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Attention Pyramid Module for Scene Recognition

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Outline

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Background

Scene Recognition:

Scenery images often represent a complex view that includes multiple objects at different scales and a complicated background.

(a) ImageNet (b) Place365

Introduction

Related work & Limitations:

Conventional multi-scale scene classification methods commonly follow a four-step pipeline:

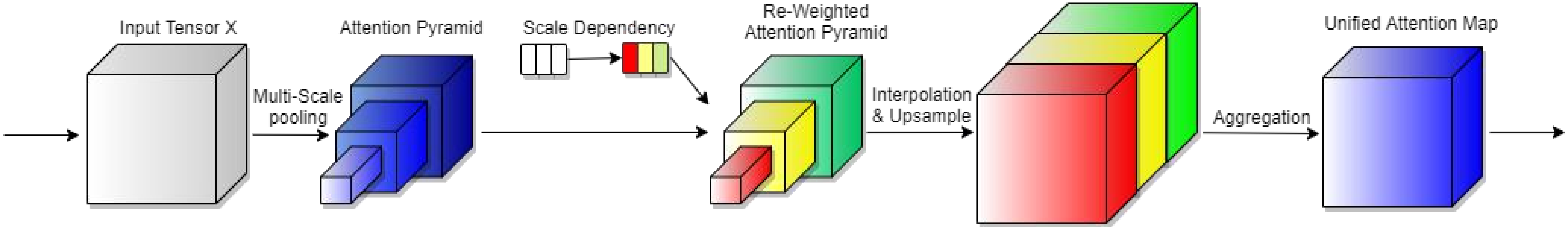
1. Training multi-scale networks.
2. Extracting features .
3. Concatenating or summing the features.
4. Making the final prediction.

Limitation:

Each level of the pyramid requires to train a separate network, these methods often face expensive computation cost, especially when the number of levels of the pyramid increases.

APM

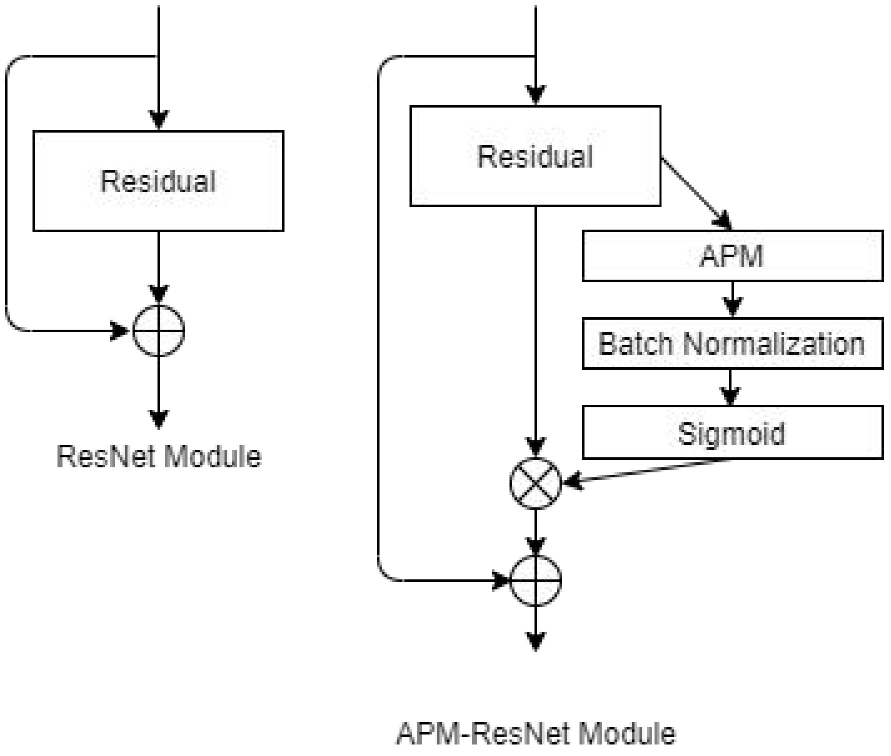
Attention Pyramid Module (APM)



Details of our Attention Pyramid Module .

- **Attention Pyramid:**
  Scale-aware Attention Map Extraction.
- **Scale Dependency:**
  Learning the Weight of Scales.
- **Scale Aggregation:**
  Aggregating Re-weighted Scale-aware Attention Maps.

APM: Implementation and Efficiency



The schema of a residual block (left) and an APM embedded residual block (right).

APM introduces an extremely modest parameter increase.

For example, for the benchmark CNN model ResNet-50, the three-scale APM only adds 48 parameters (16×3) to the network, which is negligible compared with the 24.26 million parameters of ResNet-50.

APM

Classification Results on Places365

Settings: We implement APM using PyTorch. The optimizer is SGD, with a 0.9 momentum and a 1e−4 weight decay. The batch size is 256 and the learning rate is initialized as 0.1. We set the epoch size to 100 and divide the learning rate by 10 at the 30th, 60th, and 90th epochs. All experiments are conducted on a server with 8 Tesla V100 GPUs.

Network	ResNet-18			ResNet-50			ResNet-101		
	Top-1	Top-5	Params	Top-1	Top-5	Params	Top-1	Top-5	Params
Vanilla	53.693	83.778	11.36 M	54.767	84.932	24.26 M	56.471	86.249	43.25 M
APM	**54.978**	**84.786**	11.37 M	**56.707**	**86.597**	24.29 M	**56.740**	**86.770**	43.31 M

	Top-1	Top-5	GFLOPs	Params
ResNet-50	54.767	84.932	4.12	24.26 M
GC-ResNet-50 [17]	55.614	85.718	**4.13**	26.80 M
SK-ResNet-50 [14]	56.142	86.274	4.18	24.85 M
GE-ResNet-50 [16]	56.148	86.340	4.14	24.75 M
SE-ResNet-50 [12]	56.162	86.258	**4.13**	26.79 M
CBAM-ResNet-50 [13]	56.652	86.534	4.14	26.79 M
APM-ResNet-50	**56.707**	**86.597**	**4.13**	**24.29** M

Highlight: Our proposed module with the vanilla ResNet50 improves the performance by 3.54% top-1 classification accuracy, whereas almost no additional computations are introduced.

APM

The influence of Scales of APM

Model	ResNet-18		ResNet-50	
	Top-1	Top-5	Top-1	Top-5
Vanilla	53.693	83.778	54.767	84.932
- L_1	54.523	84.838	56.019	86.011
- L_2	54.636	**84.978**	56.482	86.518
- L_3	54.540	84.767	56.099	86.403
$L_1 + L_2 + L_3$	**54.978**	84.786	**56.707**	**86.597**

Highlight: The best result, in terms of top-1 accuracy, for ResNet18 and ResNet-50 is achieved when all three scales, L1, L2, and L3 are involved.

APM

Ablation Study

Pyramid Attention (Non-learnable)		✓	✓	✓	✓	
Batch Normalization			✓		✓	✓
Sigmoid				✓	✓	✓
Pyramid Attention (Learnable)						✓
Top-1	54.767	54.896	55.318	55.477	56.162	**56.707**
Top-5	84.932	84.942	85.499	85.592	86.129	**86.597**

Highlight: 1) We can observe that using APM alongside all the components except the non-learnable module leads to achieving the best result.

2) Switching a non-learnable multiscale module to APM achieved a 0.97% top-1 accuracy improvement.

Conclusion

- We have presented a simple yet effective module, called APM for building attention pyramids inside benchmark networks and further assisting the task of scene recognition.

- The APM can be combined with any existing backbone architectures in a plug-and-play manner with marginal computation increase.

- We also experimentally demonstrated that our APM is more parameter efficient while achieving better performance against state-of-the-art attention modules.