A Memory and Speed Analysis

We carefully analyzed the training speed and memory usage of the frozen backbone with additional tunable parameters and full finetuning on COCO object detection, ADE20K semantic segmentation and K400 video action recognition using various sized models from SwinV2-T to SwinV2-G. As shown in Table 1 and 2, even with more trainable parameters in the head network, training with a frozen backbone can significantly improve speed and reduce memory cost, especially for large-scale models. Moreover, freezing the backbone reduces the memory consumption of a billion-level model to less than 32G, which makes it possible to run on regular GPUs, thus helping institutions with limited resources to take advantage of such large models.

Base Network	COCO			ADE20K			Kinetics-400		
	Batch	Frozen	Full ft.	Batch	Frozen	Full ft.	Batch	Frozen	Full ft.
	Size	5× BiFPN	FPN	Size	6× Pix. Dec.	1× Pix. Dec.	Size	4× Blocks	Linear
SwinV2-T	16	9.74G	9.78G	16	4.24G	5.04G	64	10.43G	15.87G
SwinV2-B	16	10.38G	17.29G	16	4.42G	7.84G	64	13.46G	31.47G
SwinV2-L	16	10.56G	25.81G	16	4.84G	11.77G	32	12.80G	27.05G
SwinV2-G	8	31.05G	>80G	8	23.84G	78.77G	16	30.54G	>80G

Table 1: Memory usage for models of different sizes.

Base Network	COCO			ADE20K			Kinetics-400		
	Batch	Frozen	Full ft.	Batch	Frozen	Full ft.	Batch	Frozen	Full ft.
	Size	5× BiFPN	FPN	Size	6× Pix. Dec.	1× Pix. Dec.	Size	4× Blocks	Linear
SwinV2-T	16	0.44s	0.46s	16	0.28s	0.34s	64	0.31s	0.51s
SwinV2-B	16	0.50s	0.65s	16	0.31s	0.41s	64	0.52s	0.96s
SwinV2-L	16	0.57s	0.84s	16	0.34s	0.48s	32	0.45s	0.78s
SwinV2-G	8	1.20s	-	8	1.23s	3.08s	16	1.14s	-

Table 2: Speed of each iteration for models of different sizes.

B ADE20K with UPerNet vs. Mask2former

For ADE20K semantic segmentation, we further adopt UPerNet [9], another widely used framework, to conduct comparisons on different pretrained models. We first evaluate four different pretrained Swin Transformers [7] with UPerNet, including supervised pretraining on ImageNet-1K (SUP-1K), supervised pretraining on ImageNet-22K (SUP-22K), contrastive learning of EsViT[5] on ImageNet-1K (EsViT-1K), and masked image modeling of SimMIM [10] on ImageNet-1K (SimMIM-1K). Results are shown in Table 3. Similar to the results of Mask2former, we can find that the SUP-22K model works the best in both frozen and finetuning settings. The SUP-1K and the EsViT-1K models have competitive results. The SimMIM-1K model achieves performance similar to the SUP-1K model in the finetuning setting but lags behind other models in the frozen setting.

Approach	Frozen		Full ft.	
	mIoU	mIoU (ms+flip)	mIoU	mIoU (ms+flip)
SUP-1K	43.9	45.5	49.3	50.2
SUP-22K	48.8	50.0	51.3	52.2
EsViT-1K	41.8	43.4	48.8	49.7
SimMIM-1K	26.0	27.6	48.6	49.3

Table 3: Comparisons of different pretraining tasks on frozen and full finetuning settings with SwinV2-B as the base network. An UPerNet framework is adopted. Results of mIoU for ADE20K semantic segmentation are reported. SUP denotes supervised classification as pretraining. *ms+flip* denotes multi-scale testing with horizontal flip augmentation.

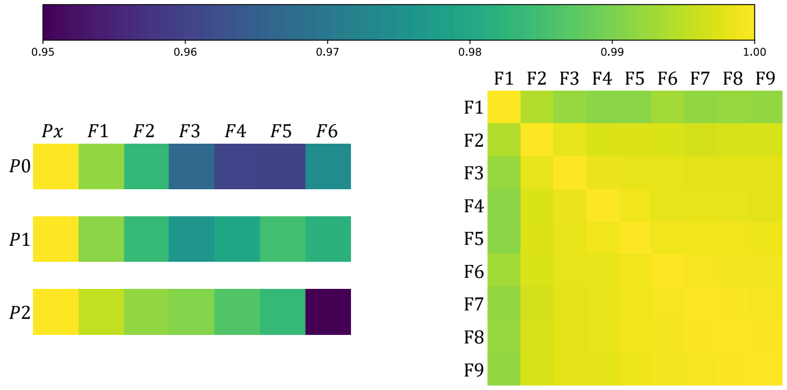
Even though the SUP-22K model preforms best among different pretrained models, there is a gap of -2.5 mIoU between the frozen setting and full finetuning. We thus add more parameters in the head network and see if this could close the gap. As UPerNet has an FPN-like head network, we add parameters by replacing FPN with BiFPN. As shown in Table 4, with a 5-layer BiFPN, the performance gap between the frozen setting and the full finetuning is reduced to -0.2 mIoU.

Head Network	Frozen		Full ft.	
	mIoU	mIoU (ms+flip)	mIoU	mIoU (ms+flip)
FPN	48.8	50.0	51.3	52.2
1× BiFPN Layer	49.3	50.5	51.4	52.2
2× BiFPN Layer	49.8	50.8	51.4	52.3
3× BiFPN Layer	50.8	51.4	51.5	52.2
4× BiFPN Layer	50.7	51.9	51.6	52.5
5× BiFPN Layer	51.3	52.6	51.5	52.4

Table 4: Comparisons with different head networks on ADE20K semantic segmentation: FPN or BiFPN with different layers, using UperNet as the segmentation framework and SwinV2-B with SUP-22K training as the base network. *ms+flip* denotes multi-scale testing with horizontal flip augmentation.

C CKA Analysis on Mask2Former

To further understand the behavior of Mask2Former on ADE20K semantic segmentation, we conduct a similar Centered Kernel Alignment (CKA) [4] analysis of the feature similarity across different layers in the pixel decoders and Transformer decoders as done for object detection on COCO. As show in Figure 1 (a), for each stage (with different resolutions of feature map) of the pixel decoder, we plot the CKA similarity between the input features (Px of stage x) and the output of each block (Fx of block x). For the Transformer decoder, as shown in Figure 1 (b), we plot the CKA similarity between the output features (Fx of head x) of each Transformer decoder. From this figure, we can observe that the features across heads in the Transformer decoder are almost the same. But in the pixel decoder, features across different blocks are somewhat different (with lower CKA similarity). In other words, adding parameters in the pixel decoder provides more useful capacity for transformation, but adding parameters in the Transformer decoder provides much less useful computation. This well matches the previous observation on COCO with BiFPN and cascade head (shown in Figure 3 of the main paper).



(a) CKA Similarity of Pixel-Decoder (b) CKA Similarity of Transformer-Head

Figure 1: CKA heatmap on the features across different layers in the pixel decoder (a) and Transformer decoder (b) in Mask2former on ADE20K semantic segmentation.

D Detailed Settings

Object Detection and Instance Segmentation on COCO Object detection and instance segmentation experiments are conducted on COCO 2017 [6]. We adopt a Mask R-CNN framework and the large-scale jittering augmentation [3]. Detailed configurations are listed in Table 5.

Hyperparameters	**1%**		**10%**		**100%**	
	Frozen	**Full Ft.**	**Frozen**	**Full Ft.**	**Frozen**	**Full Ft.**
Detector	Mask RCNN		Mask RCNN		Mask RCNN	
Training input size	(1024, 1024)		(1024, 1024)		(1024, 1024)	
Training scale ratio	(0.1, 2.0)		(0.1, 2.0)		(0.1, 2.0)	
Rand horizontal flip	0.5		0.5		0.5	
Test input size	(1333, 800)		(1333, 800)		(1333, 800)	
Training epochs	12		12		72	
Warm-up iterations	500		500		500	
Batch size	16		16		16	
Layer decay	✗	0.95	✗	0.95	✗	0.95
Base learning rate	1e-3	1e-5	3e-4	3e-5	3e-4	3e-5
Weight decay	0.5	0.1	0.1	0.05	0.05	0.05
Optimizer	AdamW		AdamW		AdamW	
Adam β	(0.9, 0.999)		(0.9, 0.999)		(0.9, 0.999)	
Learning rate scheduler	Multi-Step		Multi-Step		Multi-Step	
Step γ	0.1		0.1		0.1	
Step epochs	(8, 11)		(8, 11)		(63, 69)	
Stochastic depth	0.3		0.3		0.3	

Table 5: Hyperparameters for the frozen setting and the full finetuning on COCO object detection dataset with 1%, 10% and all training data.

Semantic Segmentation on ADE20K For the semantic segmentation task, we adopt widely-used ADE20K [11] as the benchmark. Experiments are conducted with both Mask2former [2] and UPerNet [9]. All experiments follow the settings listed in Table 6 except for those with the SimMIM-1K pretrained model. For SimMIM-1K with Mask2former, we use a learning rate of 3e-4 for full finetuning. For SimMIM-1K with UPerNet, we use a learning rate of 2e-4 and a weight decay of 0.05 for full finetuning.

Hyperparameters	**Mask2former**		**UPerNet**	
	Frozen	**Full Ft.**	**Frozen**	**Full Ft.**
Training input size	(512, 512)		(512, 512)	
Training scale ratio	(0.5, 2.0)		(0.5, 2.0)	
Rand horizontal flip	0.5		0.5	
PhotoMetricDistortion	✓		✓	
Test input size	(2048, 512)		(2048, 512)	
Training iterations	160,000		160,000	
Warm-up iterations	0		1,500	
Batch size	16		16	
Backbone lr ratio	✗	0.1	✗	✗
Layer decay	✗	✗	✗	0.95
Base learning rate	3e-4	1e-4	2e-3	2e-5
Weight decay	0.02	0.05	0.05	0.01
Optimizer	AdamW		AdamW	
Adam β	(0.9, 0.999)		(0.9, 0.999)	
Learning rate scheduler	Poly (power=0.9)		Linear	
Stochastic depth	0.3		0.3	

Table 6: Hyperparameters for the frozen setting and full finetuning on ADE20K semantic segmentation.

Video Action Recognition on Kinetics-400 Video action recognition experiments are evaluated on the Kinetics-400 dataset. We follow Video Swin Transformer [8] for most of the settings. Detailed hyperparameters are shown in Table 7.

Swin-G Setting To explore the performance upper bound under the frozen setting, we use a strong training setting for the Swin-G model. For COCO object detection, we adopt a framework of HTC [1, 7] and a large scale jittering augmentation with an input size of (1024, 1024). The window

Hyperparameters	Froze	Full Ft.
Training Input size	(16, 224, 224)	
Patch size	(1, 4, 4)	
Rand horizontal flip	0.5	
Rand resized crop	✓	
Training scale ratio	(0.5, 2.0)	
Test view	4×3	
Training epochs	30	
Warm-up epochs	2.5	
Batch size	64	
Base learning rate	3e-4	
Weight decay	0.05	
Optimizer	AdamW	
Adam β	(0.9, 0.999)	
Learning rate scheduler	Cosine	
Stochastic depth	0.2	

Table 7: Hyperparameters for the frozen setting and full finetuning on Kinetics-400 video action recognition.

size is set as 32, the learning rate is 6e-4, and the batch size is 32. A weight decay of 0.05 and a stochastic depth rate of 0.3 are used. For ADE20K semantic segmentation, we set the image input size as (640, 640) and the window size as 40. The learning rate is 3e-4 and the batch size is 16. A weight decay of 0.02 and a stochastic depth rate of 0.3 are used. For Kinetics-400 video action recognition, we use a window size of 16, a learning rate of 2e-4, a stochastic depth of 0.1 and a batch size of 128.

References

[1] Chen, K., Pang, J., Wang, J., Xiong, Y., Li, X., Sun, S., Feng, W., Liu, Z., Shi, J., Ouyang, W., et al. (2019). Hybrid task cascade for instance segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4974–4983.

[2] Cheng, B., Misra, I., Schwing, A. G., Kirillov, A., and Girdhar, R. (2021). Masked-attention mask transformer for universal image segmentation. *arXiv preprint arXiv:2112.01527*.

[3] Ghiasi, G., Cui, Y., Srinivas, A., Qian, R., Lin, T.-Y., Cubuk, E. D., Le, Q. V., and Zoph, B. (2021). Simple copy-paste is a strong data augmentation method for instance segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2918–2928.

[4] Kornblith, S., Norouzi, M., Lee, H., and Hinton, G. (2019). Similarity of neural network representations revisited. In *International Conference on Machine Learning*, pages 3519–3529. PMLR.

[5] Li, C., Yang, J., Zhang, P., Gao, M., Xiao, B., Dai, X., Yuan, L., and Gao, J. (2021). Efficient self-supervised vision transformers for representation learning. *arXiv preprint arXiv:2106.09785*.

[6] Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., and Zitnick, C. L. (2014). Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer.

[7] Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., and Guo, B. (2021a). Swin transformer: Hierarchical vision transformer using shifted windows. *arXiv preprint arXiv:2103.14030*.

[8] Liu, Z., Ning, J., Cao, Y., Wei, Y., Zhang, Z., Lin, S., and Hu, H. (2021b). Video swin transformer.

[9] Xiao, T., Liu, Y., Zhou, B., Jiang, Y., and Sun, J. (2018). Unified perceptual parsing for scene understanding. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 418–434.

[10] Xie, Z., Zhang, Z., Cao, Y., Lin, Y., Bao, J., Yao, Z., Dai, Q., and Hu, H. (2021). Simmim: A simple framework for masked image modeling. *arXiv preprint arXiv:2111.09886*.

[11] Zhou, B., Zhao, H., Puig, X., Xiao, T., Fidler, S., Barriuso, A., and Torralba, A. (2018). Semantic understanding of scenes through the ade20k dataset. *International Journal on Computer Vision*.