# Vision Mamba: Efficient Visual Representation Learning with Bidirectional State Space Model

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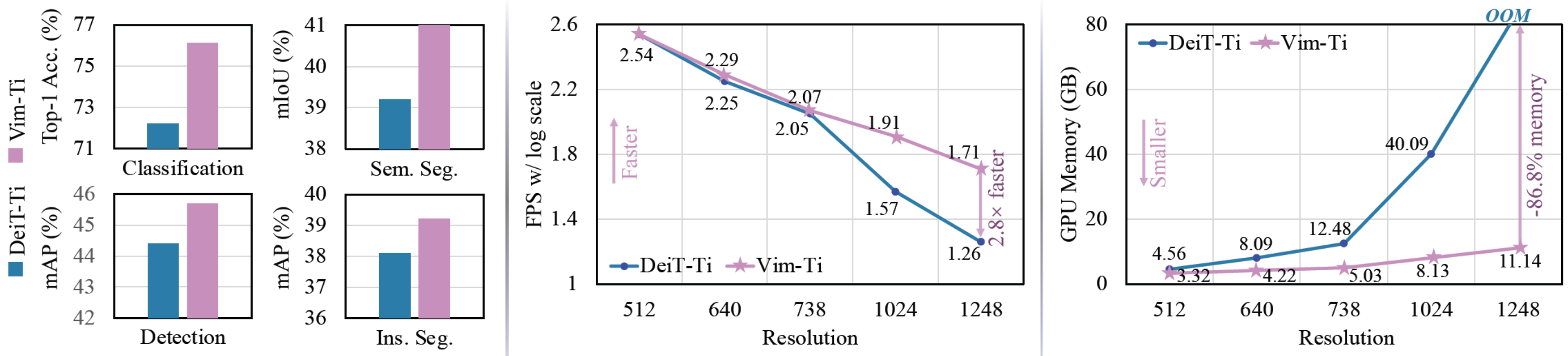
# Motivation

- Introducing Vision Mamba (Vim) with **Bidirectional SSM**
- Improving existing SOTA Transformer based models (DeiT) for high resolution in terms of:
    - **Memory efficiency**
    - **Performance in Vision Tasks**




(a) Accuracy Comparison (b) Speed Comparison (c) GPU Memory Comparison

# State Space Models (SSM)

They are inspired in basic 1-D continuous differential models for sequences

$$
\begin{aligned}
h'(t) &= \mathbf{A}h(t) + \mathbf{B}x(t),\\
y(t) &= \mathbf{C}h(t).
\end{aligned}
$$

Discretization

$$
\begin{aligned}
\overline{\mathbf{A}} &= \exp(\mathbf{\Delta A}),\\
\overline{\mathbf{B}} &= (\mathbf{\Delta A})^{-1}(\exp(\mathbf{\Delta A}) - \mathbf{I}) \cdot \mathbf{\Delta B}.
\end{aligned}
$$

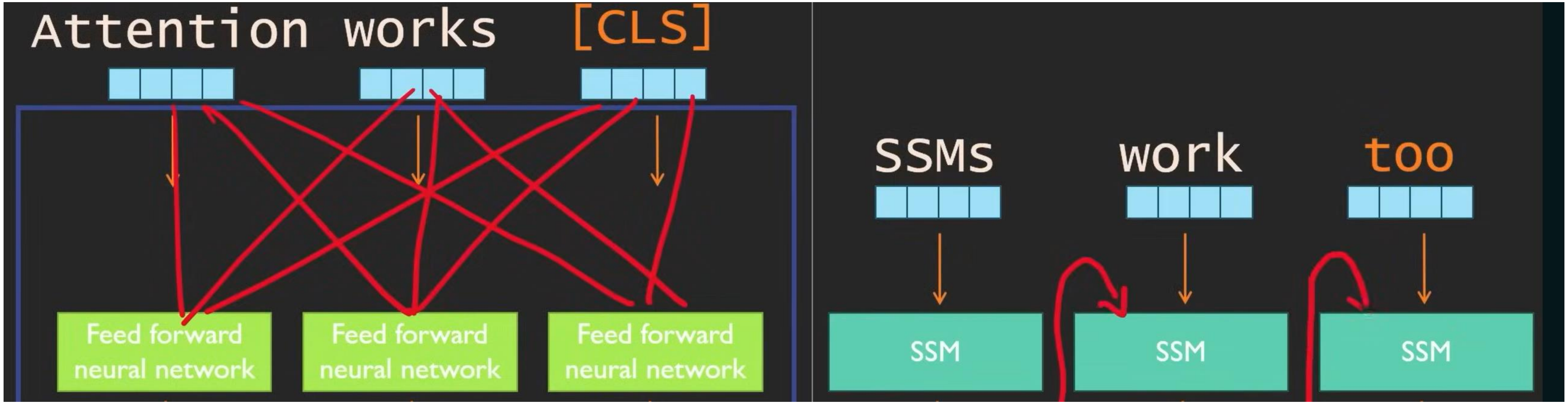
$$
\begin{aligned}
h_t &= \overline{\mathbf{A}}h_{t-1} + \overline{\mathbf{B}}x_t,\\
y_t &= \mathbf{C}h_t.
\end{aligned}
$$

**Learnable parameters:** Step size (Δ)

**Method:** Convolution (Efficient in GPU)

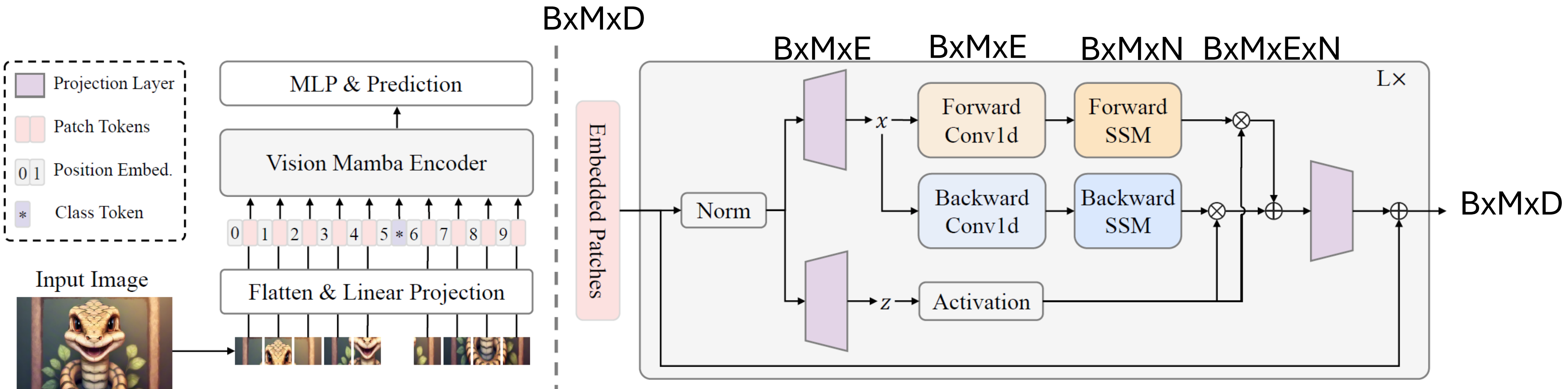
$$
\begin{aligned}
\overline{\mathbf{K}} &= (\mathbf{C}\overline{\mathbf{B}}, \mathbf{C}\overline{\mathbf{AB}}, \dots, \mathbf{C}\overline{\mathbf{A}}^{\mathtt{M}-1}\overline{\mathbf{B}}),\\
\mathbf{y} &= \mathbf{x} * \overline{\mathbf{K}},
\end{aligned}
$$

# SSMs vs. Transformers (Efficiency)




*Images: AICoffeeBreak, (2024, April 08). *MAMBA and State Space Models explained | SSM explained* [Video]. YouTube.
URL: https://www.youtube.com/watch?v=vrF3MtGwD0Y&t=1s&ab_channel=AICoffeeBreakwithLetitia

# Vision Mamba




Vision Mamba (Vim)

Vision Mamba Encoder

$$\mathbf{T}_0 = [\mathbf{t}_{cls}; \mathbf{t}_p^1\mathbf{W}; \mathbf{t}_p^2\mathbf{W}; \cdots; \mathbf{t}_p^J\mathbf{W}] + \mathbf{E}_{pos},$$

$$\mathbf{T}_l = \mathbf{Vim}(\mathbf{T}_{l-1}) + \mathbf{T}_{l-1},$$

$$\mathbf{f} = \mathbf{Norm}(\mathbf{T}_L^0),$$

$$\hat{p} = \mathbf{MLP}(\mathbf{f}),$$

| | Tiny | Small |
|---|---|---|
| L : Number of vim blocks | 24 | 24 |
| D: Hidden state dimension | 192 | 384 |
| E: Expanded state dimension | 384 | 768 |
| N: SSM dimensión | 16 | 16 |

# Experiments: Classification

| Method | image size | #param. | ImageNet top-1 acc. |
|---|---|---|---|
| **Convnets** | | | |
| ResNet-18 | $224^2$ | 12M | 69.8 |
| ResNet-50 | $224^2$ | 25M | 76.2 |
| ResNet-101 | $224^2$ | 45M | 77.4 |
| ResNet-152 | $224^2$ | 60M | 78.3 |
| ResNeXt50-32×4d | $224^2$ | 25M | 77.6 |
| RegNetY-4GF | $224^2$ | 21M | 80.0 |
| **Transformers** | | | |
| ViT-B/16 | $384^2$ | 86M | 77.9 |
| ViT-L/16 | $384^2$ | 307M | 76.5 |
| DeiT-Ti | $224^2$ | 6M | 72.2 |
| DeiT-S | $224^2$ | 22M | 79.8 |
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Table 1. Comparison with different backbones on ImageNet-1K validation set. $^\dagger$ represents the model is fine-tuned with our long sequence setting.

**ImageNet-1K** Dataset:

- **1.28M training** images
- **50K validation** images
- 1,000 categories

**Long Sequence Fine-Tuning**: Double of patches than DeiT with the same size (stride 8, 16x16).

**Results**:

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- **3.9 points** higher for **Vim-Tiny** over **DeiT-Tiny**

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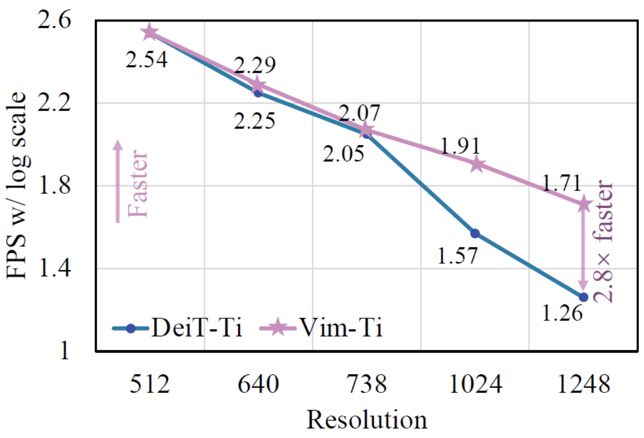
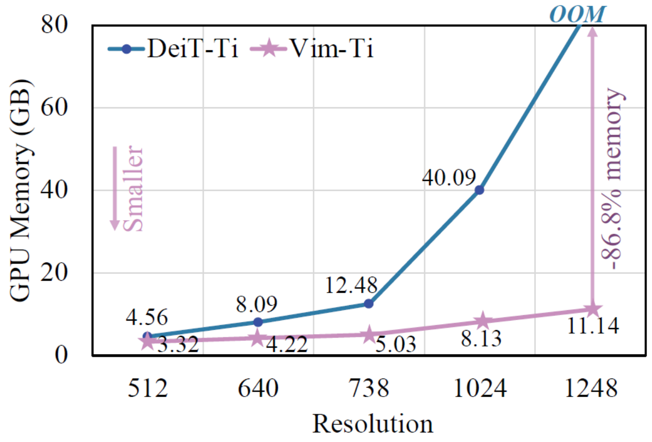
- **3.9 points** higher for **Vim-Tiny** over **DeiT-Tiny**
- **0.7 points** higher for **Vim-Small** over **DeiT-Small**
- **Vim-S** achieves results **similar to DeiT-B** with LSFT
- **1248×1248: Vim** is **2.8× faster** than DeiT and **saves 86.8% GPU memory**



# Experiments: Semantic Segmentation

| Method | Backbone | image size | #param. | *val* mIoU |
|---|---|---|---|---|
| DeepLab v3+ | ResNet-101 | $512^2$ | 63M | 44.1 |
| UperNet | ResNet-50 | $512^2$ | 67M | 41.2 |
| UperNet | ResNet-101 | $512^2$ | 86M | 44.9 |
| UperNet | DeiT-Ti | $512^2$ | 11M | 39.2 |
| UperNet | DeiT-S | $512^2$ | 43M | 44.0 |
| UperNet | Vim-Ti | $512^2$ | 13M | 41.0 |
| UperNet | Vim-S | $512^2$ | 46M | 44.9 |

Table 2. Results of semantic segmentation on the ADE20K *val* set.

**ADE20K** Dataset:

- **20K training** images
- **2K validation** images
- 150 categories
- **UperNet** framework

**Results**:

# Experiments: Semantic Segmentation

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**Results**:

- **1.8 mIoU** higher for **Vim-Ti** over **DeiT-Ti**
- **0.9 mIoU** higher for **Vim-S** over **DeiT-S**

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**Results**:

- **1.8 mIoU** higher for **Vim-Ti** over **DeiT-Ti**
- **0.9 mIoU** higher for **Vim-S** over **DeiT-S**
- **Vim-S similar to ResNet-101** but **2x fewer parameters**

# Experiments: Object Detection and Instance Segmentation

| Backbone | $AP^{box}$ | $AP^{box}_{50}$ | $AP^{box}_{75}$ | $AP^{box}_{s}$ | $AP^{box}_{m}$ | $AP^{box}_{l}$ |
|---|---|---|---|---|---|---|
| DeiT-Ti | 44.4 | 63.0 | 47.8 | 26.1 | 47.4 | 61.8 |
| Vim-Ti | 45.7 | 63.9 | 49.6 | 26.1 | 49.0 | 63.2 |
| Backbone | $AP^{mask}$ | $AP^{mask}_{50}$ | $AP^{mask}_{75}$ | $AP^{mask}_{s}$ | $AP^{mask}_{m}$ | $AP^{mask}_{l}$ |
| DeiT-Ti | 38.1 | 59.9 | 40.5 | 18.1 | 40.5 | 58.4 |
| Vim-Ti | 39.2 | 60.9 | 41.7 | 18.2 | 41.8 | 60.2 |

Table 3. Results of object detection and instance segmentation on the COCO *val* set using Cascade Mask R-CNN [4] framework.

**COCO 2017** Dataset:

- **118K training** images
- **5K validation** images
- Cascade Mask R-CNN base framework

**Results**:

- Vim-Ti **surpasses** DeiT-Ti for **medium-size** and **big** objects
- **Better long-range context learning**
- Not necessary window attention

# Experiments: Ablation Study for Design

| Bidirectional strategy | ImageNet top-1 acc. | ADE20K mIoU |
|---|---|---|
| None | 73.2 | 32.3 |
| Bidirectional Layer | 70.9 | 33.6 |
| Bidirectional SSM | 72.8 | 33.2 |
| Bidirectional SSM + Conv1d | 73.9 | 35.9 |

Table 4. Ablation study on the bidirectional design. To ensure a fair comparison, we do not use the class token for each experiment. The default setting for Vim is marked in blue.

- Unidirectionality makes Mamba Block (None) fail in dense classification tasks (i.e. segmentation)
- Bidirectional Block improves segmentation (+1.3 mIoU).
- **Further enhancement with Bidirectional SSM + Conv1D**.

| Classification strategy | ImageNet top-1 acc. |
|---|---|
| Mean pool | 73.9 |
| Max pool | 73.4 |
| Head class token | 75.2 |
| Double class token | 74.3 |
| Middle class token | 76.1 |

Table 5. Ablation study on the classification design. The default setting for Vim is marked in blue.

- Concatenating class token to the visual sequence and performing classification on it outperforms pooling strategy .
- The best design is by adding **class token at the middle of the visual sequence** and then perform classification on the final middle class token.

# Conclusions

- Possible alternative to Transformer based backbones
- **Computational complexity** linear on sequence length as shown for text
- **Modeling power** similar to DeiT and superior for higher resolution images thanks to efficient long sequences management

# Possible Improvements and Future Work

- Different Datasets and Frameworks
- Ablation study on Hyperparameters
- Self-Supervised Learning
- Comparison of improvements for SOTA systems based on Transformers