Sequence Models

Sequence Modelling

- Texts as sequences
  - Sequences are natural representations for text data

"This party was boring"

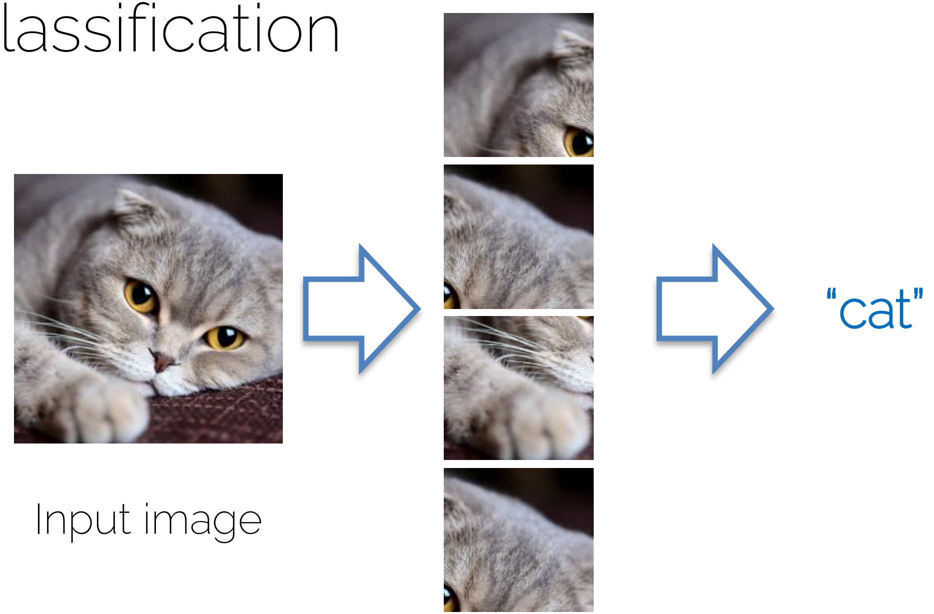
classification → Negative / Positive

translation → "Diese Party war langweilig"

generation → "so I went home"

Sequence Modelling

- Images can also be represented as sequences!
  - Classification

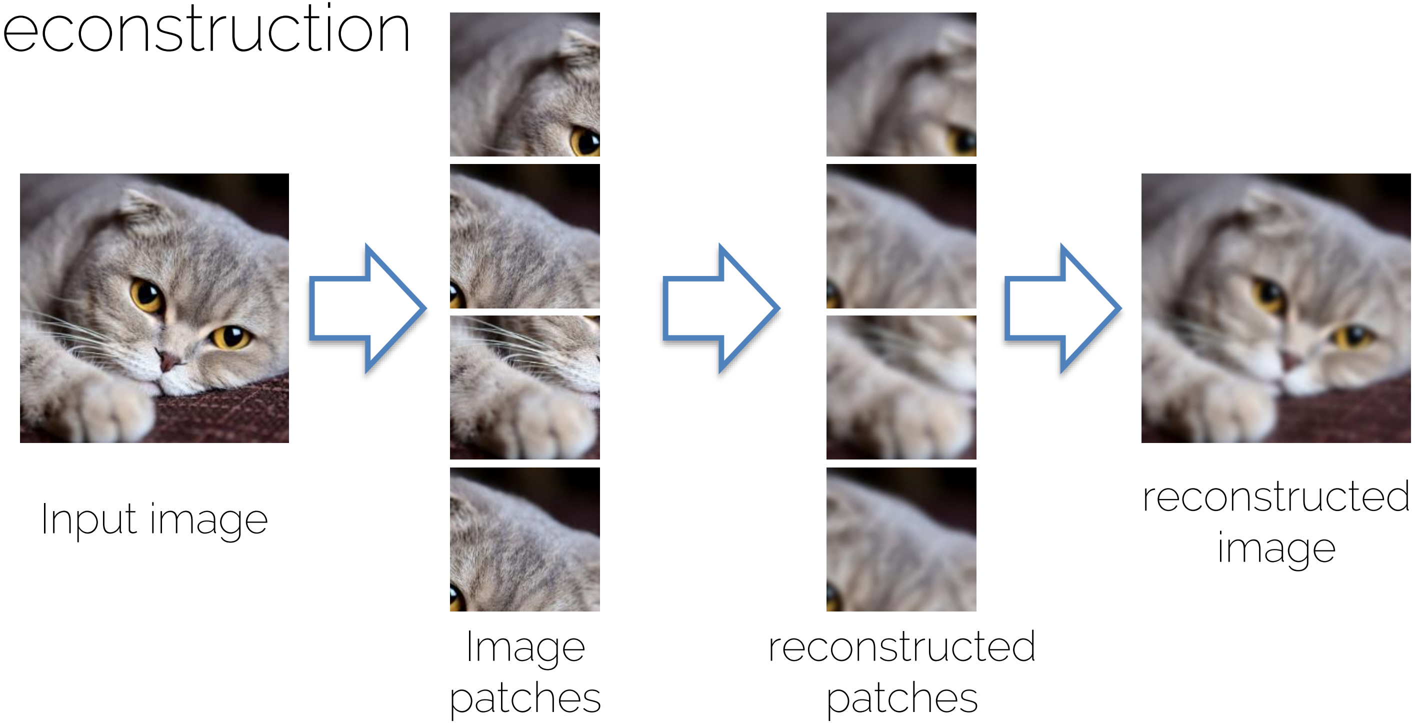


Input image

Image patches

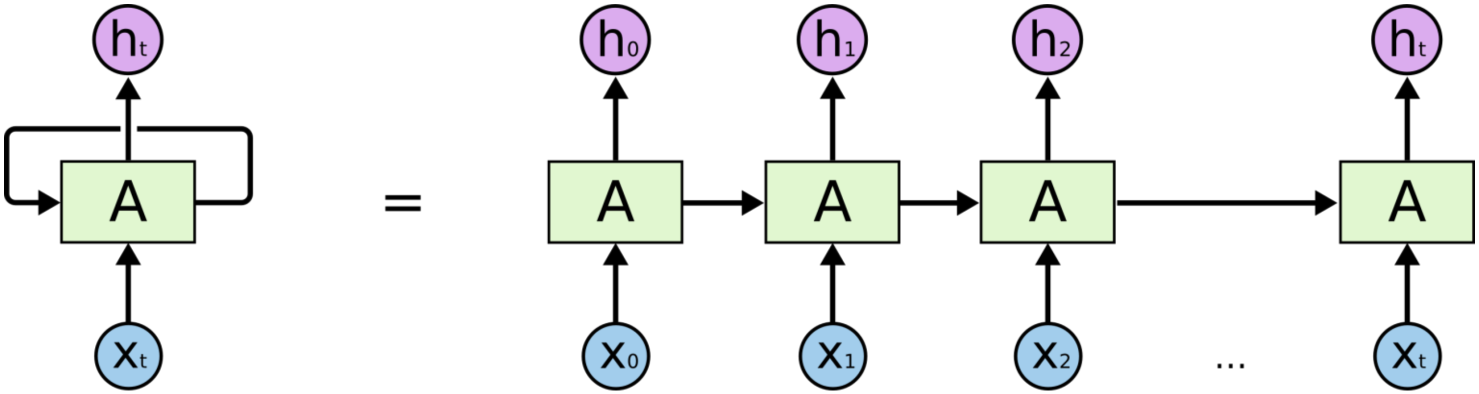
Sequence Modelling

- Images can also be represented as sequences!
  - Reconstruction



Traditional Sequence Models

- RNNs
  - Recurrent Neural Networks
  - Can be unrolled in time

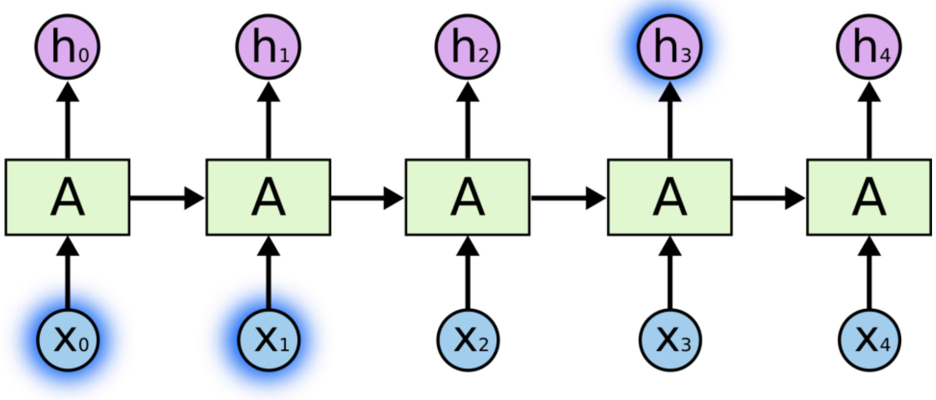


https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Traditional Sequence Models

- RNNs
  - Good at handling short sequences

“so I speak fluent French”



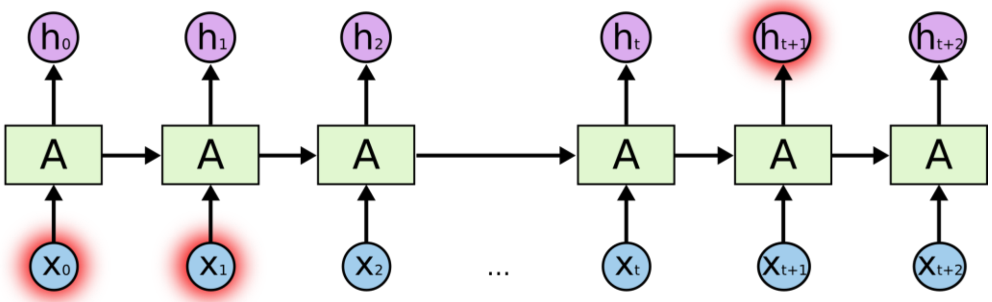
“I lived in France”

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Traditional Sequence Models

- RNNs
  - Long sequences are difficult -> long-term dependency issue

"so I speak fluent __?__"
(I forgot what I said!)

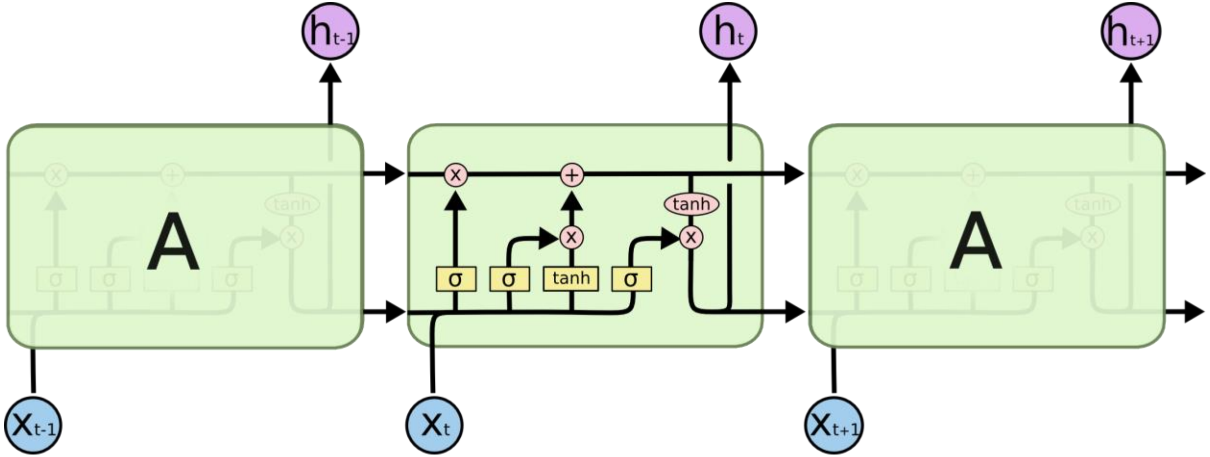


"I lived in France"

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Traditional Sequence Models

- LSTMs
  - Long-short Term Memory networks



https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Traditional Sequence Models

- LSTMs alleviates the long-term dependency issue. However, the issue still exists for extremely long sequences, e.g., documents!

- Not all words are born equal.

"I lived in France, so I speak fluent __?__."

"France" is more important for predicting the word "French" ⇨ Attention mechanism!

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Attention Mechanism

- Deterministic vs. stochastic
  - Soft attention
    - Attend to each part of the input signal
    - Attention weights sum to 1
    - Deterministic and differentiable
    - E.g., when predicting the word “French”:

“I lived in France, so I speak fluent French.”

Attention Mechanism

- Deterministic vs. stochastic
  - Hard attention
    - Attend to one part of the input signal (one-hot)
    - Stochastic and non-differentiable
    - Need to use Monte Carlo estimator to approximate the gradients
    - E.g., when predicting the word "French":

"I lived in France, so I speak fluent French."

Attention Mechanism

- Modality for attention
  - Self-attention
    - Attend to the input signal itself

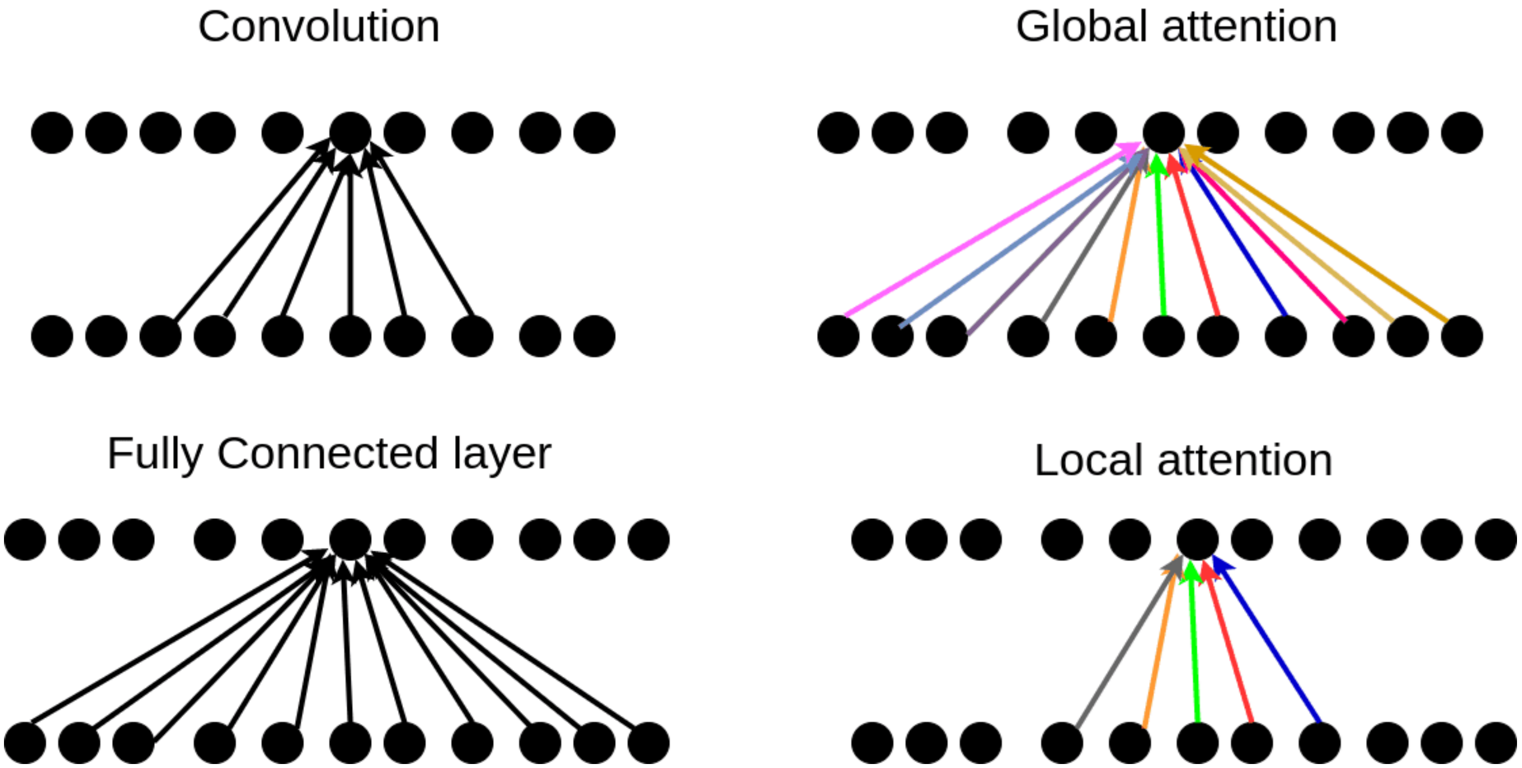
Attention Mechanism

- Modality for attention
  - Cross-attention
    - Attend to another input signal as side information

A person is standing on a beach with a surfboard.

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

Attention vs Convolution



Attention Mechanism

- Attention mechanism is a powerful tool to handle sequence data
- It used to be an additional plug-and-play module on top of the recurrent neural networks
- Can attention mechanism be used for handling sequence data DIRECTLY? -> Yes, transformers!

Transformers in Language

Attention is All You Need

Attention Is All You Need

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Attention is All You Need

- Scale up pure self-attention layers as the first transformer architecture
- Solve the long-term dependency issue in sequence modelling
- Extremely powerful at handling sequence data (texts)
- Bigger model, bigger capacity -> better performance when trained on large-scale datasets

Attention

Index the values via a differentiable operator

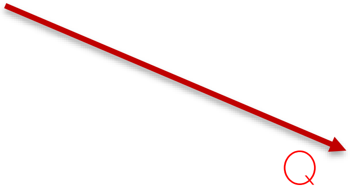
Multiply queries with keys

Get the values

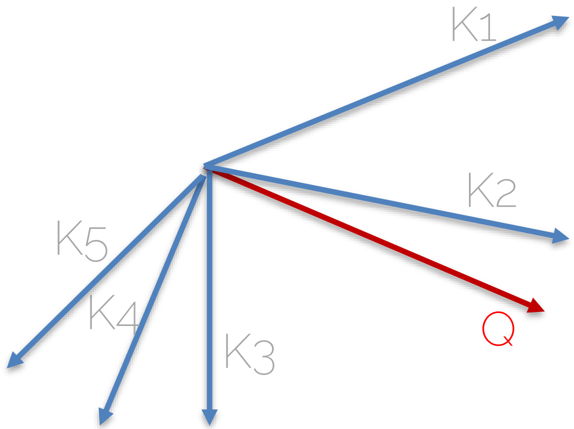
$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

To train them well, divide by $\sqrt{d_k}$, "probably" because for large values of the key's dimension, the dot product grows large in magnitude, pushing the softmax function into regions where it has extremely small gradients.

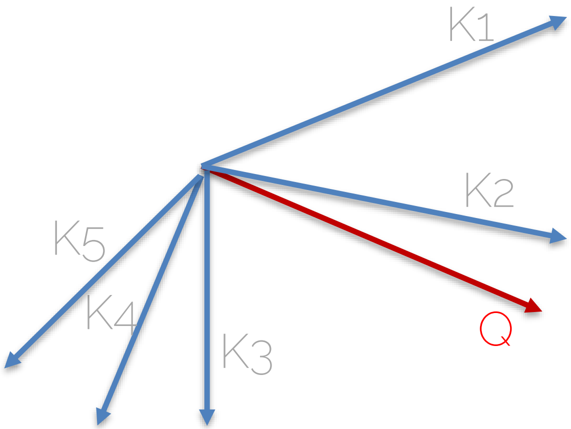
Attention



Attention

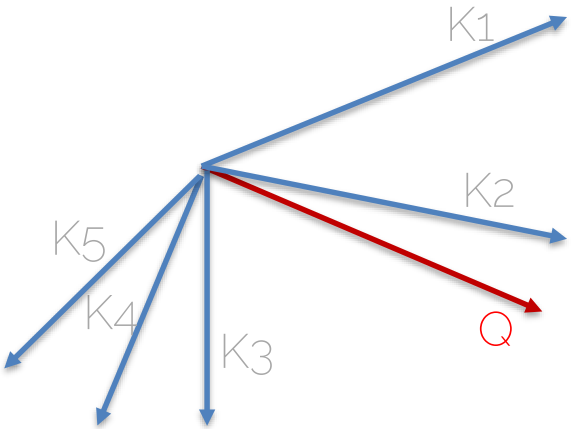


Attention



Values
V1
V2
V3
V4
V5

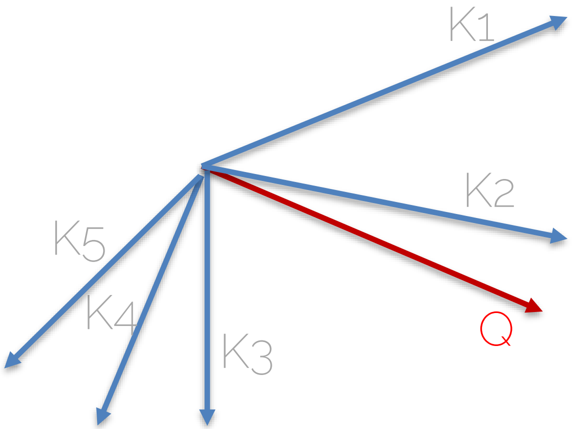
Attention



Values
V1
V2
V3
V4
V5

QK^T Dot product between (<Q,K1>), (<Q,K2>), (<Q,K3>), (<Q,K4>), (<Q,K5>).

Attention

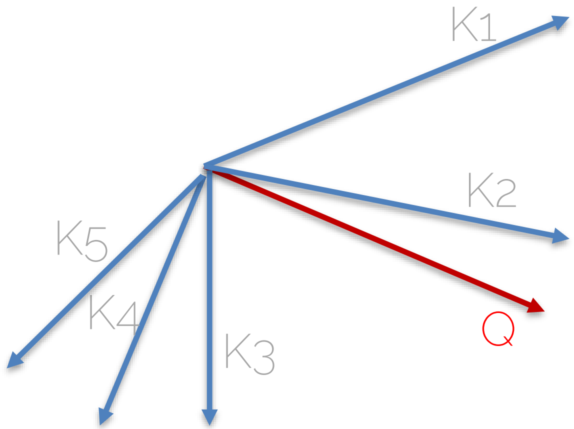


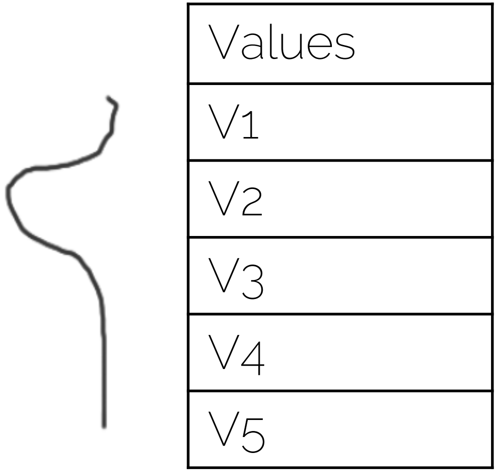
Values
V1
V2
V3
V4
V5

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

Is simply inducing a distribution over the values.
The larger a value is, the higher is its softmax value.
Can be interpreted as a differentiable soft indexing.

Attention





$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

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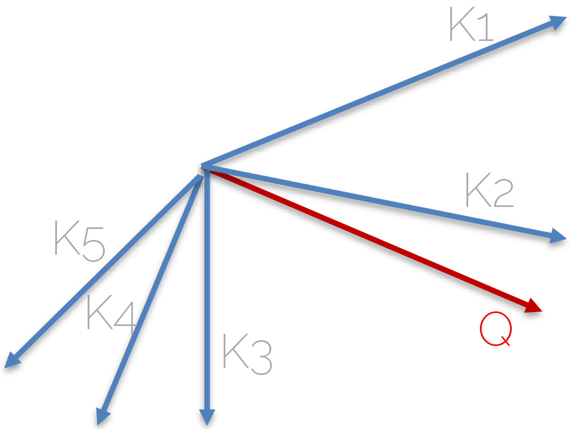
Attention



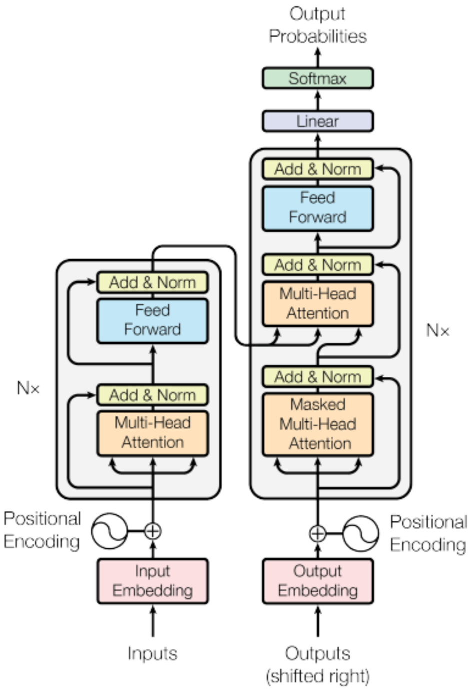
Values
V1
V2
V3
V4
V5

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

Selecting the value V where the network needs to attend..

Attention is All You Need

- Transformers under the hood



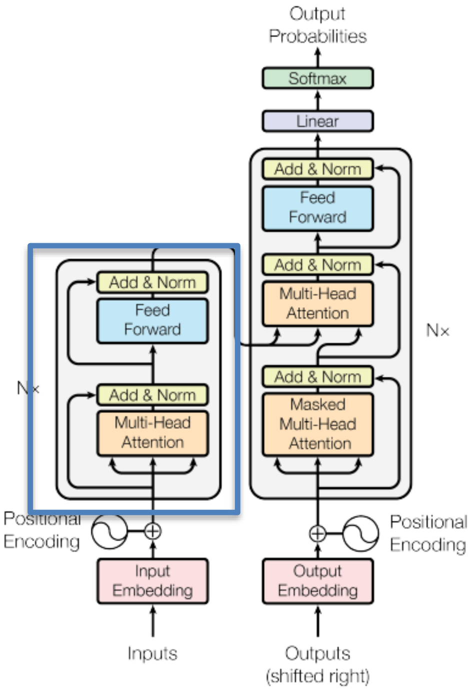
Not a single recurrent layer!

Vaswani et al. "Attention is All You Need".

Attention is All You Need

- Transformers under the hood

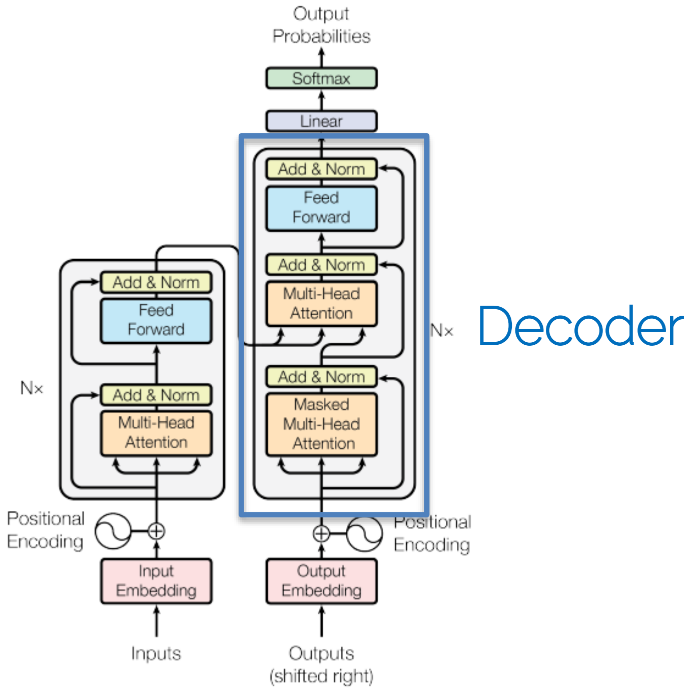
Encoder



Vaswani et al. "Attention is All You Need".

Attention is All You Need

- Transformers under the hood

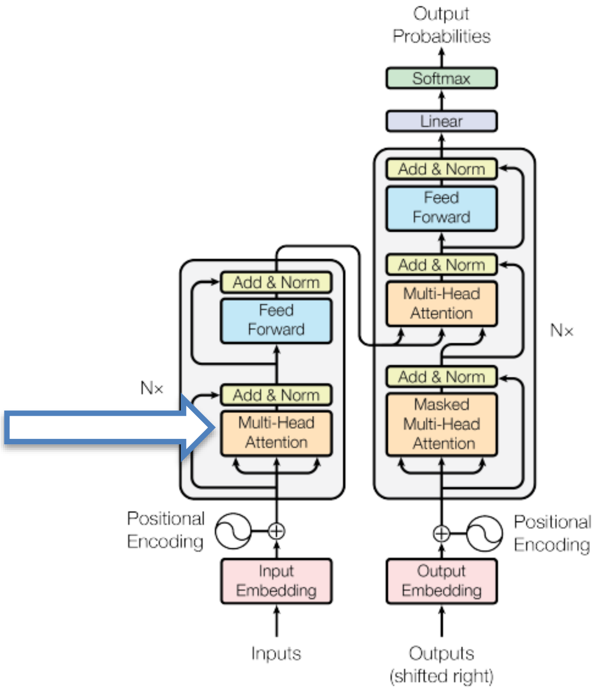


Vaswani et al. "Attention is All You Need".

Attention is All You Need

- Transformers under the hood

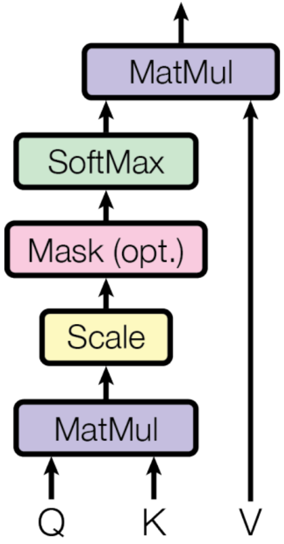
Core unit: scaled dot-product attention



Vaswani et al. “Attention is All You Need”.

Attention is All You Need

- Scaled dot-product attention

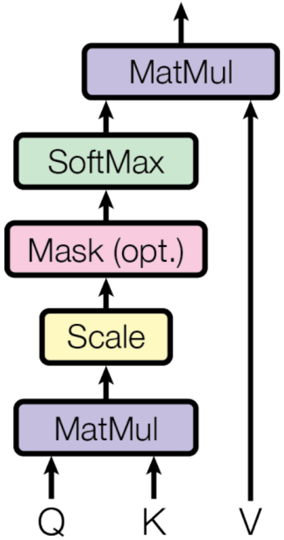


$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Vaswani et al. "Attention is All You Need".

Attention is All You Need

- Scaled dot-product attention



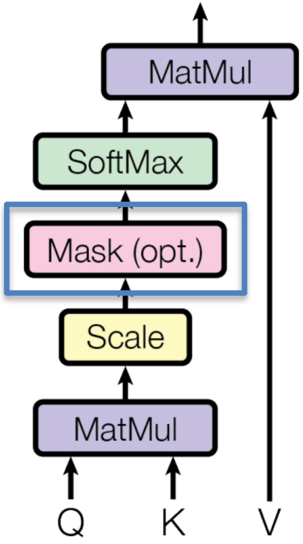
$$\mathrm{Attention}(Q, K, V) = \boxed{\mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})} V$$

Self-attention masks

Vaswani et al. "Attention is All You Need".

Attention is All You Need

- Scaled dot-product attention



Triangular masking for unidirectional (left-to-right) modelling

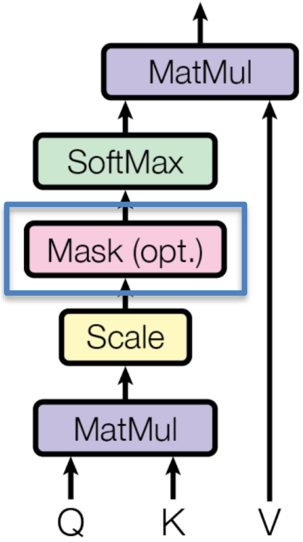
"German people <u>speak</u> German"

Only attend to the words **before it and itself**

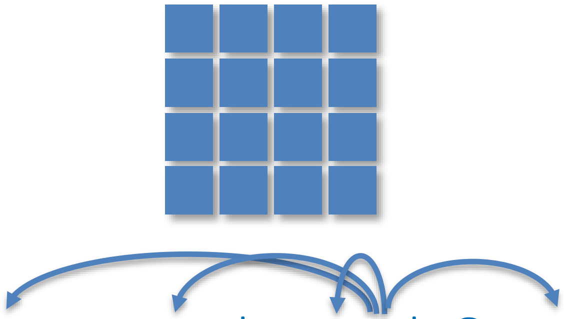
Vaswani et al. "Attention is All You Need".

Attention is All You Need

- Scaled dot-product attention



Full masking for bidirectional modelling



"German people speak German"

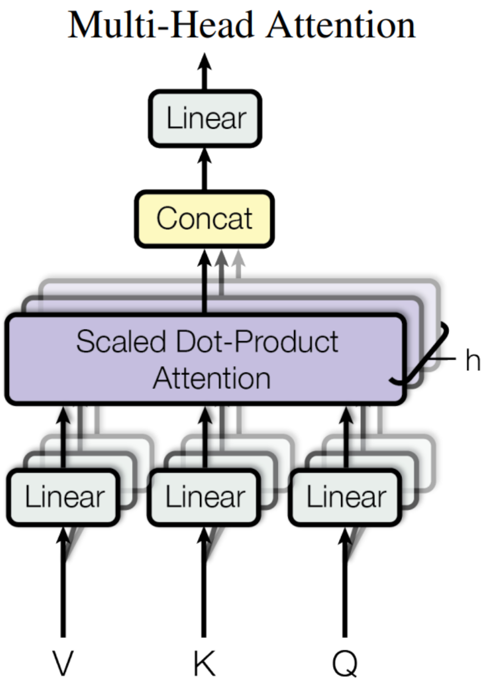
Attend to the words **before and after it, and itself**

Vaswani et al. "Attention is All You Need".

Attention is All You Need

- Multi-head Attention

Stack up the scaled dot-product attention module as attention heads



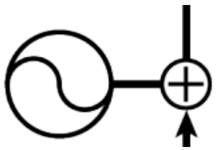
Different heads attend to different parts of the input signals

Vaswani et al. "Attention is All You Need".

Positional Encoding

Uses fixed positional encoding based on trigonometric series, in order for the model to make use of the order of the sequence

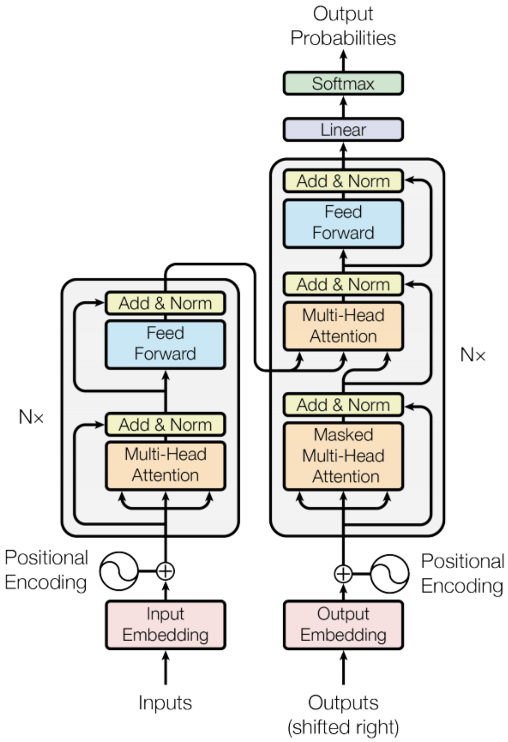
Positional Encoding



dimension

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{\text{model}}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{\text{model}}}}\right)$$

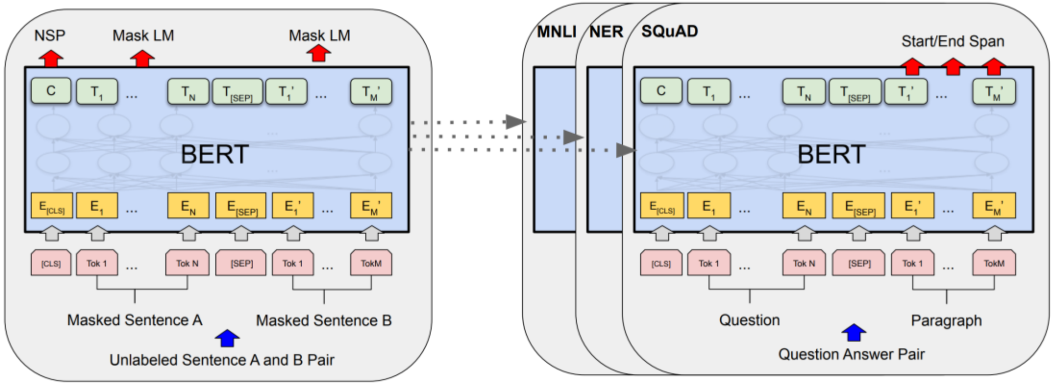


Attention is All You Need

- Significantly improved SOTA in Machine Translation
- Launched a transformer revolution in the NLP field
- Foundation of large NLP models like BERT (Google) and GPT-3, ChatGPT (OpenAI)!
- Transformers finally made its way to compute vision (will talk about it later!)

BERT

- Bidirectional Encoder Representations from Transformers
  - A big transformer as a text encoder



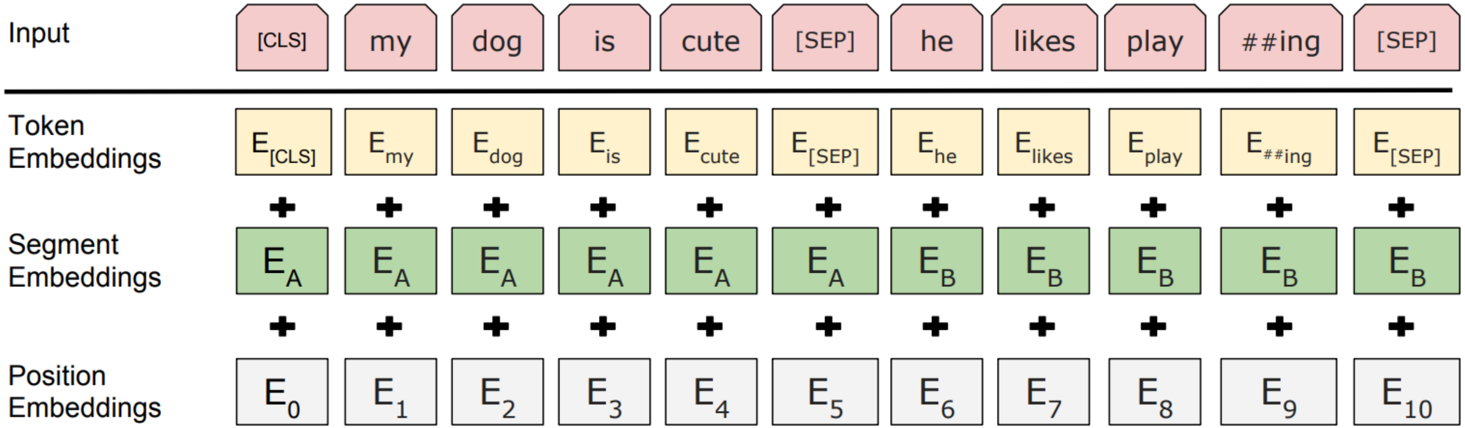
Pre-training

Fine-Tuning

Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding".

BERT

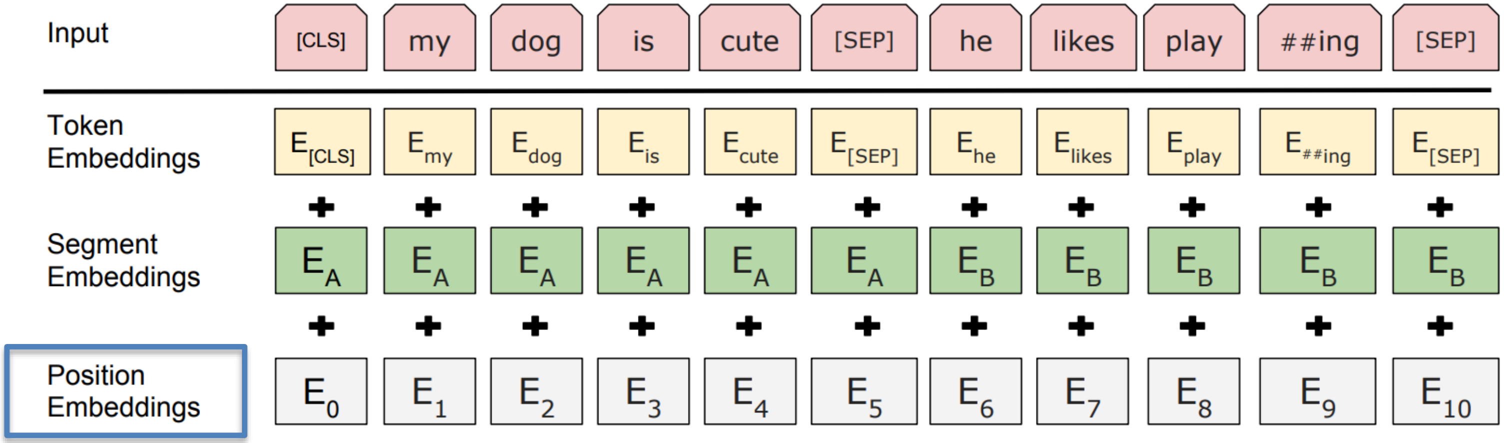
- BERT Input Representations – Three embeddings



Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding".

BERT

- BERT Input Representations

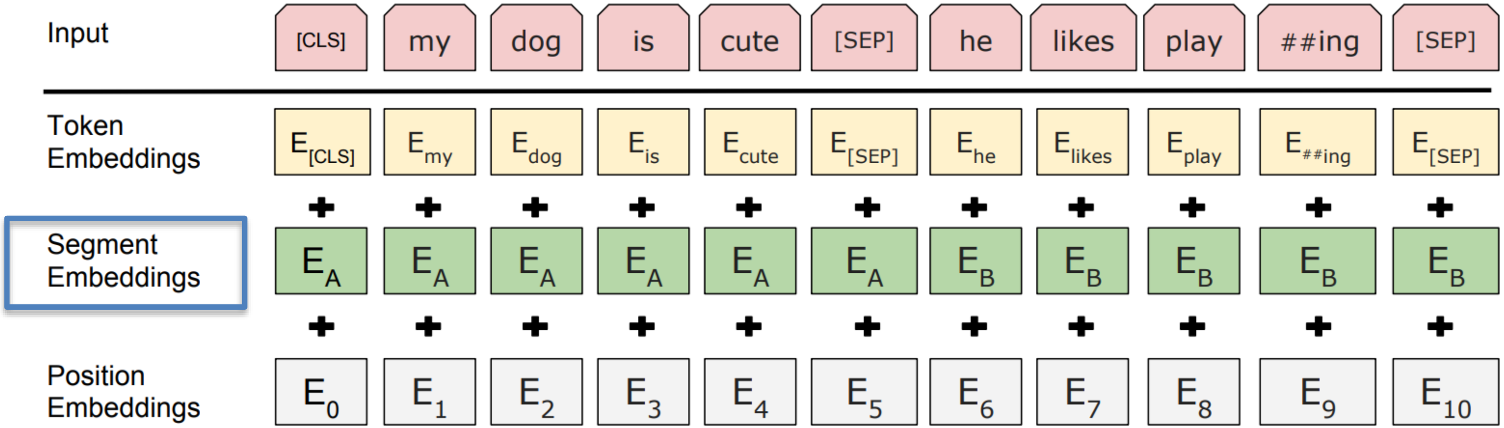


To indicate the positions in the sequence

Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding".

BERT

- BERT Input Representations

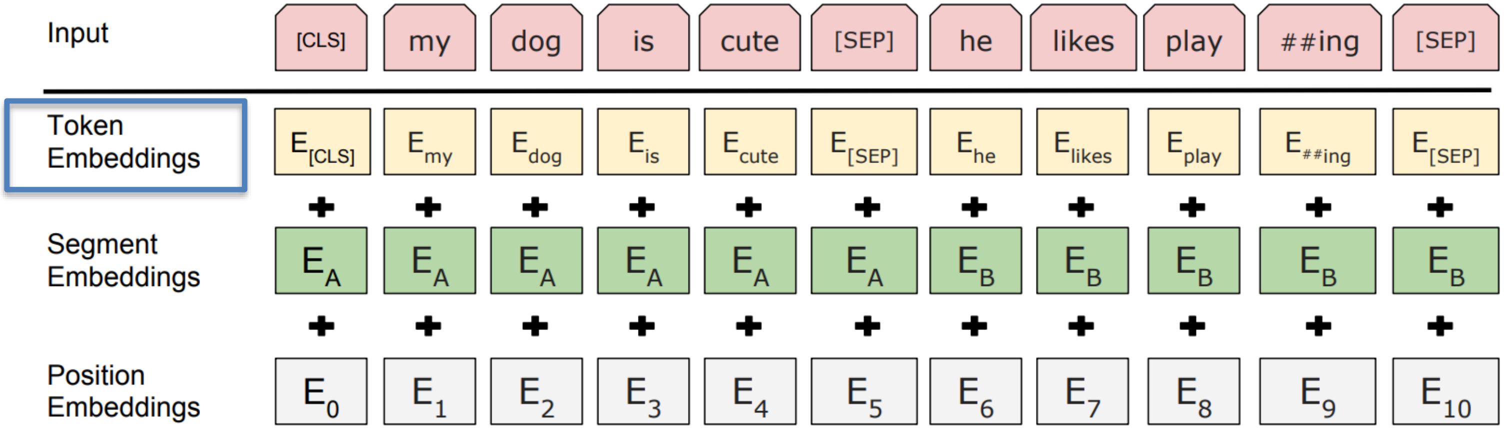


To indicate the sentence A or B

Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding".

BERT

- BERT Input Representations

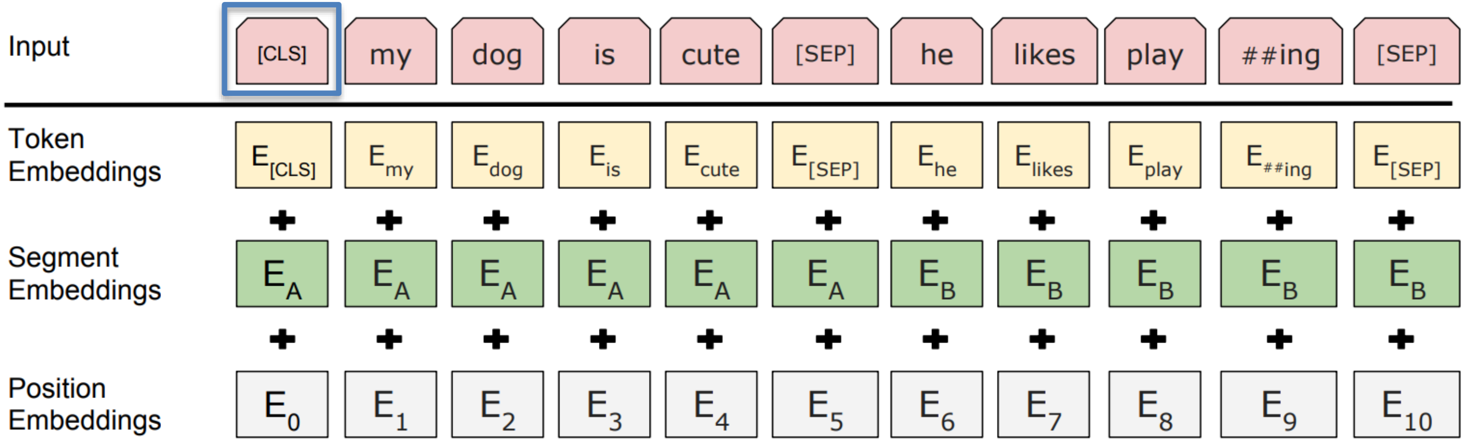


Word embeddings

Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding".

BERT

- BERT Input Representations

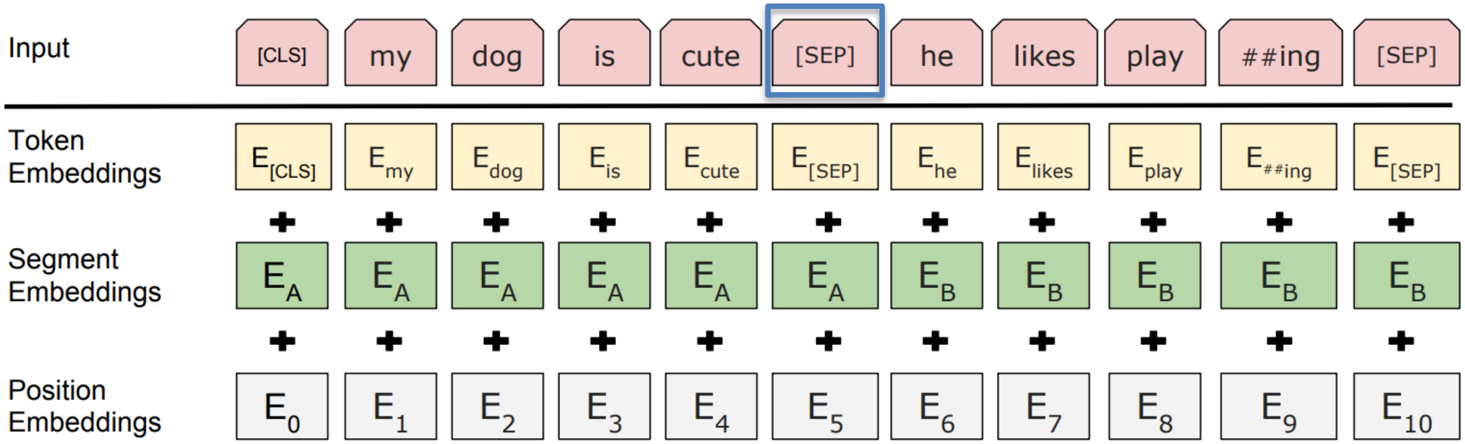


Learnable token for Next Sentence Prediction

Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding".

BERT

- BERT Input Representations



Indicate the end of the sentence(s)

Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding".

BERT

- Pre-training Objectives
  - Two unsupervised tasks
    - Masked Language Modelling (MLM)
    - Next Sentence Prediction (NSP)
  - No human annotation needed!

BERT

- Masked Language Modelling (MLM)
  - Key idea:
    - Randomly mask out some words from the input
    - Predict the masked words with the context from the input itself
    - Enforce the network to learn the word-level context

BERT

- Masked Language Modelling (MLM)

Input texts "In Germany, people speak German"

BERT

- Masked Language Modelling (MLM)

Masked input "In Germany, people [MASK] [MASK]"

Input texts "In Germany, people speak German"

Random Masking

BERT

- Masked Language Modelling (MLM)

Encode — BERT

Masked input — "In Germany, people [MASK] [MASK]"

Input texts — "In Germany, people speak German"

Random Masking

BERT

- Masked Language Modelling (MLM)

Predict [MASK] = speak [MASK] = German

Encode BERT

Masked input "In Germany, people [MASK] [MASK]"

Input texts "In Germany, people speak German"

Random Masking

BERT

- Next Sentence Prediction (NSP)
  - Key idea:
    - Take two sentence A and B from the dataset
    - 50% of the time B is the actual next sentence of B, another 50% of the time B is randomly sampled from the dataset
    - Predict if B is the next sentence of A
    - Enforce the network to learn the sentence-level context

BERT

- Next Sentence Prediction (NSP)

A sample from the dataset

"In Germany, people speak German. So German is the native language of the German people."

Break up

Sentence A

"In Germany, people speak German. "

Sentence B

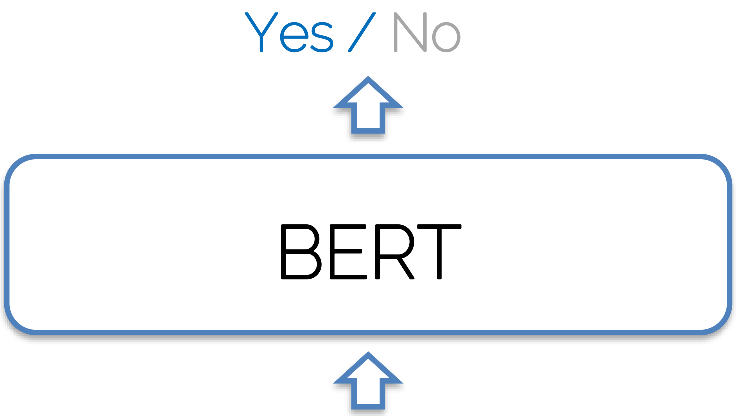
"So German is the native language of the German people."

"Today is Wednesday."

Sentence B'
(another sentence from the dataset)

BERT

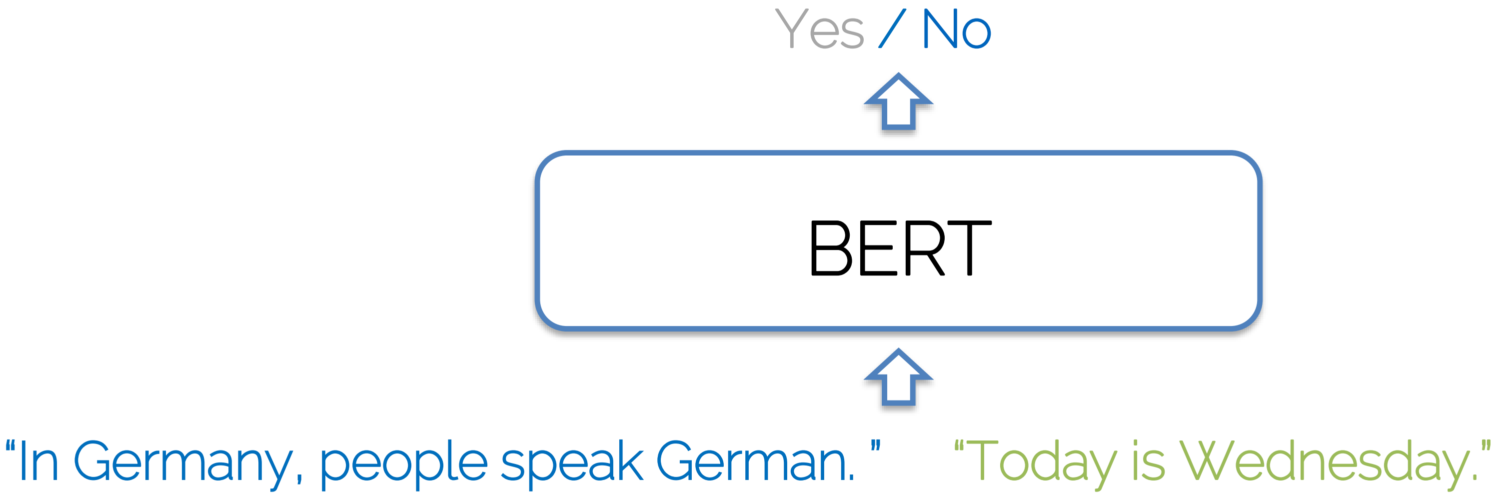
- Next Sentence Prediction (NSP)



"In Germany, people speak German. " "So German is the native language of the German people."

BERT

- Next Sentence Prediction (NSP)

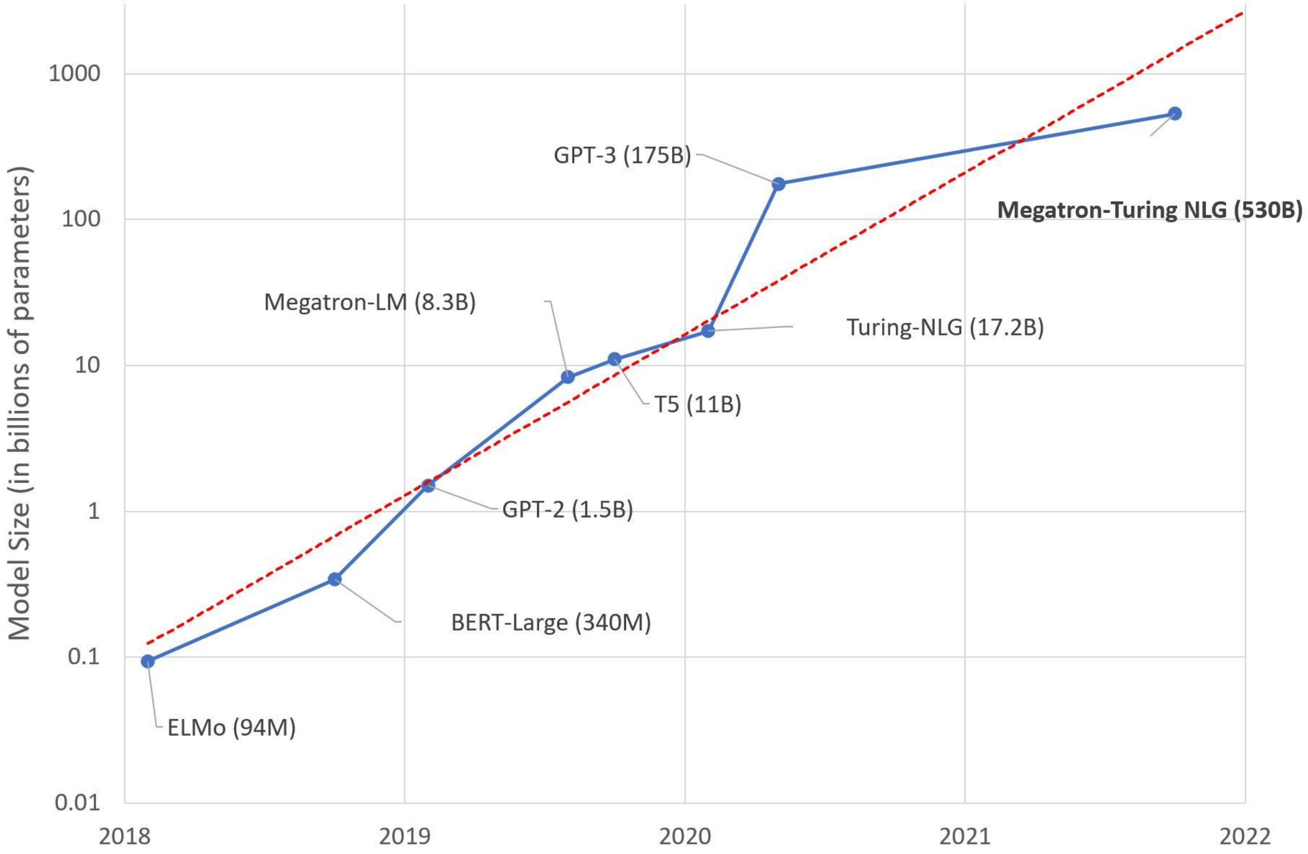


BERT

- Pre-training with two self-supervised objectives, then fine-tuned on downstream tasks
- No human annotations needed for pre-training! -> can be pre-trained on large-scale datasets, even those ones that have not been annotated, e.g., web documents.
- VERY BIG (back then in 2018)! – $\text{BERT}_{\text{large}}$ has 340M parameters
- Masked Language Modelling has a huge impact for representation learning, even for Computer Vision!

Language Model Sizes

GPT-4 1.7 trillion



How to build your GPT Model?

GPT: Generative Pre-trained Transformer

- Tokenization / Dictionary
- Sequence model (transformer)
- Training scheme (context etc.)

Dictionary

- 1 char == 1 token
- 1 word == 1 token
- Optimize for dictionary
- Learn embedding / token (e.g., WordNet)

Dictionary: Byte Pair Encoding

```
aaabdaaabac
```

The byte pair "aa" occurs most often, so it will be replaced by a byte that is not used in the data, such as "Z". Now there is the following data and replacement table:

```
ZabdZabac
Z=aa
```

Then the process is repeated with byte pair "ab", replacing it with "Y":

```
ZYdZYac
Y=ab
Z=aa
```

The only literal byte pair left occurs only once, and the encoding might stop here. Alternatively, the process could continue with recursive byte pair encoding, replacing "ZY" with "X":

```
XdXac
X=ZY
Y=ab
Z=aa
```

Dictionary size: of GPT-3.5 and GPT-4
https://platform.openai.com/tokenizer

https://en.m.wikipedia.org/wiki/Byte_pair_encoding

Context

- **Llama: 2K**
- **Llama 2: 4K**
- **GPT-3.5-turbo: 4K.** However, GPT-3.5-16k has a context length of 16K.
- **GPT-4: 8K**. Similarly, GPT-4-32k has a context window of up to 32K.
- **Mistral 7B: 8K**
- **Palm-2: 8k**. However, Google has reported their new Gemini multi-modal model as having a 32K
- **Claude: 9K**
- **Claude 2: 100,000K** (in beta stage at the time of writing).

Common trick to improve context: fine-tune with LoRA variant

https://symbl.ai/developers/blog/guide-to-context-in-llms/

Training Scheme

- Loss is usually a variant of cross entropy
- Multi-modal modals
- Scale, scale, scale…

Literature

- Transformer: [Vaswani et al. 2017] Attention is All You Need
  - https://arxiv.org/pdf/1706.03762.pdf

- BERT: [Devlin et al. 2020] BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding
  - https://arxiv.org/pdf/1810.04805.pdf

- Let's build GPT: from scratch, in code, spelled out (by Andrej Karpathy) https://www.youtube.com/watch?v=kCc8FmEb1nY

- Let's build the GPT Tokenizer (by Andrej Karpathy) https://www.youtube.com/watch?v=zduSFxRajkE

- Great visualization of Transformers (by 3Blue1Brown) https://www.youtube.com/watch?v=eMlx5fFNoYc

What's next?

Do research yourself!

- Check out the publications of the respective labs
- Have a look at some of the interesting works
- Reach out to respective supervisors

Thanks for watching!

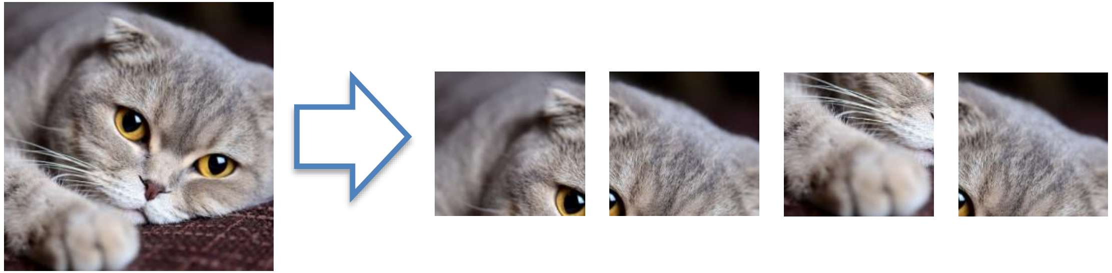
Some extra content…

Transformers in Computer Vision

Vision Transformers (ViTs)

- CNNs can be computationally demanding and require a great amount of design tricks and efforts

- Images can be modelled as sequences of patches
  - Vision Transformers (ViTs)



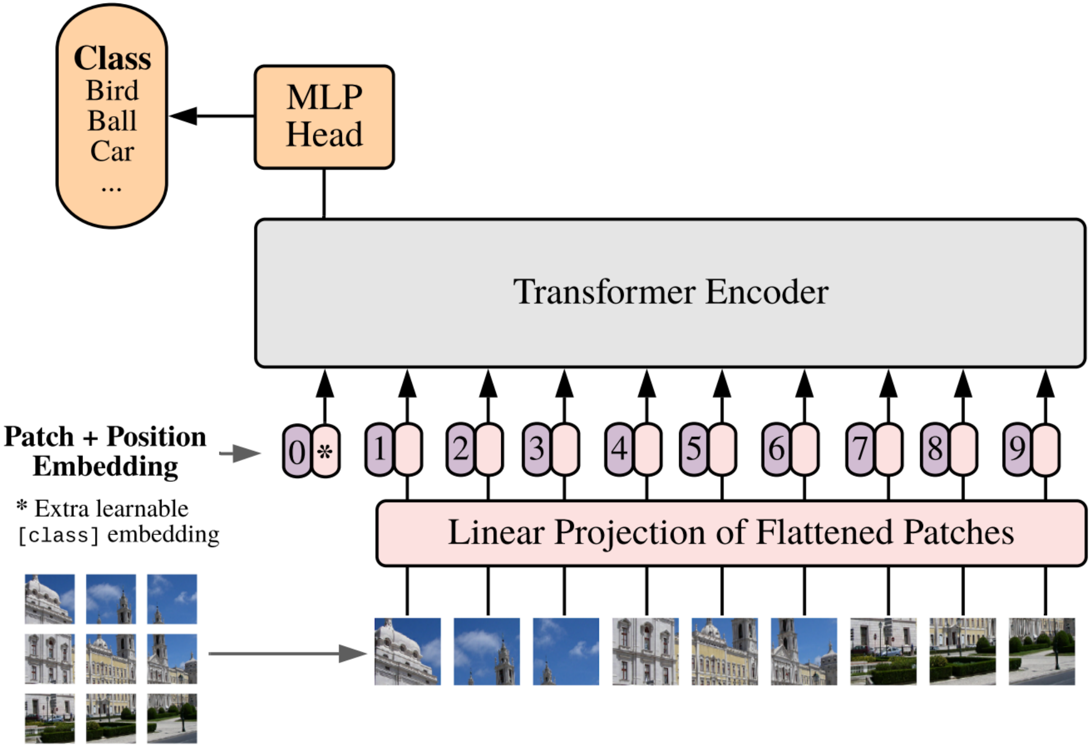
Input image

Image patches

Vision Transformers (ViTs)

https://ai.googleblog.com/2020/12/transformers-for-image-recognition-at.html

Vision Transformers (ViTs)



Dosovitskiy et al. “AN IMAGE IS WORTH 16X16 WORDS”.

Vision Transformers (ViTs)

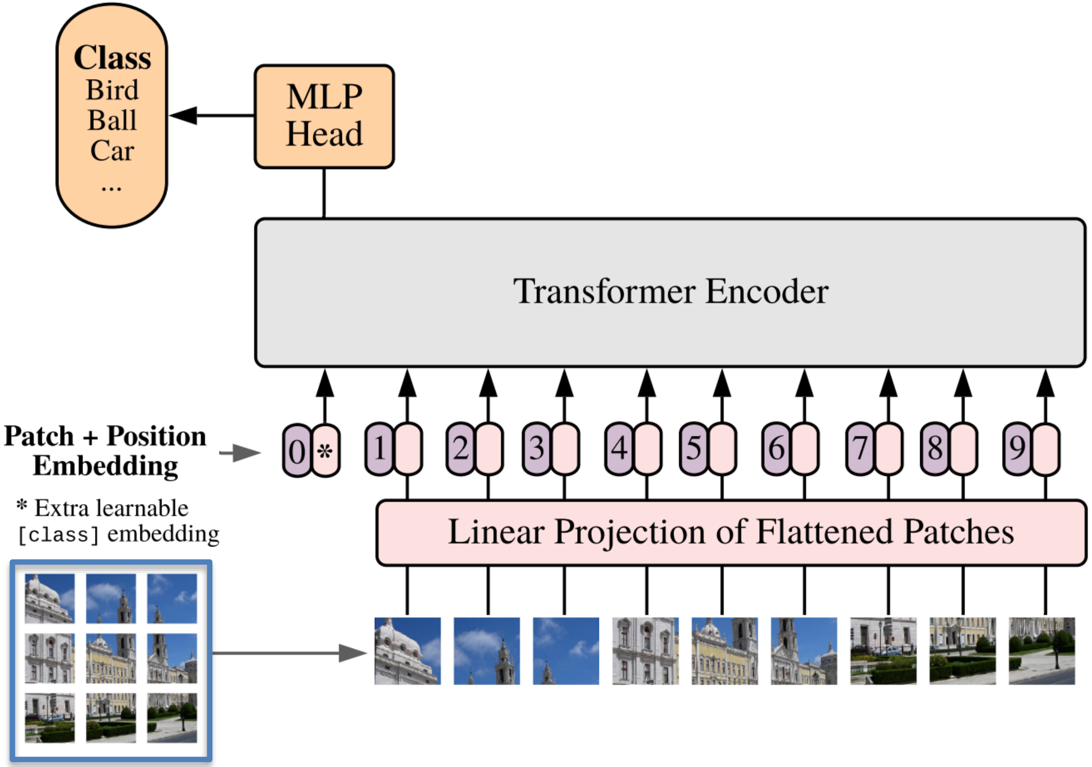
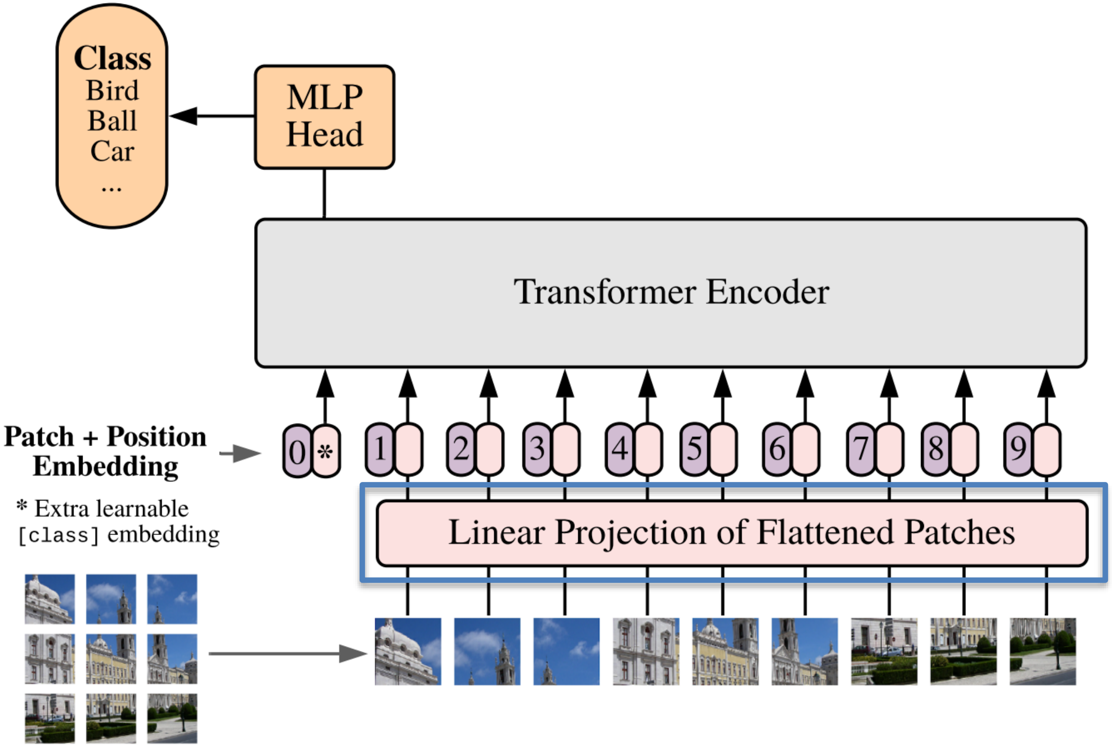


Image patches

Dosovitskiy et al. "AN IMAGE IS WORTH 16X16 WORDS".

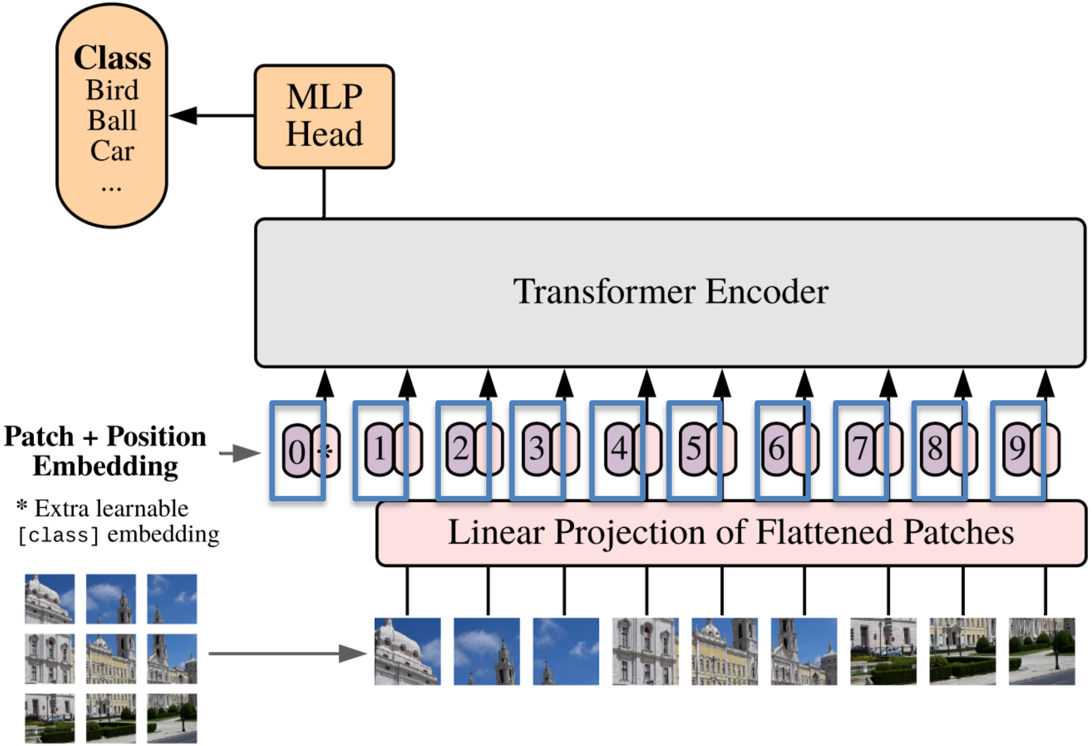
Vision Transformers (ViTs)



MLP (can be replaced by a tiny CNN)

Dosovitskiy et al. "AN IMAGE IS WORTH 16X16 WORDS".

Vision Transformers (ViTs)

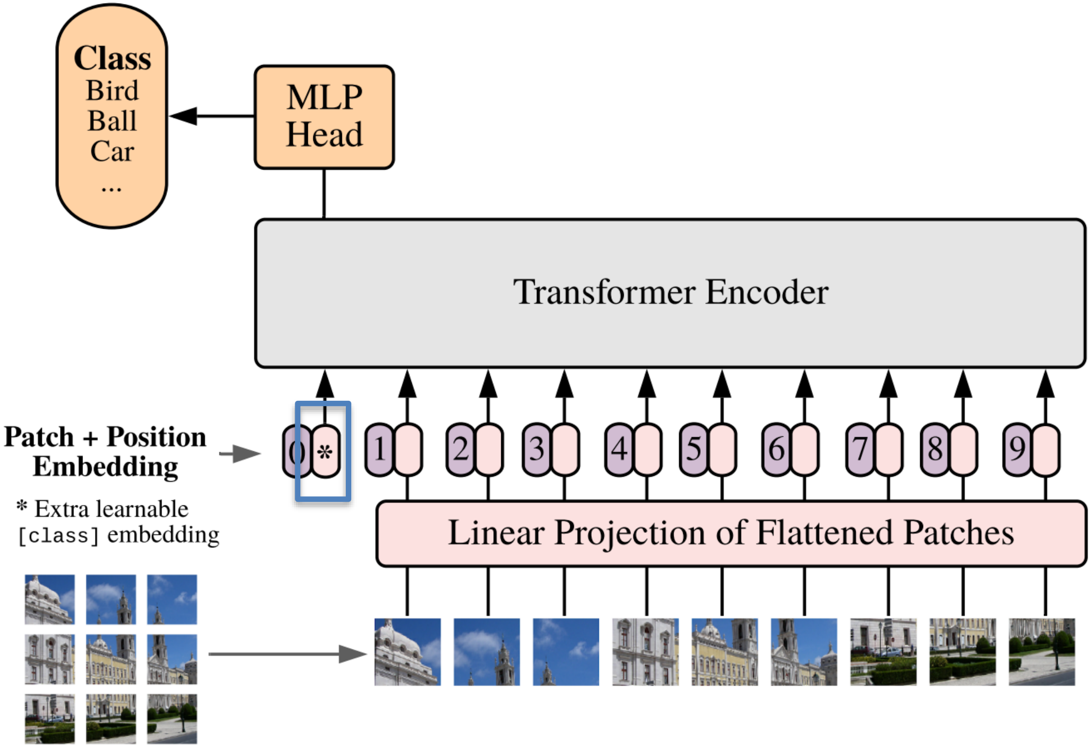


Indicate the positions of the patches

Dosovitskiy et al. "AN IMAGE IS WORTH 16X16 WORDS".

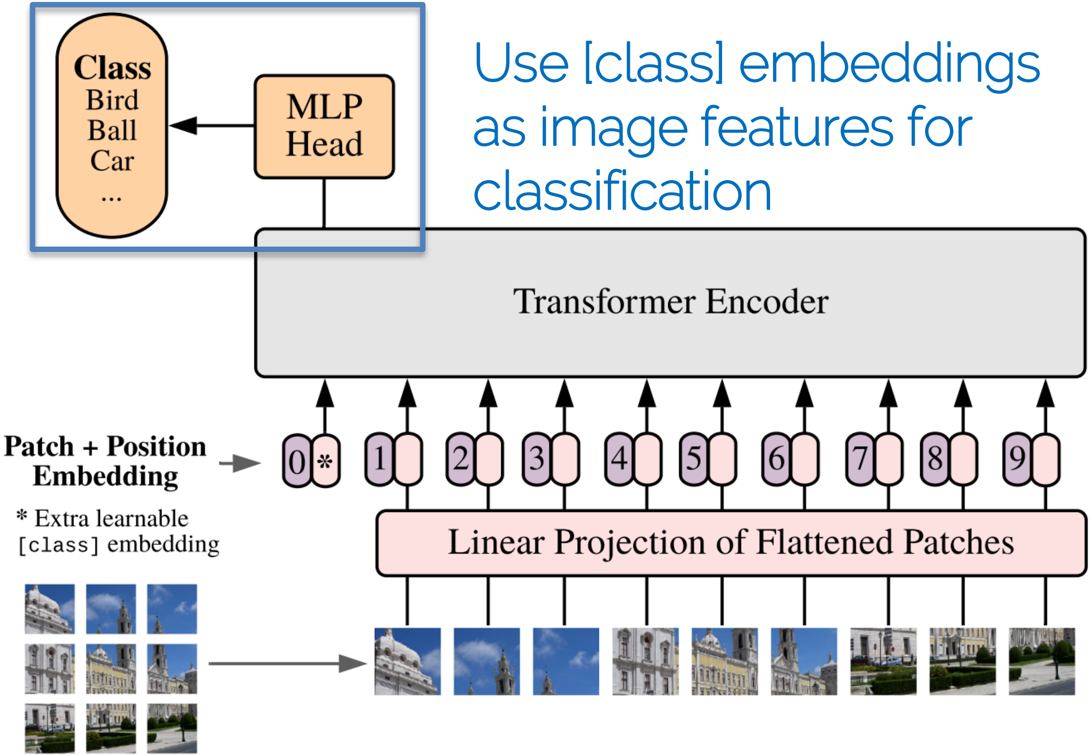
Vision Transformers (ViTs)

Learnable special token (similar to [CLS] in BERT)



Dosovitskiy et al. "AN IMAGE IS WORTH 16X16 WORDS".

Vision Transformers (ViTs)



Use [class] embeddings as image features for classification

Dosovitskiy et al. “AN IMAGE IS WORTH 16X16 WORDS”.

Vision Transformers (ViTs)

- Pre-trained on several big datasets

- Perform transfer learning on target datasets/benchmarks (freeze the pre-trained transformer backbone, fine-tune the classifier only)

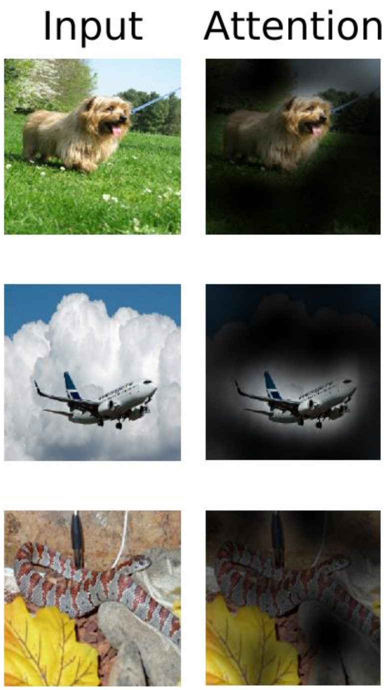
- Outperform the ResNet baseline with substantially less computational resources for pre-training

Vision Transformers (ViTs)

- A closer look at ViTs
  - Transformers in language can give us the attention maps on the input words
  - Can ViTs provide the attention maps on the input image patches? -> YES!

Vision Transformers (ViTs)

- Attention maps in ViTs



Attention maps on the input image while computing the attended [class] embedding for classification

i.e., to classify an image, ViTs give us a hint for which part is most relevant to the predicted label.

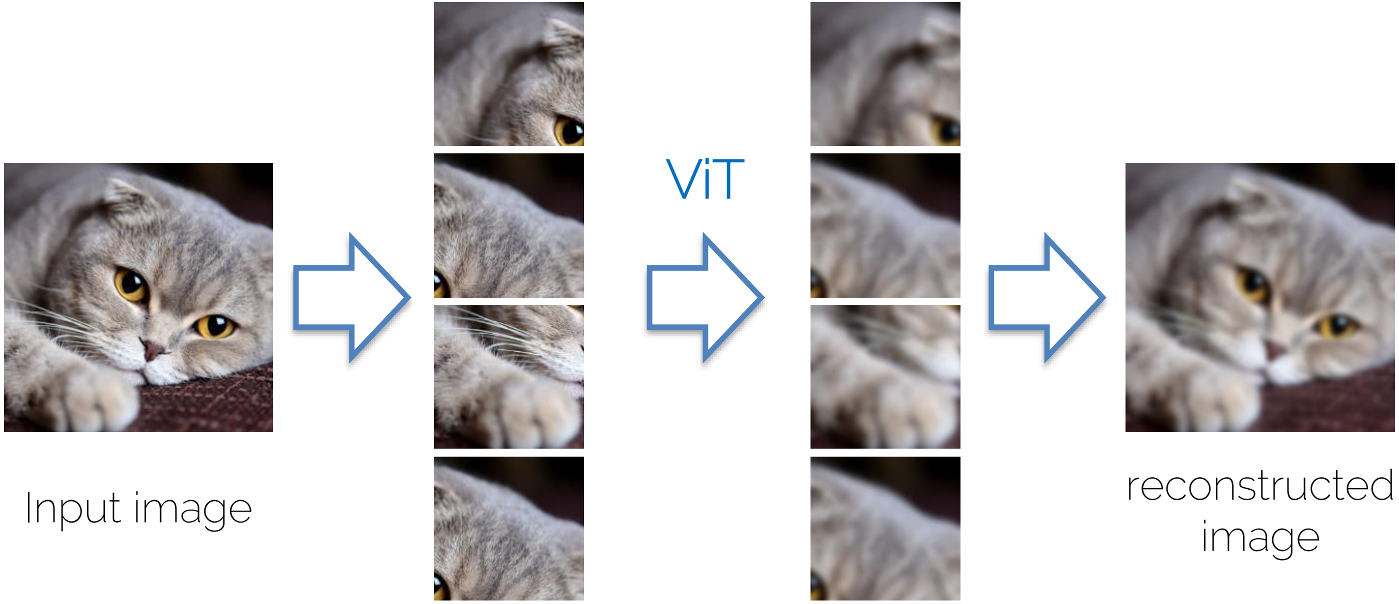
Dosovitskiy et al. "AN IMAGE IS WORTH 16X16 WORDS".

Vision Transformers (ViTs)

- ViTs set a new form for image recognition
- ViTs are extremely powerful at representing image features
- ViTs are also applied in many other domains, such as representation learning (e.g., DINO, MoCo, CLIP, etc.), object detection, and multimodal learning.

Masked Auto-encoder (MAE)

- ViTs as auto-encoders

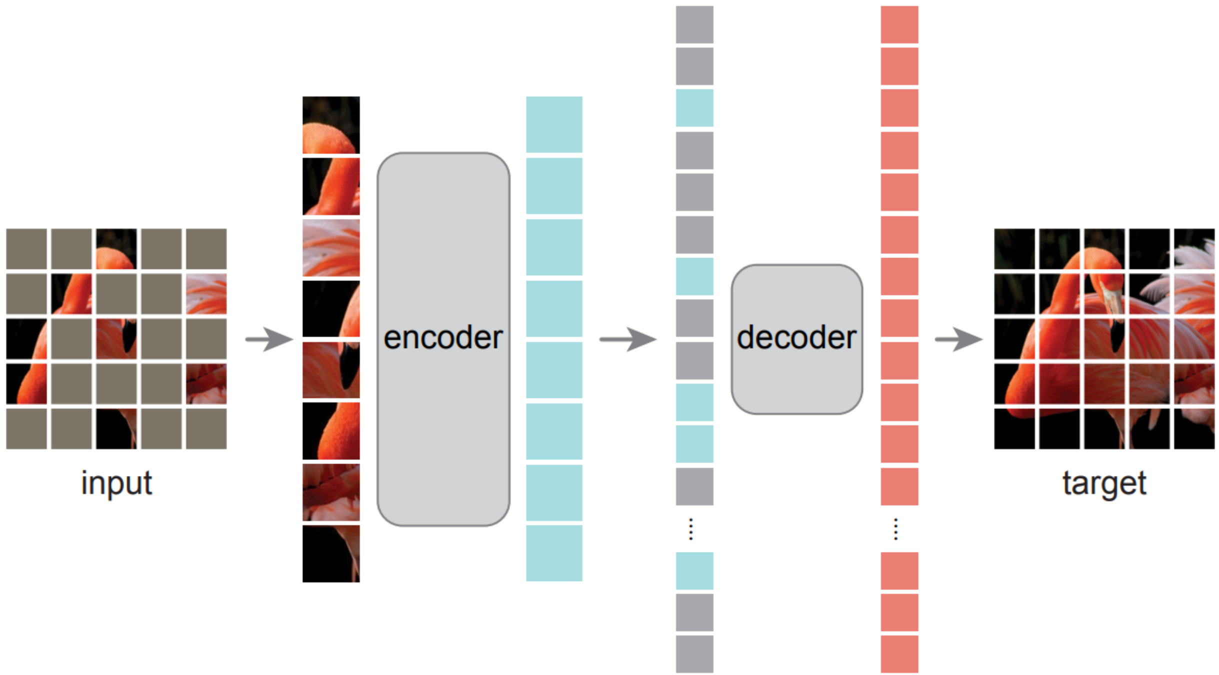


Masked Auto-encoder (MAE)

- What's new?
  - Mask out a lot of patches in the input image
  - Inputting the unmasked patches into the ViT only
    - -> Reduce the computational needs
  - Reconstruct the masked patches

Masked Auto-encoder (MAE)

- Masked Image Modelling (MIM)

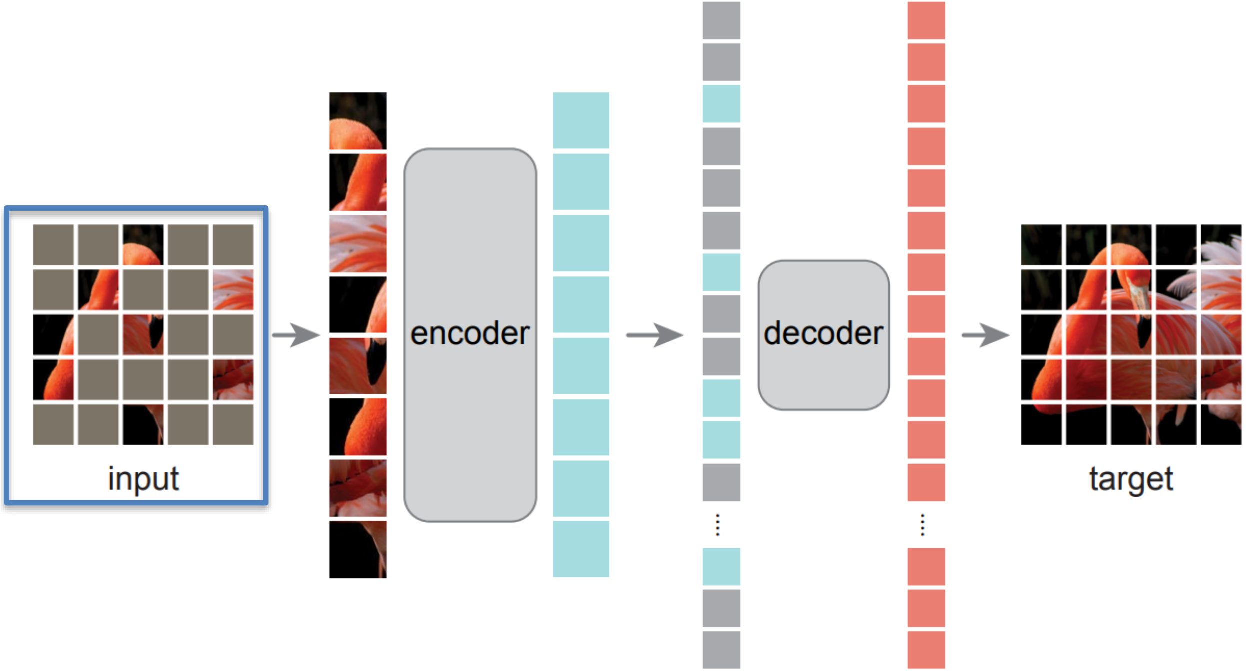


He et al. "Masked Autoencoders Are Scalable Vision Learners".

Masked Auto-encoder (MAE)

- Masked Image Modelling (MIM)

Masked input image

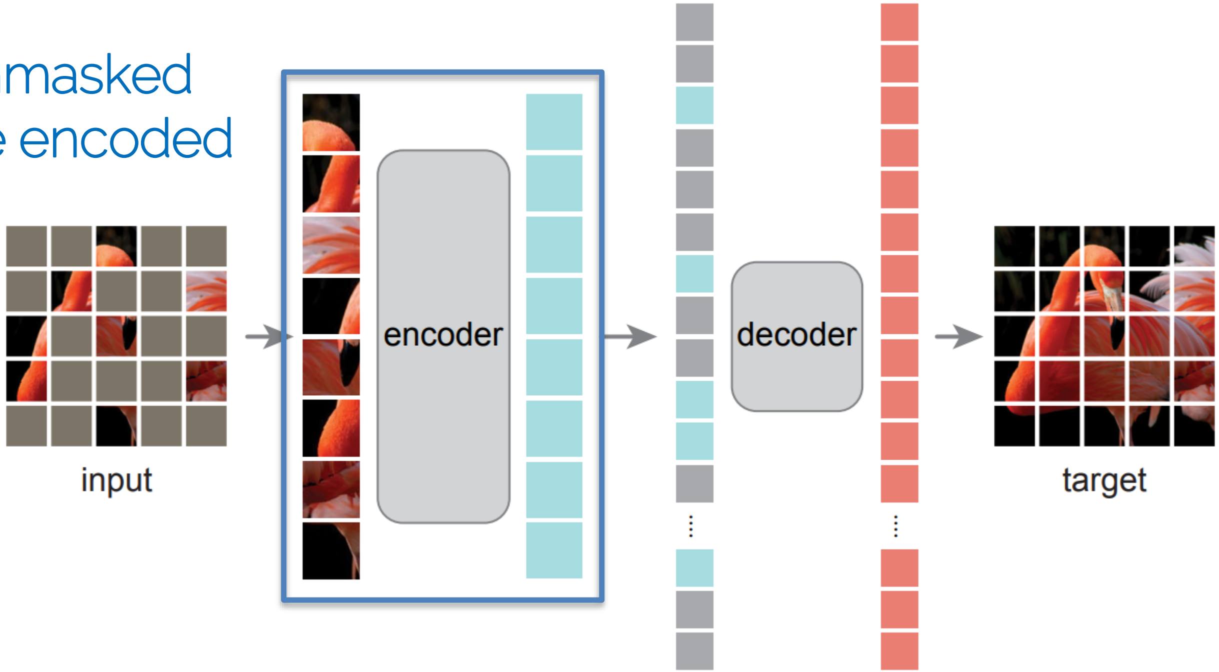


He et al. "Masked Autoencoders Are Scalable Vision Learners".

Masked Auto-encoder (MAE)

- Masked Image Modelling (MIM)

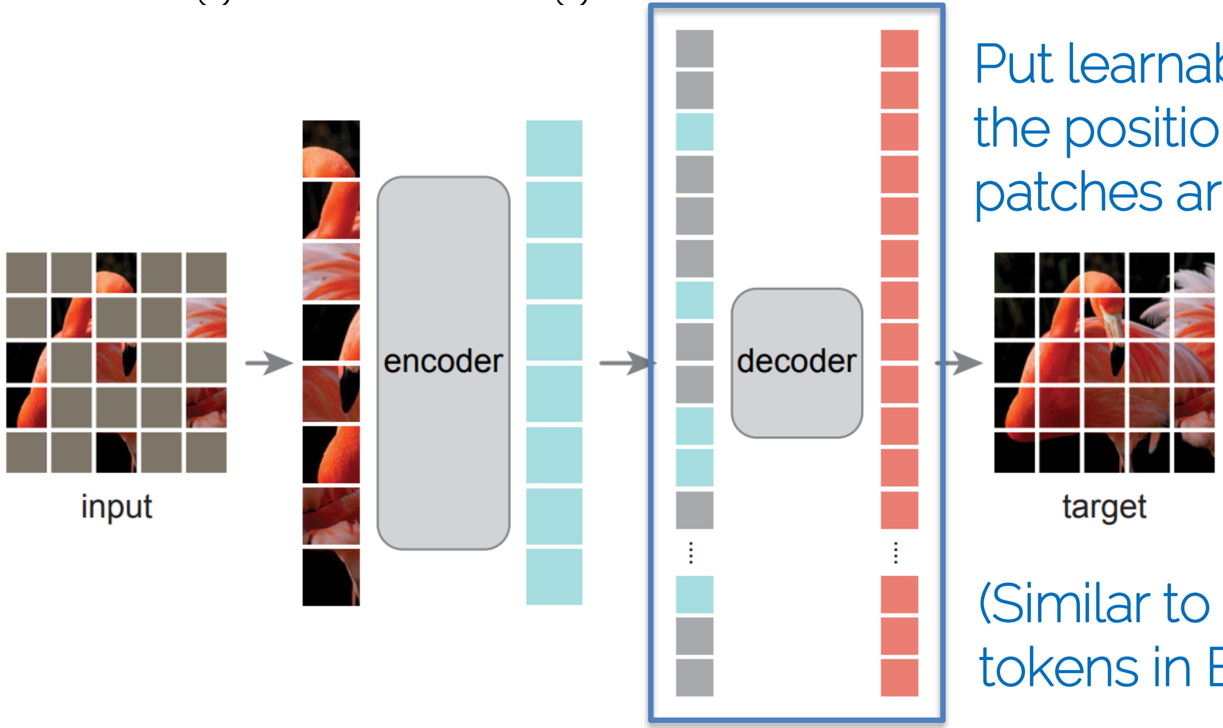
Only the unmasked patches are encoded



He et al. "Masked Autoencoders Are Scalable Vision Learners".

Masked Auto-encoder (MAE)

- Masked Image Modelling (MIM)



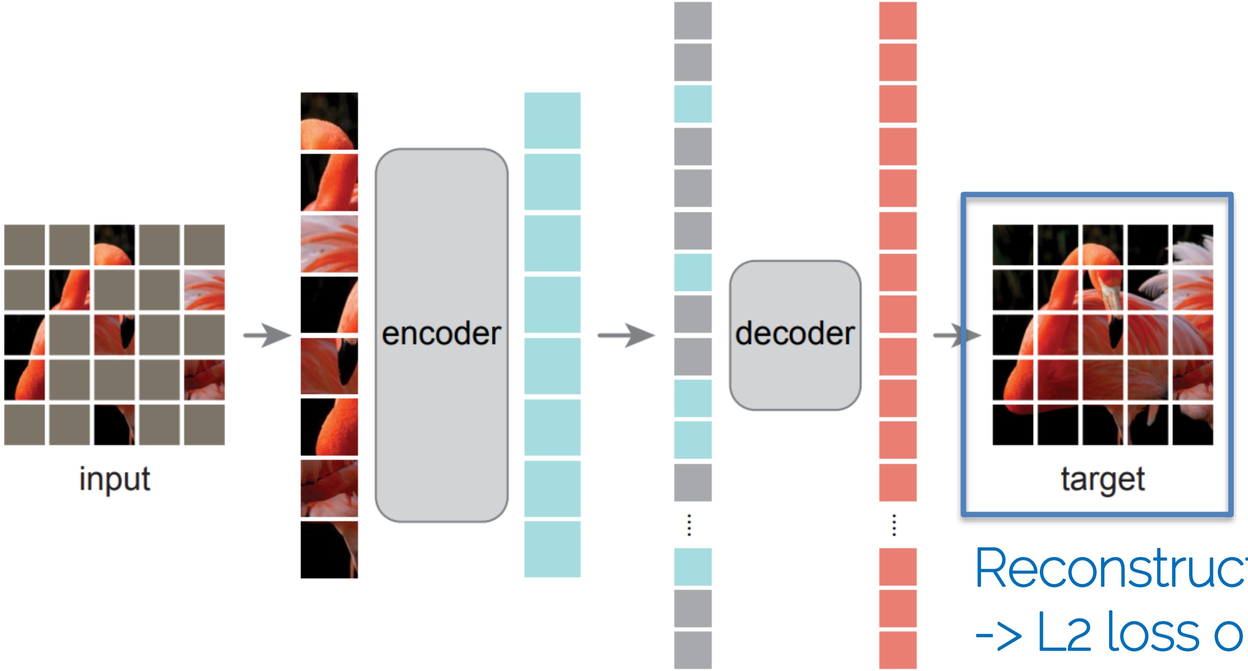
Put learnable tokens to the positions where the patches are masked

(Similar to the [MASK] tokens in BERT)

He et al. "Masked Autoencoders Are Scalable Vision Learners".

Masked Auto-encoder (MAE)

- Masked Image Modelling (MIM)

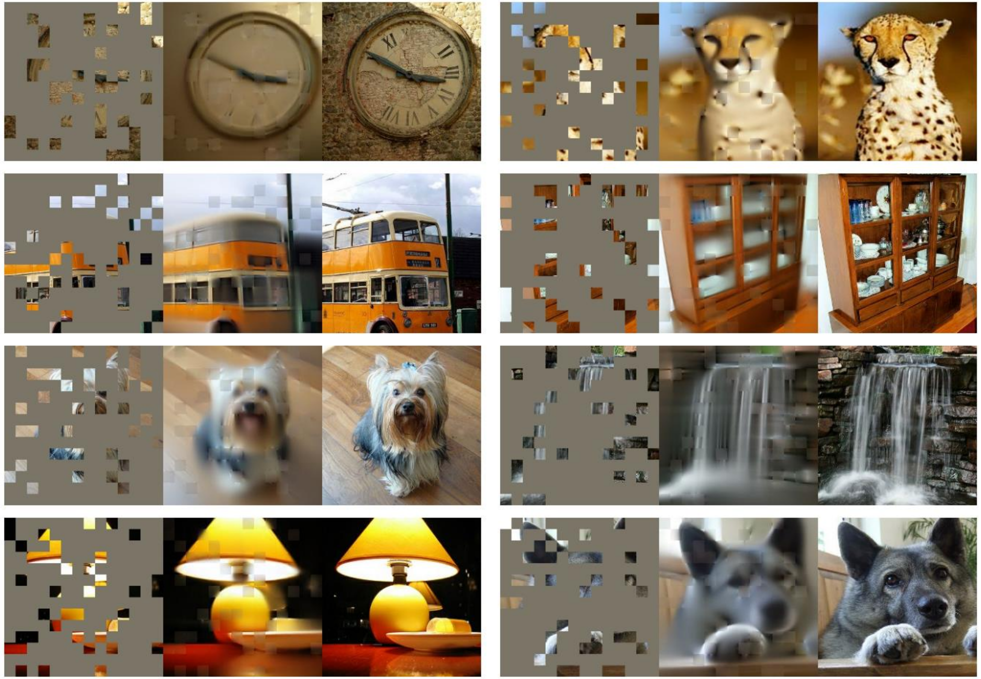


Reconstruct the image
-> L2 loss on the
masked patches

He et al. "Masked Autoencoders Are Scalable Vision Learners".

Masked Auto-encoder (MAE)

- Visualized reconstructions



He et al. “Masked Autoencoders Are Scalable Vision Learners”.

Masked Auto-encoder (MAE)

- By inputting the unmasked patches into the ViT only, MAEs require less computes and training time

- Masked Image Modelling enforces the ViT encoder to learn the local and global context of the input images

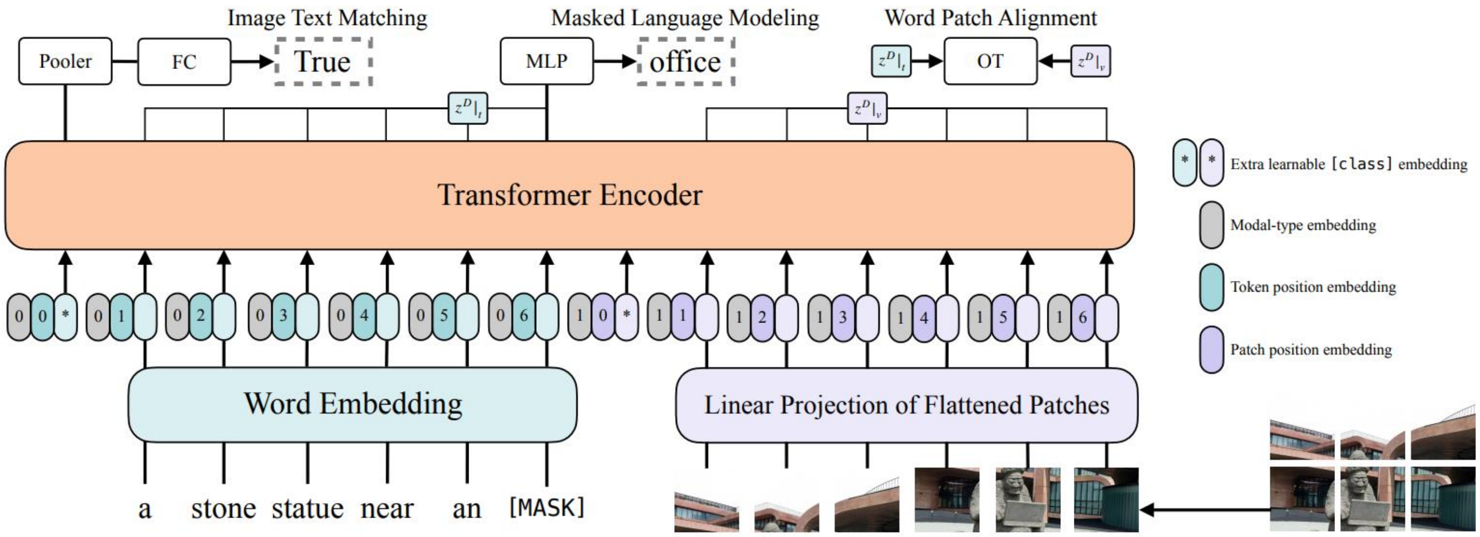
Transformers in Multimodal Learning

Vision-Language Transformers

- ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision
  - Concatenate image patches with text sequence as the input sequence
  - Pre-training with two self-supervised objectives
    - Image text matching
    - Masked language modelling

Vision-Language Transformers

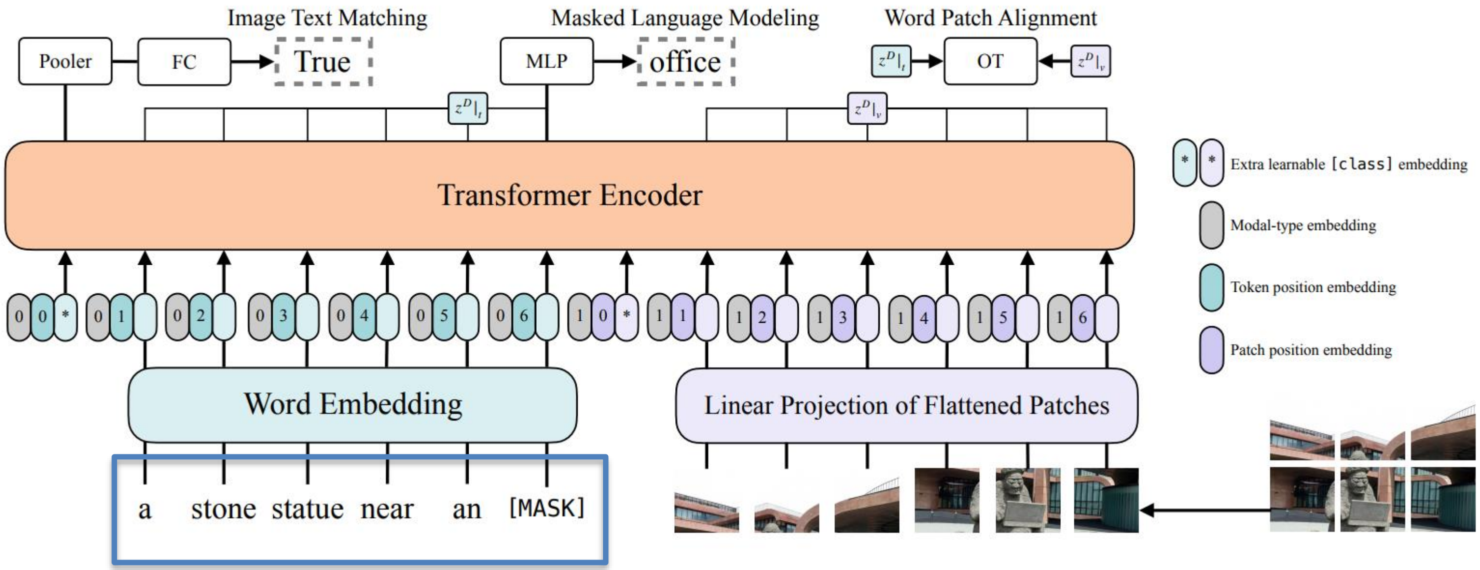
- ViLT under the hood



 Kim et al. "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision".

Vision-Language Transformers

- ViLT under the hood

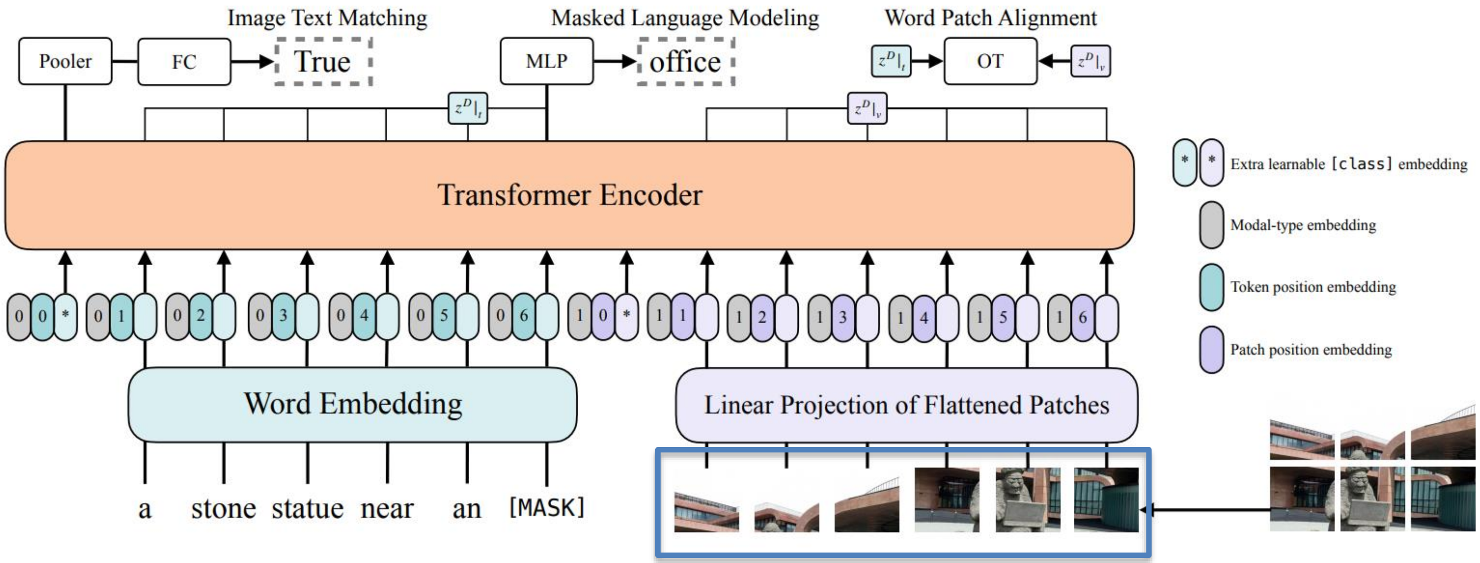


Masked input texts

 Kim et al. "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision".

Vision-Language Transformers

- ViLT under the hood

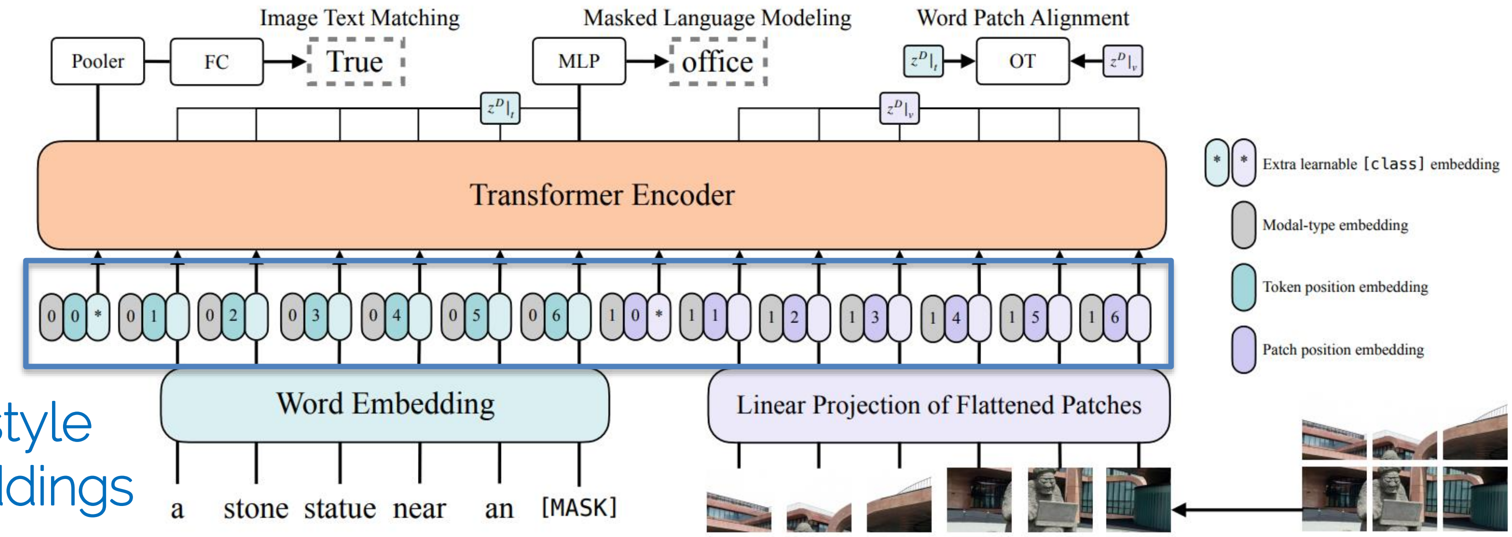


Input image patches

 Kim et al. "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision".

Vision-Language Transformers

- ViLT under the hood



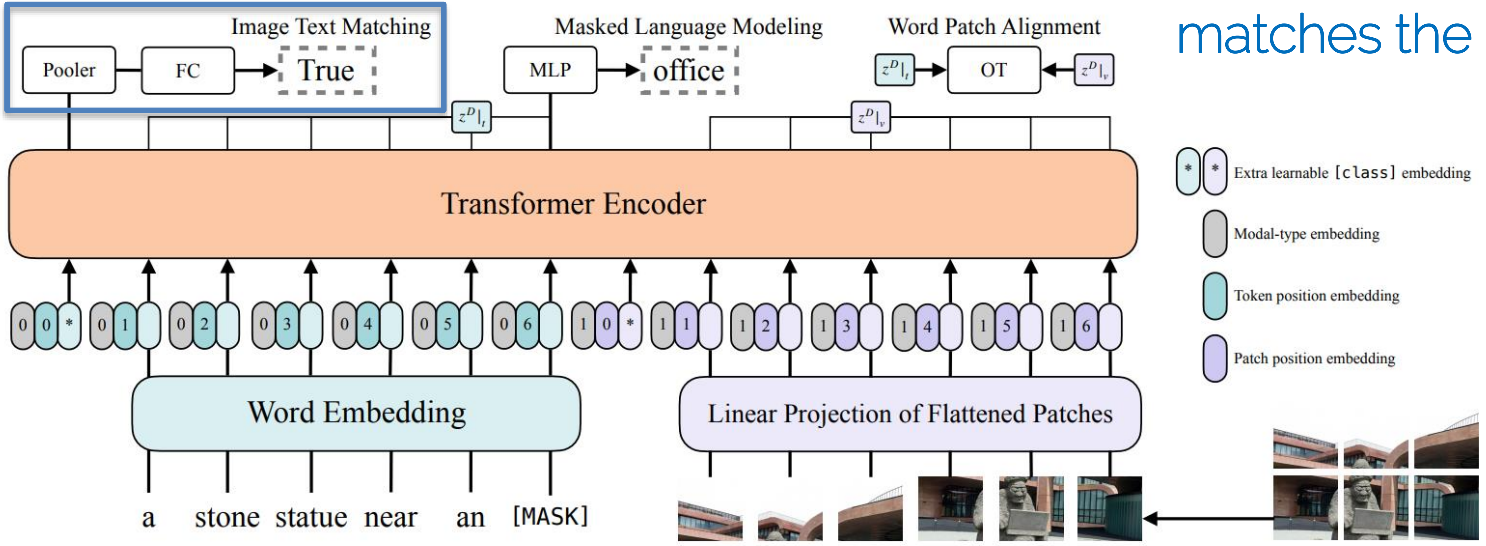
BERT style embeddings

Kim et al. "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision".

Vision-Language Transformers

- ViLT under the hood

Predict if the image matches the text

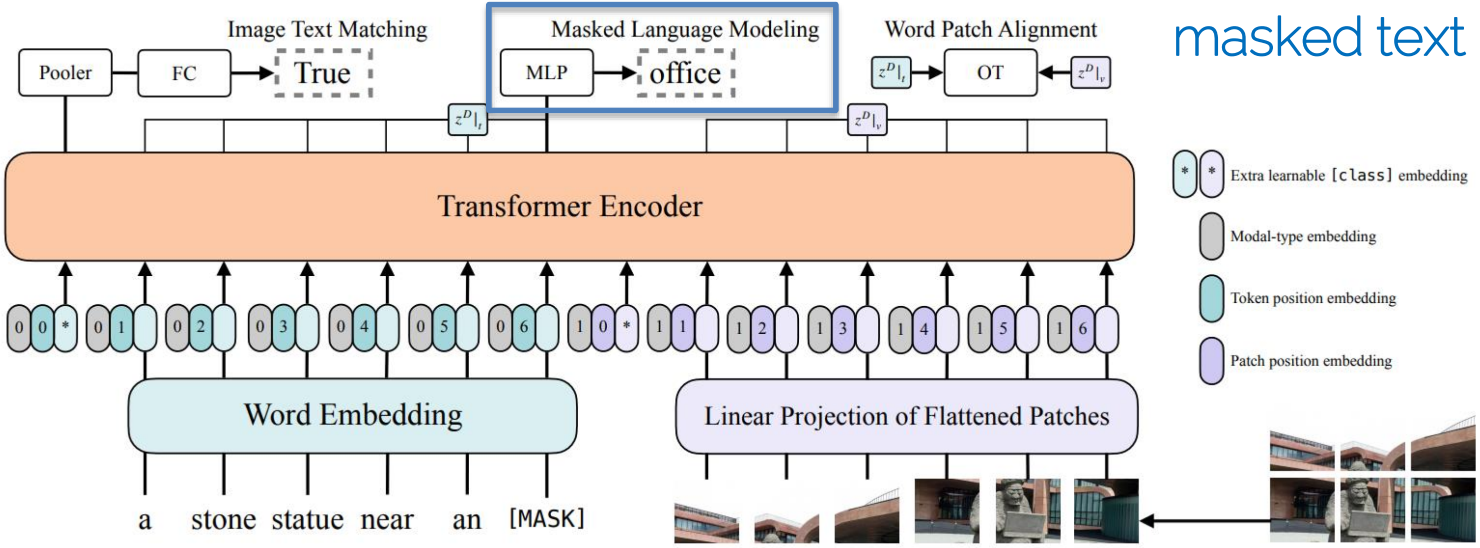


(Similar to BERT's next sentence prediction)

Kim et al. "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision".

Vision-Language Transformers

- ViLT under the hood



Predict if the masked text

(Similar to BERT's masked language modelling)

Kim et al. "ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision".

Vision-Language Transformers

- ViLT is pre-trained on large-scale vision-language datasets in a self-supervised manner.

- Without any image region information (object detection bounding boxes), ViLT achieves strong performance in downstream tasks, e.g., text-to-image retrieval and visual question answering, by using the image patches only.

- ViLT is simple to implement and fast to train.

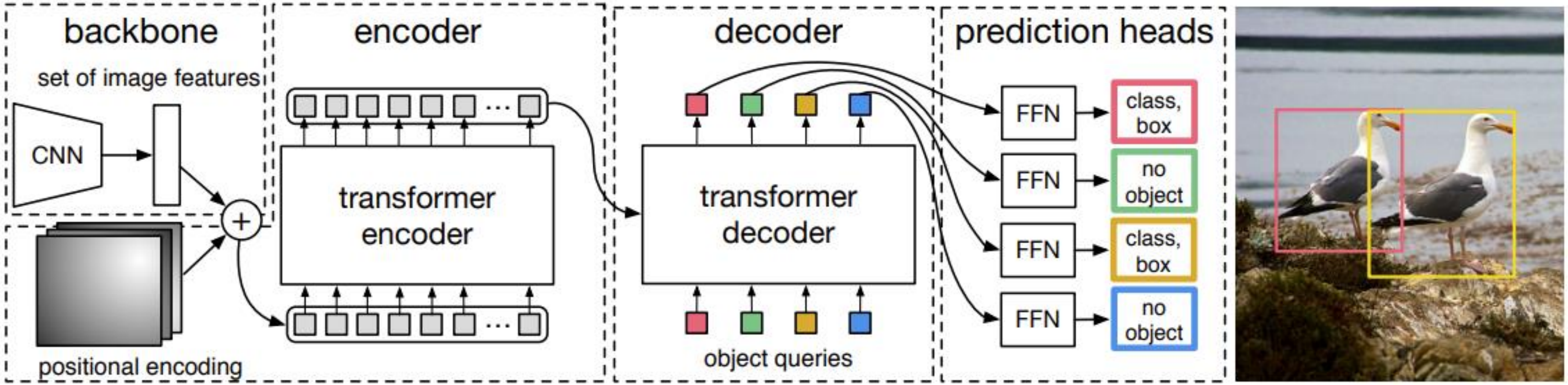
Transformers in Object Detection

DETR

- **De**tection **Tr**ansformer
  - A set-based object detection using a Transformer on top of a CNN backbone
  - A Transformer encoder encodes the CNN features with positional embeddings
  - A Transformer decoder "translates" the input positional embeddings (object queries) into object detections or "no object"

DETR

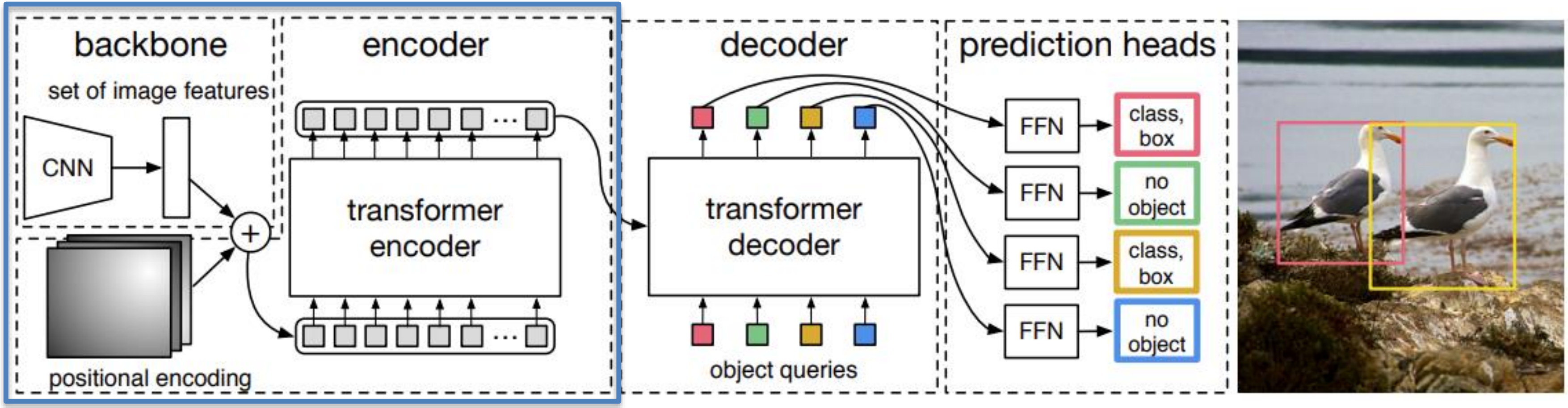
- DETR works in a similar way as Machine Translation



Carion et al. "End-to-End Object Detection with Transformers".

DETR

- DETR works in a similar way as Machine Translation

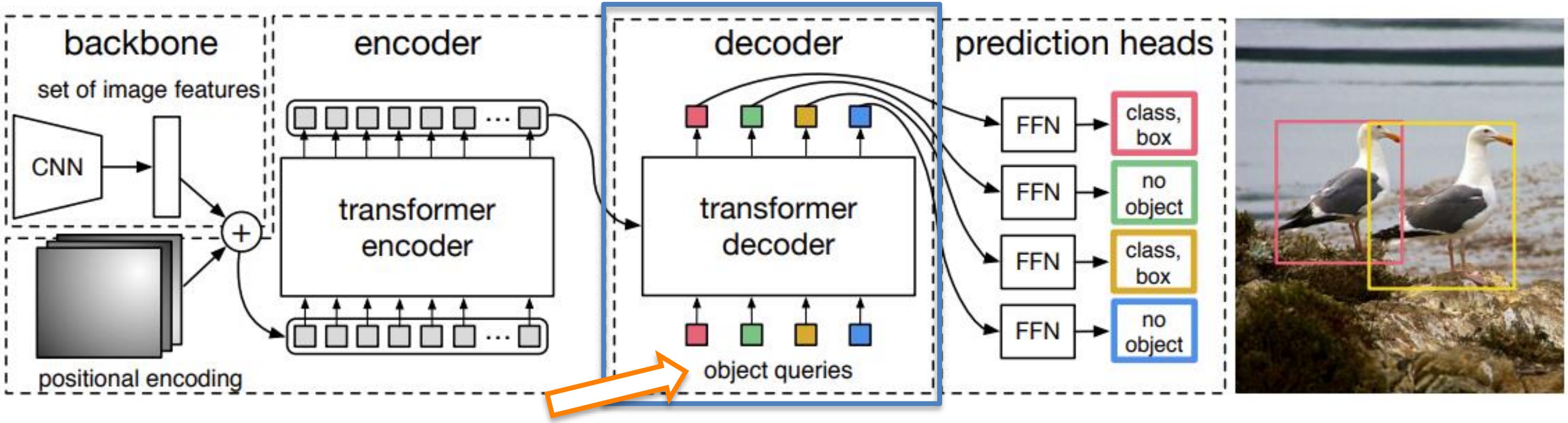


Encode the input image into a sequence of image tokens (similar to ViT's encoding process)

Carion et al. "End-to-End Object Detection with Transformers".

DETR

- DETR works in a similar way as Machine Translation



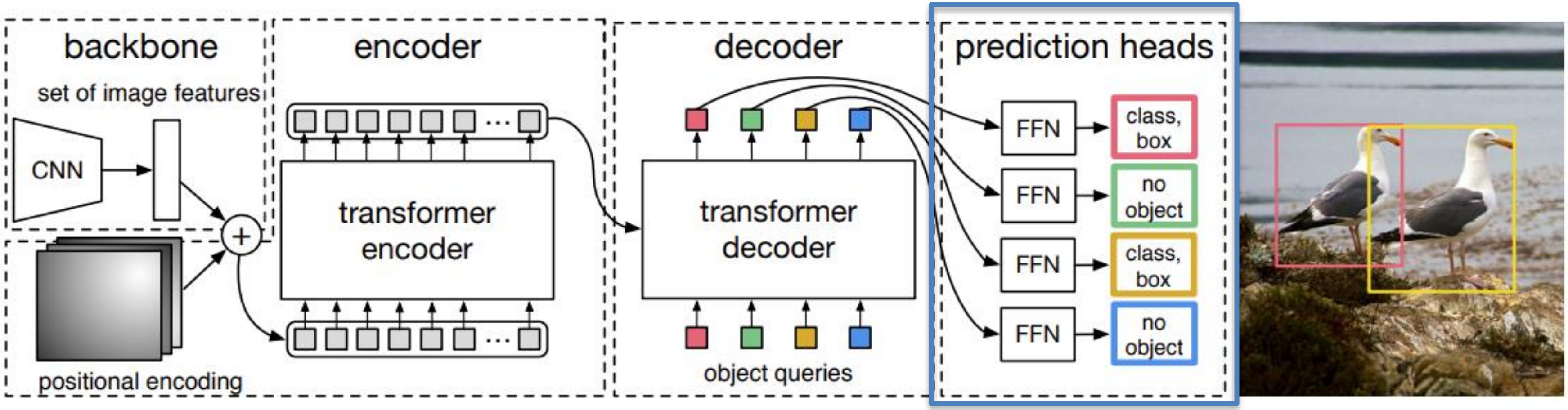
New positional embeddings as object queries

decode the object queries into output embeddings, while referring to the encoded image tokens

Carion et al. “End-to-End Object Detection with Transformers”.

DETR

- DETR works in a similar way as Machine Translation

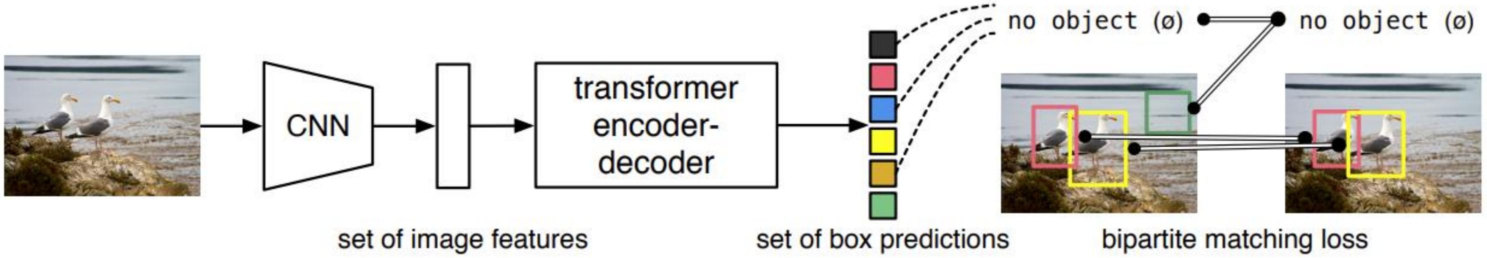


An output layer predicts the object classes and bounding boxes, or "no object"

Carion et al. "End-to-End Object Detection with Transformers".

DETR

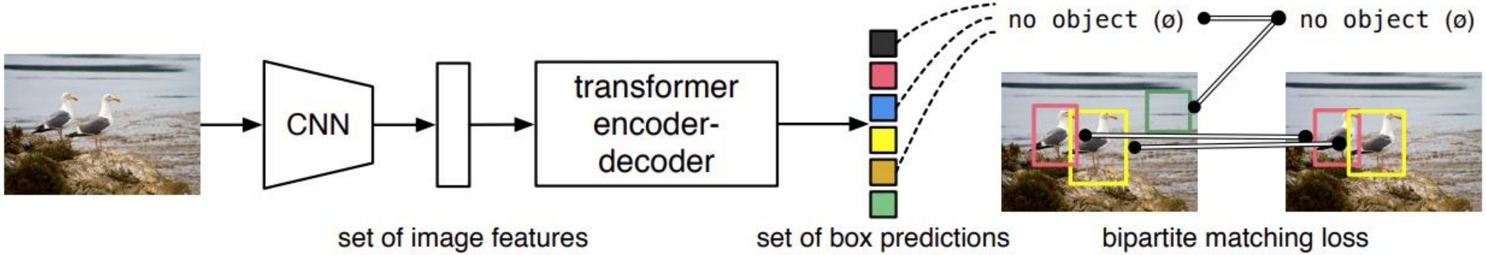
- Object detection as set prediction
  - Each box prediction is matches with only **ONE** ground truth (**one-to-one assignment**), i.e., only match the best prediction out of duplicated ones to the GT, the others will be assigned to "no object"



Carion et al. "End-to-End Object Detection with Transformers".

DETR

- Object detection as set prediction
  - Bipartite matching with pair-wise matching cost



L1 loss and generalized IoU loss

$$\hat{\sigma} = \arg\min_{\sigma \in \mathfrak{S}_N} \sum_{i}^{N} \boxed{-\mathbb{1}_{\{c_i \neq \varnothing\}} \hat{p}_{\sigma(i)}(c_i)} + \boxed{\mathbb{1}_{\{c_i \neq \varnothing\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\sigma(i)})}$$

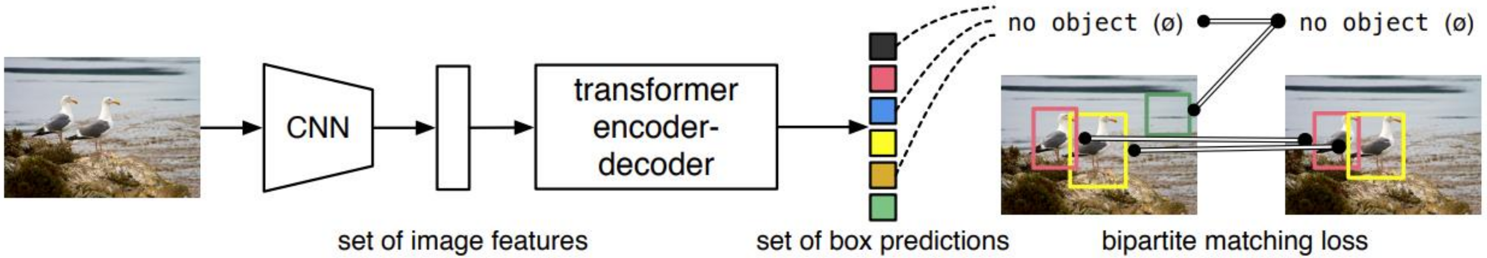
Find prediction-GT assignments that minimize this cost

Predicted class probability ("no object" class excluded)

Carion et al. "End-to-End Object Detection with Transformers".

DETR

- Object detection as set prediction
  - Bipartite matching with pair-wise matching cost



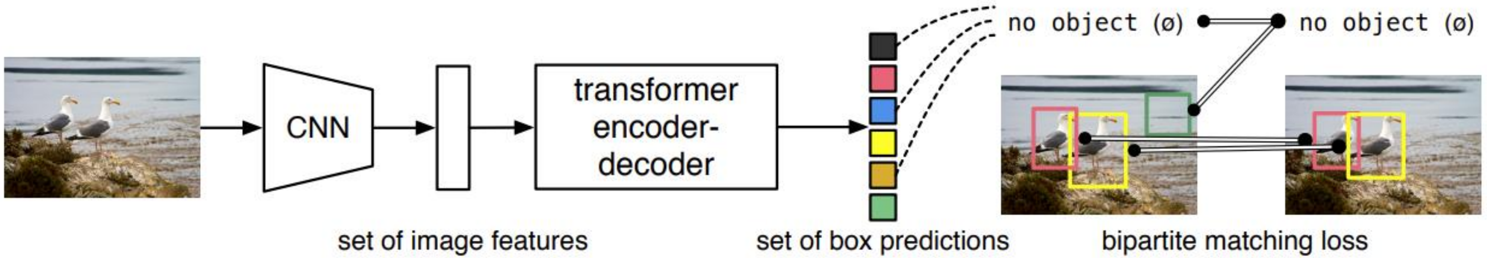
Matching via Hungarian Algorithm, non-matched predictions will be assigned to "no object" class

$$\hat{\sigma} = \underset{\sigma \in \mathfrak{S}_N}{\arg\min} \sum_{i}^{N} -\mathbb{1}_{\{c_i \neq \varnothing\}} \hat{p}_{\sigma(i)}(c_i) + \mathbb{1}_{\{c_i \neq \varnothing\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\sigma(i)})$$

Carion et al. "End-to-End Object Detection with Transformers".

DETR

- Object detection as set prediction
  - Hungarian loss (after bipartite matching)



L1 loss and generalized IoU loss

$$\mathcal{L}_{\text{Hungarian}}(y,\hat{y}) = \sum_{i=1}^{N}\left[\boxed{-\log \hat{p}_{\hat{\sigma}(i)}(c_i)} + \boxed{\mathbb{1}_{\{c_i \neq \varnothing\}}\mathcal{L}_{\text{box}}(b_i, \hat{b}_{\hat{\sigma}}(i))}\right]$$

Predicted class probability
(including the "no object" class)

Carion et al. "End-to-End Object Detection with Transformers".

DETR

- DETR works in a similar way as Neural Machine Translation.
- The bipartite matching enforces DETR to predict non-overlapping bounding boxes; DETR does not need non-maximum suppression (NMS) by design.
- Can be easily extended to panoptic segmentation by adding a mask head on top of the decoder outputs.

Reading Homework

- Understanding BERT
  – https://jalammar.github.io/illustrated-bert/

- BEiT: [Bao et al. 2021] BEIT: BERT Pre-Training of Image Transformers
  – https://arxiv.org/pdf/2106.08254.pdf

- Pix2Seq: [Chen et al. 2021] Pix2seq: A Language Modeling Framework for Object Detection
  – https://arxiv.org/pdf/2109.10852.pdf

Literature

- Attention: [Xu. 2015] Show, Attend and Tell: Neural Image Caption Generation with Visual Attention
  - https://arxiv.org/pdf/1502.03044.pdf
- Transformer: [Vaswani et al. 2017] Attention is All You Need
  - https://arxiv.org/pdf/1706.03762.pdf
- BERT: [Devlin et al. 2020] BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding
  - https://arxiv.org/pdf/1810.04805.pdf
- ViT: [Dosovitskiy et al. 2020] An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale
  - https://arxiv.org/pdf/2010.11929.pdf
- MAE: [He et al. 2022] Masked Autoencoders Are Scalable Vision Learners
  - https://arxiv.org/pdf/2111.06377.pdf
- ViLT: [Kim et al. 2019] ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision
  - https://arxiv.org/pdf/2102.03334.pdf
- DETR: [Carion et al. 2022] End-to-End Object Detection with Transformers
  - https://arxiv.org/pdf/2005.12872.pdf