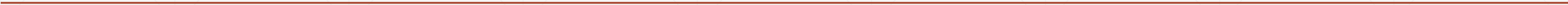
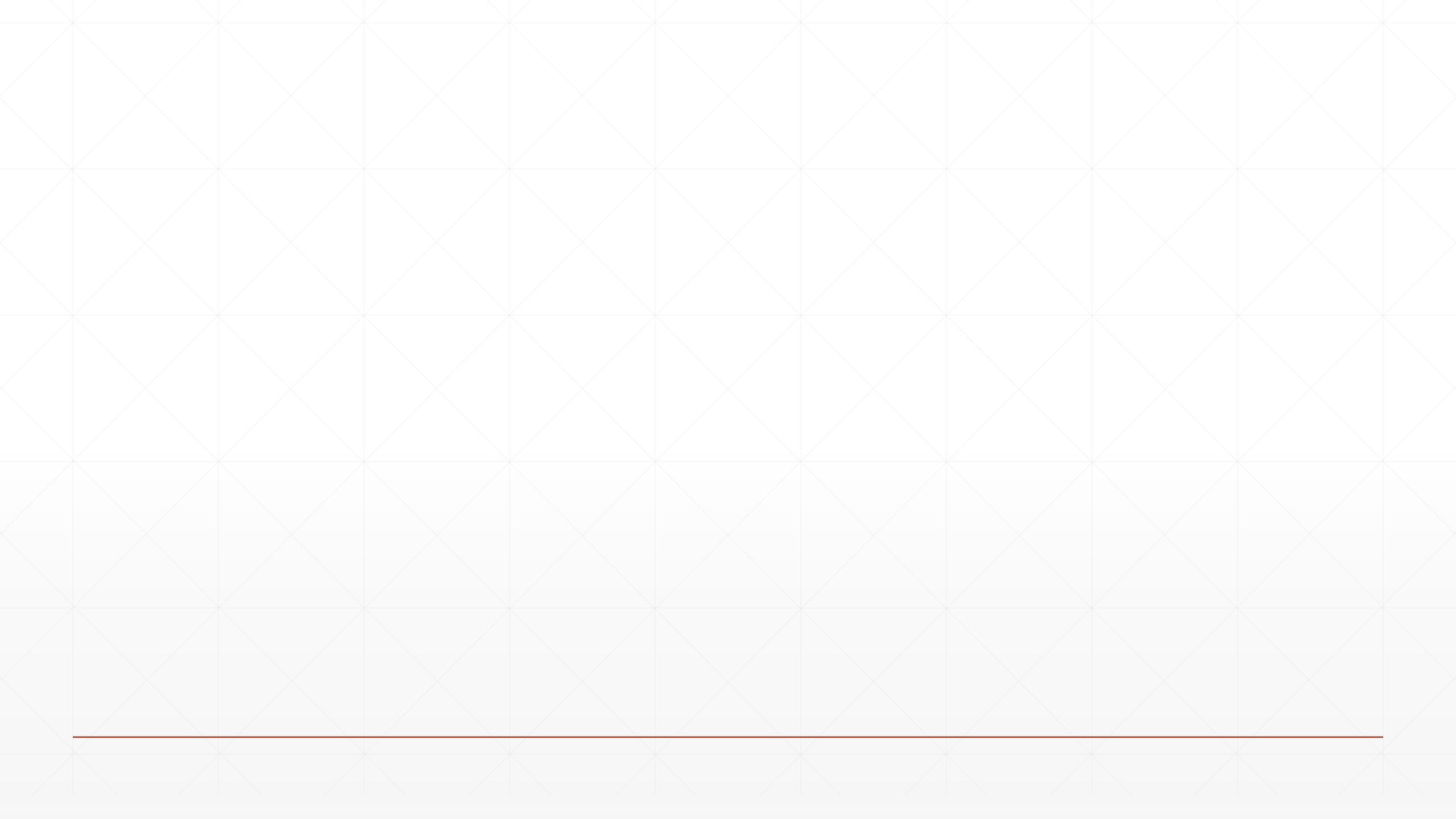


# ResNet 与 DenseNet

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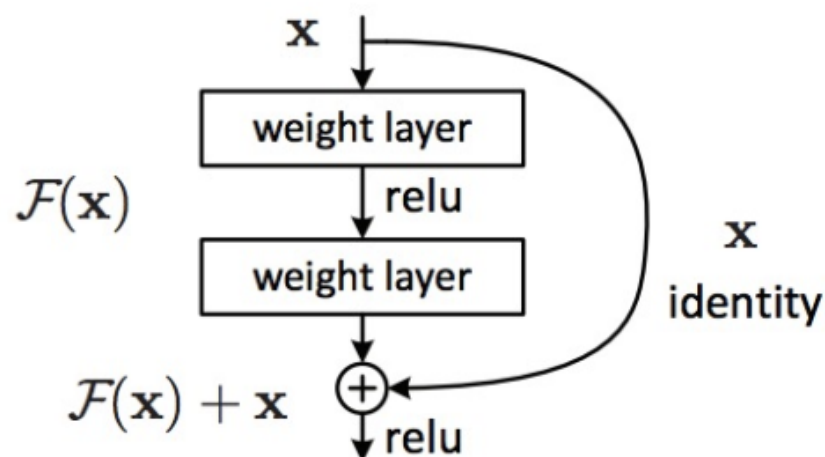
主讲：龙良曲



# ResNet

---

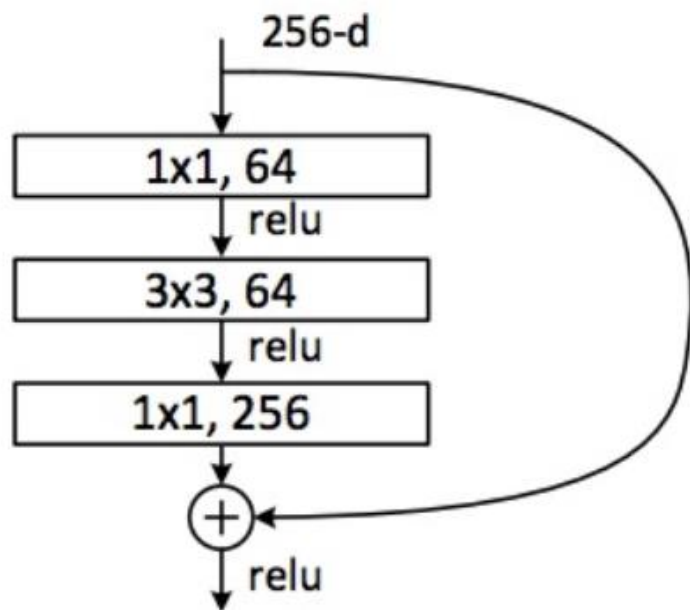
- The residual module
  - Introduce *skip* or shortcut connections (existing before in various forms in literature)
  - Make it easy for network layers to represent the identity mapping
  - For some reason, need to skip at least two layers



Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun,  
[Deep Residual Learning for Image Recognition](#), CVPR 2016 (Best Paper)

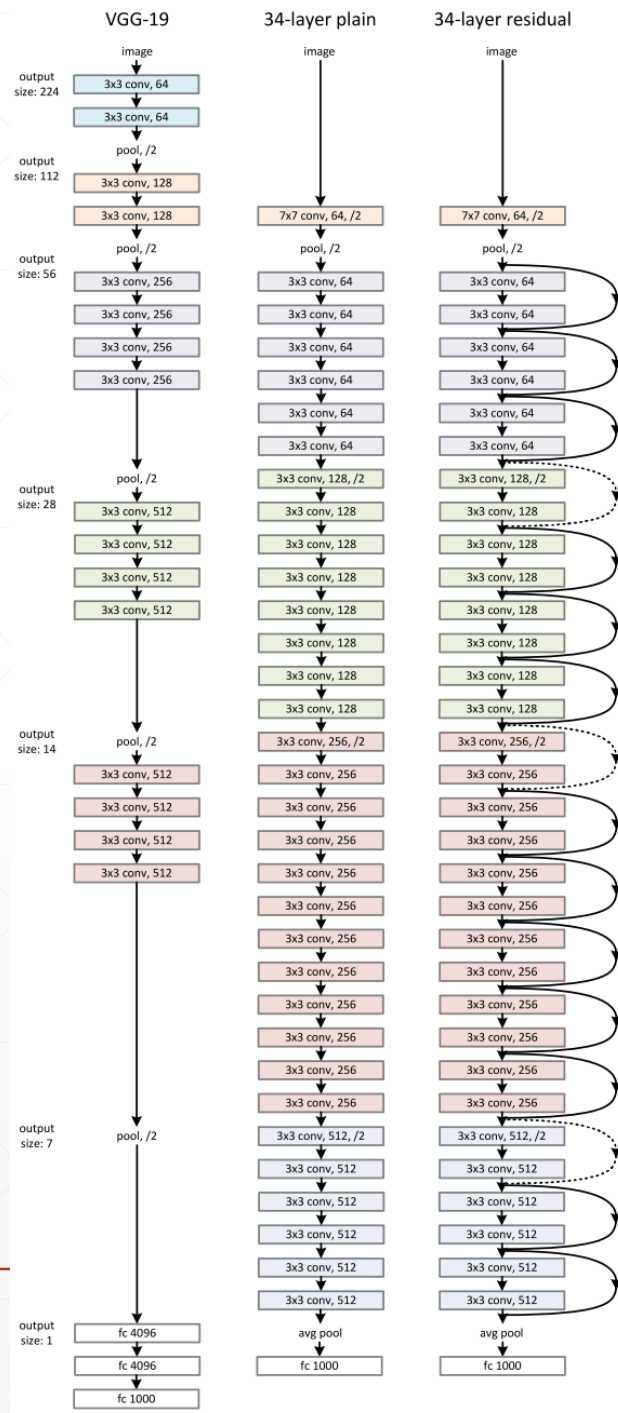
# ResNet

## Deeper residual module (bottleneck)



- Directly performing 3x3 convolutions with 256 feature maps at input and output:  
 $256 \times 256 \times 3 \times 3 \sim 600K$  operations
- Using 1x1 convolutions to reduce 256 to 64 feature maps, followed by 3x3 convolutions, followed by 1x1 convolutions to expand back to 256 maps:  
 $256 \times 64 \times 1 \times 1 \sim 16K$   
 $64 \times 64 \times 3 \times 3 \sim 36K$   
 $64 \times 256 \times 1 \times 1 \sim 16K$   
Total:  $\sim 70K$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun,  
[Deep Residual Learning for Image Recognition](#), CVPR 2016 (Best Paper)



# ResNet: ILSVRC 2015 winner

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## Revolution of Depth

AlexNet, 8 layers  
(ILSVRC 2012)



VGG, 19 layers  
(ILSVRC 2014)



ResNet, 152 layers  
(ILSVRC 2015)



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Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun,  
[Deep Residual Learning for Image Recognition](#), CVPR 2016



# BOOM!

Microsoft  
Research

## MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places** in all five main tracks

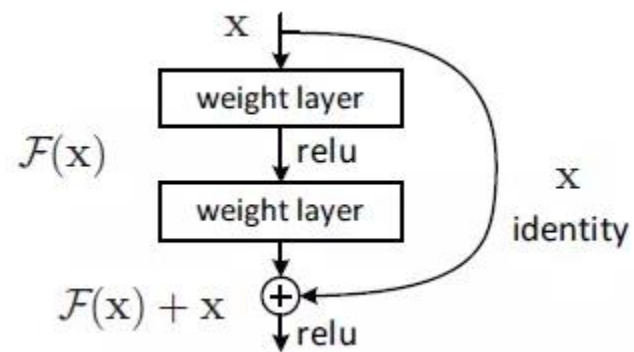
- ImageNet Classification: *"Ultra-deep"* (quote Yann) **152-layer** nets
- ImageNet Detection: **16%** better than 2nd
- ImageNet Localization: **27%** better than 2nd
- COCO Detection: **11%** better than 2nd
- COCO Segmentation: **12%** better than 2nd

\*improvements are relative numbers



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

# Why call Residual?

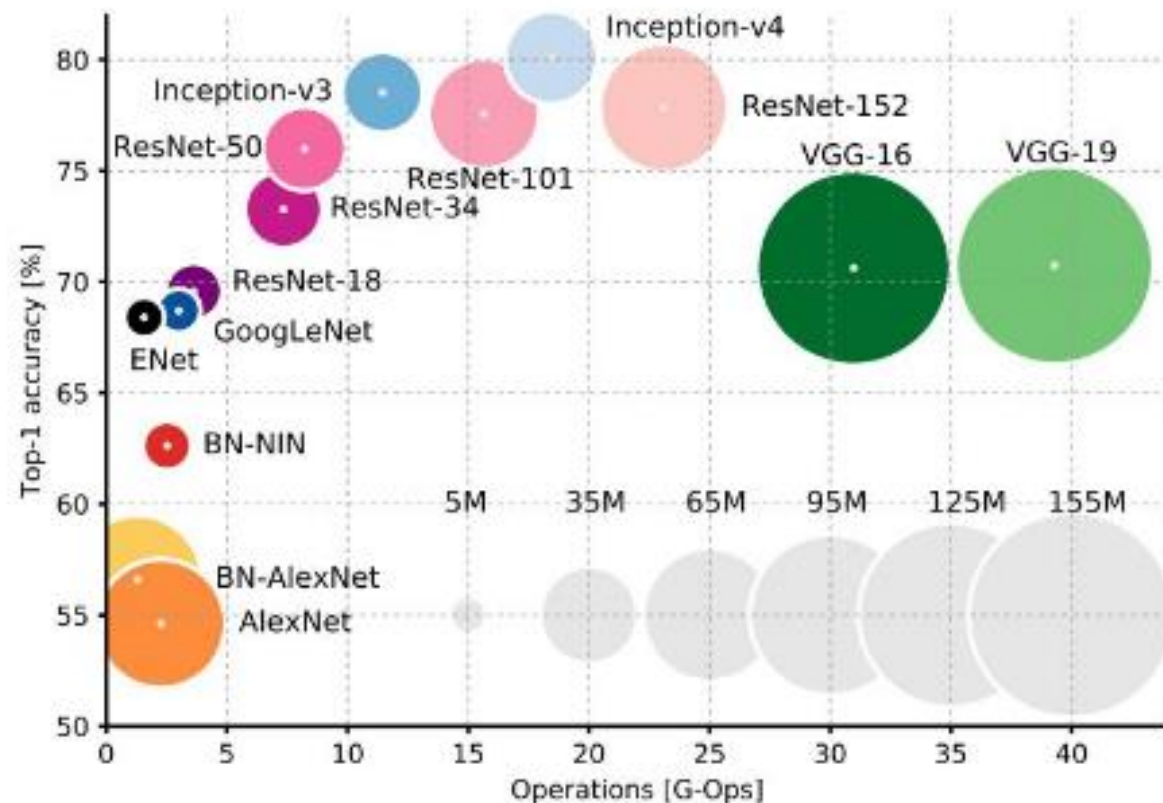
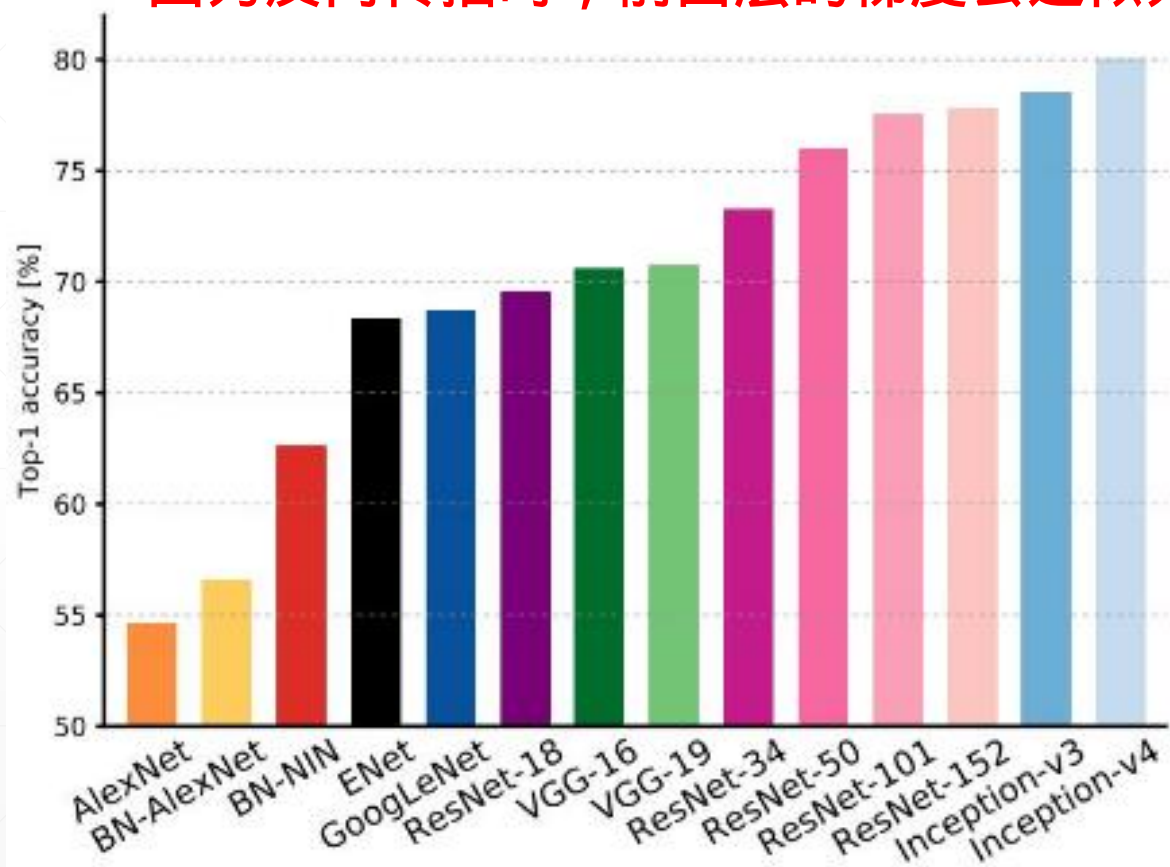


$$\mathcal{F}(x) := \mathcal{H}(x) - x$$

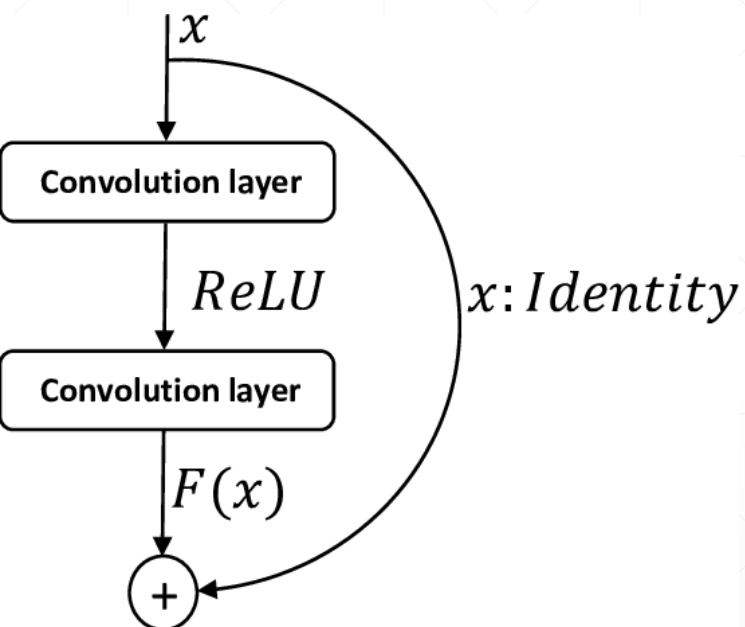
残差



20层以后，层数的简单堆叠对结果帮助不大  
因为反向传播时，前面层的梯度会近似为0



# Basic Block



```
class BasicBlock(layers.Layer):
    def __init__(self, filter_num, stride=1):
        super(BasicBlock, self).__init__()

        self.conv1 = layers.Conv2D(filter_num, (3, 3), strides=stride, padding='same')
        self.bn1 = layers.BatchNormalization()
        self.relu = layers.Activation('relu')
        self.conv2 = layers.Conv2D(filter_num, (3, 3), strides=1, padding='same')
        self.bn2 = layers.BatchNormalization()
        if stride != 1:
            self.downsample = Sequential()
            self.downsample.add(layers.Conv2D(filter_num, (1, 1), strides=stride))
            self.downsample.add(layers.BatchNormalization())
        else:
            self.downsample = lambda x: x

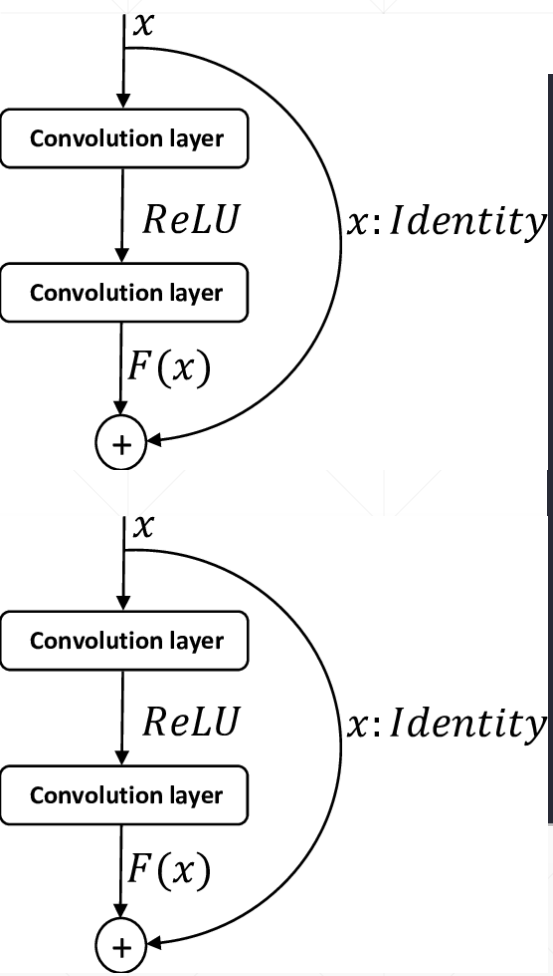
        self.stride = stride

    def call(self, inputs, training=None):
        residual = self.downsample(inputs)

        conv1 = self.conv1(inputs)
        bn1 = self.bn1(conv1)
        relu1 = self.relu(bn1)
        conv2 = self.conv2(relu1)
        bn2 = self.bn2(conv2)

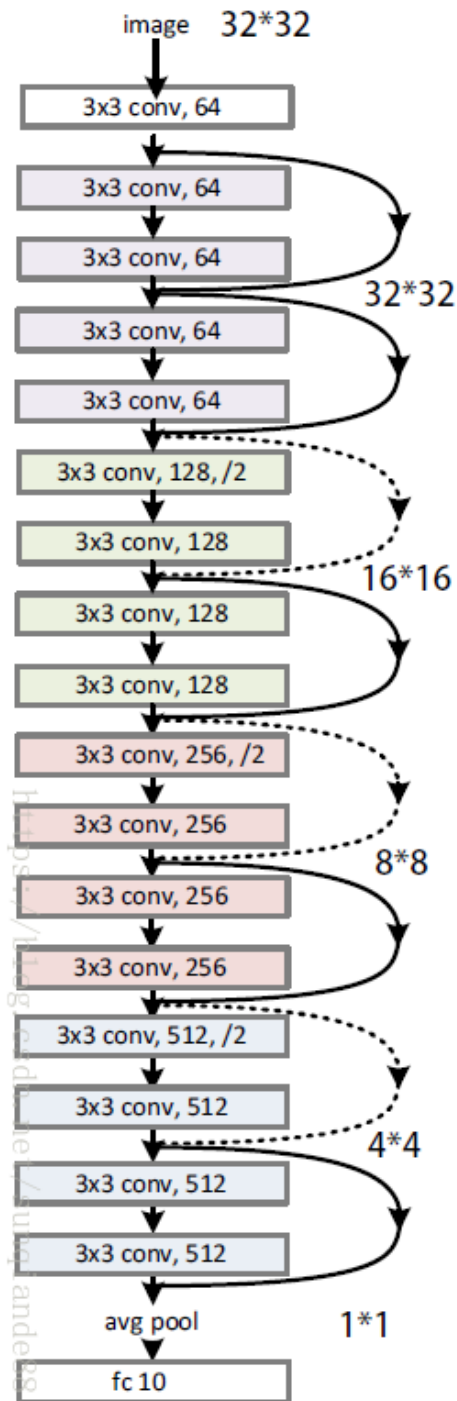
        add = layers.add([bn2, residual])
        out = self.relu(add)
        return out
```

# Res Block

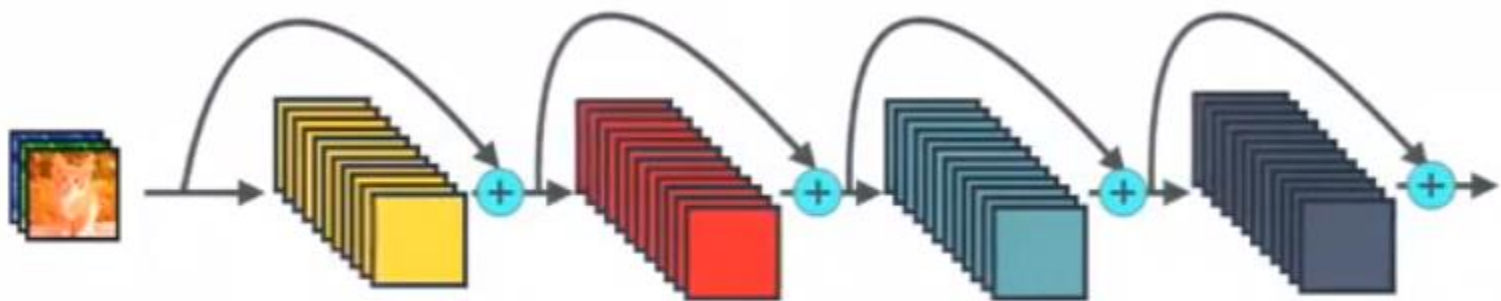
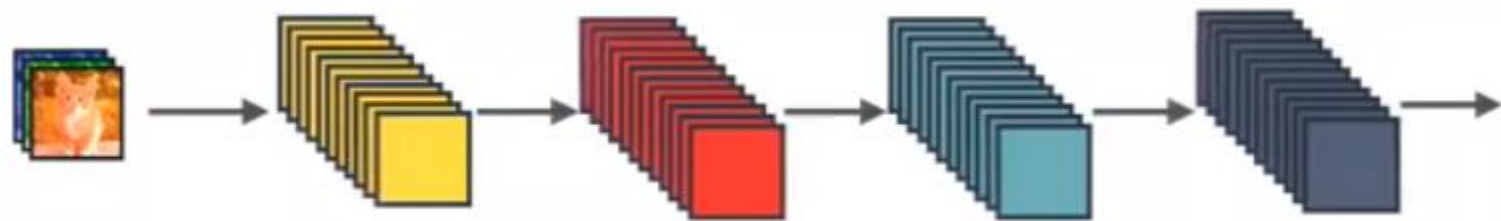


```
def _build_resblock(self, block, filter_num, blocks, stride=1):  
  
    res_blocks = keras.Sequential()  
    res_blocks.add(block(filter_num, stride))  
  
    for _ in range(1, blocks):  
        res_blocks.add(block(filter_num, stride=1))  
  
    return res_blocks
```

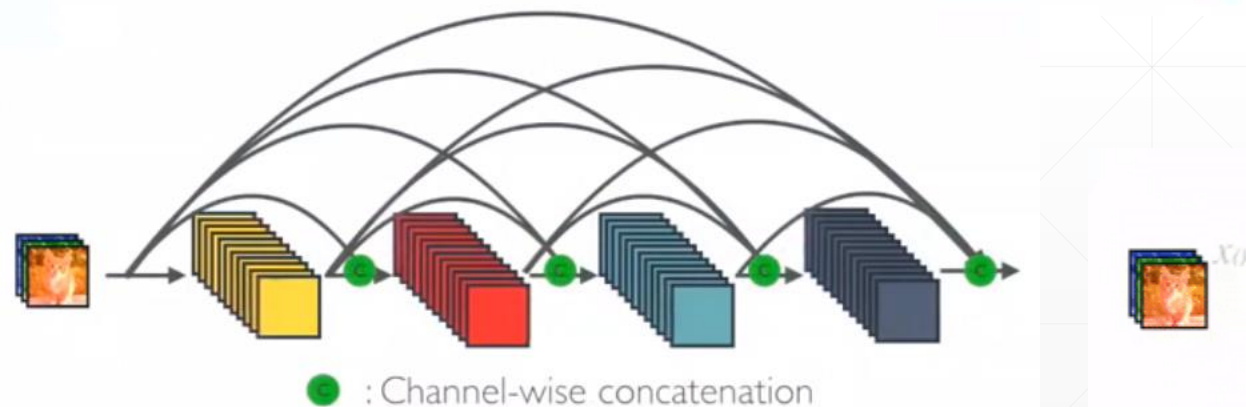
# ResNet-18



# DenseNet



⊕ : Element-wise addition



⊕ : Channel-wise concatenation

后面层与前面每一层都有机会短接

下一课时

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ResNet实战



**Thank You.**

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