Swin Transformers

Hierarchical Vision Transformer using Shifted Windows

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Agenda

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Opening

Motivation

Leverage the advantages of transformer architecture to tackle a variety of computer vision tasks, addressing complex and non-trivial challenges effectively.

Problem Statement

Previous attempts to adapt transformers for vision tasks, like in ViT*, struggle with high computational costs and scalability issues, making them inefficient for handling high-resolution images and capturing both local and global features.

Solution

A hierarchical architecture with shifted windows efficiently captures both local and global features while significantly reducing computational costs for high-resolution vision tasks.

* AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE, Alexey Dosovitskiy et al.

What are SWIN Transformers?

- SWIN (Shifted Window) Transformers are a type of Vision Transformer (ViT) designed for **computer vision tasks**.
- Developed by **Microsoft Research**.
- Addresses limitations of standard ViTs by introducing **hierarchical feature maps** and **shifted windows**.

CNNs: Foundations of Modern Vision Tasks

- **Early Approaches**: Handcrafted features and classical machine learning methods.
- **Rise of CNNs**: Revolutionized image processing with layers mimicking human visual perception.
- **Key Vision Tasks**:
  - Image Classification: ResNet, VGG..
  - Object Detection: YOLO, Faster R-CNN..
  - Semantic Segmentation: U-Net, DeepLab...
- **Advantages of CNNs:** Spatial hierarchies, local receptive fields, parameter efficiency.

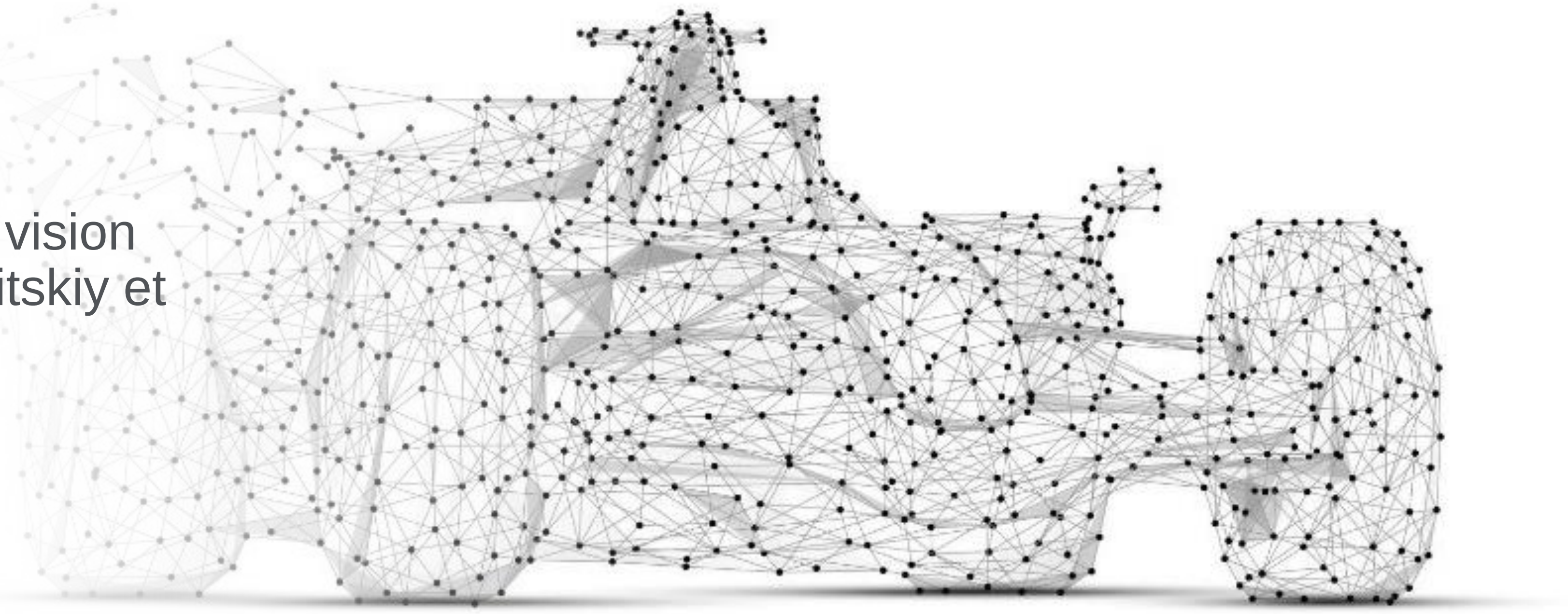
Transformers in Natural Language Processing

- Transformers introduced in "**Attention is All You Need**" paper by Google Brain (2017).
- **Key Features**:
  - Encoder-Decoder Architecture: Processes input to output sequences
  - Self-Attention: Each token attends to all other tokens in a sequence, capturing contextual relationships.
  - Multi-Head Attention: Multiple attention heads allow the model to focus on different parts of the sequence simultaneously.

Evolution from NLP to Vision Tasks

- **Inspiration from NLP Success**: Transformers' ability to handle long-range dependencies and parallelize training.

- **Initial attempts**: Directly applying Transformers to vision tasks (e.g., ViT by Dosovitskiy et al. 2020*).



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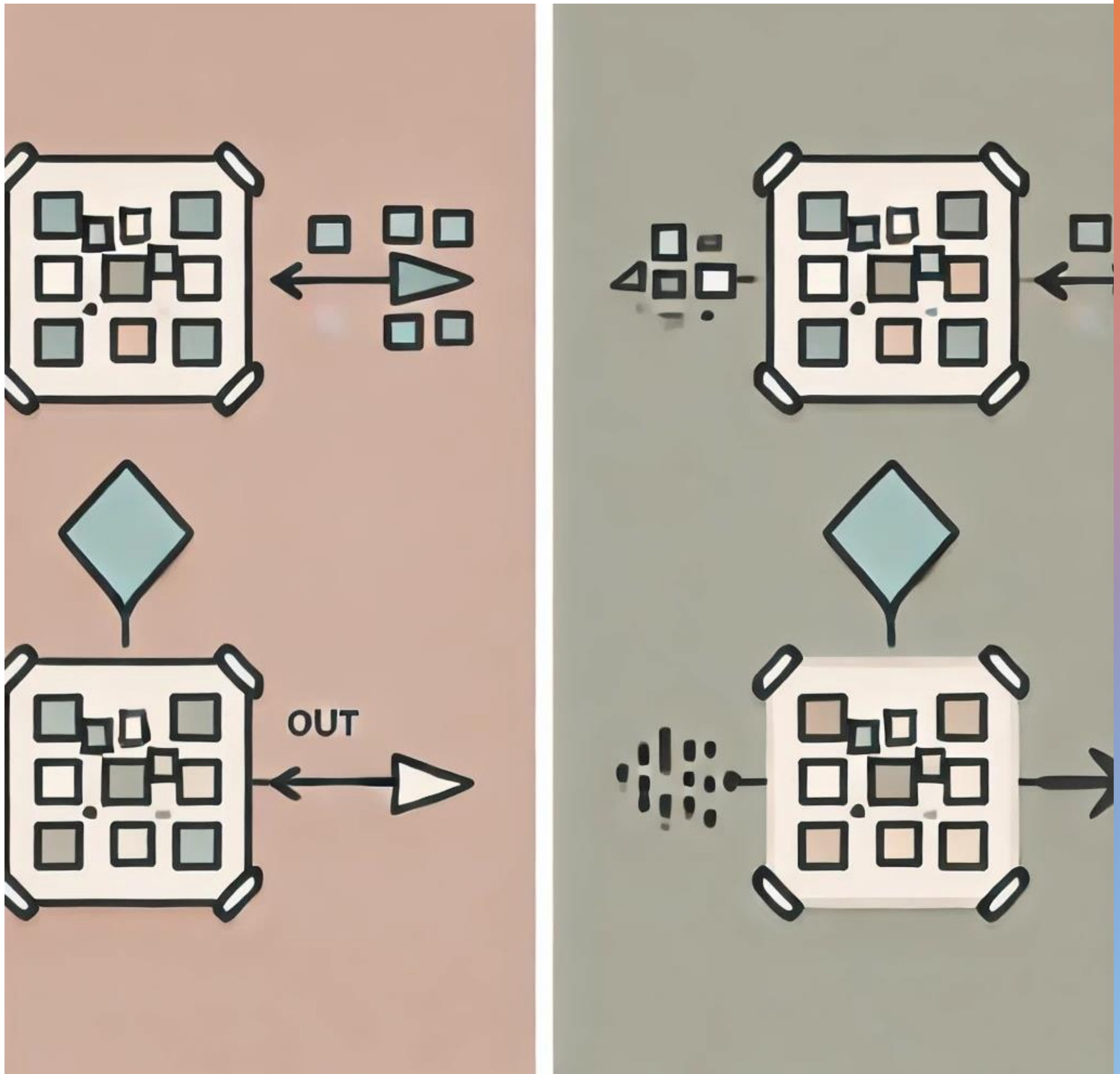
Vision Transformers (ViT)

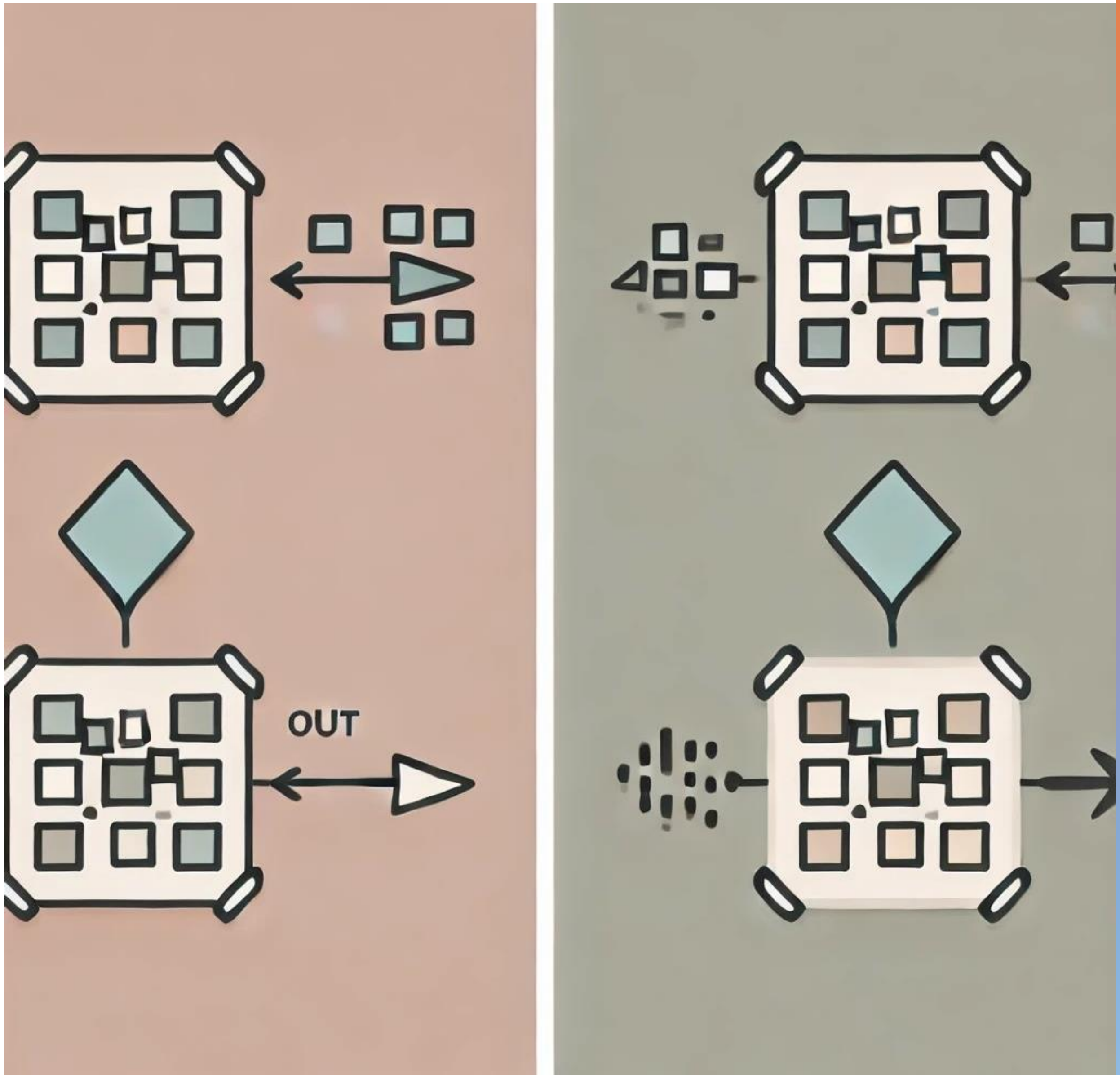
- **Concept**: Treats image patches as sequence tokens, similar to words in a text sequence.

- **How ViT Works**:
  - Image Patches
  - Embedding
  - Model
  - Output

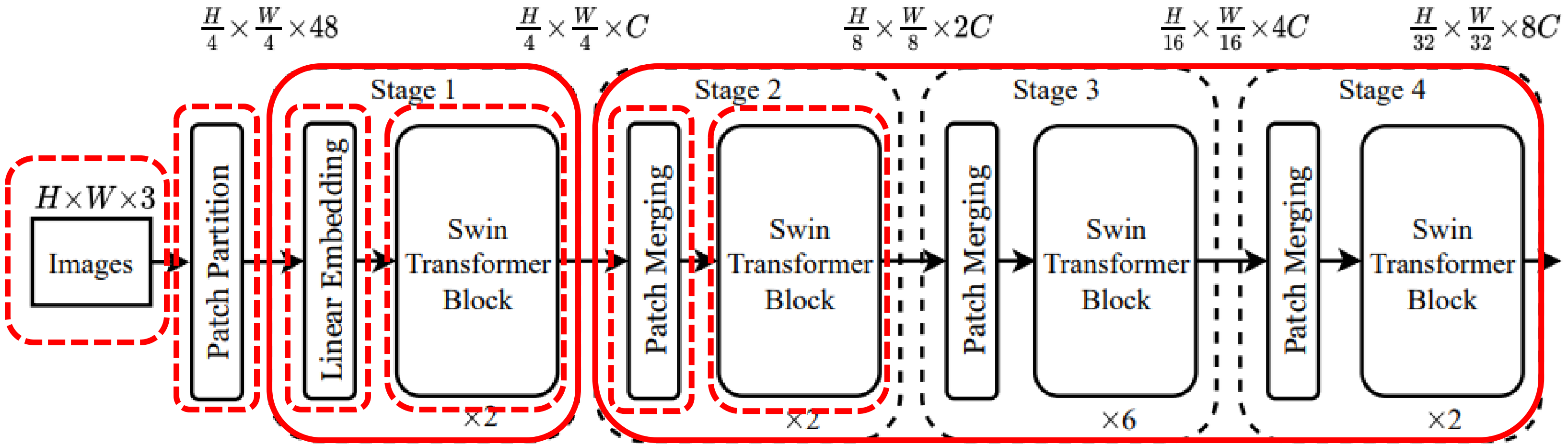


Vision Transformers (ViT)

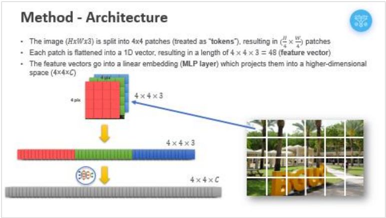
- Challenges of ViT:
  - High Computational Cost
  - Lack of Inductive Biases
  - Data Efficiency

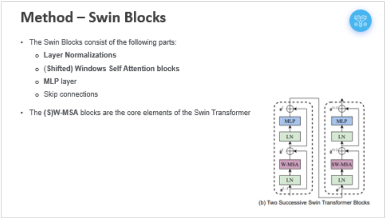


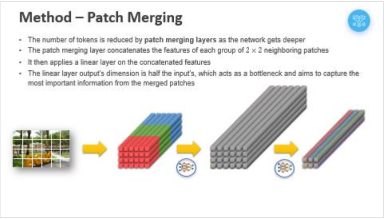
Method - Architecture

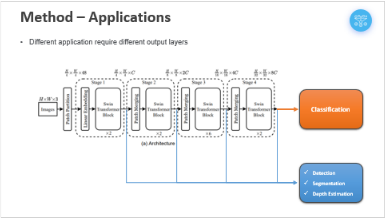


(a) Architecture





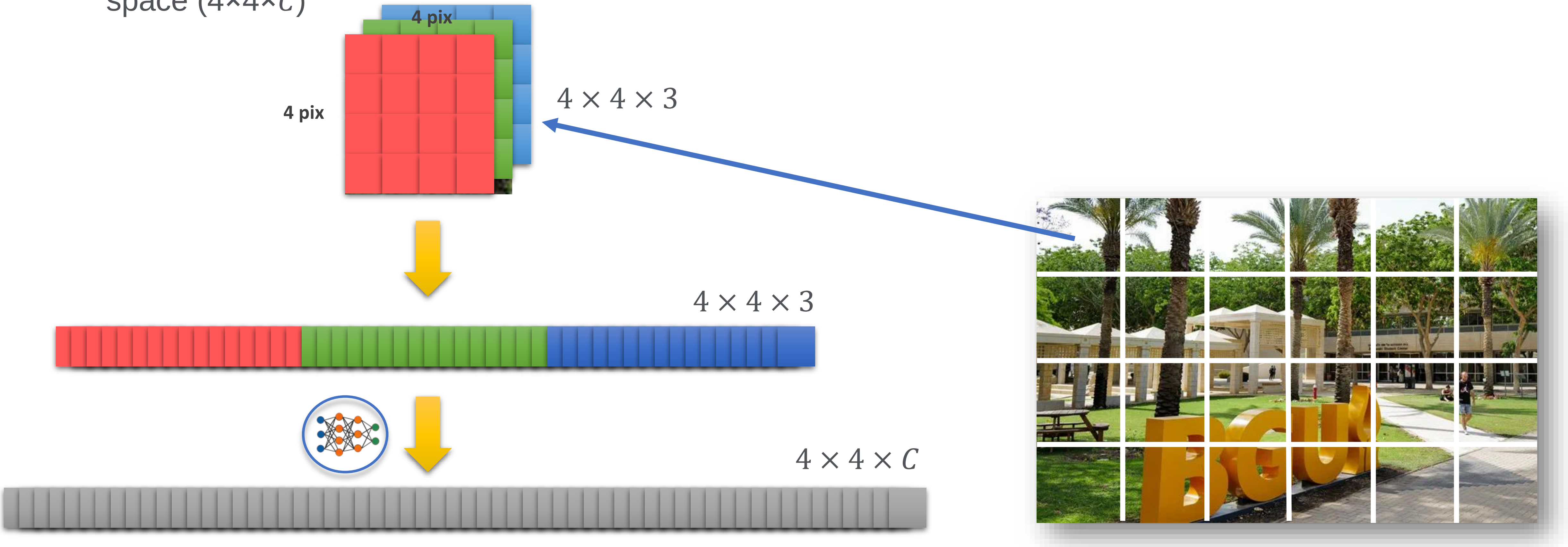




Model	C	Layer Numbers
Swin-T	96	2,2,6,2
Swin-S	96	2,2,18,2
Swin-B	128	2,2,18,2
Swin-L	192	2,2,18,2

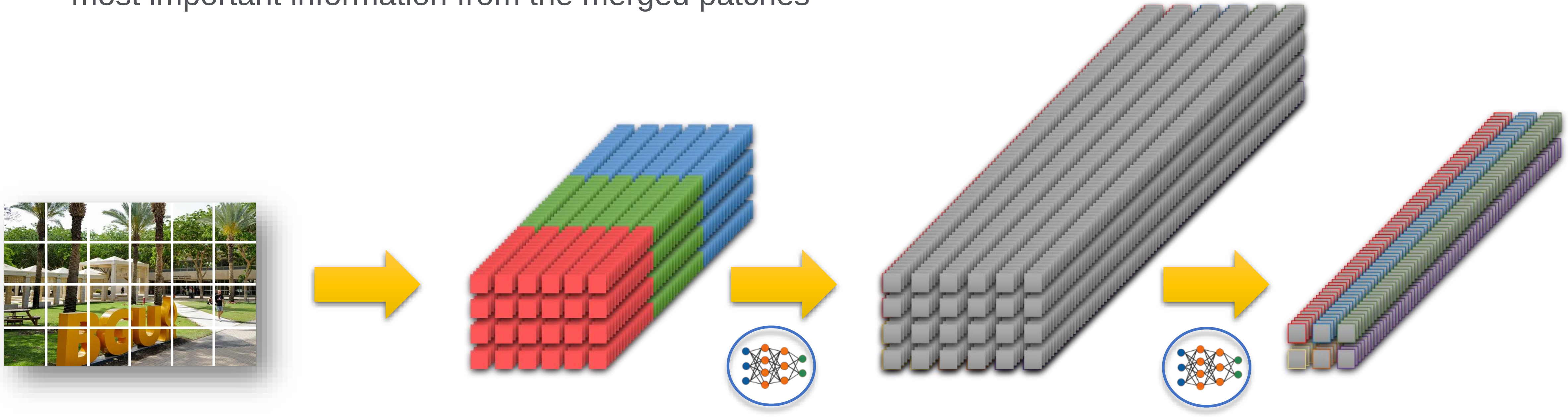
Method - Architecture

- The image ($HxWx3$) is split into 4x4 patches (treated as "**tokens**"), resulting in $(\frac{H}{4} \times \frac{W}{4})$ patches
- Each patch is flattened into a 1D vector, resulting in a length of $4 \times 4 \times 3 = 48$ (**feature vector**)
- The feature vectors go into a linear embedding (**MLP layer**) which projects them into a higher-dimensional space ($4{\times}4{\times}C$)



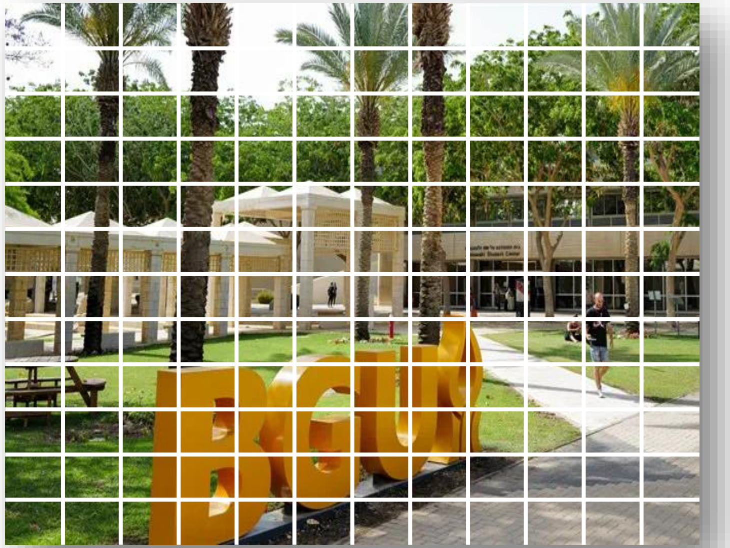
Method – Patch Merging

- The number of tokens is reduced by **patch merging layers** as the network gets deeper
- The patch merging layer concatenates the features of each group of 2×2 neighboring patches
- It then applies a linear layer on the concatenated features
- The linear layer output's dimension is half the input's, which acts as a bottleneck and aims to capture the most important information from the merged patches



Method – Patch Merging

$\frac{H}{4} \times \frac{W}{4} \times C$

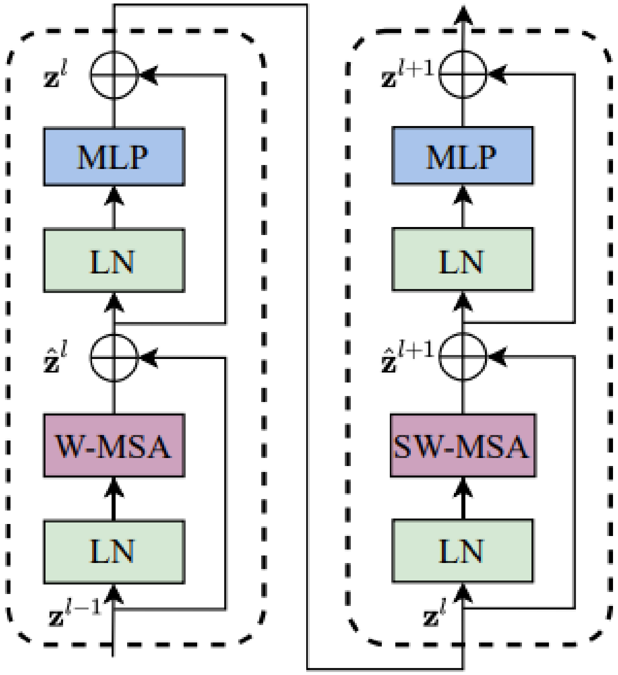


$\frac{H}{8} \times \frac{W}{8} \times 2C$

$\frac{H}{16} \times \frac{W}{16} \times 4C$

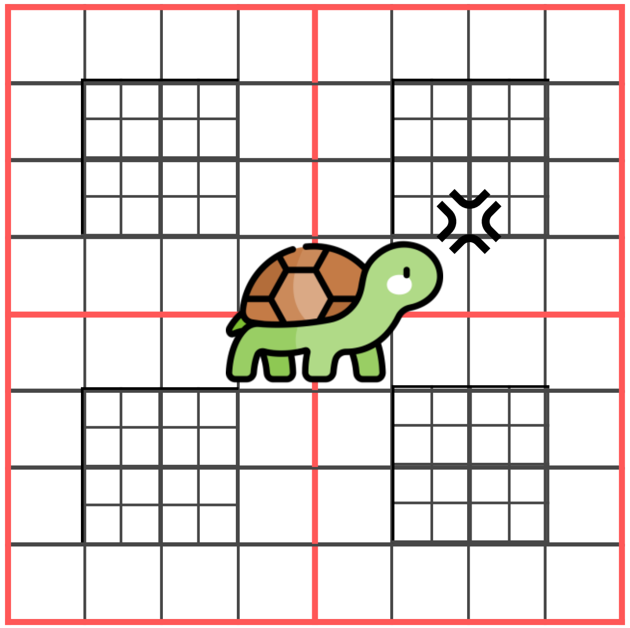
Method – Swin Blocks

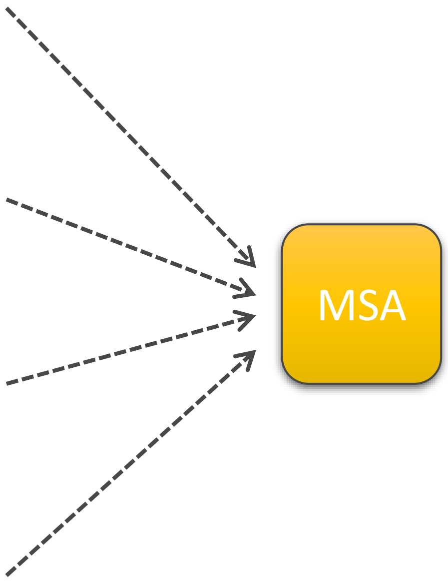
- The Swin Blocks consist of the following parts:
  - **Layer Normalizations**
  - **(Shifted) Windows Self Attention blocks**
  - **MLP** layer
  - Skip connections
- The **(S)W-MSA** blocks are the core elements of the Swin Transformer

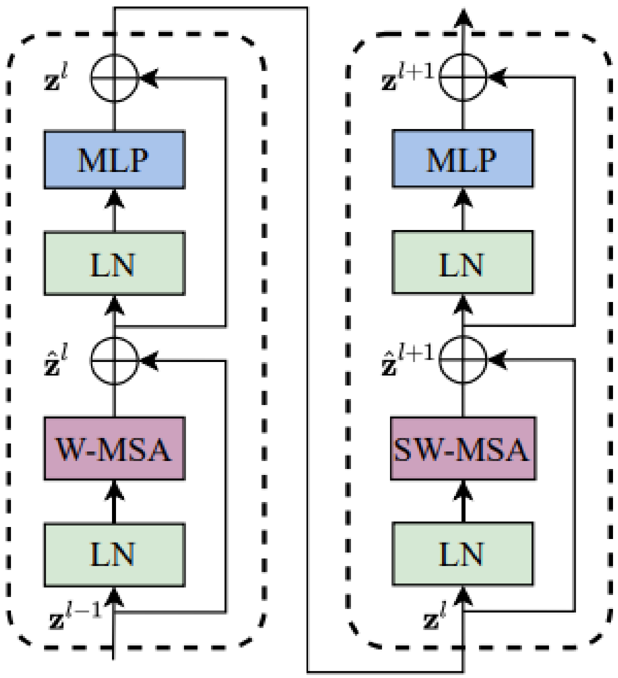


(b) Two Successive Swin Transformer Blocks

Method – Swin Blocks – (S)W-MSA

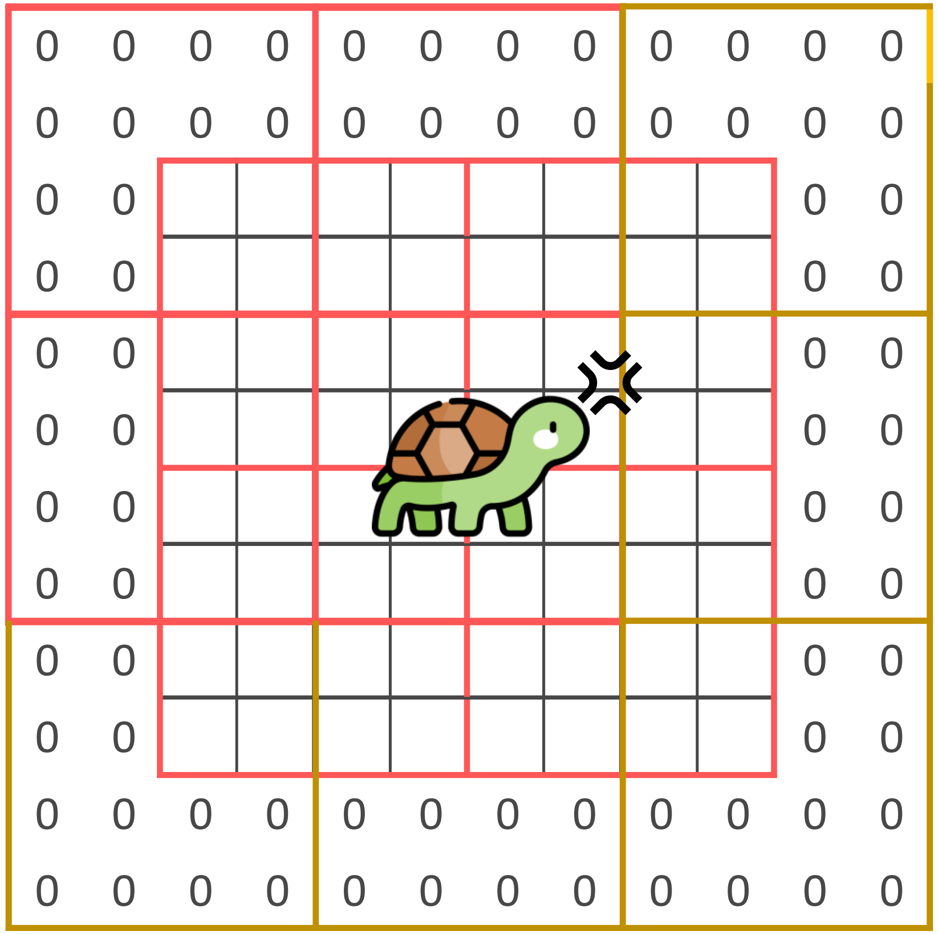




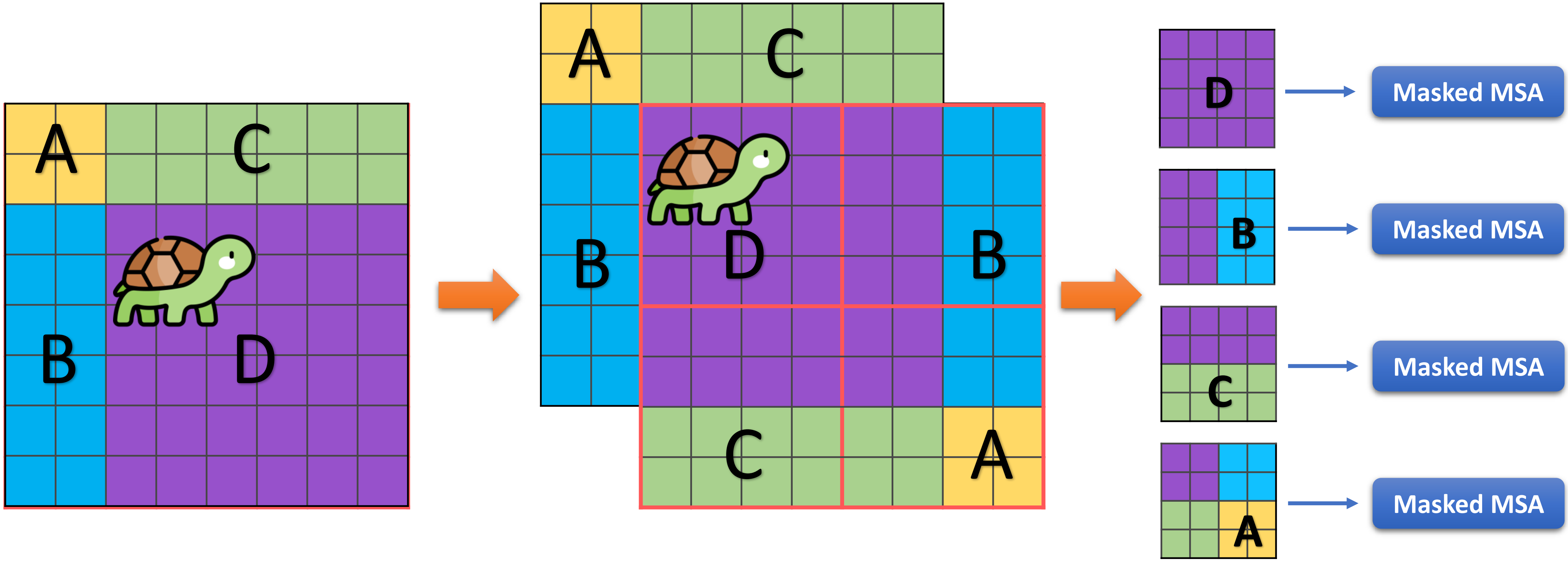


(b) Two Successive Swin Transformer Blocks

Method – Swin Blocks – (S)W-MSA



Method – Swin Blocks – (S)W-MSA



Experiments and Results

- **Objective**:
  - Validate the effectiveness of Swin Transformers across various computer vision tasks.
  - Understand the impact of key design elements of Swin Transformers.

- **Tasks Evaluated**:
  - Image Classification on ImageNet-1K and ImageNet-22K
  - Object Detection on COCO
  - Semantic Segmentation on ADE20K

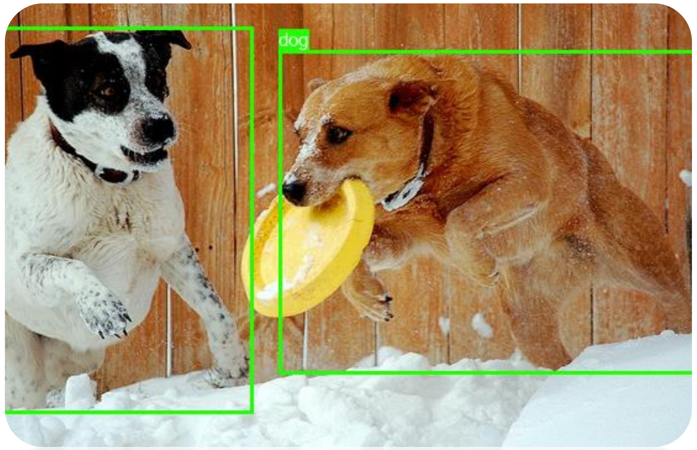
MiDaS Datasets

Dataset	Description	Vision Task	Train	Validation	Test	Link
ImageNet-1k	The ImageNet dataset is a large, diverse collection of annotated images used for image classification tasks	Classification	1.28M	50k	100k	Link
COCO	COCO is a large-scale object detection, segmentation, and captioning dataset	Object Detection	118k	5k	20k	Link
ADE20K	Comprehensive dataset for semantic segmentation and scene parsing tasks	Semantic Segmentation	20k	2k	3k	Link

ImageNet-1k

n01443537_**goldfish**.JPEG

COCO



ADE20k

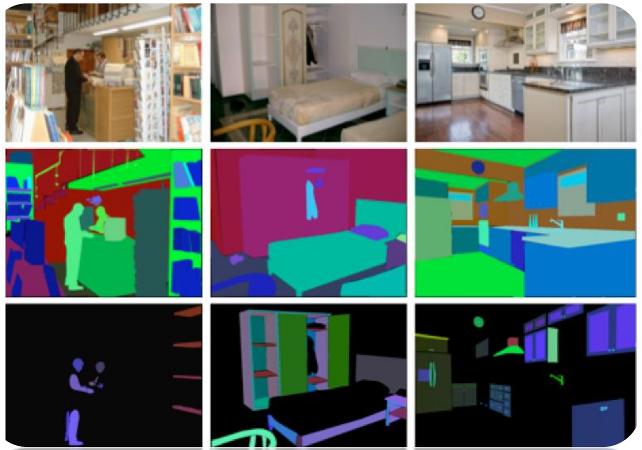


Image Classification on ImageNet-1K

- **Settings:**
  - **Training on ImageNet-1K:**
    - **Optimizer**: AdamW
    - **Epochs**: 300 with cosine decay learning rate
    - **Warm-up**: 20 epochs linear
    - **Batch size**: 1024
    - **Initial learning rate**: 0.001
    - **Weight decay**: 0.05

  - **Pre-training on ImageNet-22K and fine-tuning on ImageNet-1K:**
    - **Optimizer**: AdamW
    - **Pre-training**: 90 epochs, fine-tuning: 30 epochs
    - **Batch size**: Pre-training 4096, fine-tuning 1024
    - **Learning rate**: 0.001 for pre-training, 10^-5 for fine-tuning
    - **Weight decay**: 0.01 for pre-training, 10^-8 for fine-tuning

Image Classification on ImageNet-1K

- **Results:**
  - Comparisons with other backbones:
    - **Swin-T vs. DeiT-S:** +1.5 top-1 acc. (81.3 vs. 79.8 top-1 acc.) using 224x224 input
    - **Swin-B vs. DeiT-B:** +1.5 top-1 acc. /1.4 top-1 acc. (83.3/84.5 top-1 acc. vs. 81.8/83.1 top-1 acc.) using 224x224/384x384 input
    - **Swin-T vs. RegNetY-8G:** -0.4 top-1 acc. (81.3 vs. 81.7 top-1 acc.) using 224x224 input
    - **Swin-T vs. EffNet-B3:** -0.3 top-1 acc. (81.3 vs. 81.6 top-1 acc.) using 224x224 input
  - ImageNet-22K Pre-training Results:
    - **Swin-B:** 86.4 top-1 accuracy (+2.4 top-1 acc. higher than ViT-B/16 and +2 top-1 acc. higher than R-101x3)
    - **Swin-L:** 87.3 top-1 accuracy (+2.1 top-1 acc. better than ViT-L/16 and +2.9 top-1 acc. higher than R-101x3)

(a) Regular ImageNet-1K trained models					
method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
RegNetY-4G [48]	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G [48]	224^2	39M	8.0G	591.6	81.7
RegNetY-16G [48]	224^2	84M	16.0G	334.7	82.9
EffNet-B3 [58]	300^2	12M	1.8G	732.1	81.6
EffNet-B4 [58]	380^2	19M	4.2G	349.4	82.9
EffNet-B5 [58]	456^2	30M	9.9G	169.1	83.6
EffNet-B6 [58]	528^2	43M	19.0G	96.9	84.0
EffNet-B7 [58]	600^2	66M	37.0G	55.1	84.3
ViT-B/16 [20]	384^2	86M	55.4G	85.9	77.9
ViT-L/16 [20]	384^2	307M	190.7G	27.3	76.5
DeiT-S [63]	224^2	22M	4.6G	940.4	79.8
DeiT-B [63]	224^2	86M	17.5G	292.3	81.8
DeiT-B [63]	384^2	86M	55.4G	85.9	83.1
Swin-T	224^2	29M	4.5G	755.2	81.3
Swin-S	224^2	50M	8.7G	436.9	83.0
Swin-B	224^2	88M	15.4G	278.1	83.5
Swin-B	384^2	88M	47.0G	84.7	84.5
(b) ImageNet-22K pre-trained models					
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

Table 1. Comparison of different backbones on ImageNet-1K classification. Throughput is measured using the GitHub repository of [68] and a V100 GPU, following [63].

Object Detection on COCO

- **Settings:**
  - Models Evaluated:
    - **Faster R-CNN**
    - **Mask R-CNN**
    - **Cascade Mask R-CNN**

  - Training Configuration:
    - **Backbone**: Swin-T, Swin-B, Swin-L
    - **Optimizer**: AdamW
    - **Learning Rate Schedule**: Cosine decay
    - **Batch Size**: 16
    - **Epochs**: 36 (3x schedule)

Object Detection on COCO

- **Results:**
  - **Swin-T vs. ResNet-50**:
    - Achieves +3.4 to 4.2 box AP gains over ResNet-50.
  - **Comparison with Other Backbones**:
    - **ResNet-50 (R-50):**
      - Swin-T achieves +4.2 box AP over ResNet-50.
    - **DeiT-S:**
      - Swin-T achieves +2.5 box AP over DeiT-S.
    - **ResNeXt101-32:**
      - Swin-S shows +3.7 box AP over ResNeXt101-32.
    - **ResNeXt101-64:**
      - Swin-B shows +3.6 box AP over ResNeXt101-64.

(a) Various frameworks

Method	Backbone	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	#param.	FLOPs	FPS
Cascade	R-50	46.3	64.3	50.5	82M	739G	18.0
Mask R-CNN	Swin-T	**50.5**	**69.3**	**54.9**	86M	745G	15.3
ATSS	R-50	43.5	61.9	47.0	32M	205G	28.3
	Swin-T	**47.2**	**66.5**	**51.3**	36M	215G	22.3
RepPointsV2	R-50	46.5	64.6	50.3	42M	274G	13.6
	Swin-T	**50.0**	**68.5**	**54.2**	45M	283G	12.0
Sparse	R-50	44.5	63.4	48.2	106M	166G	21.0
R-CNN	Swin-T	**47.9**	**67.3**	**52.3**	110M	172G	18.4

(b) Various backbones w. Cascade Mask R-CNN

	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	AP^{mask}	AP^{mask}_{50}	AP^{mask}_{75}	param	FLOPs	FPS
DeiT-S†	48.0	67.2	51.7	41.4	64.2	44.3	80M	889G	10.4
R50	46.3	64.3	50.5	40.1	61.7	43.4	82M	739G	18.0
Swin-T	**50.5**	**69.3**	**54.9**	**43.7**	**66.6**	**47.1**	86M	745G	15.3
X101-32	48.1	66.5	52.4	41.6	63.9	45.2	101M	819G	12.8
Swin-S	**51.8**	**70.4**	**56.3**	**44.7**	**67.9**	**48.5**	107M	838G	12.0
X101-64	48.3	66.4	52.3	41.7	64.0	45.1	140M	972G	10.4
Swin-B	**51.9**	**70.9**	**56.5**	**45.0**	**68.4**	**48.7**	145M	982G	11.6

(c) System-level Comparison

Method	mini-val AP^{box}	mini-val AP^{mask}	test-dev AP^{box}	test-dev AP^{mask}	#param.	FLOPs
RepPointsV2* [12]	-	-	52.1	-	-	-
GCNet* [7]	51.8	44.7	52.3	45.4	-	1041G
RelationNet++* [13]	-	-	52.7	-	-	-
SpineNet-190 [21]	52.6	-	52.8	-	164M	1885G
ResNeSt-200* [78]	52.5	-	53.3	47.1	-	-
EfficientDet-D7 [59]	54.4	-	55.1	-	77M	410G
DetectoRS* [46]	-	-	55.7	48.5	-	-
YOLOv4 P7* [4]	-	-	55.8	-	-	-
Copy-paste [26]	55.9	47.2	56.0	47.4	185M	1440G
X101-64 (HTC++)	52.3	46.0	-	-	155M	1033G
Swin-B (HTC++)	56.4	49.1	-	-	160M	1043G
Swin-L (HTC++)	57.1	49.5	57.7	50.2	284M	1470G
Swin-L (HTC++)*	**58.0**	**50.4**	**58.7**	**51.1**	284M	-

Table 2. Results on COCO object detection and instance segmentation. †denotes that additional decovolution layers are used to produce hierarchical feature maps. * indicates multi-scale testing.

Semantic Segmentation on ADE20K

- **Settings:**
  - **Dataset:** ADE20K
  - **Base Framework:** UperNet

- **Results:**
  - **Swin-S**
    - Achieves 49.3 mIoU, which is +5.3 mIoU higher than DeiT-S (44.0) with similar computation cost.
    - Outperforms ResNet-101 by +4.4 mIoU.
    - Outperforms ResNeSt-101 by +2.4 mIoU.
  - **Swin-L:**
    - With ImageNet-22K pre-training, achieves 53.5 mIoU on the validation set.
    - Surpasses the previous best model (SETR) by +3.2 mIoU, which had 50.3 mIoU with a larger model size.

ADE20K Method	Backbone	val mIoU	test score	#param.	FLOPs	FPS
DANet [23]	ResNet-101	45.2	-	69M	1119G	15.2
DLab.v3+ [11]	ResNet-101	44.1	-	63M	1021G	16.0
ACNet [24]	ResNet-101	45.9	38.5	-		
DNL [71]	ResNet-101	46.0	56.2	69M	1249G	14.8
OCRNet [73]	ResNet-101	45.3	56.0	56M	923G	19.3
UperNet [69]	ResNet-101	44.9	-	86M	1029G	20.1
OCRNet [73]	HRNet-w48	45.7	-	71M	664G	12.5
DLab.v3+ [11]	ResNeSt-101	46.9	55.1	66M	1051G	11.9
DLab.v3+ [11]	ResNeSt-200	48.4	-	88M	1381G	8.1
SETR [81]	T-Large‡	50.3	61.7	308M	-	-
UperNet	DeiT-S†	44.0	-	52M	1099G	16.2
UperNet	Swin-T	46.1	-	60M	945G	18.5
UperNet	Swin-S	49.3	-	81M	1038G	15.2
UperNet	Swin-B‡	51.6	-	121M	1841G	8.7
UperNet	Swin-L‡	**53.5**	**62.8**	234M	3230G	6.2

Table 3. Results of semantic segmentation on the ADE20K val and test set. † indicates additional deconvolution layers are used to produce hierarchical feature maps. $\ddagger$ indicates that the model is pre-trained on ImageNet-22K.

Ablation Studies

- **Importance of Shifted Windows:**
  - **Comparison with single window partitioning shows:**
    - +1.1% top-1 accuracy on ImageNet-1K
    - +2.8 box AP and +2.2 mask AP on COCO
    - +2.8 mIoU on ADE20K

- **Effect of Relative Position Bias:**
  - **Improves performance across all tasks:**
    - +1.2%/+0.8% top-1 accuracy on ImageNet-1K
    - +1.3/+1.5 box AP and +1.1/+1.3 mask AP on COCO
    - +2.3/+2.9 mIoU on ADE20K

	ImageNet		COCO		ADE20k
	top-1	top-5	AP^{box}	AP^{mask}	mIoU
w/o shifting	80.2	95.1	47.7	41.5	43.3
shifted windows	**81.3**	**95.6**	**50.5**	**43.7**	**46.1**
no pos.	80.1	94.9	49.2	42.6	43.8
abs. pos.	80.5	95.2	49.0	42.4	43.2
abs.+rel. pos.	81.3	95.6	50.2	43.4	44.0
rel. pos. w/o app.	79.3	94.7	48.2	41.9	44.1
rel. pos.	**81.3**	**95.6**	**50.5**	**43.7**	**46.1**

Table 4. Ablation study on the *shifted windows* approach and different position embedding methods on three benchmarks, using the Swin-T architecture. w/o shifting: all self-attention modules adopt regular window partitioning, without *shifting*; abs. pos.: absolute position embedding term of ViT; rel. pos.: the default settings with an additional relative position bias term (see Eq. (4)); app.: the first scaled dot-product term in Eq. (4).

Conclusions

- **Summary**:
  - Introduced a hierarchical vision Transformer using shifted windows.
  - Addressed limitations of standard ViTs by incorporating hierarchical feature maps and shifted windows.
  - Achieves **linear** computational complexity with respect to input image size.
  - Outperforms previous methods in COCO object detection and ADE20K semantic segmentation.

- **Key Innovations**:
  - **Shifted Window Mechanism:** Effective and efficient for vision tasks.
  - **Hierarchical Feature Maps:** Enables efficient computation and better handling of high-resolution images.
  - **Relative Position Bias:** Enhances spatial understanding and performance.

Future Directions

Optimization: Further research into more efficient training methods and architectures.

Applications: Explore the use of shifted window-based self-attention in NLP.

Integration: Combining Swin Transformers with other models and techniques for enhanced performance.

End

Thanks for listening!