

Attention Branch Network: Learning of Attention Mechanism for Visual Explanation

汇报人: Lee 日期: 2020年10月18日

Part 1 背景与动机
Part 2 网络结构与训练
Part 3 实验结果
Part 4 问题与讨论



PART 01

第一部分

背景与动机

动机



> 使人们理解CNN的决策

- ✓ 得到客户的认可
- ✓ 研究模型的泛化能力、安全性问题及模型局限
- ✓ 追溯模型预测结果

> 提高分类器的表现

- ✓ 通过注意力机制自动去除干扰特征
- ✓ 指导数据增强策略

ABN的主要贡献



- > 提高CNN的分类效果的首次尝试
- > 适用于多种基线模型,可多任务训练
- > 用注意力激活图可视化

已有的一些工作



- ✓ CAM
- ✓ Grad-CAM
- ✓ Grad-CAM ++
- ✓ interpretable CNN

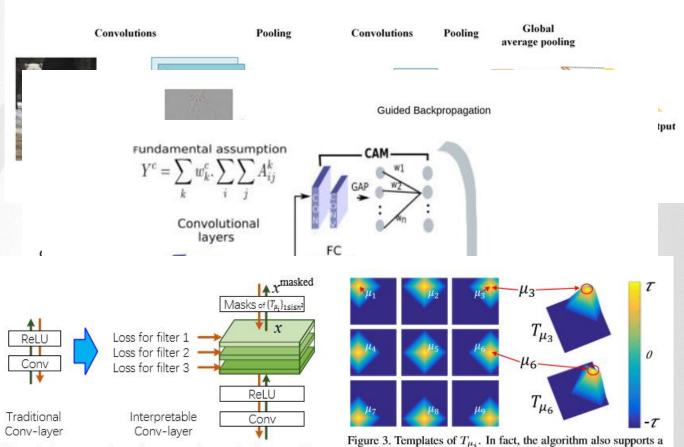


Figure 2. Structures of an ordinary conv-layer and an interpretable conv-layer. Green and red lines indicate the forward and backward propagations, respectively.

Figure 3. Templates of T_{μ_i} . In fact, the algorithm also supports a round template based on the L-2 norm distance. Here, we use the L-1 norm distance instead to speed up the computation.

$$w_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial Y^c}{\partial A_{ij}^k}$$

ABN与CAM和Grad-CAM区别



- > 不用像Grad-CAM那样要做反向传播
- > 可以使用全连接网络,提高CNN的表达能力

PART 02

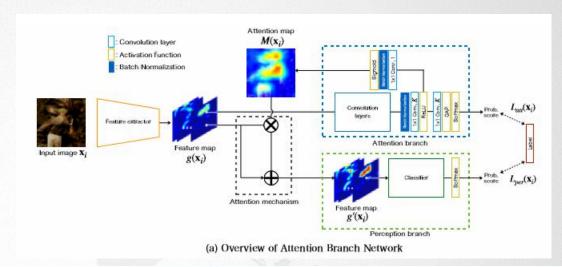
第二部分

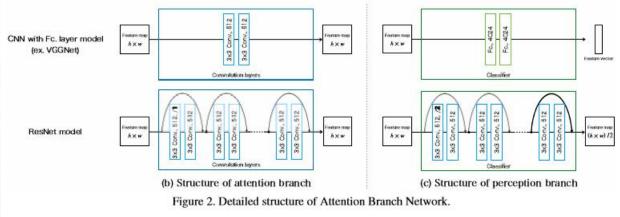
网络结构与实现原理

网络结构



- > 特征提取器
- > 注意力分支
- > 感知分支





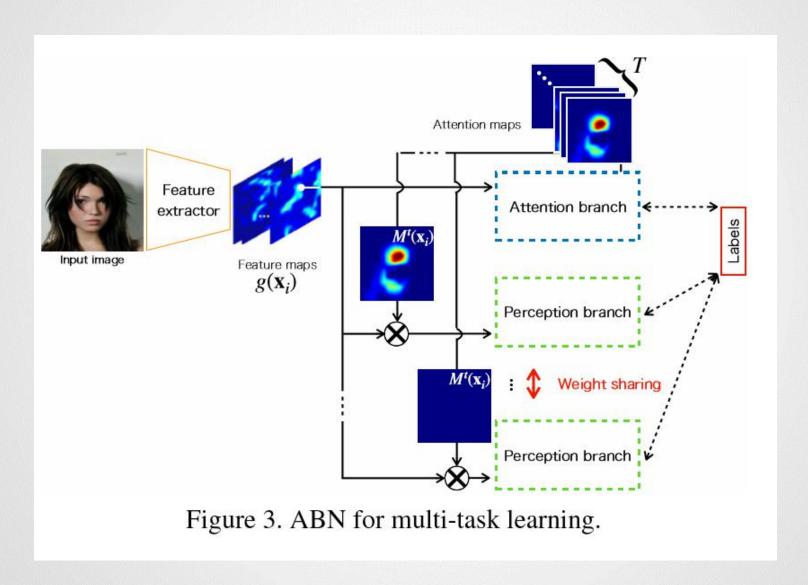
Loss



$$L(\mathbf{x}_i) = L_{att}(\mathbf{x}_i) + L_{per}(\mathbf{x}_i)$$

 $L_{att}(x_i)$ denotes training loss at the attention branch with an input sample x_i , and $L_{per}(x_i)$ denotes training loss at the perception branch.





PART 03

第三部分

实验结果



Table 1. Comparison of the top-1 errors on CIFAR100 with attention mechanism.

	$g(\mathbf{x})$	$g(\mathbf{x}) \cdot M(\mathbf{x})$	$g(\mathbf{x}) \cdot (1 + M(\mathbf{x}))$
ResNet20	31.47	30.61	30.46
ResNet32	30.13	28.34	27.91
ResNet44	25.90	24.83	25.59
ResNet56	25.61	24.22	24.07
ResNet110	24.14	23.28	22.82

图像分类



Table 2. Comparison of top-1 errors on CIFAR10, CIFAR100, SVHN, and ImageNet dataset.

Dataset	CIFAR10	CIFAR100	SVHN [23]	ImageNet [5]
VGGNet [14]	_	_	_	31.2
VGGNet+BN	_	_	_	26.24*
ResNet [9]	6.43	24.14*	2.18*	22.19*
VGGNet+CAM [41]	_	-	_	33.4
VGGNet+BN+CAM	_	-	_	27.42*(+1.18)
ResNet+CAM	-	_	-	$22.11^*_{(-0.08)}$
WideResNet [38]	4.00	19.25	2.42*	21.9
DenseNet [11]	4.51	22.27	2.07*	22.2
ResNeXt [34]	3.84*	18.32*	2.16*	22.4
Attention [32]	3.90	20.45	_	21.76
AttentionNeXt [32]	_	_	_	21.20
SENet [12]	_	-	_	21.57
VGGNet+BN+ABN	_	_	_	25.55 (-0.69)
ResNet+ABN	$4.91_{(-1.52)}$	$22.82_{(-1.32)}$	$1.86_{\ (-0.32)}$	$21.37_{(-0.82)}$
WideResNet+ABN	$3.78_{\ (-0.22)}$	$18.12_{(-1.13)}$	$2.24_{(-0.18)}$	_
DenseNet+ABN	$4.17_{(-0.34)}$	$21.63_{(-0.64)}$	$2.01_{(-0.06)}$	_
ResNeXt+ABN	$3.80_{(-0.04)}$	$17.70_{\ (-0.62)}$	$2.01_{(-0.15)}$	_
SENet+ABN	_	_		$20.77_{\;(-0.80)}$

* indicates results of re-implementation accuracy

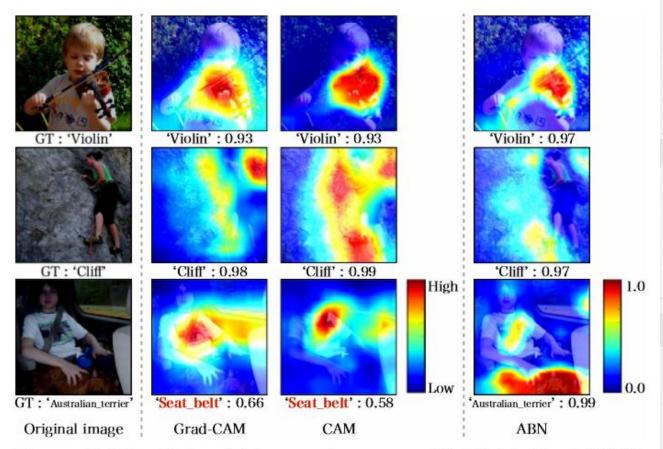


Figure 4. Visualizing high attention area with CAM, Grad-CAM, and our ABN. CAM and Grad-CAM are visualized attention maps at top-1 result.

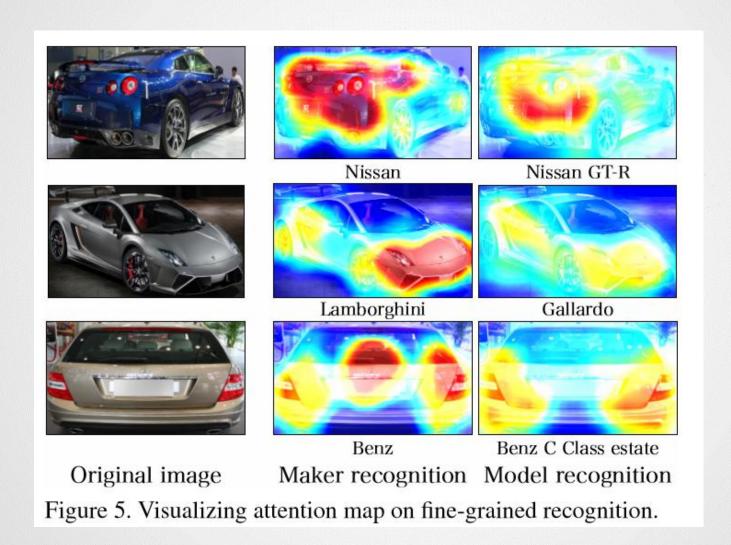
细粒度识别



Table 3. Comparison of car model and maker accuracy on Comp-Cars dataset

task	model [%]	maker [%]
VGG16	85.9	90.4
ResNet101	90.2	90.1
VGG16+ABN	90.7	92.9
ResNet101+ABN	97.1	98.1





多任务学习



Table 4. Comparison of multiple facial attribute recognition accuracy on CelebA dataset

Method	Average of accuracy [%]	Odds	
FaceTracer [16]	81.13	40/40	
PANDA-1 [40]	85.43	39/40	
LNet+ANet [42]	87.30	37/40	
MOON [28]	90.93	29/40	
ResNet101	90.69	27/40	
ABN	91.07	_	

多任务学习



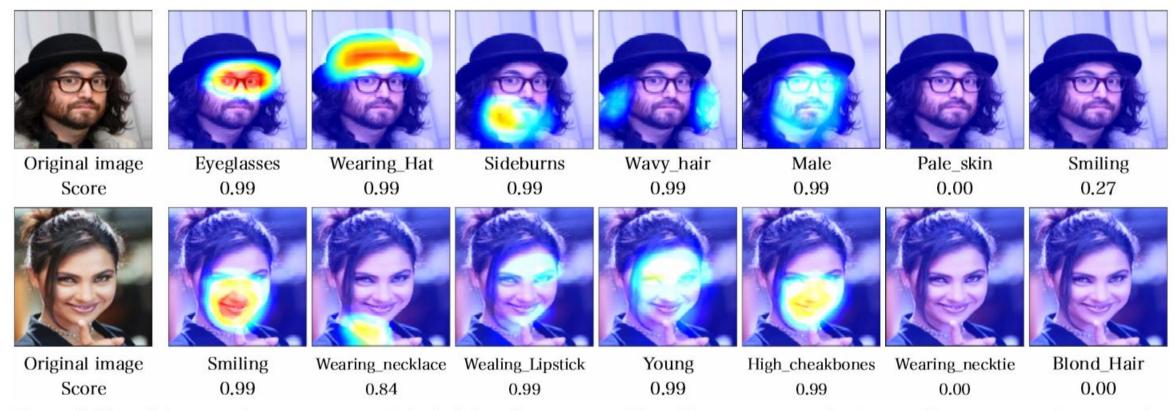


Figure 7. Visualizing attention maps on multiple facial attributes recognition. These scores are final recognition scores at the perception branch.

PART 04

第四部分

问题与讨论

谢谢!