Lecture 23: Recent architectures

Transformer slides from S. Lazebnik

Announcements

- Mon. Dec. 11: 10:30am - 1:30pm in FXB1109
- Mon. Dec. 11: 2:30pm - 4:30pm over Zoom
- Tues. Dec. 12: 10:30am - 1:30pm in FXB1109

- In-person split in two halves (e.g., 10:30-12pm, 12pm - 1:30pm), so you can leave for lunch if you want.

- Video submission option for those who can't make it (due on Dec. 11 at **noon**), with explanation for why you can't come.

Today

- Neural fields
- Transformers for vision

3D view synthesis

Input views

Create model

Render new views

What representation should we use?

[Source: Mildenhall et al., “NeRF”, 2020]

Idea #1: Image-based rendering

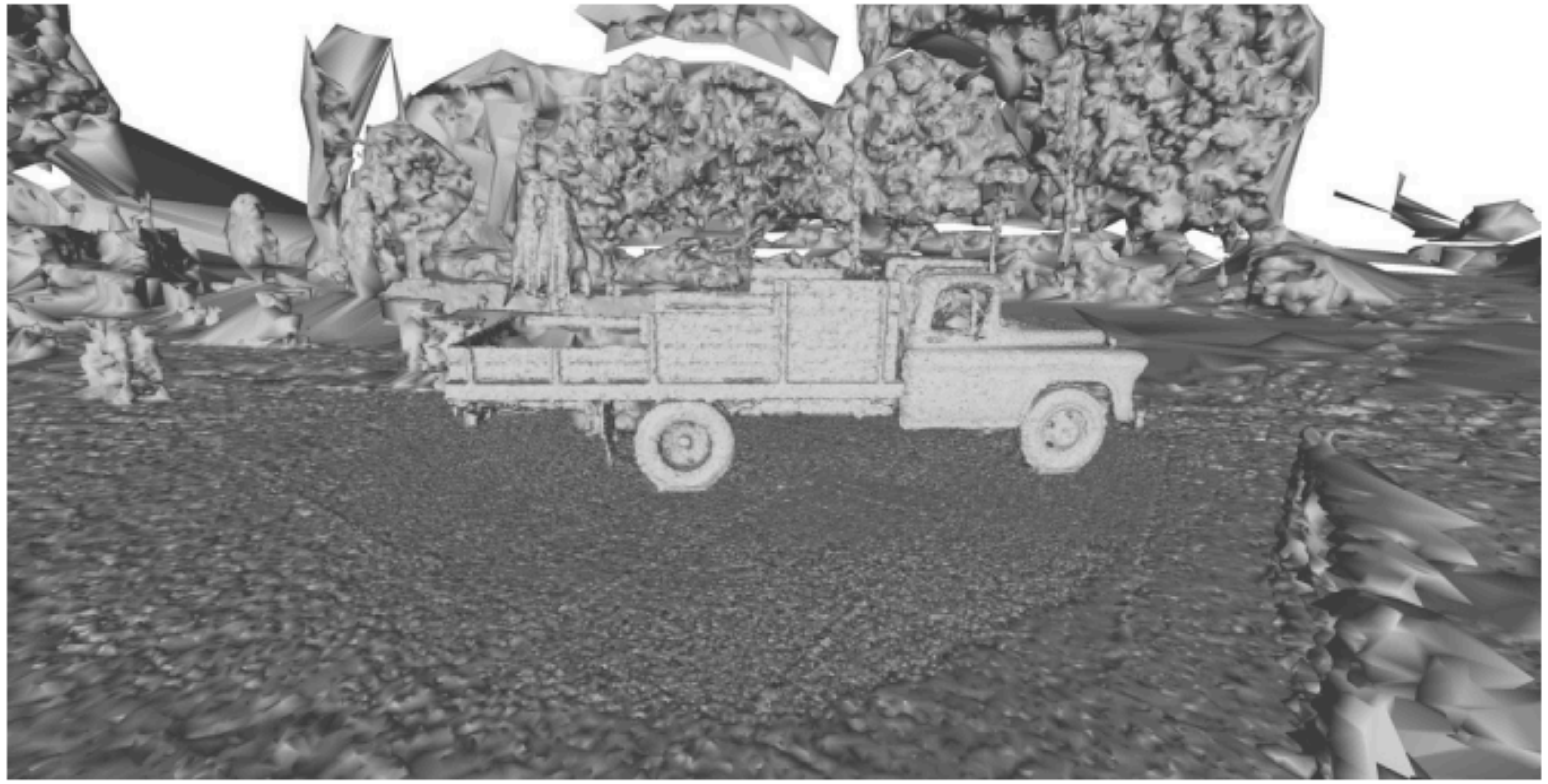
Point cloud
(reconstructed with SfM + multi-view stereo)

→ View from a different angle

[Riegler and Koltun, 2020]

Idea #1: Image-based rendering

Point cloud

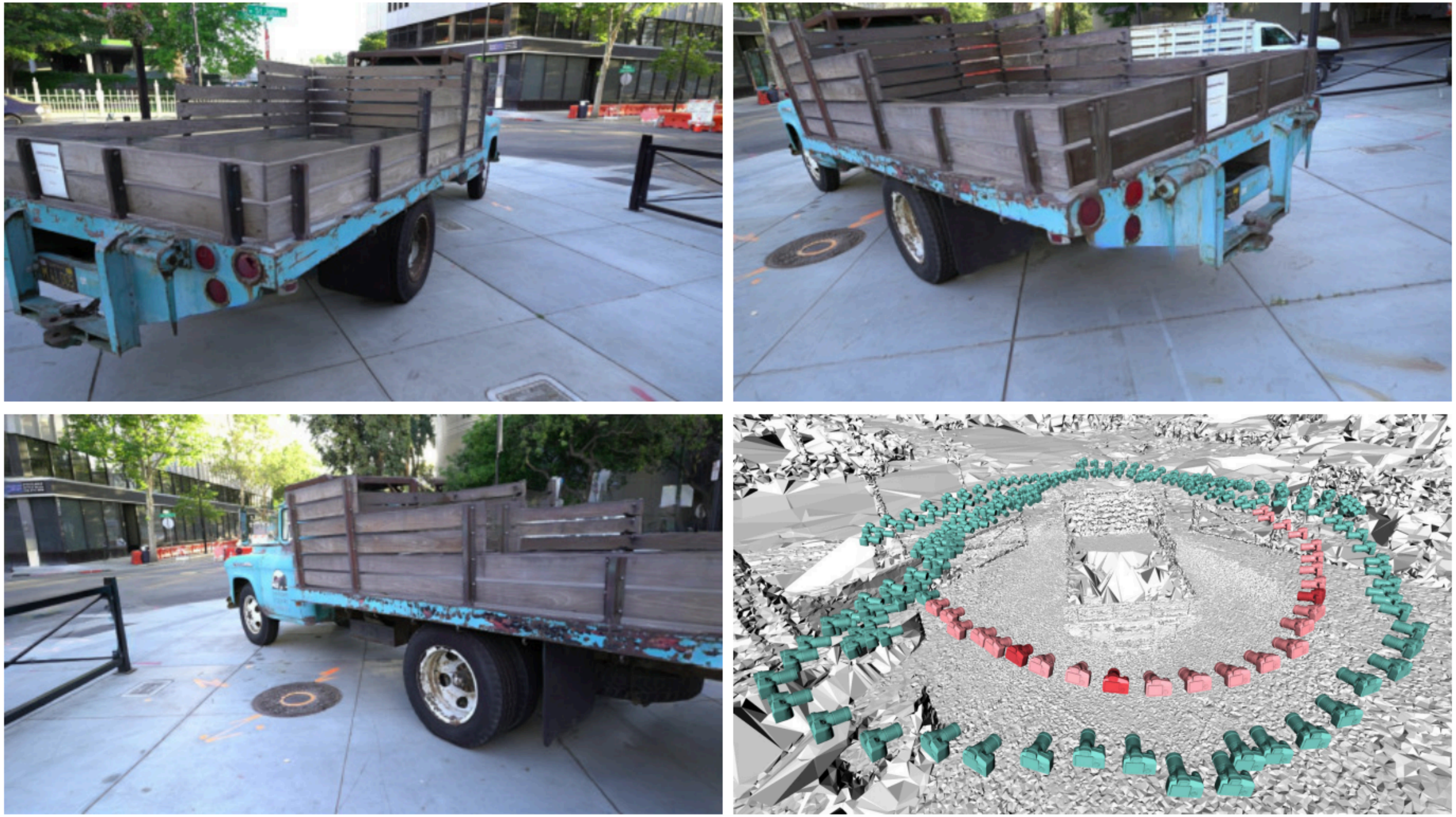


Proxy geometry (a mesh)

To synthesize a new view, select colors from existing views using proxy geometry.

[Riegler and Koltun, 2020]

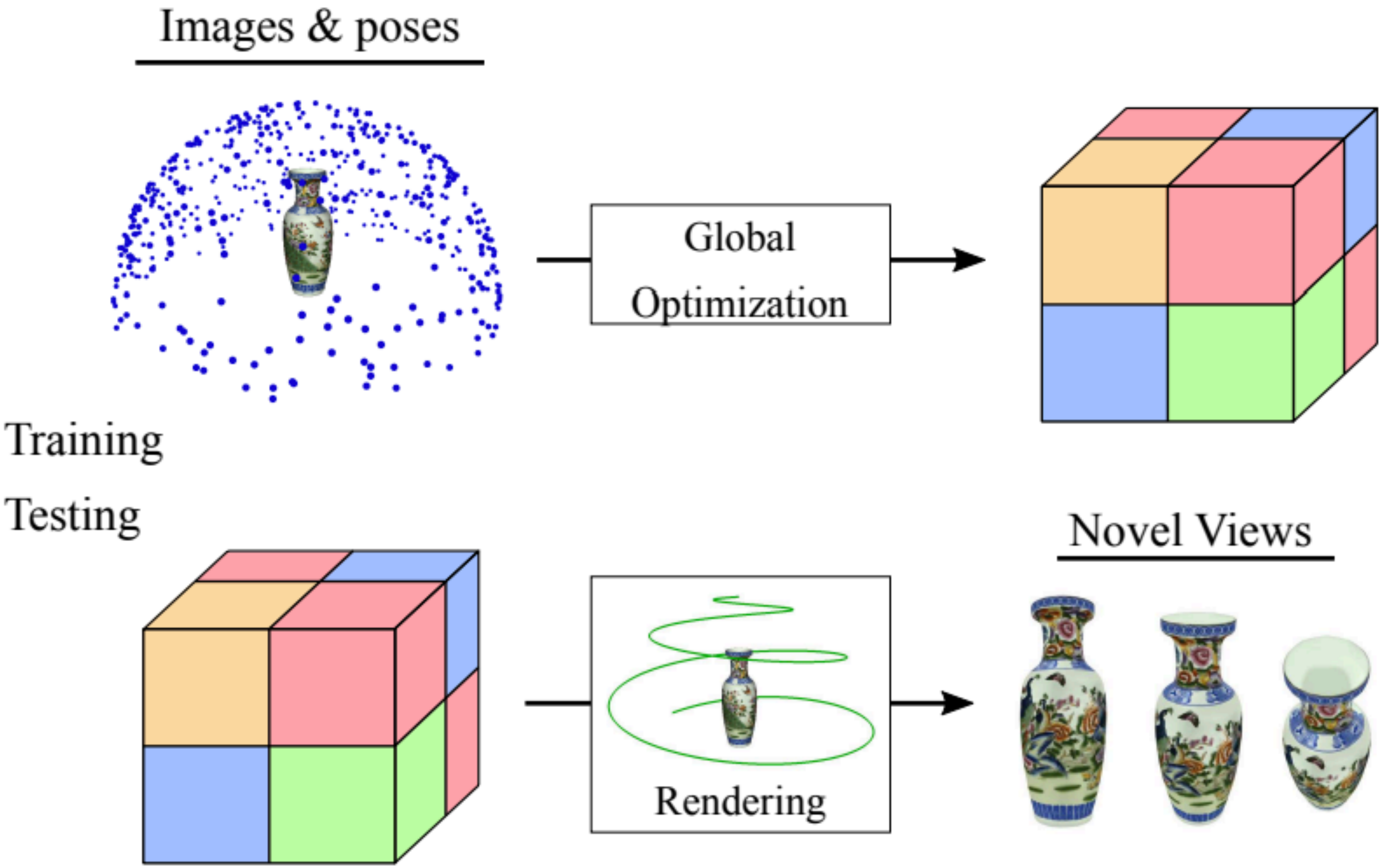
Idea #1: Image-based rendering



7

[Riegler and Koltun, 2020]

Idea #2: voxel representation



[Source: Sitzmann et al., “DeepVoxels”, 2019]

Idea #2: voxel representation

Input views

$\rightarrow$

Position, Viewing direction, Color, Density

$$\underbrace{V[x, y, z}_{\text{Position}}, \underbrace{\theta, \phi}_{\text{Viewing direction}}] = (\underbrace{R, G, B}_{\text{Color}}, \underbrace{\sigma}_{\text{Density}})$$

Idea #2: voxel representation

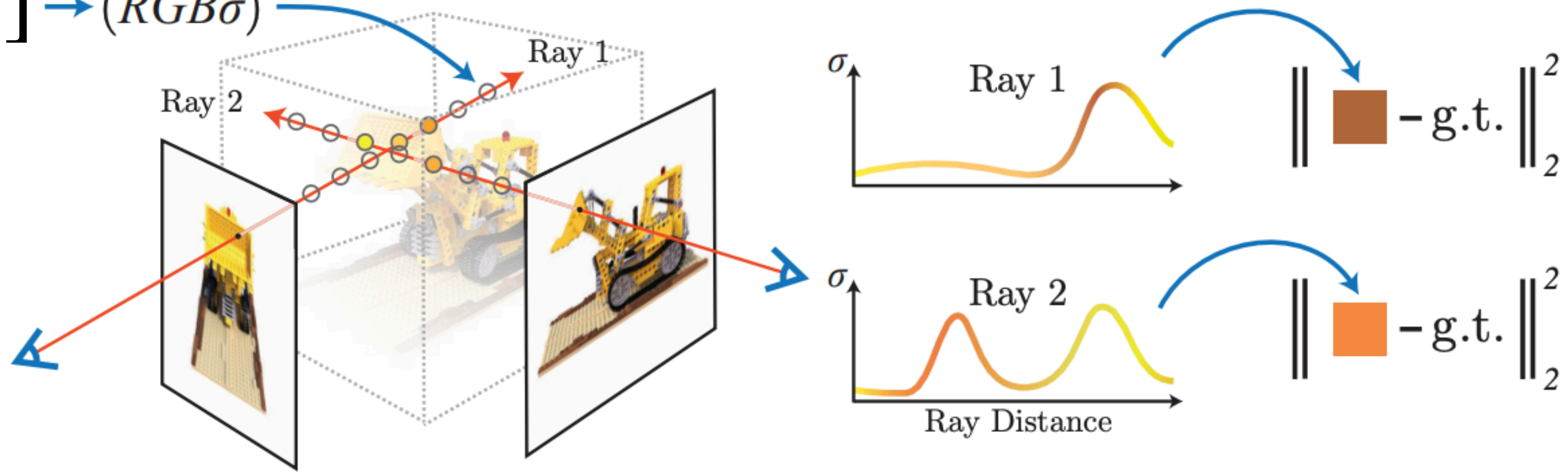
Input views

Position Viewing direction Color Density

$$V[x, y, z, \theta, \phi] = (R, G, B, \sigma)$$

Training:

$$V[x, y, z, \theta, \phi] \rightarrow (RGB\sigma)$$



Problem: A huge table! $\mathcal{O}(D^3A^2)$

Idea #3: neural radiance field (NeRF)

Input views

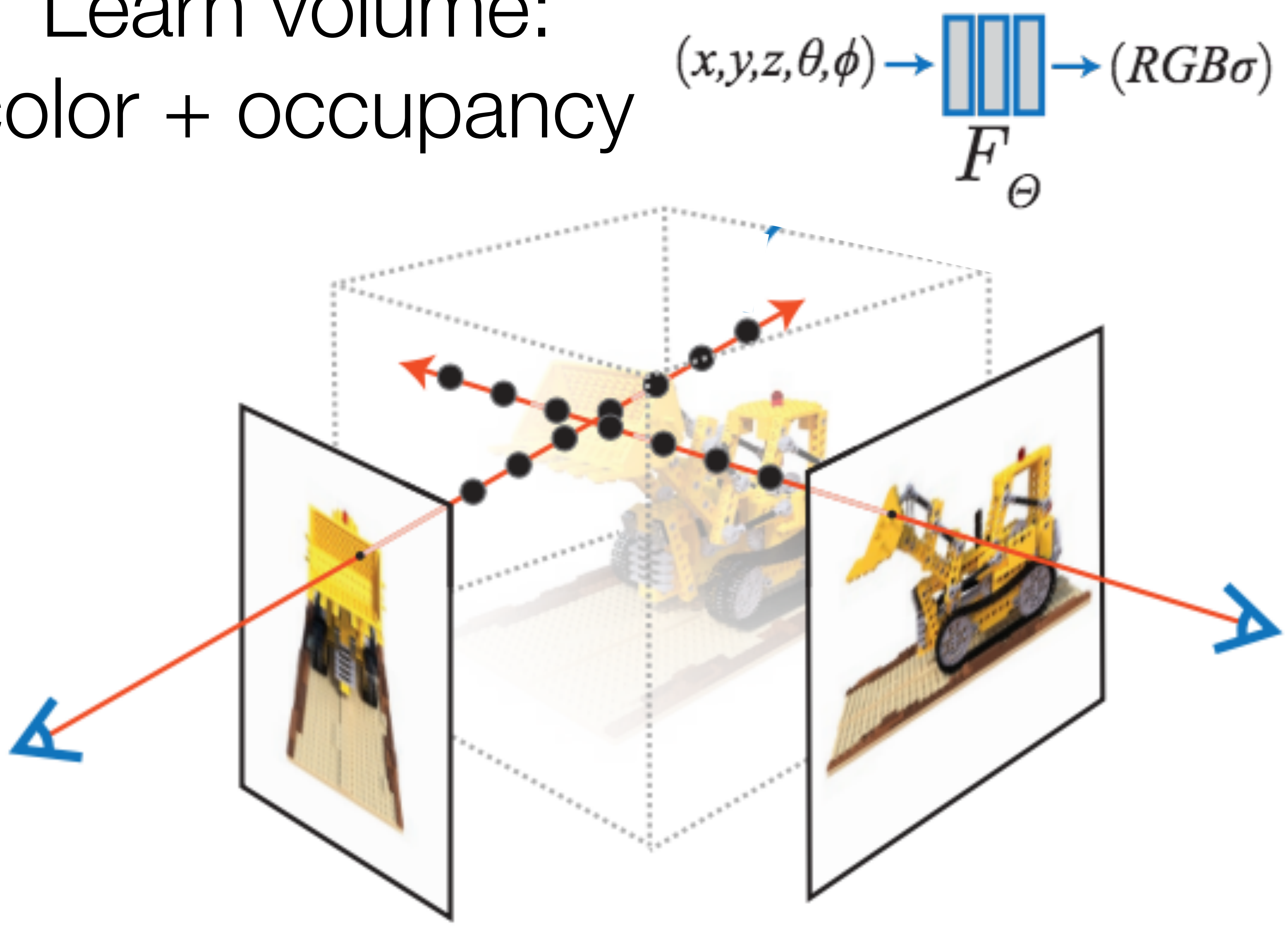
$$\rightarrow \quad F_\Theta(x, y, z, \theta, \phi) = (R, G, B, \sigma)$$

- Represent using a **neural radiance field**.
- Function that maps a (x, y, z, θ, ϕ) to a color and density.
- Typically parameterized as a multi-layer perceptron (MLP)
- Goal: find parameters Θ for MLP that explain the images

Idea #3: neural radiance field (NeRF)

Learn volume:
color + occupancy

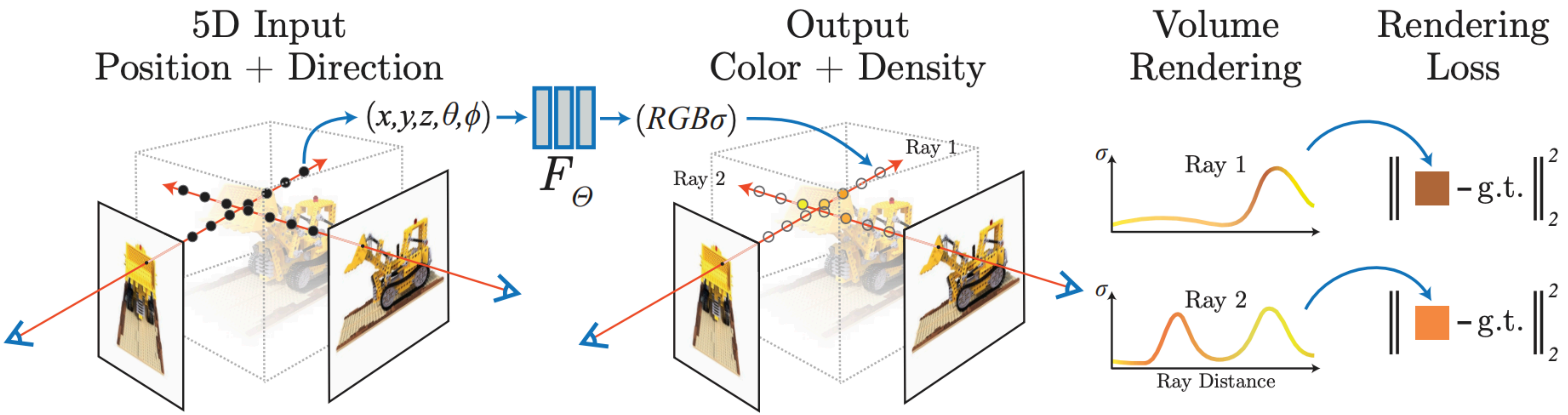
3D scene



Viewpoints

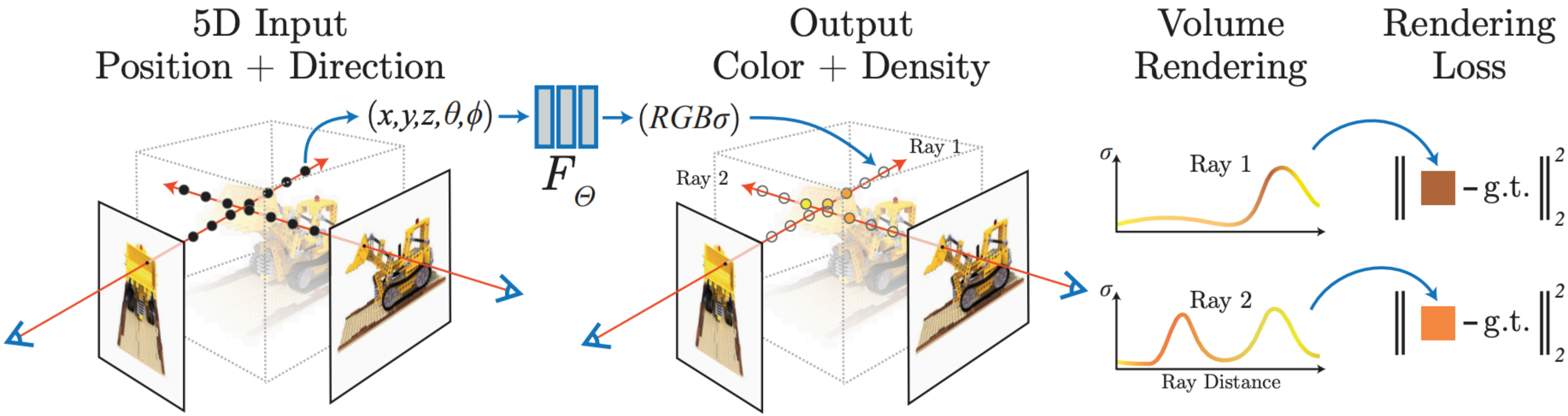
[Mildenhall*, Srinivasan*, Tanick*, et al., Neural radiance fields, 2020]

Learning a NeRF



[Source: Mildenhall et al., "NeRF", 2020]

Neural rendering



$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))\mathbf{c}(\mathbf{r}(t),\mathbf{d})dt\,,\ \text{where } T(t) = \exp\left(-\int_{t_n}^{t}\sigma(\mathbf{r}(s))ds\right)$$

Ray: $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ For color c and density σ.

[Source: Mildenhall et al., “NeRF”, 2020]

Neural rendering

Color for ray $\mathbf{r}$

$$\boxed{C(\mathbf{r})} = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))\mathbf{c}(\mathbf{r}(t), \mathbf{d})dt\,, \text{ where } T(t) = \exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right)$$

Ray: $\boxed{\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}}$ For color c and density σ.

A point distance t along $\mathbf{r}$, centered at

[Source: Mildenhall et al., “NeRF”, 2020]

Neural rendering

Color for ray $\mathbf{r}$

Weight

Color at 3D point $\mathbf{r}(t)$

and direction $\mathbf{d}$

$$\boxed{C(\mathbf{r})} = \int_{t_n}^{t_f} \boxed{T(t)\sigma(\mathbf{r}(t))}\boxed{\mathbf{c}(\mathbf{r}(t), \mathbf{d})}dt\,, \text{ where } T(t) = \exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right)$$

Ray: $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ For color c and density $\boldsymbol{\sigma}$.

[Source: Mildenhall et al., “NeRF”, 2020]

Neural rendering

Density at point $\mathbf{r}(t)$

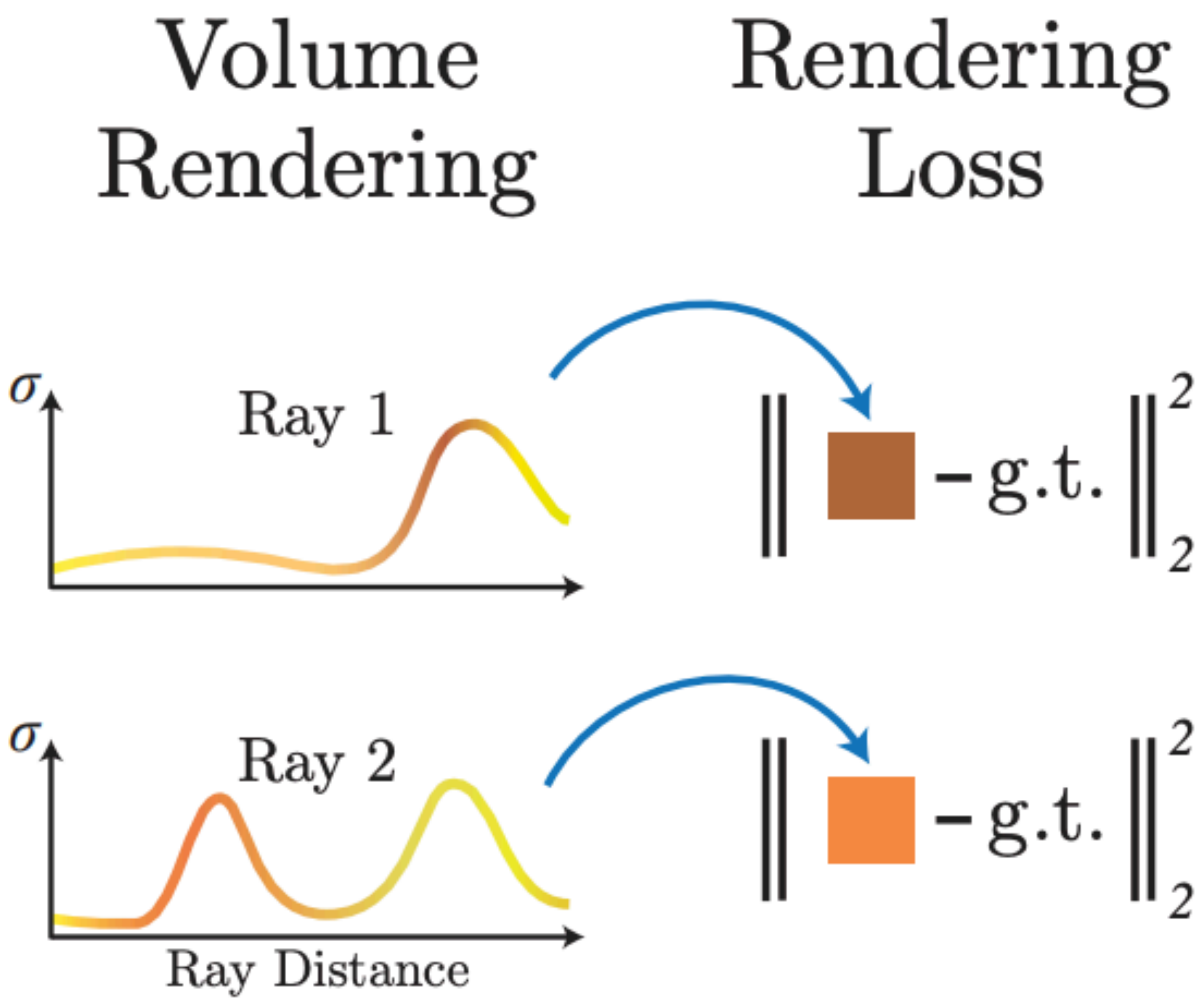
Probability that ray hasn't been absorbed

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\boxed{\sigma(\mathbf{r}(t))}\mathbf{c}(\mathbf{r}(t), \mathbf{d})dt\,, \text{ where } T(t) = \boxed{\exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right)}$$

Ray: $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ For color c and density $\boldsymbol{\sigma}$.

[Source: Mildenhall et al., "NeRF", 2020]

Loss function



$$\mathscr{L} = \sum_{\mathbf{r} \in \mathscr{R}} \| C(\mathbf{r}) - C_{gt}(\mathbf{r}) \|_2^2$$

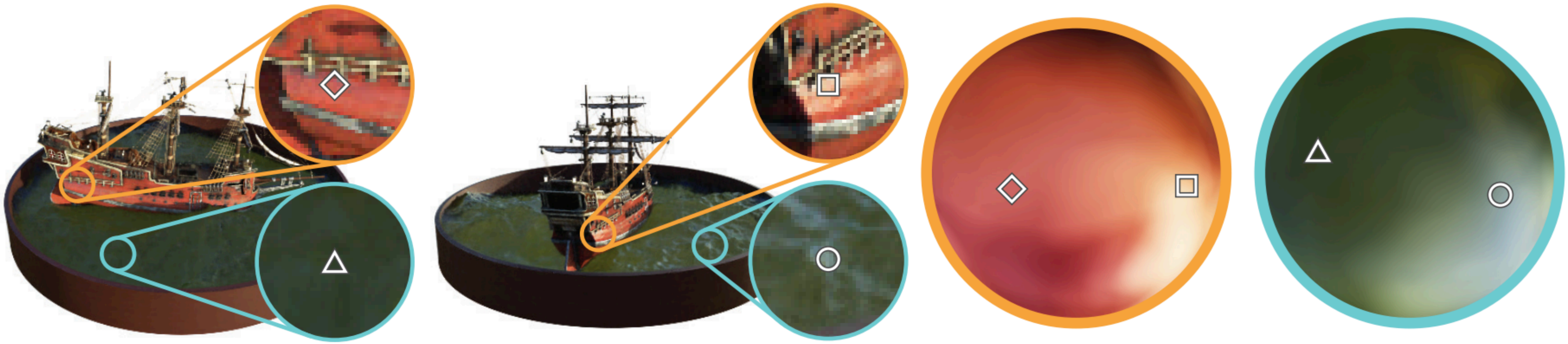
Minimize difference between predicted and observed colors.

In practice: coarse-to-fine and other tricks.

[Source: Mildenhall et al., "NeRF", 2020]

Implementation details

Why is it good to be view-dependent?



(a) View 1 (b) View 2 (c) Radiance Distributions

[Source: Mildenhall et al., “NeRF”, 2020]

Representing the inputs

Input views

$$\rightarrow \quad F_{\Theta}(x, y, z, \theta, \phi) = (R, G, B, \sigma)$$

- In theory, could just plug in 4 inputs x, y, z, θ, ϕ
- However, this leads to blurry results.
- Neural nets show a bias toward low frequency functions [Tancik et al., 2020]

Fourier features

Input views

$$\rightarrow \quad F_{\Theta}(x, y, z, \theta, \phi) = (R, G, B, \sigma)$$

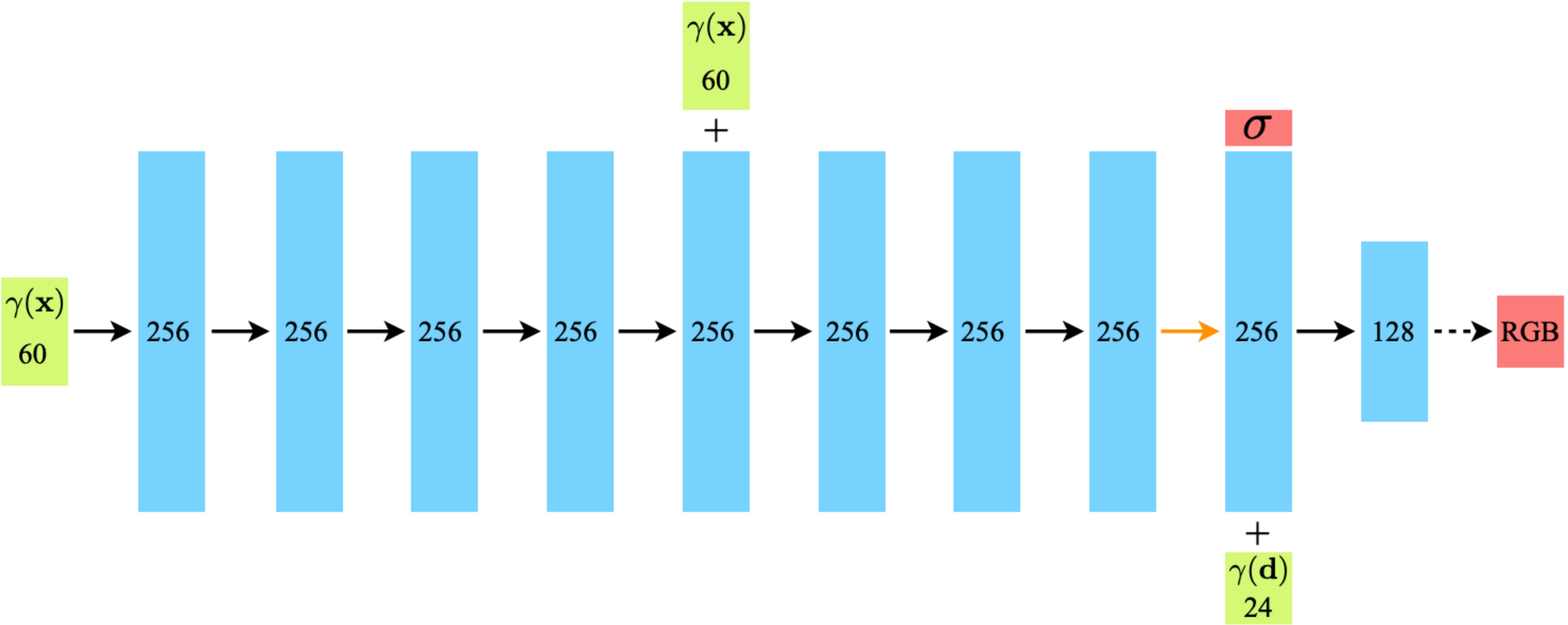
- Use a **positional encoding**. Given a scalar p, compute:

$$\gamma(p) = \left(\sin\left(2^0 \pi p\right), \cos\left(2^0 \pi p\right), \cdots, \sin\left(2^{L-1} \pi p\right), \cos\left(2^{L-1} \pi p\right) \right)$$

- Plug in the coordinate to sinusoids at different frequencies (e.g. L = 10).

[Source: Mildenhall et al., “NeRF”, 2020]

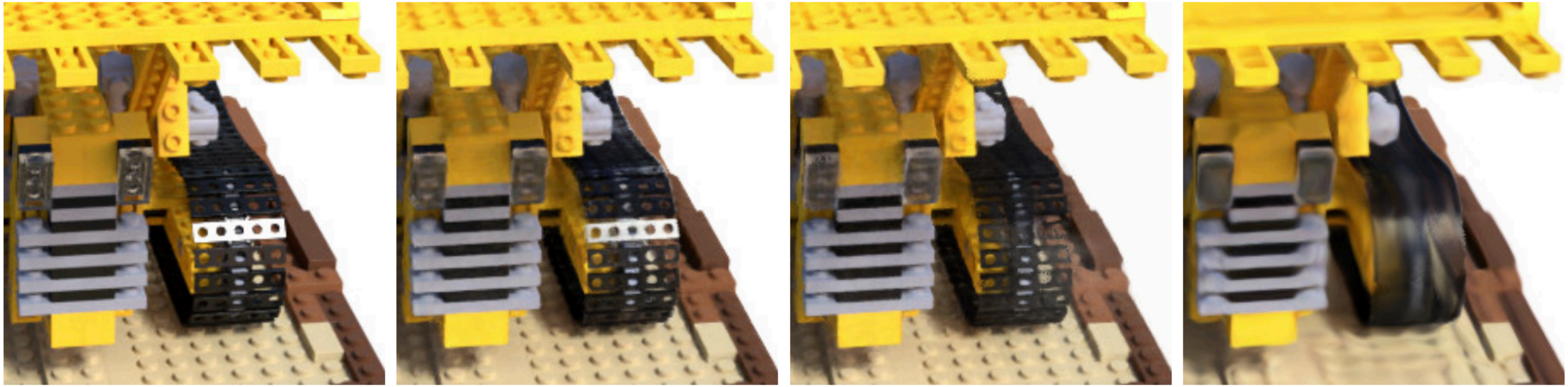
MLP architecture



$$\gamma(p) = \left(\sin\left(2^0 \pi p\right), \cos\left(2^0 \pi p\right), \cdots, \sin\left(2^{L-1} \pi p\right), \cos\left(2^{L-1} \pi p\right) \right)$$

[Source: Mildenhall et al., “NeRF”, 2020]

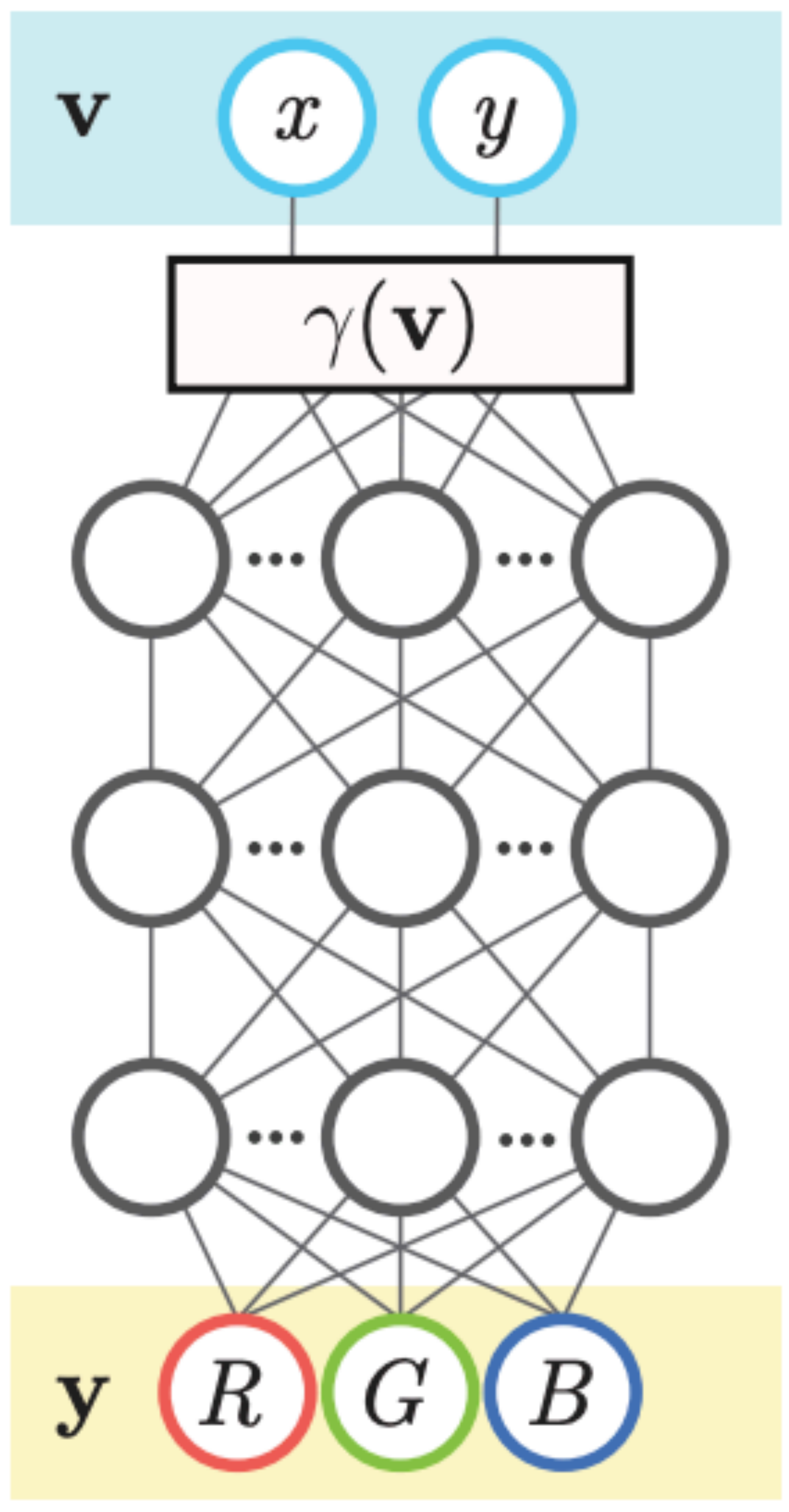
Results for a novel viewpoint



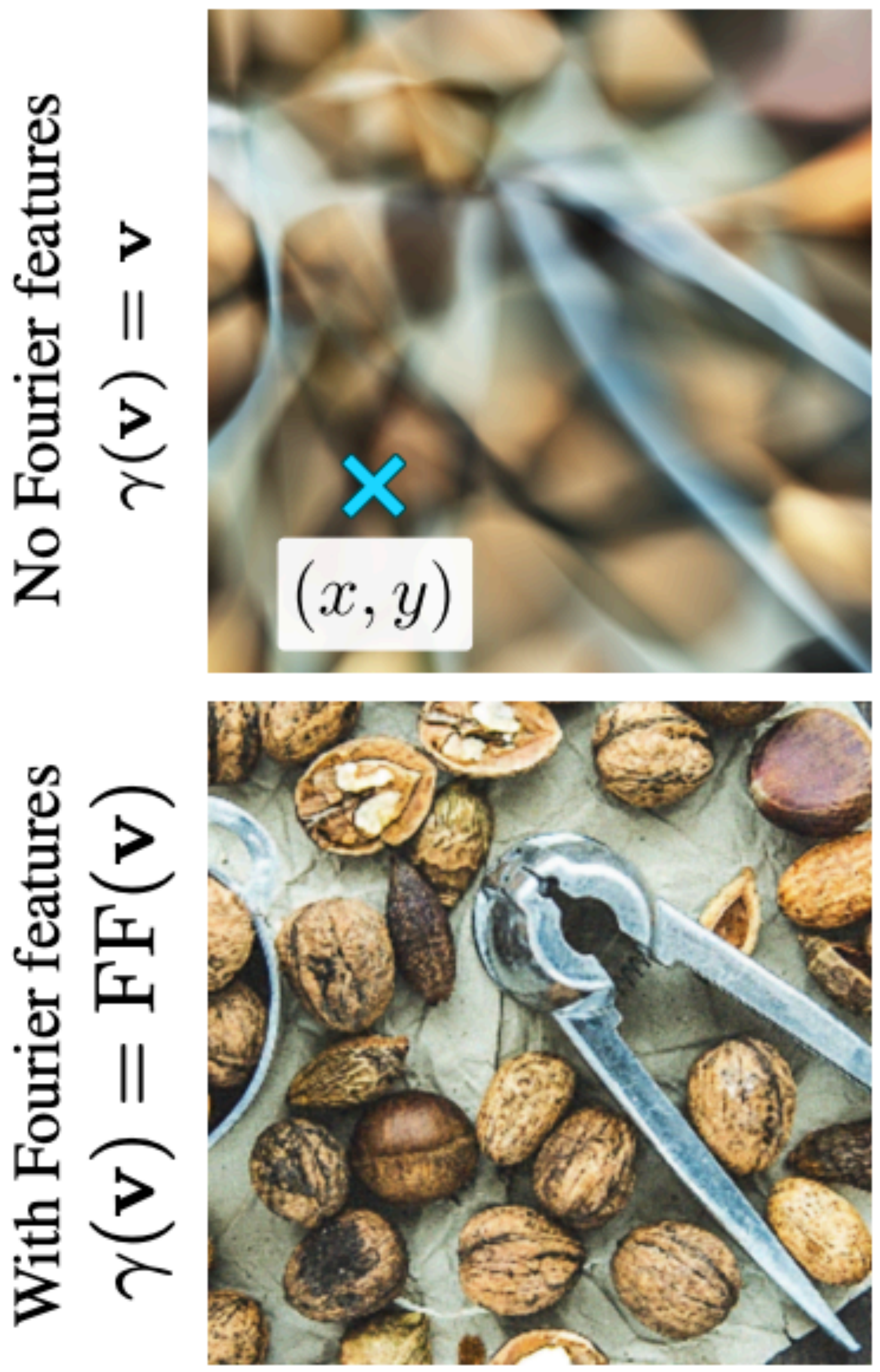
Ground Truth | Complete Model | No View Dependence | No Positional Encoding

[Source: Mildenhall et al., “NeRF”, 2020]

Fourier features



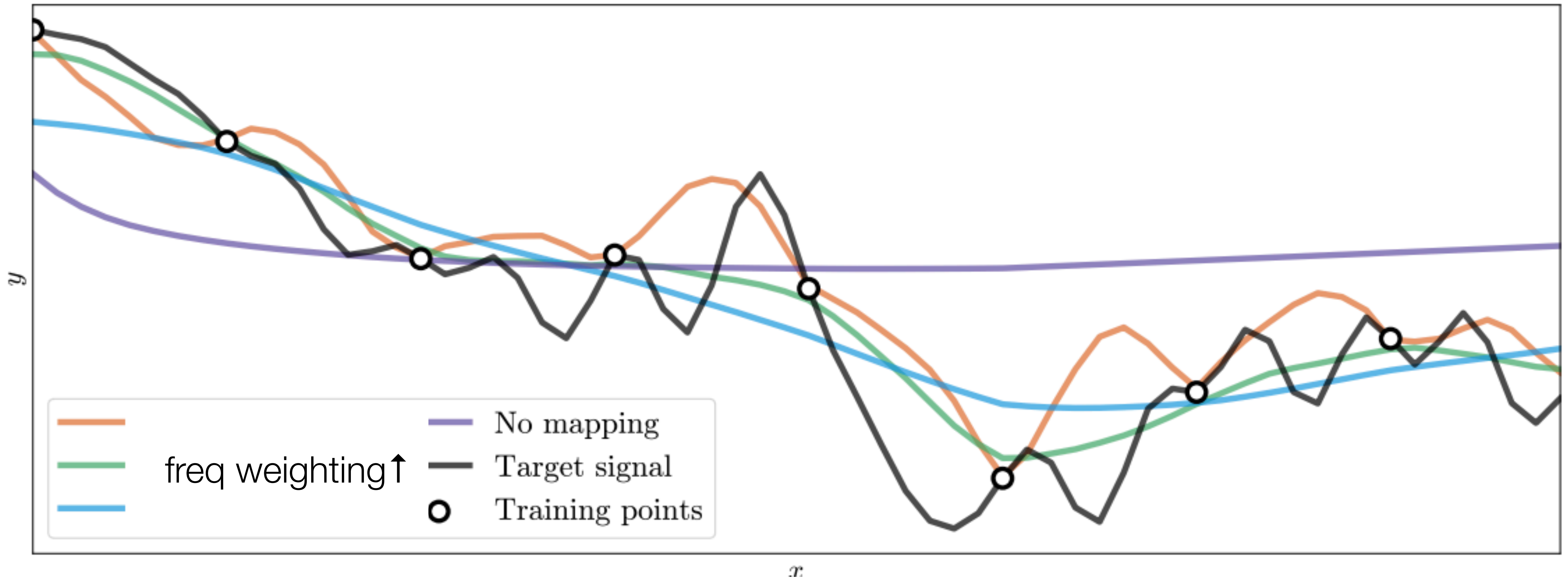
(a) Coordinate-based MLP



(b) Image regression

$(x,y) \rightarrow$ RGB

- Neural nets have trouble learning high frequency functions
- This mapping explicitly represents different frequencies (forces net to pay more attention high frequencies)



See [Tancik et al., "Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains", 2020]

Results

[Mildenhall*, Srinivasan*, Tanick*, et al. 2020]

Results

[Mildenhall*, Srinivasan*, Tanick*, et al. 2020]

Results

[Mildenhall*, Srinivasan*, Tanick*, et al. 2020]

NeRF state-of-the-art

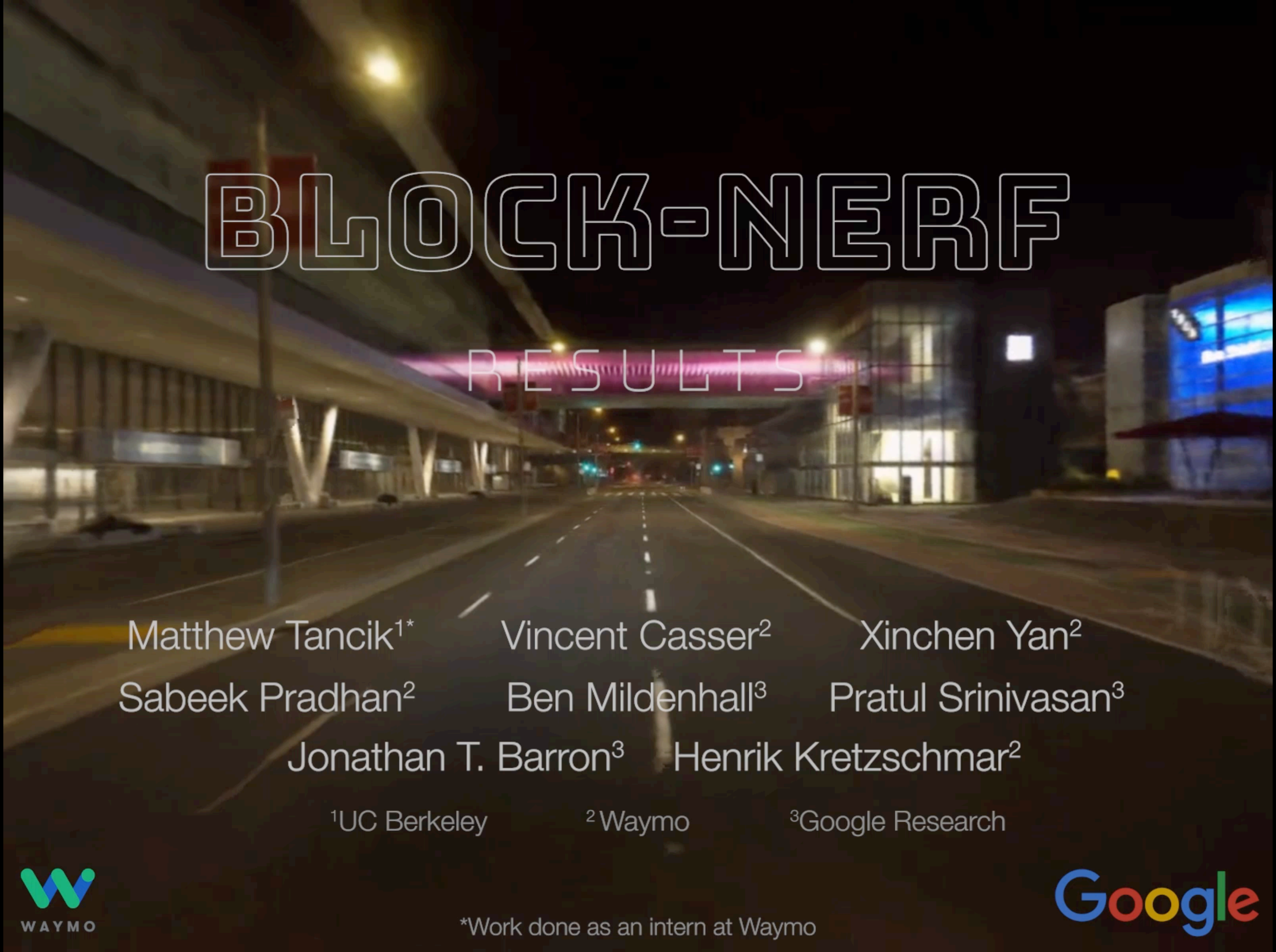
[Barron et al., “Zip-NeRF: Anti-Aliased Grid-Based Neural Radiance Fields. 2023]

Extension: internet photo collections

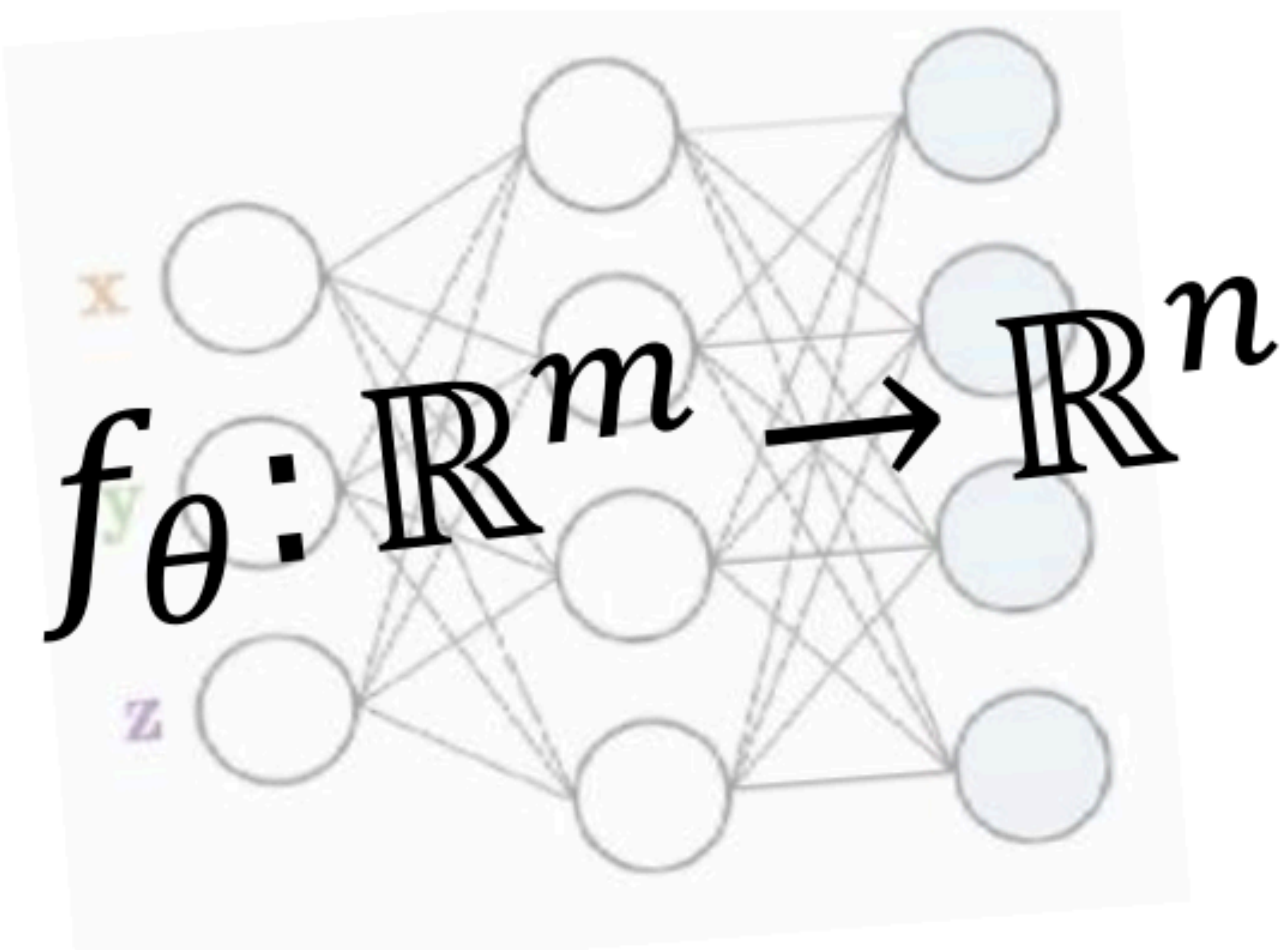
[Martin-Brualla, Radwan et al. “NeRF in the Wild”, 2020]

Extension: internet photo collections

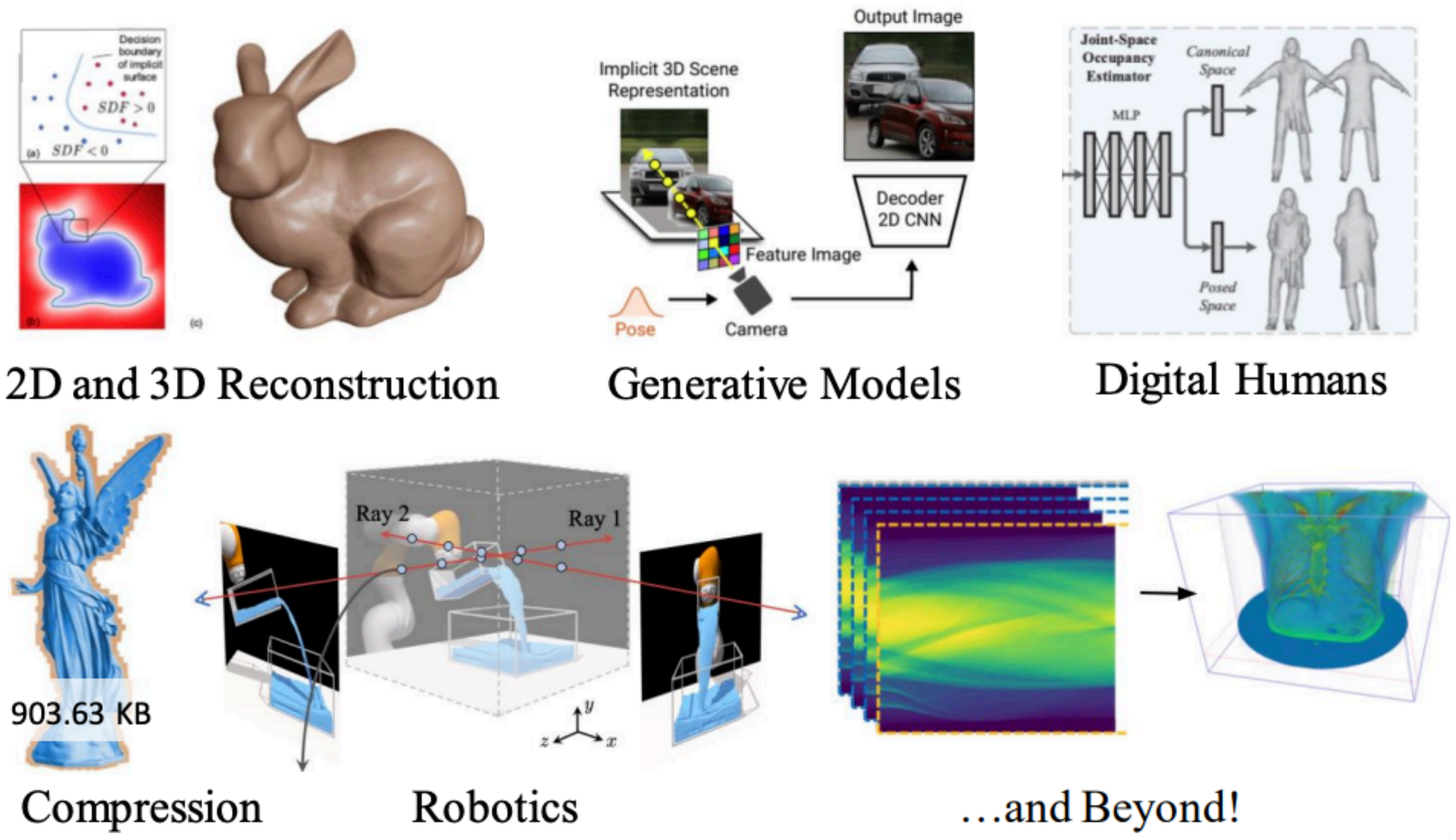
[Martin-Brualla, Radwan et al. "NeRF in the Wild", 2020]


BLOCK-NERF
RESULTS
Matthew Tancik[1*] Vincent Casser[2] Xinchen Yan[2]
Sabeek Pradhan[2] Ben Mildenhall[3] Pratul Srinivasan[3]
Jonathan T. Barron[3] Henrik Kretzschmar[2]
[1]UC Berkeley [2]Waymo [3]Google Research
WAYMO
Google
*Work done as an intern at Waymo

Lots of other applications



Neural field



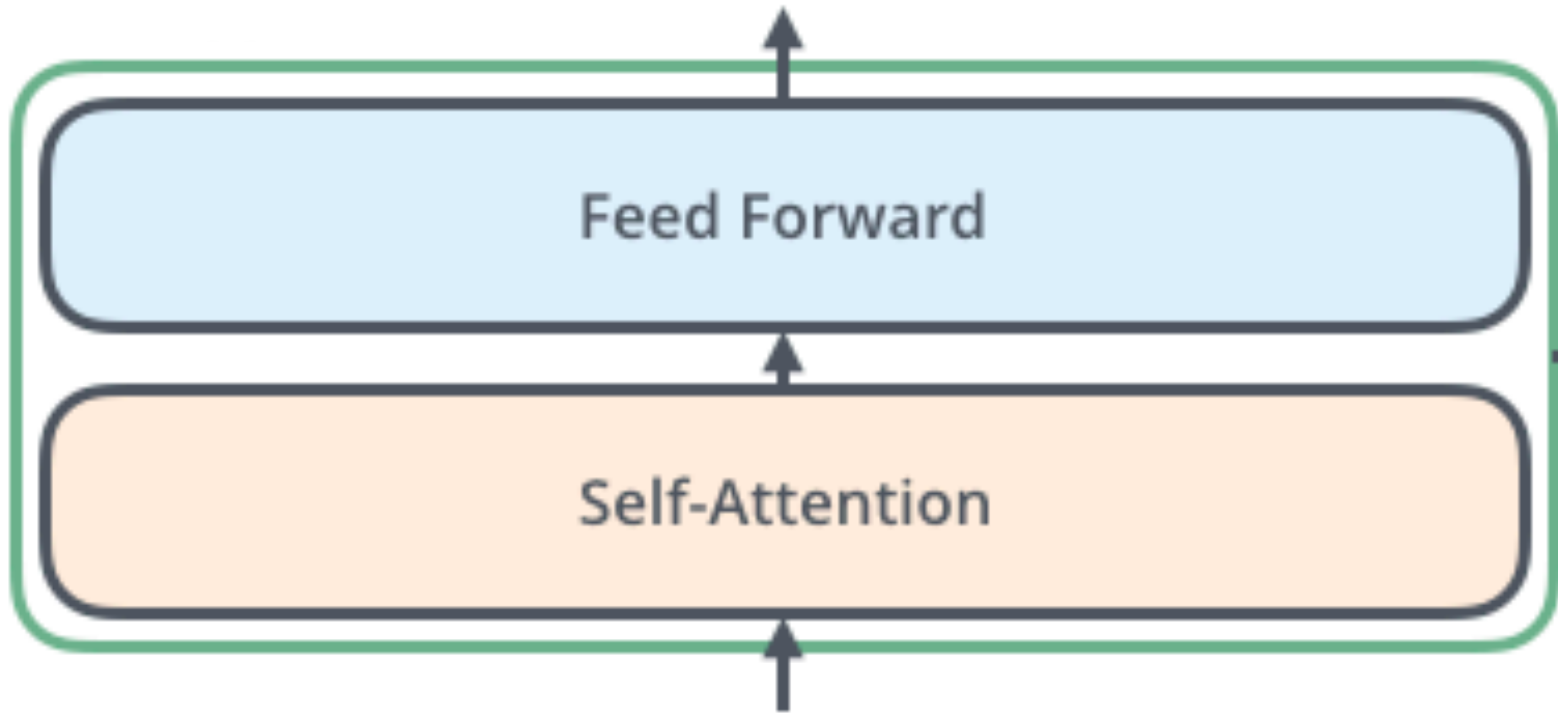
[Xie et al., "Neural Fields in Visual Computing and Beyond", 2021]

Today

- Neural fields
- **Transformers for vision**

Recall: Transformers

- Build whole model out of self-attention
- Uses only point-wise processing and attention (no recurrent units or convolutions)



A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. Gomez, L. Kaiser, I. Polosukhin, [Attention is all you need](), NeurIPS 2017

Source: S. Lazebnik

[Image source]()

Self-attention layer

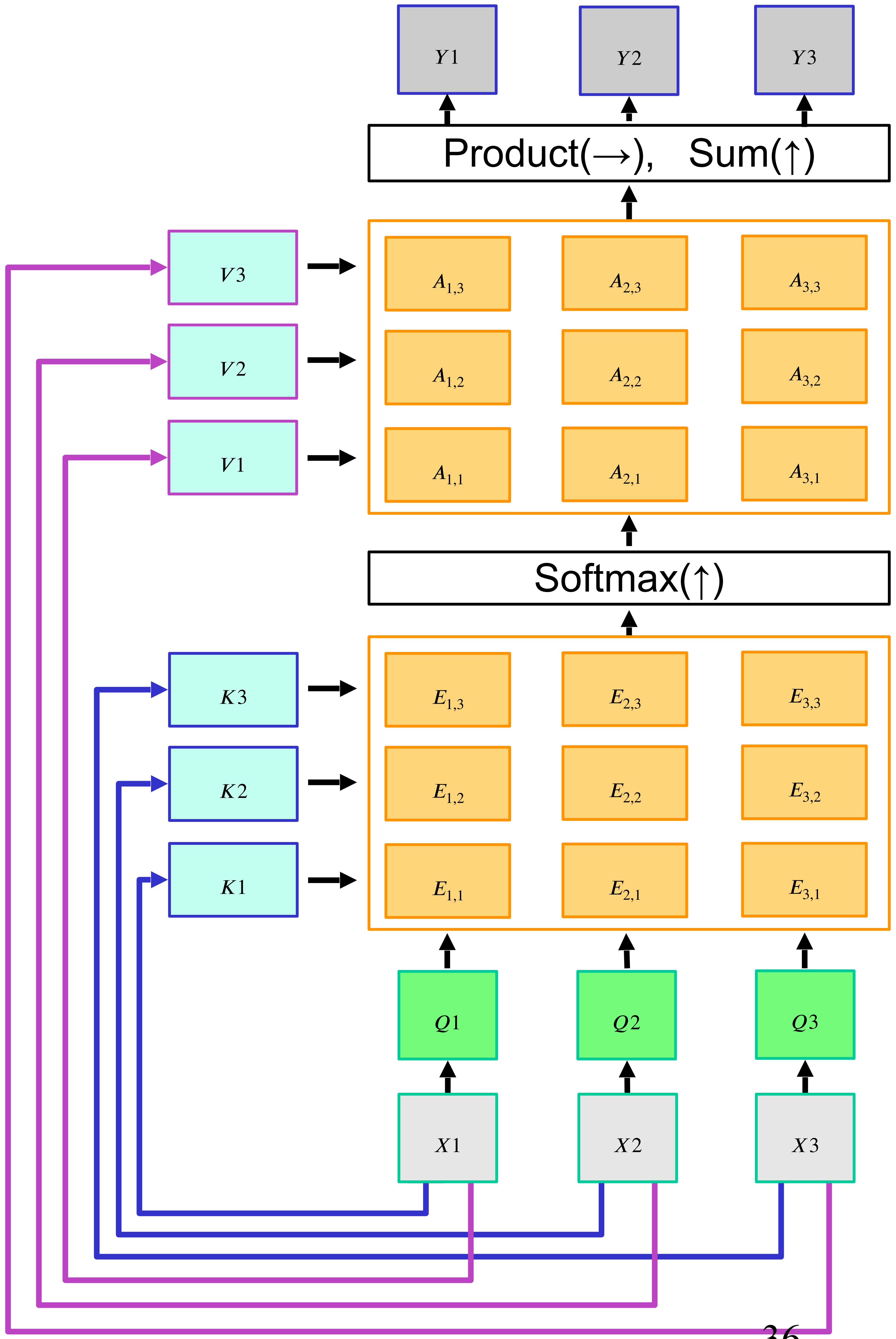
- Query vectors: $Q = XW_Q$
- Key vectors: $K = XW_K$
- Value vectors: $V = XW_V$
- Similarities: *scaled dot-product attention*

$$E_{i,j} = \frac{(Q_i \cdot Kj)}{\sqrt{D}} \quad \text{or} \quad E = QK^T / \sqrt{D}$$

(D is the dimensionality of the keys)

- Attn. weights: $A = \mathrm{softmax}(E, \dim = 1)$
- Output vectors:

$$Y_i = \sum_j A_{i,j} V_j \quad \text{or} \quad Y = AV$$

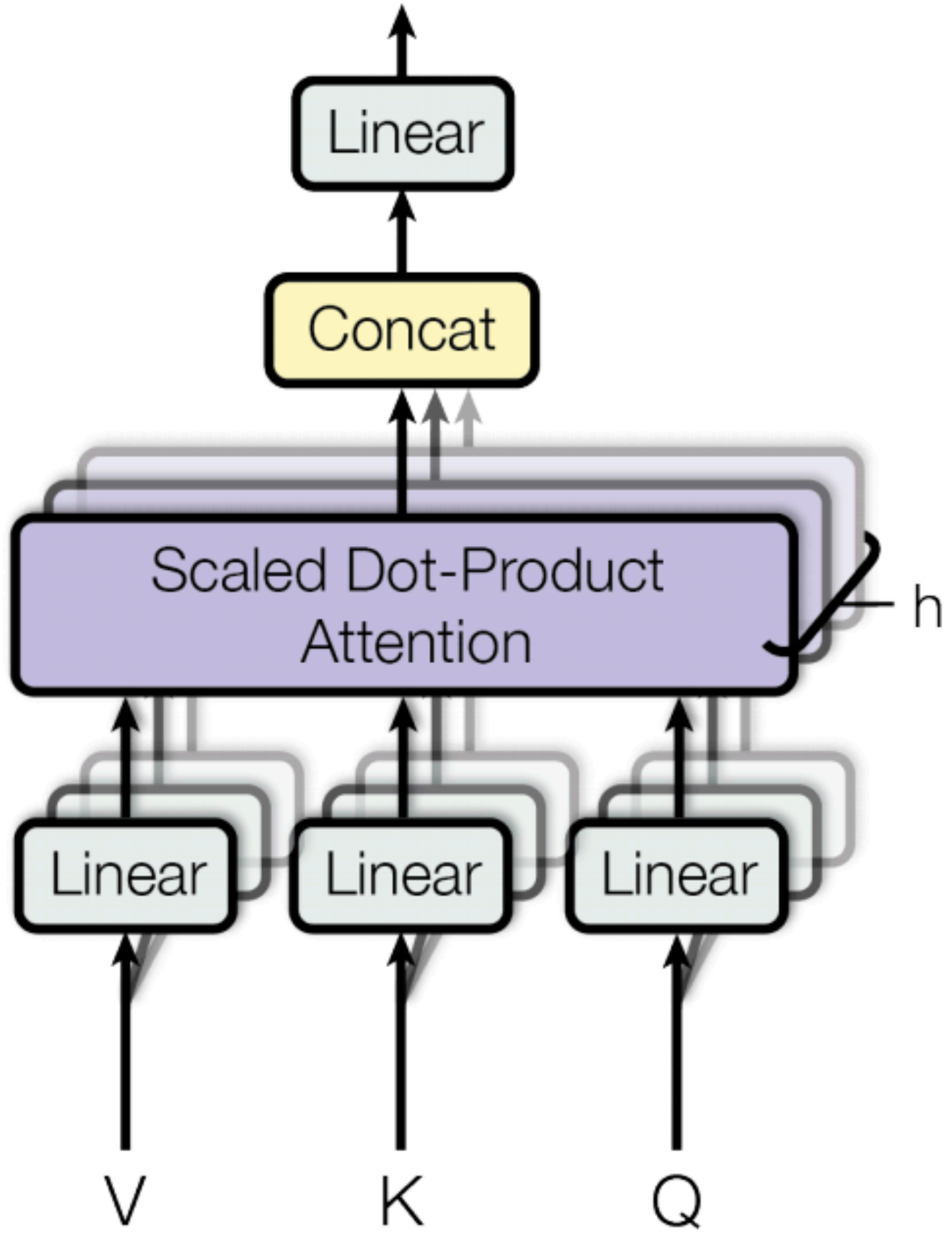


One query per input vector

Adapted from J. Johnson and S. Lazebnik.

Multi-head attention

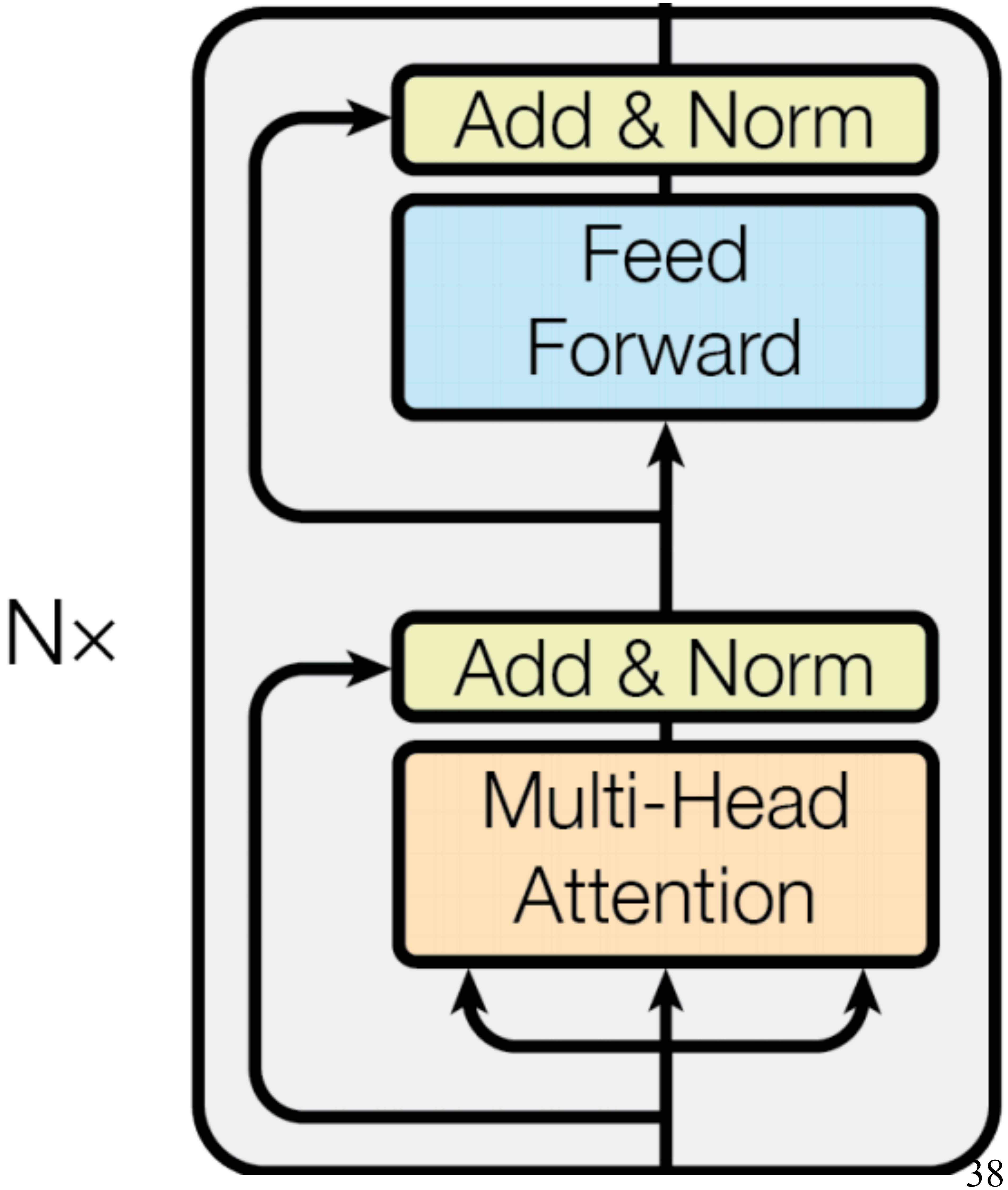
- Run h attention models in parallel on top of different linearly projected versions of Q, K, V; concatenate and linearly project the results
- Intuition: enables model to attend to different kinds of information at different positions



Source: S. Lazebnik

Transformer blocks

- A **Transformer** is a sequence of transformer blocks
  - Vaswani et al.: N=12 blocks, embedding dimension = 512, 6 attention heads
  - **Add & Norm:** residual connection followed by layer normalization
  - **Feedforward:** two linear layers with ReLUs in between, applied independently to each vector
- Attention is the only interaction between inputs!



Source: S. Lazebnik

Self-supervised learning in Natural Language Processing

1. Download A LOT of text from the internet
2. Train a giant transformer using a suitable pretext task
3. Fine-tune the transformer on desired NLP task

Model Alias	Org.	Article Reference
ULMfit	fast.ai	*Universal Language Model Fine-tuning for Text Classification* Howard and Ruder
 ELMo	AllenNLP	*Deep contextualized word representations* Peters et al.
OpenAI GPT	OpenAI	*Improving Language Understanding by Generative Pre-Training* Radford et al.
 BERT	Google	*BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding* Devlin et al.
XLM	Facebook	*Cross-lingual Language Model Pretraining* Lample and Conneau

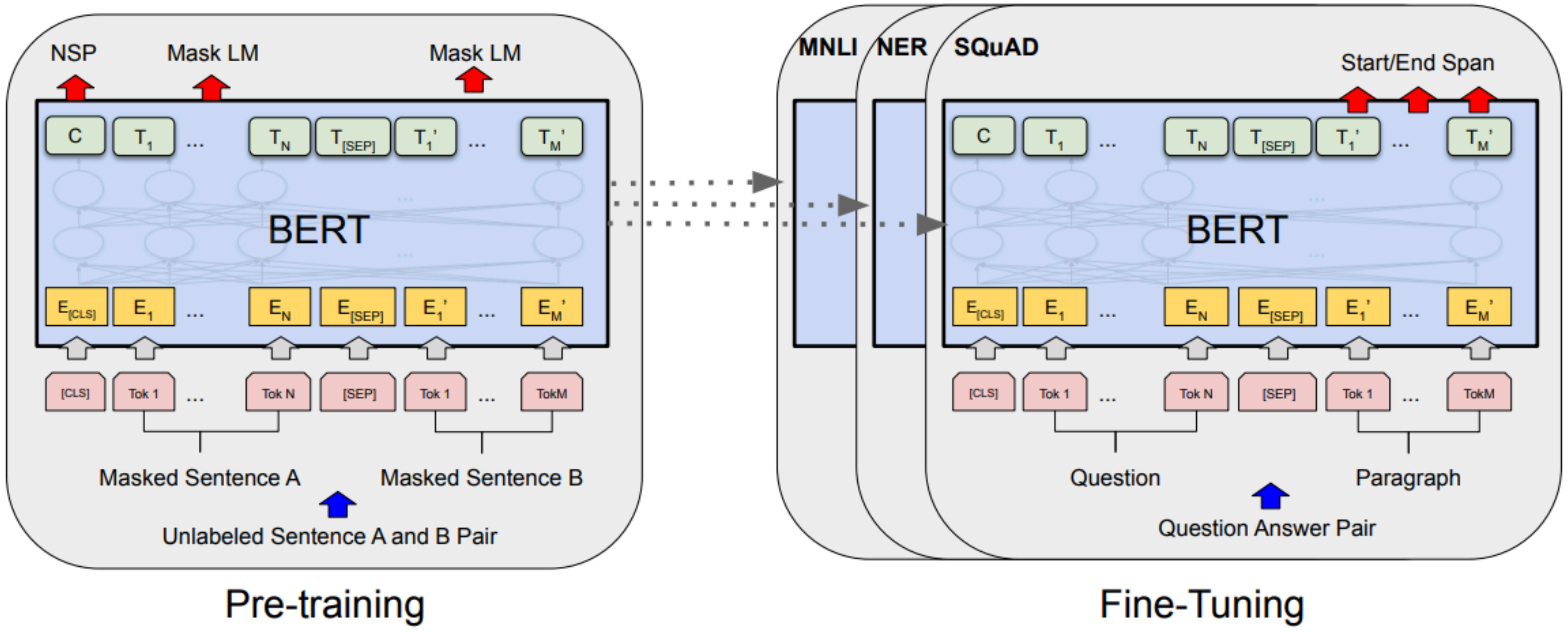
Source: S. Lazebnik

Image source

Self-supervised language modeling with transformers

1. Download A LOT of text from the internet
2. Train a giant transformer using a suitable pretext task
3. Fine-tune the transformer on desired NLP task

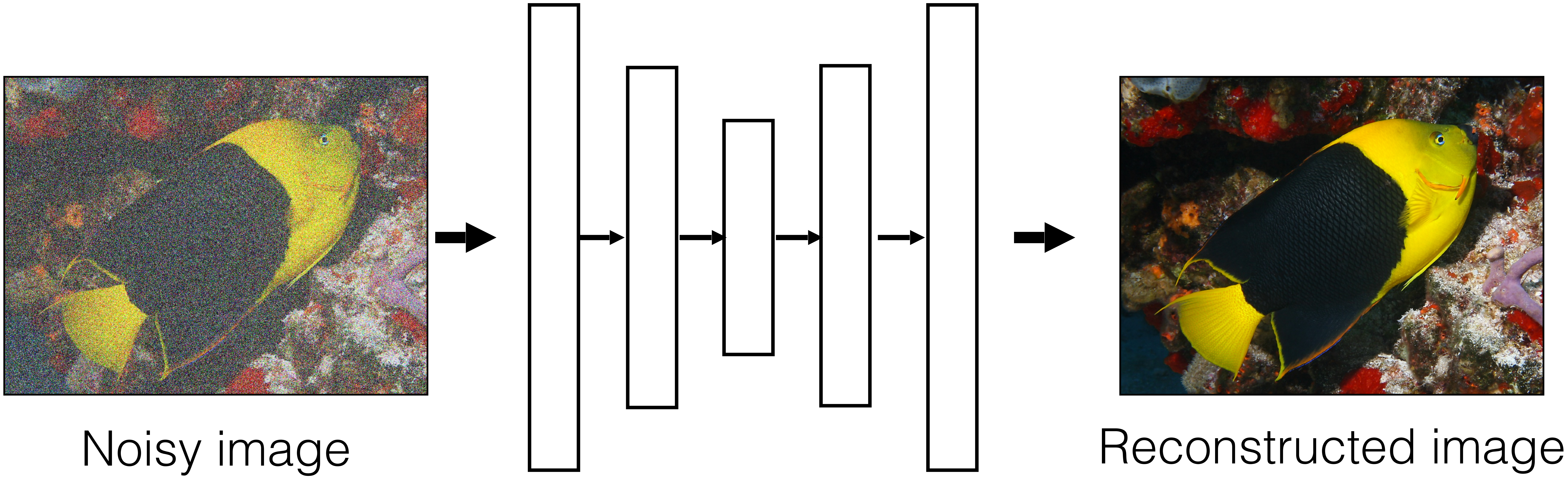
Bidirectional Encoder Representations from Transformers (BERT)



J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, EMNLP 2018

Source: S. Lazebnik

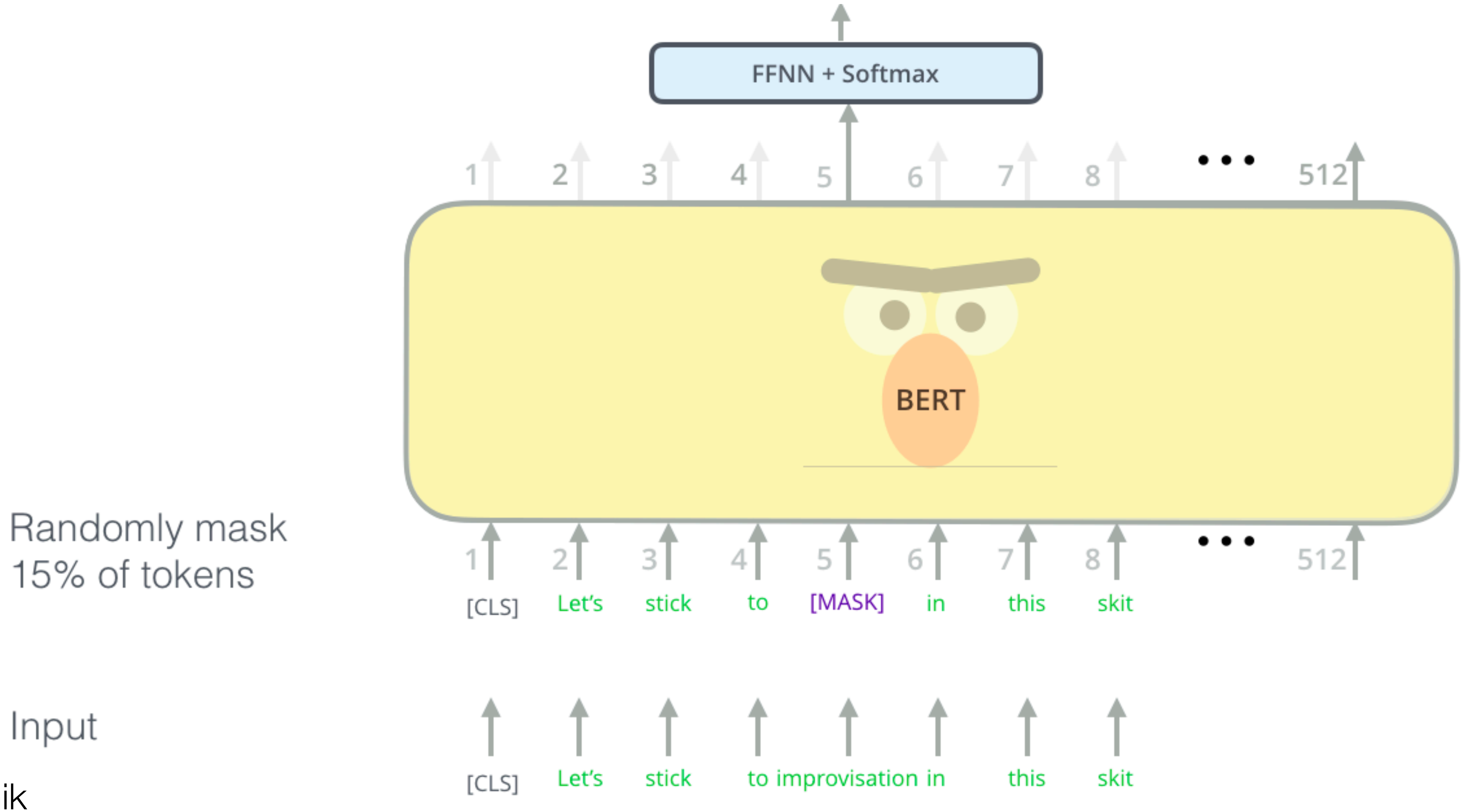
Recall: denoising autoencoder



[Vincent et al., 2008]

BERT: Pretext tasks

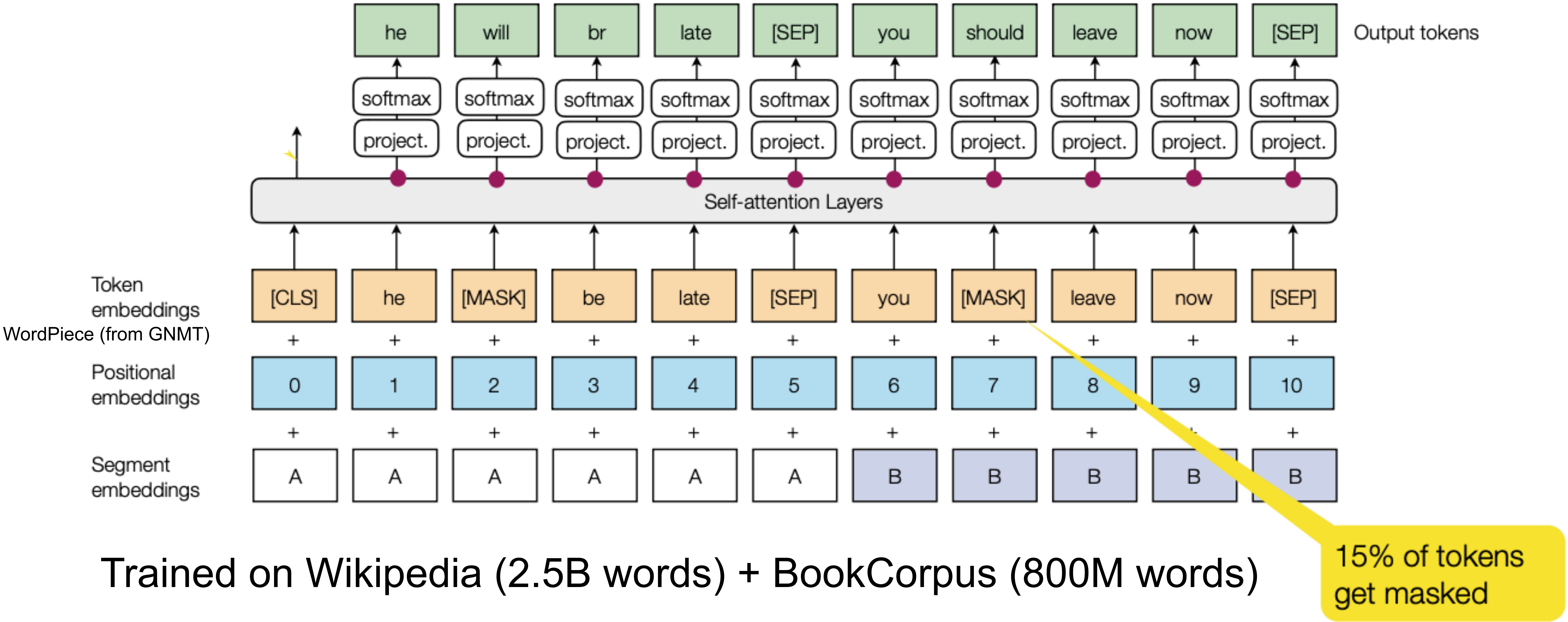
- Masked language model (MLM)
  - Randomly mask 15% of tokens in input sentences, goal is to reconstruct them using bidirectional context



Source: S. Lazebnik

Image source

BERT: More detailed view



Trained on Wikipedia (2.5B words) + BookCorpus (800M words)

Source: S. Lazebnik

Image source

BERT: Evaluation

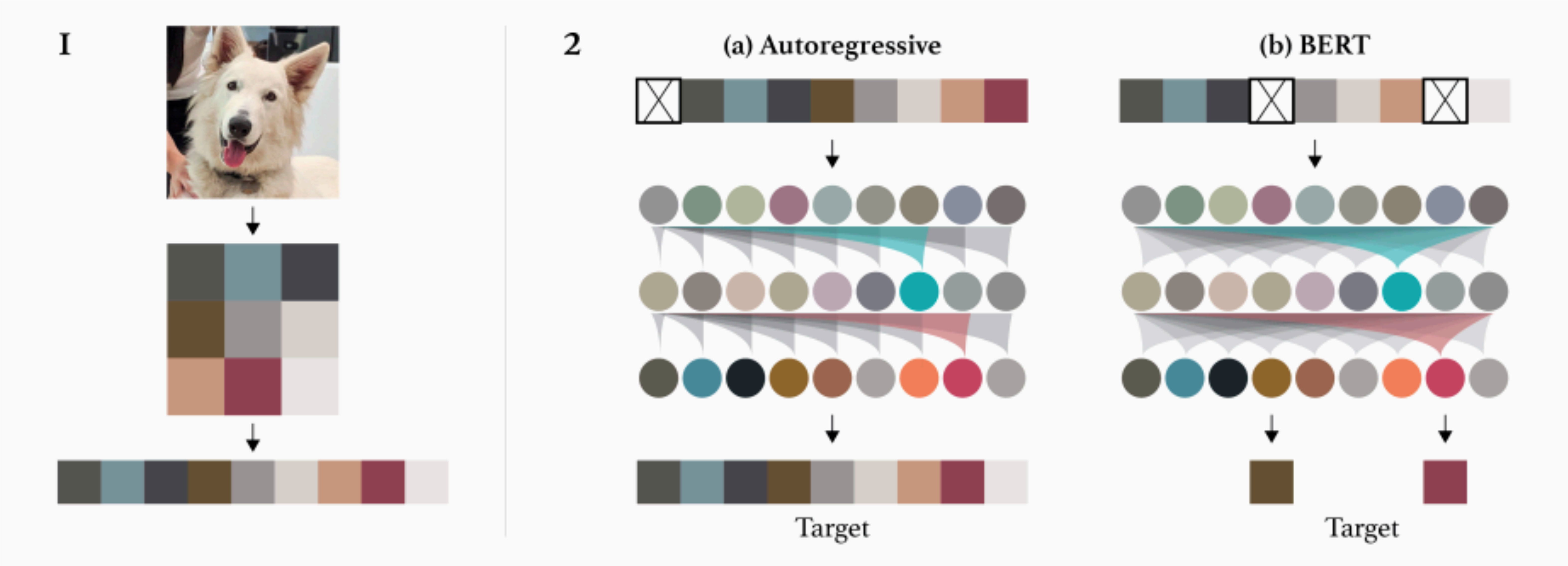
- General Language Understanding Evaluation (GLUE) benchmark (gluebenchmark.com)

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Source: S. Lazebnik

Image GPT

- Image resolution up to 64x64, color values quantized to 512 levels (9 bits), dense attention
- For transfer learning, average-pool encoded features across all positions



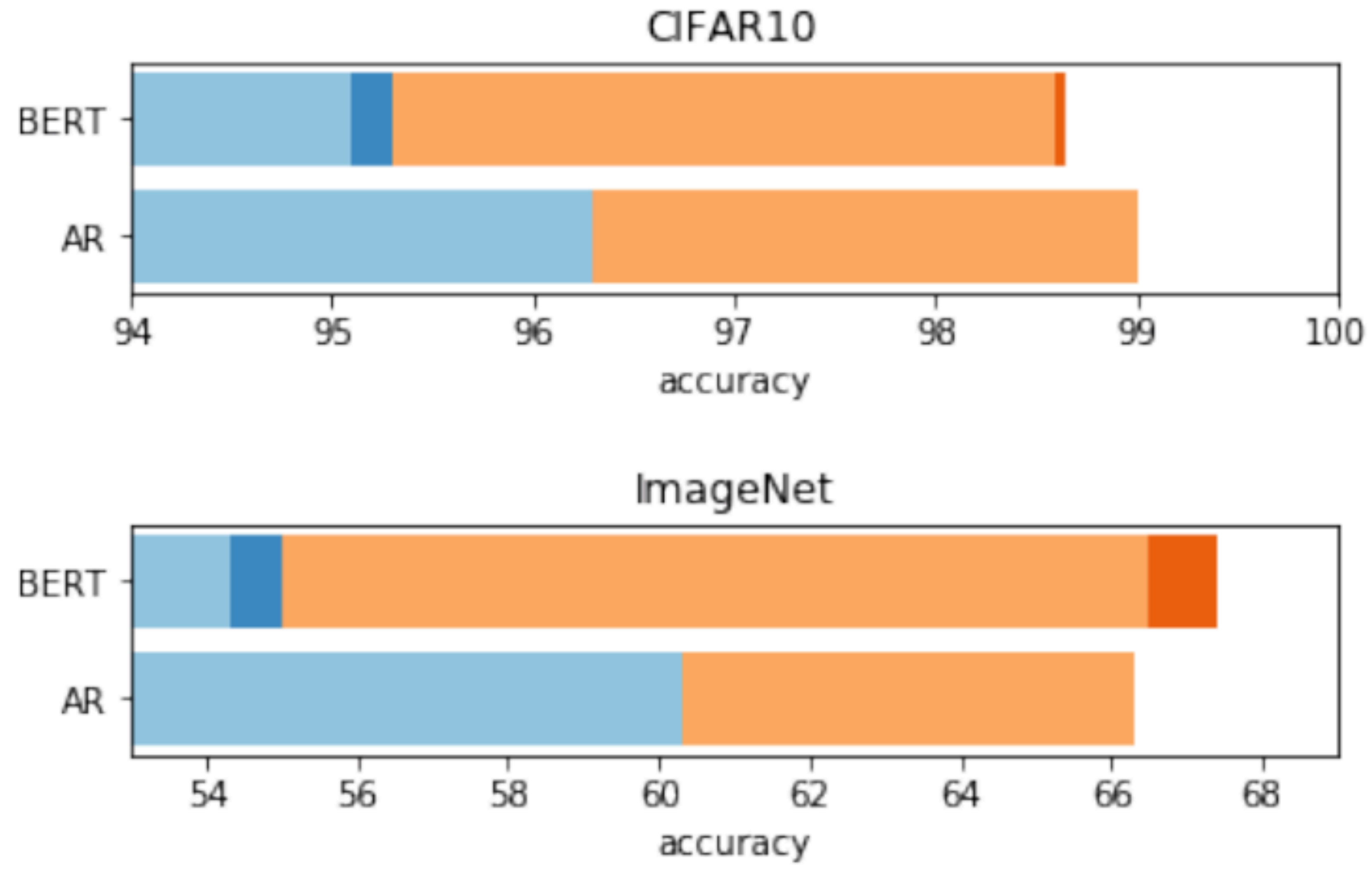
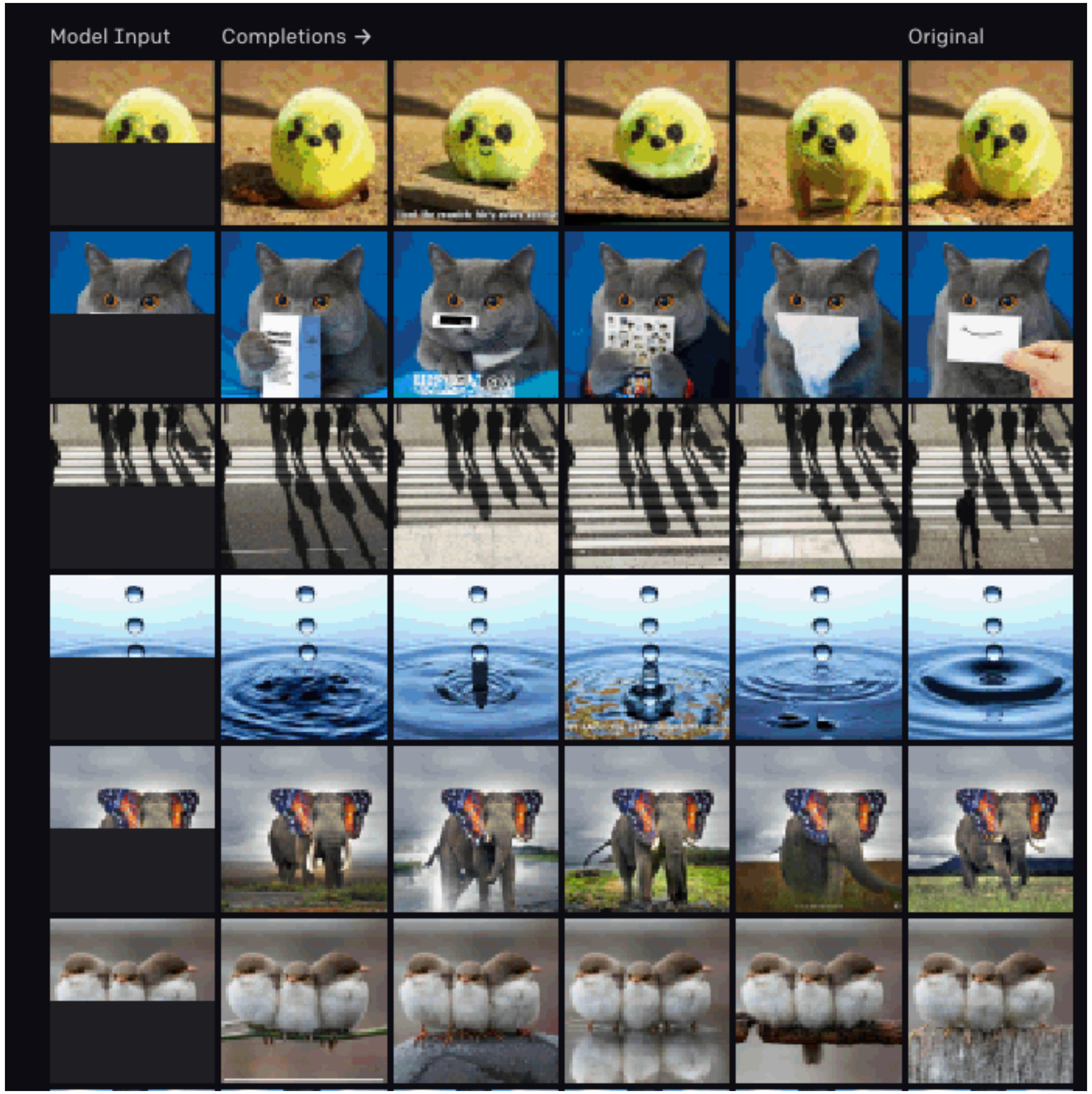


Figure 4. Comparison of auto-regressive pre-training with BERT pre-training using iGPT-L at an input resolution of $32^2 \times 3$. Blue bars display linear probe accuracy and orange bars display fine-tune accuracy. Bold colors show the performance boost from ensembling BERT masks. We see that auto-regressive models produce much better features than BERT models after pre-training, but BERT models catch up after fine-tuning.

M. Chen et al., Generative pretraining from pixels, ICML 2020

Source: S. Lazebnik

Image GPT – OpenAI



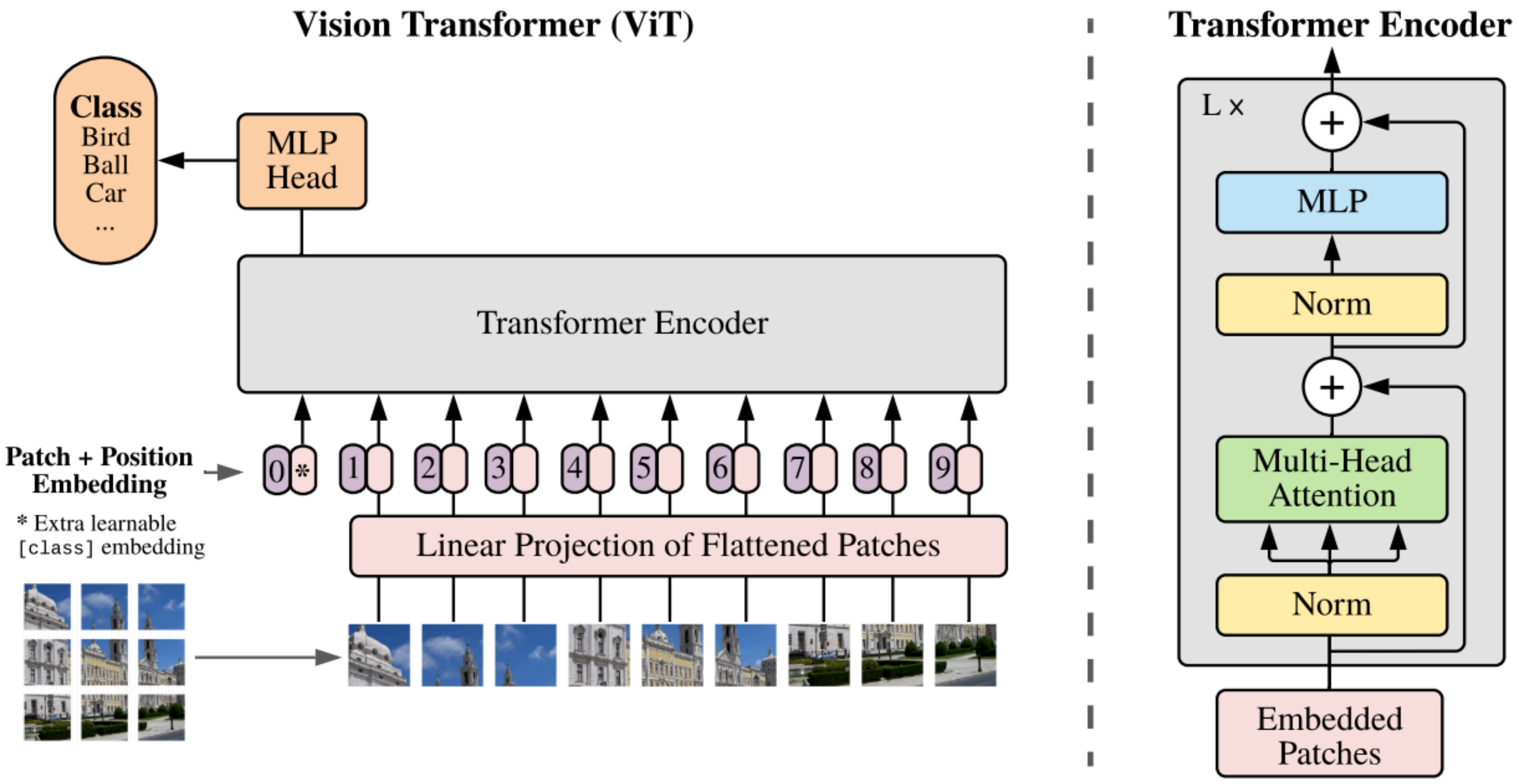
https://openai.com/blog/image-gpt/

M. Chen et al., Generative pretraining from pixels, ICML 2020

Source: S. Lazebnik

Vision transformer (ViT)

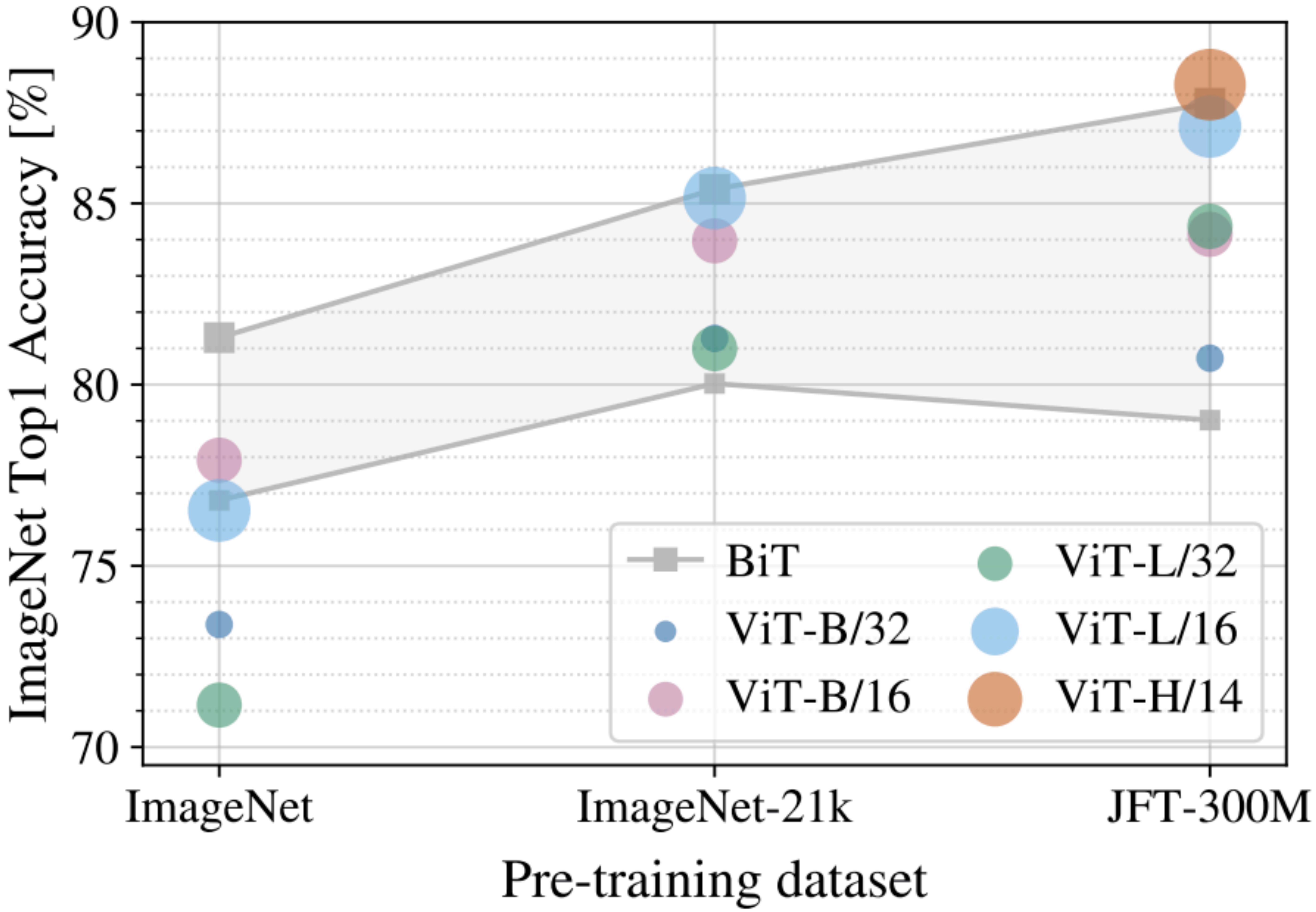
- Split an image into patches, feed linearly projected patches into standard transformer encoder
  - With patches of 14x14 pixels, you need 16x16=256 patches to represent 224x224 images



A. Dosovitskiy et al. [An image is worth 16x16 words: Transformers for image recognition at scale](). ICLR 2021

Source: S. Lazebnik

Vision transformer (ViT)



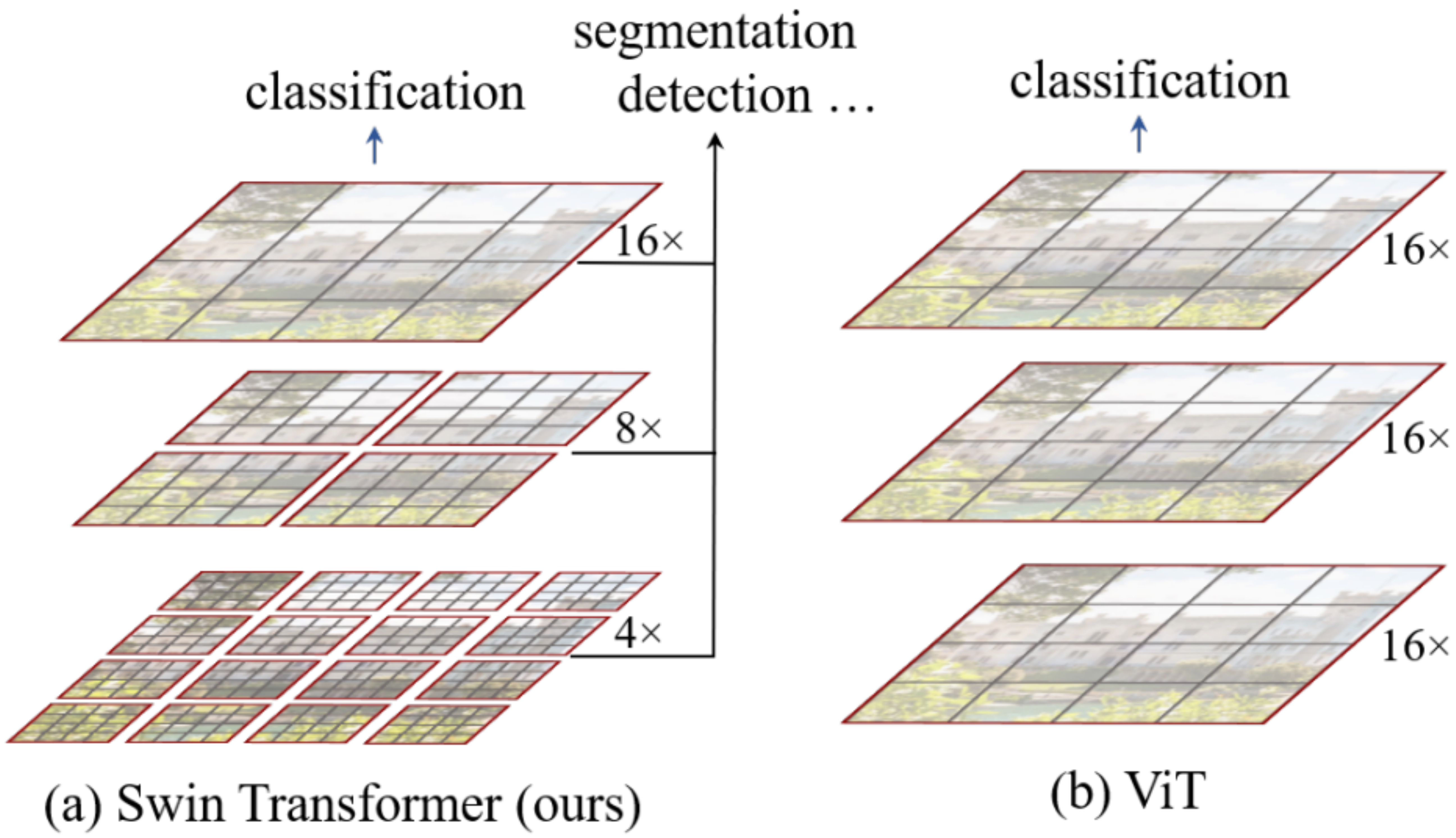
BiT: Big Transfer (ResNet)
ViT: Vision Transformer (Base/Large/Huge, patch size of 14x14, 16x16, or 32x32)

Internal Google dataset (not public)

A. Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. ICLR 2021

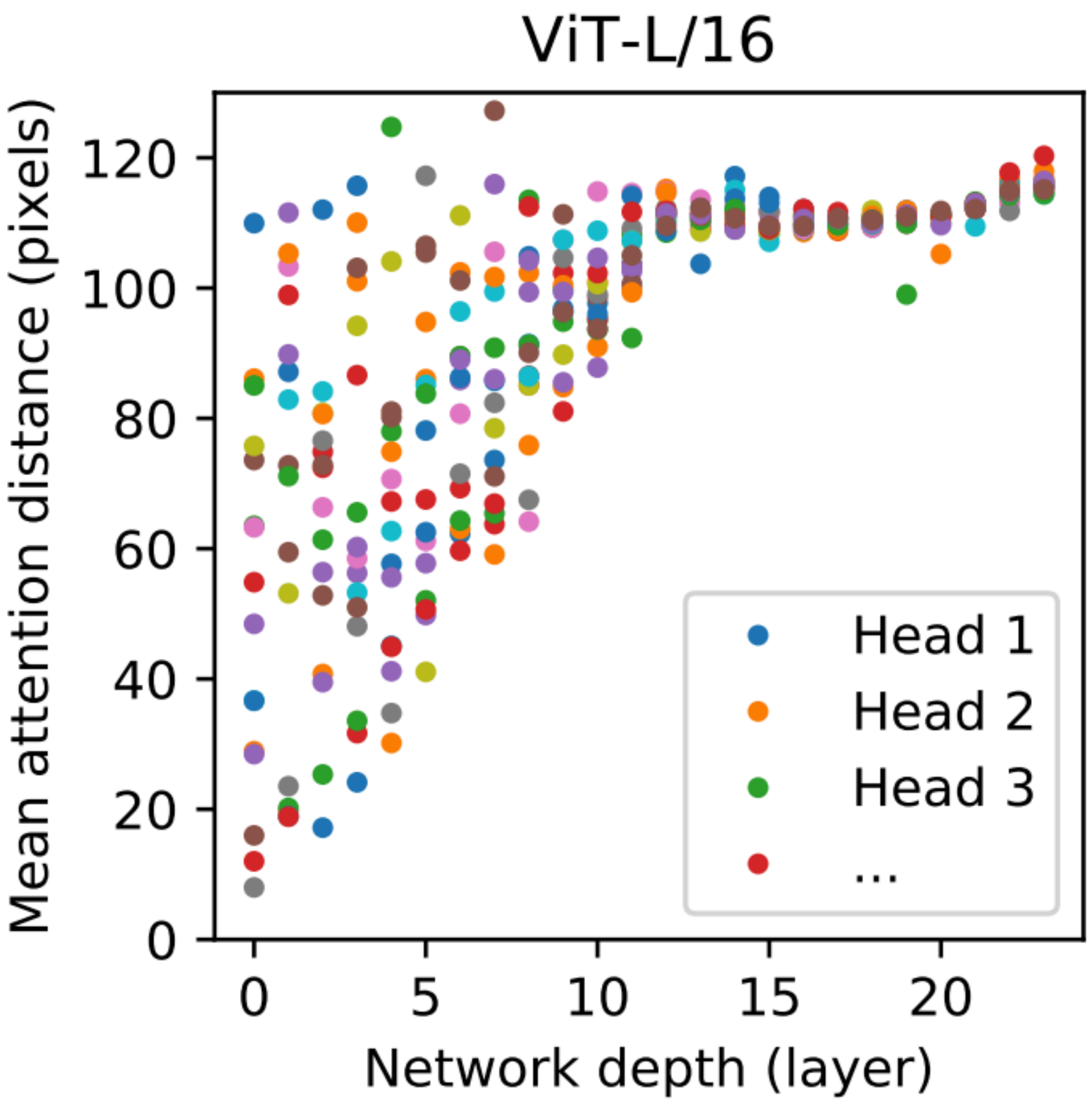
Source: S. Lazebnik

Swin Transformer: windowed attention



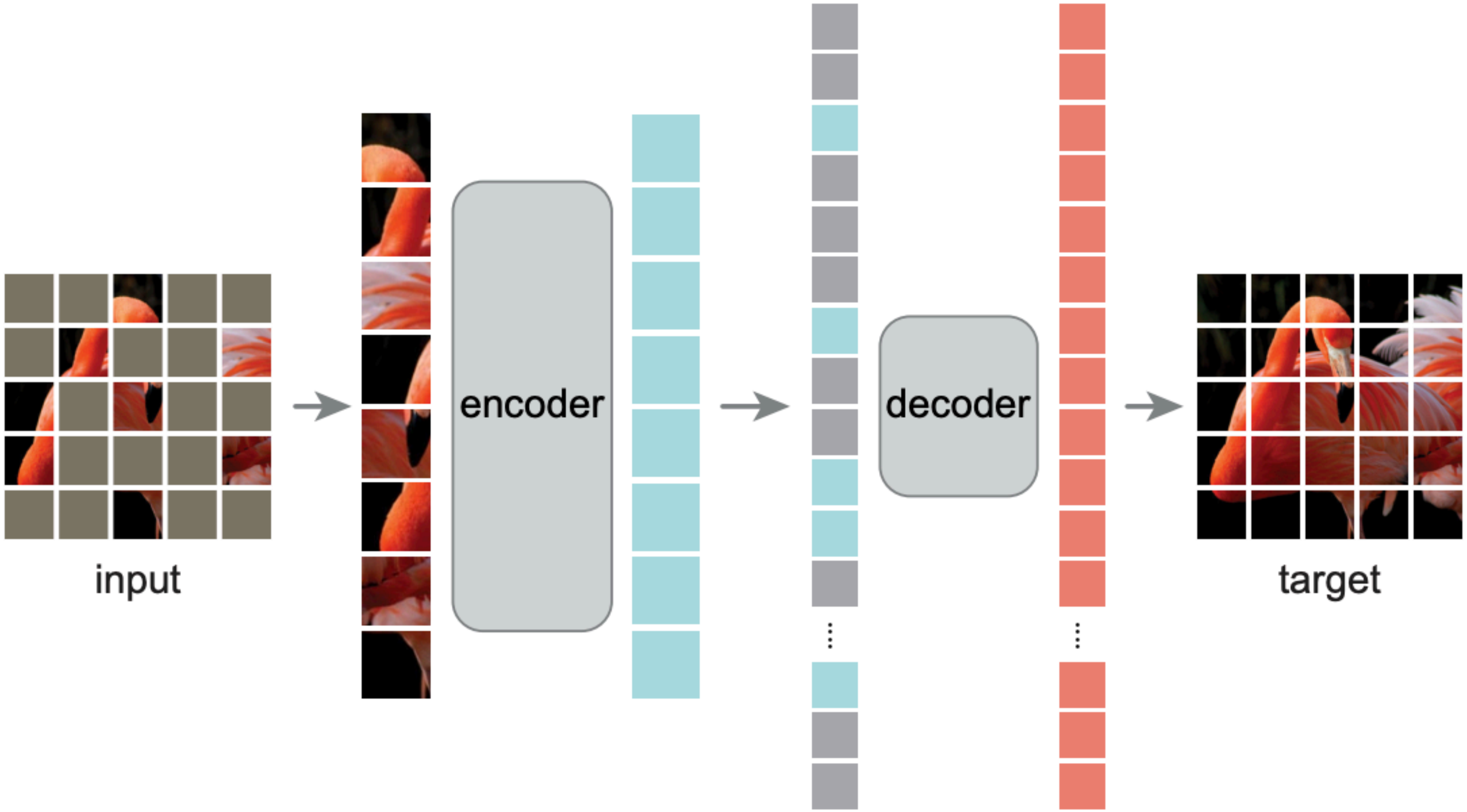
[Liu et al., “Swin Transformer: Hierarchical Vision Transformer using Shifted Windows”]

Vision transformer (ViT)



A. Dosovitskiy et al. [An image is worth 16x16 words: Transformers for image recognition at scale](). ICLR 2021

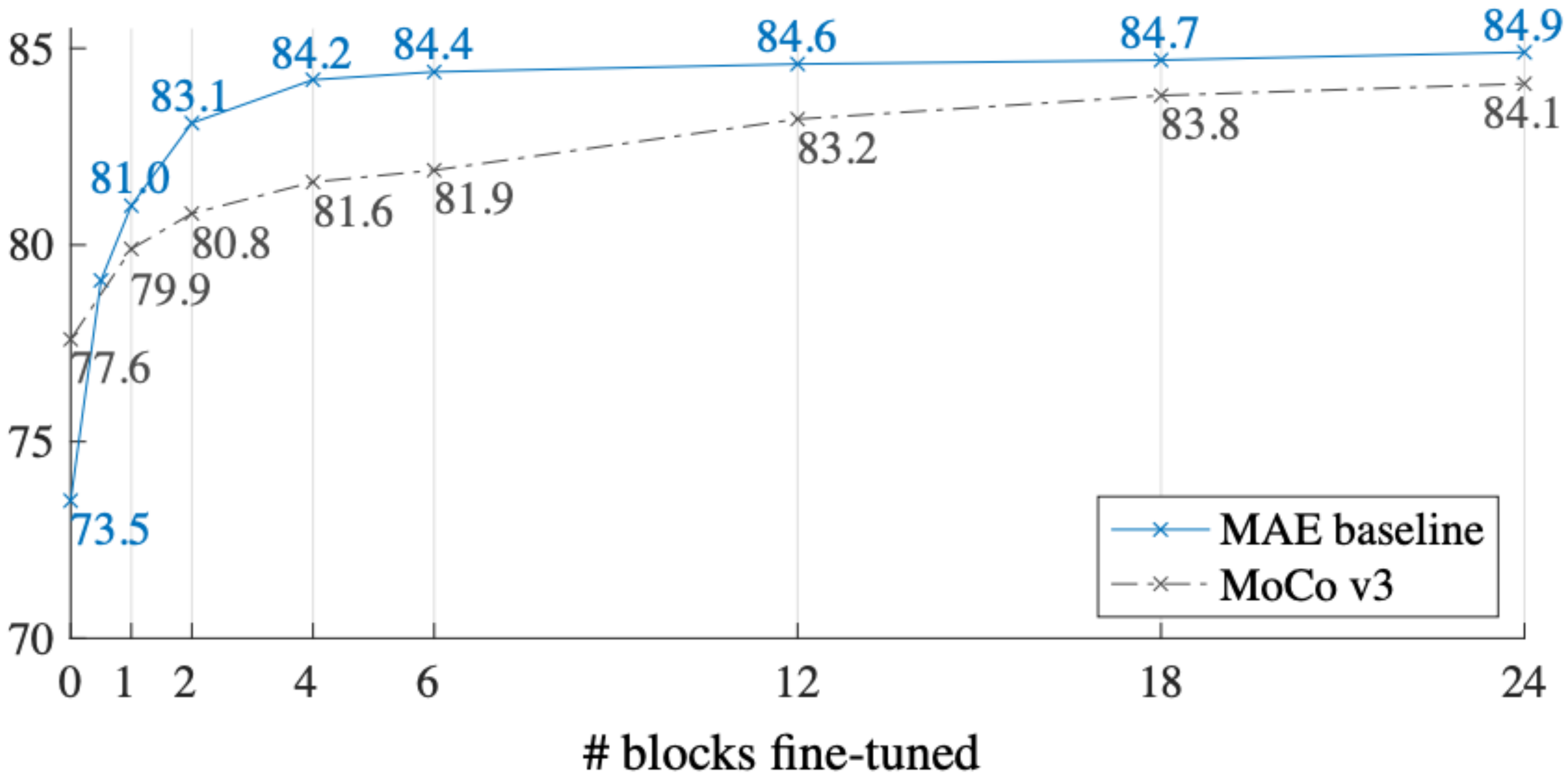
Application: self-supervised learning with masked autoencoders



Source: S. Lazebnik

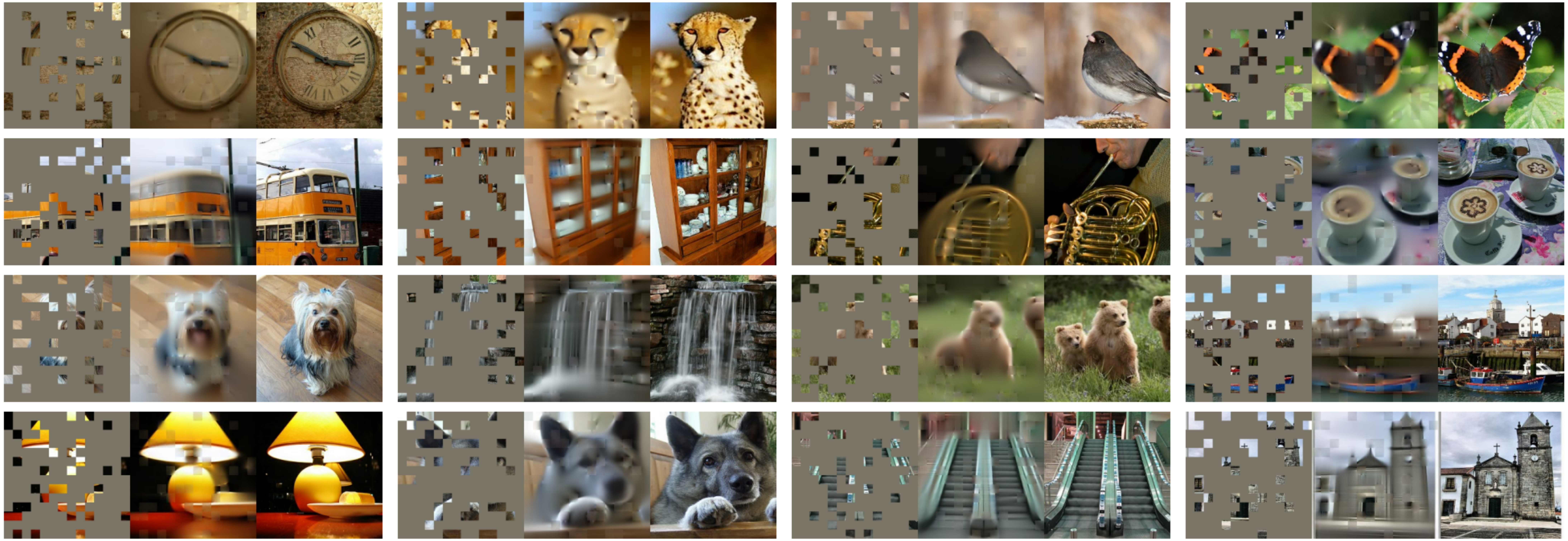
[Kaiming He et al., “Masked Autoencoders Are Scalable Vision Learners”, 2021]

Application: self-supervised learning



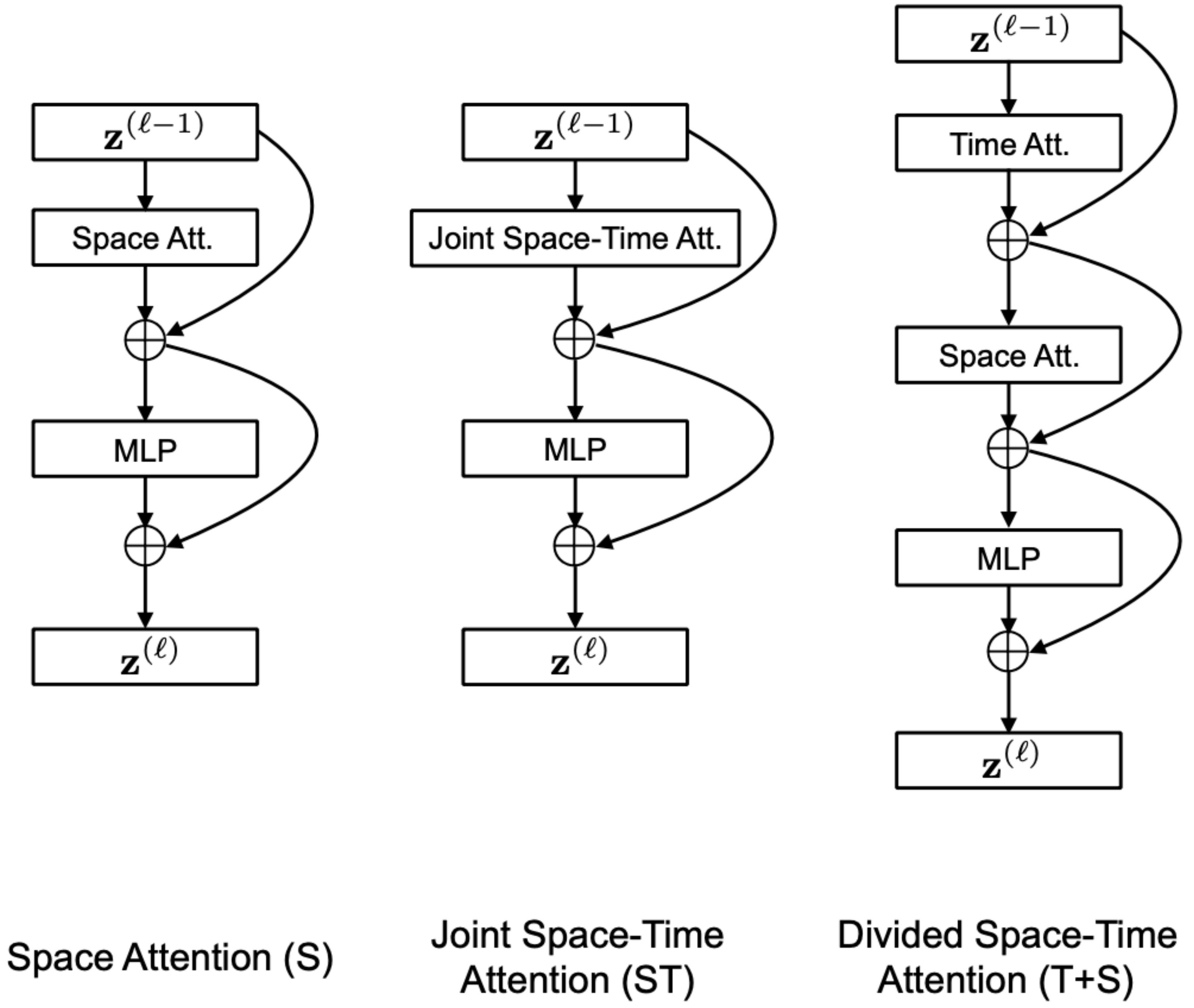
[Kaiming He et al., "Masked Autoencoders Are Scalable Vision Learners", 2021]

Application: self-supervised learning



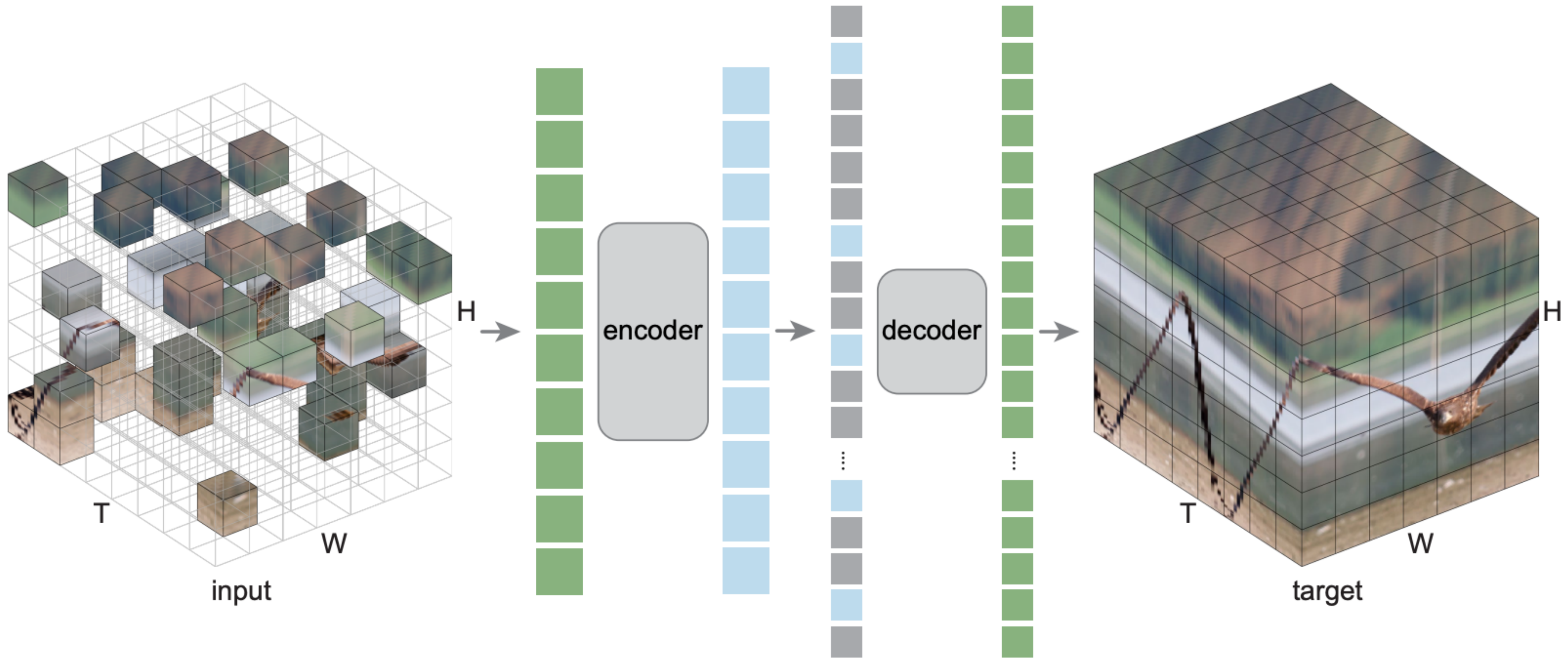
[Kaiming He et al., “Masked Autoencoders Are Scalable Vision Learners”, 2021]

Application: video



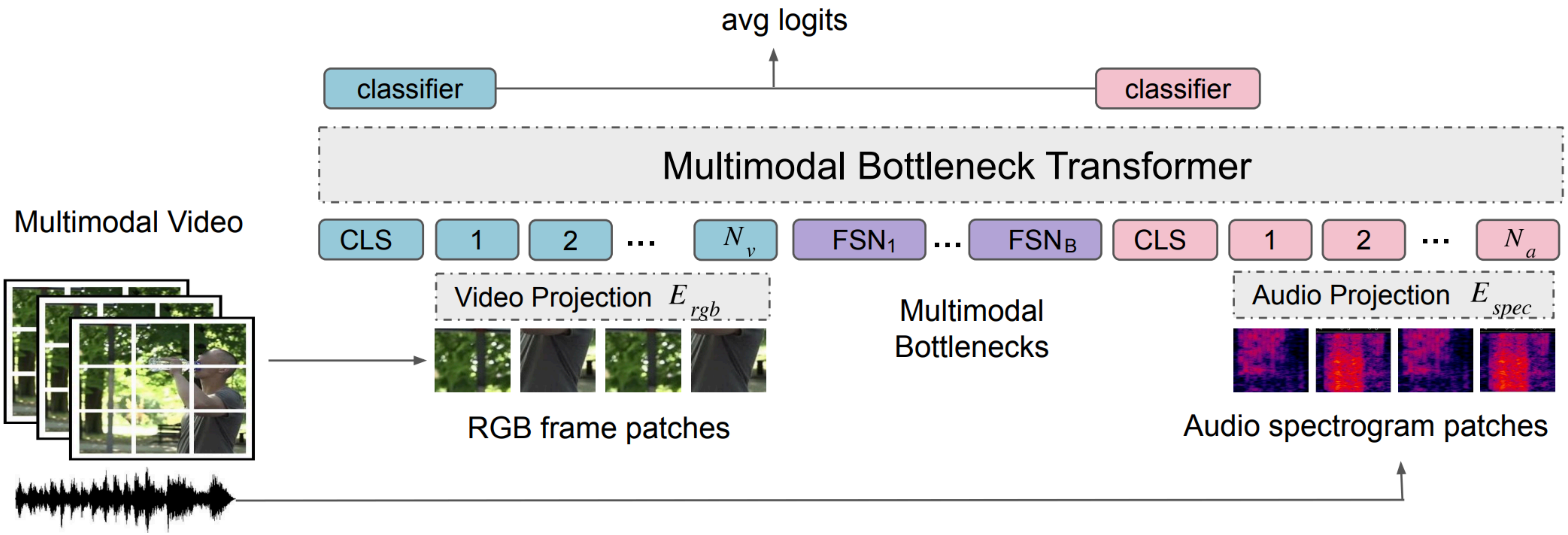
Source: [Gedas Bertasius et al, “Is Space-Time Attention All You Need for Video Understanding?”, 2021]

Application: video self-supervised learning



Source: [Feichtenhofer et al., “Masked Autoencoders As Spatiotemporal Learners”, 2022]

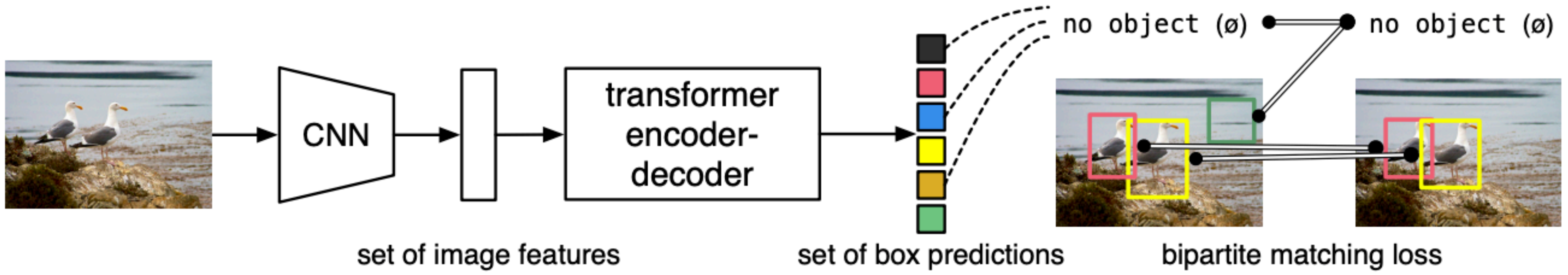
Application: multimodal models

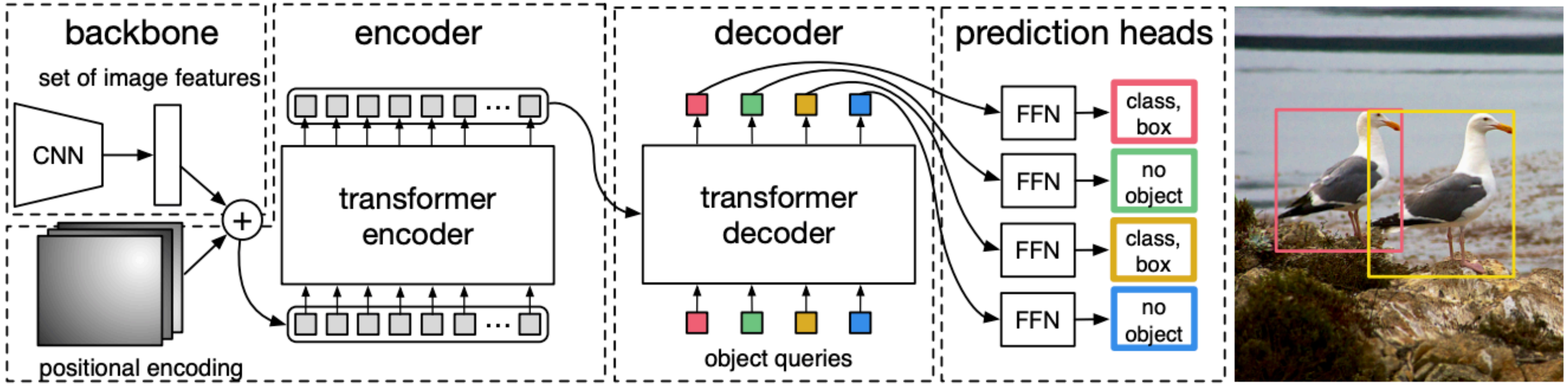


[Arsha Nagrani et al, “Attention Bottlenecks for Multimodal Fusion”, 2021]

Detection Transformer (DETR) – Facebook AI

- Hybrid of CNN and transformer, aimed at standard recognition task



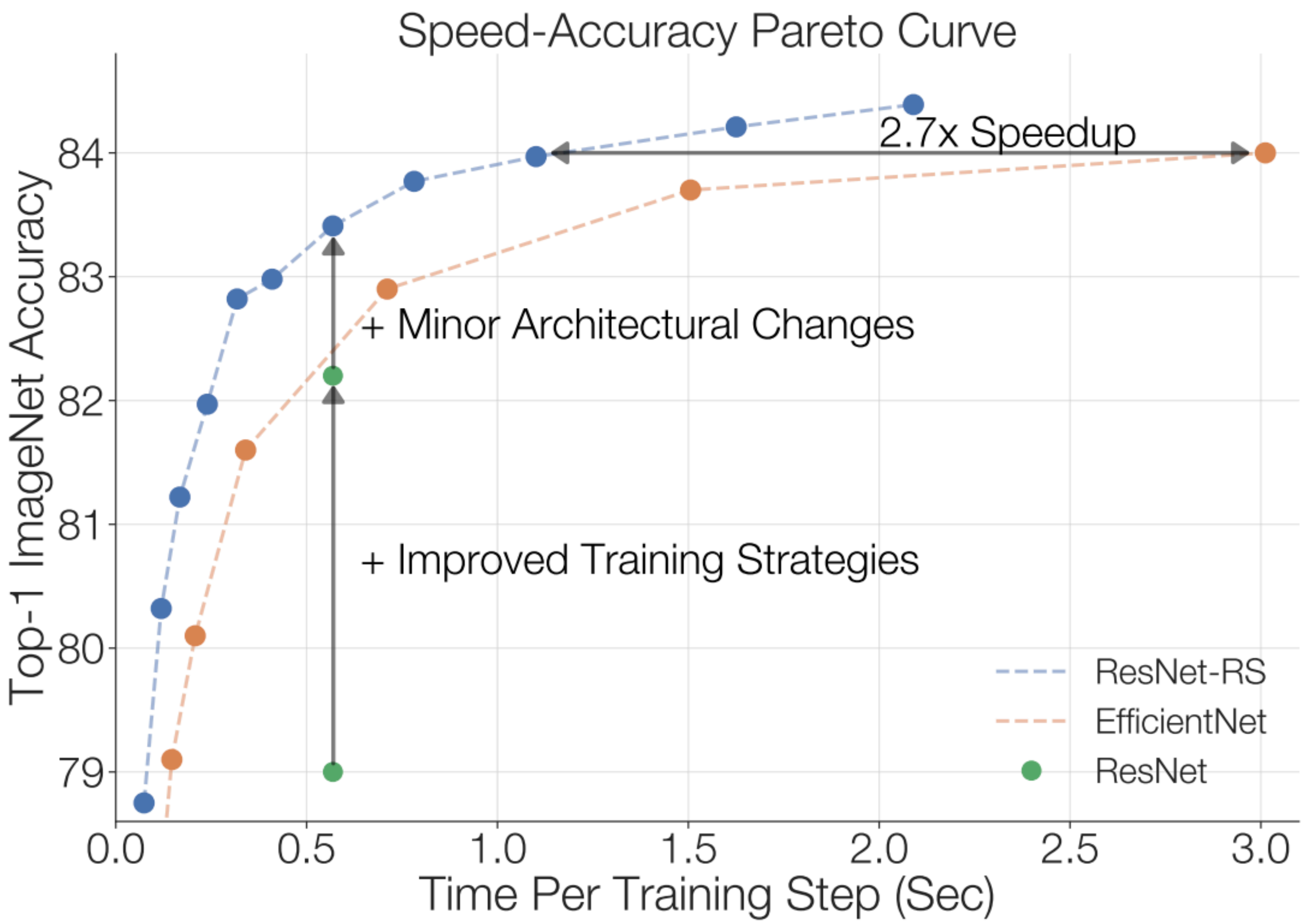


N. Carion et al., [End-to-end object detection with transformers](), ECCV 2020

Source: S. Lazebnik

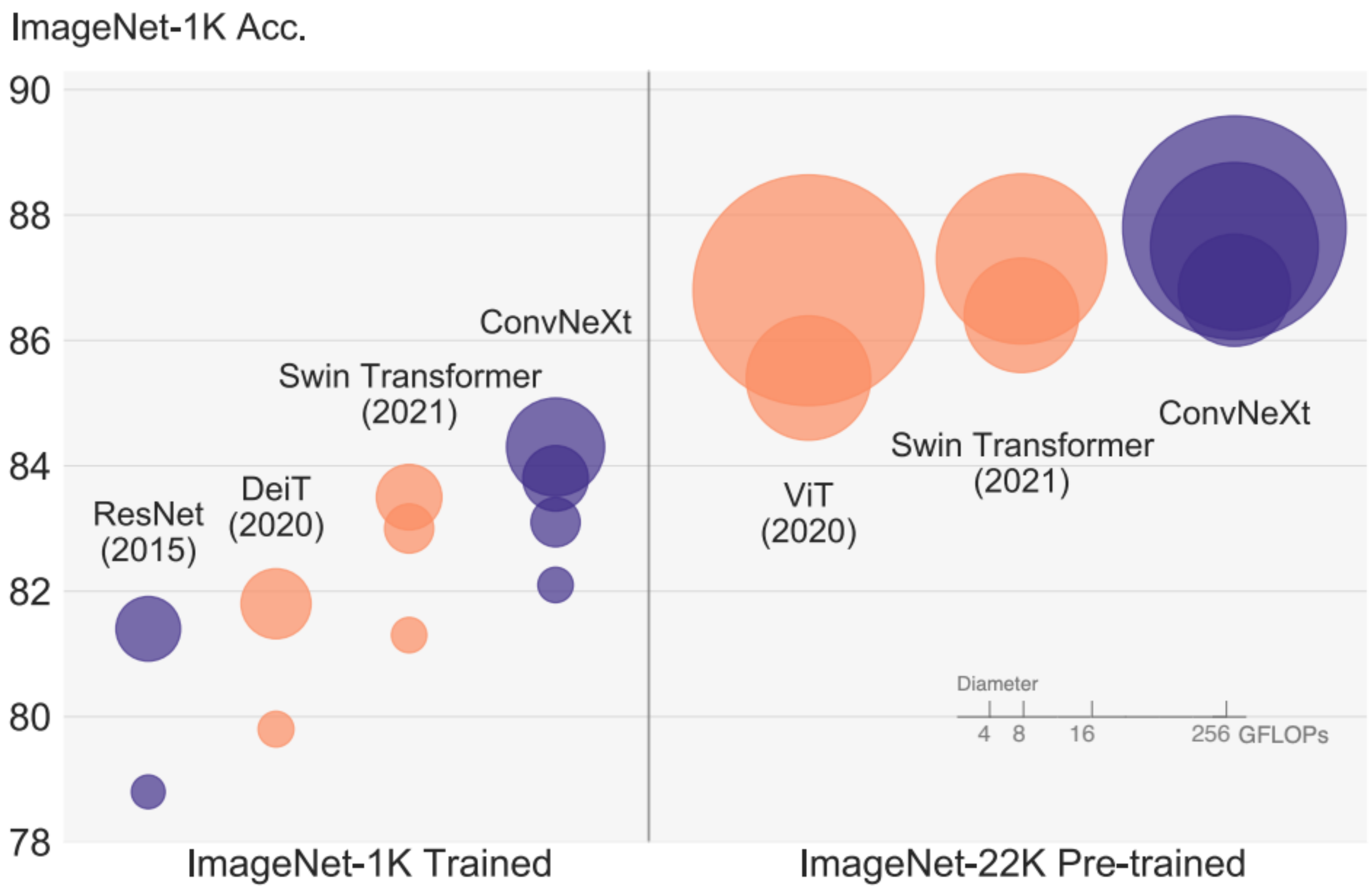
CNNs vs. Transformer performance: pretty similar

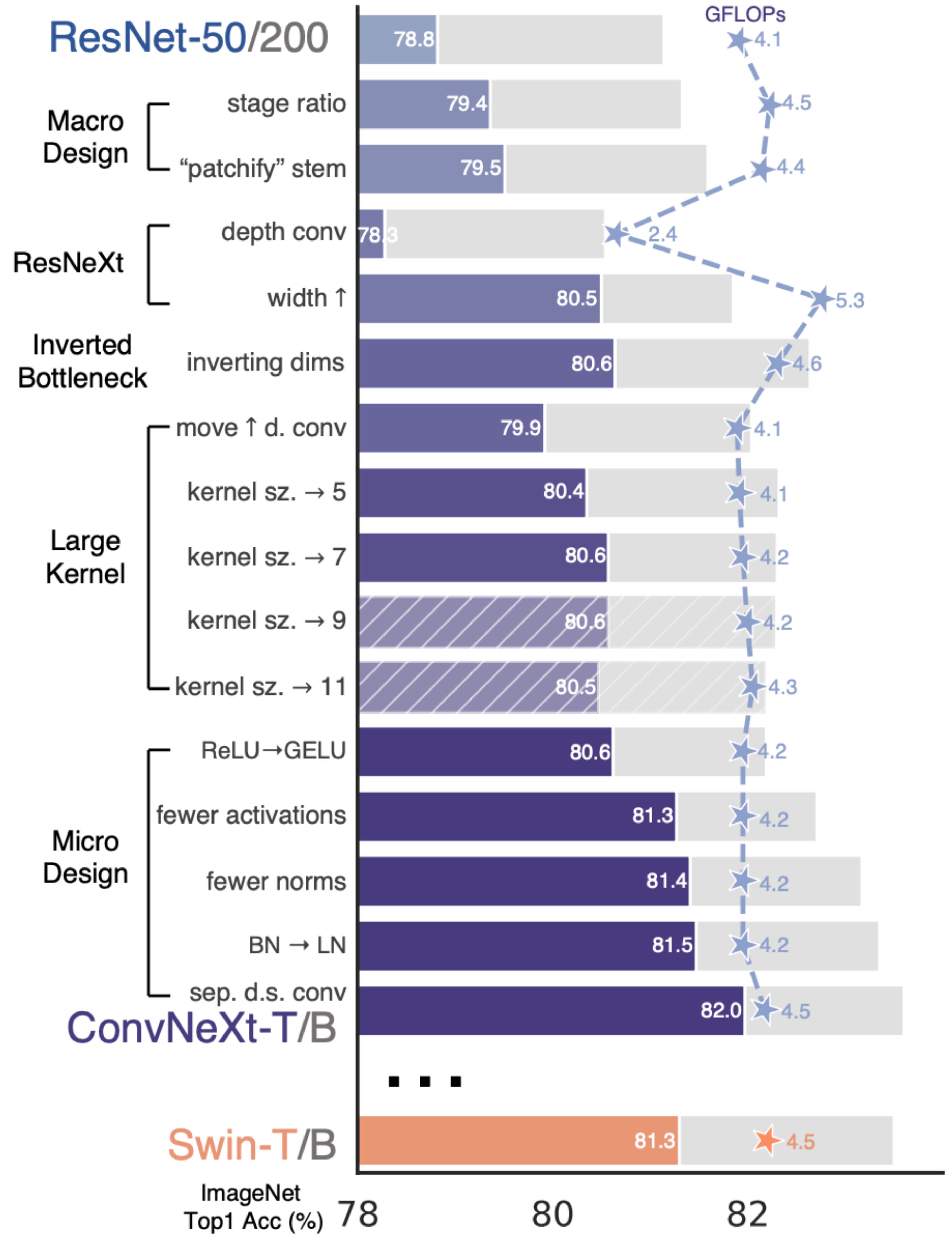
Improvements	Top-1	Δ
ResNet-200	79.0	—
+ Cosine LR Decay	79.3	**+0.3**
+ Increase training epochs	78.8 †	-0.5
+ EMA of weights	79.1	**+0.3**
+ Label Smoothing	80.4	**+1.3**
+ Stochastic Depth	80.6	**+0.2**
+ RandAugment	81.0	**+0.4**
+ Dropout on FC	80.7 ‡	-0.3
+ Decrease weight decay	82.2	**+1.5**
+ Squeeze-and-Excitation	82.9	**+0.7**
+ ResNet-D	83.4	**+0.5**



[Irwan Bello et al. "Revisiting ResNets: Improved Training and Scaling Strategies", 2021]

Improving CNNs





[Liu et al. "A ConvNet for the 2020s", 2022]

Also: [Smith et al., ConvNets Match Vision Transformers at Scale, 2023]

Next class: Bias and ethics