Friedrich-Alexander-Universität
Technische Fakultät

Vision Transformer – A Deep Learning model for Image Analysis and Understanding

CML: Control, Machine Learning and Numerics

Group 29

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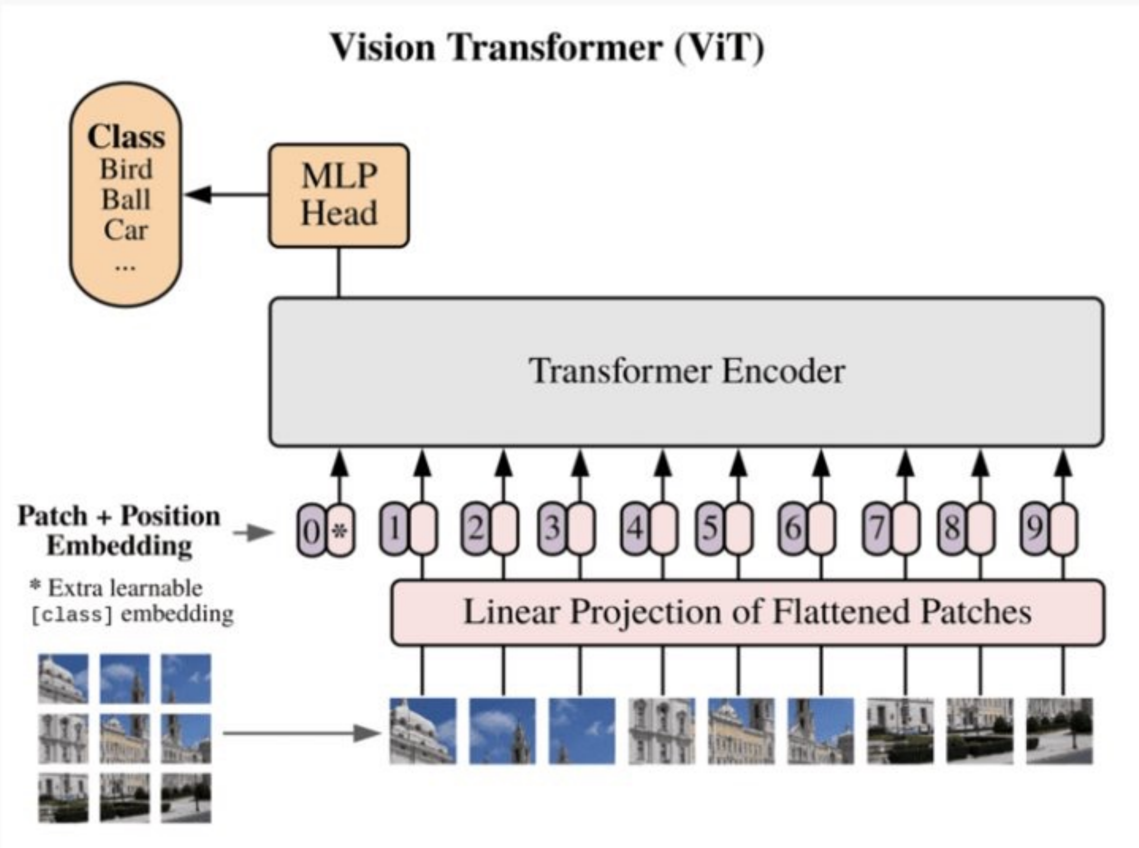
Table of Content

Introduction

Introduction

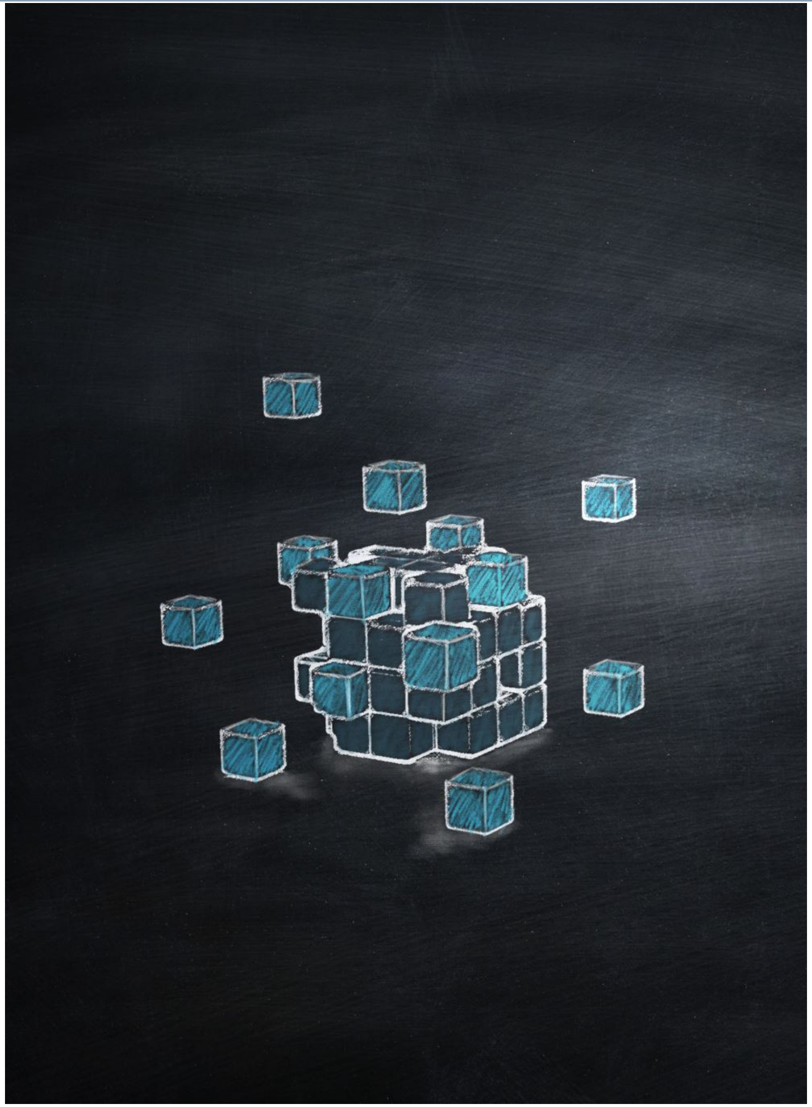
- Ability to extract meaningful insights from images is crucial for driving advancements across various industries and disciplines.
- CNNs faces problem in **capturing long-range dependencies** and modelling global context within images.
- ViT extends the success of the Transformer architecture.
- ViT understand **complex relationships** within images and make informed predictions.



Motivation

Motivation

- Capturing Long-Range Dependencies.
- Flexibility with Variable-Sized Inputs.
- Transferability and Generalization.
- Learning Abstract Representations.



Evolution of Transformers

Evolution of Transformers

2017.6 | Transformer
Solely based on attention mechanism, the Transformer is proposed and shows great performance on NLP tasks.

2018.10 | BERT
Pre-training transformer models begin to be dominated in the field of NLP.

2020.5 | GPT-3
A huge transformer with 170B parameters, takes a big step towards general NLP model.

2020.5 | DETR
A simple yet effective framework for high-level vision by viewing object detection as a direct set prediction problem.

2020.7 | iGPT
The transformer model for NLP can also be used for image pre-training.

2020.10 | ViT
Pure transformer architectures work well for visual recognition.

End of 2020 | IPT/SETR/CLIP
Applications of transformer model on low-level vision, segmentation and multimodality tasks, respectively.

2021 | ViT Variants
Variants of ViT models, e.g., DeiT, PVT, TNT, and Swin.

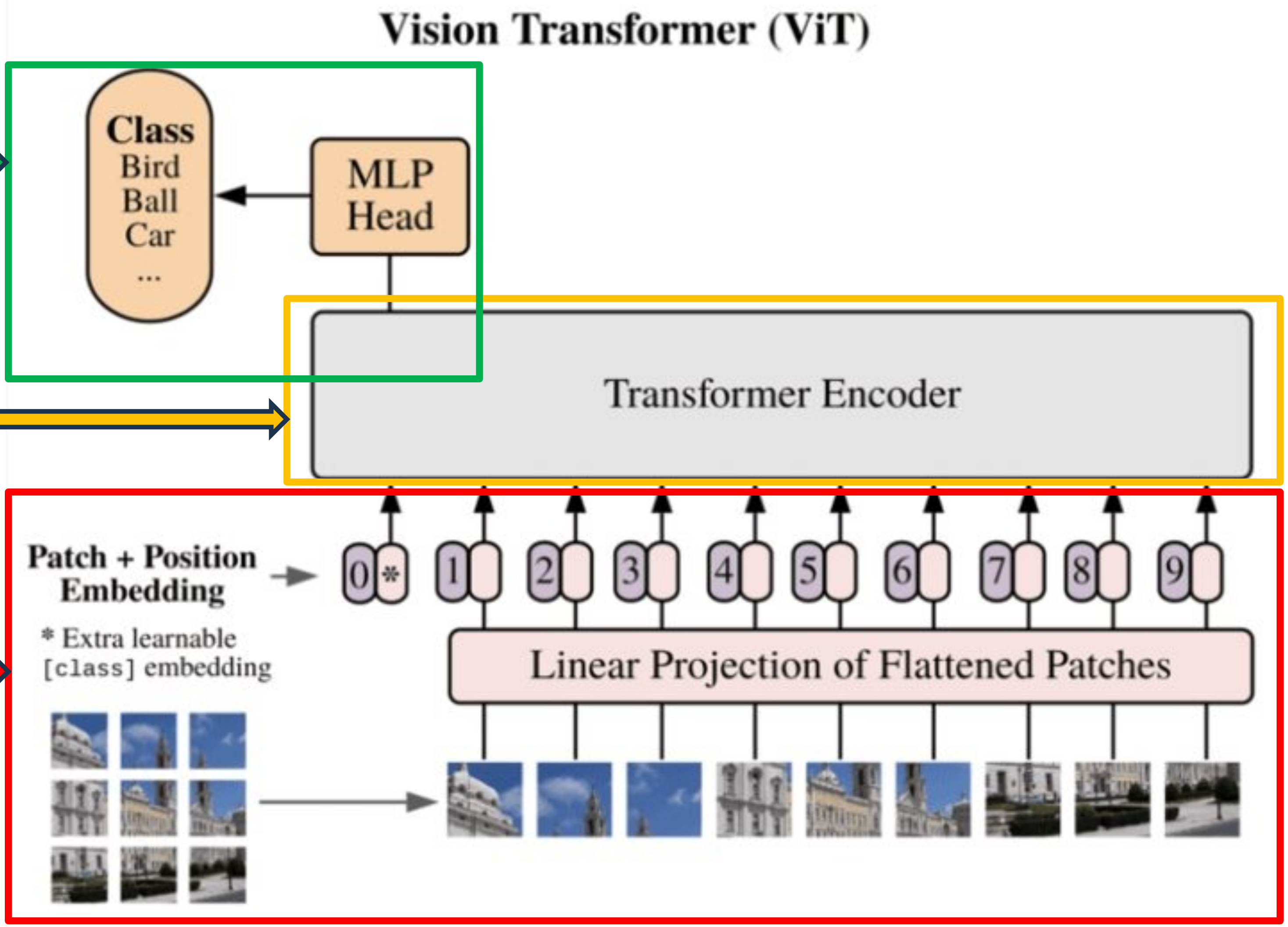
Vision Transformer Architecture

3 Parts of Architecture

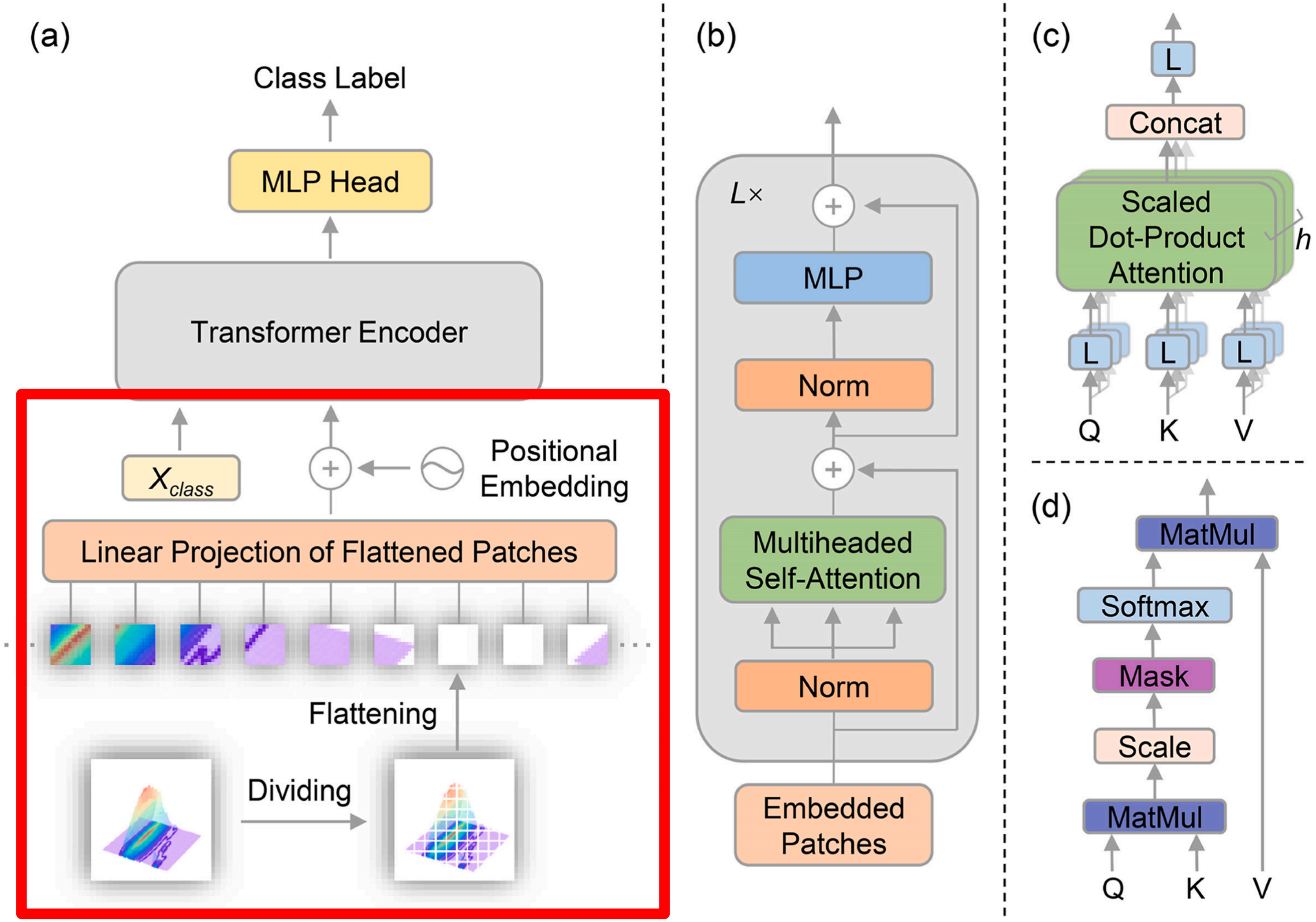
3. The classification head.

2. Feature extraction via stacked transformer encoders.

1. Patch embedding.



1. Patch Embedding



1. Patch Embedding

Batch of
images **b**

1. Patch Embedding

Batch of
images **b**

One of the images
(b, h, w, c)

b = batch
h = height
w = width
c = channel

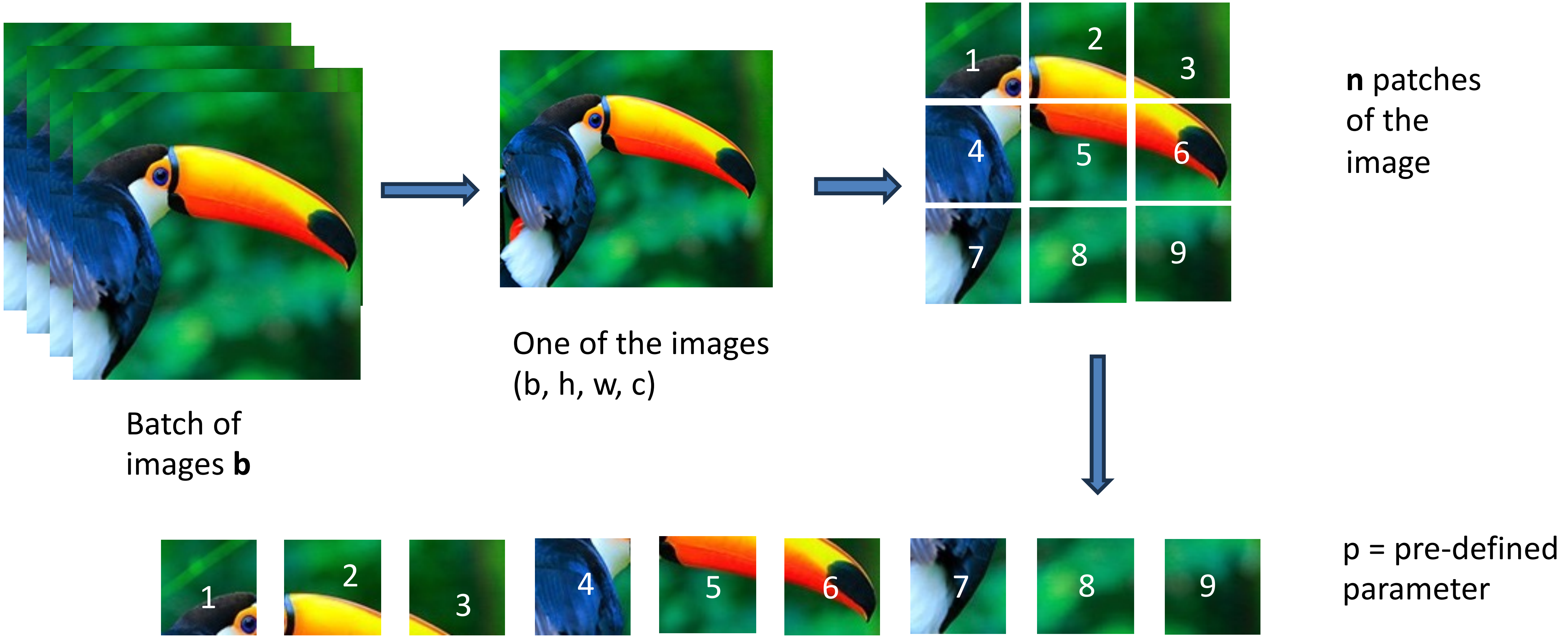
1. Patch Embedding

Batch of
images **b**

One of the images
(b, h, w, c)

n patches
of the
image

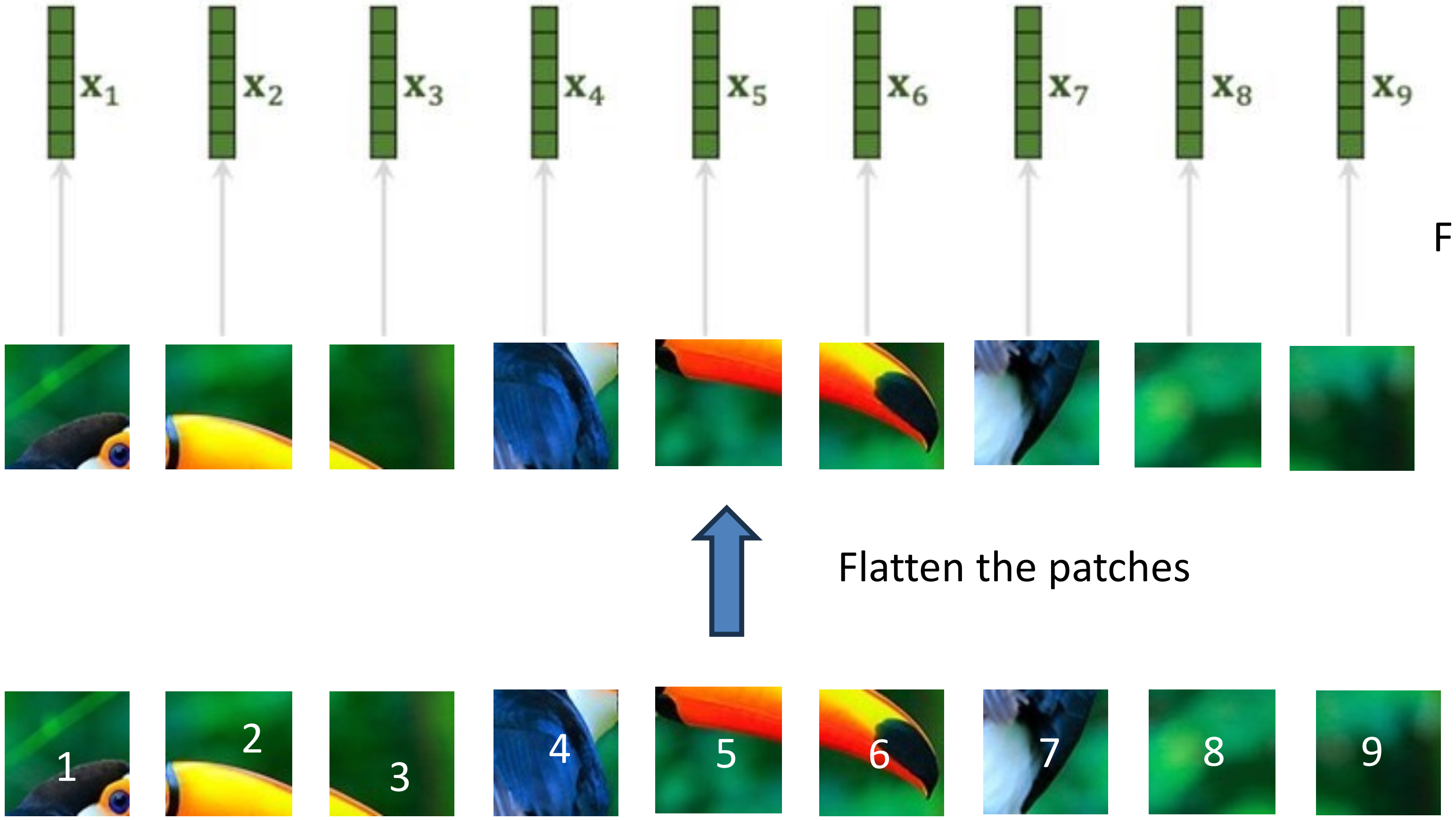
1. Patch Embedding



The image is split into n square patches of shape (p,p,c),

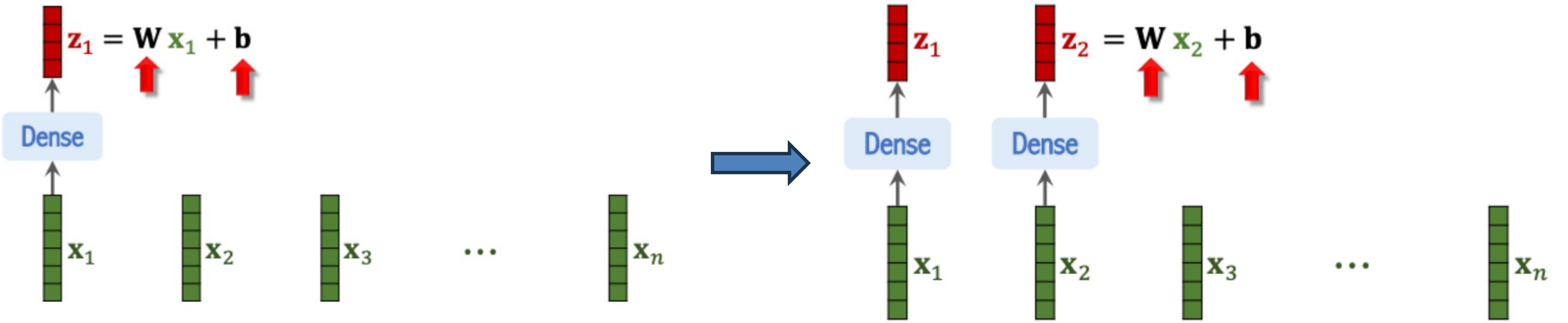
1. Patch Embedding

Flat patches (b, n, (p^2*c))



Every patch has a feature vector of dimesion (1, p^2*c)

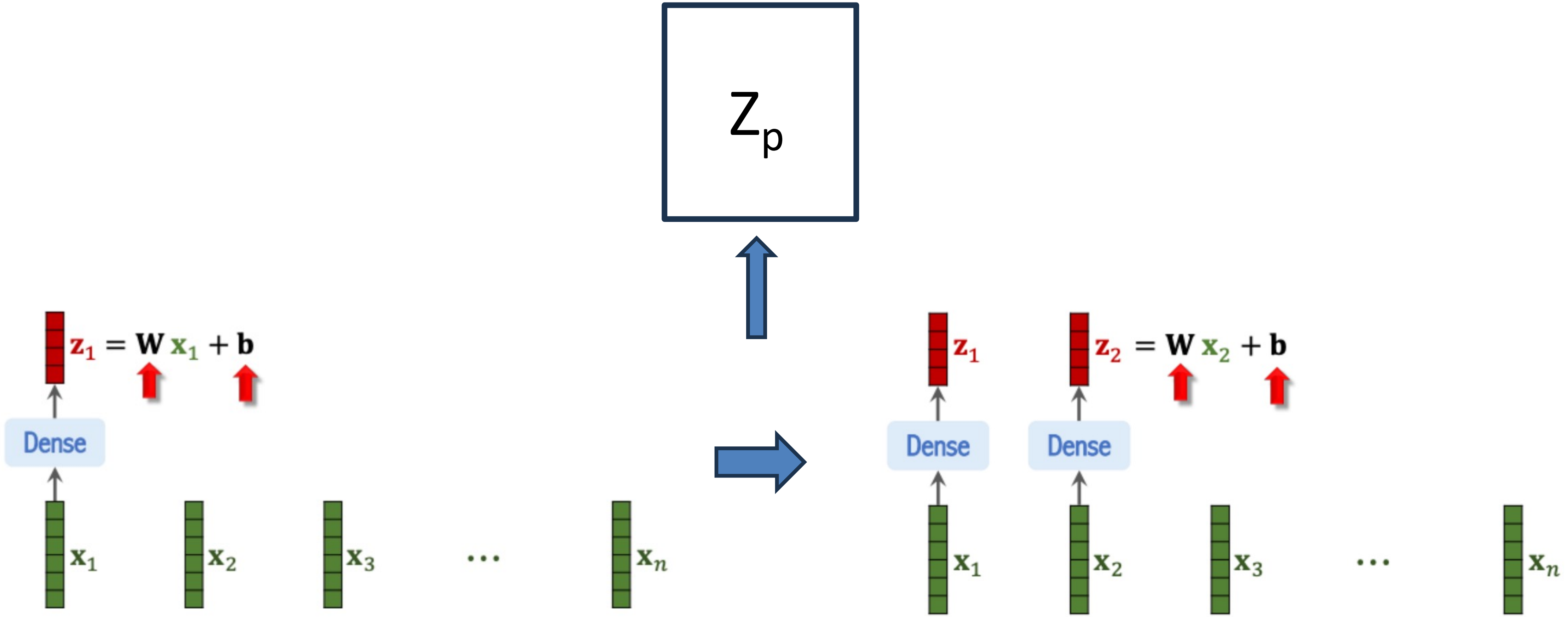
1. Patch Embedding



Embeddings ((p^2 * c), d)

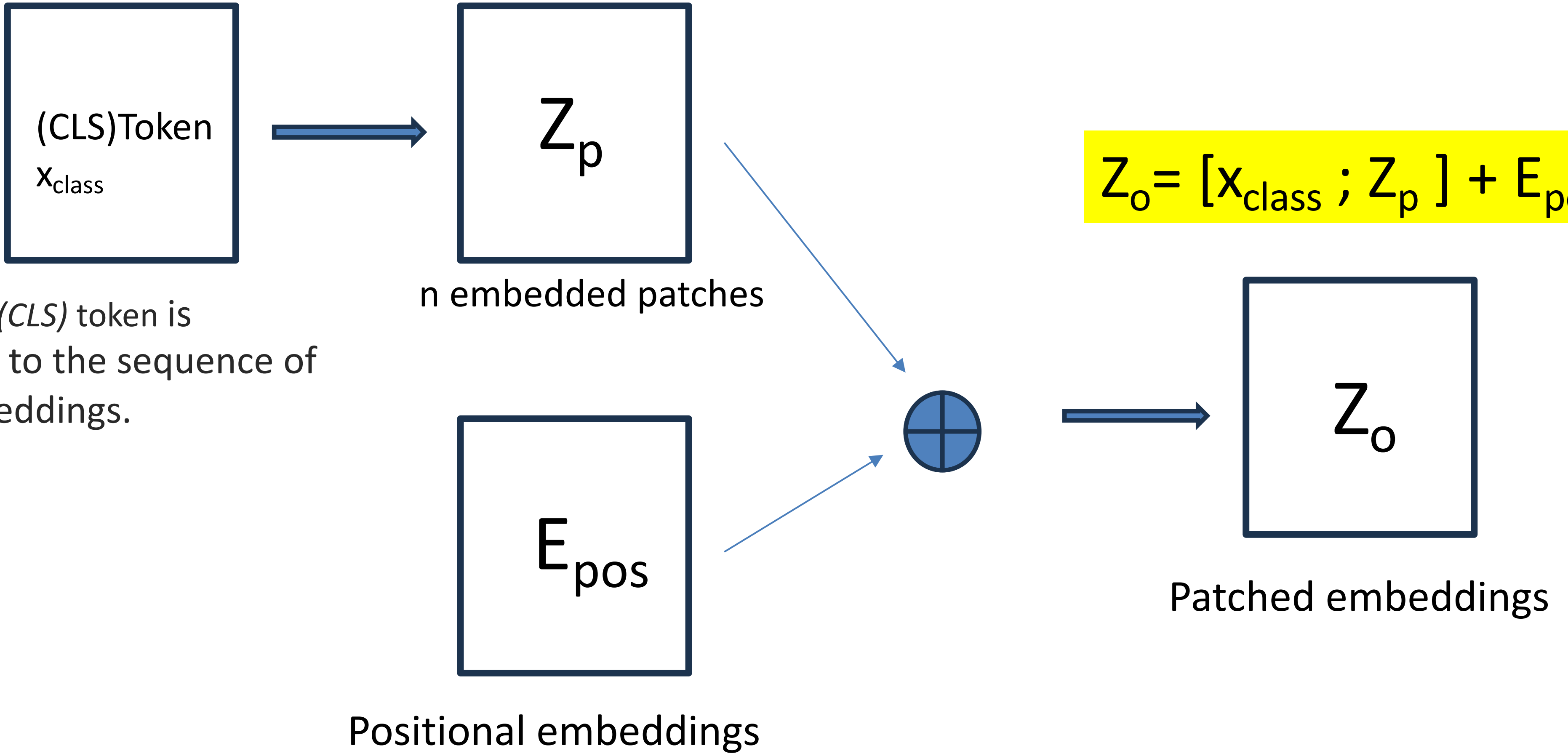
The flattened patches are multiplied with a **trainable** embedding tensor, which learns to linearly project each flat patch

1. Patch Embedding



Embeddings

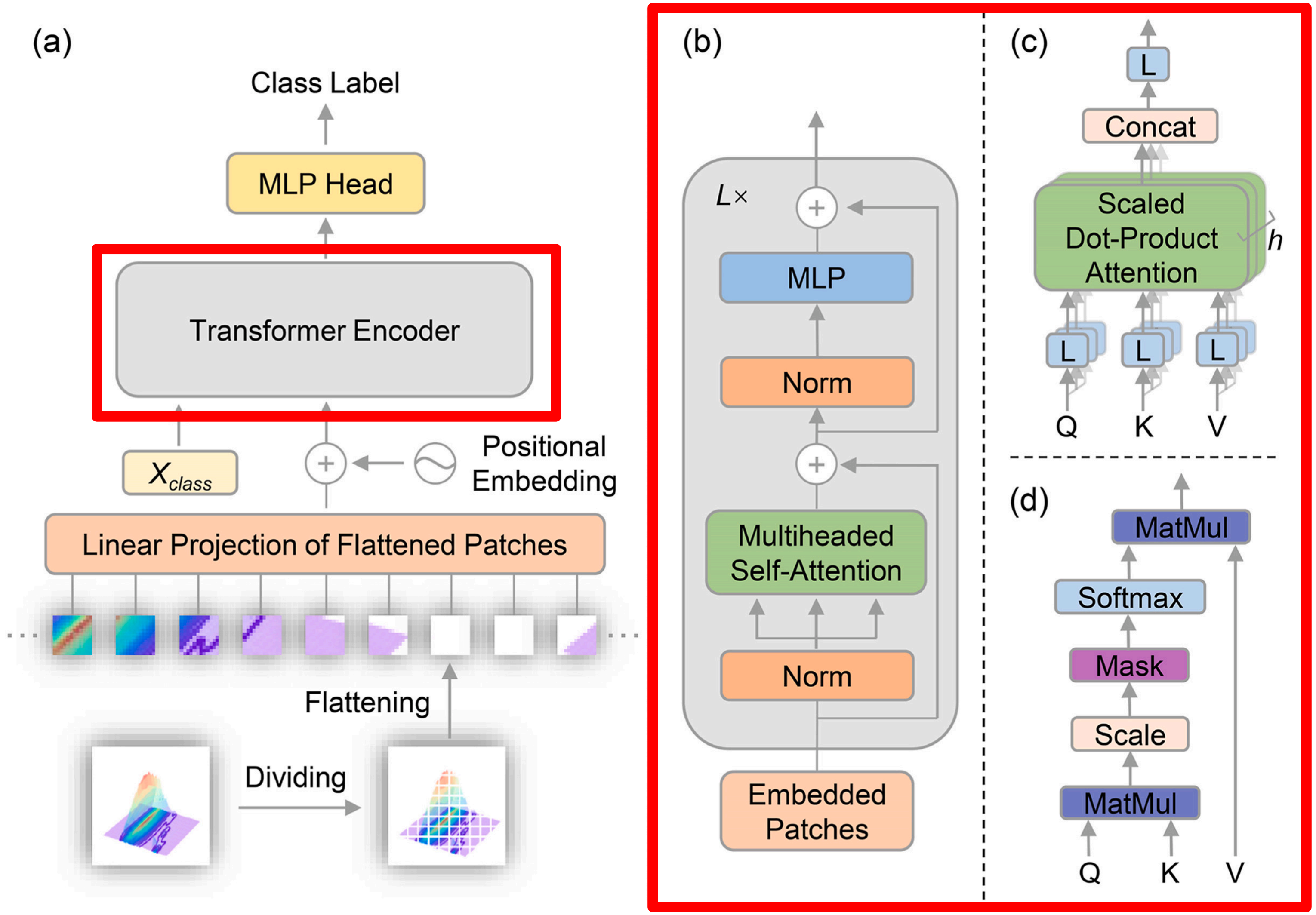
1. Patch Embedding



A learnable *(CLS)* token is prepended to the sequence of patch embeddings.

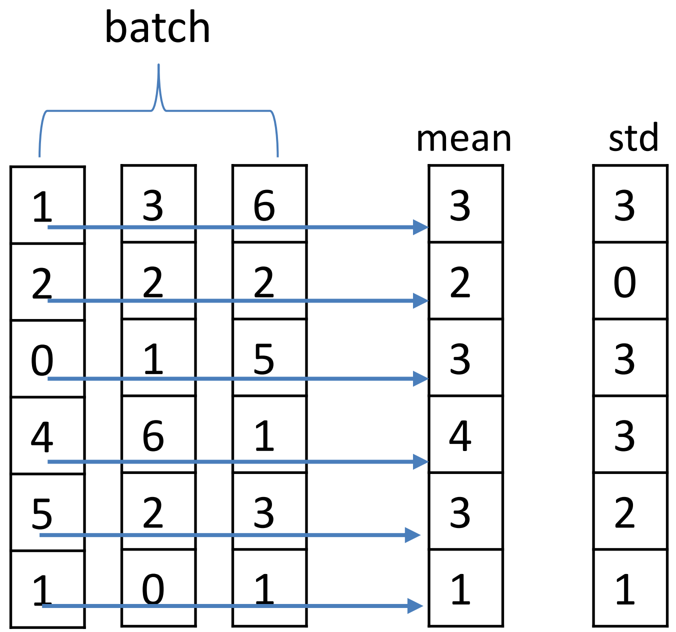
$$Z_o = [x_{class} ; Z_p] + E_{pos}$$

2. Transformer Encoding



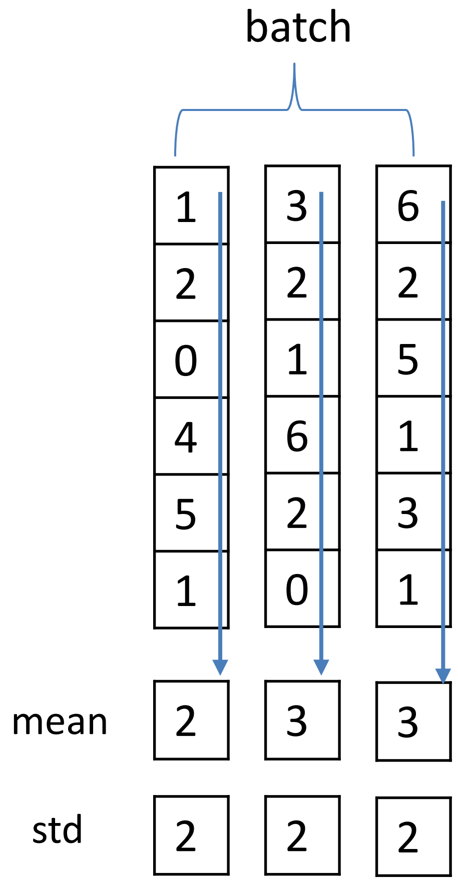
2.1 Layer Normalization

Batch Normalization



Sample for all training examples

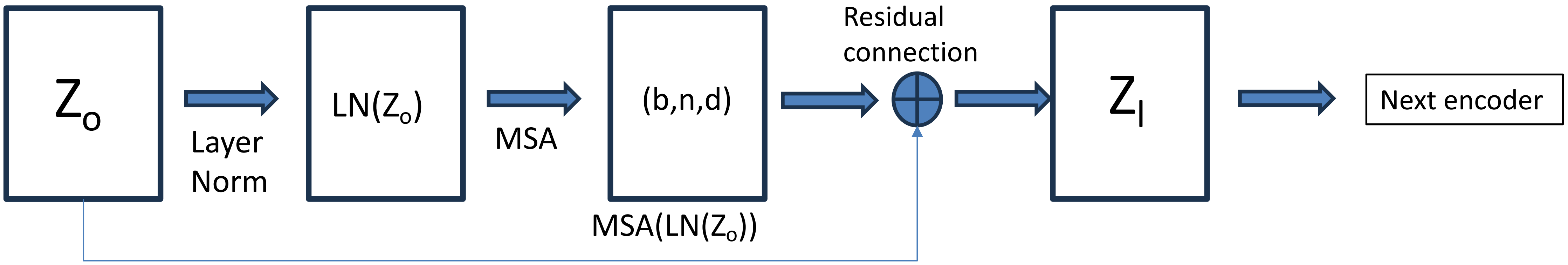
Layer Normalization



Same for all features dimensions

2.1 Layer Normalization

2. Transformer Encoding



Layer Normalization:

$$\mu_i = \frac{1}{n}\sum_{i=1}^{n} z_{ij}$$

$$\sigma_i^2 = \frac{1}{n}\sum_{i=1}^{n}(zij_{-}\mu_i)^2$$

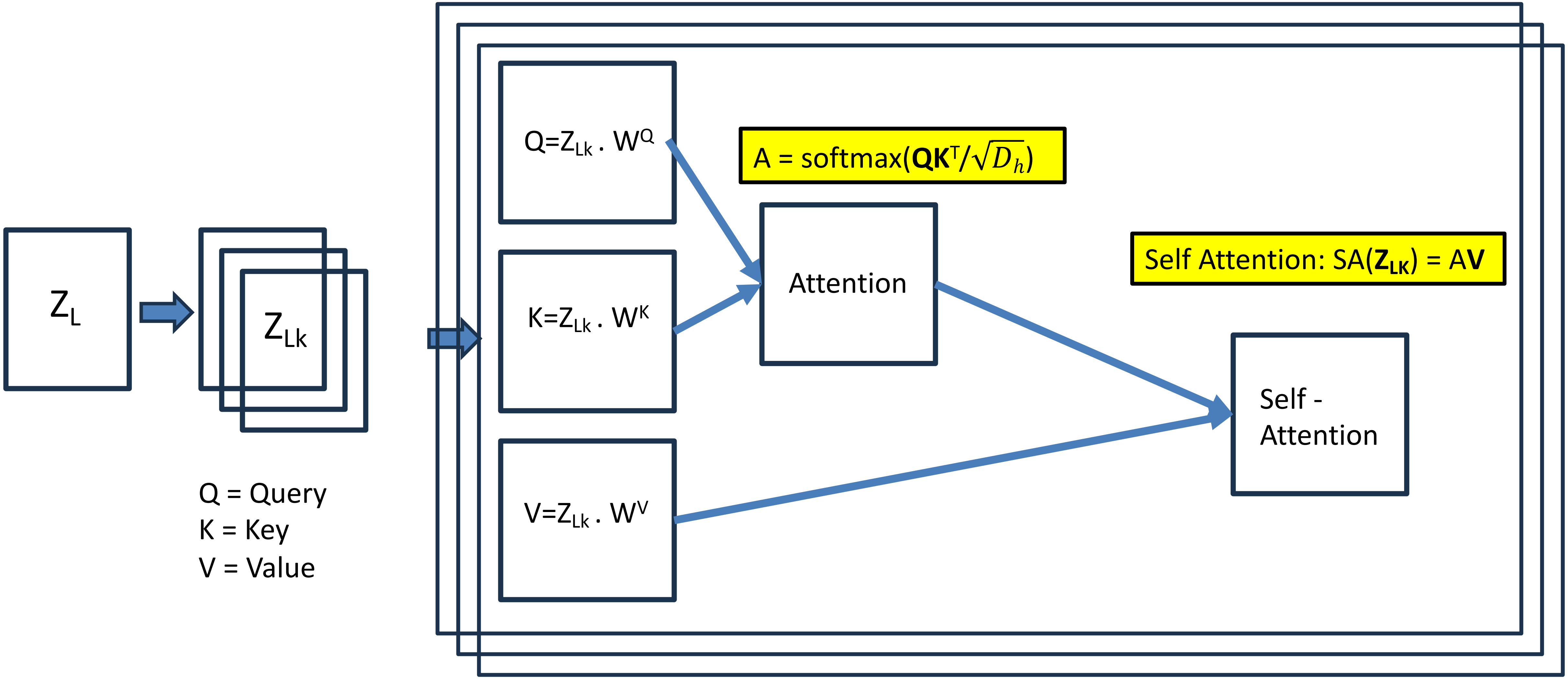
$$\hat{X}_{ij} = \frac{z_{ij} - \mu_i}{\sqrt{\sigma^2_i + \varepsilon}}$$

$$LN(Z_o) = \hat{X}$$

Z'_e = MSA(LN(Z_o)) + Z_l , where e = 1 … L (2)

2.2 Multi-head Attention

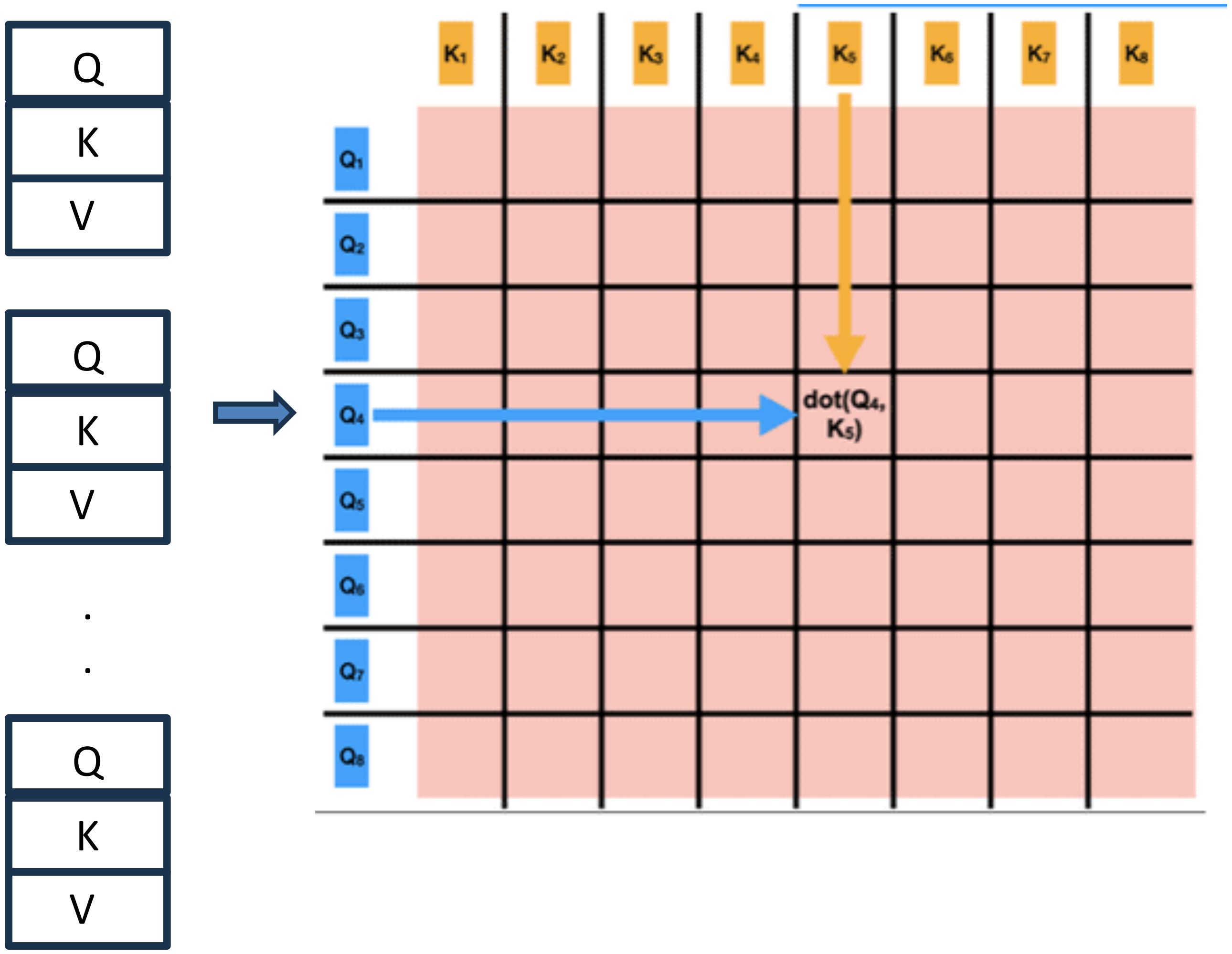
2. Transformer Encoding



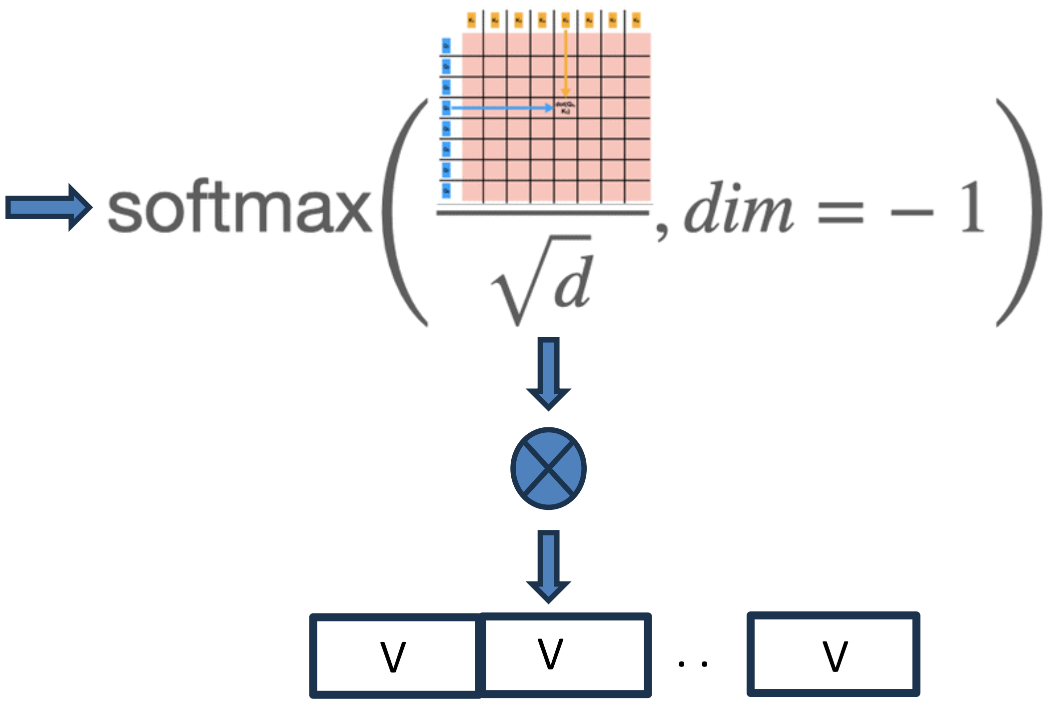
Q = Query
K = Key
V = Value

2.2 Multi-head Attention

2. Transformer Encoding



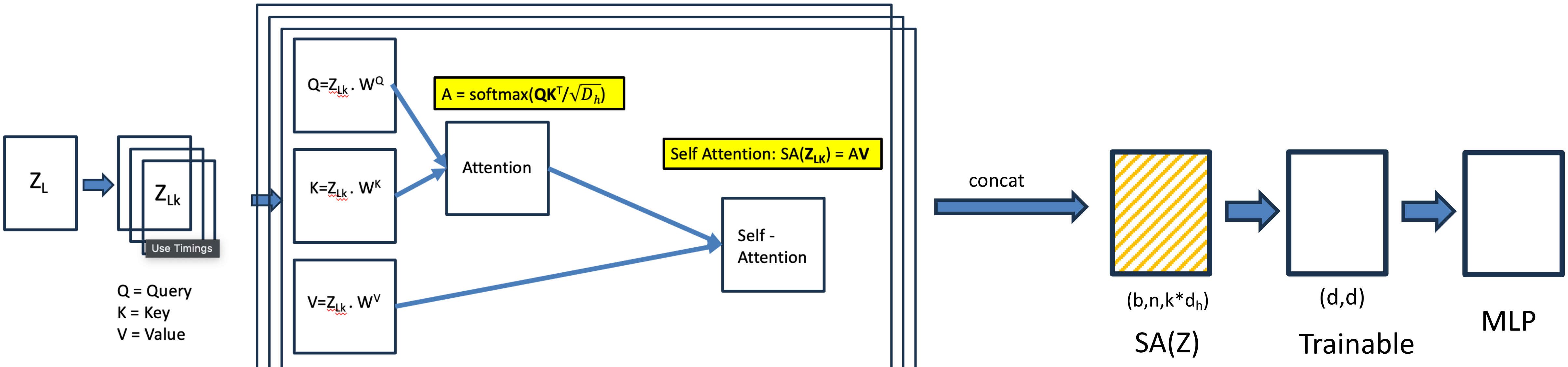
$A = \text{softmax}(\mathbf{QK}^T/\sqrt{D_h})$



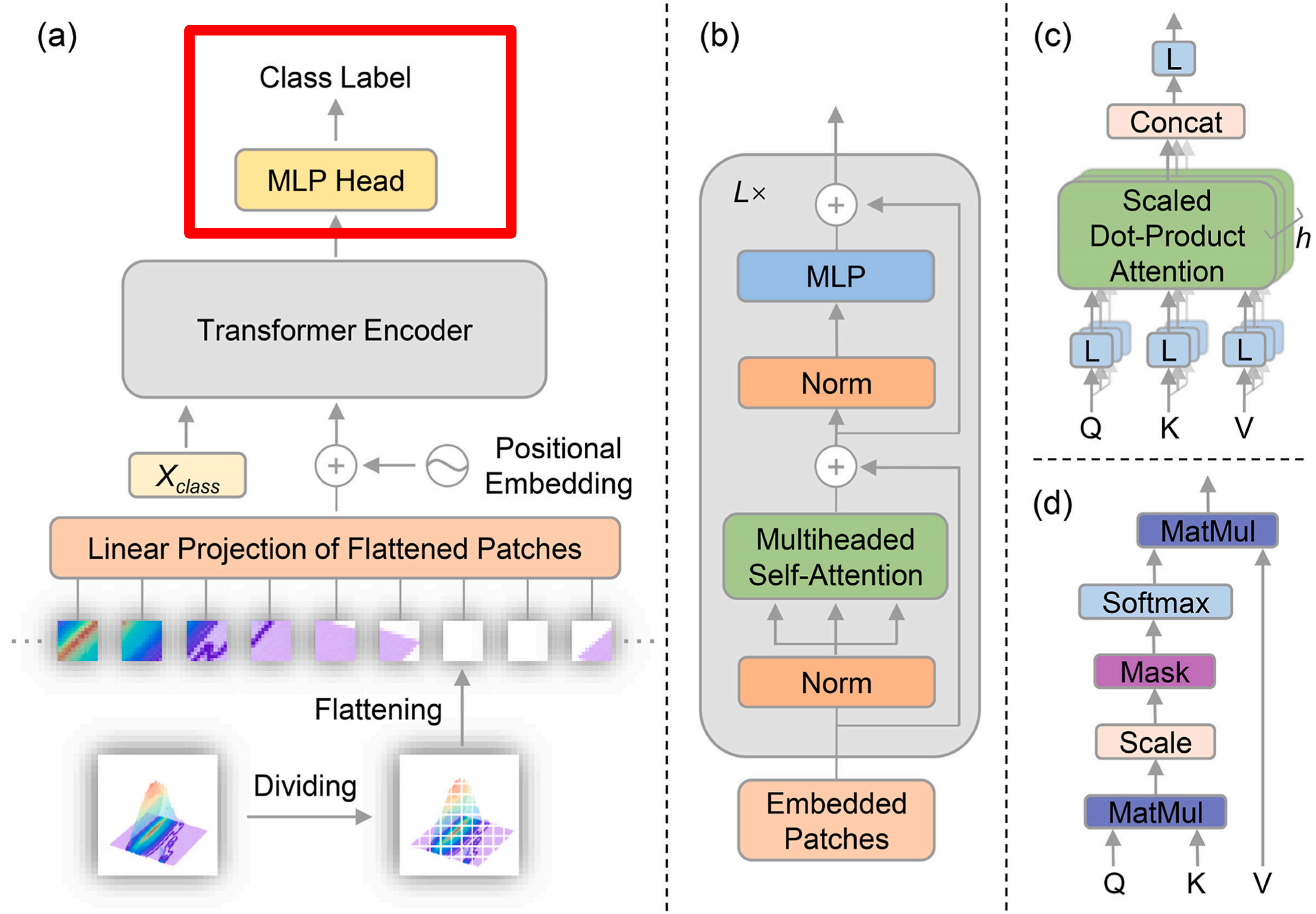
Self Attention: $SA(\mathbf{Z}_{LK}) = A\mathbf{V}$

2.2 Multi-head Attention

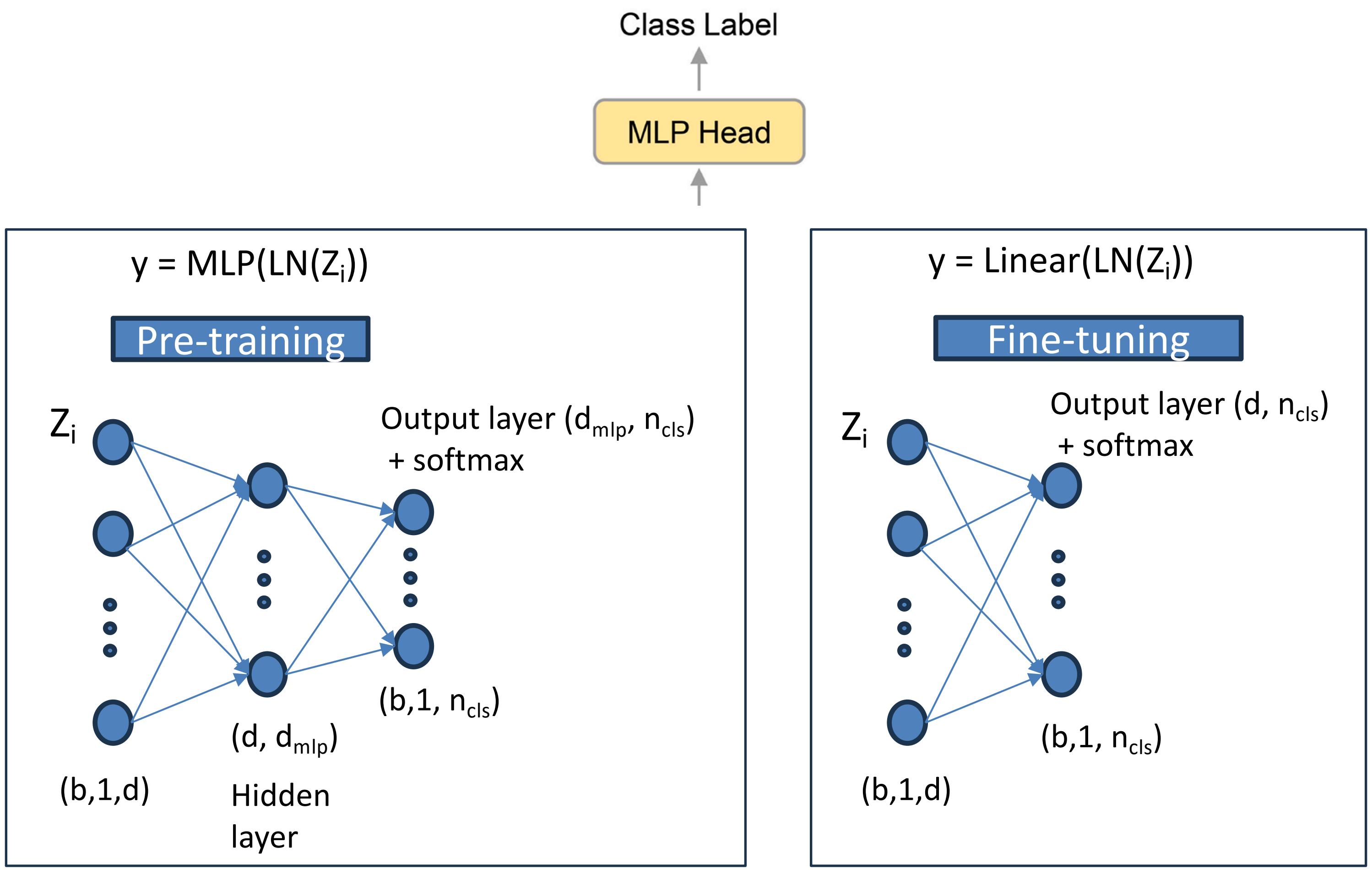
2. Transformer Encoding



3. Classification Head



3. Classification Head



- [cls] token is used in the classification head.
- Pre-training - 2 layer of MLP used, hence 2 weight matrices
  - W_h [d, d_{mlp}]
  - W_o [d_{mlp}, d]
- Fine-tuning – single layer used, hence only 1 tensor [d, n_cls]
- Output: Probability associated with each of n_{cls} classes

Training Vision Transformer

Training Vision Transformers

Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

Applications of ViT

- Image Classification
- Image captioning
- Object Detection
- Semantics Segmentation
- Video Understanding
- Image Generation

Performance, Limitations and Future Improvements

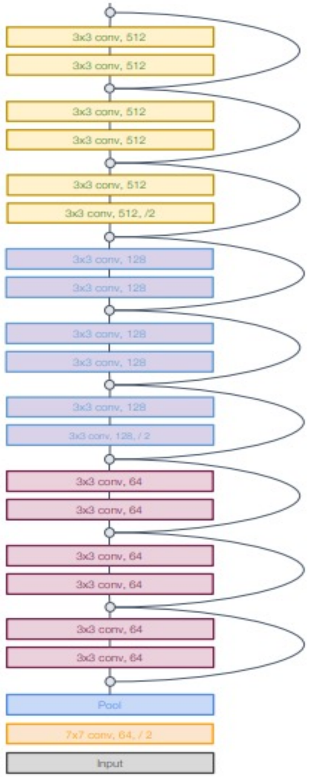
VIT vs CNN

Stage 3:
256 x 14 x 14

Stage 2:
128 x 28 x 28

Stage 1:
64 x 56 x 56

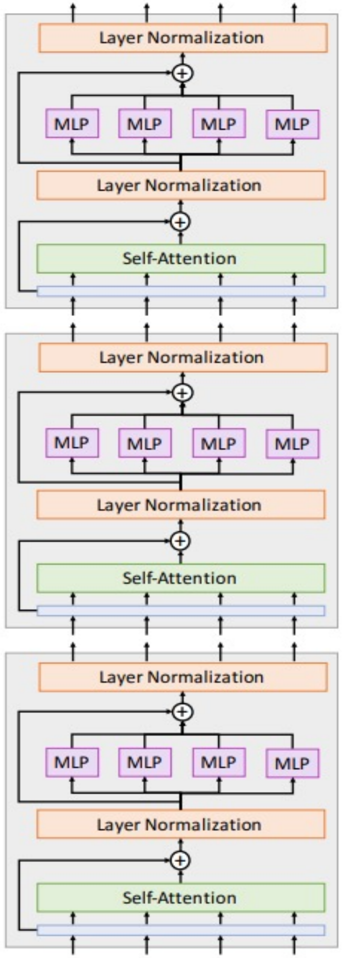
Input:
3 x 224 x 224



In most CNNs (including ResNets), **decrease** resolution and **increase** channels as you go deeper in the network (Hierarchical architecture)

Useful since objects in images can occur at various scales

In a ViT, all blocks have same resolution and number of channels (Isotropic architecture)



3rd block:
768 x 14 x 14

2nd block:
768 x 14 x 14

1st block:
768 x 14 x 14

Input:
3 x 224 x 224

Limitations of ViT

- Limited spatial information
- Computational Complexity
- Generalization to Diverse Data
- Memory and Computational Efficiency
- Continual Learning and Adaptability

Discussion and Conclusion

- **Superior Performance:**
  - Demonstrated exceptional performance, surpassing traditional CNNs in various image analysis tasks..
- **Global Context Modelling:**
  - capture global contextual information, enabling modeling of long-range dependencies and interactions between image elements.
- **Scalability and Adaptability:**
  - Scalability and Adaptability: ViTs are highly scalable and adaptable, making them suitable for diverse applications and datasets.

Future Improvements

- Enhanced attention mechanism for better long-range dependency modeling.
- Improved model efficiency with reduced computational complexity.
- Advancements in interpretability for better understanding of attention maps.
- Integration of multimodal information for enhanced performance.

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Thankyou