Multi-Order Feature Statistical Model for Fine-Grained Visual Categorization

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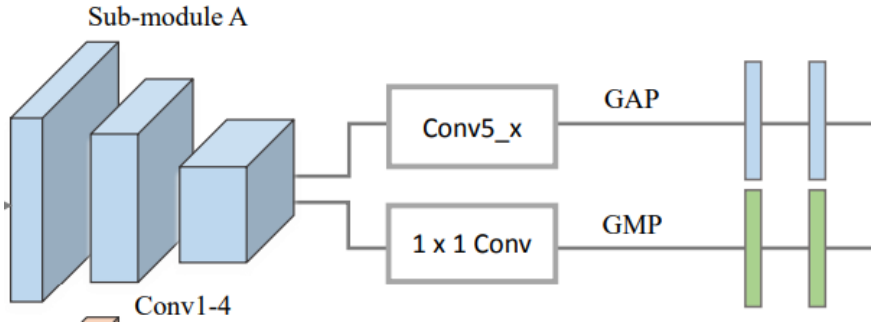
Background

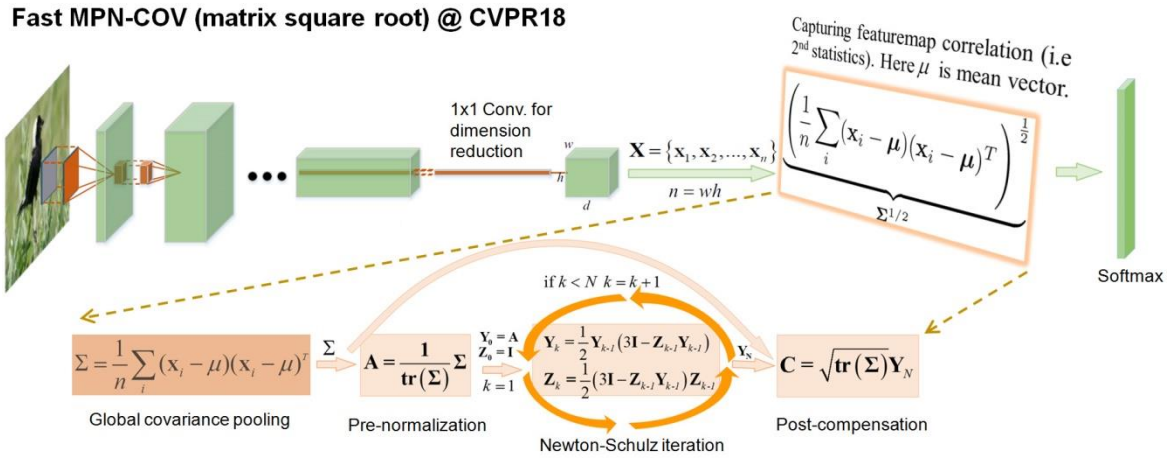
The key to address the problem of fine-grained categorization is to learn a discriminative representation that captures the subtle difference of similar class.

Existing methods generate high-level feature mostly by performing global **first-order** pooling, such as global average pooling (GAP), global max pooling (GMP).



The first-order module in proposed MOFS, using GMP and GAP.

Higher-order method

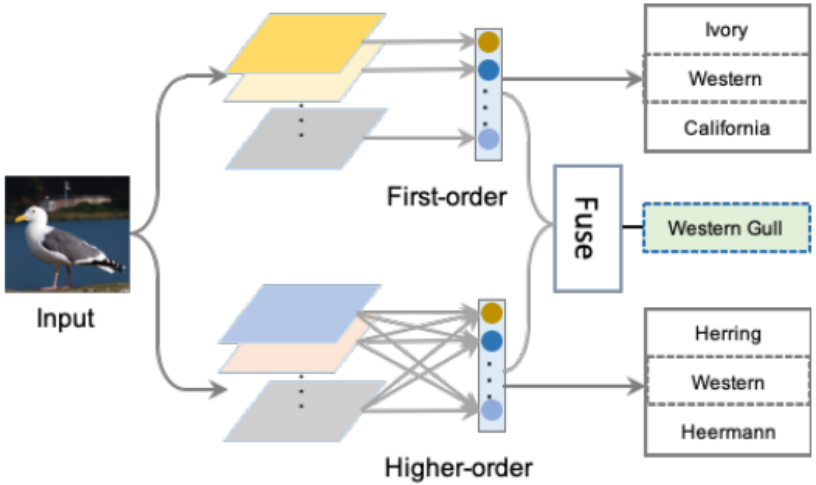


Li's method(iSQRT) obtains an impressive result on fine-grained datasets.
Our MOFS model adopts this method as the second-order extractor.

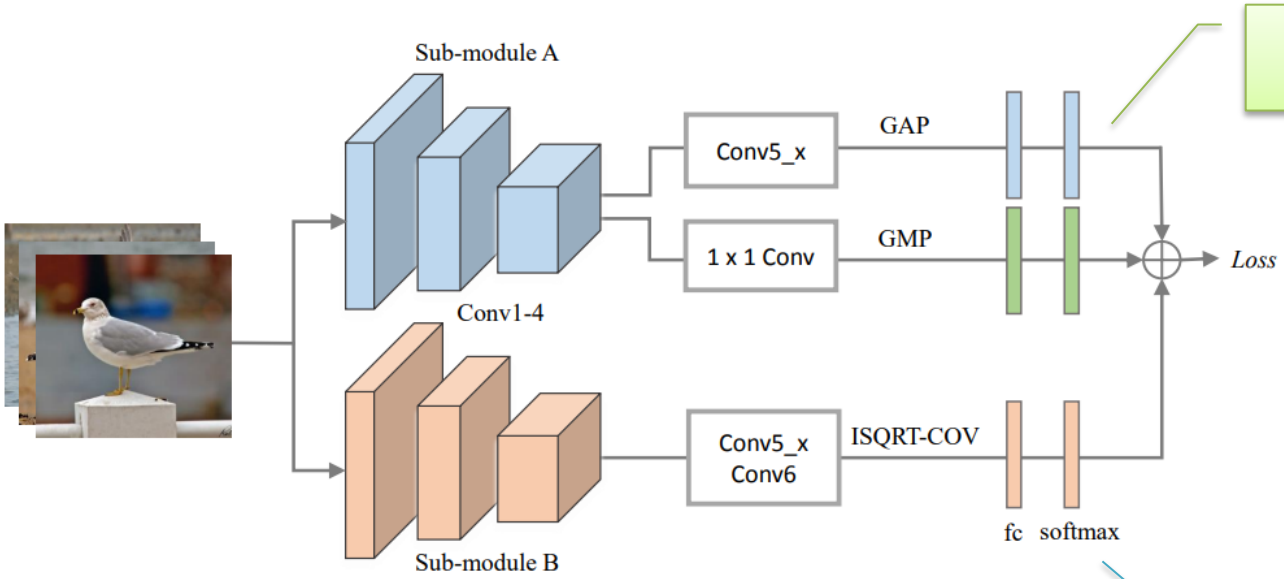
[1]Towards Faster Training of Global Covariance Pooling Networks by Iterative Matrix Square Root Normalization
Li, Peihua and Xie, Jiangtao and Wang, Qilong and Gao, Zilin.

Contribution

- We proposed a multi-order feature statistical method that integrates both first-order and covariance statistics to build strong representation.
- Our method consistently outperforms the state-of-the-art fine-grained method.



The Multi-Order Feature Statistical model



Sub-module A extracts high-level and mid-level first-order feature statistics by tow branches with GAP and GMP layers respectively. Sub-module B obtain second-order statistics following iSQRT-COV method

Results

- No part or bounding box annotations are used during training and testing.
- Compare to existing methods that only extract first-order or higher-order feature statistics, our approach with different order pooling layers obtain a higher accuracy on three datasets for fine-grained.

Method	Backbone	Accuracy(%)		
		CUB-200-211	FGVC-Aircraft	Stanford-Cars
VGG-19	VGG-19	77.8	-	84.9
ResNet-50	ResNet-50	85.4	90.3	91.7
ResNet-101	ResNet-101	86.8	-	91.9
RA-CNN[28]	VGG-19	85.3	88.2	92.5
MA-CNN[6]	VGG-19	86.5	89.9	91.5
B-CNN[16]	VGG-16	84.1	84.1	91.3
Compact B-CNN[17]	VGG-16	84.0	-	-
Low-ran B-CNN[18]	VGG-16	84.2	87.3	90.9
Kernel-Activation[19]	VGG-16	85.3	88.3	91.7
Kernel-Pooling[24]	VGG-16	86.2	86.9	92.4
MG-CNN[6]	VGG-19	82.6	86.6	-
RAM[29]	ResNet-50	86.0	-	-
MAMC[30]	ResNet-101	86.5	-	93.0
DFL-CNN[21]	ResNet-50	87.4	91.7	93.1
DFL-CNN[21]	VGG-16	87.4	92.0	93.8
NTS-Net[31]	ResNet-50	87.5	91.4	93.9
iSQRT-COV[22]	ResNet-50	88.1	90.0	92.8
iSQRT-COV[22]	ResNet-101	88.7	91.4	93.3
MOFS(ours)	ResNet-50	88.8	91.7	94.7
MOFS(ours)	ResNet-101	**89.2**	**93.0**	**94.9**

Ablation Study

For understanding the importance of each branch and model on the decision of interest, we draw the attention map by Grad-CAM method.

Method	Accuracy(%)		
	shared	separate	MOFS
GAP	80.7	85.1	85.7
GMP	76.8	78.7	81.1
GAP+GMP	83.2	84.3	86.2
ISQRT	87.8	88.0	88.0
GAP+GMP+ISQRT	87.7	87.9	**88.8**