# Deep Learning (M1)
## Attention mechanisms

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# Goals of this course

## Knowledge

- Principle of attention mechanisms
- Transformer architecture
- Transformer attention formula

## Skills and know-how

- Integrate transformer attention in encoder / decoder
- Determine size and meaning of intermediate representations in attention mechanisms
- Analyze attention maps

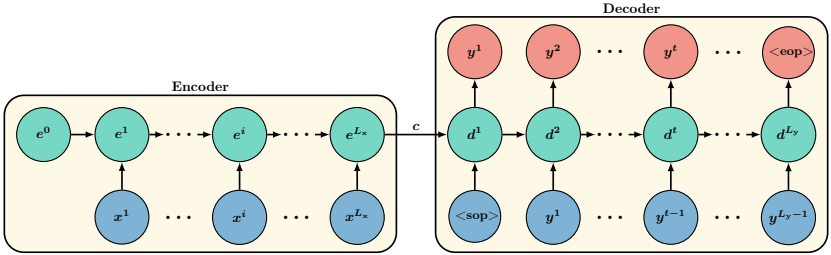
## Limitations of RNNs for large sequences

For feature extraction (encoder):

- Difficult to preserve information from start to end of the sequence

For seq2seq:

- The size of the context vector $c$ is fixed, no matter the sequence length (compression, information loss)



# Plan du cours

## Idea

From a static context vector:

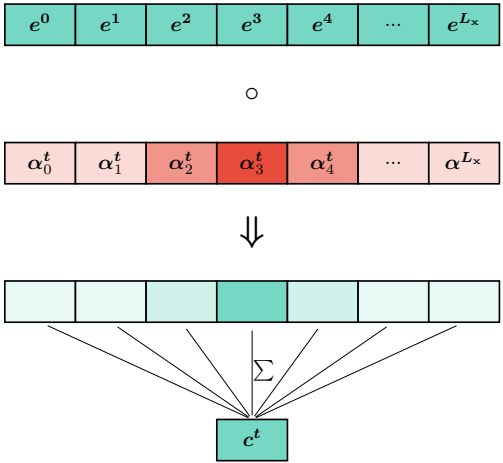
$$\boldsymbol{c} = f(\boldsymbol{x})$$

to a dynamic context vector:

$$\boldsymbol{c}^t = \sum_{i=1}^{L_x} \boldsymbol{\alpha}_i^t \boldsymbol{e}^i$$

with: $\sum_i \boldsymbol{\alpha}_i = 1$.

$\boldsymbol{\alpha}_i$ are called attention weights



## Encoder

Forward pass performed only once leading to $\{\boldsymbol{e}^1, ..., \boldsymbol{e}^{L_\times}\}$

## Decoder

Iterative process, at iteration $t$:

1. Compute score/energy for each encoded features $\boldsymbol{s}_i^t = a(...)$
2. Normalize these scores through softmax, leading to attention weights:

$$\boldsymbol{\alpha}_i^t = \frac{e^{\boldsymbol{s}_i^t}}{\sum_j e^{\boldsymbol{s}_j^t}}$$

3. Compute the context vector: $\boldsymbol{c}^t = \sum_i \boldsymbol{\alpha}_i^t \boldsymbol{e}^i$
4. Make prediction for iteration $t$: $\hat{\boldsymbol{y}}^t = b(\boldsymbol{c}^t)$

### Content-based attention

The scores are based on features and previous context: $\boldsymbol{s}_i^t = a(\boldsymbol{c}^{t-1}, \boldsymbol{e}^i)$

### Location-based attention

The scores are based on previous attention weights and previous context: $\boldsymbol{s}_i^t = a(\boldsymbol{c}^{t-1}, \boldsymbol{\alpha}^{t-1})$

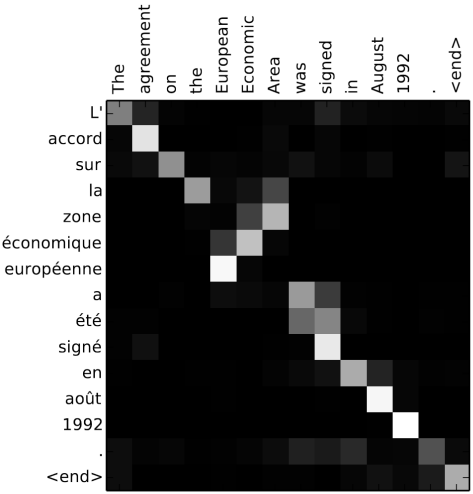
### Hybrid attention

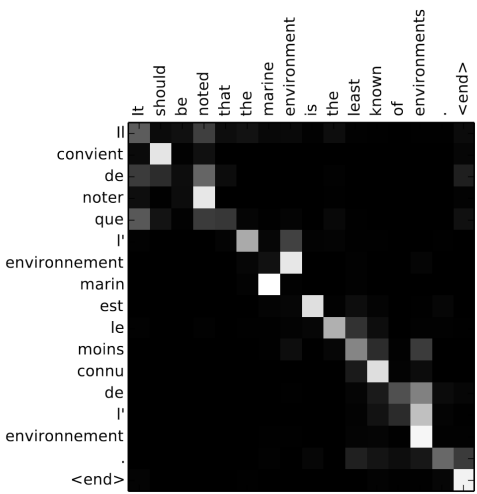
Generally, both approaches are mixed together: $\boldsymbol{s}_i^t = a(\boldsymbol{c}^{t-1}, \boldsymbol{\alpha}^{t-1}, \boldsymbol{e}^i)$

### Example

$\boldsymbol{s}_i^t = \boldsymbol{v}^T \tanh(\boldsymbol{W}_c \boldsymbol{c}^{t-1} + \boldsymbol{W}_\alpha \boldsymbol{\alpha}^{t-1} + \boldsymbol{W}_e \boldsymbol{e}^i)$

# Attention maps for encoder-decoder attention




Images from [1]

➤ Size: target sequence length × source sequence length

## Goal

Embed a token as a weighted sum of the other tokens of the sequence
Input: a set of token embeddings $\{\boldsymbol{e}^1, ..., \boldsymbol{e}^{L_x}\}$
Output: a new set of token embeddings $\{\boldsymbol{o}^1, ..., \boldsymbol{o}^{L_x}\}$

## For each token $\boldsymbol{e}^i$

1. Compute a score with respect to each token: $\boldsymbol{s}^i_j = a(\boldsymbol{e}^i, \boldsymbol{e}^j)$
2. Normalize the scores:
$$\boldsymbol{\alpha}^i_j = \frac{e^{\boldsymbol{s}^i_j}}{\sum_k e^{\boldsymbol{s}^i_k}}$$
3. Compute the context vector: $\boldsymbol{c}^i = \sum_j \boldsymbol{\alpha}^i_j \boldsymbol{e}^j$
4. Compute the new token representation: $\boldsymbol{o}^i = b(\boldsymbol{c}^i)$

➤ All $\boldsymbol{o}^i$ can be computed in parallel

Let's assume an input sequence $\boldsymbol{e} = [\boldsymbol{e}^1, ..., \boldsymbol{e}^{L_x}]$ with $\boldsymbol{e}^i \in \mathbb{R}^C$ and $\boldsymbol{W} \in \mathbb{R}^{C_o \times C}$.

- What is the size of $\boldsymbol{s}^i, \boldsymbol{\alpha}^i, \boldsymbol{c}^i$ and $\boldsymbol{o}^i$?

$$\boldsymbol{s}^i_j = \sum_k \boldsymbol{e}^i_k \boldsymbol{e}^j_k$$

$$\boldsymbol{\alpha}^i_j = \frac{e^{\boldsymbol{s}^i_j}}{\sum_k e^{\boldsymbol{s}^i_k}}$$

$$\boldsymbol{c}^i = \sum_j \boldsymbol{\alpha}^i_j \boldsymbol{e}^j$$

$$\boldsymbol{o}^i = \boldsymbol{W}\boldsymbol{c}^i$$

Let's assume an input sequence $\boldsymbol{e} = [\boldsymbol{e}^1, ..., \boldsymbol{e}^{L_x}]$ with $\boldsymbol{e}^i \in \mathbb{R}^C$

- There are $L_x$ tokens
- For a given token $i$, one score per token $j$: $\boldsymbol{s}^i \in \mathbb{R}^{L_x}$
- For a given token, we want one attention weight for each token: $\boldsymbol{\alpha}^i \in \mathbb{R}^{L_x}$
- Context vector is a weighted sum of vectors of size $C$: $\boldsymbol{c}^i \in \mathbb{R}^C$
- Fully connected layer applied to the context vector: $\boldsymbol{o}^i \in \mathbb{R}^{C_o}$

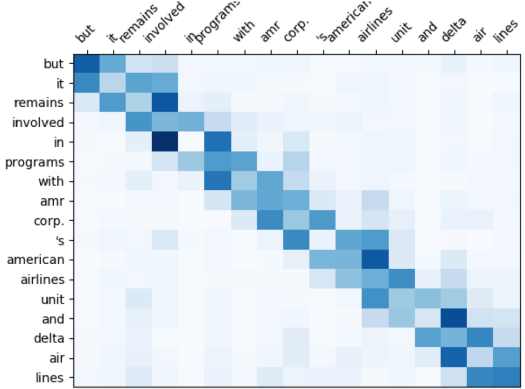
$$\boldsymbol{s}^i_j = \sum_k \boldsymbol{e}^i_k \boldsymbol{e}^j_k$$

$$\boldsymbol{\alpha}^i_j = \frac{e^{\boldsymbol{s}^i_j}}{\sum_k e^{\boldsymbol{s}^i_k}}$$

$$\boldsymbol{c}^i = \sum_j \boldsymbol{\alpha}^i_j \boldsymbol{e}^j$$

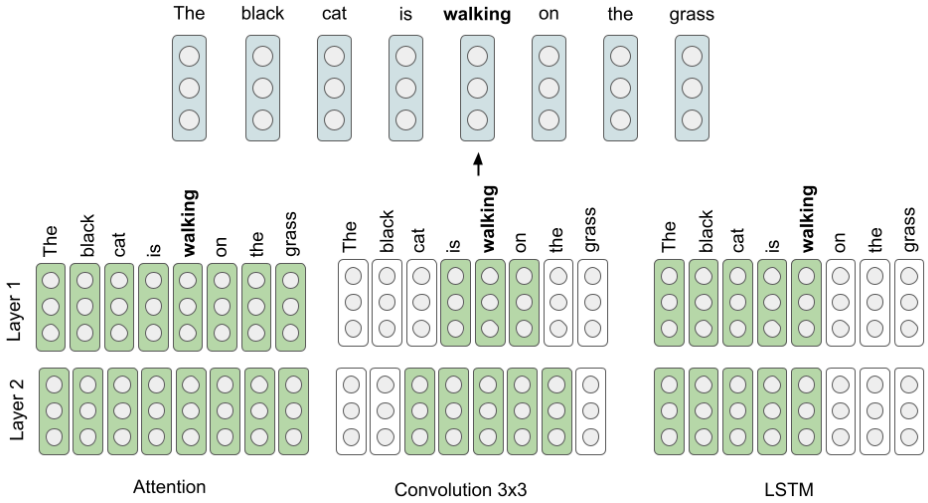
$$\boldsymbol{o}^i = \boldsymbol{W}\boldsymbol{c}^i$$

# Attention map for self-attention

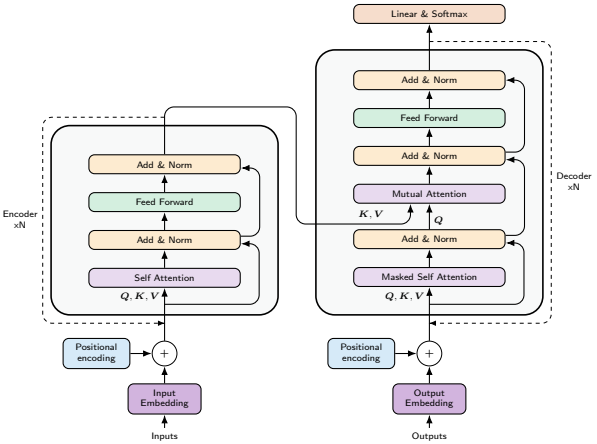



➤ Size: source sequence length $\times$ source sequence length

# Context modeling comparison



# Plan du cours




Two main blocks:

- Transformer encoder
- Transformer decoder

**One-shot encoding**

$$\boldsymbol{f} = \text{encoder}(\boldsymbol{x} + \text{PE})$$

**Iterative decoding**

$$\boldsymbol{c}^t = \text{decoder}(\boldsymbol{f}, \{\hat{\boldsymbol{y}}^0, ..., \hat{\boldsymbol{y}}^{t-1}\} + \text{PE})$$

$$\hat{\boldsymbol{y}}^t = \arg\max(\boldsymbol{W}\boldsymbol{c}^t)$$

➤ Mainly relies on the Query-Key-Value attention paradigm

## Concept

Goal: retrieve the useful information among a collection of data
Inputs: a *query* and a set of data

## Approach

- Compute a similarity score between the query and all the data
- Generate an answer based on the most relevant data

➤ Two representations of the data are used: *keys* for comparison with the query, and *values* for the answer

## Analogy with library search engine

Query: keywords; Keys: book titles; Values: book contents

## Issue

Gradient propagation for hard attention (select only the most relevant item)

➤ Soft attention (weighted sum of items)

## Scaled Dot-Product Attention

$\boldsymbol{q} \in \mathbb{R}^d$: a query vector

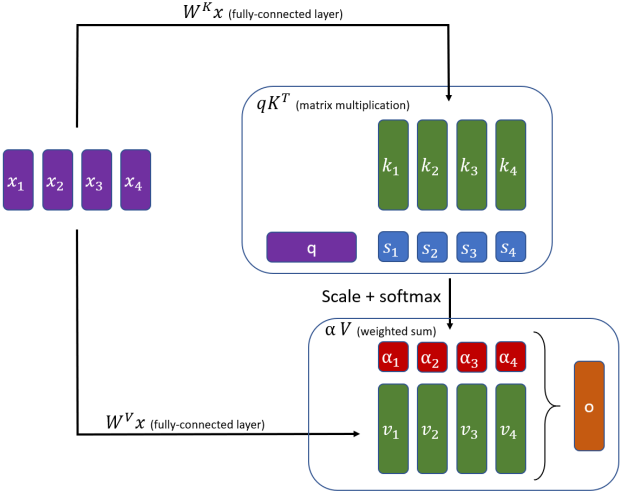
$\boldsymbol{K} \in \mathbb{R}^{L \times d}$: a matrix gathering key vectors for each available item

$\boldsymbol{V} \in \mathbb{R}^{L \times d}$: a matrix gathering values vectors for each available item

$$\text{Attention}(\boldsymbol{q}, \boldsymbol{K}, \boldsymbol{V}) = \underbrace{\text{softmax}\left(\frac{\boldsymbol{q}\boldsymbol{K}^T}{\sqrt{d}}\right)}_{\alpha} \boldsymbol{V} = \boldsymbol{c} \quad (\in \mathbb{R}^d)$$

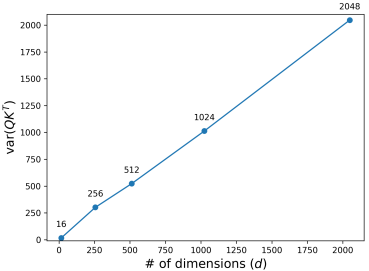
➤ Dot product as distance function

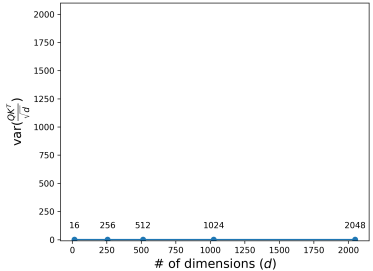
# Illustration of the computations

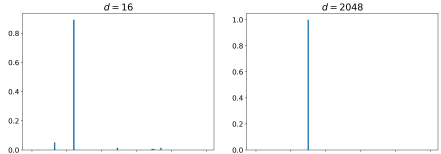


# Why scaling by $\frac{1}{\sqrt{d}}$?

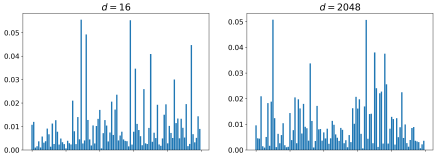
For 1 query and 10,000 keys (from normal distribution):




Softmax over the first 100 keys




Softmax over the first 100 keys

➤ Queries, Keys and Values are from the same source

**Query-key-value for feature extraction**

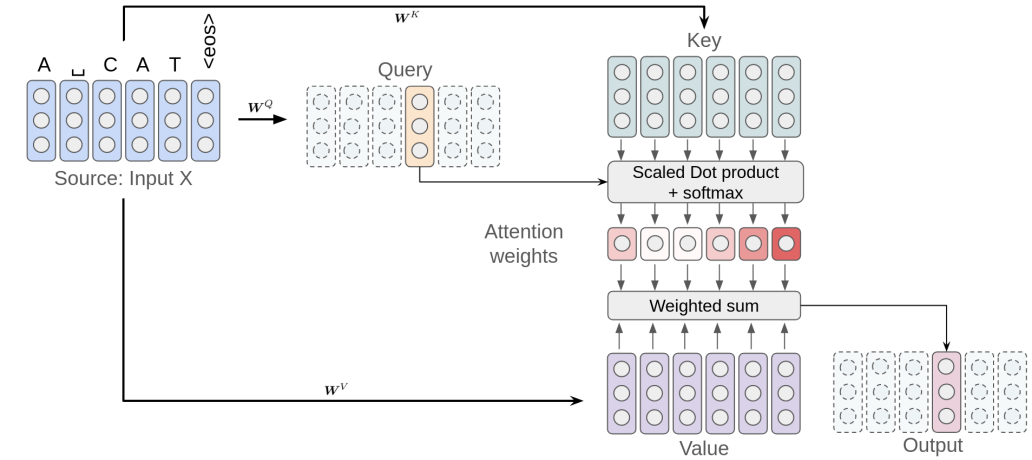
$\boldsymbol{X}$: the latent representation of an input sequence.

$$\boldsymbol{Q} = \boldsymbol{X}\boldsymbol{W}^{Q} (\in \mathbb{R}^{L_x \times d})$$
$$\boldsymbol{K} = \boldsymbol{X}\boldsymbol{W}^{K} (\in \mathbb{R}^{L_x \times d})$$
$$\boldsymbol{V} = \boldsymbol{X}\boldsymbol{W}^{V} (\in \mathbb{R}^{L_x \times d})$$

$$\boldsymbol{Y} = \text{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^{T}}{\sqrt{d}}\right)\boldsymbol{V}$$

$\boldsymbol{W}^{Q}, \boldsymbol{W}^{K}$ and $\boldsymbol{W}^{V}$ are matrices of trainable weights (fully-connected layers)

# Self-attention




- Output can be computed in parallel through matrix multiplications
- Output length = Query length ( = Key length = Value length)

## $h$ self-attention in parallel

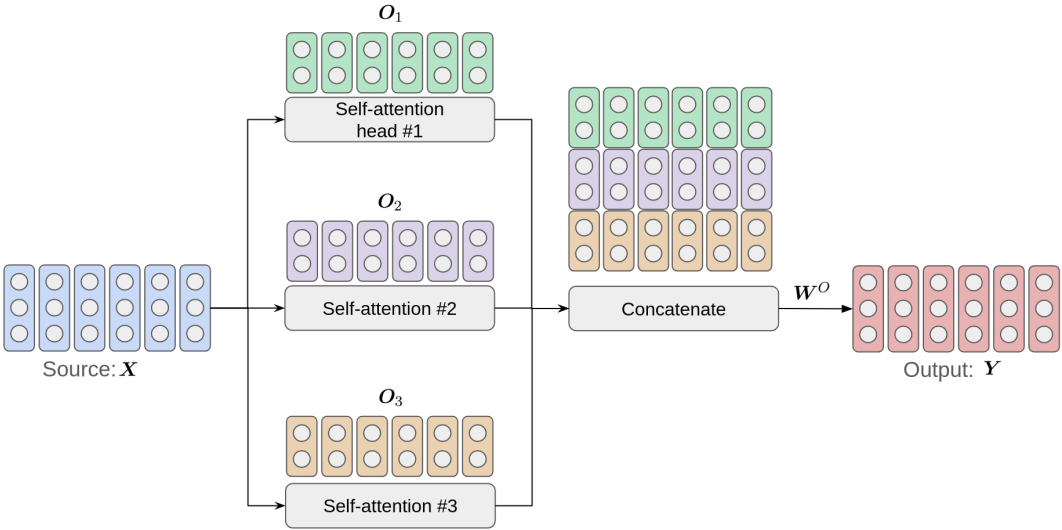
$$\begin{aligned} \boldsymbol{Q}_1 &= \boldsymbol{X}\boldsymbol{W}_1^Q \quad \dots \quad \boldsymbol{Q}_h = \boldsymbol{X}\boldsymbol{W}_h^Q \\ \boldsymbol{K}_1 &= \boldsymbol{X}\boldsymbol{W}_1^K \quad \dots \quad \boldsymbol{K}_h = \boldsymbol{X}\boldsymbol{W}_h^K \\ \boldsymbol{V}_1 &= \boldsymbol{X}\boldsymbol{W}_1^V \quad \dots \quad \boldsymbol{V}_h = \boldsymbol{X}\boldsymbol{W}_h^V \end{aligned}$$

$$\boldsymbol{O}_1 = \text{softmax}\left(\frac{\boldsymbol{Q}_1\boldsymbol{K}_1^T}{\sqrt{d}}\right)\boldsymbol{V}_1 \quad \dots \quad \boldsymbol{O}_h = \text{softmax}\left(\frac{\boldsymbol{Q}_h\boldsymbol{K}_h^T}{\sqrt{d}}\right)\boldsymbol{V}_h$$

$$\boldsymbol{Y} = \text{concat}(\boldsymbol{O}_1, \dots, \boldsymbol{O}_h)\boldsymbol{W}^O$$

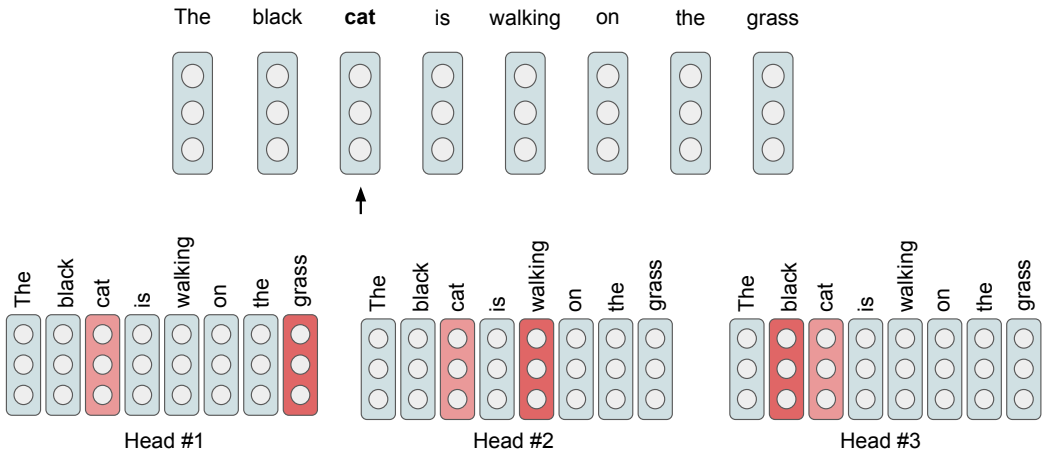
Heads can be seen as the equivalent of convolutional kernels

# Multi-head Self-Attention (MSA)



## Intuition

Each head is specialized for a specific query (*e.g.*, action, location, description)



## Issue with Multi-head Self Attention (MSA)

Self-attention is equivariant to input permutation:
$\text{MSA}([\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3]) = [\boldsymbol{y}_1, \boldsymbol{y}_2, \boldsymbol{y}_3] \Rightarrow \text{MSA}([\boldsymbol{x}_2, \boldsymbol{x}_1, \boldsymbol{x}_3]) = [\boldsymbol{y}_2, \boldsymbol{y}_1, \boldsymbol{y}_3]$

The position information is lost whereas it is crucial

➤ A word/sentence is a sequence of characters, not a set of characters

## Goal

Inject positional information to preserve the sequentiality

## Solution

Additive positional encoding:

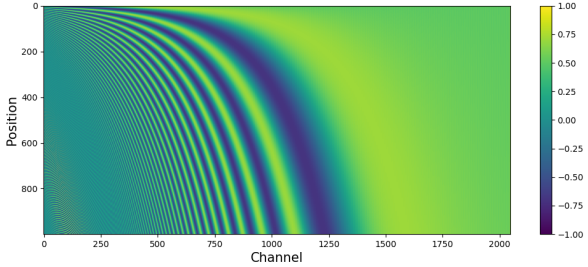
➤ Input of transformer encoder: $\boldsymbol{I} = \boldsymbol{X} + \text{PE}$

## A combination of sines and cosines

PE$(p, k)$: $k^{\text{th}}$ value of positional embedding vector for position $p$.

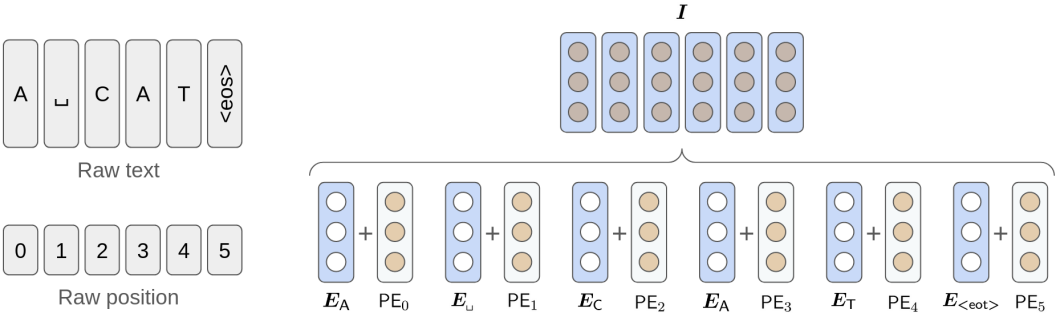
$$\text{PE}(p, 2k) = \sin(w_k \cdot p)$$
$$\text{PE}(p, 2k+1) = \cos(w_k \cdot p)$$

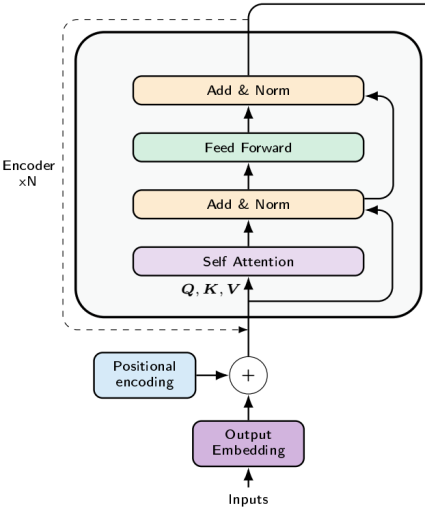
$\forall k \in [0, d/2]$, with $w_k = 1/10000^{2k/d}$



## Advantages

- Does not depend on the input length
- Encoding unique for each position
- Periodicity of sine/cosine could help to adapt to unseen position
- Bonus: no additional trainable parameters






## A stack of 6 transformer encoder layers

- Multi-head Self Attention
  - ➤ Global context modeling
- Add: residual connections
  - ➤ Multi-scale representation
  - ➤ Reinforce identity
- Norm: layer normalization
  - ➤ Stabilize training (range of values)
- Feed Forward: 2 fully-connected layers
  - ➤ Local projection

Input sequence of $L_x$ token embeddings: $\boldsymbol{X} \in \mathbb{R}^{L \times d}$

A simplified version of the attention layer, keeping the same dimension:
$\boldsymbol{Y} = (\boldsymbol{X}\boldsymbol{W}^{\mathsf{Q}})(\boldsymbol{X}\boldsymbol{W}^{\mathsf{K}})^T(\boldsymbol{X}\boldsymbol{W}^{\mathsf{V}})\boldsymbol{W}^{\mathsf{O}}$

$\boldsymbol{W}^{\mathsf{Q}} \in \mathbb{R}^{d \times d}, \boldsymbol{W}^{\mathsf{K}} \in \mathbb{R}^{d \times d}, \boldsymbol{W}^{\mathsf{V}} \in \mathbb{R}^{d \times d}, \boldsymbol{W}^{\mathsf{O}} \in \mathbb{R}^{d \times d} \rightarrow 4d^2$ parameters

$\boldsymbol{X}\boldsymbol{W}^{\mathsf{i}}$: from $L \times d$ to $L \times d$; $2d^2L$ FLOPs ($\times 3$)

$\boldsymbol{S} = (\boldsymbol{X}\boldsymbol{W}^{\mathsf{Q}})(\boldsymbol{X}\boldsymbol{W}^{\mathsf{K}})^T$: output $L \times L$; $2dL^2$ FLOPs

$\boldsymbol{O} = \boldsymbol{S}(\boldsymbol{X}\boldsymbol{W}^{\mathsf{V}})$: output $L \times d$; $2dL^2$ FLOPs

$\boldsymbol{Y} = \boldsymbol{O}\boldsymbol{W}^{\mathsf{O}}$: output $L \times d$; $2d^2L$ FLOPs

- $8d^2L + 4dL^2$ FLOPs
- Quadratic complexity with respect to the input length

➤ Queries from target domain, and keys and values from source domain

## General case

Inputs: $\boldsymbol{X}$: the features from the encoded input sequence (source domain),
$\tilde{\boldsymbol{z}}$: the query sequence (*e.g.*, a question)
$\boldsymbol{z}$: the query vector ($\boldsymbol{z} = g(\tilde{\boldsymbol{z}})$).

$$\boldsymbol{q} = \boldsymbol{z}\boldsymbol{W}^Q (\in \mathbb{R}^d)$$
$$\boldsymbol{K} = \boldsymbol{X}\boldsymbol{W}^K (\in \mathbb{R}^{L_x \times d})$$
$$\boldsymbol{V} = \boldsymbol{X}\boldsymbol{W}^V (\in \mathbb{R}^{L_x \times d})$$

$$\boldsymbol{c} = \text{Attention}(\boldsymbol{q}, \boldsymbol{K}, \boldsymbol{V}) = \underbrace{\text{softmax}\left(\frac{\boldsymbol{q}\boldsymbol{K}^T}{\sqrt{d}}\right)}_{\alpha}\boldsymbol{V}$$

Prediction: $\hat{\boldsymbol{y}} = h(\boldsymbol{c})$, with $g$ and $h$ parametric functions

➤ Queries from target domain, and keys and values from source domain

**The iterative decoding process case**

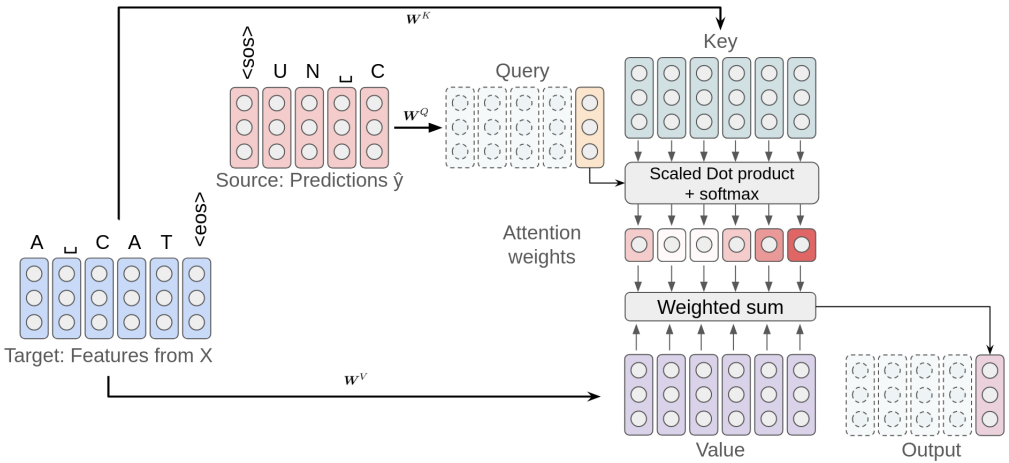
Inputs: $\boldsymbol{X}$: the features from the encoded input sequence (source domain),
$\tilde{\boldsymbol{z}} = \hat{\boldsymbol{y}}^{0:t-1}$: an ouput sequence (target domain)
$\boldsymbol{z}^t$: a query vector at iteration $t$ ($\boldsymbol{z}^t = g(\hat{\boldsymbol{y}}^0, ..., \hat{\boldsymbol{y}}^{t-1})$).

$$\boldsymbol{q}^t = \boldsymbol{z}^t \boldsymbol{W}^Q (\in \mathbb{R}^d)$$
$$\boldsymbol{K} = \boldsymbol{X} \boldsymbol{W}^K (\in \mathbb{R}^{L_x \times d})$$
$$\boldsymbol{V} = \boldsymbol{X} \boldsymbol{W}^V (\in \mathbb{R}^{L_x \times d})$$

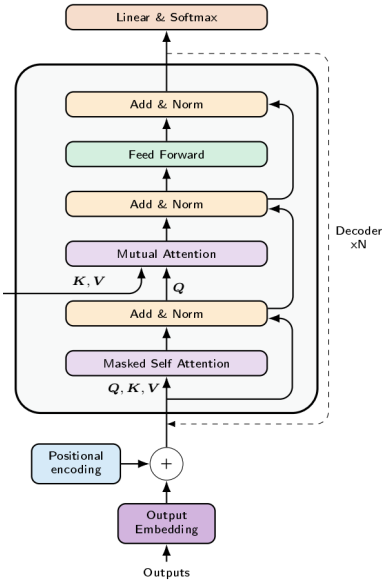
$$\boldsymbol{c}^t = \text{Attention}(\boldsymbol{q}^t, \boldsymbol{K}, \boldsymbol{V}) = \underbrace{\text{softmax}\left(\frac{\boldsymbol{q}^t \boldsymbol{K}^T}{\sqrt{d}}\right)}_{\alpha^t} \boldsymbol{V}$$

New prediction: $\hat{\boldsymbol{y}}^t = h(\boldsymbol{c}^t)$, with $g$ and $h$ parametric functions

# Cross attention attention



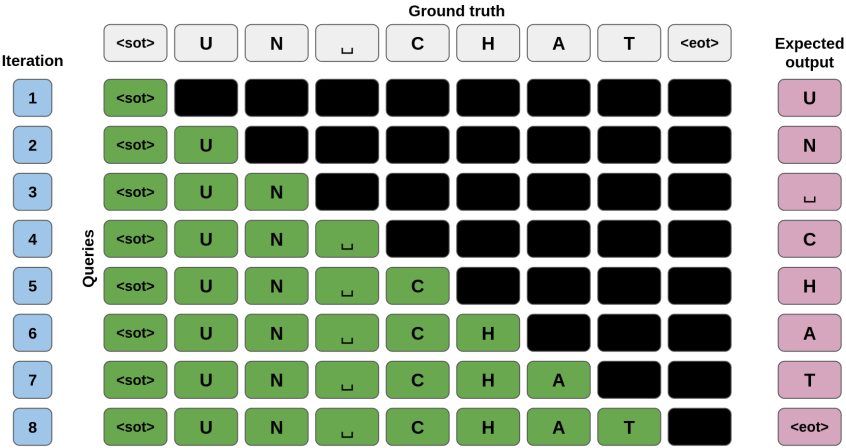

➤ Output length = Query length ($\neq$ Key length = Value length)




## A stack of 6 transformer decoder layers

- Multi-head Masked Self Attention
  ➤ Global query modeling
- Add: residual connections
  ➤ Multi-scale representation
  ➤ Reinforce identity
- Norm: layer normalization
  ➤ Stabilize training (range of values)
- Multi-head mutual attention
  ➤ Look for relevant information from source
- Feed Forward: 2 fully-connected layers
  ➤ Local projection

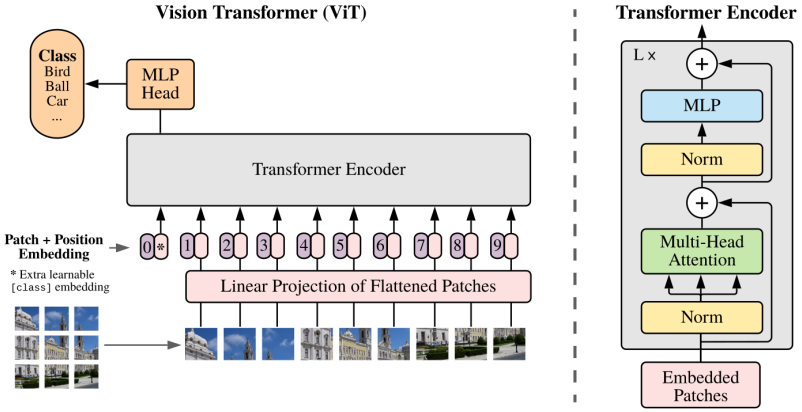
➤ Parallelize decoding process at training time using ground truth



## Conclusion

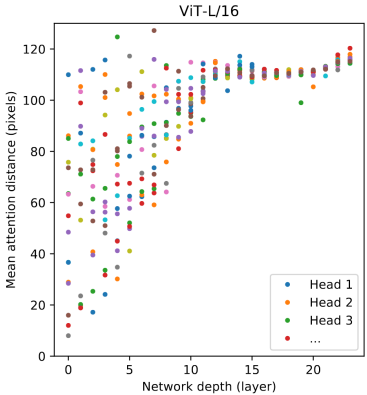
- A modular approach: expressivity can be enhanced by adding more encoder/decoder layers
  ➤ But slower training/inference and more required data
- Self attention: a way to model global context without sequential computations (at each layer, each token can attend to all the other tokens)
  ➤ But a quadratic complexity
- Parameter-free additive positional encoding
  ➤ But the relation between positions must be learned through training
- Defined for Natural Language Processing: SOTA architecture
  ➤ How to adapt it for computer vision?

# Transformer for image classification: Vision Transformer (2021) [3]




Input image: $224 \times 224$, patch size: $16 \times 16 \Rightarrow 196$ patches
Introduction of a trainable class token used for prediction


Attention map for the class token



| Architecture | Top-1 accuracy (%) on ImageNet | # params (M) |
|---|---|---|
| ResNet-50 | 79.26 | 26 |
| ResNet-101 | 80.13 | 45 |
| ResNet-152 | **80.62** | 60 |
| ViT-B/16 | 77.91 | 86 |
| ViT-B/32 | 73.38 | 86 |
| ViT-L/16 | 76.53 | 307 |
| ViT-L/32 | 71.16 | 307 |

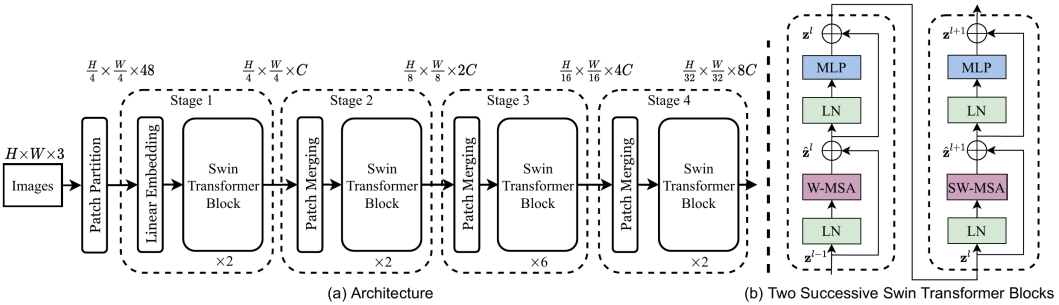
Attention-based architectures require more data to exploit their full potential:

➤ Spatial relations between patches must be learned from scratch

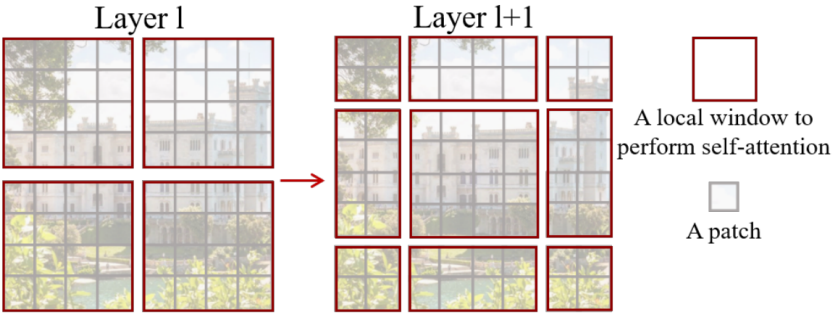
Performance on ImageNet (fine-tuning included)

| Architecture | Top-1 accuracy (%) on ImageNet | |
|---|---|---|
| | Pre-trained on ImageNet | Pre-trained on JFT-300M |
| ResNet-50 | 79.26 | ✗ |
| ResNet-101 | 80.13 | ✗ |
| ResNet-152 | 80.62 | ✗ |
| ViT-B/16 | 77.91 | 84.15 |
| ViT-B/32 | 73.38 | 80.73 |
| ViT-L/16 | 76.53 | 87.12 |
| ViT-L/32 | 71.16 | 84.37 |
| ViT-H/14 | ✗ | **88.04** |

➤ Hierarchical Vision Transformer using Shifted windows (Swin)




Patch size: $4 \times 4$
Patch merging: $2 \times 2$ adjacent patches are merged together
(S)W-MSA: (Shifted) Window Multi Self-Attention
➤ Idea: perform attention on patch windows (locally), in parallel




**Modeling global context with shifted windows**

Windows are shifted from one layer to another to propagate the information from one window to its neighbours

**Reminder: simplified self-attention**

Number of FLOPs: $8d^2L + 4dL^2$
With $d$ the number of dimensions and $L$ the sequence length

Compute the number of FLOPs for a latent representation of an image of size $(H = 1024, W = 1024, C = 256)$

- for a traditional self-attention layer
- for the shifted windows approach (window size: $8 \times 8$, first step only)

➤ Remark: the number of dimensions is preserved (from 256 to 256)

## Reminder: simplified self-attention

Number of FLOPs: $8d^2L + 4dL^2$
With $d$ the number of dimensions and $L$ the sequence length

## For a traditional self-attention layer

Flatten: $L = HW = 1024 \times 1024 = 1,048,576$
➤ $8 \times 256^2 \times 1,048,576 + 4 \times 256 \times 1,048,576^2 = 1.1 \times 10^{15}$ FLOPs

## For a shifted-window self-attention layer

Window size: $8 \times 8$
Flatten: $L = HW = 8 \times 8 = 64$
➤ $8 \times 256^2 \times 64 + 4 \times 256 \times 64^2 = 37.7 \times 10^6$ FLOPs per window

Number of windows: $\frac{1024}{8} \times \frac{1024}{8} = 16,384$
➤ $16,384 \times 37.7 \times 10^6 = 0.6 \times 10^9$ FLOPs

| method | image size | #param. | FLOPs | throughput (image / s) | ImageNet top-1 acc. |
|---|---|---|---|---|---|
| R-101x3 [38] | $384^2$ | 388M | 204.6G | - | 84.4 |
| R-152x4 [38] | $480^2$ | 937M | 840.5G | - | 85.4 |
| ViT-B/16 [20] | $384^2$ | 86M | 55.4G | 85.9 | 84.0 |
| ViT-L/16 [20] | $384^2$ | 307M | 190.7G | 27.3 | 85.2 |
| Swin-B | $224^2$ | 88M | 15.4G | 278.1 | 85.2 |
| Swin-B | $384^2$ | 88M | 47.0G | 84.7 | 86.4 |
| Swin-L | $384^2$ | 197M | 103.9G | 42.1 | 87.3 |

Pre-training on ImageNet-22k

# Plan du cours

## Create artificial examples

- Data augmentation
- Synthetic data

## Benefit from other annotated datasets

- Transfer learning
- Fine-tuning
- Multi-tasking

## Benefit from unlabeled data

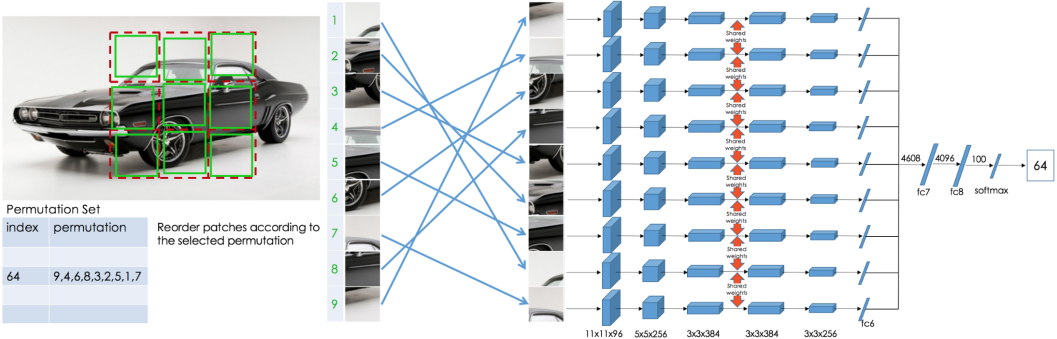
- Semi-supervised learning
- **Self-supervised learning**

**The goal is to solve a pretext task**

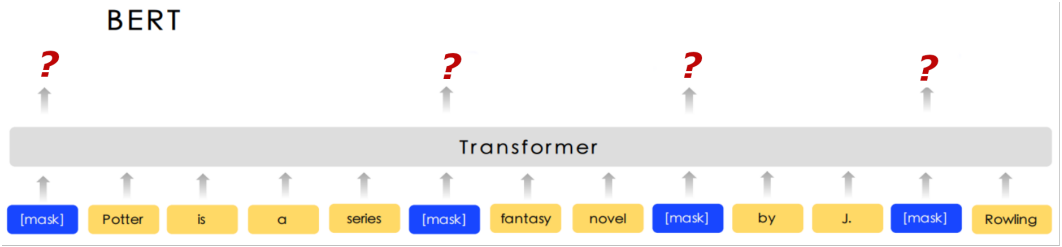
Some examples:

- Solve Jigsaw puzzles
- Reconstruct the input image:
  (Variational) Auto-encoders, Masked auto-encoders
- Contrastive learning: SimCLR, CLIP
  Learning from positive and negative samples

➤ Find the right permutation: classification formulation

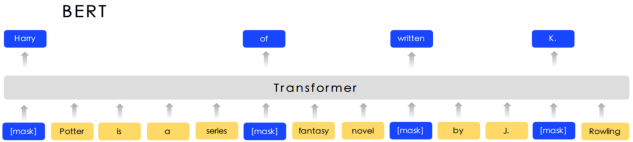


➤ Two self-supervised strategies

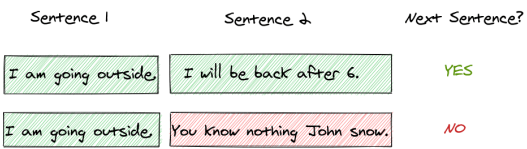


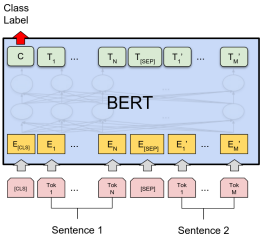

Masked LM

➤ Two self-supervised strategies



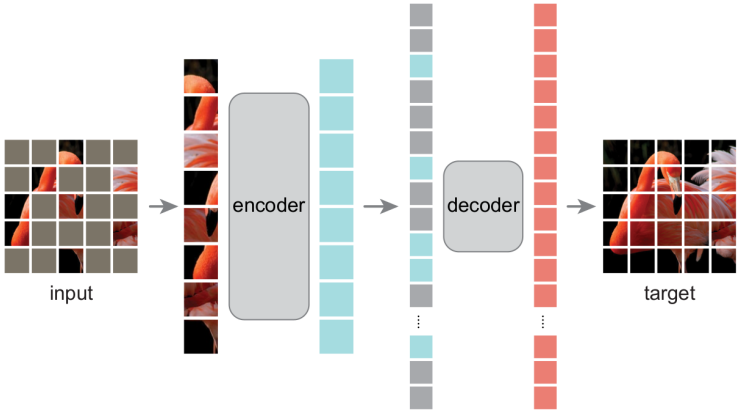

Masked LM




Next Sentence Prediction

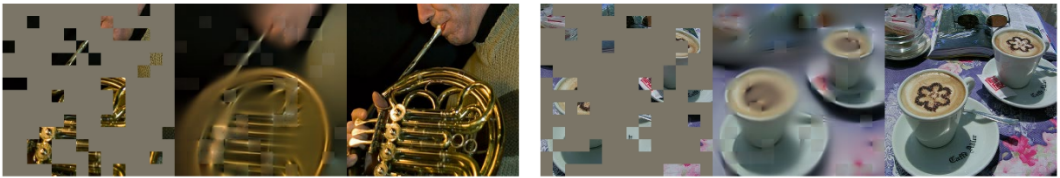
➤ Reconstruct the missing parts (pixel-level MSE loss)




➤ Vision Transformer architecture

➤ Classification performance (Top-1 accuracy) with ViT architectures, pre-trained and evaluated on ImageNet

| Approach | ViT-B | ViT-L | ViT-H | ViT-$H_{488}$ |
|---|---|---|---|---|
| Supervised | 82.3 | 82.6 | 83.1 | ✗ |
| MAE | 83.6 | 85.9 | 86.9 | **87.8** |



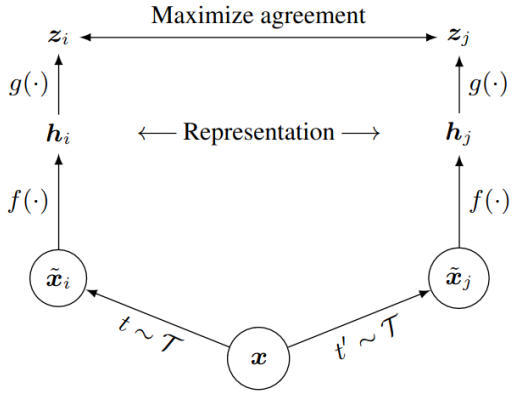
Left: masked input, Middle: reconstructed image, Right: ground truth

➤ Idea: generate two views for each input (= positive pair). Bring latent representations of positives closer and keep latent representations of negatives away

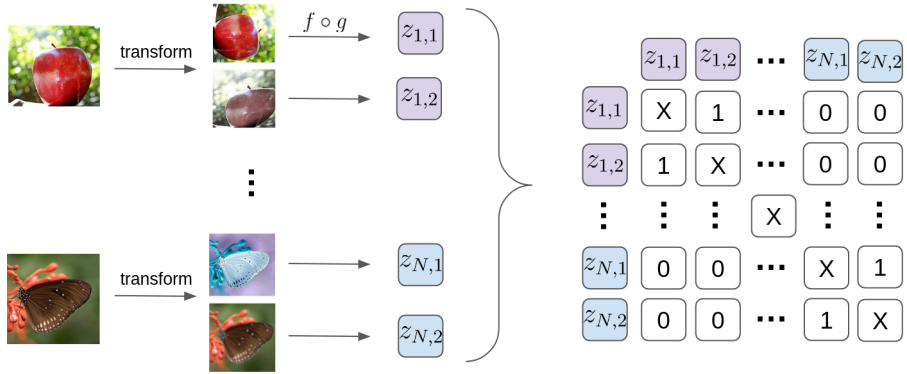
➤ Siamese networks: same architecture with same weights used on different inputs while comparing outputs

**Algorithm 1** SimCLR's main learning algorithm.

**input:** batch size $N$, constant $\tau$, structure of $f, g, \mathcal{T}$.
**for** sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^{N}$ **do**
  **for all** $k \in \{1, \dots, N\}$ **do**
    draw two augmentation functions $t \sim \mathcal{T}, t' \sim \mathcal{T}$
    # the first augmentation
    $\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  **end for**
  **for all** $i \in \{1, \dots, 2N\}$ and $j \in \{1, \dots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  **end for**
  **define** $\ell(i, j)$ **as** $\ell(i, j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks $f$ and $g$ to minimize $\mathcal{L}$
**end for**
**return** encoder network $f(\cdot)$, and throw away $g(\cdot)$



- Find the matching pairs
- Cosine similarity as distance metric




- Efficiency depends on mini-batch size

➤ Contrastive Language-Image Pre-training (CLIP)

**Idea**

Jointly train two encoders to avoid human annotation effort:

- An image encoder $f$: ResNet/ViT
- A text encoder $g$: transformer

➤ Both encoders are trained to generate a fixed-length latent representation from text/image input sharing the same feature space

**How?**

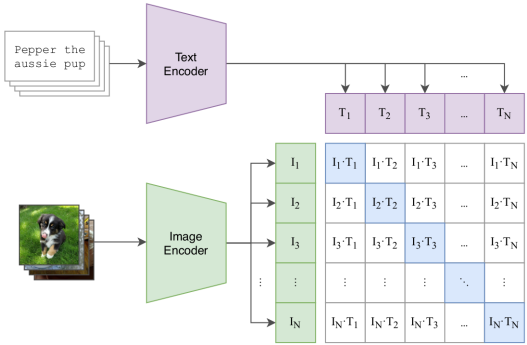
Constrative learning between images and captions

➤ 400 million pairs (image, text) collected from the web

$x$: image
$y$: caption

Image encoder: $f(x) = I$

Text encoder: $g(y) = T$




## Symmetric loss

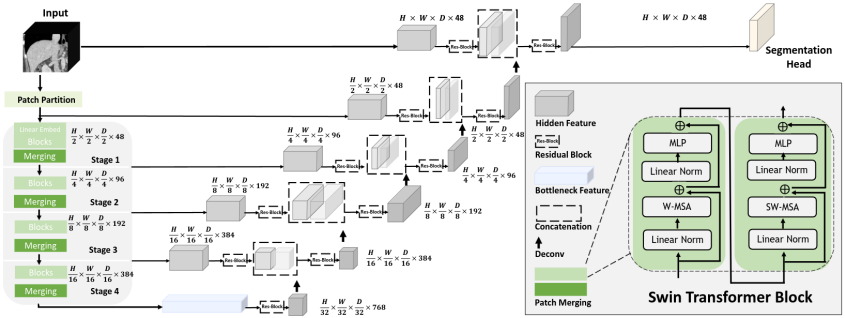
$$\mathcal{L} = \frac{1}{2}\Big(\sum_{i=1}^{N} \underbrace{\mathcal{L}_{\text{CE}}(\hat{y}_i^I, y_i^I)}_{\substack{\text{image } i \text{ compared} \\ \text{to all texts}}} + \sum_{t=1}^{N} \underbrace{\mathcal{L}_{\text{CE}}(\hat{y}_t^T, y_t^T)}_{\substack{\text{text } t \text{ compared} \\ \text{to all images}}}\Big)$$

$$\hat{y}_{i,j}^I = I_i \cdot T_j$$

$$\hat{y}_{t,j}^T = I_j \cdot T_t$$

# Plan du cours

➤ Medical image segmentation

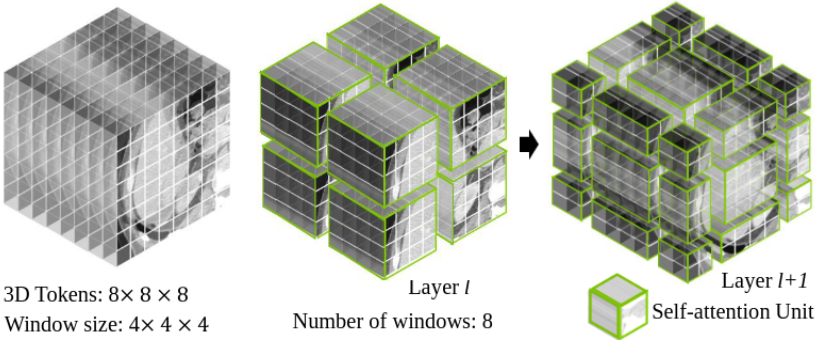



## Goal: reducing information compression when patching

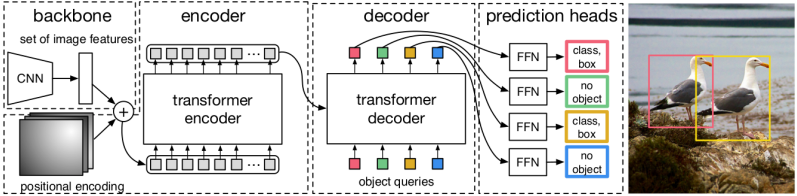
Size of input sub-volume: $128 \times 128 \times 128 \times 4$

Patch size: $2 \times 2 \times 2$

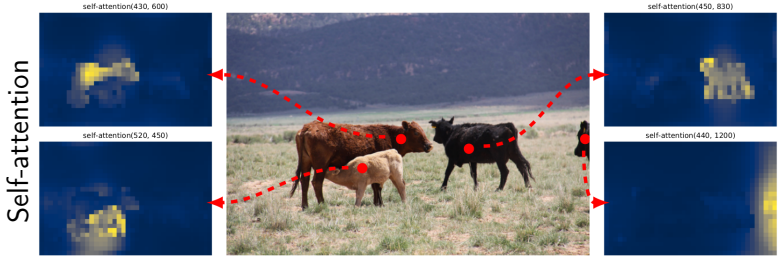
Input dimension for Swin: $(64 \times 64 \times 64) \times 48 \rightarrow 262,144 \times 48$

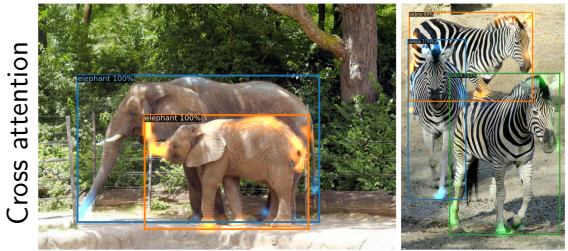

3D Tokens: 8× 8 × 8
Window size: 4× 4 × 4
Layer l
Number of windows: 8
Layer l+1
Self-attention Unit

➤ Object detection

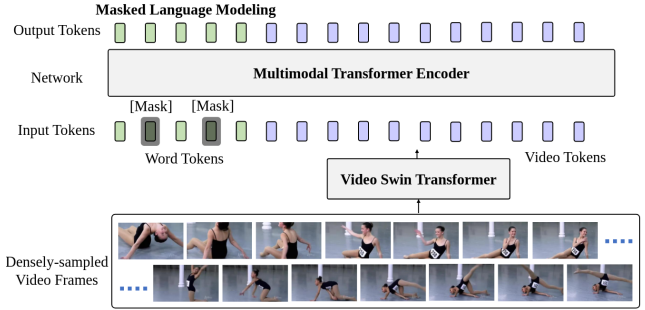



Set of $N$ learned object queries (must be high enough)
All predictions in parallel


Self-attention
self-attention(430, 600)
self-attention(520, 450)
self-attention(450, 830)
self-attention(440, 1200)


Cross attention
elephant 100%
elephant 100%

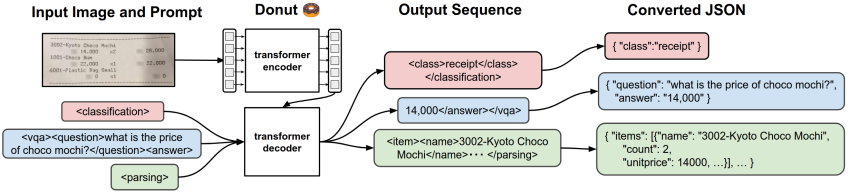
➤ Video captioning



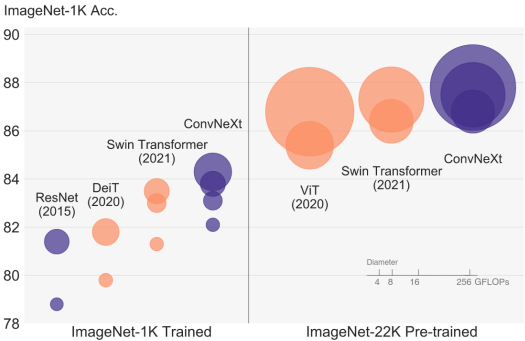

Generated caption: A dog is eating a watermelon
GT1: A dog is eating a watermelon
GT2: A dog eats watermelon

Generated caption: A boy is jumping on a trampoline
GT1: A boy jumps on a trampoline
GT2: Boy jumping on trampoline

➤ Document analysis and recognition



➤ ConvNext (2022) [14]




CNN with ViT/Swin patterns:

- ReLU $\rightarrow$ GELU
- Batch Norm $\rightarrow$ Layer Norm
- Less activations
- Larger kernel size
- etc

## Attention

- ✚ A powerful tool for feature extraction and encoder/decoder paradigm
- ━ Requires more data

## Transformer

- ✚ State of the art
- ✚ The same architecture for many modalities (text, image, audio)
- ✚ Parallelizable decoding at training time (teacher forcing)
- ━ Prohibitive for high resolution data (quadratic complexity)

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