1 Pascal VOC semantic segmentation

Settings Semantic segmentation experiments are conducted on Pascal VOC 2012, which contains 20 foreground classes and 1 background. For training, we use an augmented version of the dataset [9] with extra annotations of 10582 images (trainaug). The default training setup uses scale jittering of [0.5, 2.0] and random horizontal image flipping.

1.1 Scaling rule of UViTs

To also achieve the best performance-efficiency trade-off on semantic segmentation task, we further systematically study the model scaling of UViTs on depths and widths on the Pascal VOC dataset. We show our results in Figure 1. For all models (circle markers), we first train them on ImageNet-1k, then directly fine-tune them on Pascal VOC. We fix the input size as $512 \times 512$.

- Depth (number of attention blocks): we study different UViT models of depths selected from \{12, 18, 24, 32\}.
- Width (i.e. hidden size, or output dimension of attention blocks): we will tune the width to further control different model sizes and computation costs to make different scaling rules fairly comparable.

In summary, based on our compound scaling rule, we find the UViT of depth 32 performs the best on Pascal VOC.

$^\dagger$ Work done during the first author’s research internship with Google.

$^3$ This scaling rule is studied before we study the attention window strategy in Section 1.3. Thus for all models in Figure 1, we adopt the window scale as $\frac{1}{2}$, for fair comparisons.
1.2 Architectures

We propose three variants of our UViT variants. The architecture configurations of our model variants are listed in Table 1 and are also annotated in Figure 1 ("T", "S", "B" in white). The number of heads is fixed as six, and the expansion ratio of each FFN (feed-forward network) layer is fixed as four in all experiments. We also scale up our UViT into a huge version following the design in [7,15], and denote it as “UViT-H”.

1.3 Attention windows on Pascal VOC

In this section, we further study the attention window strategy on the Pascal VOC dataset, using our UViT-B. As shown in Table 2, progressive attention
Table 1: Architecture variants of our UViT for Pascal VOC semantic segmentation.

| Name   | Depth | Hidden Size | Params. (M) |
|--------|-------|-------------|-------------|
| UViT-T | 32    | 192         | 18.1        |
| UViT-S | 32    | 240         | 26.7        |
| UViT-B | 32    | 342         | 50.7        |
| UViT-H | 32    | 1280        | 529.9       |

Global attentions in deep layers are vital, and a smaller window in early attentions can improve efficiency. In conclusion, we set the window scale of our UViT as $\left[2^{-1}\right] \times 28 \rightarrow \left[1^{-1}\right] \times 4$ for its reduced computation cost.

Table 2: Local attention windows in early layers can improve model efficiency, and global attention windows in deep layers are vital to the final performance on Pascal VOC. Model: UViT-B.

| [window\_scale] $\times$ #layers | GFLOPs | AP \_val |
|----------------------------------|--------|----------|
| $[1] \times 32$                  | 596.7  | 81.1     |
| $[2^{-1}] \times 32$            | 315.2  | 80.6     |
| $[2^{-1}] \times 28 \rightarrow [1^{-1}] \times 4$ | 350.4  | 81.2     |

1.4 Final performance on Pascal VOC

Following the same procedure in [3, 13, 8, 4, 5, 1, 12, 16, 10, 14], we employ the COCO dataset [11] to pretrain our model. From Table 3 we can see that our UViT is highly compact in terms of the number of parameters, and achieve competitive mIoU with comparable FLOPs. In addition, it is worth noting that since we only leverage a single-scale feature map, we do not adopt advanced segmentation decoders like ASPP [4] but just use plain convolutional layers for predictions, which is to our disadvantage. Again, without adopting any design conventions from CNNs, the results of our simple UViT architectures suggest that, a simple single-scale transformer backbone can fulfill the dense prediction tasks.
Table 3: Segmentation results on Pascal VOC 2012. Our UViT leverages a plain convolutional segmentation head, without any test-time augmentation.

| Backbone                        | Resolution | GFLOPs | Params. (M) | mIoU  |
|---------------------------------|------------|--------|-------------|-------|
| WASPnet-CRF [2]                 | -          | -      | 47.5        | 80.4  |
| DeepLabv3+ (ResNet-101) [6]    | 512×512    | 298    | 58.6        | 79.4  |
| UViT-T (ours)                   | 512×512    | 163    | 18.1        | 79.0  |
| UViT-S (ours)                   | 512×512    | 215    | 26.7        | 79.9  |
| UViT-B (ours)                   | 512×512    | 350    | 50.7        | 81.2  |
| UViT-H (ours)                   | 640×640    | 3846   | 529.9       | 88.1  |

2 Model architectures studied in Figure 2

We show details of all architectures studied in Figure 2 (main body) in Table 4 below. As mentioned in Section 3.1 (main body), we study all combinations of the above three techniques (spatial downsampling “SD”, multi-scale features “MF”, doubled channels “2x”), i.e. eight settings in total, and show the results in Figure 2 (main body). Each dot in Figure 2 (main body) indicates an individually designed and trained model. To make all comparisons fair, we carefully design all models such that they are all of around 72 million parameters. We control their FLOPs by changing the depths or attention windows allocated to different stages.

3 Model architectures in Figure 4 and Figure 5

We show all architectures studied in our compound scaling rule in Figure 4 and Figure 5 (main body). All models are of $2^{-1}$-scale attention windows for fair comparisons.
Table 4: Model architectures in Figure 2 (main body), all studied under a 640×640 input size on MS-COCO. “SD”: spatial downsampling, “MF”: multi-scale features, “2X”: doubled channels. Without any of these three techniques (first section in this table), the whole network has a constant feature resolution and hidden size; all other seven settings below will split the network into three stages, since they require either a progressive feature downsampling or multi-scale features from each stage. Input scale is relative to the 2D shape of the input image $H \times W$ (e.g. $8^{-1}$ indicates the 2D shape of the UViT’s sequence feature is $\frac{1}{8}H \times \frac{1}{8}W$). The window scale is relative to the 2D shape of sequence feature’s $h \times w$ (e.g. $8^{-1}$ indicates the 2D shape of the attention window is $\frac{1}{8}h \times \frac{1}{8}w$). Numbers with underscores in the column “Output Scale” indicate feature maps that will be fed into the FPN detection head (i.e., the last output of backbone if no “MF” is applied, or features from all three stages if “MF” is applied).
Table 5: Model architectures in Figure 4 and Figure 5 (MS-COCO) (in main body). Configurations (depth, width) of UViT-T/S/B are annotated.

| Input Size | Depth | Width | Params. (M) | FLOPs (G) | mAP  |
|------------|-------|-------|-------------|-----------|------|
| 640 × 640  | 18    | 384   | 72.1        | 676.2     | 50.4 |
|            |       | 432   | 80.9        | 748.3     | 50.5 |
|            |       | 462   | 86.9        | 796.6     | 50.7 |
|            |       | 492   | 93.3        | 847.4     | 50.4 |
|            |       | 564   | 110.2       | 979.4     | 50.1 |
| 768 × 768  | 18    | 288   | 58.2        | 725.9     | 51.1 |
|            |       | 306   | 60.7        | 761.1     | 51.5 |
|            |       | 330   | 64.3        | 810.0     | 51.3 |
|            |       | 384   | 73.1        | 928.5     | 51.5 |
|            |       | 432   | 82.1        | 1043.5    | 51.6 |
|            |       | 462   | 88.2        | 1120.1    | 51.3 |
| 896 × 896  | 18    | 186   | 47.4        | 710.2     | 51   |
|            |       | 222   | 51.0        | 801.4     | 51.3 |
|            |       | 246   | 53.8        | 866.1     | 51.7 |
|            |       | 288   | 59.2        | 986.8     | 51.7 |
|            |       | 330   | 65.4        | 1117.1    | 52.1 |
|            |       | 384 (UViT-T) | 74.4      | 1298.7    | 52.3 |
| 1024 × 1024| 18   | 120   | 42.6        | 710.3     | 47.9 |
|            |       | 132   | 43.5        | 750.1     | 48.9 |
|            |       | 144   | 44.4        | 791.0     | 49.3 |
|            |       | 162   | 45.8        | 854.3     | 50.4 |
|            |       | 198   | 49.3        | 987.6     | 51.4 |
|            |       | 246   | 54.7        | 1179.7    | 51.7 |
|            |       | 288   | 60.3        | 1361.2    | 52.0 |
| 896 × 896  | 12    | 276   | 52.1        | 748.4     | 50.8 |
|            |       | 300   | 54.4        | 796.2     | 50.8 |
|            |       | 324   | 56.9        | 846.2     | 51.0 |
|            |       | 360   | 60.9        | 925.0     | 51.5 |
|            |       | 390   | 64.5        | 994.2     | 51.5 |
| 896 × 896  | 24    | 156   | 46.5        | 739.0     | 50.6 |
|            |       | 180   | 49.2        | 813.8     | 50.8 |
|            |       | 192   | 50.6        | 852.7     | 51.3 |
|            |       | 258   | 60.1        | 1085.4    | 51.8 |
|            |       | 294   | 66.3        | 1225.7    | 51.6 |
| 896 × 896  | 32    | 120   | 44.6        | 732.5     | 50   |
|            |       | 132   | 45.9        | 777.4     | 50.4 |
|            |       | 144   | 47.3        | 823.8     | 51.2 |
|            |       | 180   | 52.3        | 971.1     | 51.5 |
|            |       | 240   | 62.8        | 1244.4    | 52.0 |
| 896 × 896  | 40    | 96    | 43.2        | 723.2     | 48.5 |
|            |       | 102   | 43.8        | 749.3     | 49.1 |
|            |       | 114   | 45.2        | 802.9     | 50.1 |
|            |       | 126   | 46.8        | 858.2     | 50.7 |
|            |       | 150   | 50.3        | 974.0     | 51.2 |
|            |       | 156   | 51.2        | 1094.0    | 51.2 |
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