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

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"ImageNet Moment for Natural Language Processing"

Pretraining:
Download a lot of text from the internet

Train a giant Transformer model for language modeling

Finetuning:
Fine-tune the Transformer on your own NLP task

On the Opportunities and Risks of Foundation Models

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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
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Li Fei-Fei Chelsea Finn Trevor Gale Lauren Gillespie Karan Goel Noah Goodman
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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
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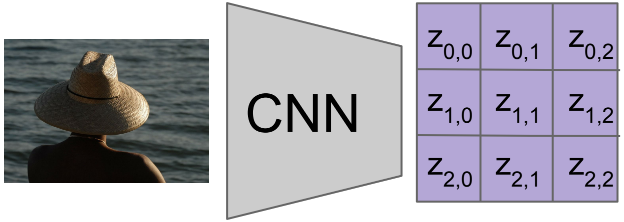
Image Captioning using Transformers

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



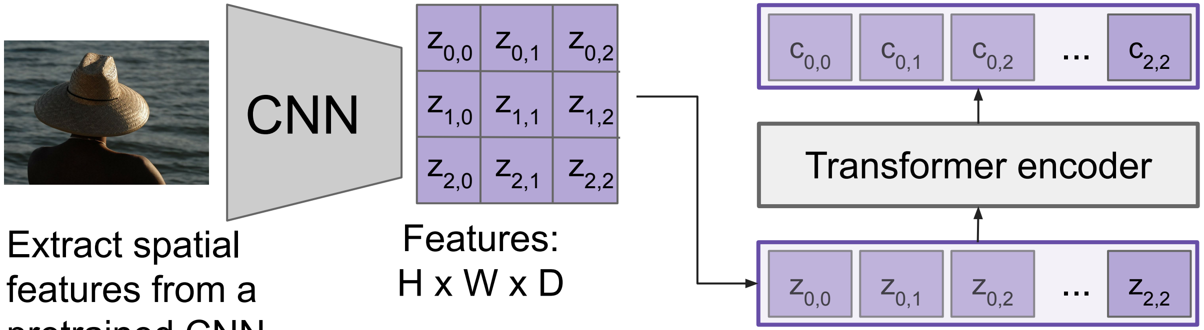
Extract spatial features from a pretrained CNN

Features: H x W x D

Image Captioning using Transformers

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

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



Extract spatial features from a pretrained CNN

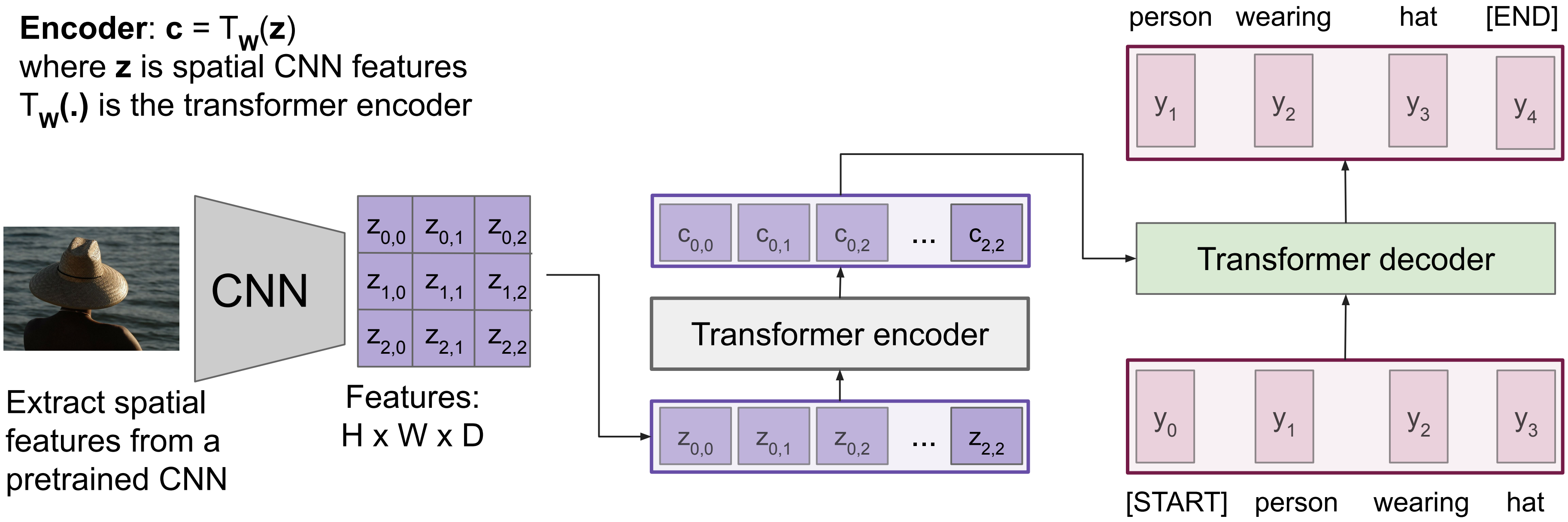
Features: H x W x D

Image Captioning using Transformers

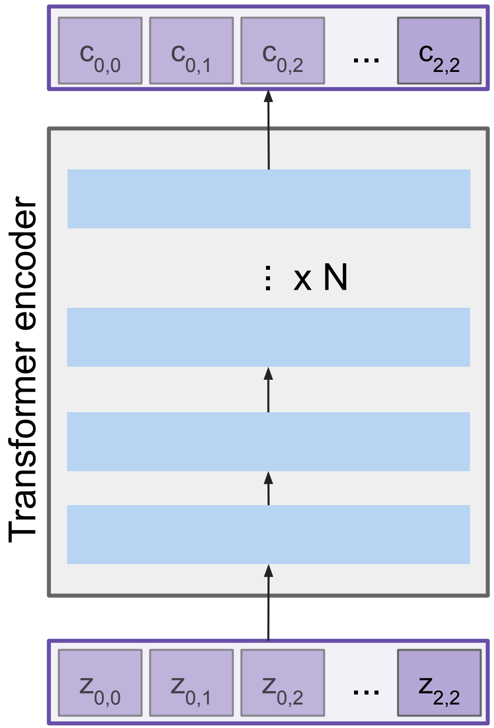
Input: Image **I**
Output: Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$

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 $\mathbf{z}$ is spatial CNN features
$T_W(.)$ is the transformer encoder



The Transformer encoder block

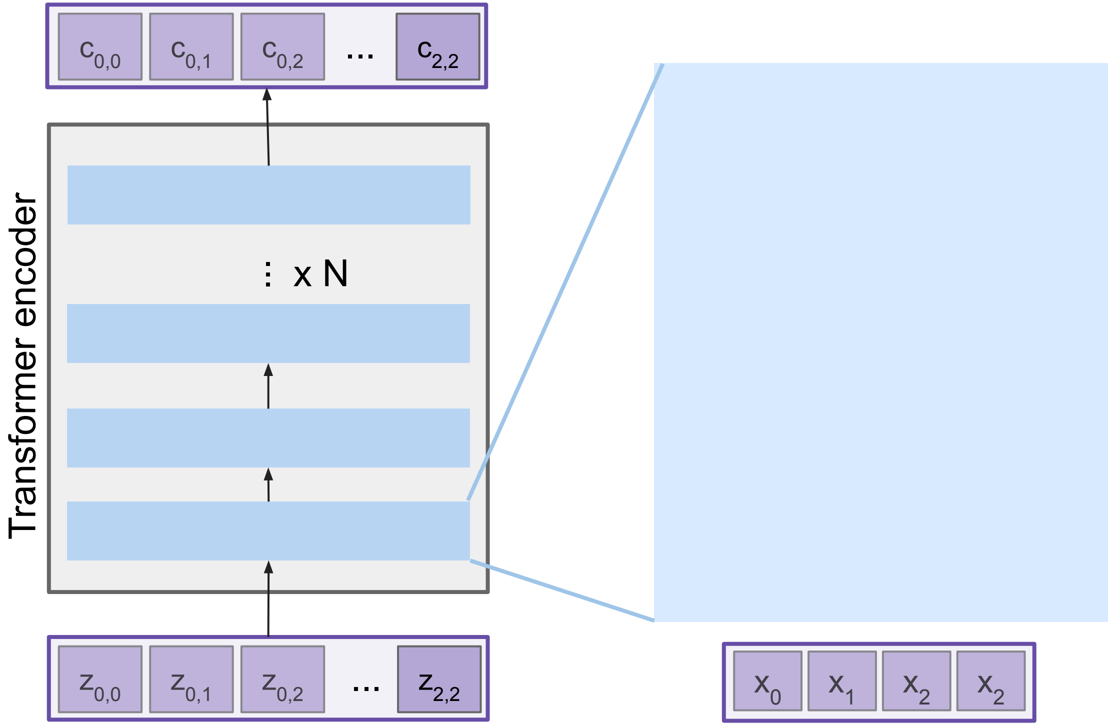


Made up of N encoder blocks.

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

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

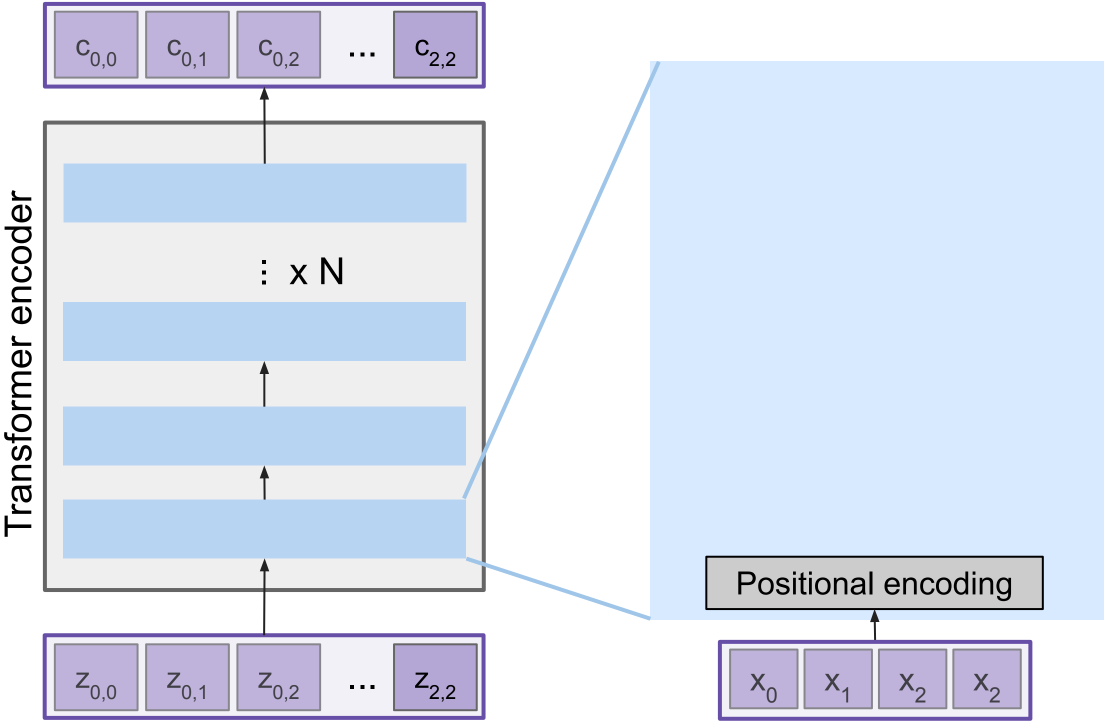
The Transformer encoder block



Let's dive into one encoder block

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

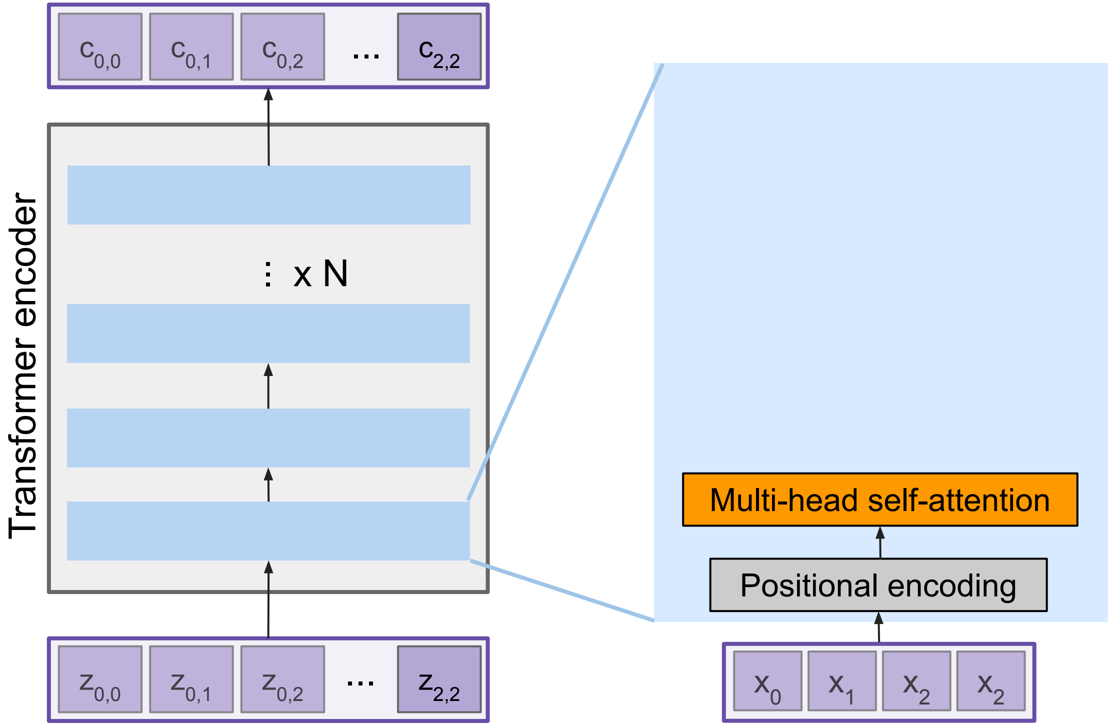
The Transformer encoder block



Add positional encoding

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

The Transformer encoder block

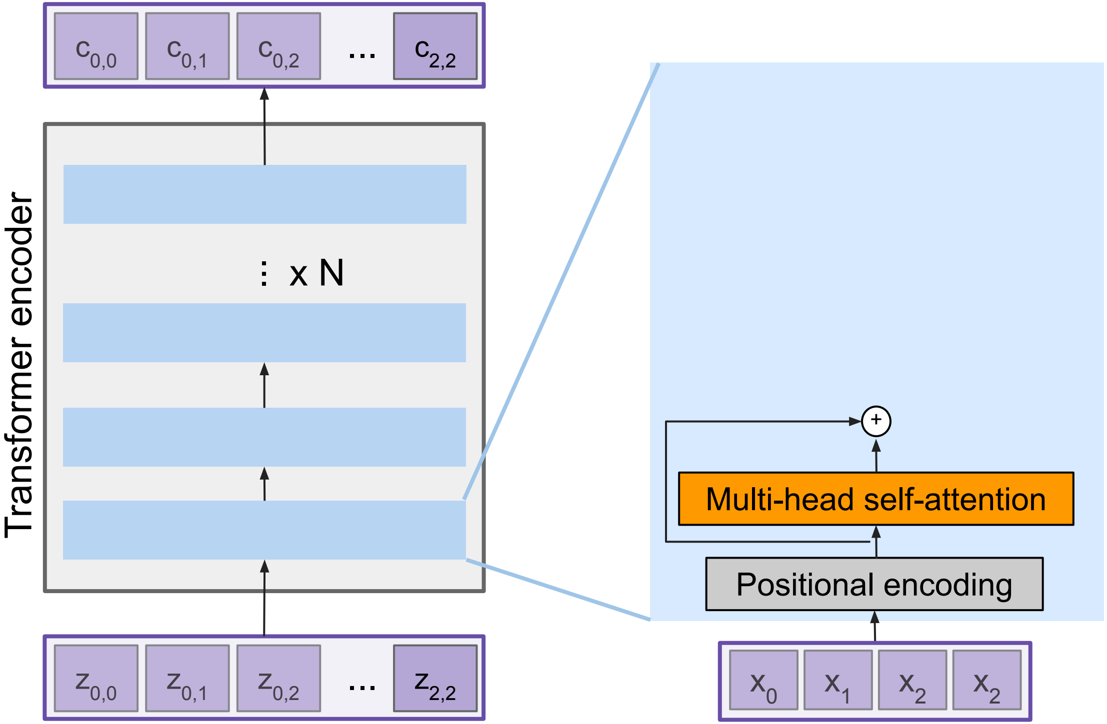


Attention attends over all the vectors

Add positional encoding

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

The Transformer encoder block



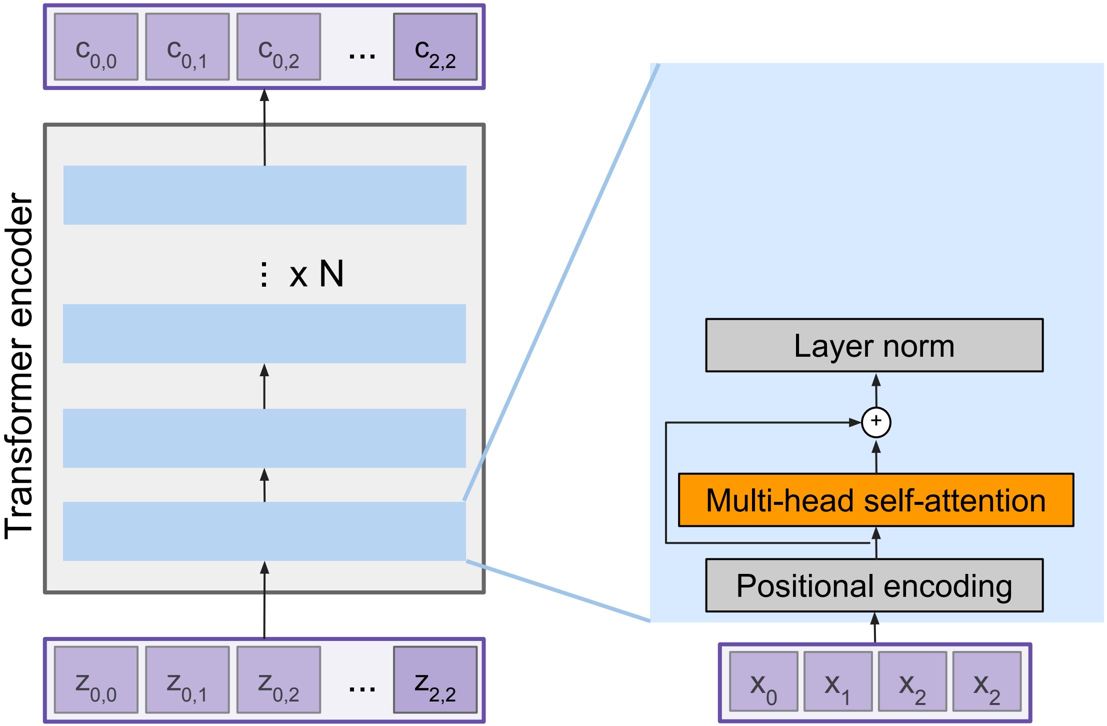
Residual connection

Attention attends over all the vectors

Add positional encoding

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

The Transformer encoder block



LayerNorm over each vector individually

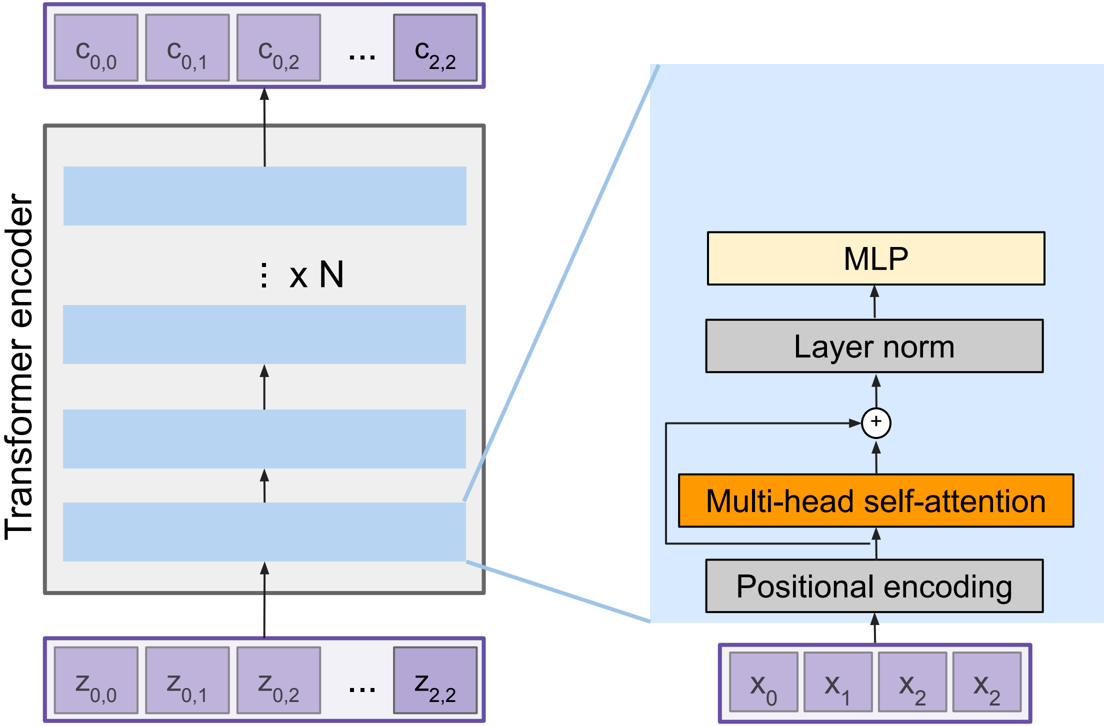
Residual connection

Attention attends over all the vectors

Add positional encoding

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

The Transformer encoder block



MLP over each vector individually

LayerNorm over each vector individually

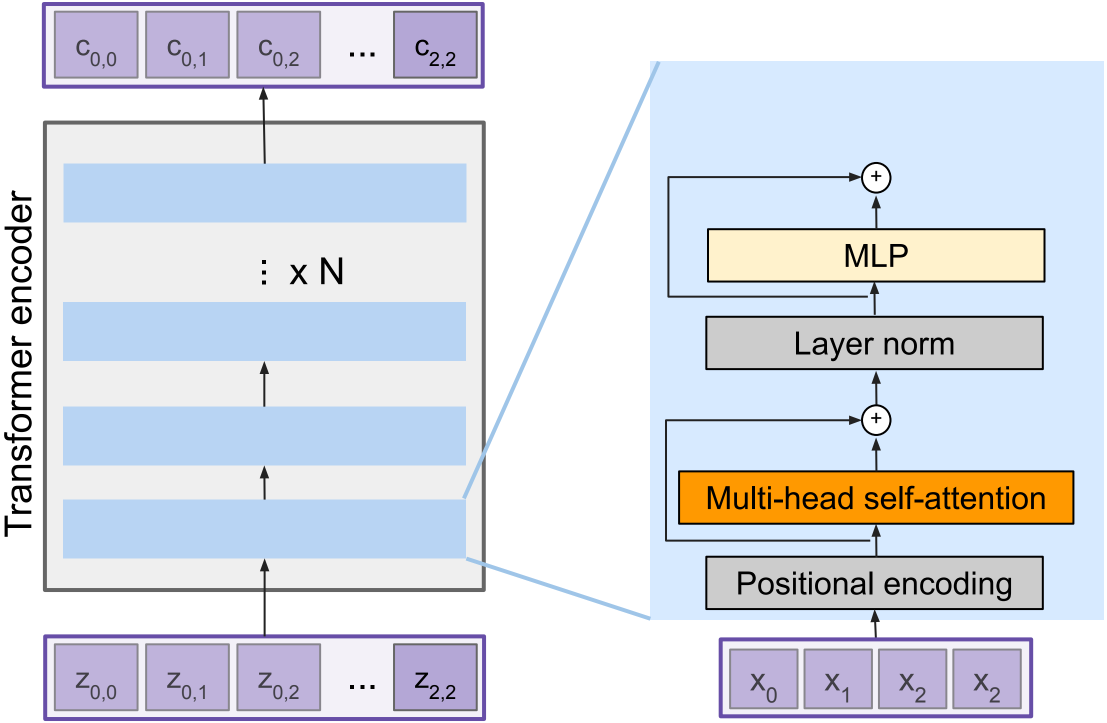
Residual connection

Attention attends over all the vectors

Add positional encoding

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

The Transformer encoder block



Residual connection

MLP over each vector individually

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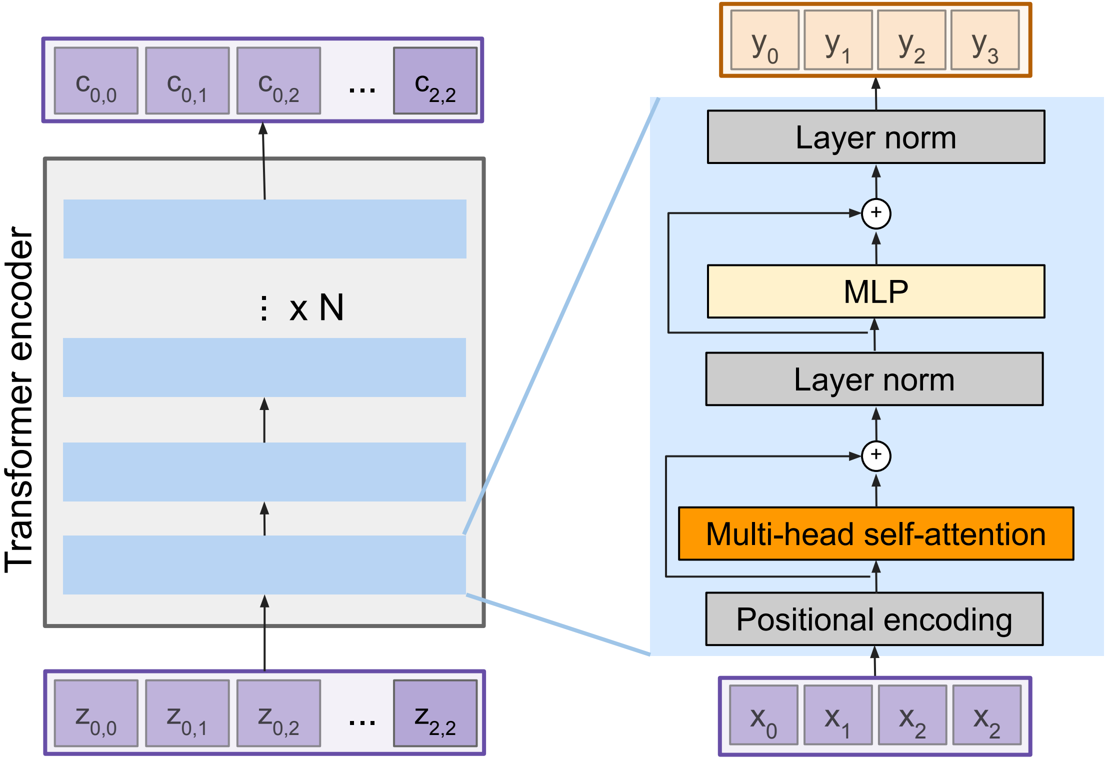
Residual connection

Attention attends over all the vectors

Add positional encoding

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

The Transformer encoder block



Transformer Encoder Block:

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

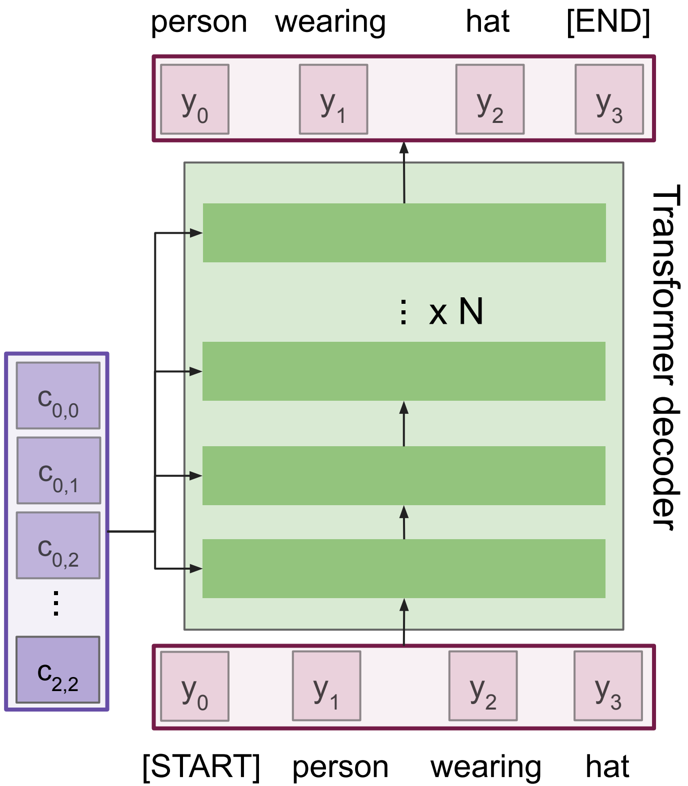
Self-attention is the only interaction between vectors.

Layer norm and MLP operate independently per vector.

Highly scalable, highly parallelizable, but high memory usage.

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

The Transformer decoder block

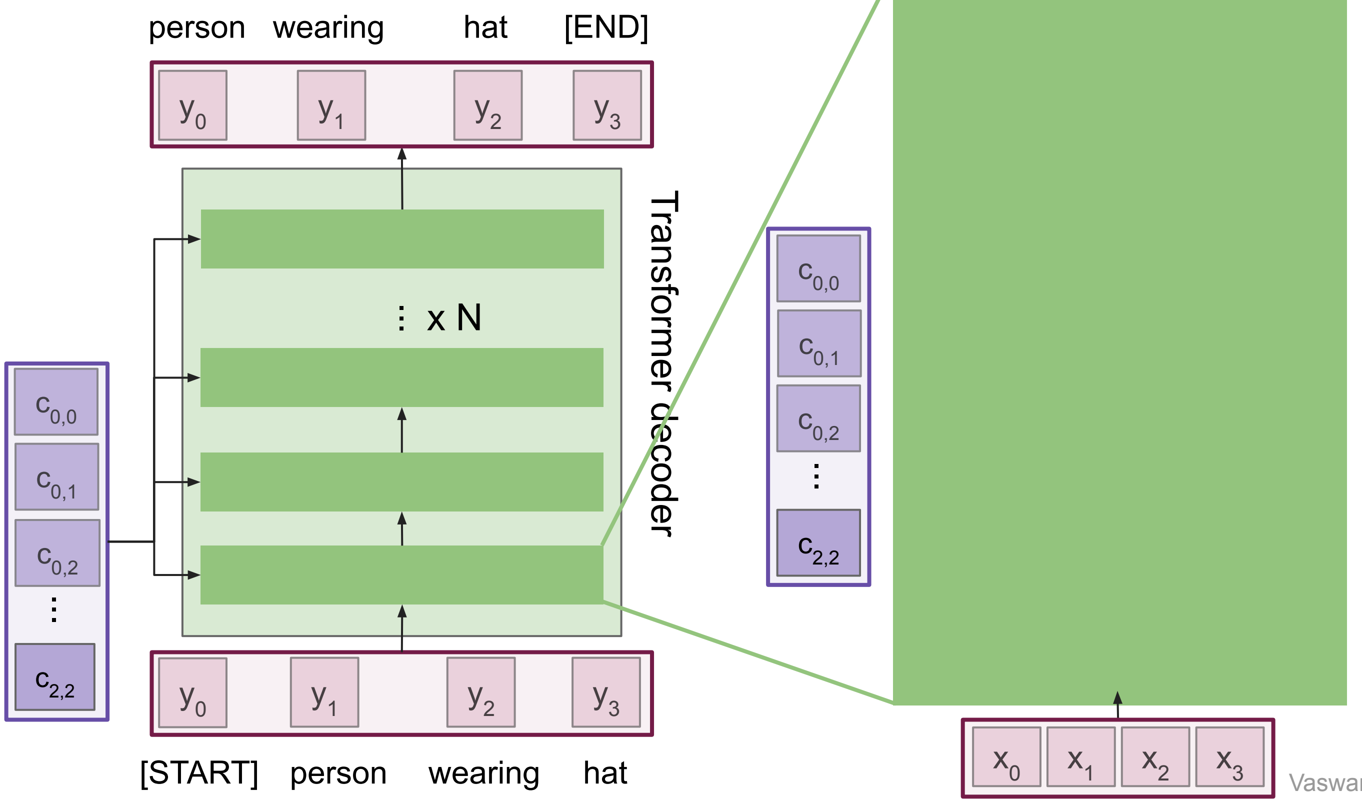


Made up of N decoder blocks.

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

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

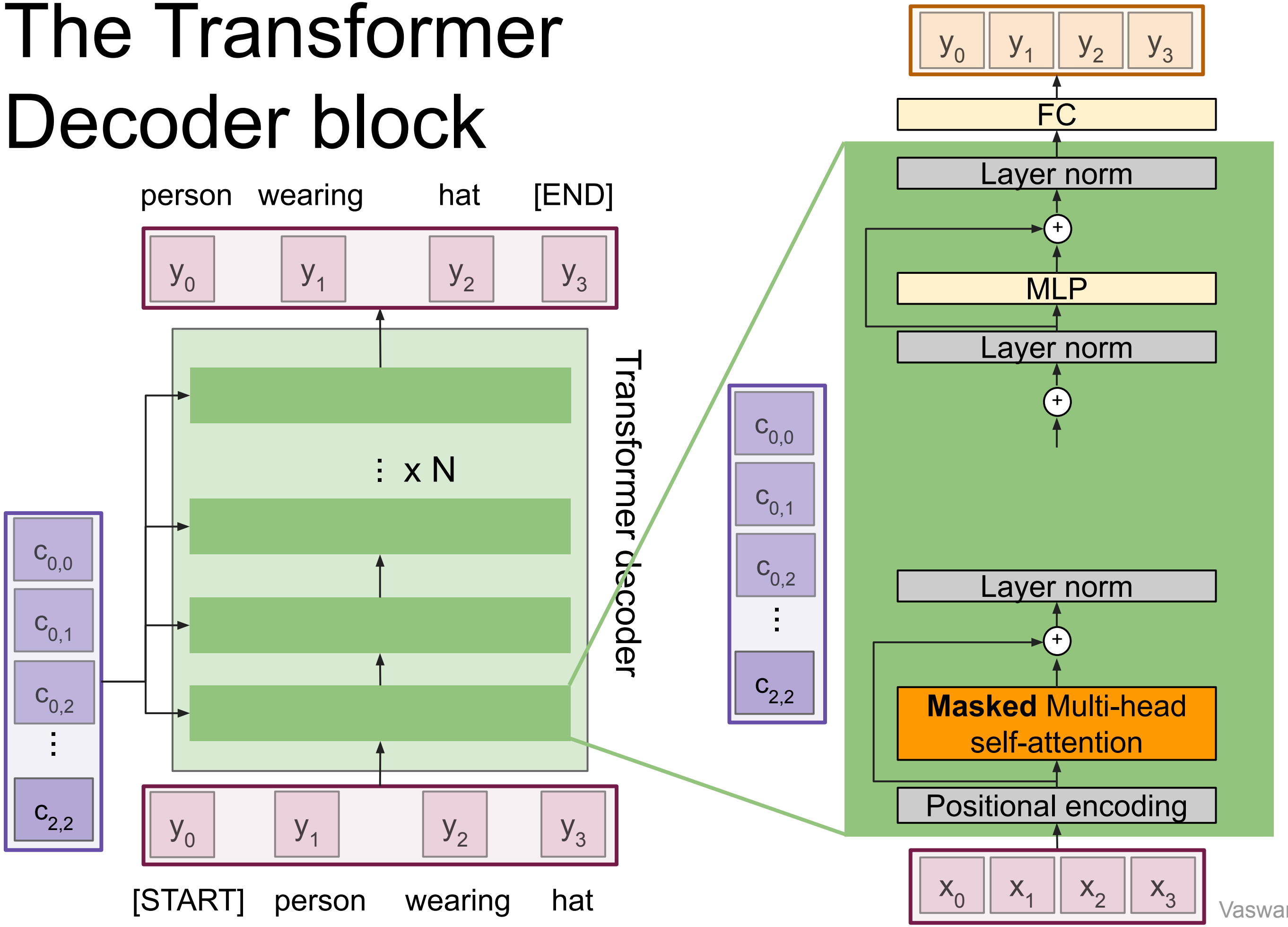
The Transformer decoder block



Let's dive into the transformer decoder block

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

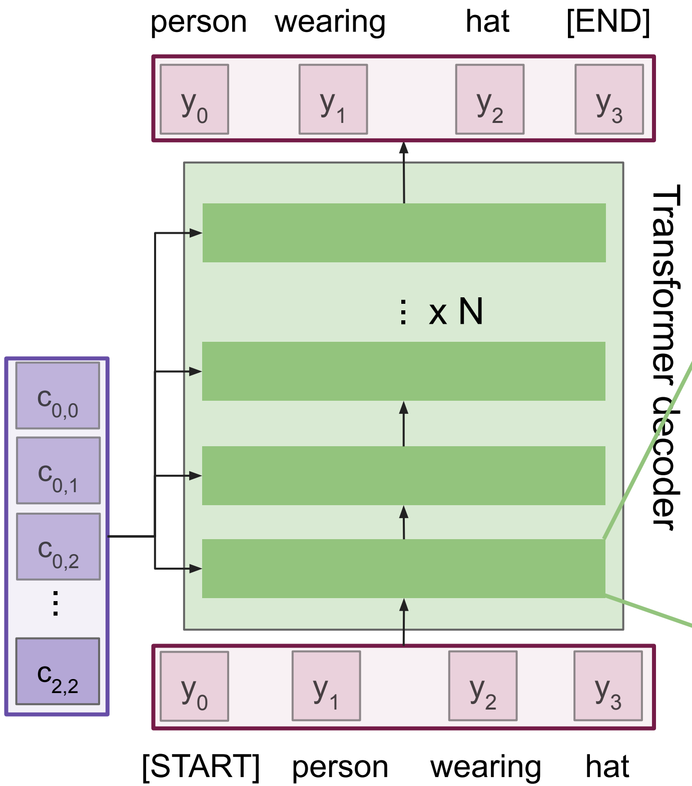
The Transformer Decoder block

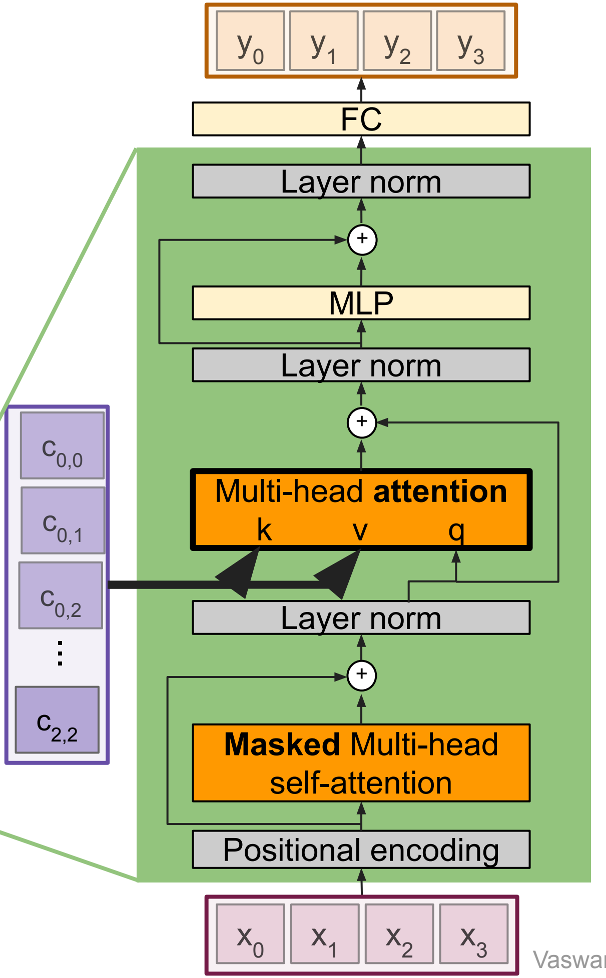


Most of the network is the same the transformer encoder.

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

The Transformer Decoder block



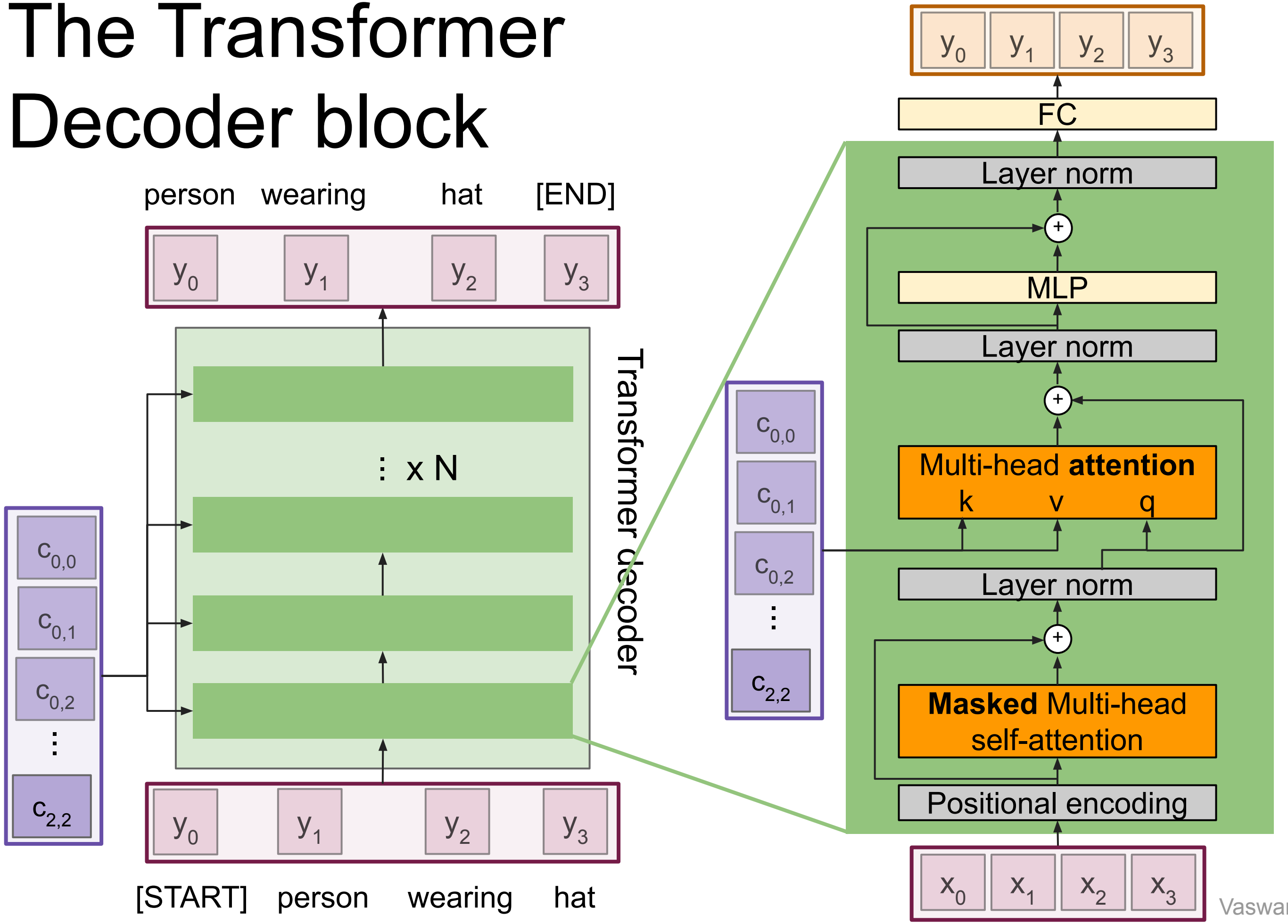


Multi-head attention block attends over the transformer encoder outputs.

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**

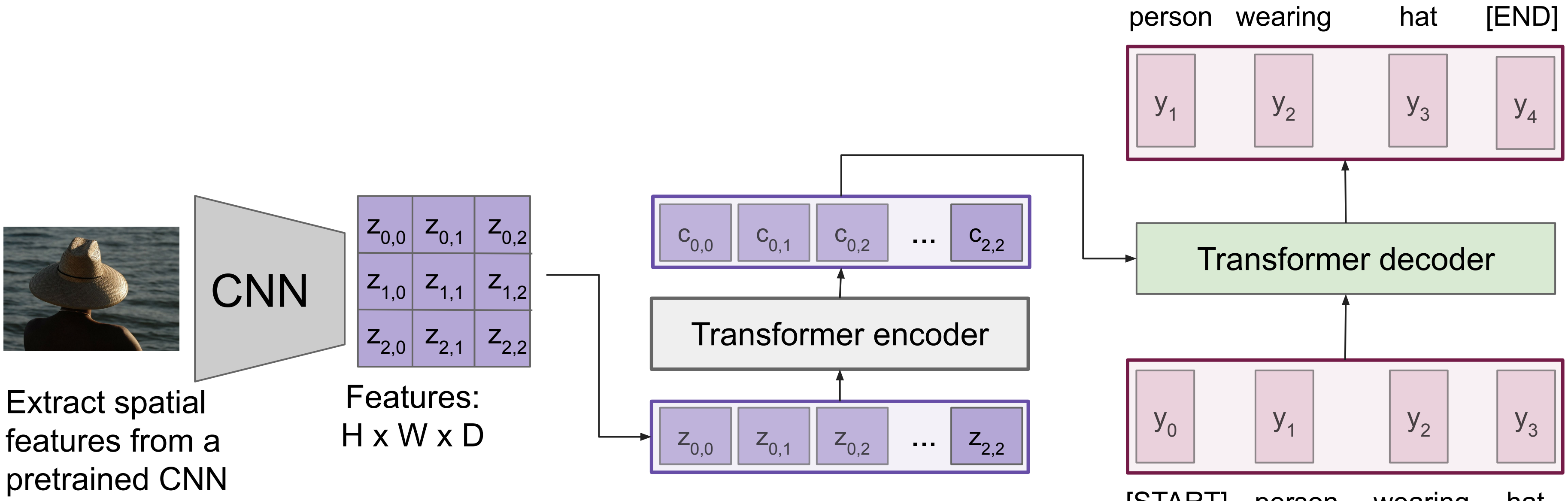


Image Captioning using transformers

- **Perhaps we don't need convolutions at all?**

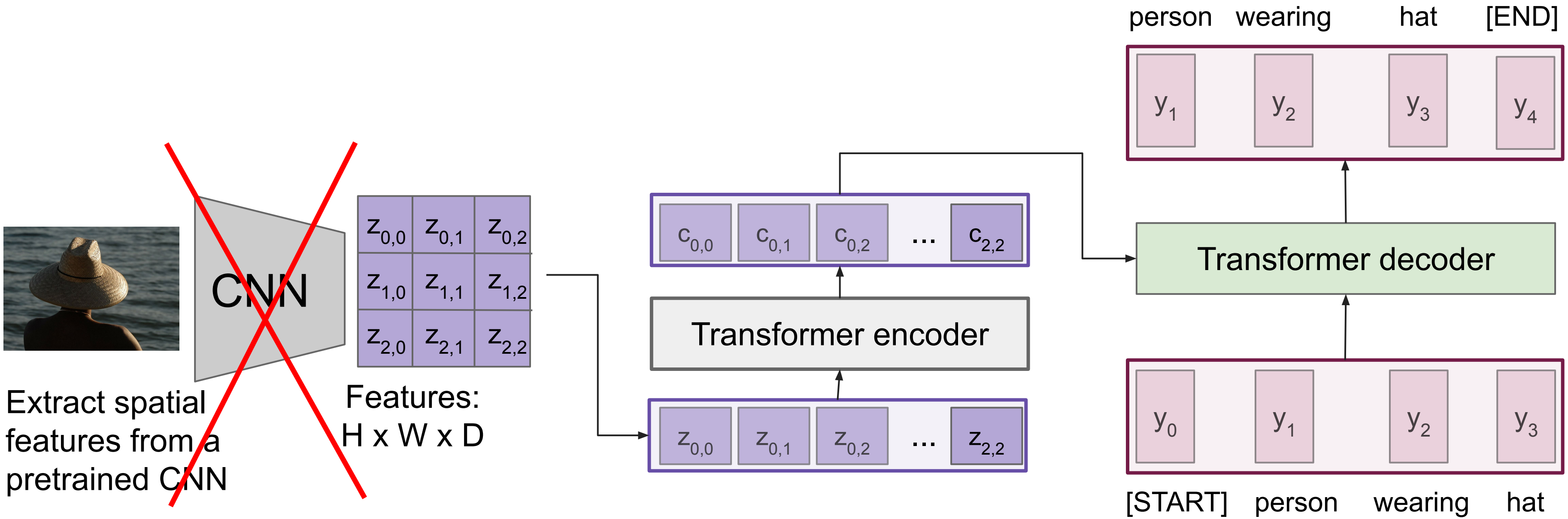
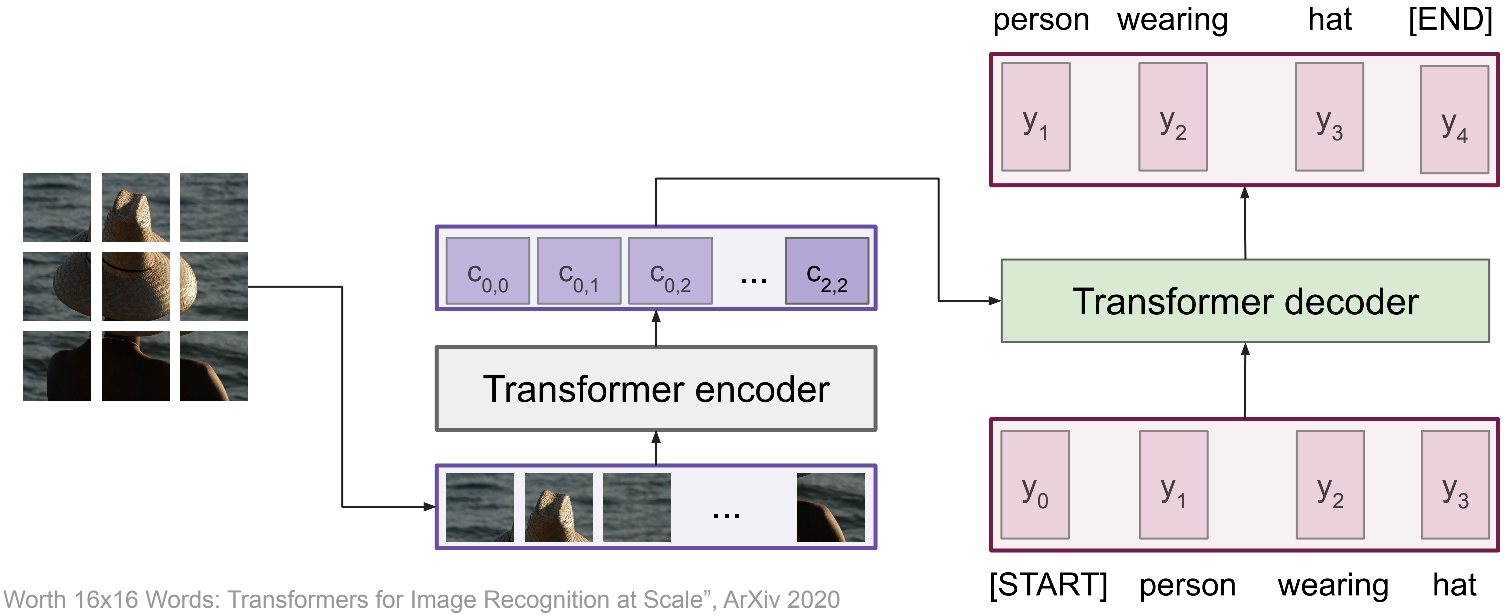


Image Captioning using ONLY transformers

- **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

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.