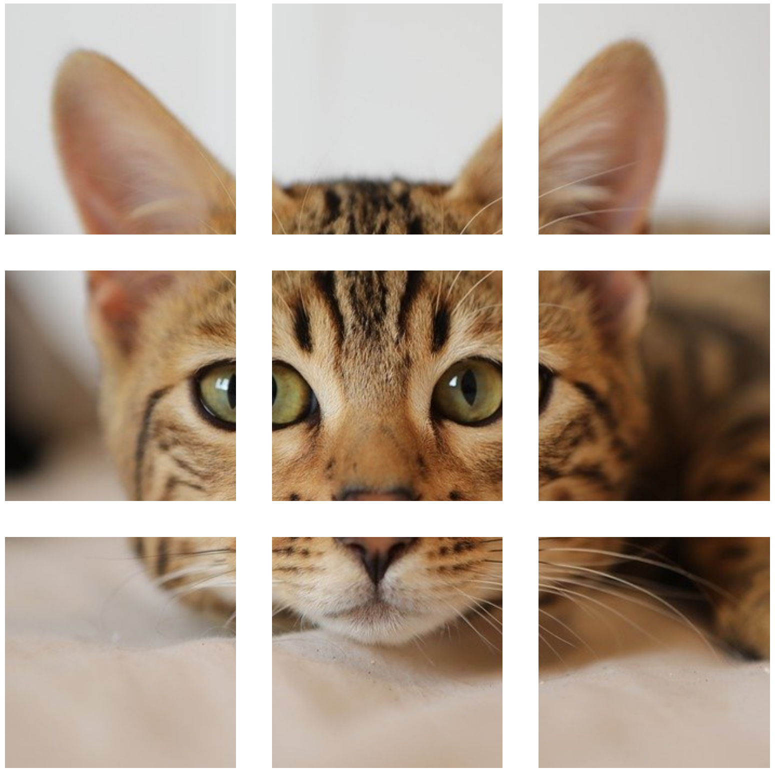
Vision Transformer

Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Standard Transformer on Patches



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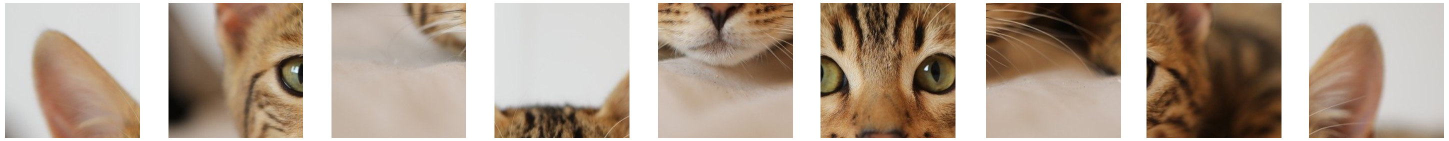
Standard Transformer on Patches

N input patches, each of shape 3x16x16



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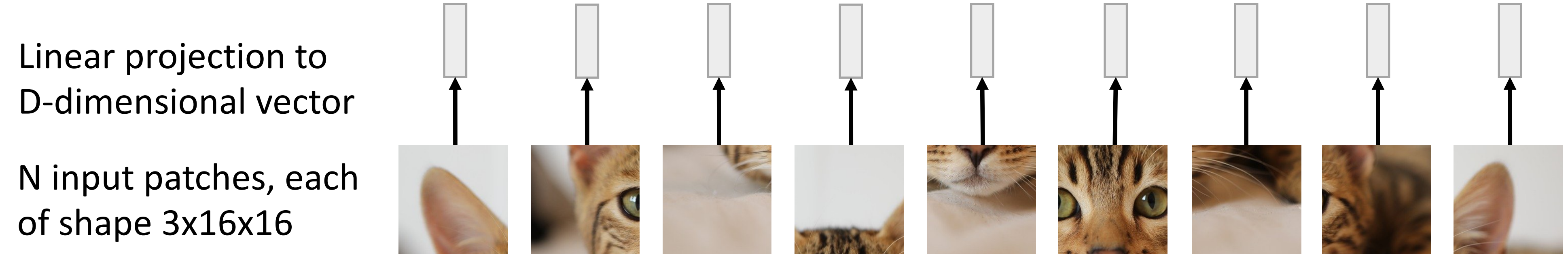

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Standard Transformer on Patches

Add positional embedding: learned D-dim vector per position

Linear projection to D-dimensional vector

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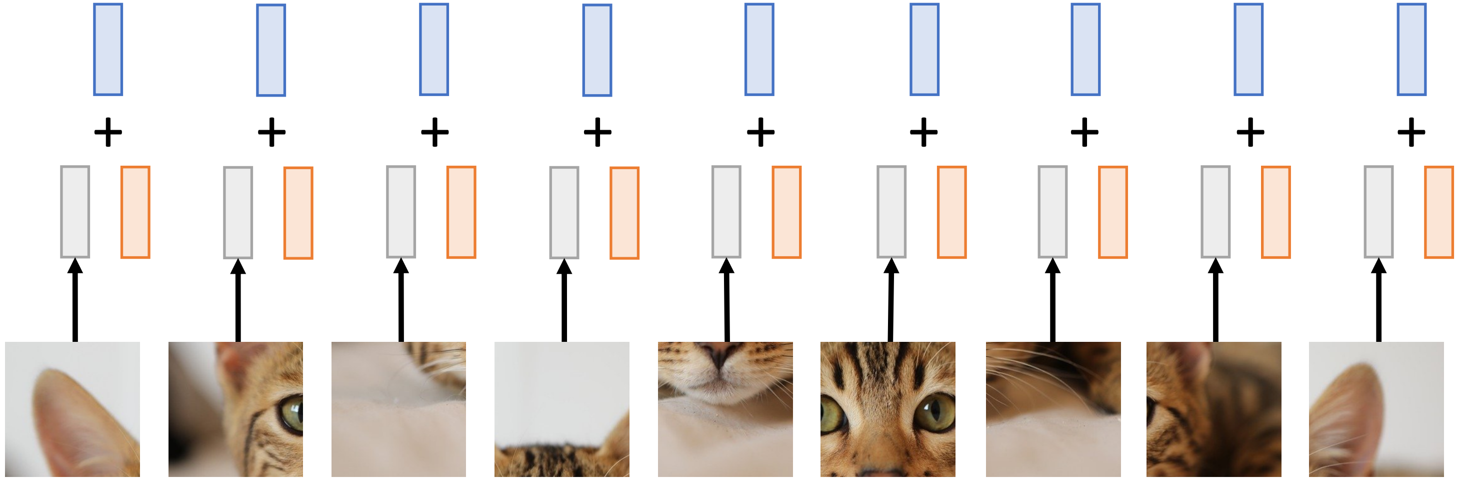

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Standard Transformer on Patches

Output vectors

Exact same as
NLP Transformer!

Add positional embedding: learned D-dim vector per position

Linear projection to D-dimensional vector

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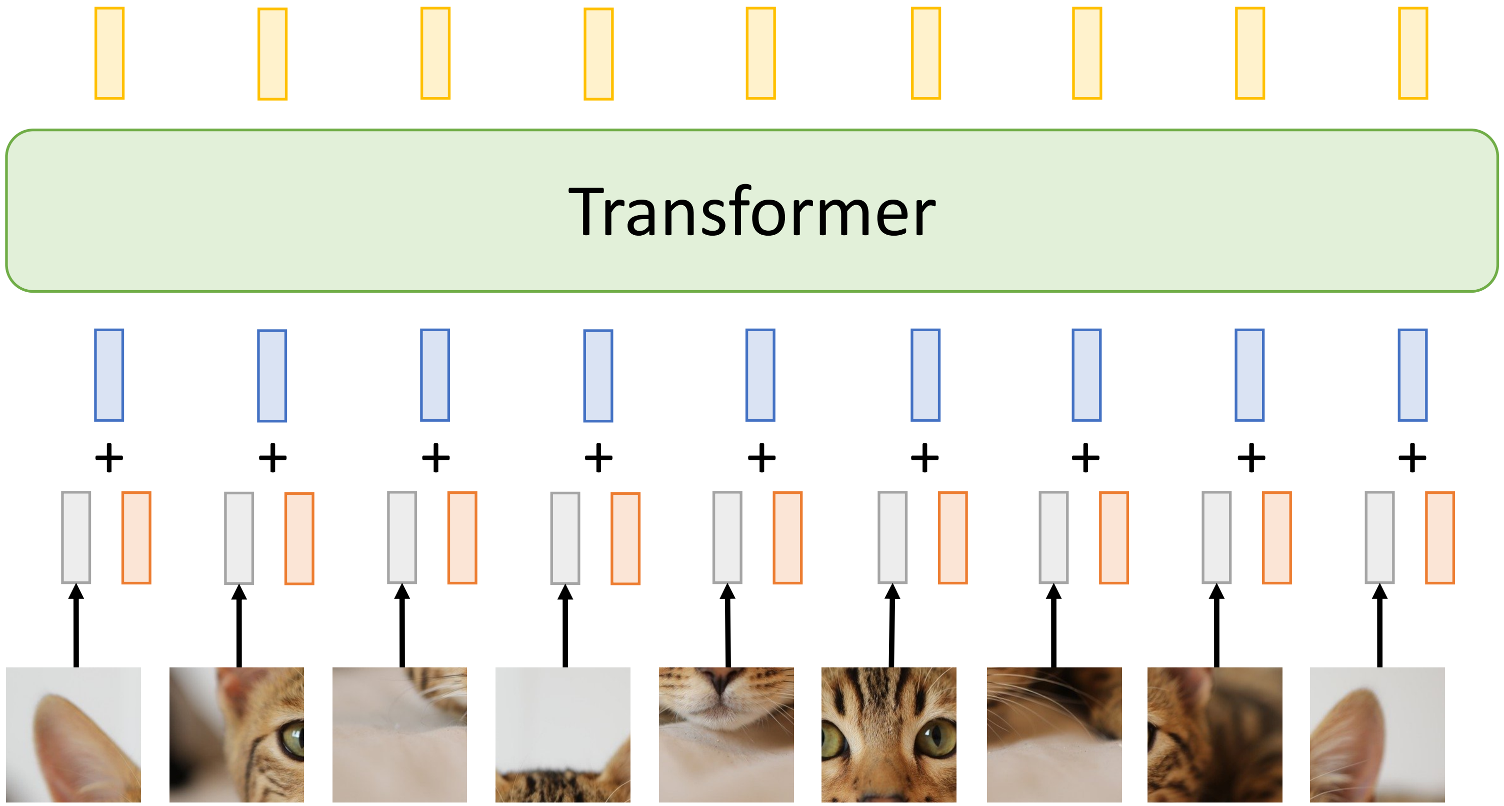

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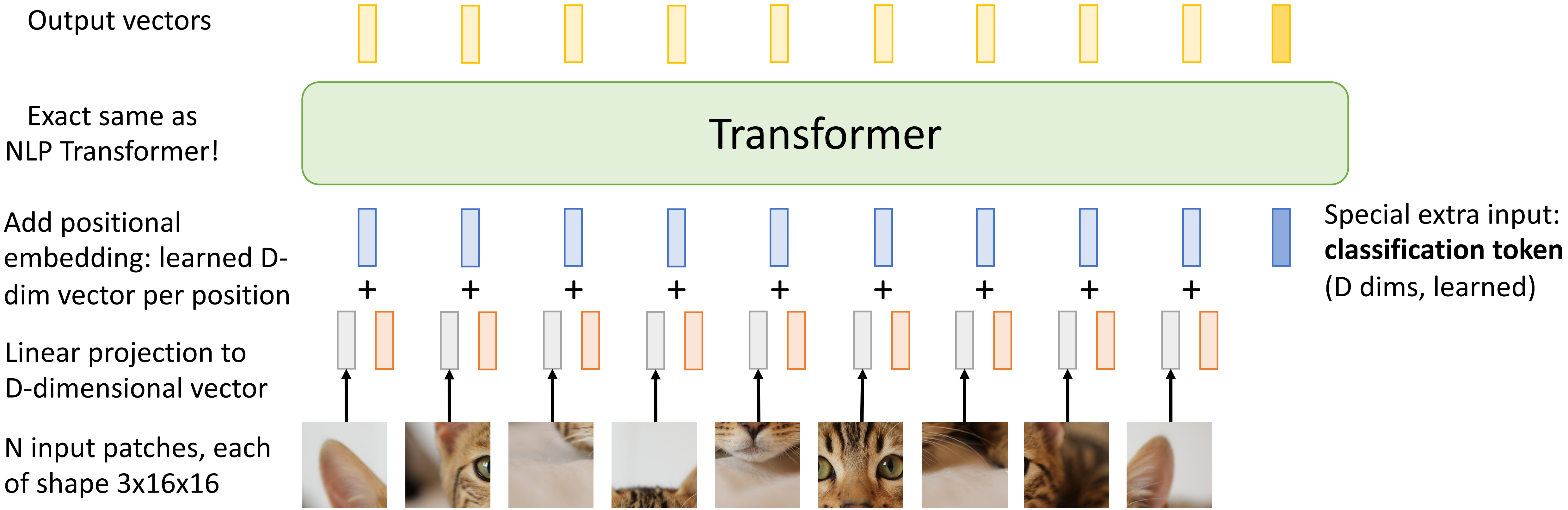

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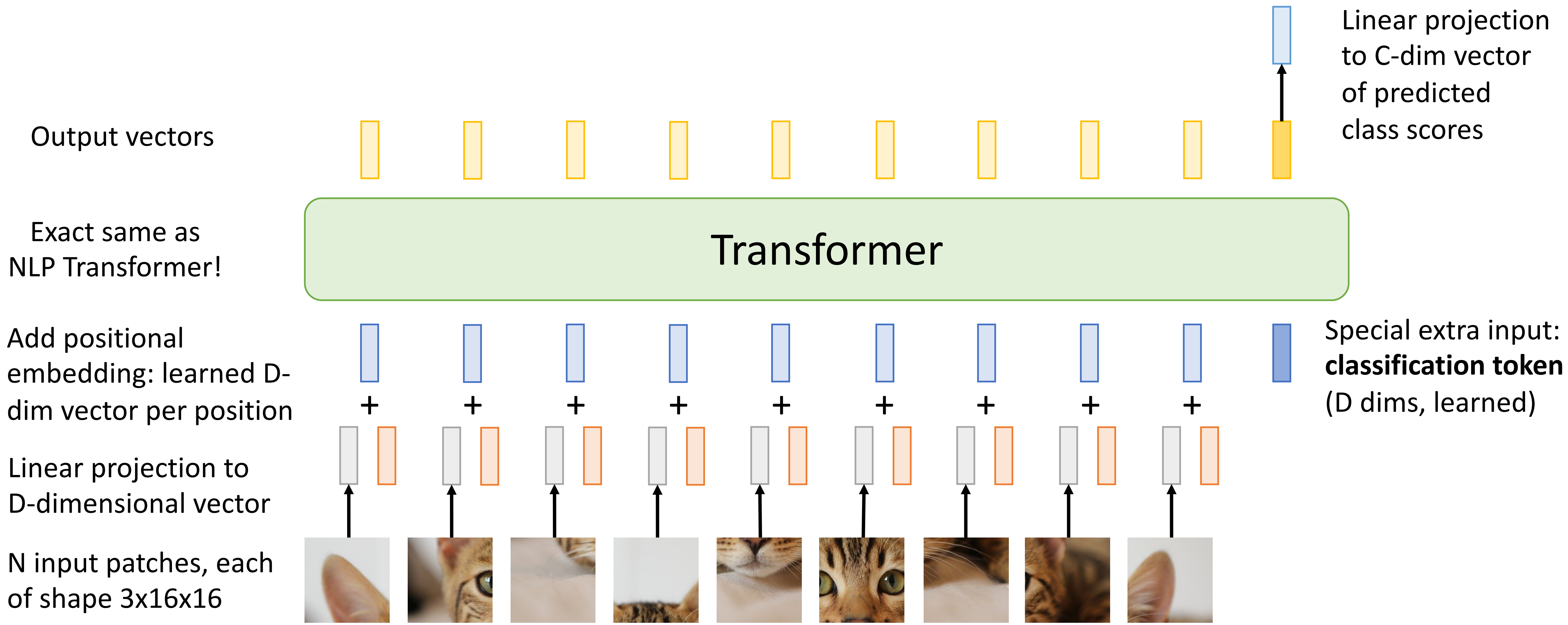

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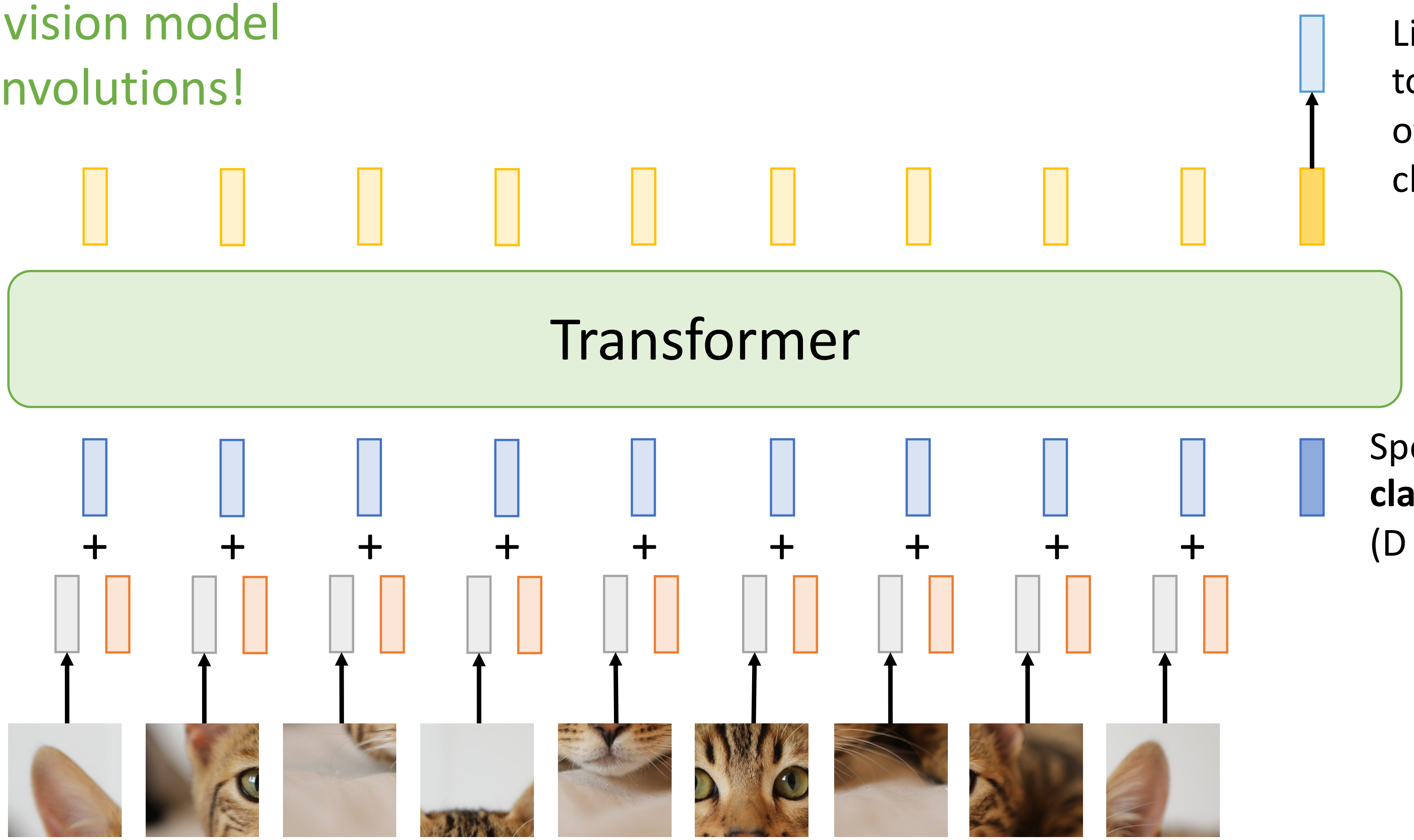
Vision Transformer (ViT)

Computer vision model
with no convolutions!



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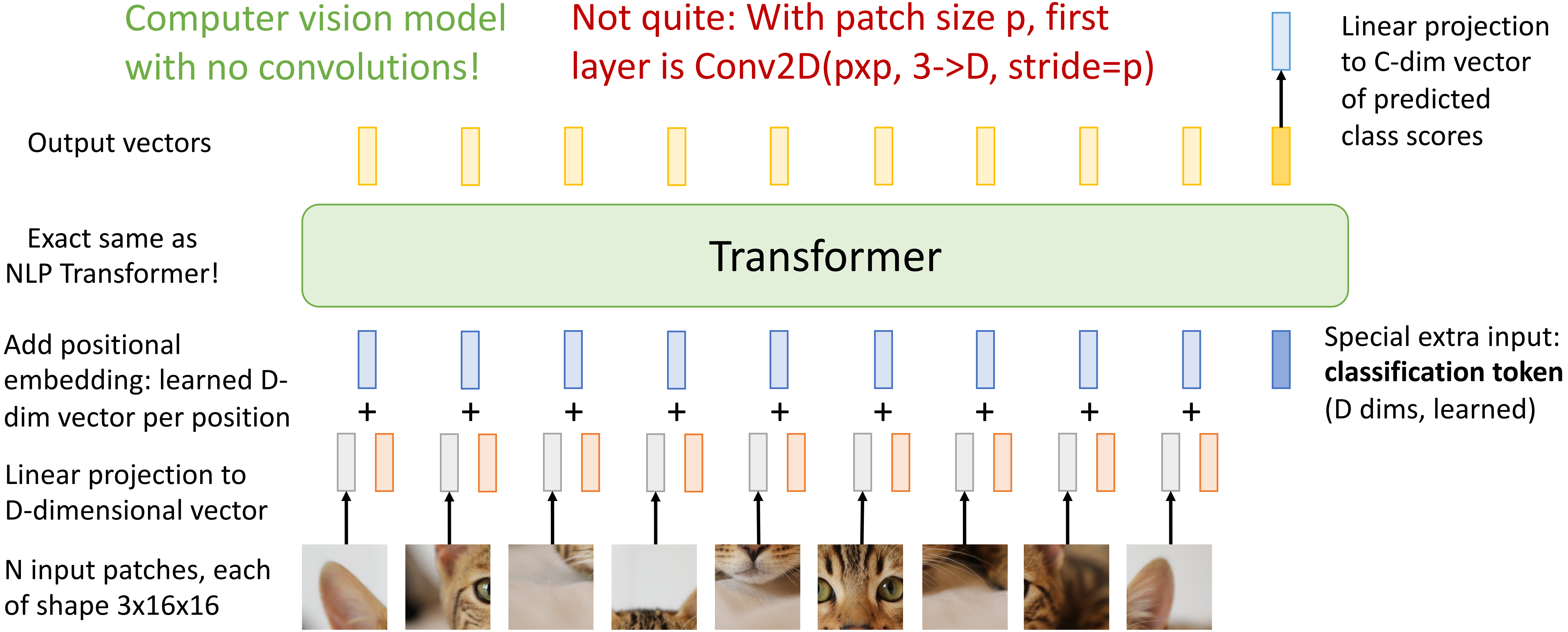
Vision Transformer (ViT)

Computer vision model with no convolutions!

Not quite: With patch size p, first layer is Conv2D(pxp, 3->D, stride=p)



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Vision Transformer (ViT)

Computer vision model with no convolutions!

Not quite: MLPs in Transformer are stacks of 1x1 convolution

Output vectors

Exact same as NLP Transformer!

Add positional embedding: learned D-dim vector per position

Linear projection to D-dimensional vector

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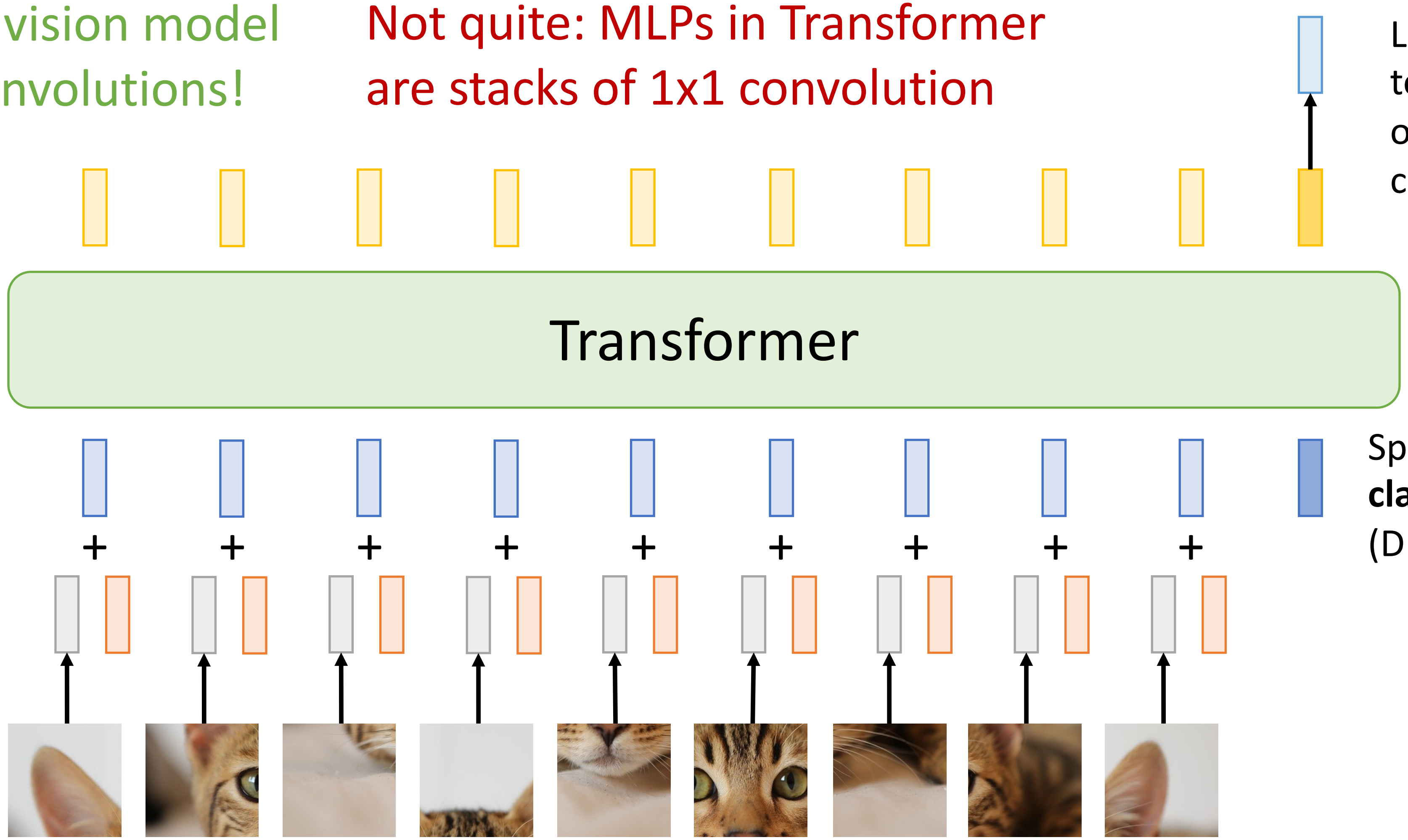

Linear projection to C-dim vector of predicted class scores

Special extra input: **classification token** (D dims, learned)

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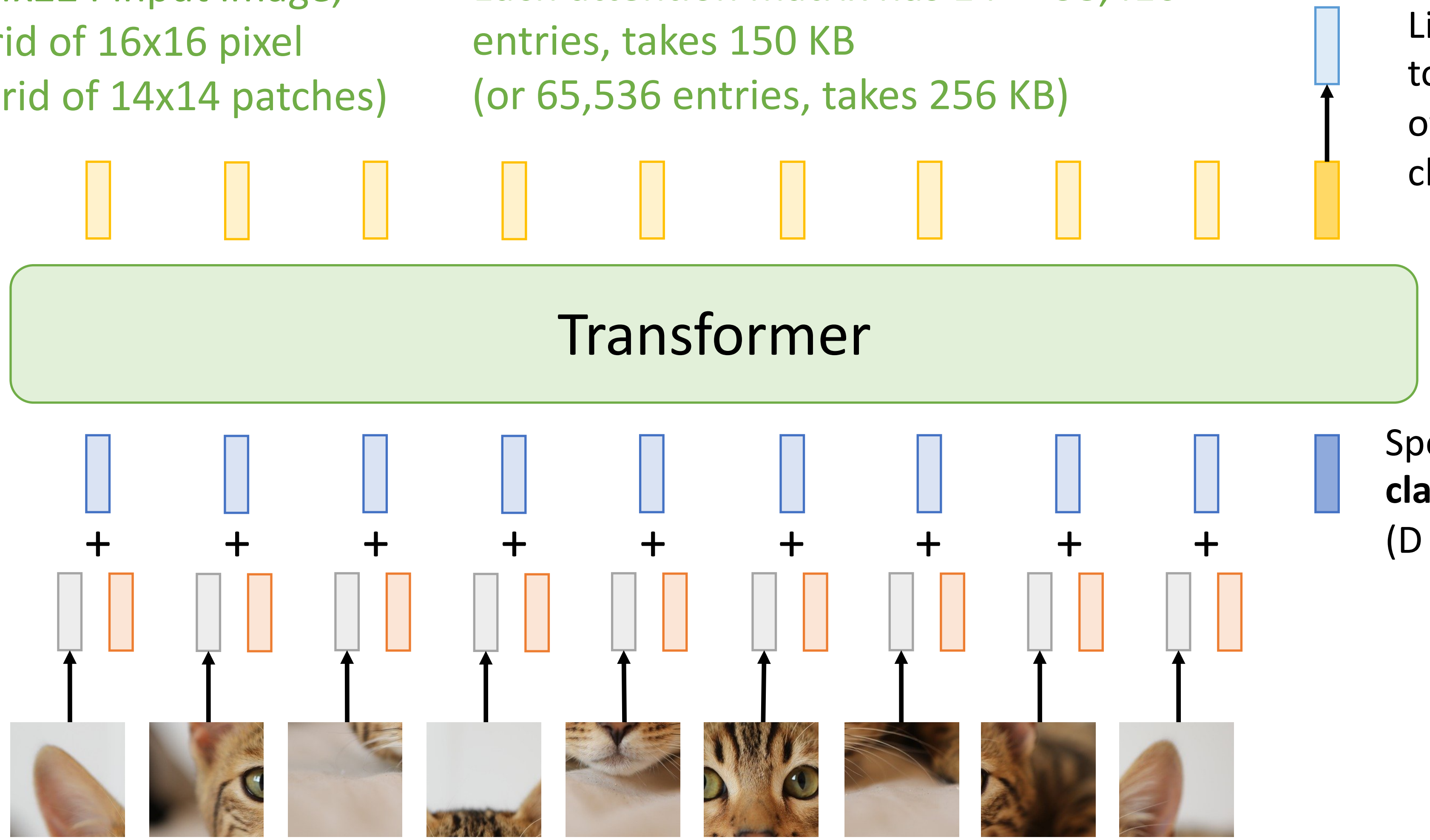
Vision Transformer (ViT)

In practice: take 224x224 input image, divide into 14x14 grid of 16x16 pixel patches (or 16x16 grid of 14x14 patches)

Each attention matrix has 14^4 = 38,416 entries, takes 150 KB (or 65,536 entries, takes 256 KB)



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Linear projection to D-dimensional vector

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Vision Transformer (ViT)

In practice: take 224x224 input image, divide into 14x14 grid of 16x16 pixel patches (or 16x16 grid of 14x14 patches)

With 48 layers, 16 heads per layer, all attention matrices take 112 MB (or 192MB)

Linear projection to C-dim vector of predicted class scores

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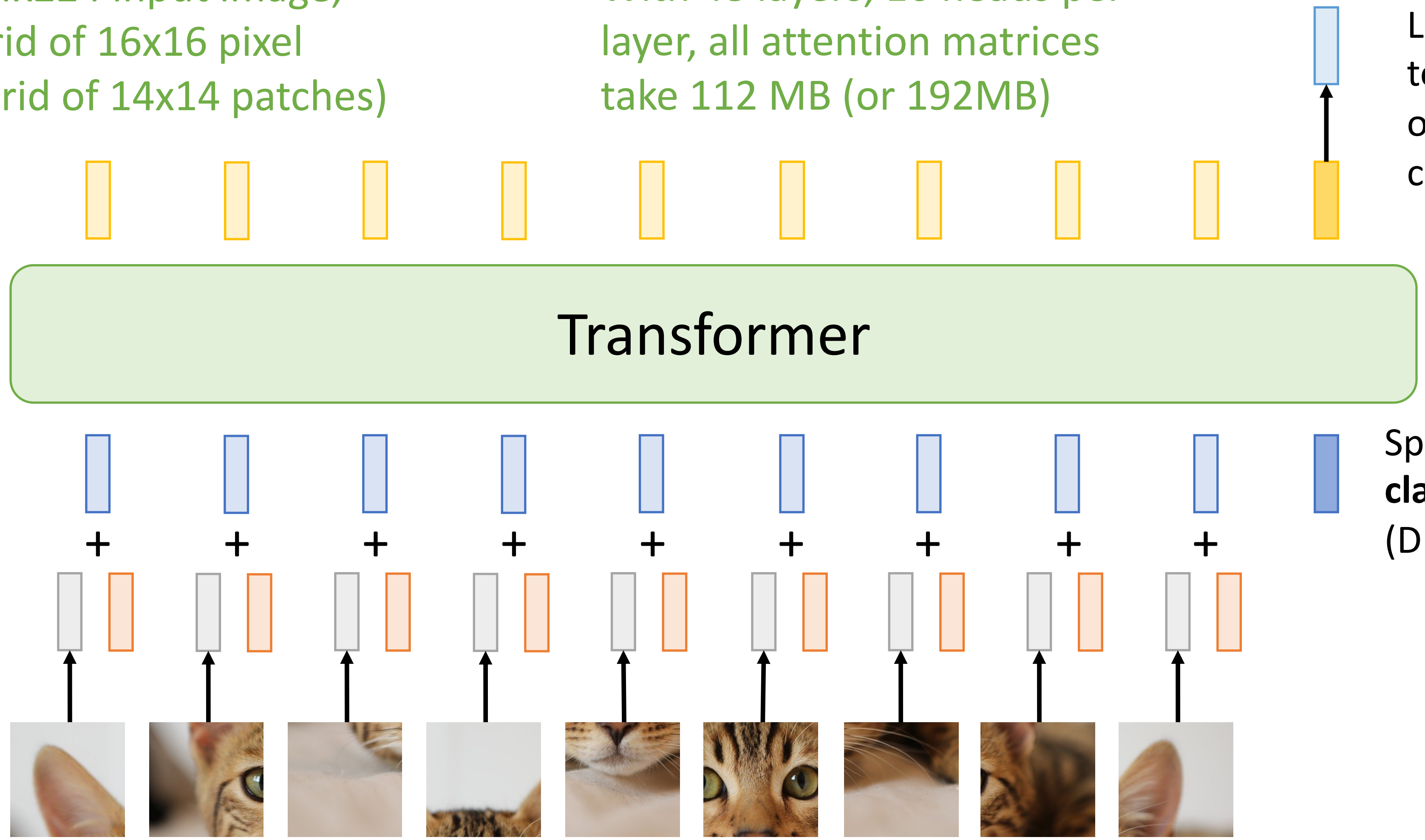

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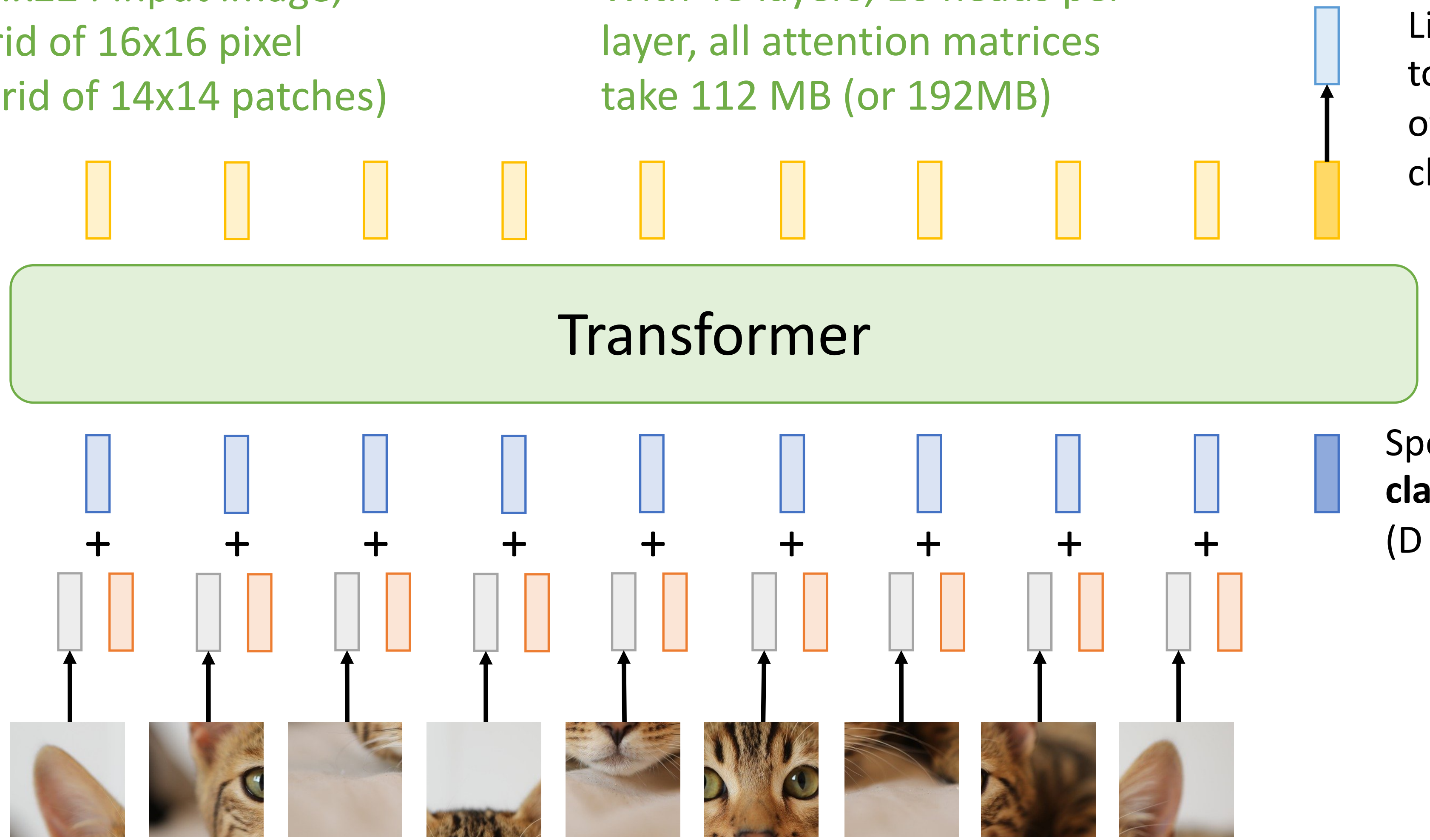

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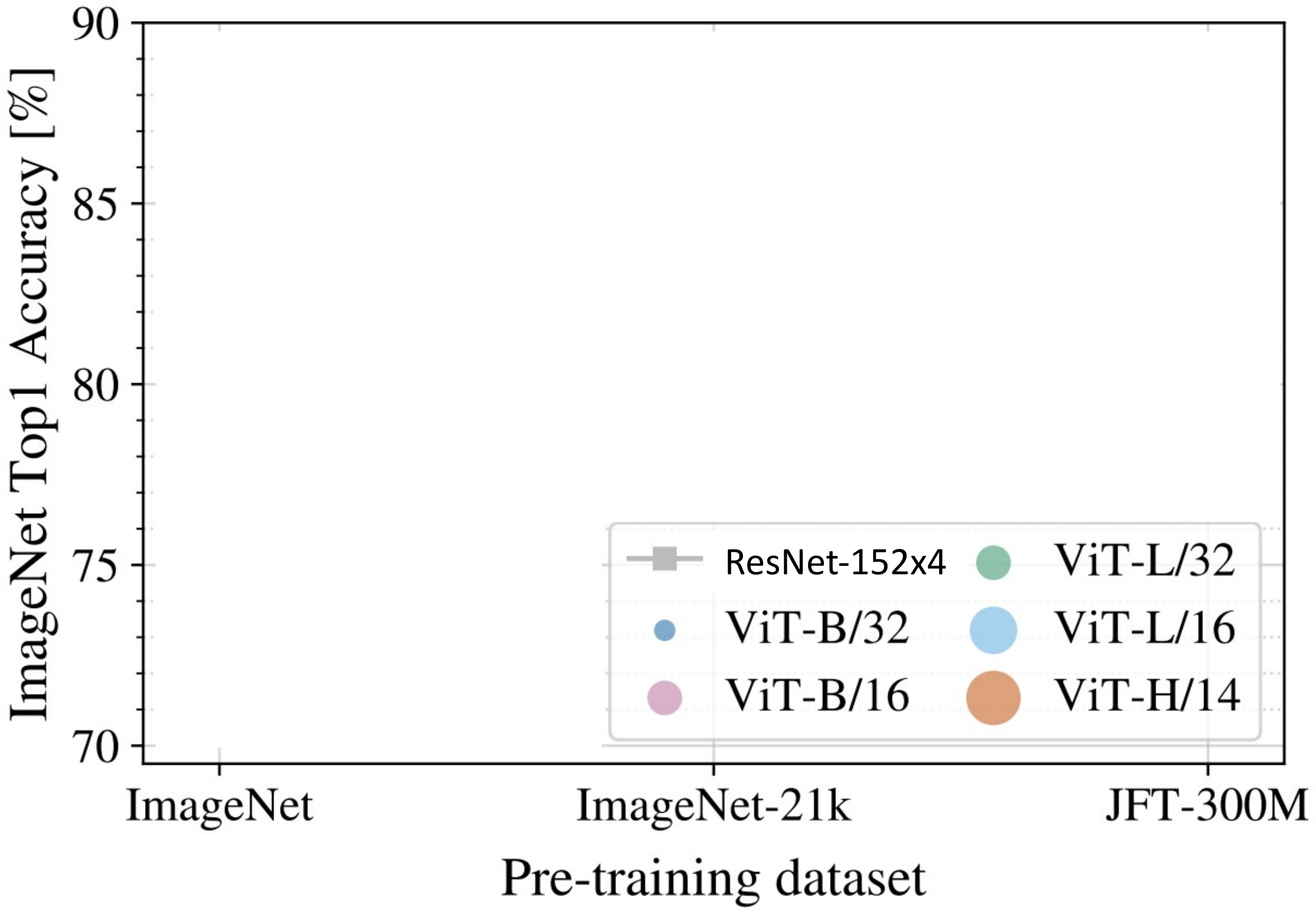
Vision Transformer (ViT) vs ResNets



B = Base
L = Large
H = Huge

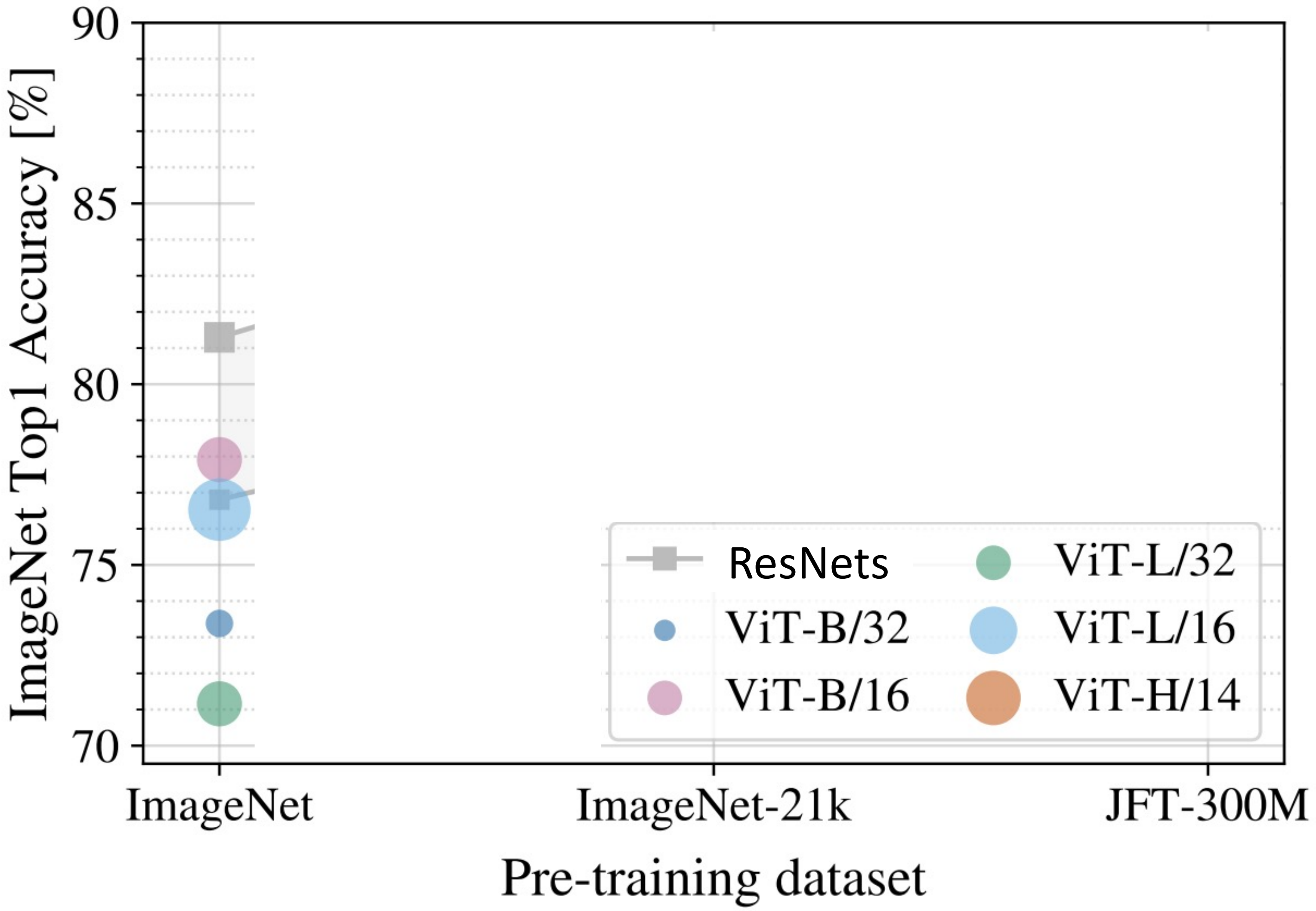
/32, /16, /14 is patch size; smaller patch size is a bigger model (more patches)

Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

Vision Transformer (ViT) vs ResNets

Recall: ImageNet dataset has 1k categories, 1.2M images

When trained on ImageNet, ViT models perform worse than ResNets



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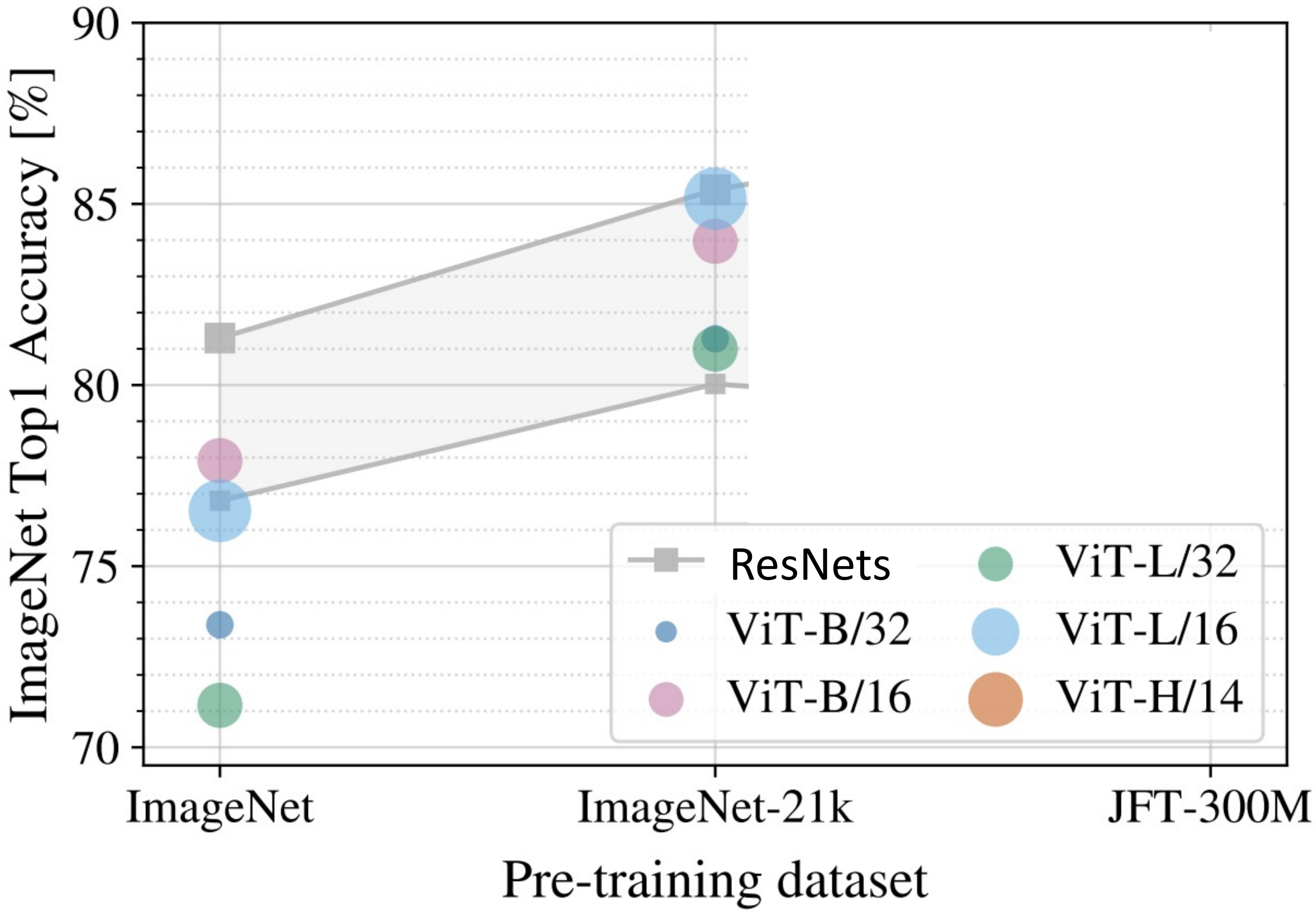
Vision Transformer (ViT) vs ResNets

ImageNet-21k has 14M images with 21k categories

If you pretrain on ImageNet-21k and fine-tune on ImageNet, ViT does better: big ViTs match big ResNets



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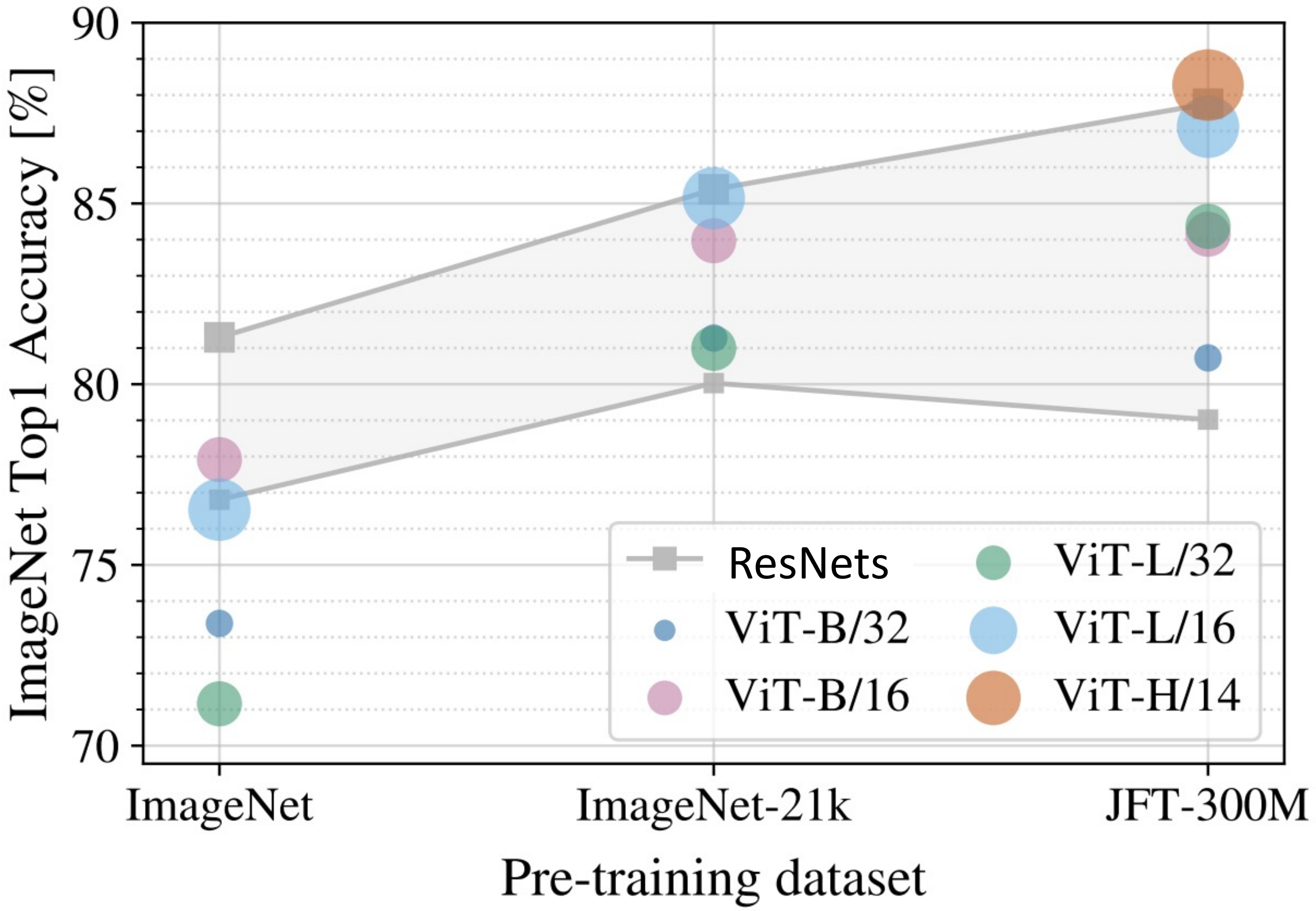
Vision Transformer (ViT) vs ResNets

JFT-300M is an internal Google dataset with 300M labeled images

If you pretrain on JFT and finetune on ImageNet, large ViTs outperform large ResNets



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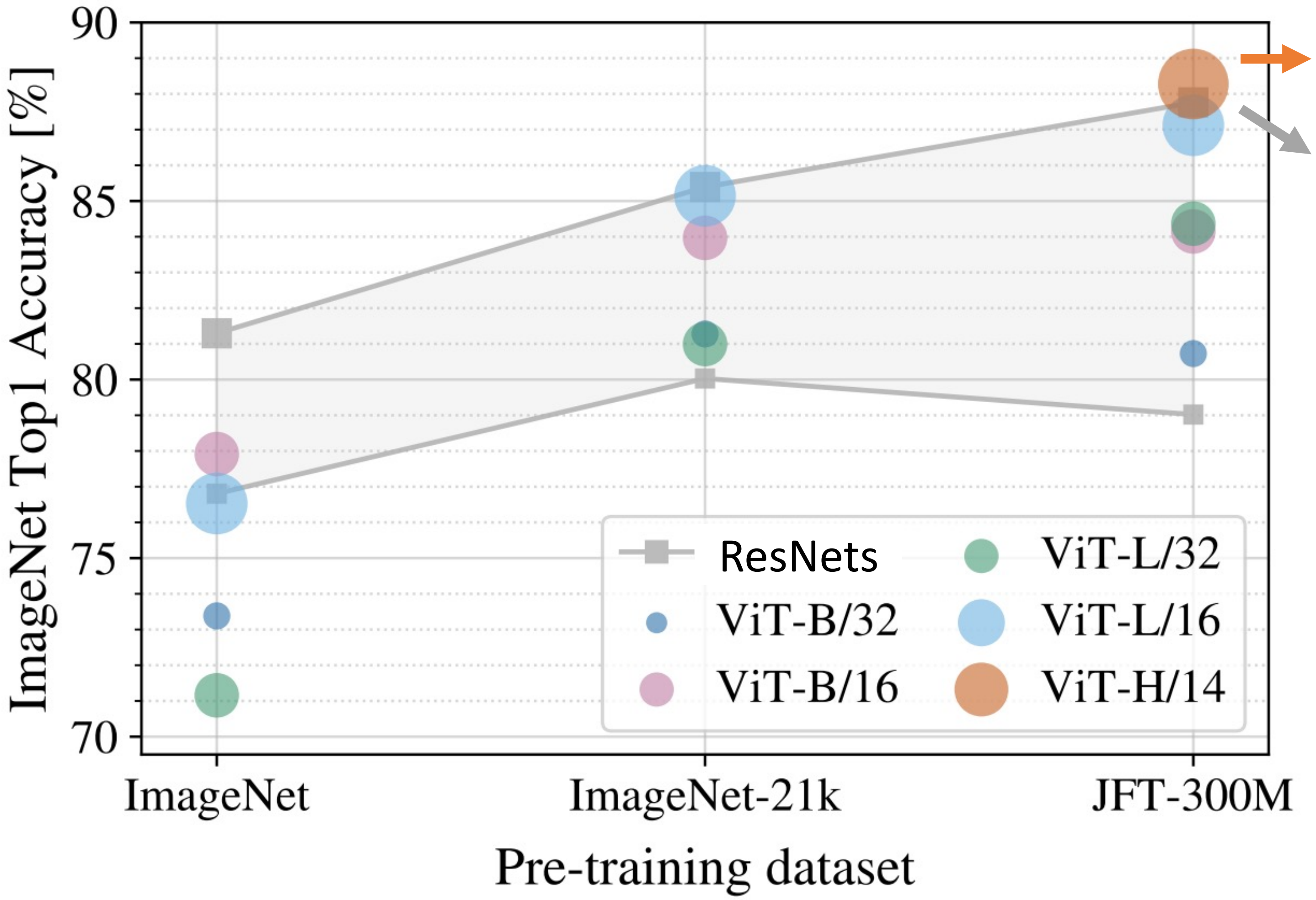

ViT: 2.5k TPU-v3 core days of training

ResNet: 9.9k TPU-v3 core days of training

ViTs make more efficient use of GPU / TPU hardware (matrix multiply is more hardware-friendly than conv)

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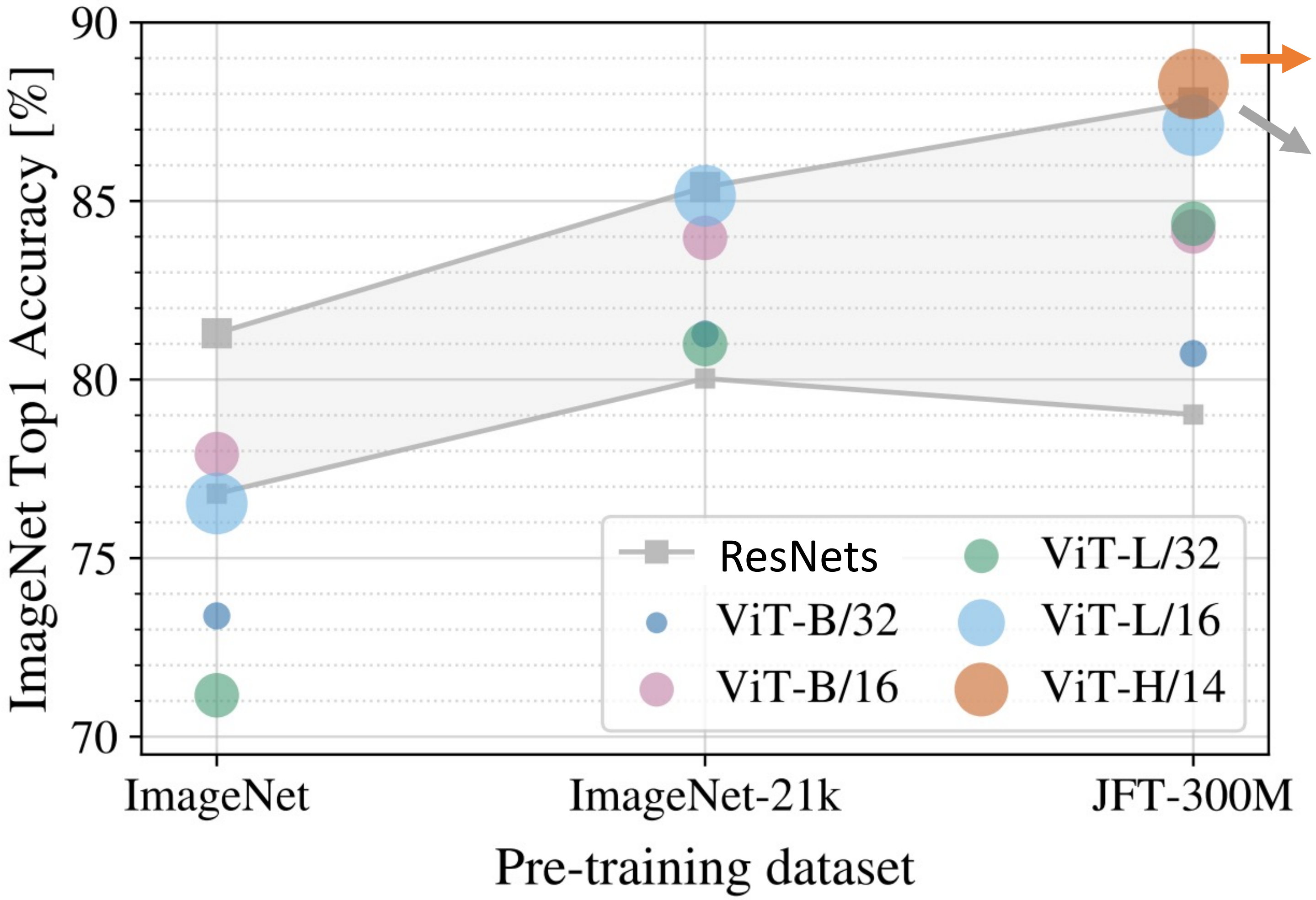
Vision Transformer (ViT) vs ResNets

Claim: ViT models have "less inductive bias" than ResNets, so need more pretraining data to learn good features

(Not sure I buy this explanation: "inductive bias" is not a well-defined concept we can measure!)



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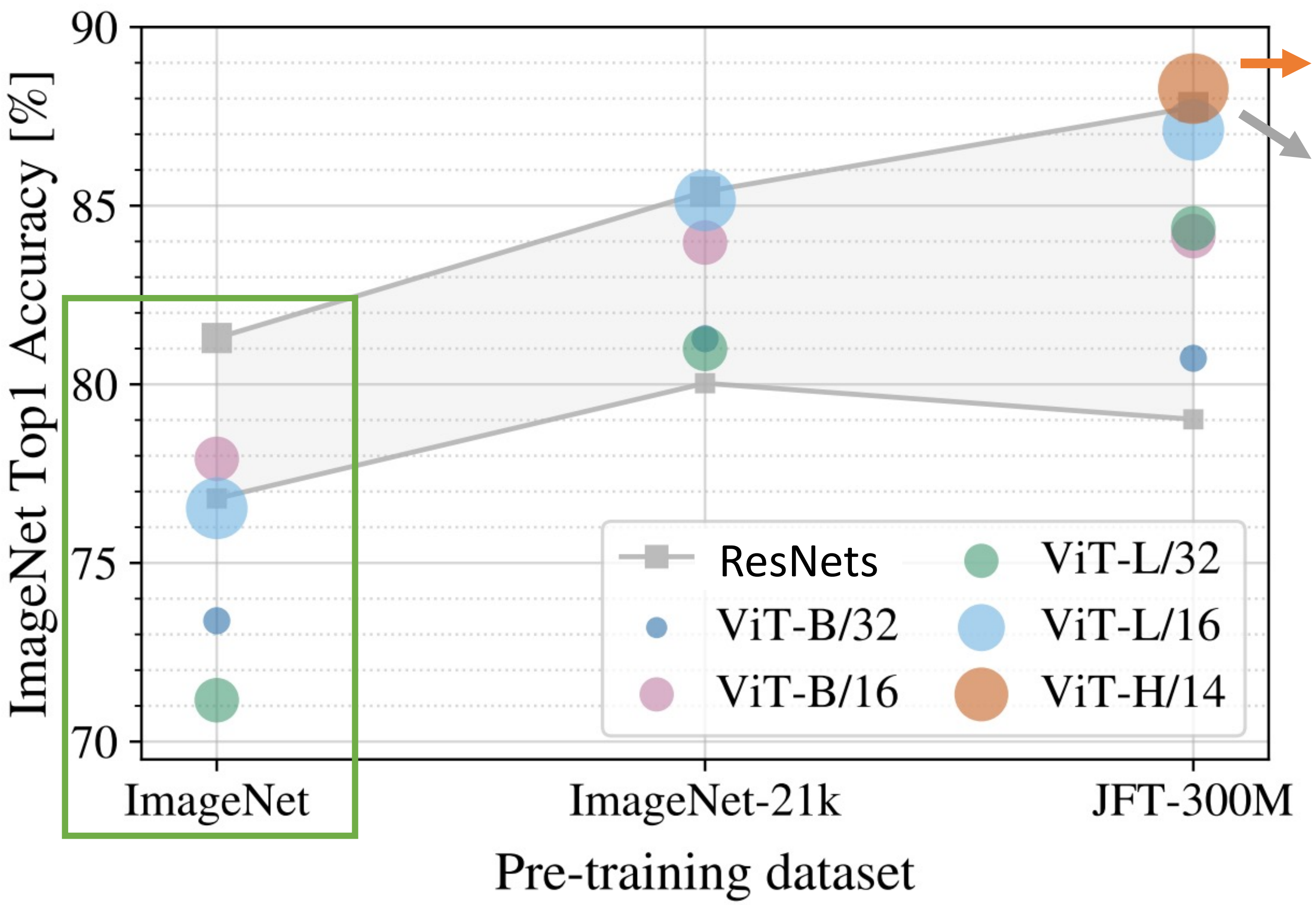
Vision Transformer (ViT) vs ResNets

How can we improve the performance of ViT models on ImageNet?



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