
Dual Path Networks

– Supplementary Material

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1 Testing with Mean-Max Pooling

Here, we introduce a new testing technique by using Mean-Max Pooling which can further improve the performance of a well trained CNN in the testing phase without any noticeable computational overhead. This testing technique is very effective for testing images with size larger than training crops. The idea is to first convert a trained CNN model into a convolutional network [2] and then insert the following Mean-Max Pooling layer (*a.k.a.* Max-Avg Pooling [1]), *i.e.* $0.5 * (\text{global average pooling} + \text{global max pooling})$, just before the final softmax layer.

Table 1: Comparison with different testing techniques on ImageNet-1k dataset. Single crop validation error rate (%) on validation set.

Method	Model Size	GFLOPs	w/o Mean-Max Pooling		w/ Mean-Max Pooling	
			top-1	top-5	top-1	top-5
DPN-92 ($32 \times 3d$)	145 MB	6.5	19.34	4.66	19.04	4.53
DPN-98 ($40 \times 4d$)	236 MB	11.7	18.94	4.44	18.72	4.40
DPN-131 ($40 \times 4d$)	304 MB	16.0	18.62	4.23	18.55	4.16

Comparisons between the models with and without Mean-Max Pooling are shown in Table 1. As can be seen from the results, the simple Mean-Max Pooling testing strategy successfully improves the testing accuracy for all models.

References

- [1] Chen-Yu Lee, Patrick W Gallagher, and Zhuowen Tu. Generalizing pooling functions in convolutional neural networks: Mixed, gated, and tree. In *Artificial Intelligence and Statistics*, pages 464–472, 2016.
- [2] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3431–3440, 2015.