# Hiera: A Hierarchical Vision Transformer without the Bells-and-Whistles

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Feb 16, 2024

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# Outline

# Multiscale Feature Hierarchies

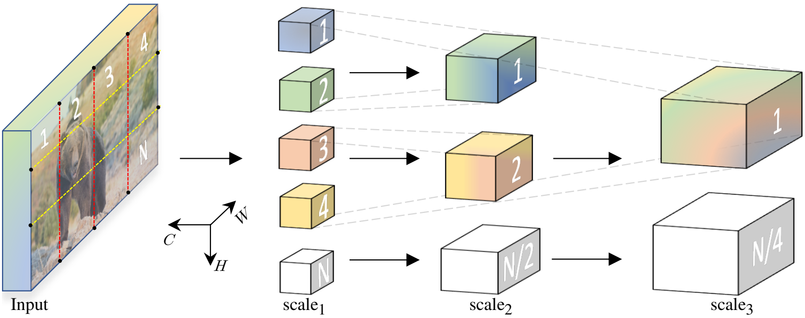
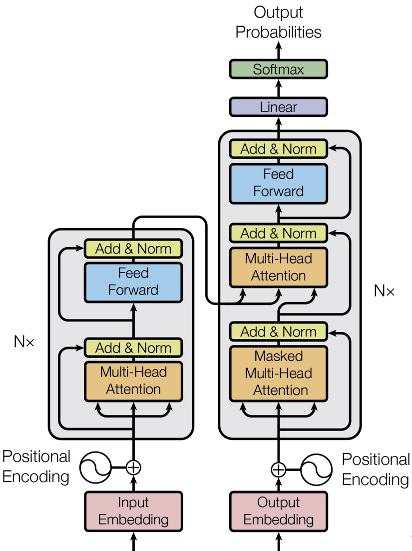



Figure: Several resolution-channel *scale* stages of MViT[1].

[1] ICCV-2021

# Transformer Revisit



# Things to Think About

- A stack of **identical** blocks (Single Scale)
- Computational complexity of canonical self-attention

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{\tilde{d}}}\right)V \tag{1}$$

where

$$X \in \mathbb{R}^{n \times d}, Q = XW_Q, K = XW_K, V = XW_V$$

$$W_Q, W_K, W_V \in \mathbb{R}^{d \times \tilde{d}}$$

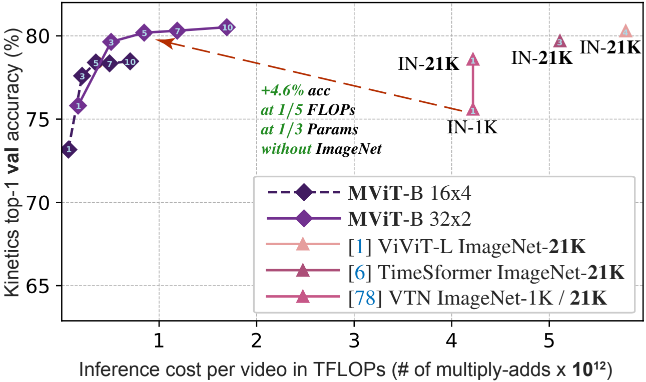
# Self-Attention Computational Complexity

Scales quadratically in input sequence length $n$

1. Calculation of $S = \frac{QK^T}{\sqrt{\tilde{d}}}$ takes $\mathcal{O}(n^2\tilde{d})$
2. Exponentiation and calculation of row sum of $S$ takes $\mathcal{O}(n^2)$
3. Division of each element of $S$ with the corresponding row sum takes $\mathcal{O}(n^2)$
4. Post-multiplication with $V$ takes $\mathcal{O}(n^2\tilde{d})$

# Motivation

- Decrease computing requirements
- A better sense of “context” at the lower resolutions guiding the processing at higher resolutions

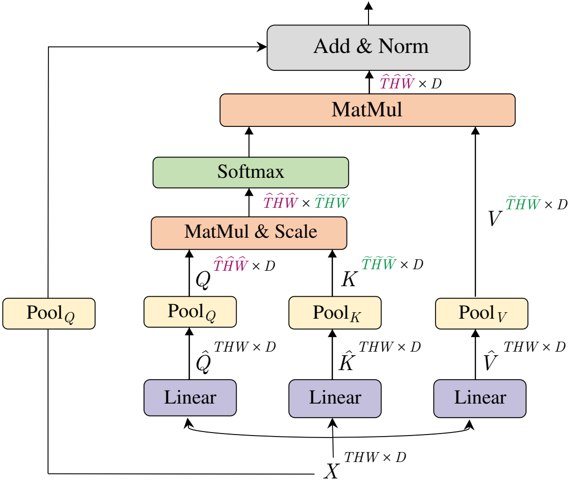


# Multiscale: Step by Step

- Scale stages: Transformer blocks that operates on the same scale (identical resolution and channel capacity).

| stages | operators | output sizes |
|---|---|---|
| data layer | stride $\tau \times 1 \times 1$ | $D \times T \times H \times W$ |
| cube$_1$ | $c_T \times c_H \times c_W$, $D$<br>stride $s_T \times 4 \times 4$ | $D \times \frac{T}{s_T} \times \frac{H}{4} \times \frac{W}{4}$ |
| scale$_2$ | $\begin{bmatrix} \text{MHPA}(D) \\ \text{MLP}(4D) \end{bmatrix} \times N_2$ | $D \times \frac{T}{s_T} \times \frac{H}{4} \times \frac{W}{4}$ |
| scale$_3$ | $\begin{bmatrix} \text{MHPA}(2D) \\ \text{MLP}(8D) \end{bmatrix} \times N_3$ | $2D \times \frac{T}{s_T} \times \frac{H}{8} \times \frac{W}{8}$ |
| scale$_4$ | $\begin{bmatrix} \text{MHPA}(4D) \\ \text{MLP}(16D) \end{bmatrix} \times N_4$ | $4D \times \frac{T}{s_T} \times \frac{H}{16} \times \frac{W}{16}$ |
| scale$_5$ | $\begin{bmatrix} \text{MHPA}(8D) \\ \text{MLP}(32D) \end{bmatrix} \times N_5$ | $8D \times \frac{T}{s_T} \times \frac{H}{32} \times \frac{W}{32}$ |

# Reduce Resolution by Pooling



# Pooling Operator

$$\mathscr{P}(\cdot;\Theta) \tag{2}$$

where

$$\Theta := (\mathbf{k}, \mathbf{s}, \mathbf{p})$$

$$\text{poling kernel } \; \mathbf{k} \in \mathbb{R}^{k_T \times k_H \times k_W}$$

$$\text{stride } \; \mathbf{s} \in \mathbb{R}^{s_T \times s_H \times s_W}$$

$$\text{padding } \; \mathbf{p} \in \mathbb{R}^{p_T \times p_H \times p_W}$$

then

$$\tilde{\mathbf{L}} = \left\lfloor \frac{\mathbf{L} + 2\mathbf{p} - \mathbf{k}}{\mathbf{s}} \right\rfloor + 1$$

where

$$\mathbf{L} = T \times H \times W, \;\; \tilde{\mathbf{L}} = \tilde{T} \times \tilde{H} \times \tilde{W}$$

length reduced by a factor of $s_T s_H s_W$

# Computational Complexity

Given sequence length $L = THW$

After pooling $L/f_K, \; L/f_Q, \; L/f_V$

$$f_j = s_T^j s_H^j s_W^j, \;\; \forall j \in \{Q, K, V\}$$

1. Compute key, query, value embeddings

$$\mathcal{O}(THWD^2/h)$$

2. Calculate attention matrix and post-multiply with value vectors

$$\mathcal{O}(T^2H^2W^2D/(f_Q f_K h))$$

<u>Overall</u> $\mathcal{O}(THWD/h(D + THW/(f_Q f_K)))$

# Multiscale Transformer Networks

- Channel expansion:
  e.g., $2D \times \frac{T}{s_T} \times \frac{H}{8} \times \frac{W}{8}$ to $4D \times \frac{T}{s_T} \times \frac{H}{16} \times \frac{W}{16}$
- Query pooling: $\mathscr{P}(Q; \mathbf{k}; \mathbf{p}; \mathbf{s})$
- Key-Value pooling: $\Theta_K \equiv \Theta_V$
- Skip connections
- Multiscale attention block

# Experimental Results on Kinetics-400

| model | pre-train | top-1 | top-5 | FLOPs×views | Param |
|---|---|---|---|---|---|
| Two-Stream I3D [11] | - | 71.6 | 90.0 | 216 × NA | 25.0 |
| ip-CSN-152 [96] | - | 77.8 | 92.8 | 109×3×10 | 32.8 |
| SlowFast 8×8 +NL [30] | - | 78.7 | 93.5 | 116×3×10 | 59.9 |
| SlowFast 16×8 +NL [30] | - | 79.8 | 93.9 | 234×3×10 | 59.9 |
| X3D-M [29] | - | 76.0 | 92.3 | 6.2×3×10 | 3.8 |
| X3D-XL [29] | - | 79.1 | 93.9 | 48.4×3×10 | 11.0 |
| ViT-B-VTN [78] | ImageNet-1K | 75.6 | 92.4 | 4218×1×1 | 114.0 |
| ViT-B-VTN [78] | ImageNet-**21K** | 78.6 | 93.7 | 4218×1×1 | 114.0 |
| ViT-B-TimeSformer [6] | ImageNet-**21K** | 80.7 | 94.7 | 2380×3×1 | 121.4 |
| ViT-L-ViViT [1] | ImageNet-**21K** | 81.3 | 94.7 | 3992×3×4 | 310.8 |
| ViT-B (our baseline) | ImageNet-**21K** | 79.3 | 93.9 | 180×1×5 | 87.2 |
| ViT-B (our baseline) | - | 68.5 | 86.9 | 180×1×5 | 87.2 |
| **MViT**-S | - | 76.0 | 92.1 | 32.9×1×5 | 26.1 |
| **MViT**-B, 16×4 | - | 78.4 | 93.5 | 70.5×1×5 | 36.6 |
| **MViT**-B, 32×3 | - | 80.2 | 94.4 | 170×1×5 | 36.6 |
| **MViT**-B, 64×3 | - | **81.2** | **95.1** | 455×3×3 | 36.6 |

# Good Enough?

MViTv2: Improved Multiscale Vision Transformers for Classification and Detection[2]

1. Decomposed relative positional embeddings
2. Residual pooling connection

[2] CVPR-2022

# Decomposed Relative Positional Embedding

$$\text{Attn}(Q, K, V) = \text{Softmax}\left((QK^T + E^{(\text{rel})})/\sqrt{d}\right)V \tag{3}$$

where

$$E_{ij}^{(\text{rel})} = Q_i \cdot R_{p(i),p(j)}, \quad R_{p(i),p(j)} \in \mathbb{R}^d$$

decompose along axes

$$R_{p(i),p(j)} = R^{\text{h}}_{h(i),h(j)} + R^{\text{w}}_{w(i),w(j)} + R^{\text{t}}_{t(i),t(j)} \tag{4}$$

# Wait...

$$e_{ij} = \frac{Q_i K_j + E_{ij}^{(\text{rel})}}{\sqrt{d}}, \quad E_{ij}^{(\text{rel})} = Q_i \cdot R_{p(i),p(j)} \tag{5}$$

vs.

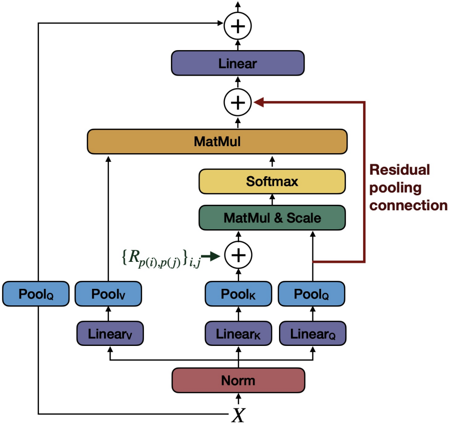
$$e_{ij} = \frac{Q_i (K_j + R_{p(i),p(j)})}{\sqrt{d}} \tag{6}$$

why?

1. Compute all (original) $e_{ij}$ in a single matrix multiplication
2. Avoid broadcasting relative position representations

# Residual Pooling Connection

$$Z := \text{Attn}(Q, K, V) + Q \tag{7}$$



# Pooling Attention vs. Window Attention

**Local** aggregation then **global** self-attention computation vs. computing self-attention **locally** within non-overlapping windows

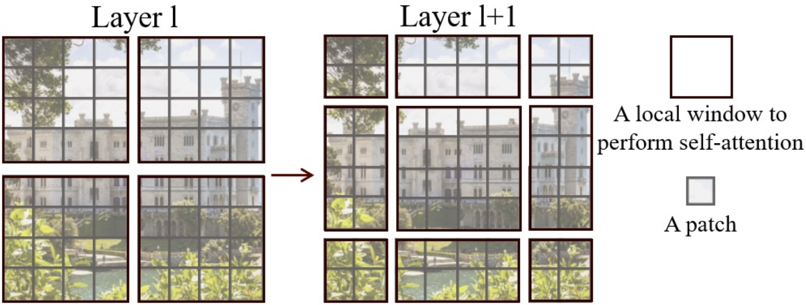



Figure: An illustration of the *shifted window* approach in Swin

# Experimental Results on Kinetics-400

| model | pre-train | top-1 | top-5 | FLOPs×views | Param |
|---|---|---|---|---|---|
| SlowFast 16×8 +NL [23] | - | 79.8 | 93.9 | 234×3×10 | 59.9 |
| X3D-XL [22] | - | 79.1 | 93.9 | 48.4×3×10 | 11.0 |
| MoViNet-A6 [45] | - | 81.5 | 95.3 | 386×1×1 | 31.4 |
| MViTv1, 16×4 [21] | - | 78.4 | 93.5 | 70.3×1×5 | 36.6 |
| MViTv1, 32×3 [21] | - | 80.2 | 94.4 | 170×1×5 | 36.6 |
| **MViTv2**-S, 16×4 | - | 81.0 | 94.6 | 64×1×5 | 34.5 |
| **MViTv2**-B, 32×3 | - | **82.9** | **95.7** | 225×1×5 | 51.2 |
| ViT-B-VTN [59] | IN-21K | 78.6 | 93.7 | 4218×1×1 | 114.0 |
| ViT-B-TimeSformer [3] | IN-21K | 80.7 | 94.7 | 2380×3×1 | 121.4 |
| ViT-L-ViViT [1] | IN-21K | 81.3 | 94.7 | 3992×3×4 | 310.8 |
| Swin-L↑ $384^2$ [56] | IN-21K | 84.9 | 96.7 | 2107×5×10 | 200.0 |
| **MViTv2**-L↑ $312^2$, 40×3 | IN-21K | **86.1** | **97.0** | 2828×3×5 | 217.6 |

# Are They Necessary?

Hiera: A Hierarchical Vision Transformer without Bells-and-Whistles[3]

- Observation:

  Vision-specific modules make models slower

  - e.g., attention pooling, relative positional embedding

- Question:

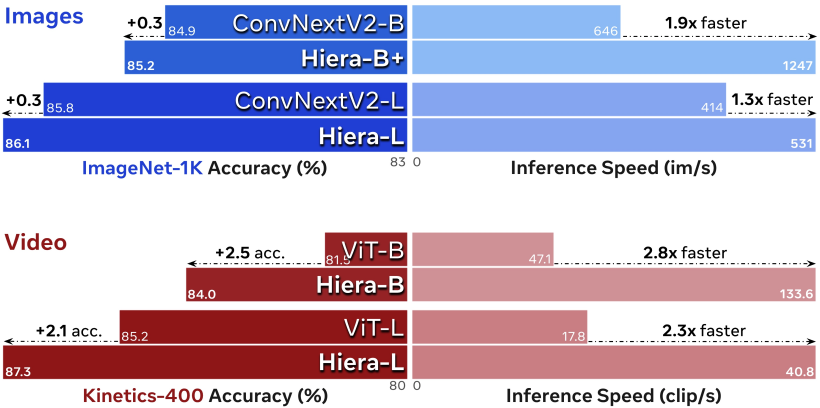
  Why should we slow down our architecture to add the spatial biases?

- Hypothesis:

  Use MAE pretraining to teach ViTs spatial reasoning

[3] ICML-2023

# Test Hypothesis on MViTv2



# Hiera Setup

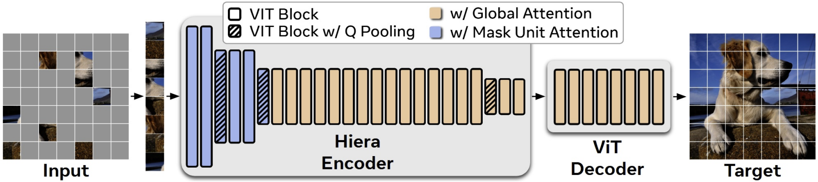
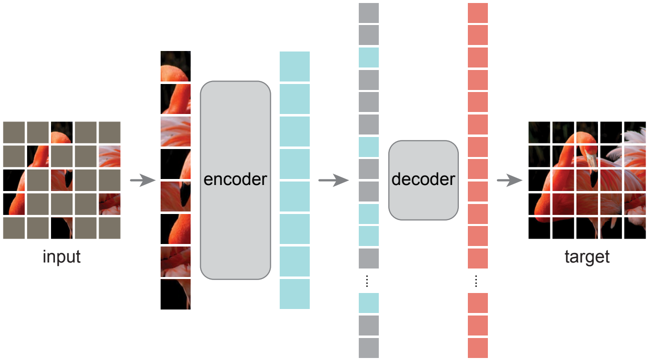



Figure: Local attention within “mask units" for the first two stages and global attention for the rest

# MAE Recap

- encoder: e.g., ViT, applied to **visible, unmasked** patches
- decoder: lightweight, **independent** of the encoder design
- reconstruction target: **pixel** values for masked tokens



# MAE for Hierarchical Models

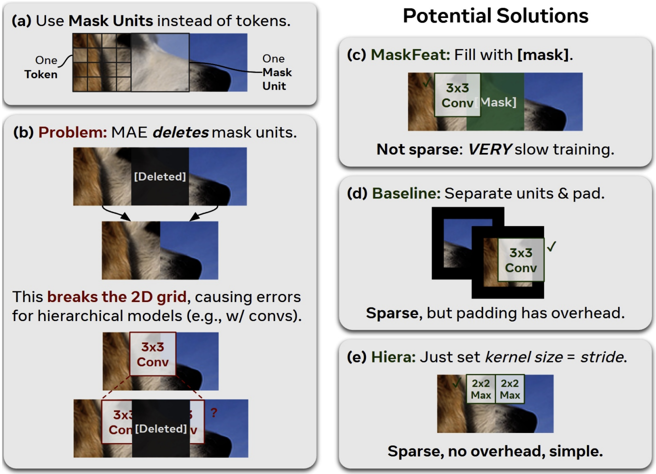



Figure: Random mask units rather than tokens

# Mask Unit Attention

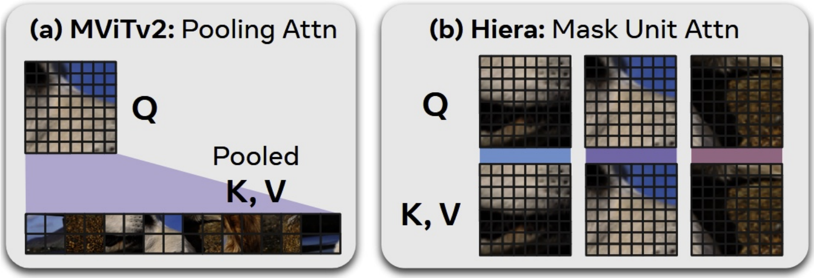



Figure: Mask Unit Attention performs local attention within mask units

# Simplifying MViTv2

| | Image | | Video | |
|---|---|---|---|---|
| Setting | acc. | im/s | acc. | clip/s |
| MViTv2-L Supervised | 85.3 | 219.8 | 80.5 | 20.5 |
| **Hiera-L** MAE | | | | |
| a. replace rel pos with absolute * | 85.6 | 253.3 | 85.3 | 20.7 |
| b. replace convs with maxpools * | 84.4 | 99.9† | 84.1 | 10.4† |
| c. delete stride=1 maxpools * | 85.4 | 309.2 | 84.3 | 26.2 |
| d. set kernel size equal to stride | **85.7** | 369.8 | **85.5** | 29.4 |
| e. delete q attention residuals | 85.6 | 374.3 | **85.5** | 29.8 |
| f. replace kv pooling with MU attn | 85.6 | **531.4** | **85.5** | **40.8** |

# Experimental Results on Kinetics-400

| backbone | pretrain | acc. | FLOPs (G) | Param |
|---|---|---|---|---|
| ViT-B | MAE | 81.5 | 180×3×5 | 87M |
| Hiera-B | MAE | <u>84.0</u> | **102**×3×5 | **51M** |
| Hiera-B+ | MAE | **85.0** | <u>133</u>×3×5 | <u>69M</u> |
| MViTv2-L | - | 80.5 | **377**×1×10 | <u>218M</u> |
| MViTv2-L | MaskFeat | 84.3 | **377**×1×10 | <u>218M</u> |
| ViT-L | MAE | <u>85.2</u> | 597×3×5 | 305M |
| Hiera-L | MAE | **87.3** | <u>413</u>×3×5 | **213M** |
| ViT-H | MAE | 86.6 | 1192×3×5 | **633M** |
| Hiera-H | MAE | **87.8** | **1159**×3×5 | 672M |

# Future Work

- Perception (multimodal) to action learning for robotics
- Functional perspective: proactive conversational agent (demo)
- When and how to perform actions is key given good perception representation
- Can be formulated as a canonical robotic control problem

# References

[1] **ICCV 2021** - Multiscale Vision Transformers

[2] **CVPR 2022** - MViTv2: Improved Multiscale Vision Transformers for Classification and Detection

[3] **CVPR 2022** - Masked Autoencoders Are Scalable Vision Learners

[4] **ICML 2023** - Hiera: A Hierarchical Vision Transformer without the Bells-and-Whistles

# Thank you very much!
# Q&A