MViTv2: Improved Multiscale Vision Transformers for Classification and Detection

Yanghao Li*, 1  Chao-Yuan Wu*, 1  Haoqi Fan1
Karttikeya Mangalam1,2  Bo Xiong1  Jitendra Malik1,2  Christoph Feichtenhofer*, 1
*equal technical contribution

1Facebook AI Research  2UC Berkeley

Abstract

In this paper, we study Multiscale Vision Transformers (MViTv2) as a unified architecture for image and video classification, as well as object detection. We present an improved version of MViT that incorporates decomposed relative positional embeddings and residual pooling connections. We instantiate this architecture in five sizes and evaluate it for ImageNet classification, COCO detection and Kinetics video recognition where it outperforms prior work. We further compare MViTv2’s pooling attention to window attention mechanisms where it outperforms the latter in accuracy/compute. Without bells-and-whistles, MViTv2 has state-of-the-art performance in 3 domains: 88.8% accuracy on ImageNet classification, 58.7 APbox on COCO object detection as well as 86.1% on Kinetics-400 video classification. Code and models are available at https://github.com/facebookresearch/mvit.

1. Introduction

Designing architectures for different visual recognition tasks has been historically difficult and the most widely adopted ones have been the ones that combine simplicity and efficacy, e.g. VGGNet [67] and ResNet [37]. More recently Vision Transformers (ViT) [17] have shown promising performance and are rivaling convolutional neural networks (CNN) and a wide range of modifications have recently been proposed to apply them to different vision tasks [1, 2, 21, 55, 68, 73, 78, 90].

While ViT [17] is popular in image classification, its usage for high-resolution object detection and space-time video understanding tasks remains challenging. The density of visual signals poses severe challenges in compute and memory requirements as these scale quadratically in complexity within the self-attention blocks of Transformer-based [76] models. The community has approached this burden with different strategies: Two popular ones are (1) shift-invariant positional embeddings using decomposed location distances to inject position information in Transformer blocks; (b) a residual pooling connection to compensate the effect of pooling strides in attention computation. Our simple-yet-effective upgrades lead to significantly better results.

(i) We create strong baselines that improve pooling attention along two axes: (a) shift-invariant positional embeddings using decomposed location distances to inject position information in Transformer blocks; (b) a residual pooling connection to compensate the effect of pooling strides in attention computation. Our simple-yet-effective upgrades lead to significantly better results.

(ii) Using the improved structure of MViT, we employ a standard dense prediction framework: Mask R-CNN [36] with Feature Pyramid Networks (FPN) [53] and apply it to object detection and instance segmentation.
We study if MViT can process high-resolution visual input by using pooling attention to overcome the computation and memory cost involved. Our experiments suggest that pooling attention is more effective than local window attention mechanisms (e.g. Swin [55]). We further develop a simple-yet-effective Hybrid window attention scheme that can complement pooling attention for better accuracy/compute tradeoff.

(iii) We instantiate our architecture in five sizes of increasing complexity (width, depth, resolution) and report a practical training recipe for large multiscale transformers. The MViT variants are applied to image classification, object detection and video classification, with minimal modification, to study its purpose as a generic vision architecture.

Experiments reveal that our MViTv2 achieves 88.8% accuracy for ImageNet-1K classification, with pretraining on ImageNet-21K (and 86.3% without), as well as 58.7 AP\textsuperscript{bbox} on COCO object detection using only Cascade Mask R-CNN [6]. For video classification tasks, MViT achieves unprecedented accuracies of 86.1% on Kinetics-400, 87.9% on Kinetics-600, 79.4% on Kinetics-700, and 73.3% on Something-Something-v2. Our video code will be open-sourced in PyTorchVideo.\textsuperscript{1,2} [19,20].

2. Related Work

CNNs serve as the primary backbones for computer vision tasks, including image recognition [10,15,34,39,46,48,62,67,69,71], object detection [6,29,38,53,63,93] and video recognition [8,22,23,25,42,51,61,66,75,79,84,92].

Vision transformers have generated a lot of recent enthusiasm since the work of ViT [17], which applies a Transformer architecture on image patches and shows very competitive results on image classification. Since then, different works have been developed to further improve ViT, including efficient training recipes [73], multi-scale transformer structures [21,55,78] and advanced self-attention mechanism design [11,21,55]. In this work, we build upon the Multi-scale Vision Transformers (MViT) and study it as a general backbone for different vision tasks.

Vision transformers for object detection tasks [11,55,78,89] address the challenge of detection typically requiring high-resolution inputs and feature maps for accurate object localization. This significantly increases computation complexity due to the quadratic complexity of self-attention operators in transformers [76]. Recent works develop technology to alleviate this cost, including shifted window attention [55] and Longformer attention [89]. Meanwhile, pooling attention in MViT is designed to compute self-attention efficiently using a different perspective [21]. In this work, we study MViT for detection and more generally compare pooling attention to local attention mechanisms.

Vision transformers for video recognition have also recently shown strong results, but mostly [1,3,56,59] rely on pre-training with large-scale external data (e.g. ImageNet-21K [14]). MViTv1 [21] reports a good training-from-scratch recipe for Transformer-based architectures on Kinetics data [44]. In this paper, we use this recipe and improve the MViT architecture with improved pooling attention which is simple yet effective on accuracy; further, we study the (large) effect of ImageNet pre-training for video tasks.

3. Revisiting Multiscale Vision Transformers

The key idea of MViTv1 [21] is to construct different stages for both low- and high-level visual modeling instead of single-scale blocks in ViT [17]. MViT slowly expands the channel width $D$, while reducing the resolution $L$ (i.e. sequence length), from input to output stages of the network.

To perform downsampling within a transformer block, MViT introduces Pooling Attention. Concretely, for an input sequence, $X \in \mathbb{R}^{L \times D}$, it applies linear projections $W_Q, W_K, W_V \in \mathbb{R}^{D \times D}$ followed by pooling operators ($P$) to query, key and value tensors, respectively:

$$Q = P_Q(XW_Q), \ K = P_K(XW_K), \ V = P_V(XW_V),$$

where the length $\tilde{L}$ of $Q \in \mathbb{R}^{\tilde{L} \times D}$ can be reduced by $P_Q$ and $K$ and $V$ length can be reduced by $P_K$ and $P_V$.

Subsequently, pooled self-attention,

$$Z := \text{Attn}(Q, K, V) = \text{Softmax} \left( QK^\top / \sqrt{D} \right) V,$$

computes the output sequence $Z \in \mathbb{R}^{\tilde{L} \times D}$ with flexible length $\tilde{L}$. Note that the downsampling factors $P_K$ and $P_V$ for key and value tensors can be different from the ones applied to the query sequence, $P_Q$.

Pooling attention enables resolution reduction between different stages of MViT by pooling the query tensor $Q$, and to significantly reduce compute and memory complexity by pooling the key, $K$, and value, $V$, tensors.

4. Improved Multiscale Vision Transformers

In this section, we first introduce an empirically powerful upgrade to pooling attention (§4.1). Then we describe how to employ our generic MViT architecture for object detection (§4.2) and video recognition (§4.3). Finally, §4.4 shows five concrete instantiations for MViTv2 in increasing complexity.

4.1 Improved Pooling Attention

We start with re-examining two important implications of MViTv2 for potential improvement and introduce techniques to understand and address them.
where $R$ denotes the vertical, horizontal, and temporal position of token $i$, respectively. Note that $R^t$ is optional and only required to support temporal dimension in the video case. In comparison, our decomposed embeddings reduce the number of learned embeddings to $O(T + W + H)$, which can have a large effect for early-stage, high-resolution feature maps.

**Residual pooling connection.** As demonstrated [21], pooling attention is very effective to reduce the computation complexity and memory requirements in attention blocks. MViTv1 has larger strides on $K$ and $V$ tensors than the stride of the $Q$ tensors which is only downsampled if the resolution of the output sequence changes across stages. This motivates us to add the residual pooling connection with the (pooled) $Q$ tensor to increase information flow and facilitate the training of pooling attention blocks in MViT.

We introduce a new residual pooling connection inside the attention blocks as shown in Fig. 2. Specifically, we add the pooled query tensor to the output sequence $Z$. So Eq. (2) is reformulated as:

$$Z := \text{Attn}(Q, K, V) + Q. \quad (5)$$

Note that the output sequence $Z$ has the same length as the pooled query tensor $Q$.

The ablations in §6.2 and §5.3 shows that both the pooling operator ($P_Q$) for query $Q$ and the residual path are necessary for the proposed residual pooling connection. This change still enjoys the low-complexity attention computation with large strides in key and value pooling as adding the pooled query sequence in Eq. (5) comes at a low cost.

### 4.2. MViT for Object Detection

In this section, we describe how to apply the MViT backbone for object detection and instance segmentation tasks.

**FPN integration.** The hierarchical structure of MViT produces multiscale feature maps in four stages, and therefore naturally integrates into Feature Pyramid Networks (FPN) [53] for object detection tasks, as shown in Fig. 3. The top-down pyramid with lateral connections in FPN constructs semantically strong feature maps for MViT at all scales. By using FPN with the MViT backbone, we apply it to different detection architectures (e.g., Mask R-CNN [36]).

**Hybrid window attention.** The self-attention in Transformers has quadratic complexity w.r.t. the number of tokens. This issue is more exacerbated for object detection as it typically requires high-resolution inputs and feature maps. In this paper, we study two ways to significantly reduce this compute and memory complexity: First, the pooling attention designed in attention blocks of MViT. Second, window attention used as a technique to reduce computation for object detection in Swin [55].

Pooling attention and window attention both control the complexity of self-attention by reducing the size of query, decomposed relative position embedding.

While MViT has shown promises in their power to model interactions between tokens, they focus on content, rather than structure. The space-time structure modeling relies solely on the “absolute” positional embedding to offer location information. This ignores the fundamental principle of shift-invariance in vision [47]. Namely, the way MViT models the interaction between two patches will change depending on their relative positions stay unchanged. To address this issue, we incorporate relative positional embeddings [65], which only depend on the relative location distances between tokens into the pooled self-attention computation.

We encode the relative position between the two input elements, $i$ and $j$, into positional embedding $R_{p(i),p(j)} \in \mathbb{R}^d$, where $p(i)$ and $p(j)$ denote the spatial (or spatiotemporal) position of element $i$ and $j$. The pairwise encoding representation is then embedded into the self-attention module:

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

where

$$E^{(\text{rel})}_{ij} = Q_i \cdot R_{p(i),p(j)}. \quad (3)$$

However, the number of possible embeddings $R_{p(i),p(j)}$ scale in $O(TWH)$, which can be expensive to compute. To reduce complexity, we decompose the distance computation between element $i$ and $j$ along the spatiotemporal axes:

$$R_{p(i),p(j)} = R_{h(i),h(j)} + R_{w(i),w(j)} + R_{t(i),t(j)}. \quad (4)$$

where $R^h, R^w, R^t$ are the positional embeddings along the height, width and temporal axes, and $h(i), w(i), t(i)$
key and value tensors when computing self-attention. Their intrinsic nature however is different: Pooling attention pools features by downsampling them via local aggregation, but keeps a global self-attention computation, while window attention keeps the resolution of tensors but performs self-attention locally by dividing the input (patchified tokens) into non-overlapping windows and then only compute local self-attention within each window. The intrinsic difference of the two approaches motivates us to study if they could perform complementary in object detection tasks.

Default window attention only performs local self-attention within windows, thus lacking connections across windows. Different from Swin [55], which uses shifted windows to mitigate this issue, we propose a simple Hybrid window attention (Hwin) design to add cross-window connections. Hwin computes local attention within a window in all but the last blocks of the last three stages that feed into FPN. In this way, the input feature maps to FPN contain global information. The ablation in §5.3 shows that this simple Hwin performs consistently better than Swin [55] on image classification and object detection tasks. Further, we will show that combining pooling attention and Hwin works well. Different from Swin [55], which uses shifted windows to mitigate this issue, we propose a simple Hybrid window attention (Hwin) design to add cross-window connections. Hwin computes local attention within a window in all but the last blocks of the last three stages that feed into FPN. In this way, the input feature maps to FPN contain global information. The ablation in §5.3 shows that this simple Hwin performs consistently better than Swin [55] on image classification and object detection tasks. Further, we will show that combining pooling attention and Hwin works well.

Positional embeddings in detection. Different from ImageNet classification where the input is a crop of fixed resolution (e.g. 224 × 224), object detection typically encompasses inputs of varying size in training. For the positional embeddings in MViT (either absolute or relative), we first initialize the parameters from the ImageNet pre-training weights corresponding to positional embeddings with 224 × 224 input size and then interpolate them to the respective sizes for object detection training.

4.3. MViT for Video Recognition

MViT can be easily adopted for video recognition tasks (e.g. the Kinetics dataset) similar to MViTv1 [21] as the upgraded modules in §4.1 generalize to the spatiotemporal domain. While MViTv1 only focuses on the training-from-scratch setting on Kinetics, in this work, we also study the (large) effect of pre-training from ImageNet datasets.

Initialization from pre-trained MViT. Compared to the image-based MViT, there are only three differences for video-based MViT: 1) the projection layer in the patchification stem needs to project the input into space-time cubes instead of 2D patches; 2) the pooling operators now pool spatiotemporal feature maps; 3) relative positional embeddings reference space-time locations.

As the projection layer and pooling operators in 1) and 2) are instantiated by convolutional layers by default, we use an inflation initialization as for CNNs. Specifically, we initialize the conv filters for the center frame with the weights from the 2D conv layers in pre-trained models and initialize other weights as zero. For 3), we capitalize on our decomposed relative positional embeddings in Eq. 4, and simply initialize the spatial embeddings from pre-trained weights and the temporal embedding as zero.

4.4. MViT Architecture Variants

We build several MViT variants with different number of parameters and FLOPs as shown in Table 1, in order to have a fair comparison with other vision transformer works [9, 55, 72, 81]. Specifically, we design five variants (Tiny, Small, Base, Large and Huge) for MViT by changing the base channel dimension, the number of blocks in each stage and the number of heads in the blocks. Note that we use a smaller number of heads to improve runtime, as more heads lead to slower runtime but have no effect on FLOPs and Parameters.

Following the pooling attention design in MViT [21], we employ Key and Value pooling in all pooling attention blocks by default and the pooling stride is set to 4 in the first stage and adaptively decays stride w.r.t resolution across stages.

5. Experiments: Image Recognition

We conduct experiments on ImageNet classification [14] and COCO object detection [54]. We first show state-of-the-art comparisons and then perform comprehensive ablations. More results and discussions are in §A.

5.1. Image Classification on ImageNet-1K

Settings. The ImageNet-1K [14] (IN-1K) dataset has ~1.28M images in 1000 classes. Our training recipe for MViTv2 on IN-1K is following MViTv1 [21, 72]. We train

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4Note that no initialization is needed if using max-pooling variants.
Table 2. Comparison to published work on ImageNet-1K. Input images are 224×224 by default and ∗ denotes using different sizes. MVIT is trained for 300 epochs without any external data or models. We report ∗× sized crop of the (resized) original validation images, to compare to prior work. Full Table in A.3.

Table 3. ImageNet-1K fine-tuning results using IN-21K data. Fine-tuning is with 224× input size (default) or with ∗ sized images. Center denotes testing with a center crop, while resize is scaling the full image to the inference resolution (including more context). Note that MViTv2-B has over 33% fewer flops and parameters comparing DeiT-B and Swin-B. The trend is similar with ∗× input size and MViTv2-B has further +0.8% gain from the high-resolution fine-tuning under center crop testing.

In addition to center crop testing (with a 224× input size), we report a testing protocol that has been adopted recently in the community [55, 71, 81]: This protocol takes a full-sized crop of the (resized) original validation images. We observe that full crop testing can increase our MViTv2-L ∗× from 86.0 to 86.3%, which is the highest accuracy on IN-1K to date (without external data or distillation models).

Results using ImageNet-21K. Results for using the large-scale IN-21K pre-training are shown in Table 3. The IN-21K data adds +2.2% accuracy to MViTv2-L.

Compared to other Transformers, MViTv2-L achieves better results than Swin-L (+1.2%). We lastly finetune MViTv2-L with ∗ sized input to directly compare to prior models of size L: MViTv2-L achieves 88.4%, outperforming other large models. We further train a huge MViTv2-H with accuracy 88.0%, 88.6% and 88.8% at 224×, 384× and 512× resolution.

5.2. Object Detection on COCO

Settings. We conduct object detection experiments on the MS-COCO dataset [54]. All the models are trained on 118K training images and evaluated on the 5K validation images. We use standard Mask R-CNN [36] and Cascade Mask R-CNN [6] detection frameworks implemented in Detectron2 [82]. For a fair comparison, we follow the same recipe as in Swin [55]. Specifically, we pre-train the backbones on IN and fine-tune on COCO using a 3×schedule (36 epochs) by default. Detailed training recipes are in §B.3.

For MViTv2, we take the backbone pre-trained from IN and add our Hybrid window attention (Hwin) by default. The window sizes are set as [56, 28, 14, 7] for the four stages, which is consistent with the self-attention size used in IN.
Table 4. Comparison of attention mechanisms on ImageNet and COCO using ViT-B and ViTv2-S backbones. fixed win: non-overlapping window-attention in all Transformer blocks. Shifted window attention. 

(a) ImageNet-1K classification

| variant | attention | Acc | FLOPs (G) | Mem (G) |
|---------|-----------|-----|-----------|--------|
| ViT-B   | full      | 82.0 | 17.5      | 12.4   |
|         | fixed win | 80.0 | 17.0      | 9.7    |
|         | Swin [55] | 80.4 | 17.0      | 9.7    |
|         | Hwin      | 82.1 | 17.1      | 10.4   |
|         | pooling   | 81.9 | 10.9      | 8.3    |
| ViTv2-S | pooling   | 83.6 | 7.0       | 6.8    |
|         | (stride=8)| 83.2 | 6.3       | 5.5    |
|         | + Swin [55]| 82.8 | 6.4       | 6.0    |
|         | + Hwin    | 83.0 | 6.5       | 6.2    |

(b) Mask R-CNN on COCO detection

| variant | attention | AP\textsuperscript{bbox} | Train(iter/s) | Test(im/s) | Mem(G) |
|---------|-----------|---------------------------|--------------|------------|--------|
| ViT-B   | full      | 46.6                      | 2.3          | 4.6        | 24.7   |
|         | fixed win | 43.4                      | 3.3          | 7.8        | 5.6    |
|         | Swin [55] | 45.1                      | 3.1          | 7.5        | 5.7    |
|         | Hwin      | 46.1                      | 3.1          | 6.8        | 11.0   |
|         | pooling   | 47.2                      | 2.9          | 7.9        | 8.8    |
|         | + Hwin    | 46.9                      | 3.1          | 8.8        | 5.5    |
| ViTv2-S | pooling   | 50.8                      | 1.5          | 4.2        | 19.5   |
|         | (stride=8)| 48.0                      | 2.5          | 8.3        | 7.8    |
|         | + Swin [55]| 48.9                     | 2.6          | 9.2        | 4.9    |
|         | + Hwin    | 49.9                      | 2.7          | 9.4        | 5.2    |

5We adapt ViTvI [21] as a detection baseline combined with Hwin.

5.3. Ablations on ImageNet and COCO

Different self-attention mechanisms. We first study our pooling attention and Hwin self-attention mechanism in ViTv2 by comparing with different self-attention mechanisms on ImageNet and COCO. For a fair comparison, we conduct the analysis on both ViT-B and ViTv2-S networks.

In Table 4a we compare different attention schemes on IN-1K. We compare 5 attention mechanisms: global (full), default win [4], shifted win (Swin), and pooling. We observe the following:

(i) For ViT-B based models, default win reduces both FLOPs and Memory usage while the top-1 accuracy also drops by 2.0% due to the missing cross-window connection.

Main results. Table 5a shows the results on COCO using Mask R-CNN. Our ViTv2 surpasses CNN (i.e., ResNet [38] and ResNetXt [83]) and Transformer backbones (e.g., Swin [55], ViL [89] and MViTv1 [21])

E.g., ViTv2-B outperforms Swin-B by +2.5/2.3 in AP\textsuperscript{bbox}/AP\textsuperscript{mask}, with lower compute and smaller model size. When scaling up, our deeper ViTv2-L improves over ViTv2-B by +0.8 AP\textsuperscript{bbox} and using IN-21K pre-training further adds +0.9 to achieve 52.7 AP\textsuperscript{bbox} with Mask R-CNN and a standard 3× schedule.

In Table 5b we observe a similar trend among backbones for Cascade Mask R-CNN [6] which lifts Mask R-CNN accuracy (5a). We also ablate the use of a longer training schedule with large-scale jitter that boosts our AP\textsuperscript{bbox} to 55.8. ViTv2-H increases this to 56.1 AP\textsuperscript{bbox}.

We further adopt two inference strategies (SoftNMS [4] and multi-scale testing) on ViTv2-L with Cascade Mask R-CNN for system-level comparison (See Table §A.1). They boost our AP\textsuperscript{bbox} to 58.7, which is already better than the best results from Swin (58.0 AP\textsuperscript{bbox}), even ViTv2 does not use the improved HTC++ detector [55] yet.
Swin [55] attention can recover 0.4% over default win. While our Hybrid window (Hwin) attention fully recovers the performance and outperforms Swin attention by +1.7%. Finally, pooling attention achieves the best accuracy/computation trade-off by getting similar accuracy for ViT-B with significant compute reduction (~38% fewer FLOPs).

(ii) For MViTv2-S, pooling attention is used by default. We study if adding local window attention can improve MViT. We observe that adding Swin or Hwin both can reduce the model complexity with slight performance decay. However, directly increasing the pooling stride (from 4 to 8) achieves the best accuracy/compute tradeoff.

Table 4b shows the comparison of attention mechanisms on COCO: (i) For ViT-B based models, pooling and pooling + Hwin achieves even better results (+0.6/0.3 AP\textsubscript{box}) than standard full attention with ~2× test speedup. (ii) For MViTv2-S, directly increasing the pooling stride (from 4 to 8) achieves better accuracy/computation tradeoff than adding Swin. This result suggests that simple pooling attention can be a strong baseline for object detection. Finally, combining our pooling and Hwin achieves the best tradeoff.

### Positional embeddings.

Table 6 compares different positional embeddings. We observe that: (i) Comparing (2) to (1), absolute position only slightly improves over no pos.. This is because the pooling operators (instantiated by conv layers) already model positional information. (ii) Comparing (3, 4) and (1, 2), relative positions can bring performance gain by introducing shift-invariance priors to pooling attention. Finally, our decomposed relative position embedding train 3.9× faster than joint relative position on COCO.

### Residual pooling connections.

Table 7 studies the importance of our residual pooling connection. We see that simply adding the residual path (2) can improve results on both IN-1K (+0.3%) and COCO (+0.8 for AP\textsubscript{box}) with negligible cost. (3) Using residual pooling and also adding Q pooling to all other layers (with stride=1) leads to a significant boost, especially on COCO (+1.4 AP\textsubscript{box}). This suggests both Q pooling layers and residual paths are necessary in MViTv2. (4) Just adding (without residual) more Q pooling layers with stride=1 does not help and even decays (4) vs. (1).

| model   | IN-1K | COCO |
|---------|-------|------|
|         | Acc   | Test (im/s) | Acc | Test (im/s) | Mem(G) |
| Swin-B  [55] | 83.3  | 276          | 48.5 | 2.5 | 9.4 | 6.3 |
| MViTv2-S | 83.6  | 341          | 49.9 | 2.7 | 9.4 | 5.2 |
| MViTv2-B | 84.4  | 253          | 51.0 | 2.1 | 7.2 | 6.9 |

Table 8. Runtime comparison on IN-1K and COCO. We report accuracy and throughput on IN-1K, measured with a V100 GPU as in [55]. COCO models are measured similarly and also for training throughput and memory. Batch size for all measures is identical.

**Runtime comparison.** We conduct a runtime comparison for MViTv2 and Swin [55] in Table 8. We see that MViTv2-S surpasses Swin-B on both IN-1K (+0.3%) and COCO (+1.4%) while having a higher throughput (341 im/s vs. 276 im/s) on IN-1K and also trains faster (2.7iter/s vs. 2.5iter/s) on COCO with less memory cost (5.2G vs. 6.3G). MViTv2-B is slightly slower but significantly more accurate (+1.1% on IN-1K and +2.5AP\textsubscript{box} on COCO).

**Single-scale vs. multi-scale for detection.** Table 9 compares the default multi-scale (FPN) detector with the single-scale detector for ViT-B and MViTv2-S. As ViT produces feature maps at a single scale in the backbone, we adopt a simple scheme [50] to up-/downscale features to integrate with FPN. For single-scale, we directly apply the detection heads to the last Transformers block.

| variant | FPN | AP\textsubscript{box} | AP\textsubscript{mask} | FLOPs (G) |
|---------|-----|-----------------------|-----------------------|-----------|
| ViT-B   | no  | 45.1                  | 40.6                  | 725       |
| ViT-B   | yes | 46.6                  | 42.3                  | 879       |
| MViTv2-S | no  | 47.0                  | 41.4                  | 276       |
| MViTv2-S | yes | 49.9                  | 45.1                  | 326       |

Table 9. Single-scale vs. Multi-scale (FPN) on COCO. ViT-B and MViTv2-S models are equipped with or w/o a feature pyramid network (FPN). Both FPN models outperform their single-scale variant while while MViTv2 achieves even larger gains.

As shown in Table 9, FPN significantly improves performance for both backbones while MViTv2-S is consistently better than ViT-B. Note that the FPN gain for MViTv2-S (+2.9 AP\textsubscript{box}) is much larger than those for ViT-B (+1.5 AP\textsubscript{box}), which shows the effectiveness of a native hierarchical multi-scale design for dense object detection tasks.

### 6. Experiments: Video Recognition

We apply our MViTv2 on Kinetics-400 [44] (K400), Kinetics-600 (K600) [8], and Kinetics-700 (K700) [7] and Something-Something-v2 [31] (SSv2) datasets.

**Settings.** By default, our MViTv2 models are trained from scratch on Kinetics and fine-tuned from Kinetics models for SSv2. The training recipe and augmentations follow [19, 21]. When using IN-1K or IN-21K as pre-training, we adopt the initialization scheme introduced in §4.3 and shorter training.

For the temporal domain, we sample a $T \times \tau$ clip from the full-length video which contains $T$ frames with a temporal stride of $\tau$. For inference, we follow testing strategies in [21, 23] and get final score by averaged from sampled temporal clips and spatial crops. Implementation and training details are in §B.
Table 10. Comparison with previous work on Kinetics-400. We report the inference cost with a single “view” (temporal clip with spatial crop) × the number of views (FLOPs × viewspace × viewtime). Magnitudes are Giga (10^9) for FLOPs and Mega (10^6) for Param.

| model             | pretrain | top-1 | top-5 | FLOPs x views | Param       |
|-------------------|----------|-------|-------|---------------|-------------|
| SlowFast 16 × 8 +NL [23] | -        | 79.8  | 93.9  | 234 × 3 x 10  | 59.9        |
| X3D-XL [22]      | -        | 79.1  | 93.5  | 48.4 x 10     | 11.0        |
| MoViNet-A6 [45]  | -        | 81.5  | 95.3  | 386 x 1   | 31.4        |
| MViTv1, 16 × 4 [21] | -        | 78.4  | 93.5  | 70.3 x 1.5   | 36.6        |
| MViTv1, 32 × 3 [21] | -        | 80.2  | 94.4  | 35.6 x 1.5   | 66.6        |
| MViTv2-S, 16 × 4 | -        | 81.0  | 94.6  | 64 x 1.5     | 34.5        |
| MViTv2-B, 32 × 3 | -        | 82.9  | 95.7  | 225 x 1.5    | 51.2        |
| ViT-B-VTN [59]   |          | 78.6  | 93.7  | 4218 x 1     | 114.0       |
| ViT-B-TimeSformer [3] | -        | 80.7  | 94.7  | 2380 x 1     | 121.4       |
| ViT-L-ViViT [3]  |          | 81.3  | 94.7  | 3992 x 3.4   | 310.8       |
| Swin-L↑ 384² [56] | IN-21K   | 64.9  | 96.7  | 21075 × 10   | 200.0       |
| MViTv2-L↑ 312², 40×3 | -       | 86.1  | 97.0  | 28283 x 3.5  | 217.6       |

Table 11. Comparison with previous work on Kinetics-600.

| model             | pretrain | top-1 | top-5 | FLOPs x views | Param       |
|-------------------|----------|-------|-------|---------------|-------------|
| SlowFast 16 × 8 +NL [23] | K600     | 71.0  | 89.6  | 234 x 10     | 59.9        |
| MoViNet-A6 [45]  | N/A      | 72.3  | 94.9  | 386 x 1.1    | 31.4        |
| MViTv2-B, 32 × 3  | -        | 76.6  | 93.2  | 2063 x 3     | 51.4        |
| MViTv2-L↑ 312², 40×3 | IN-21K   | 79.4  | 94.9  | 28283 x 3.5  | 217.6       |

Table 12. Comparison with previous work on Kinetics-700.

6.1. Main Results

Kinetics-400. Table 10 compares MViTv2 to prior work, including state-of-the-art CNNs and ViTs.

When training from scratch, our MViTv2-S & B models produce 81.0% & 82.9% top-1 accuracy which is +2.6% & +2.7% higher than their MViTv1 [21] counterparts. These gains stem solely from the improvements in §4.1, as the training recipe is identical.

Prior ViT-based models require large-scale pre-training on IN-21K to produce best accuracy on K400. We fine-tune our MViTv2-L with large spatiotemporal input size 40 × 312² (time × space²) to reach 86.1% top-1 accuracy, showing the performance of our architecture in a large-scale setting.

Kinetics-600/-700. Table 11 shows the results on K600. We train MViTv2-B, 32 × 3 from scratch and achieve 85.5% top-1 accuracy, which is better than the MViTv1 counterpart (+1.4%), and even better than other ViTs with IN-21K pre-training (e.g., +1.5% over Swin-B [56]) while having ~2.2 × and ~40% fewer FLOPs and parameters. The larger MViTv2-L 40 × 3 sets a new state-of-the-art at 87.9%.

6.2. Ablations on Kinetics

In this section, we carry out MViTv2 ablations on K400. The video ablation our technical improvements share trends with Table 6 & 7 and are in §A.5.

Table 14. Effect of pre-training on K400. We use viewspace × viewtime = 1 × 10 crops for inference.

The effect different pre-training schemes on K400. We observe that: (i) For MViTv2-S and MViTv2-B models, using either IN1K or IN21k pre-training boosts accuracy compared to training from scratch, e.g., MViTv2-S gets +1.0% and 1.4% gains with IN1K and IN21K pre-training. (ii) For large models, ImageNet pre-training is necessary as they are heavily overfitting when trained from scratch (cf. Table 10).

7. Conclusion

We present an improved Multiscale Vision Transformer as a general hierarchical architecture for visual recognition. In empirical evaluation, MViTv shows strong performance compared to other vision transformers and achieves state-of-the-art accuracy on widely-used benchmarks across image classification, object detection, instance segmentation and video recognition. We hope that our architecture will be useful for further research in visual recognition.

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