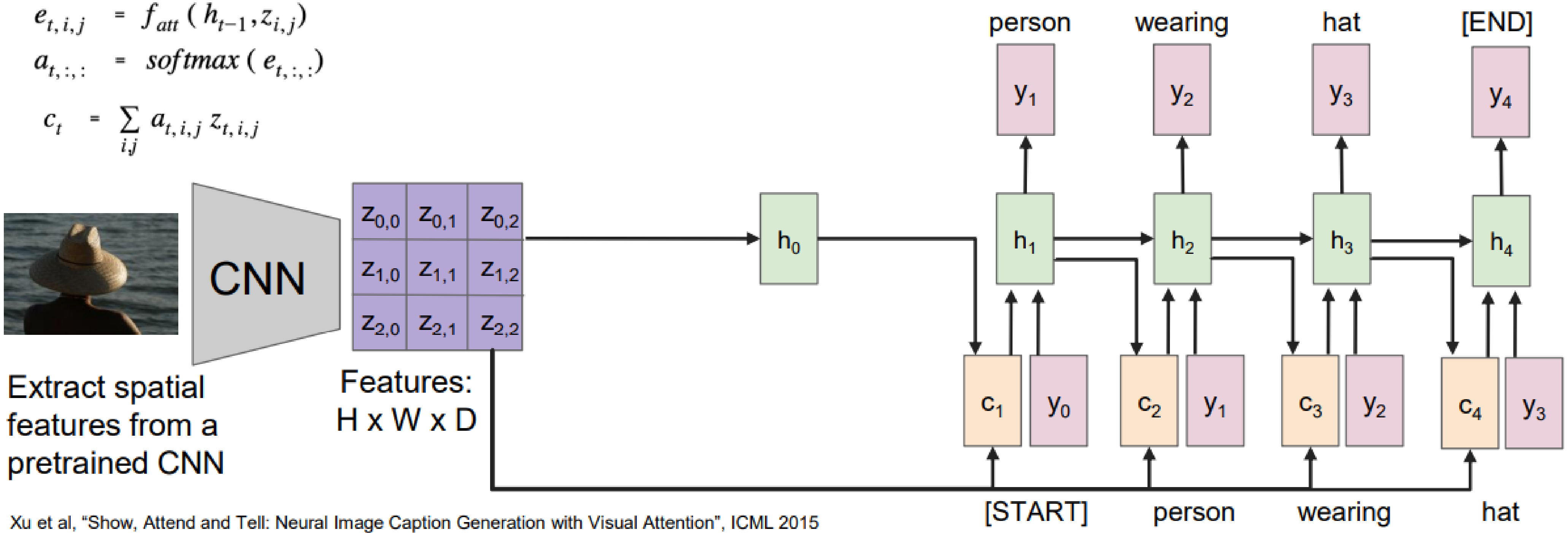


Image Captioning with RNNs and Attention

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

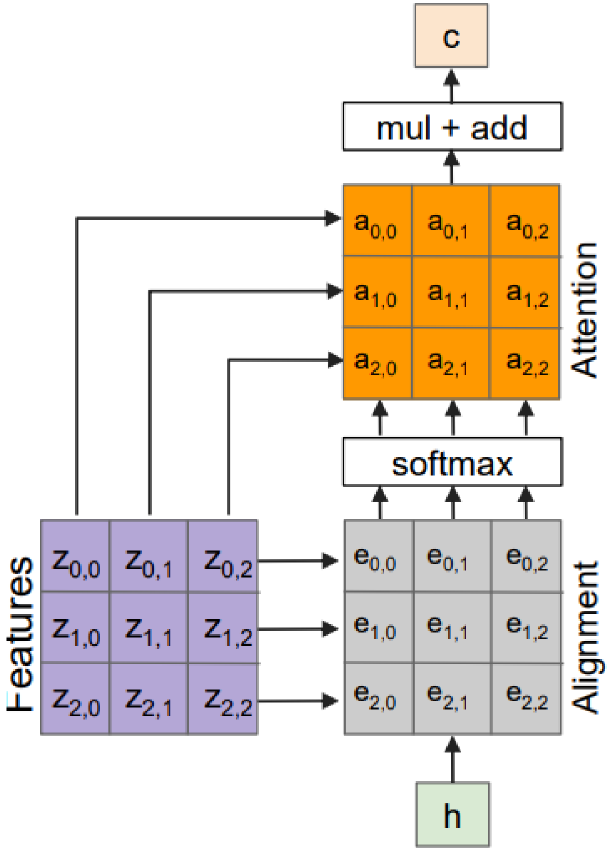
Decoder: $y_t = g_V(y_{t-1}, h_{t-1}, c_t)$
New context vector at every time step

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



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

Attention in Image Captioning



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

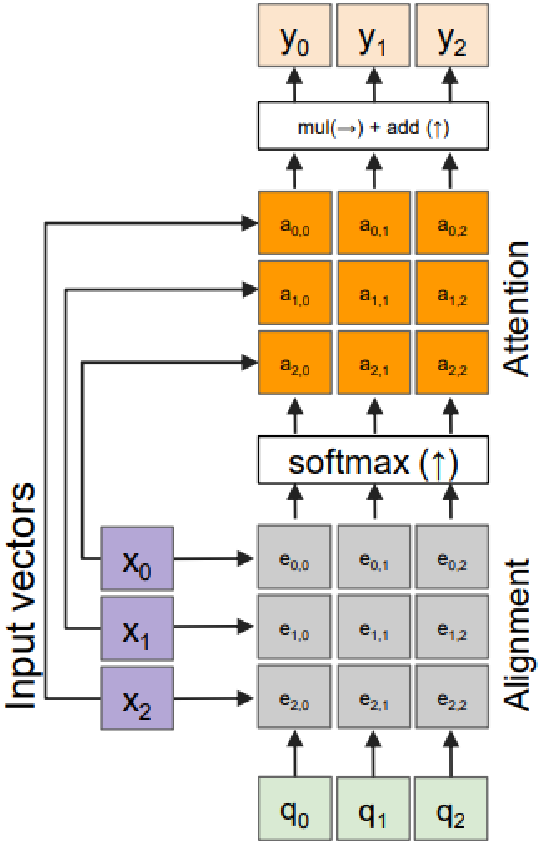
Operations:
Alignment: $e_{i,j} = f_{att}(h, z_{i,j})$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $\mathbf{c} = \sum_{i,j} a_{i,j} z_{i,j}$

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

“query” refers to a vector used to calculate a corresponding context vector.

General Attention Layer (1)

each query creates a new, corresponding output context vector



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

Operations:
Alignment: $e_{i,j} = q_j \cdot x_i / \sqrt{D}$
Attention: **a** = softmax(**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)

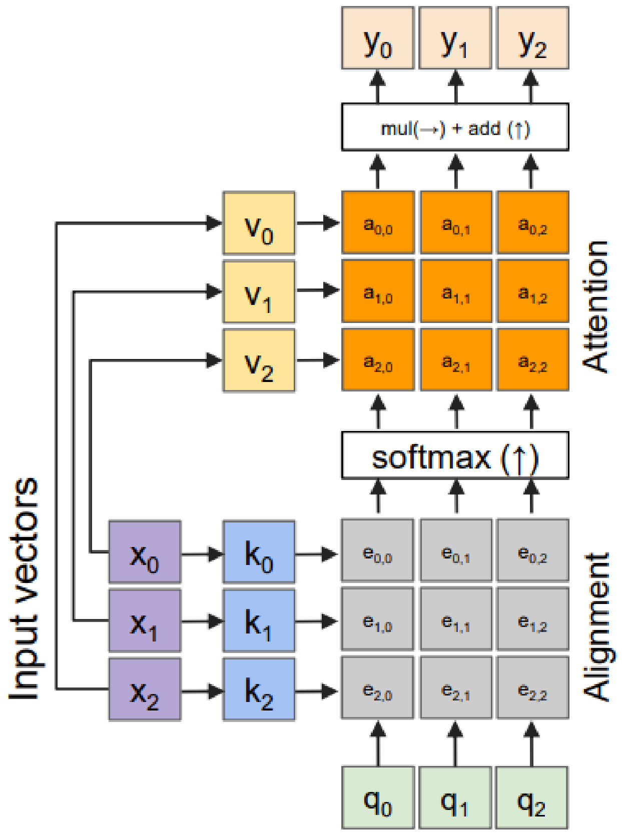
Attention operation is permutation invariant, so reshape.

Multiple query vectors

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 $\sqrt{D}$ to reduce effect of large magnitude vectors
- Similar to Xavier and Kaiming Initialization!

General Attention Layer (2)



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

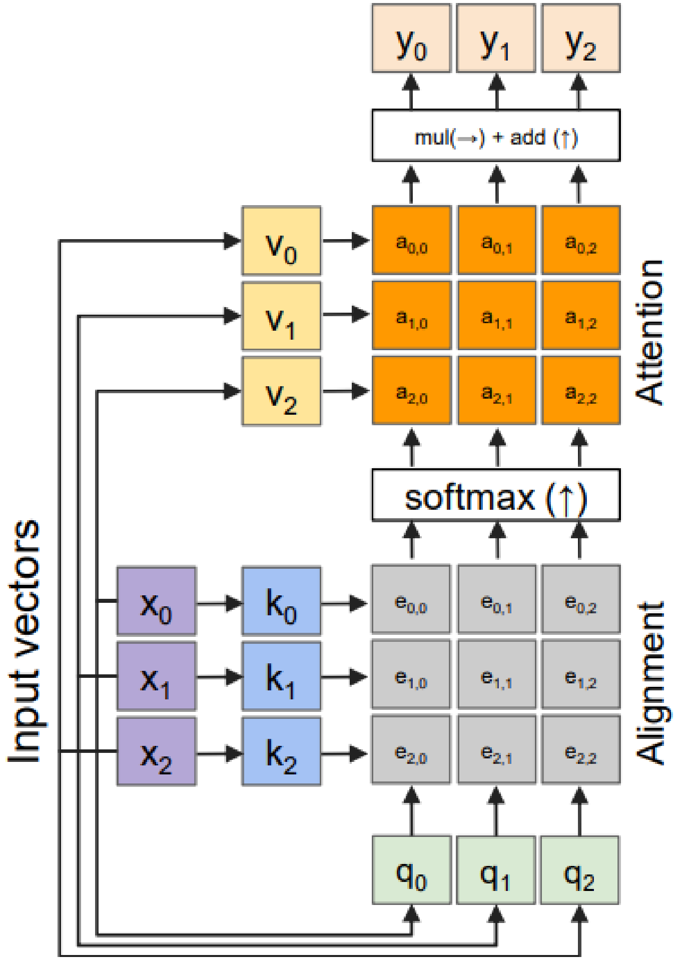
Operations:
Key vectors: $\mathbf{k} = \mathbf{x}W_k$
Value vectors: $\mathbf{v} = \mathbf{x}W_v$
Alignment: $e_{i,j} = q_j \cdot k_i / \sqrt{D}$
Attention: $\mathbf{a} = \mathrm{softmax}(\mathbf{e})$
Output: $y_j = \sum_i a_{i,j} v_i$

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

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

Self-attention Layer

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



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

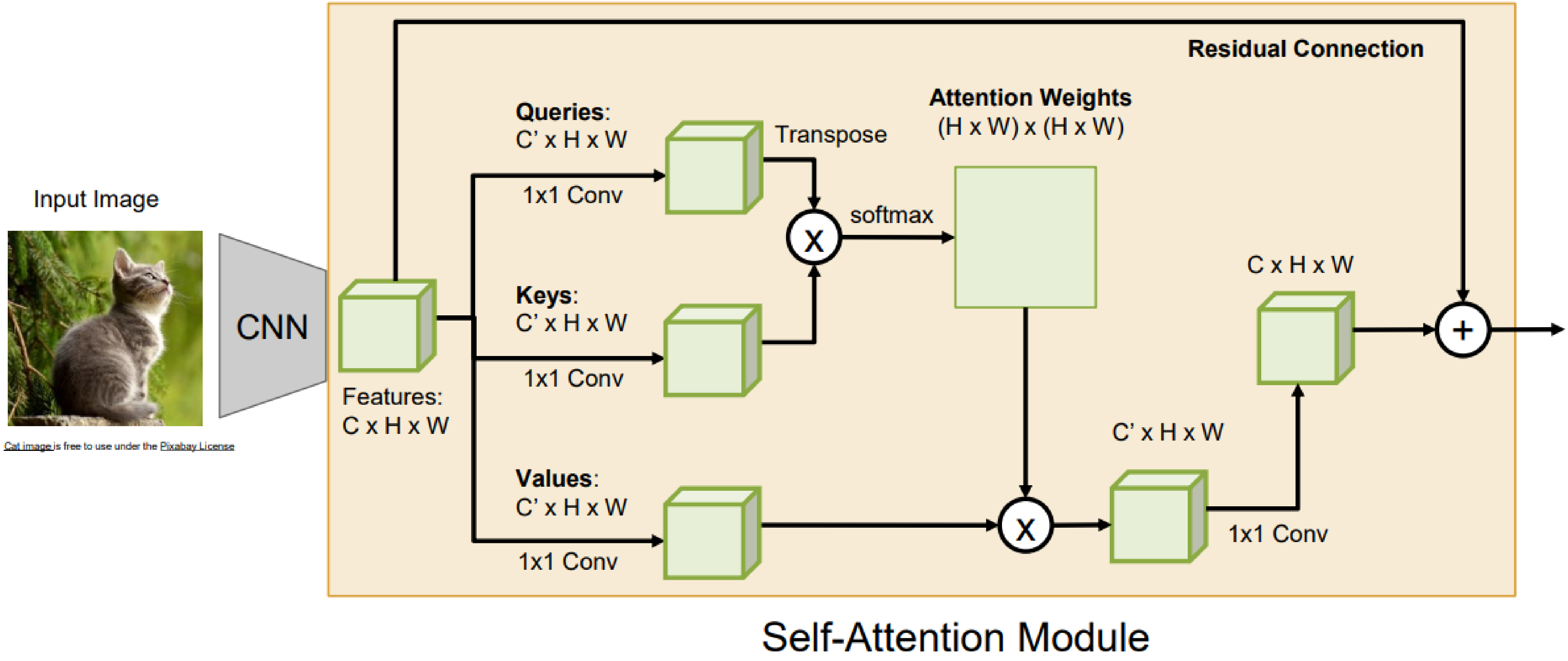
Operations:
Key vectors: $\mathbf{k} = \mathbf{x}W_k$
Value vectors: $\mathbf{v} = \mathbf{x}W_v$
Query vectors: $\mathbf{q} = \mathbf{x}W_q$
Alignment: $e_{i,j} = q_j \cdot k_i / \sqrt{D}$
Attention: $\mathbf{a} = \text{softmax}(\mathbf{e})$
Output: $y_j = \sum_i a_{i,j} v_i$

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

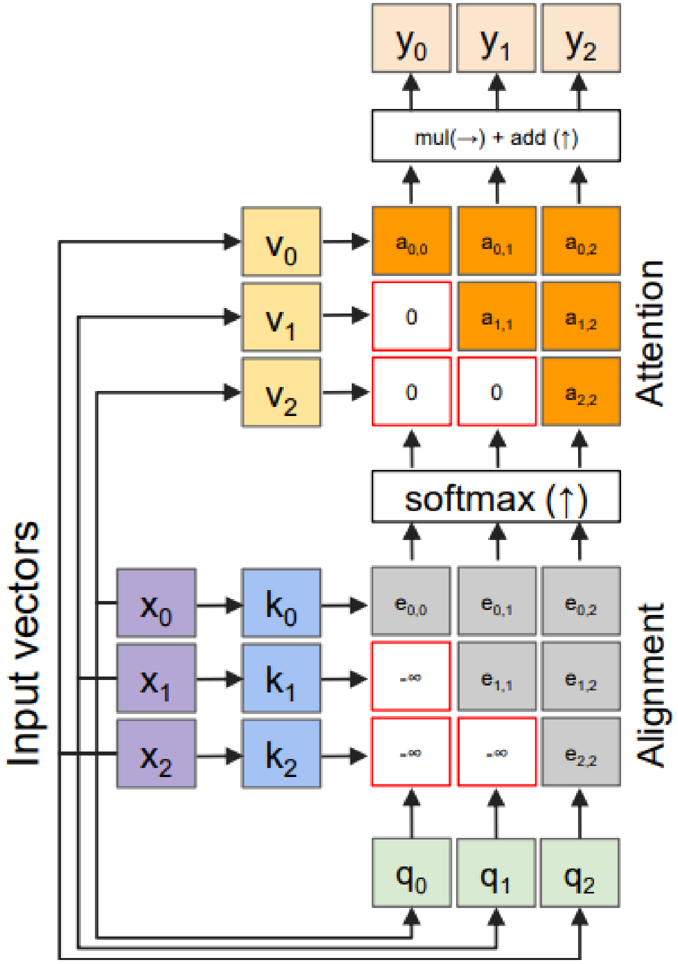
We can **calculate the query vectors from the input vectors**, therefore, defining a "self-attention" layer.

No input query vectors anymore

CNN with Self-Attention



Masked self-attention layer



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

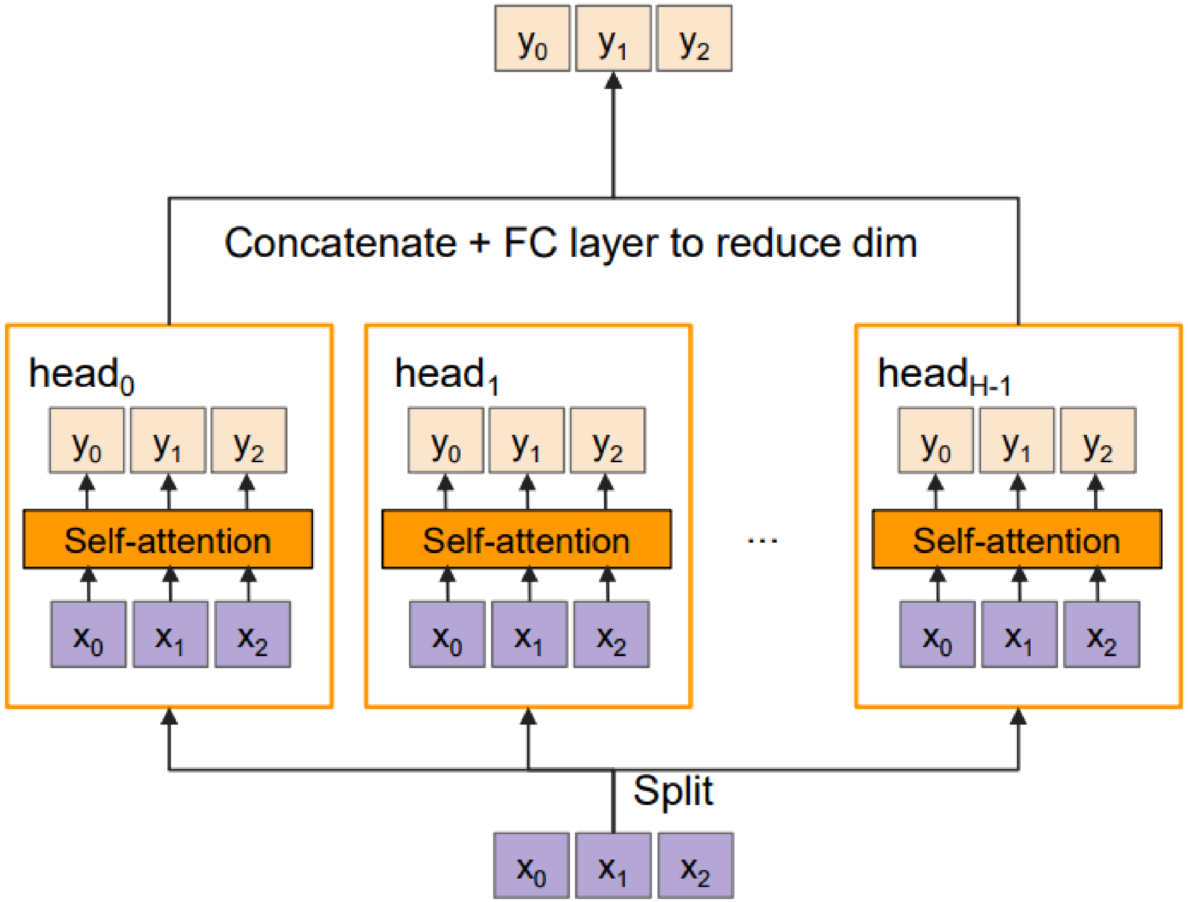
Inputs:
Input vectors: **x** (shape: N x D)

- 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

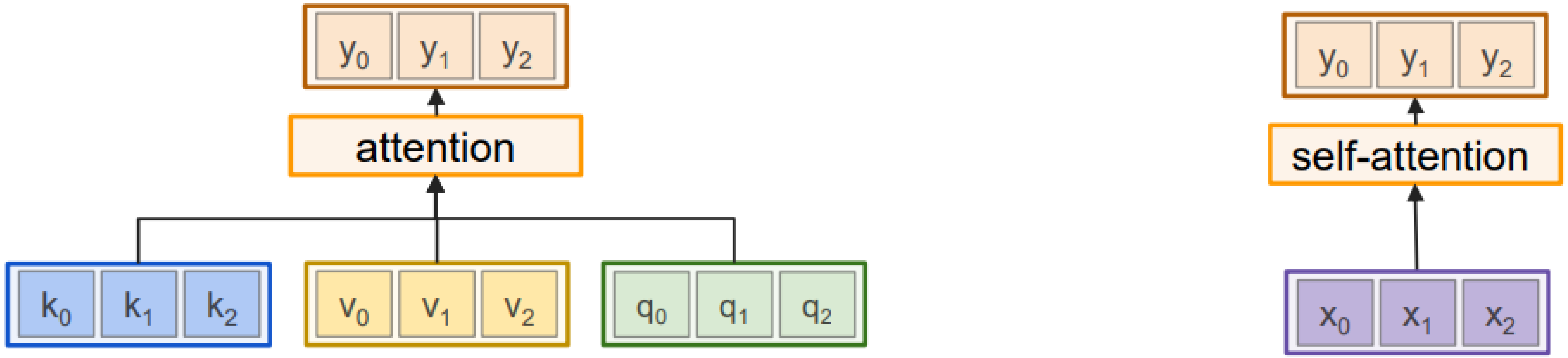


Why multi-head?

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



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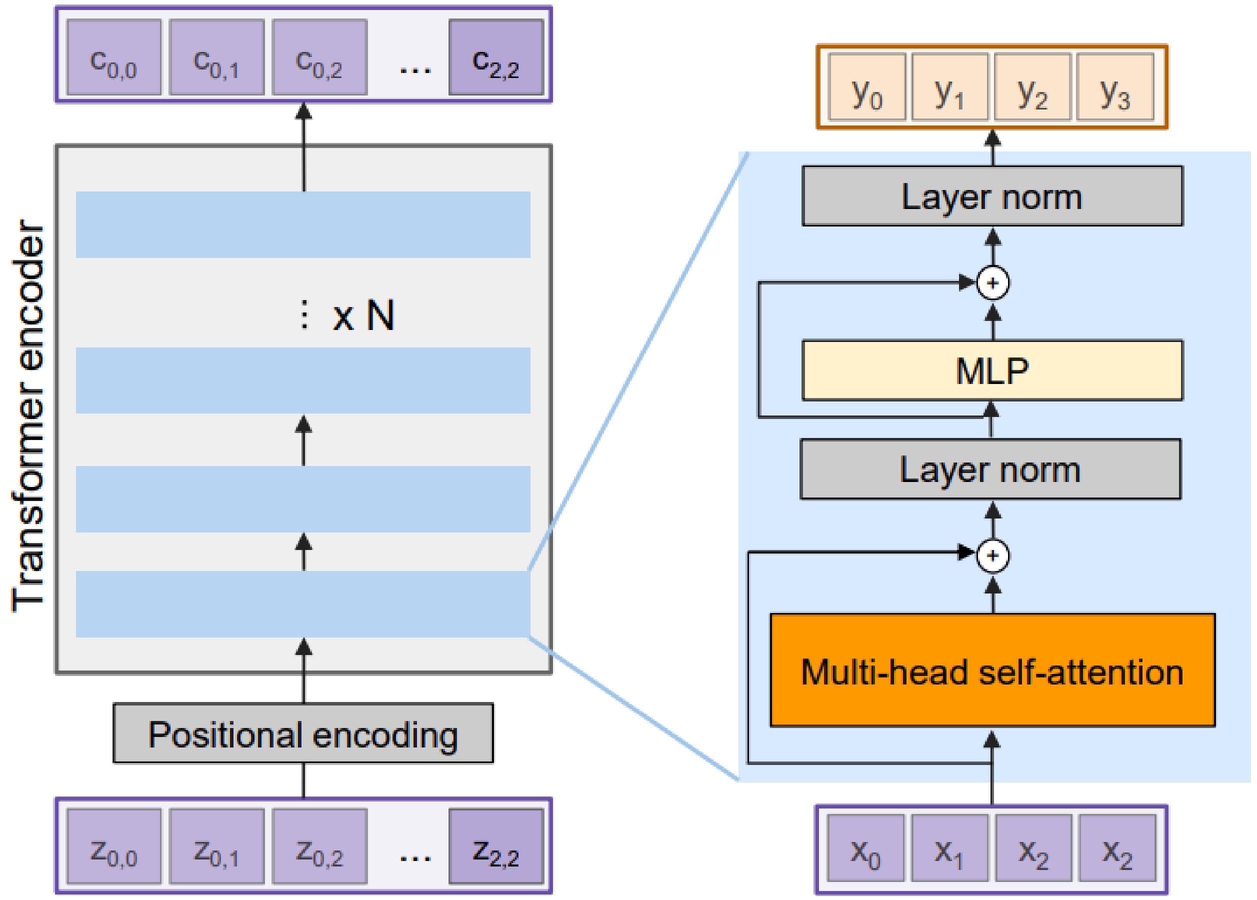
The Transformer encoder block



Transformer Encoder Block:

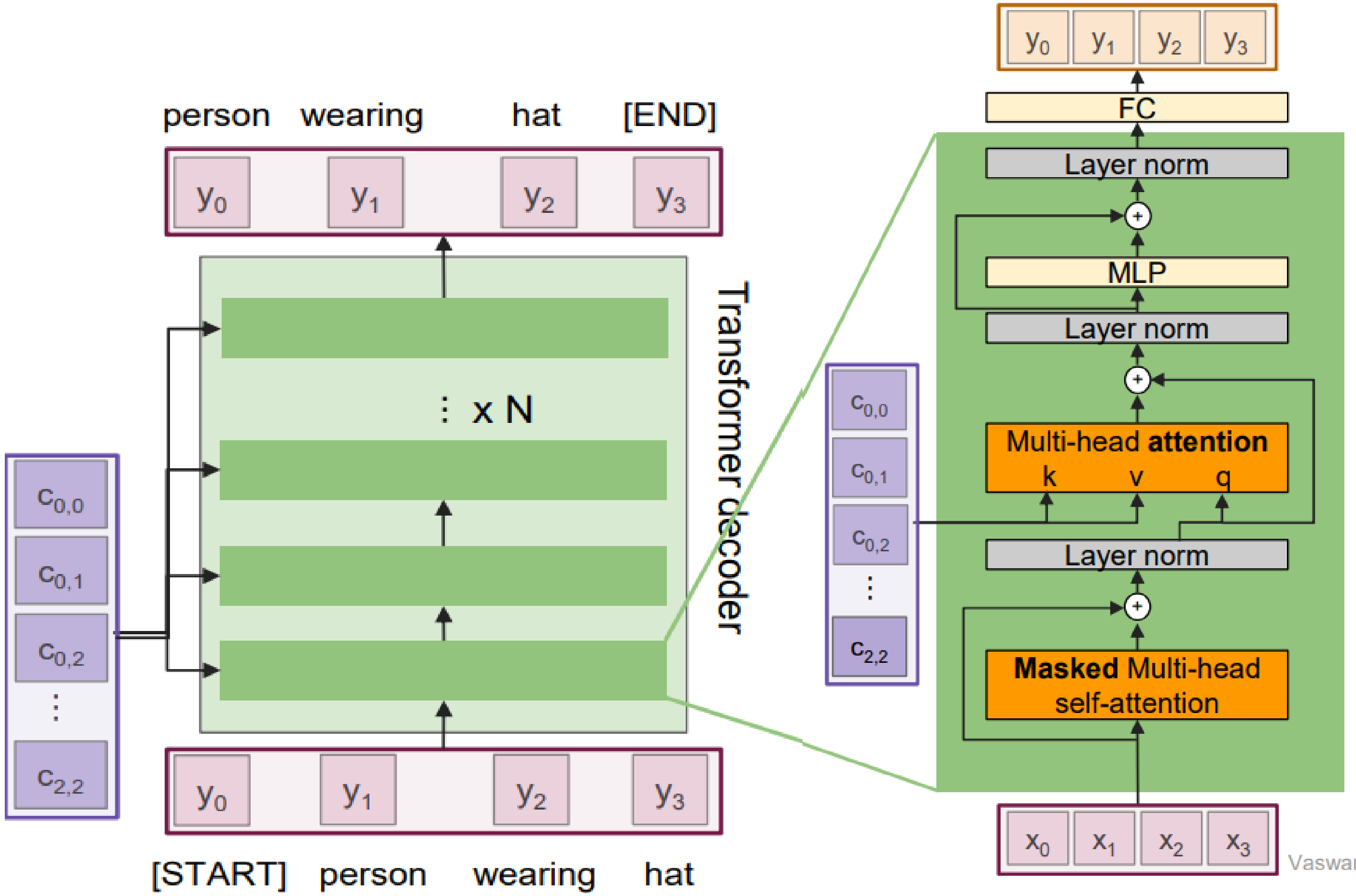
Inputs: Set of vectors **x**
Outputs: Set of vectors **y**

Self-attention is the only interaction between vectors.

Layer norm and MLP operate independently per vector.

Highly scalable, highly parallelizable, but high memory usage.

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.

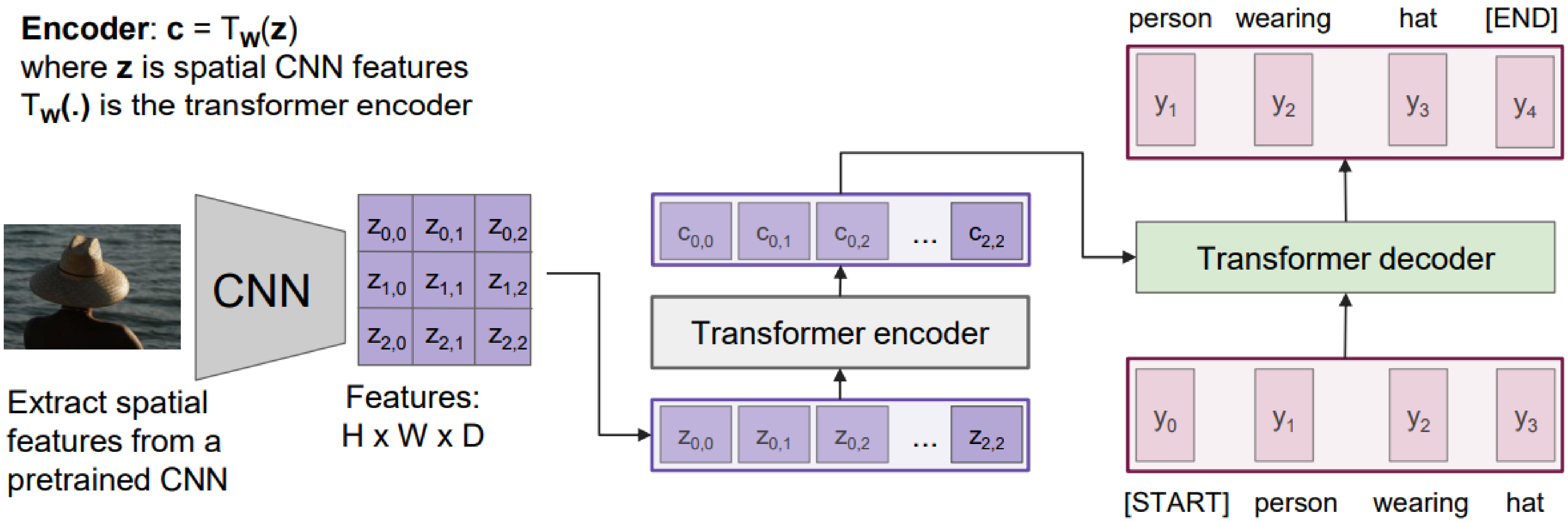
Vaswani et al, "Attention is all you need", NeurIPS 2017

Image Captioning using Transformers

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

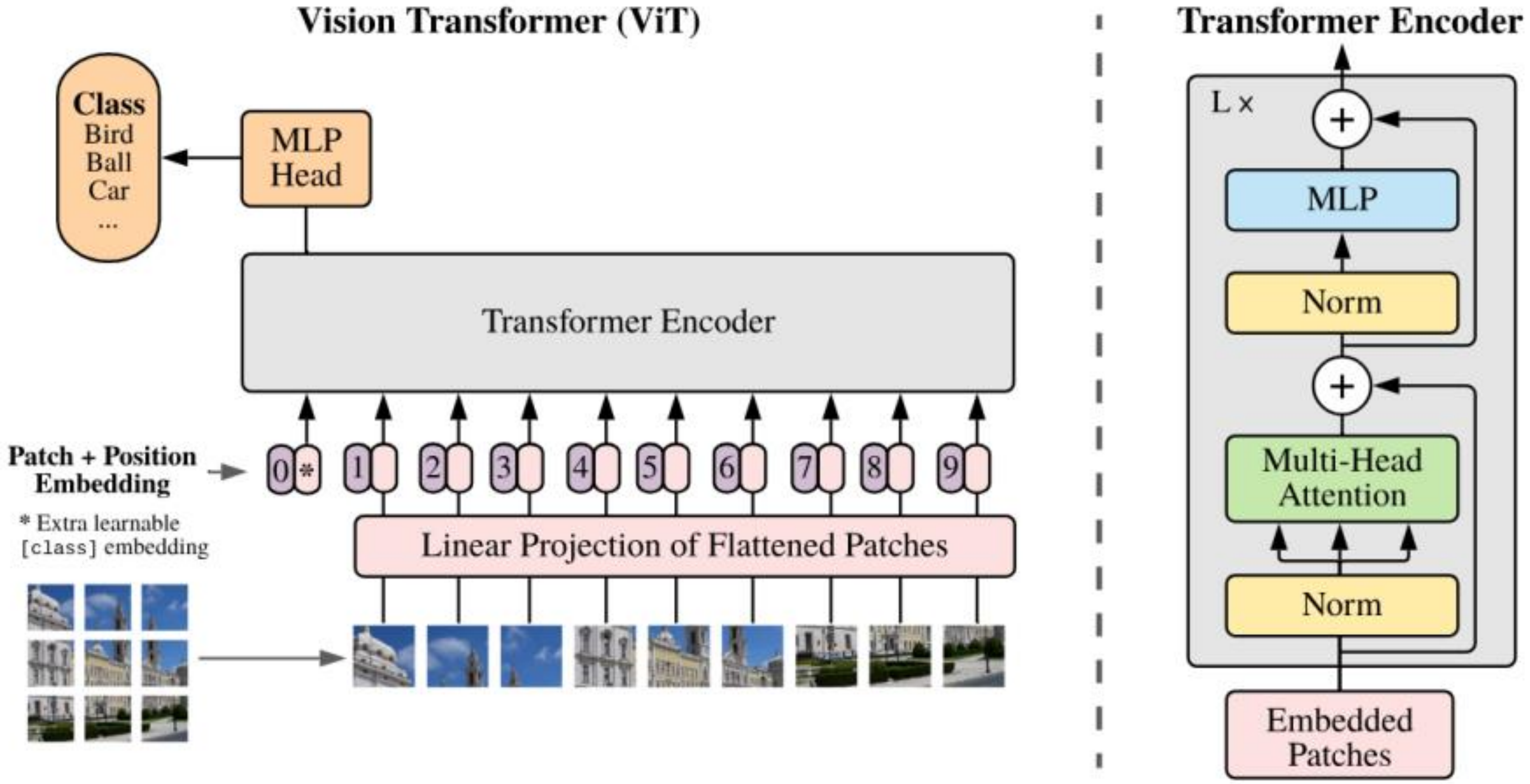
Decoder: $y_t = T_D(\mathbf{y}_{0:t-1}, \mathbf{c})$
where $T_D(.)$ is the transformer decoder

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



ViTs – Vision Transformers

- Transformers from pixels to language



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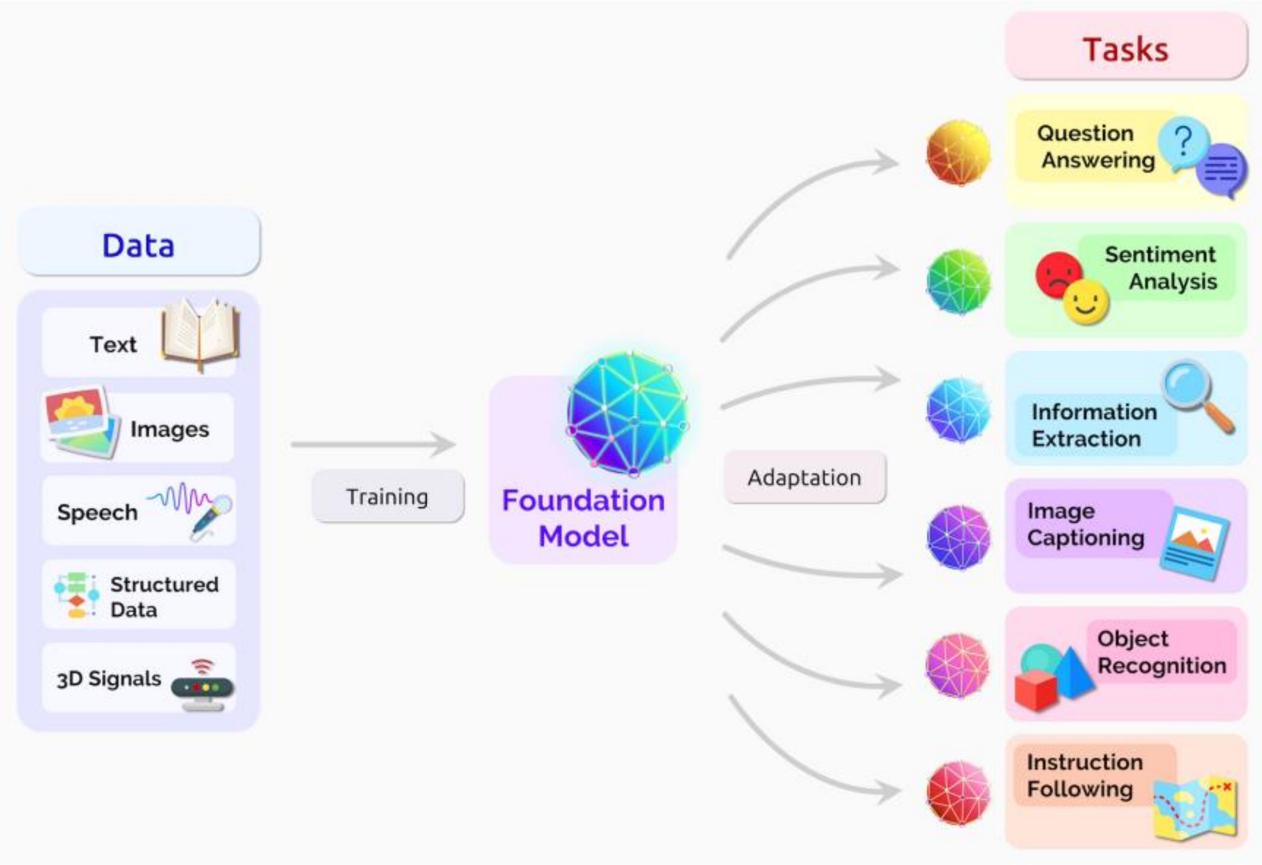
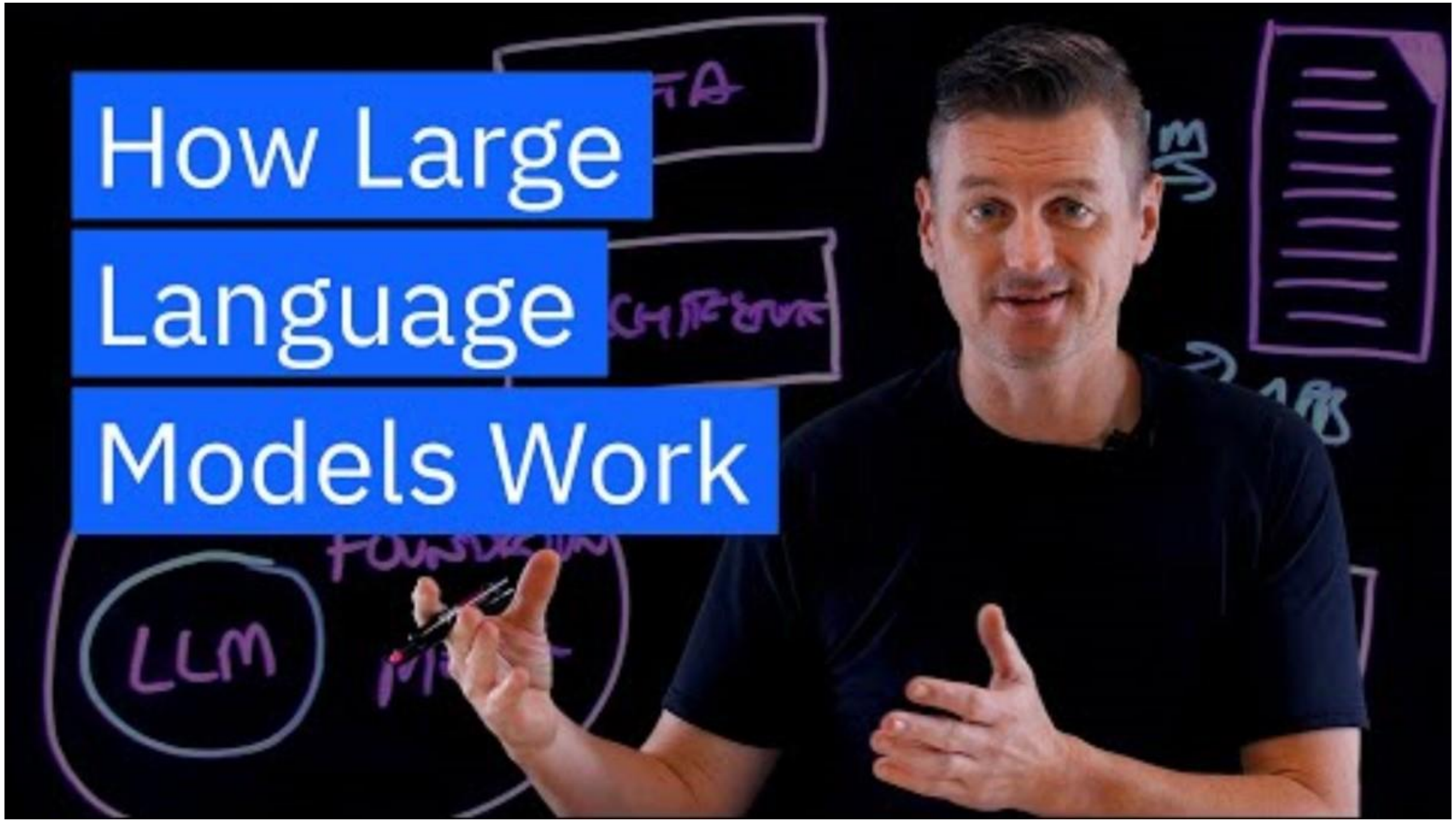
Foundation Models in Different Modalities



https://arxiv.org/pdf/2108.07258

- Foundation model is trained on large amounts of unlabeled/self-supervised data.
- A foundation model can centralize the information from all the data from various modalities.
- This one model can then be adapted to a wide range of downstream tasks.

GPT: Generative Pre-Trained Transformers



https://www.youtube.com/watch?v=5sLYAQS9sWQ

Other Foundation Model Designs in NLP

2020	ACL	CamemBERT [87]	Transformer Encoder	Contextual	MLM(WWM)	https://camembert-model.fr
2020	ACL	XLM-R [88]	Transformer Encoder	Contextual	MLM	https://github.com/.../XLM
2020	ICLR	Reformer [89]	Reformer	Permutation	-	https://github.com/.../reformer
2020	ICLR	ELECTRA [46]	Transformer Encoder	Contextual	MLM	https://github.com/.../electra
2020	AAAI	Q-BERT [90]	Transformer Encoder	Contextual	MLM	-
2020	AAAI	XNLG [91]	Transformer	Contextual	MLM+DAE	https://github.com/.../xnlg
2020	AAAI	K-BERT [92]	Transformer Encoder	Contextual	MLM	https://github.com/.../K-BERT
2020	AAAI	ERNIE 2.0 [62]	Transformer Encoder	Contextual	MLM	https://github.com/.../ERNIE
2020	NeurIPS	GPT-3 [20]	Transformer Decoder	Autoregressive	LM	https://github.com/.../gpt-3
2020	NeurIPS	MPNet [57]	Transformer Encoder	Permutation	MLM+PLM	https://github.com/.../MPNet
2020	NeurIPS	ConvBERT [93]	Mixed Attention	Contextual	-	https://github.com/.../ConvBert
2020	NeurIPS	MiniLM [94]	Transformer Encoder	Contextual	MLM	https://github.com/.../minilm
2020	TACL	mBART [95]	Transformer	Contextual	DAE	https://github.com/.../mbart
2020	COLING	CoLAKE [96]	Transformer Encoder	Contextual	MLM+KE	https://github.com/.../CoLAKE
2020	LREC	FlauBERT [97]	Transformer Encoder	Contextual	MLM	https://github.com/.../Flaubert
2020	EMNLP	GLM [98]	Transformer Encoder	Contextual	MLM+KG	https://github.com/.../GLM
2020	EMNLP (Findings)	TinyBERT [99]	Transformer	Contextual	MLM	https://github.com/.../TinyBERT
2020	EMNLP (Findings)	RobBERT [100]	Transformer Encoder	Contextual	MLM	https://github.com/.../RobBERT
2020	EMNLP (Findings)	ZEN [64]	Transformer Encoder	Contextual	MLM	https://github.com/.../ZEN
2020	EMNLP (Findings)	BERT-MK [101]	KG-Transformer Encoder	Contextual	MLM	-
2020	RepL4NLP@ACL	CompressingBERT [35]	Transformer Encoder	Contextual	MLM(Pruning)	https://github.com/.../bert-prune
2020	JMLR	T5 [102]	Transformer	Contextual	MLM(Seq2Seq)	https://github.com/...transformer
2021	T-ASL	BERT-wwm-Chinese [63]	Transformer Encoder	Contextual	MLM	https://github.com/...BERT-wwm
2021	EACL	PET [103]	Transformer Encoder	Contextual	MLM	https://github.com/.../pet
2021	TACL	KEPLER [104]	Transformer Encoder	Contextual	MLM+KE	https://github.com/.../KEPLER
2021	EMNLP	SimCSE [105]	Transformer Encoder	Contextual	MLM+KE	https://github.com/.../SimCSE
2021	ICML	GLaM [106]	Transformer	Autoregressive	LM	-
2021	arXiv	XLM-E [107]	Transformer	Contextual	MLM	
2021	arXiv	T0 [108]	Transformer	Contextual	MLM	https://github.com/.../T0
2021	arXiv	Gopher [109]	Transformer	Autoregressive	LM	-
2022	arXiv	MT-NLG [110]	Transformer	Contextual	MLM	-
2022	arXiv	LaMDA [67]	Transformer Decoder	Autoregressive	LM	https://github.com/.../LaMDA
2022	arXiv	Chinchilla [111]	Transformer	Autoregressive	LM	-
2022	arXiv	PaLM [43]	Transformer	Autoregressive	LM	https://github.com/.../PaLM
2022	arXiv	OPT [112]	Transformer Decoder	Autoregressive	LM	https://github.com/.../MetaSeq

https://arxiv.org/pdf/2302.09419

Other Foundation Model Designs in NLP

- Encoder-only: BERT
  - Bidirectional attention, low rank attention matrix
  - masked language modeling
  - understanding

- Encoder-Decoder: T5, BART
  - Large amount of parameters, hard to train

- Decoder-only: GPT
  - Next token prediction
  - Full rank attention matrix
  - Understanding and generation
  - High zero-shot/few-shot generalization

Llama 3: Openly Available LLM to Date

- Llama 3 uses a tokenizer with a vocabulary of 128K tokens that encodes language much more efficiently, which leads to substantially improved model performance.

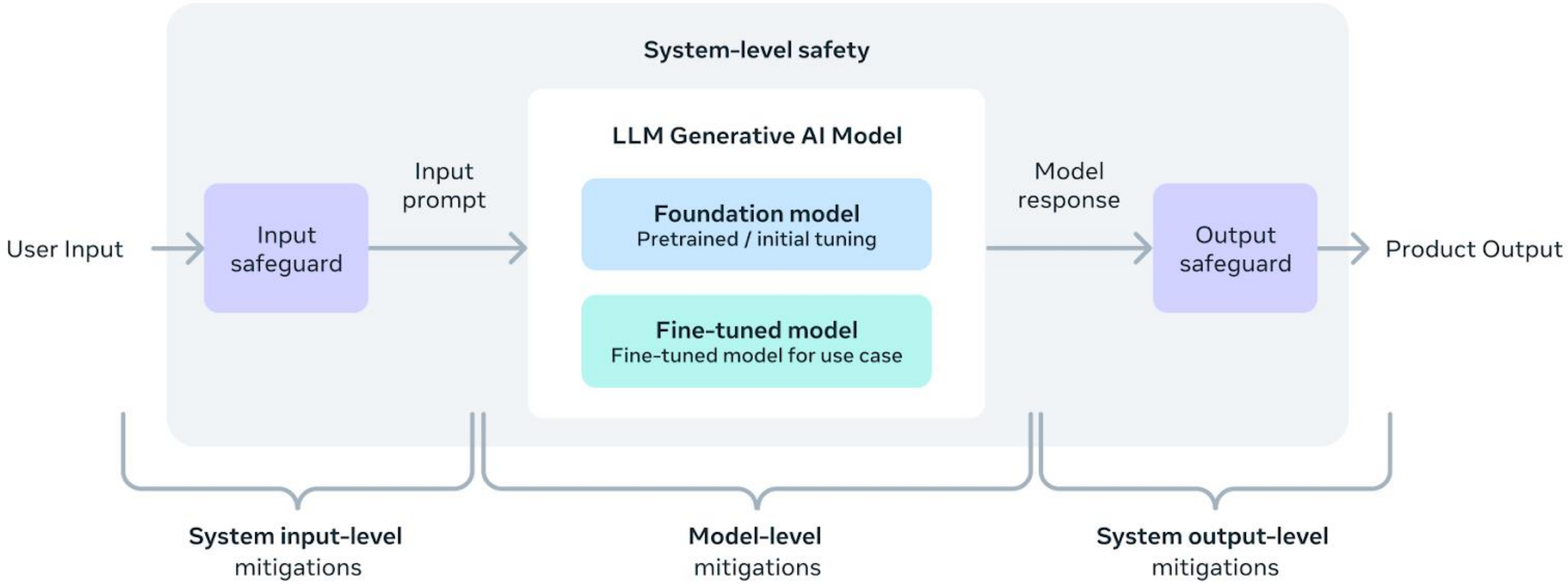
- Llama 3 is pretrained on over 15T tokens that were all collected from publicly available sources.

- The training runs on two custom-built 24K GPU clusters.

- Instruction fine-tuning: post-training is a combination of supervised fine-tuning (SFT), rejection sampling, proximal policy optimization (PPO), and direct preference optimization (DPO).

https://github.com/meta-llama/llama3

The Safety Measures of LLM (Llama)



Instruction-fine-tuned models have been red-teamed (tested) for safety through internal and external efforts.
The red teaming approach leverages human experts and automation methods to generate adversarial prompts that try to elicit problematic responses.

References

- https://cs231n.stanford.edu/slides/2024/lecture_7.pdf
- https://cs231n.stanford.edu/slides/2024/lecture_8.pdf
- On the Opportunities and Risks of Foundation Models
- A Comprehensive Survey on Pretrained Foundation Models: A History from BERT to ChatGPT