VanillaNet: the Power of Minimalism in Deep Learning

Paper Reading by Zhiying Lu

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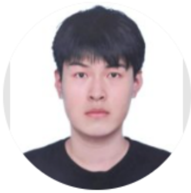
智能多媒体内容计算实验室
Intelligent Multimedia Content Computing Lab

- 作者介绍
- 研究背景
- 方法
- 实验效果
- 总结



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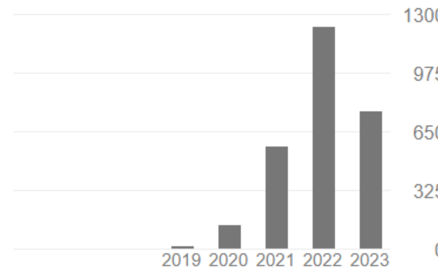

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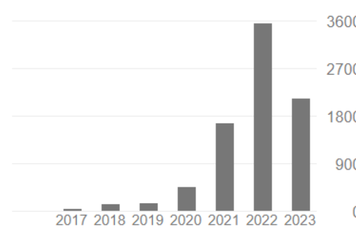

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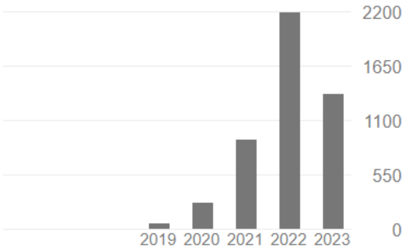

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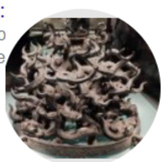

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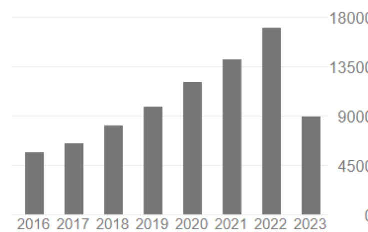

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- 作者介绍
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- 方法
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研究背景

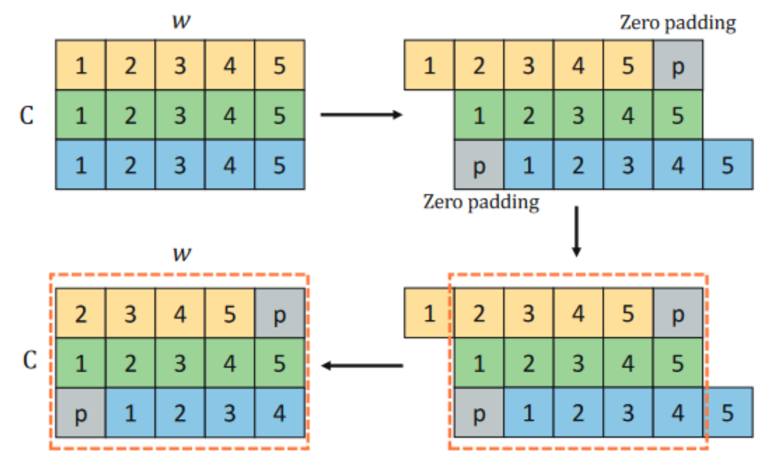
- CNN和ViT作为模型的backbone部分，承担了基础视觉特征提取任务
- 同时，嵌入式AI芯片逐渐成为主流
- AlexNet、ResNet和ViT，是视觉网络设计的里程碑，提供了网络设计的范式
- 后续提出的网络包含了大量人工设计的模块，在增加网络复杂度的同时，使网络具有更强的表征能力

研究背景

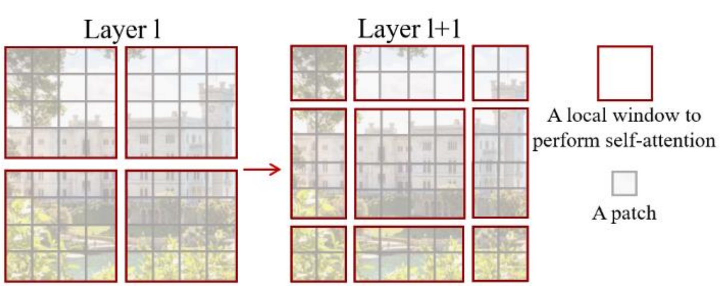
- 网络的复杂度虽然能提升表征能力，但也造成了实际部署的困难
- 例如ResNet中的shortcut就会消耗大量的off-chip memory traffic，因为它进行了多层特征的融合
- SwinTrans中的window shift和AS-MLP中的axial shift操作需要大量工程实现，包括重写CUDA等

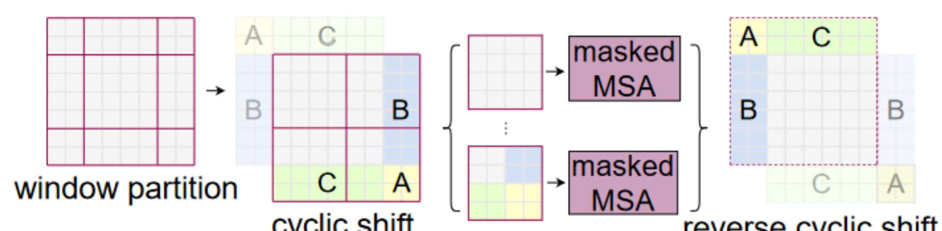
Table 1: Max memory (KB) on the mobile NPU

Input size	256	384	512
ResNet50	438737	832733	OOM
plain-CNN 50	356657	669397	1106989
Reduction	18.7%	19.6%	-



Horizontal shift

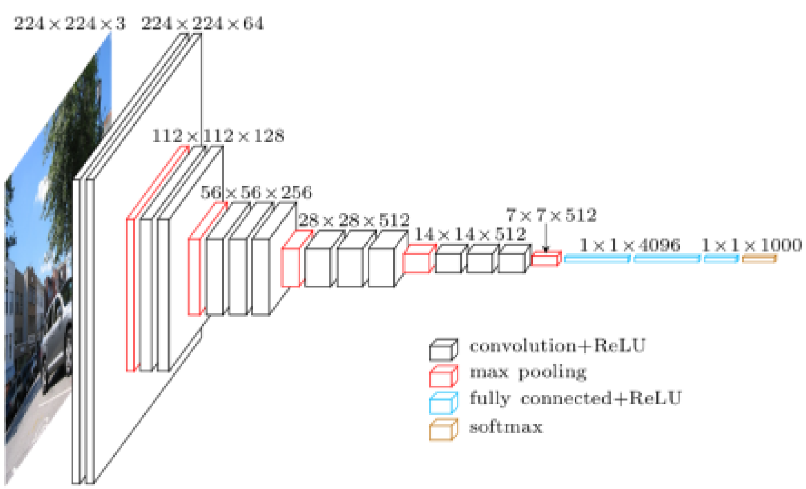


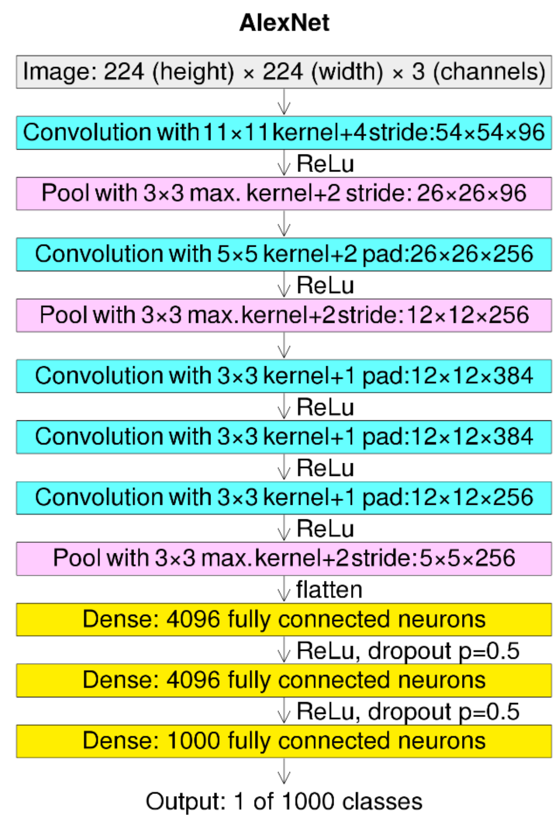


研究背景

- 因此将网络范式设计精简化很重要
- 类似ResNet网络的设计就偏离了精简化，但是不加shortcut会导致梯度消失问题，单纯增加卷积层的深度提升不如预期
- 简单网络如AlexNet和VGG的设计和优化受到的关注不多，因此该研究点具有较大的价值

	plain	ResNet
18 layers	27.94	27.88
34 layers	28.54	**25.03**





研究背景

- 随着AI芯片的发展，网络推理速度的瓶颈不再来自于FLOPs和参数量，因为GPU可以进行并行计算
- 复杂的结构和网络层数的深度在更大程度上限制了网络的推理速度
- 因此本文在设计时，采用极简的网络层数设计，抛弃复杂的操作如shortcut和attention，以极少的卷积层数和更快地推理速度，达到SOTA水平

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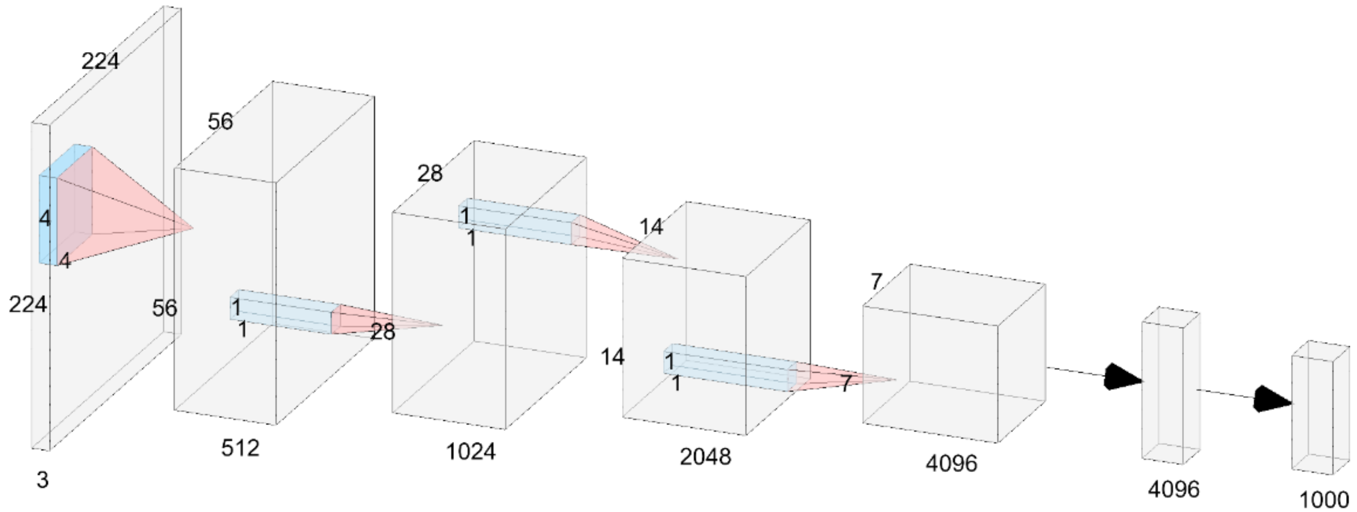
VanillaNet



- 网络遵循一贯的四个stage设计，但是每个stage只包含一层卷积
- 跨stage采用2x2的maxpooling
- 每个卷积层不含batchnorm，不含shortcut
- 每个卷积层都是1x1卷积，激活函数放在卷积后
- 如何训练这样的网络使其达到SOTA效果？

Deep Training Strategy

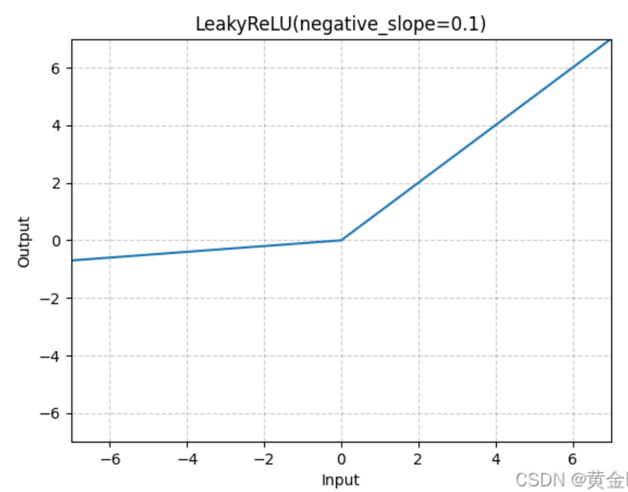
- 在网络训练的初期，通过训练两个卷积层，中间带激活函数
- 训练完成后，将二者参数融合成为单个卷积层，增加推理速度
- 激活函数会随着网络训练过程，逐步退化为identity mapping

$$A'(x) = (1-\lambda)A(x) + \lambda x, \qquad \lambda = \frac{e}{E}.$$

```python
def forward(self, x):
    if self.deploy:
        x = self.conv(x)
    else:
        x = self.conv1(x)
        x = torch.nn.functional.leaky_relu(x,self.act_learn)
        x = self.conv2(x)

    x = self.pool(x)
    x = self.act(x)
    return x
```

$$\text{LeakyRELU}(x) = \begin{cases} x, & \text{if } x \geq 0 \\ \text{negative\_slope} \times x, & \text{otherwise} \end{cases}$$



Deep Training Strategy

- 网络在训练时，结构为：conv1-bn1-relu-conv2-bn2
- 首先将relu消除得到：conv1-bn1-conv2-bn2 $W_i' = \frac{\gamma_i}{\sigma_i} W_i, B_i' = \frac{(B_i - \mu_i)\gamma_i}{\sigma_i} + \beta_i,$
- 再通过重参数化，将BN参数融入conv1中得到：conv1-conv2
- 最后融合两个1x1conv的参数，得到最终的单层conv

$$y = W^1 * (W^2 * x) = W^1 \cdot W^2 \cdot \mathrm{im2col}(x) = (W^1 \cdot W^2) * X,$$

- 卷积层与BN层合并的操作如下：

卷积层公式为

$$Conv(x) = W(x) + b$$

而BN层公式为

$$BN(x) = \gamma * \frac{(x - mean)}{\sqrt{var}} + \beta$$

然后我们将卷积层结果带入到BN公式中

$$BN(Conv(x)) = \gamma * \frac{W(x) + b - mean}{\sqrt{var}} + \beta$$

进一步化简为

$$BN(Conv(x)) = \frac{\gamma * W(x)}{\sqrt{var}} + (\frac{\gamma * (b - mean)}{\sqrt{var}} + \beta)$$

这其实就是一个卷积层，只不过权重考虑了BN的参数 我们令：

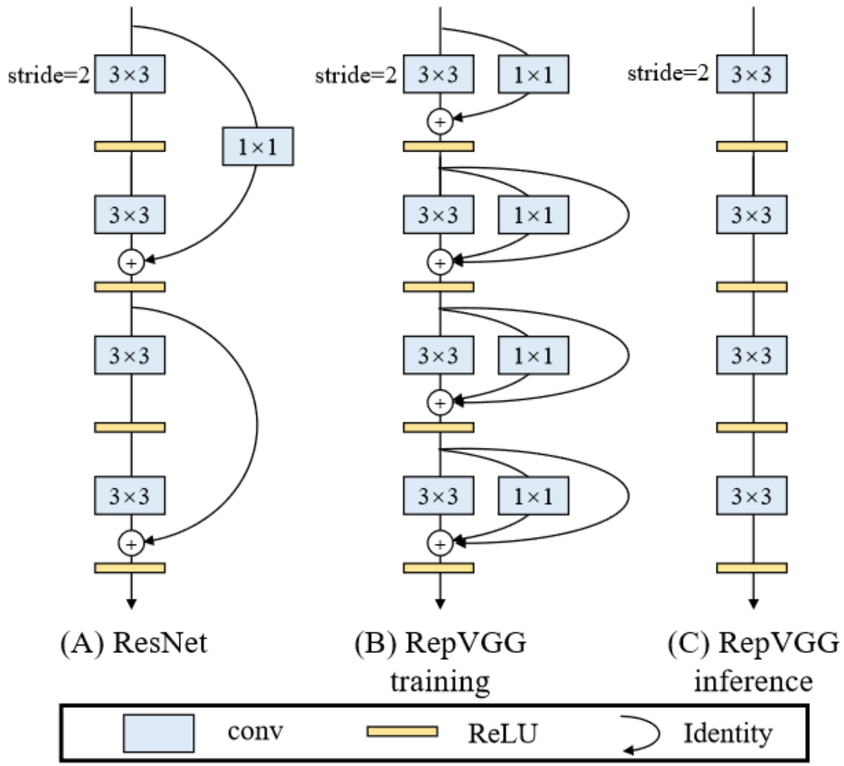
$$W_{fused} = \frac{\gamma * W}{\sqrt{var}}$$

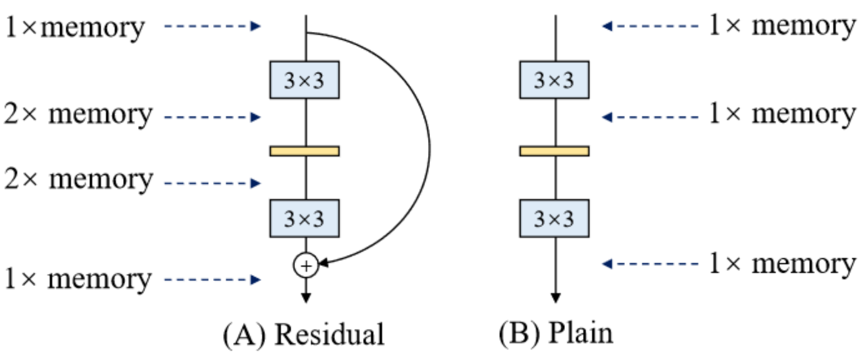
$$B_{fused} = \frac{\gamma * (b - mean)}{\sqrt{var}} + \beta$$

重参数化：RepVGG

RepVGG: Making VGG-style ConvNets Great Again

Xiaohan Ding [1*] Xiangyu Zhang [2] Ningning Ma [3]
Jungong Han [4] Guiguang Ding [1†] Jian Sun [2]
[1] Beijing National Research Center for Information Science and Technology (BNRist); School of Software, Tsinghua University, Beijing, China
[2] MEGVII Technology
[3] Hong Kong University of Science and Technology
[4] Computer Science Department, Aberystwyth University, SY23 3FL, UK





Deep Training Strategy

- 实际融合BN的操作，以及1x1卷积参数的融合：

```
if self.deploy:
    self.conv = nn.Conv2d(dim, dim_out, kernel_size=1)
else:
    self.conv1 = nn.Sequential(
        nn.Conv2d(dim, dim, kernel_size=1),
        nn.BatchNorm2d(dim, eps=1e-6),
    )
    self.conv2 = nn.Sequential(
        nn.Conv2d(dim, dim_out, kernel_size=1),
        nn.BatchNorm2d(dim_out, eps=1e-6)
    )
```

```
def _fuse_bn_tensor(self, conv, bn):
    kernel = conv.weight
    bias = conv.bias
    running_mean = bn.running_mean
    running_var = bn.running_var
    gamma = bn.weight
    beta = bn.bias
    eps = bn.eps
    std = (running_var + eps).sqrt()
    t = (gamma / std).reshape(-1, 1, 1, 1)
    return kernel * t, beta + (bias - running_mean) * gamma / std
```

```
def switch_to_deploy(self):
    kernel, bias = self._fuse_bn_tensor(self.conv1[0], self.conv1[1])
    self.conv1[0].weight.data = kernel
    self.conv1[0].bias.data = bias
    # kernel, bias = self.conv2[0].weight.data, self.conv2[0].bias.data
    kernel, bias = self._fuse_bn_tensor(self.conv2[0], self.conv2[1])
    self.conv = self.conv2[0]
    self.conv.weight.data = torch.matmul(kernel.transpose(1,3), self.conv1[0].weight.data.squeeze(3).squeeze(2)).transpose(1,3)
    self.conv.bias.data = bias + (self.conv1[0].bias.data.view(1,-1,1,1)*kernel).sum(3).sum(2).sum(1)
    self.__delattr__('conv1')
    self.__delattr__('conv2')
    self.act.switch_to_deploy()
    self.deploy = True
```

Series Informed Activation

- 一些工作发现，结构简单且层数较浅的网络主要受限于较差的非线性能力
- 有两种路线增强非线性能力：堆叠非线性层/提升单层的非线性能力
- 本文采取后者，且采用并行的非线性加权

$$A_s(x) = \sum_{i=1}^{n} a_i A(x + b_i),$$

- 为增强全局视野（卷积只是1x1大小），进一步扩展到邻域加权

$$A_s(x_{h,w,c}) = \sum_{i,j \in \{-n,n\}} a_{i,j,c} A(x_{i+h,j+w,c} + b_c),$$

Series Informed Activation

- 实际代码如下：

```
def forward(self, x):
    if self.deploy:
        x = self.conv(x)
    else:
        x = self.conv1(x)
        x = torch.nn.functional.leaky_relu(x,self.act_learn)
        x = self.conv2(x)

    x = self.pool(x)
    x = self.act(x)
    return x
```

```
class activation(nn.ReLU):
    def __init__(self, dim, act_num=3, deploy=False):
        super(activation, self).__init__()
        self.act_num = act_num
        self.deploy = deploy
        self.dim = dim
        self.weight = torch.nn.Parameter(torch.randn(dim, 1, act_num*2 + 1, act_num*2 + 1))
        if deploy:
            self.bias = torch.nn.Parameter(torch.zeros(dim))
        else:
            self.bias = None
            self.bn = nn.BatchNorm2d(dim, eps=1e-6)
        weight_init.trunc_normal_(self.weight, std=.02)

    def forward(self, x):
        if self.deploy:
            return torch.nn.functional.conv2d(
                super(activation, self).forward(x),
                self.weight, self.bias, padding=self.act_num, groups=self.dim)
        else:
            return self.bn(torch.nn.functional.conv2d(
                super(activation, self).forward(x),
                self.weight, padding=self.act_num, groups=self.dim))
```

其他细节

- 网络所有的卷积层，包括stem和head，均采用deep training方式训练：
- Stem将图像划分成4x4的不重叠区域，即non-overlap patch embedding

```
if self.deploy:
    self.stem = nn.Sequential(
        nn.Conv2d(in_chans, dims[0], kernel_size=4, stride=stride, padding=padding),
        activation(dims[0], act_num, deploy=self.deploy)
    )
else:
    self.stem1 = nn.Sequential(
        nn.Conv2d(in_chans, dims[0], kernel_size=4, stride=stride, padding=padding),
        nn.BatchNorm2d(dims[0], eps=1e-6),
    )
    self.stem2 = nn.Sequential(
        nn.Conv2d(dims[0], dims[0], kernel_size=1, stride=1),
        nn.BatchNorm2d(dims[0], eps=1e-6),
        activation(dims[0], act_num)
    )
```

```
if self.deploy:
    self.cls = nn.Sequential(
        nn.AdaptiveAvgPool2d((1,1)),
        nn.Dropout(drop_rate),
        nn.Conv2d(dims[-1], num_classes, 1),
    )
else:
    self.cls1 = nn.Sequential(
        nn.AdaptiveAvgPool2d((1,1)),
        nn.Dropout(drop_rate),
        nn.Conv2d(dims[-1], num_classes, 1),
        nn.BatchNorm2d(num_classes, eps=1e-6),
    )
    self.cls2 = nn.Sequential(
        nn.Conv2d(num_classes, num_classes, 1)
    )
```

```
def forward(self, x):
    if self.deploy:
        x = self.stem(x)
    else:
        x = self.stem1(x)
        x = torch.nn.functional.leaky_relu(x,self.act_learn)
        x = self.stem2(x)

    for i in range(self.depth):
        x = self.stages[i](x)

    if self.deploy:
        x = self.cls(x)
    else:
        x = self.cls1(x)
        x = torch.nn.functional.leaky_relu(x,self.act_learn)
        x = self.cls2(x)
    return x.view(x.size(0),-1)
```

其他细节

- 网络各种variant，scale-up主要在第三个stage：

	Input	VanillaNet-5	VanillaNet-6	VanillaNet-7/8/9/10/11/12/13
stem	224×224	4×4, 512, stride 4		
stage1	56×56	[1×1, 1024]×1 MaxPool 2×2	[1×1, 1024]×1 MaxPool 2×2	[1×1, 1024]×2 MaxPool 2×2
stage2	28×28	[1×1, 2048]×1 MaxPool 2×2	[1×1, 2048]×1 MaxPool 2×2	[1×1, 2048]×1 MaxPool 2×2
stage3	14×14	[1×1, 4096]×1 MaxPool 2×2	[1×1, 4096]×1 MaxPool 2×2	[1×1, 4096]×1/2/3/4/5/6/7 MaxPool 2×2
stage4	7×7	-	[1×1, 4096]×1	[1×1, 4096]×1
classifier	7× 7	AvgPool 7×7 1×1, 1000		

Table 6: Detailed architecture specifications.

其他细节

- 使用了较为复杂的数据增强操作（左），对比以往方法（右）：

Training Config	VanillaNet-{5/6/7/8/9/10/11/12/13}
weight init	trunc. normal (0.2)
optimizer	LAMB [51]
loss function	BCE loss
base learning rate	3.5e-3 {5,8-13} /4.8e-3 {6-7}
weight decay	0.35/0.35/0.35/0.3/0.3/0.25/0.3/0.3/0.3
optimizer momentum	β_1, β_2=0.9, 0.999
batch size	1024
training epochs	300
learning rate schedule	cosine decay
warmup epochs	5
warmup schedule	linear
dropout	0.05
layer-wise lr decay [5, 1]	0 {5,8-12} /0.8 {6-7,13}
randaugment [6]	(7, 0.5)
mixup [54]	0.1/0.15/0.4/0.4/0.4/0.4/0.8/0.8/0.8
cutmix [52]	1.0
color jitter	0.4
label smoothing [41]	0.1
exp. mov. avg. (EMA) [36]	0.999996 {5-10} /0.99992 {11-13}
test crop ratio	0.875 {5-11} /0.95 {12-13}

Table 7: ImageNet-1K training settings.

	PoolFormer				
	S12	S24	S36	M36	M48
Peak drop rate of stoch. depth d_r	0.1	0.1	0.2	0.3	0.4
LayerScale initialization ϵ	10^{-5}	10^{-5}	10^{-6}	10^{-6}	10^{-6}
Data augmentation	AutoAugment				
Repeated Augmentation	off				
Input resolution	224				
Epochs	300				
Warmup epochs	5				
Hidden dropout	0				
GeLU dropout	0				
Classification dropout	0				
Random erasing prob	0.25				
EMA decay	0				
Cutmix α	1.0				
Mixup α	0.8				
Cutmix-Mixup switch prob	0.5				
Label smoothing	0.1				
Relation between peak learning rate and batch size	$\text{lr} = \frac{\text{batch\_size}}{1024} \times 10^{-3}$				
Batch size used in the paper	4096				
Peak learning rate used in the paper	4×10^{-4}				
Learning rate decay	cosine				
Optimizer	AdamW				
Adam ϵ	1e-8				
Adam (β_1, β_2)	(0.9, 0.999)				
Weight decay	0.05				
Gradient clipping	None				

Table 7. **Hyper-parameters for image classification on ImageNet-1K**

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实验效果—消融实验

Table 1: Ablation study on the number of series.

n	FLOPs (B)	Latency (ms)	Top-1 (%)
0	5.83	1.96	60.53
1	5.86	1.97	74.53
2	5.91	1.99	75.62
3	5.99	2.01	76.36
4	6.10	2.18	76.43

Table 3: Ablation on adding shortcuts.

Type	Top-1 (%)
no shortcut	**76.36**
shortcut before act	75.92
shortcut after act	75.72

Table 2: Ablation study on different networks.

Network	Deep train.	Series act.	Top-1 (%)
VanillaNet-6			59.58
	✓		60.53
		✓	75.23
	✓	✓	76.36
AlexNet			57.52
	✓		59.09
		✓	61.12
	✓	✓	63.59
ResNet-50			76.13
	✓		76.16
		✓	76.30
	✓	✓	76.27

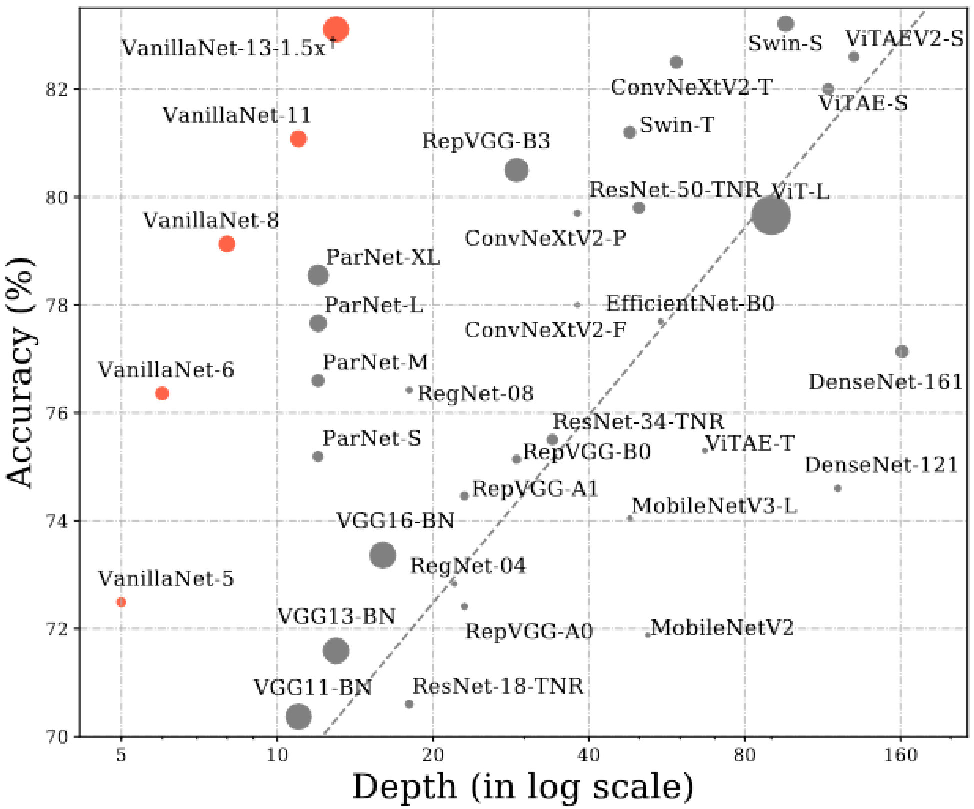
实验

Table 4: Comparison on ImageNet. Latency is tested on Nvidia A100 GPU with batch size of 1.

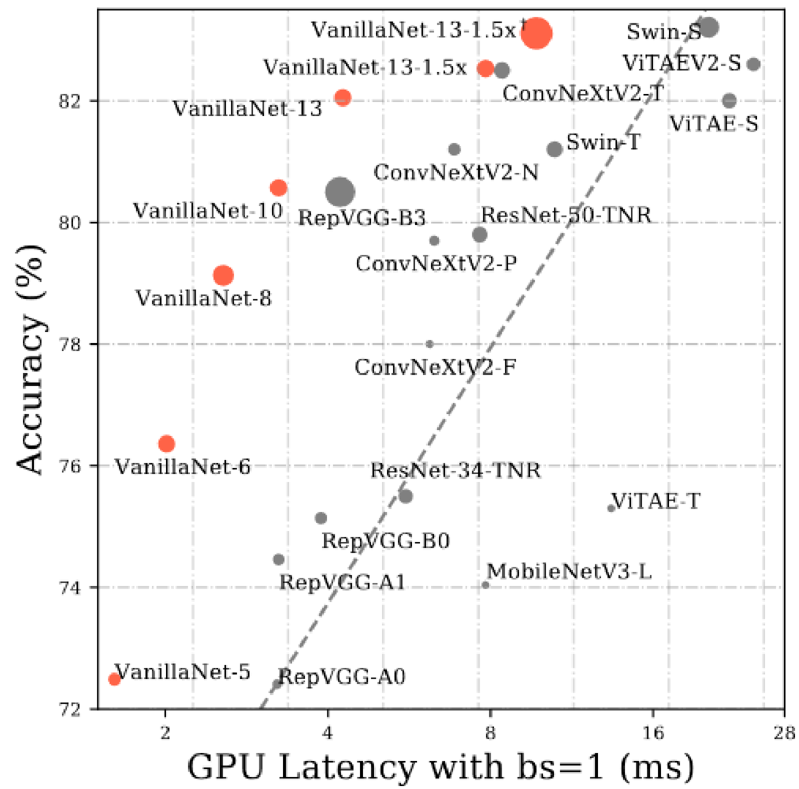
Model	Params (M)	FLOPs (B)	Depth	Latency (ms)	Acc (%)	Real Acc (%)
MobileNetV3-Small [21]	2.5	0.06	48	6.65	67.67	74.33
MobileNetV3-Large [21]	5.5	0.22	48	7.83	74.04	80.01
ShuffleNetV2x1.5 [39]	3.5	0.30	51	7.23	73.00	80.19
ShuffleNetV2x2 [21]	7.4	0.58	51	7.84	76.23	82.72
RepVGG-A0 [12]	8.1	1.36	23	3.22	72.41	79.33
RepVGG-A1 [12]	12.8	2.37	23	3.24	74.46	81.02
RepVGG-B0 [12]	14.3	3.1	29	3.88	75.14	81.74
RepVGG-B3 [12]	110.9	26.2	29	4.21	80.50	86.44
ViTAE-T [48]	4.8	1.5	67	13.37	75.3	82.9
ViTAE-S [48]	23.6	5.6	116	22.13	82.0	87.0
ViTAEV2-S [55]	19.2	5.7	130	24.53	82.6	87.6
ConvNextV2-A [46]	3.7	0.55	41	6.07	76.2	82.79
ConvNextV2-F [46]	5.2	0.78	41	6.17	78.0	84.08
ConvNextV2-P [46]	9.1	1.37	41	6.29	79.7	85.60
ConvNextV2-N [46]	15.6	2.45	47	6.85	81.2	-
ConvNextV2-T [46]	28.6	4.47	59	8.40	82.5	-
ConvNextV2-B [46]	88.7	15.4	113	15.41	84.3	-
Swin-T [31]	28.3	4.5	48	10.51	81.18	86.64
Swin-S [31]	49.6	8.7	96	20.25	83.21	87.60
ResNet-18-TNR [43]	11.7	1.8	18	3.12	70.6	79.4
ResNet-34-TNR [43]	21.8	3.7	34	5.57	75.5	83.4
ResNet-50-TNR [43]	25.6	4.1	50	7.64	79.8	85.7
VanillaNet-5	15.5	5.2	5	1.61	72.49	79.66
VanillaNet-6	32.5	6.0	6	2.01	76.36	82.86
VanillaNet-7	32.8	6.9	7	2.27	77.98	84.16
VanillaNet-8	37.1	7.7	8	2.56	79.13	85.14
VanillaNet-9	41.4	8.6	9	2.91	79.87	85.66
VanillaNet-10	45.7	9.4	10	3.24	80.57	86.25
VanillaNet-11	50.0	10.3	11	3.59	81.08	86.54
VanillaNet-12	54.3	11.1	12	3.82	81.55	86.81
VanillaNet-13	58.6	11.9	13	4.26	82.05	87.15
VanillaNet-13-1.5×	127.8	26.5	13	7.83	82.53	87.48
VanillaNet-13-1.5×†	127.8	48.9	13	9.72	83.11	87.85

容计算实验室
Content Computing Lab

实验效果—效果对比



(a) Accuracy vs. depth



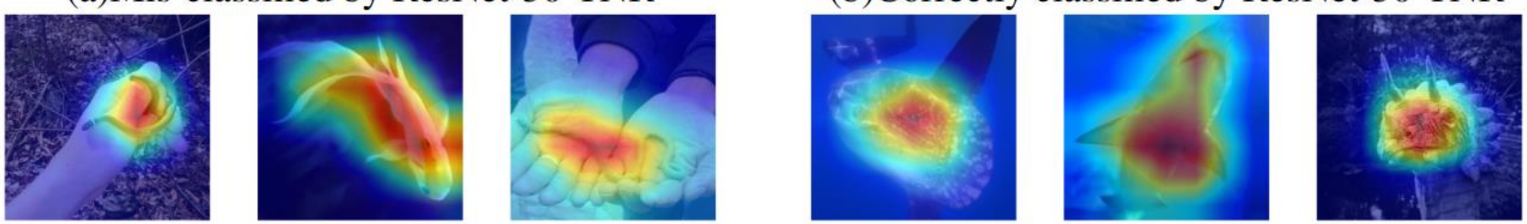
(b) Accuracy v.s. inference speed

实验效果—效果对比

Table 5: Performance on COCO detection and segmentation. FLOPs are calculated with image size (1280, 800)on Nvidia A100 GPU.

Framework	Backbone	FLOPs	Params	FPS	AP^b	AP^b_{50}	AP^b_{75}	AP^m	AP^m_{50}	AP^b_{75}
RetinaNet [29]	Swin-T [31]	245G	38.5M	27.5	41.5	62.1	44.2	-	-	-
	VanillaNet-13	397G	74.6M	29.8	41.8	62.8	44.3	-	-	-
Mask RCNN [16]	Swin-T [31]	267G	47.8M	28.2	42.7	65.2	46.8	39.3	62.2	42.2
	VanillaNet-13	421G	76.3M	32.6	42.9	65.5	46.9	39.6	62.5	42.2

(a)Mis-classified by ResNet-50-TNR (b)Correctly classified by ResNet-50-TNR



(c)Mis-classified by VanillaNet-9 (d)Correctly classified by VanillaNet-9

Figure 2: Visualization of attention maps of the classified samples by ResNet-50 and VanillaNet-9. We show the attention maps of their mis-classified samples and correctly classified samples for comparison.

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总结反思

- 在实际网络部署中，目前GPU对纯卷积网络适应性最好，因此本文设计了纯卷积网络，并且极致地压缩了网络层数，并摈弃了shortcut操作，进一步简化
- 通过重参数化方法融合BN和多层卷积，将训练时的网络参数重组，得到更简化的推理网络结构，是当今网络轻量化的常见套路
- 通过在网络训练前期引入非线性激活，以及对邻域进行加权，补足了网络的非线性能力

谢谢！