Tokens-to-Token ViT: Training Vision Transformers from Scratch on ImageNet

ICCV 2021

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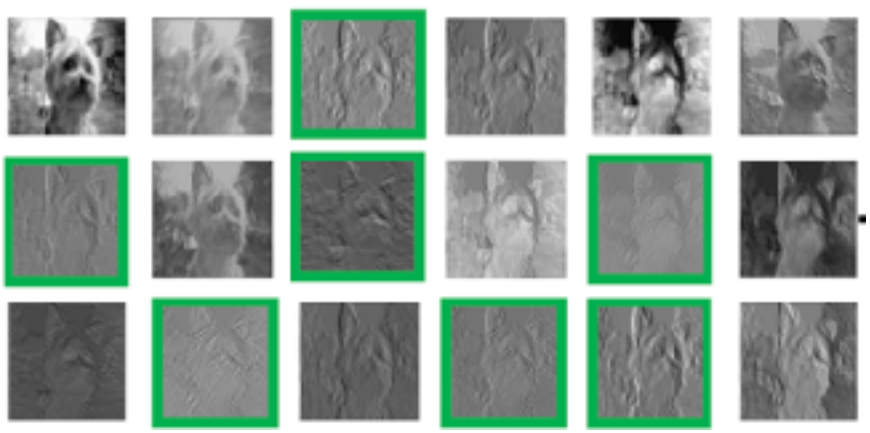
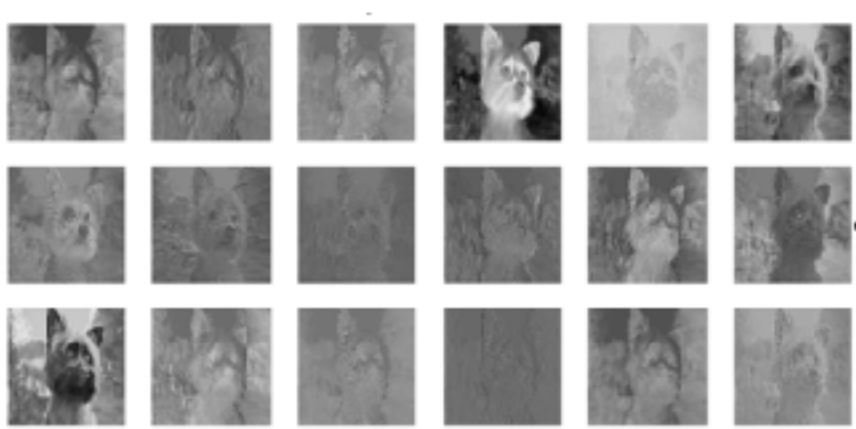
Limitations of ViTs

- ViT tokenization of images (i.e., into patches) makes it harder for the model to learn local structures such as edges, lines, etc.



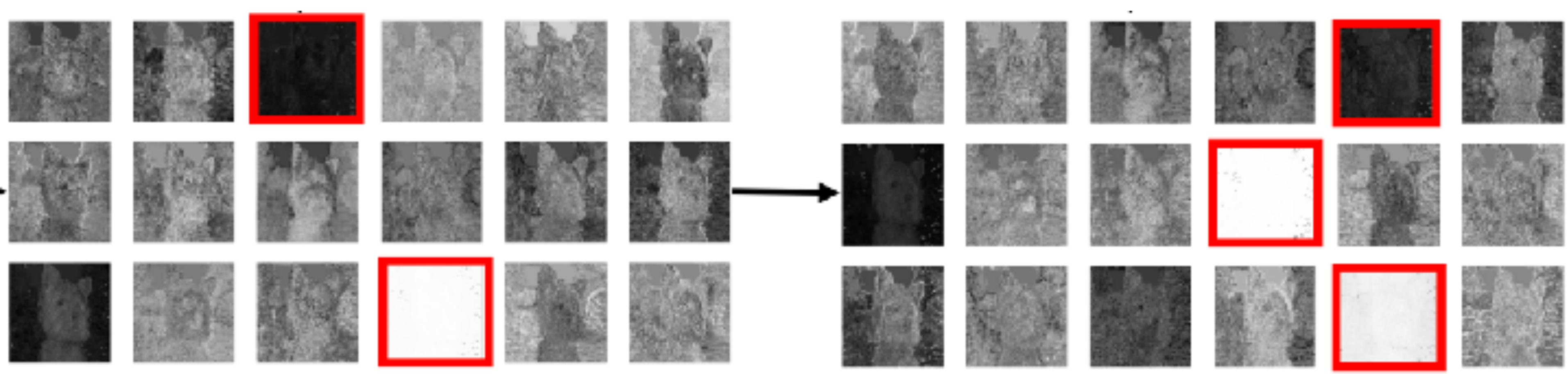
ResNet50 conv1 activations



ViT-L/16 block1 activations

Limitations of ViTs

- ViT backbone is over-parameterized for midsize datasets like ImageNet-1K.
- This leads to redundant features.

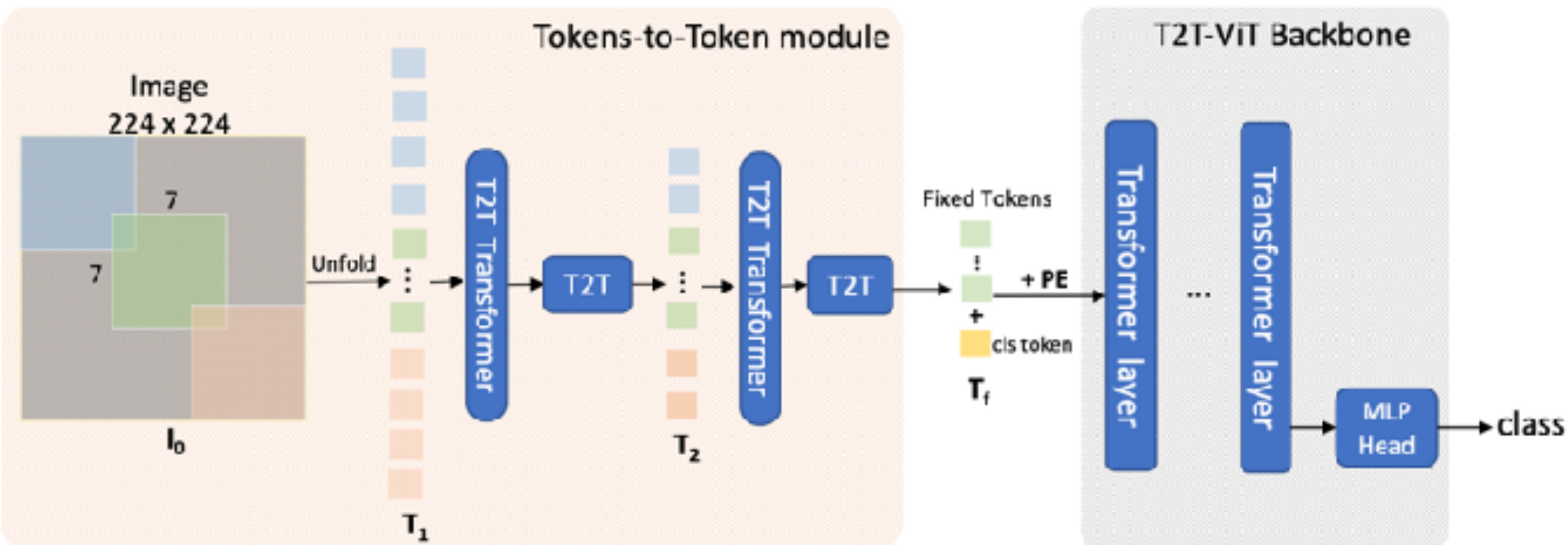


ViT-L/16 block12 activations

ViT-L/16 block24 activations

Tokens-to-Token ViT

- The authors propose a layer-wise “Tokens-to-Token module” (T2T) to model local structures in the image.
- Instead of a parameter-heavy backbone, an efficient “T2T-ViT backbone” is used to process the resulting T2T tokens.



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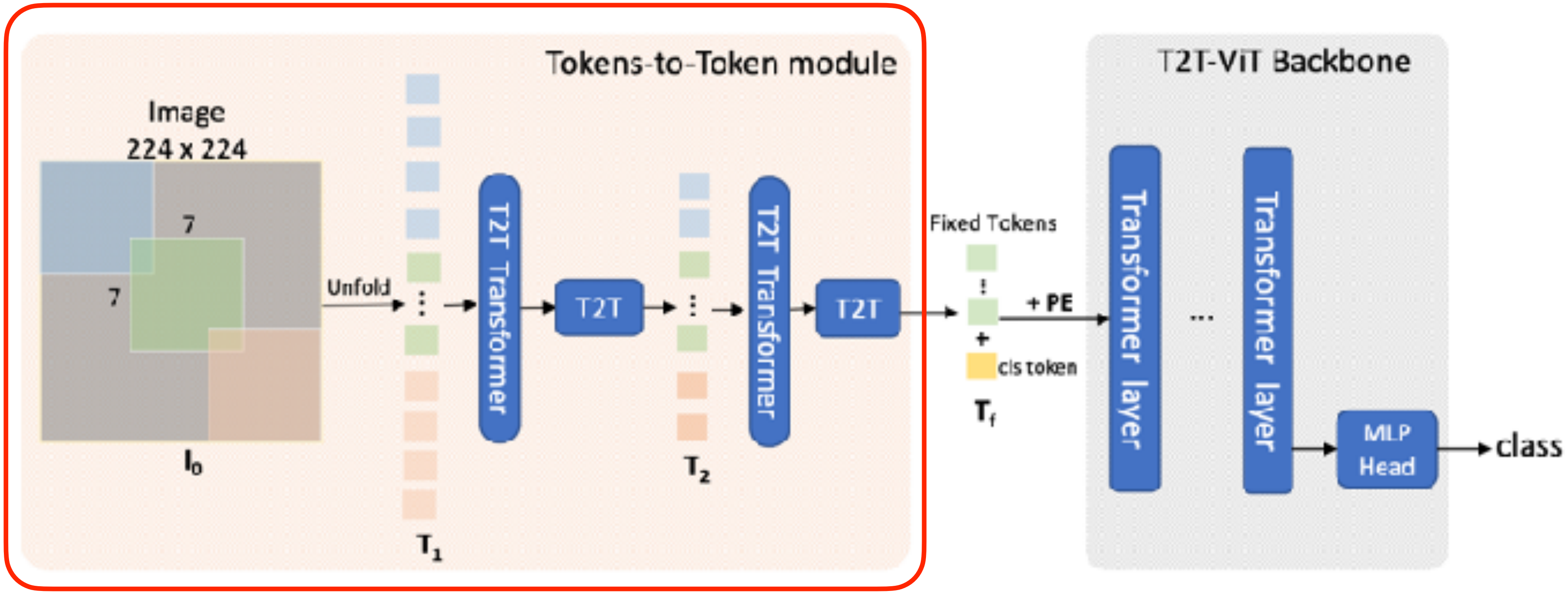
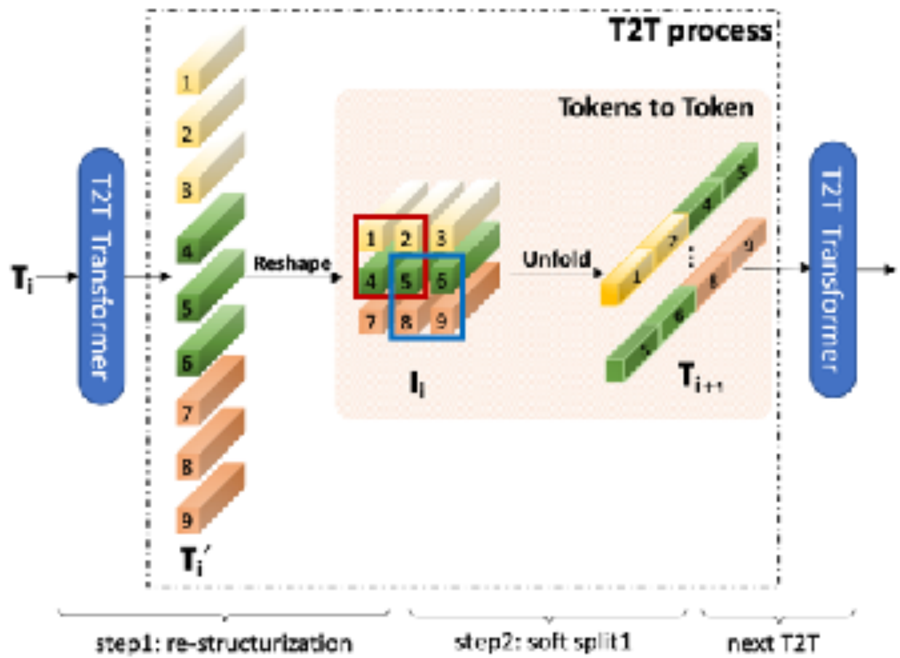


Tokens-to-Token Module

- First, patch-level tokens are processed using self-attention.
- Then, the patch-level tokens are reshaped into a 2D grid.
- Lastly, the authors apply a sliding window operation to aggregate information within local neighborhoods of tokens.



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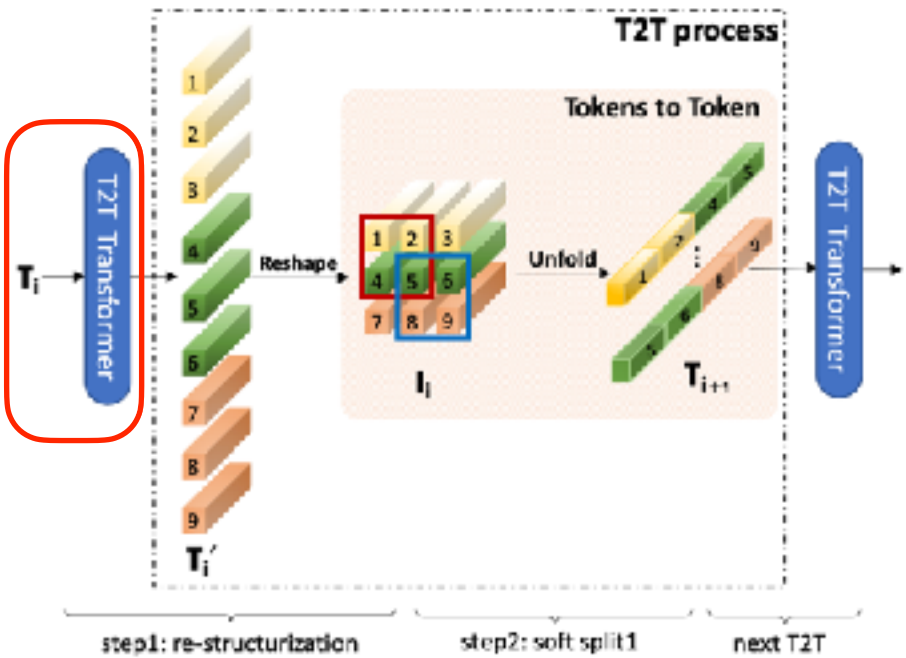

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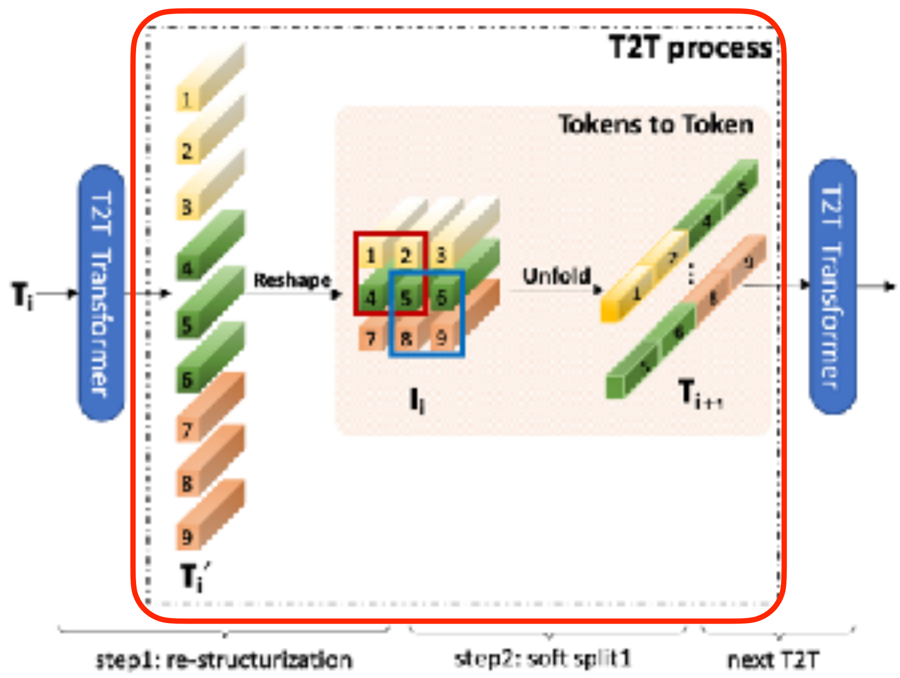
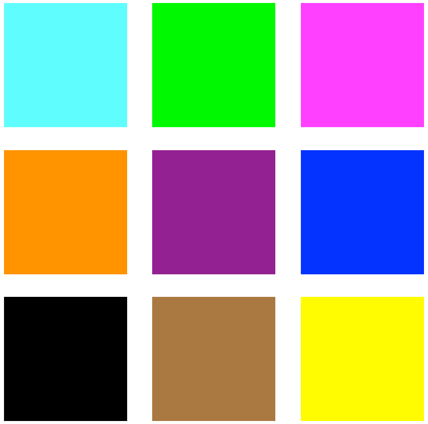


Local Patch Aggregation

- The patch-level tokens are reshaped back into a 2D grid.
- The sliding window operation is applied on the resulting 2D grid, and the neighboring patches/tokens are concatenated.



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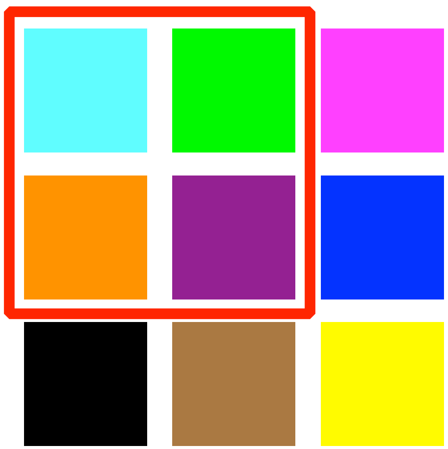

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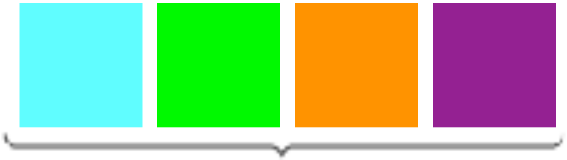
New Token 1



b) Concatenation of the Neighboring Tokens

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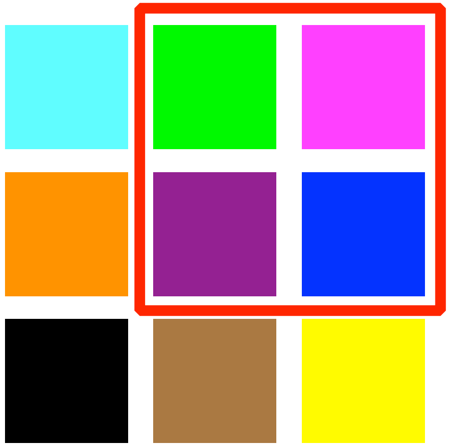

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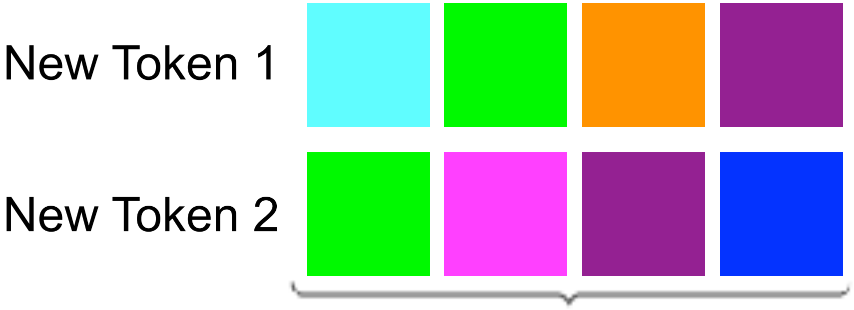

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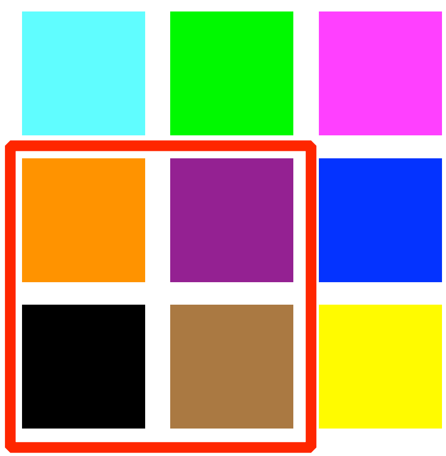

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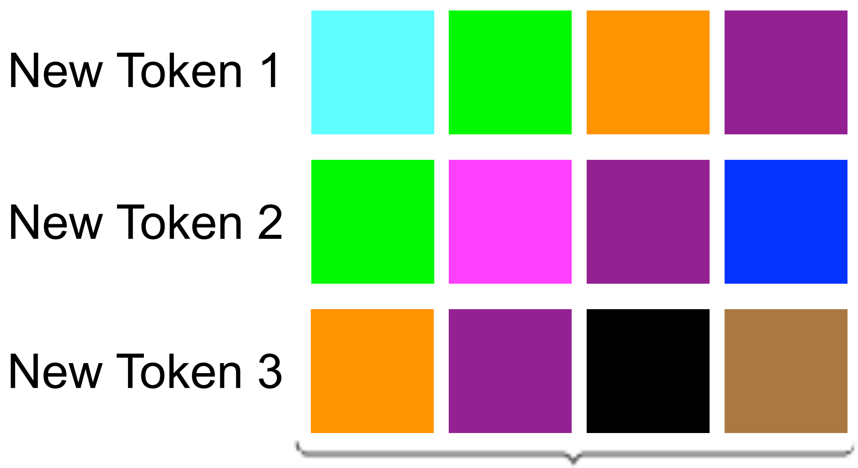

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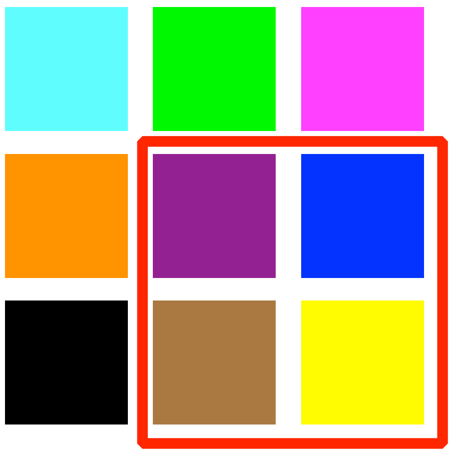

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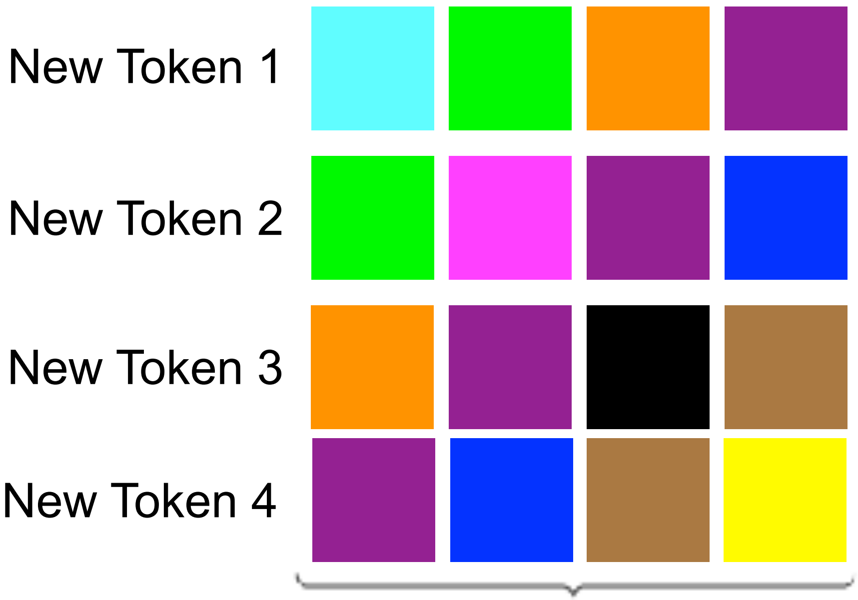

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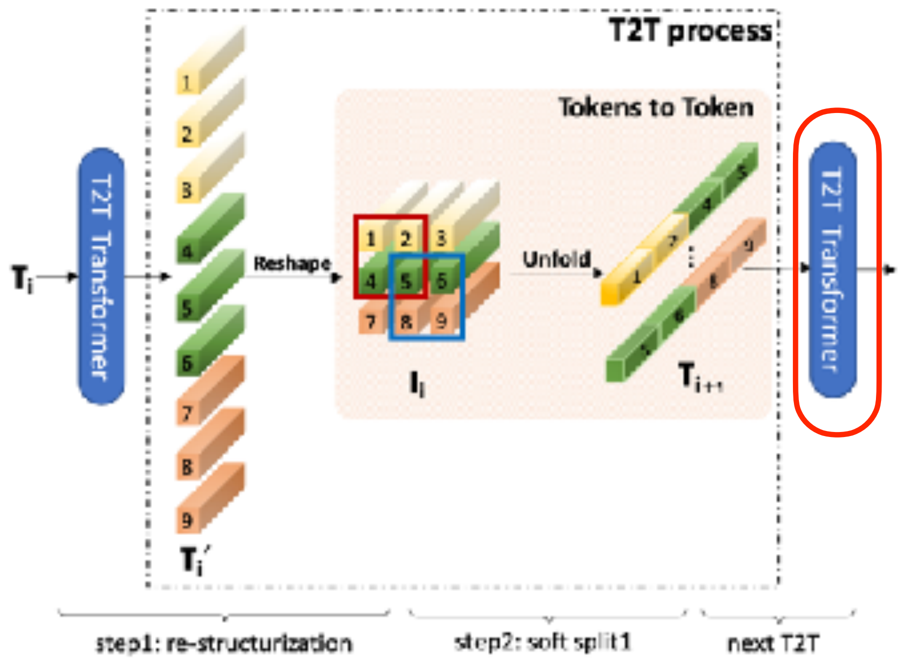
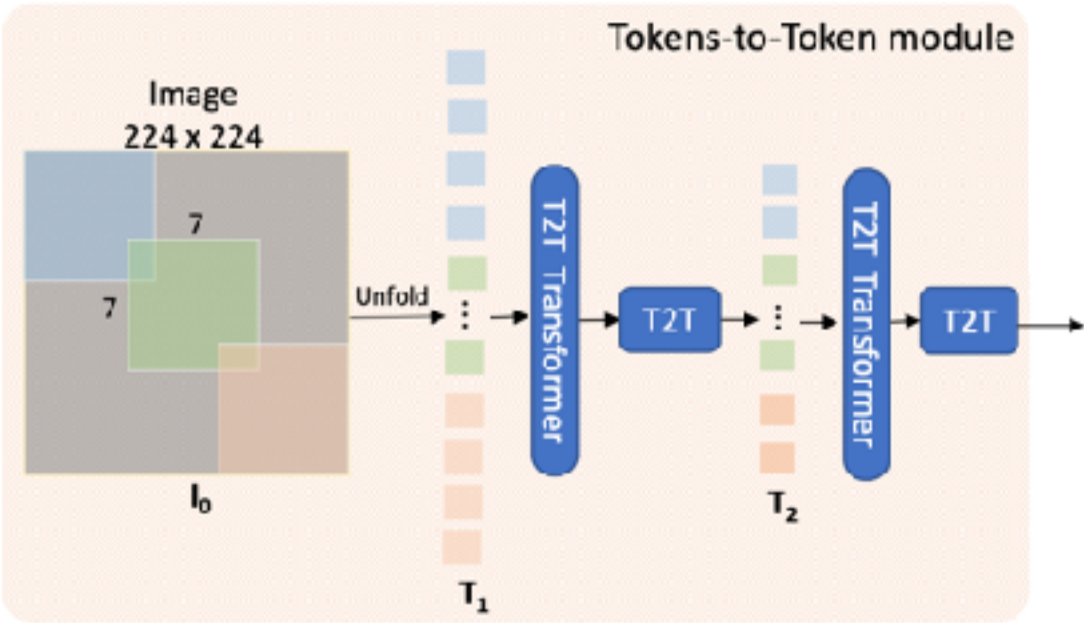


Tokens-to-Token Module

- These two steps can be conducted iteratively as many times as needed.



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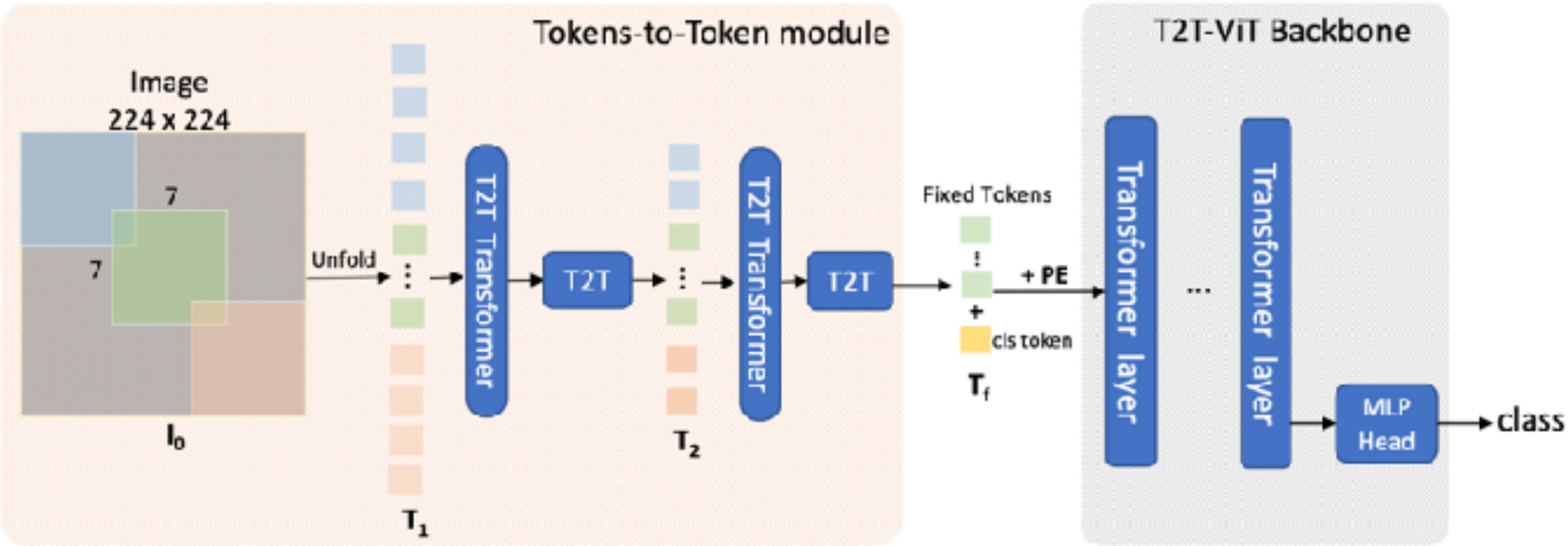

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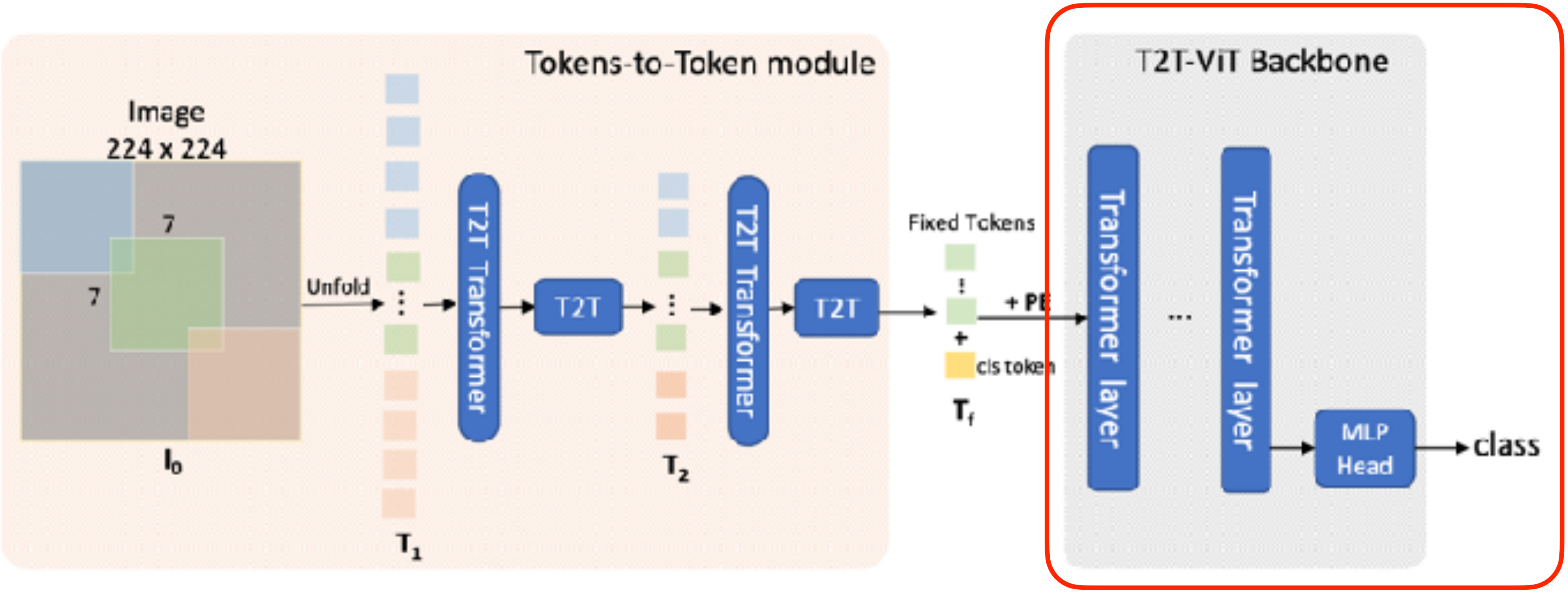

T2T-ViT vs ViT Architecture

- Unlike ViT, T2T-ViT employs a deep-narrow architecture.

Models	Tokens-to-Token module				T2T-ViT backbone			Model size	
	T2T transformer	Depth	Hidden dim	MLP size	Depth	Hidden dim	MLP size	Params (M)	MACs (G)
ViT-S/16 [12]	-	-	-	-	8	786	2358	48.6	10.1
ViT-B/16 [12]	-	-	-	-	12	786	3072	86.8	17.6
ViT-L/16 [12]	-	-	-	-	24	1024	4096	304.3	63.6
T2T-ViT-14	Performer	2	64	64	14	384	1152	21.5	4.8
T2T-ViT-19	Performer	2	64	64	19	448	1344	39.2	8.5
T2T-ViT-24	Performer	2	64	64	24	512	1536	64.1	13.8

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Ablation Studies

- Ablation study validating the effectiveness of (1) the T2T module, and (2) Deep-Narrow ViT architecture

Ablation type	Models	Top1-Acc (%)	Params (M)	MACs (G)
T2T module	T2T-ViT-14$_{wo\ T2T}$	79.5	21.1	4.2
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DN Structure	T2T-ViT-14	81.5	21.5	4.8
	T2T-ViT-d768-4	78.8 (-2.7)	25.0	5.4

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Qualitative Results

- The proposed approach addresses the two previously discussed limitations of ViTs.