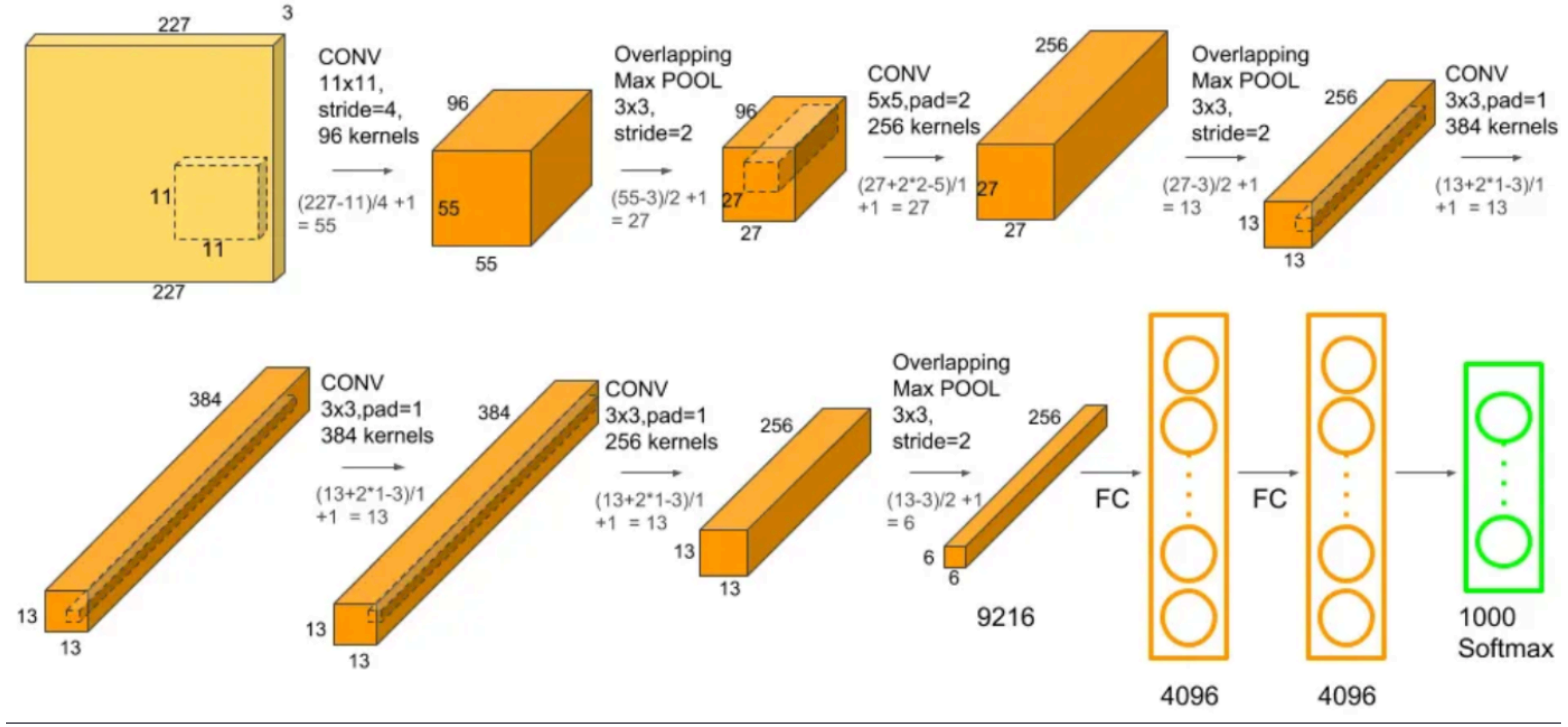
Week2 CNN Architectures

Tutor:
Email:
Tutorial:
Code: https://github.com/Jinxu-Lin/COMP5329

AlexNet

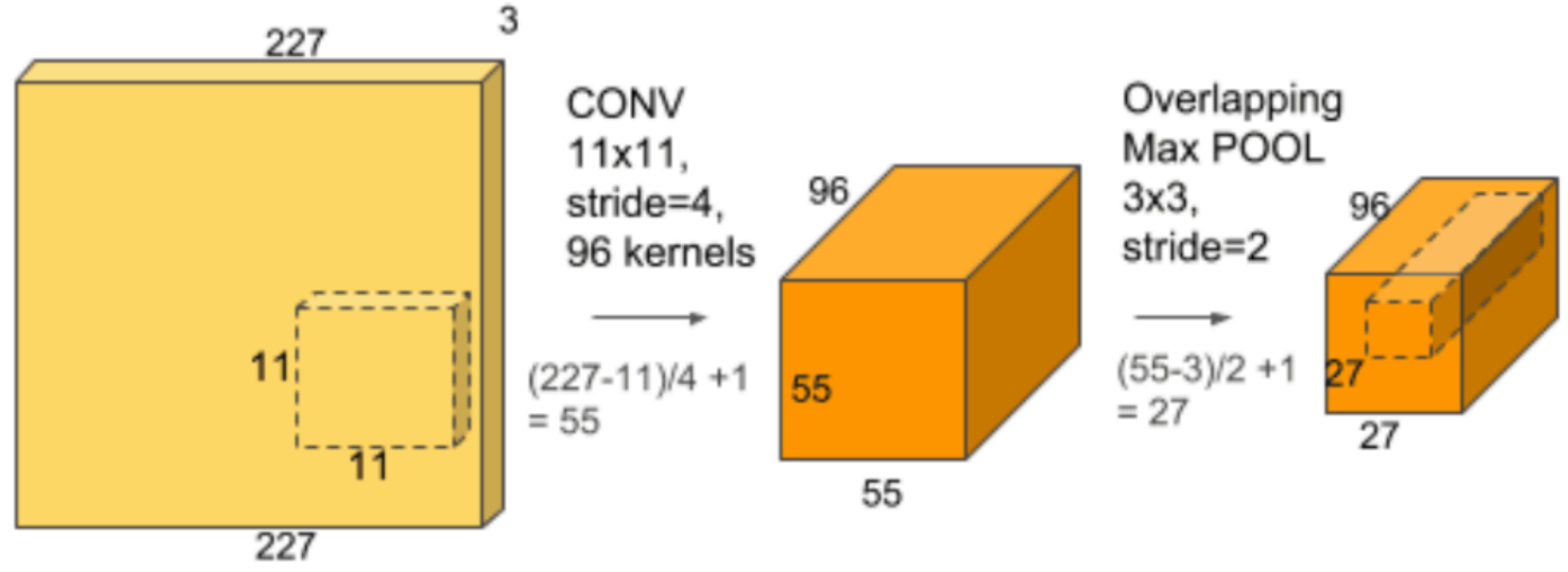
AlexNet

- Dataset: ImageNet1K
  - $(3 \times 227 \times 227, 1000)$
- AlexNet
  - Block 1
  - Block 2
  - Block 3,4
  - Block 5
  - Linear Block



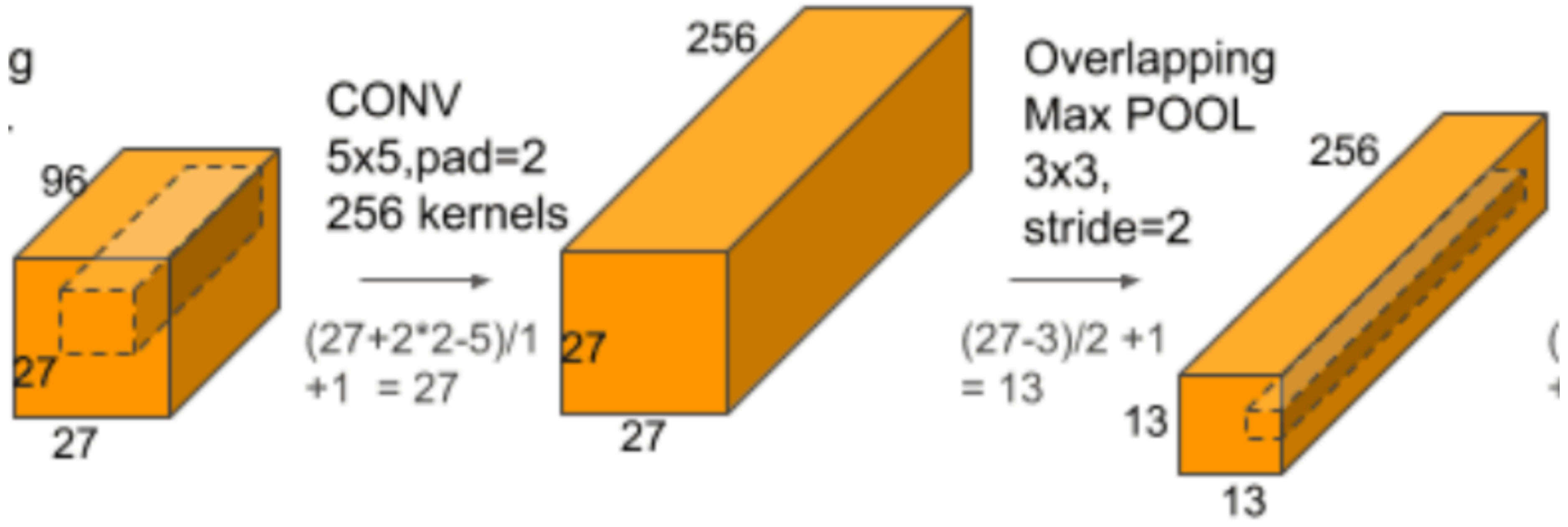
AlexNet-Block 1

- 2d Convolution Layer: 96*(11*11), s=4, p=0
  - Input Chanels: 3; Input Size: 227*227
  - Output Shape: ?
- ReLU
- MaxPooling



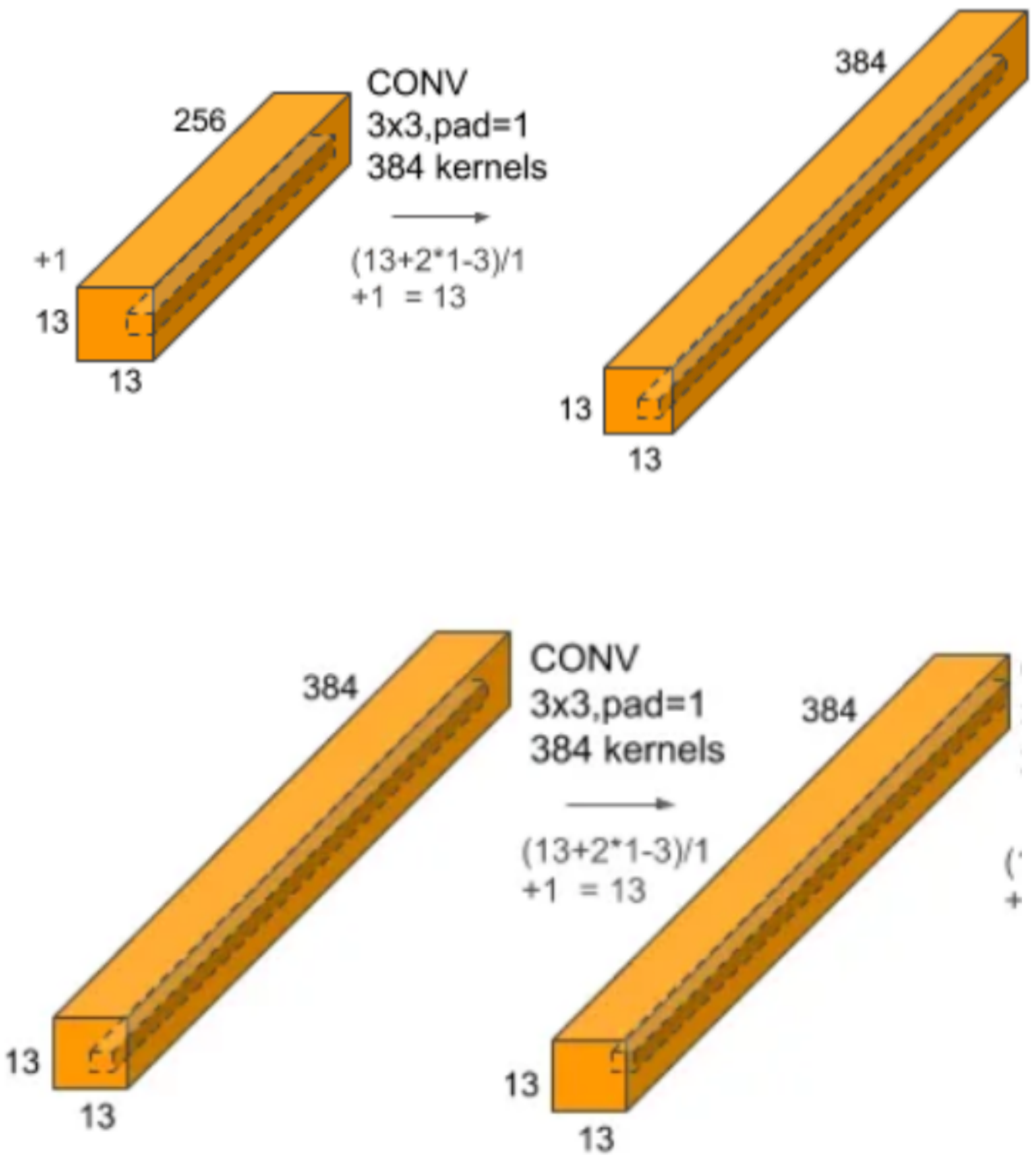
AlexNet-Block 2

- 2d Convolution Layer: 256*(5*5), s=1, p=2
  - Input Chanels: 96; Input Size: 27*27
  - Output Shape: ?
- ReLU
- MaxPooling



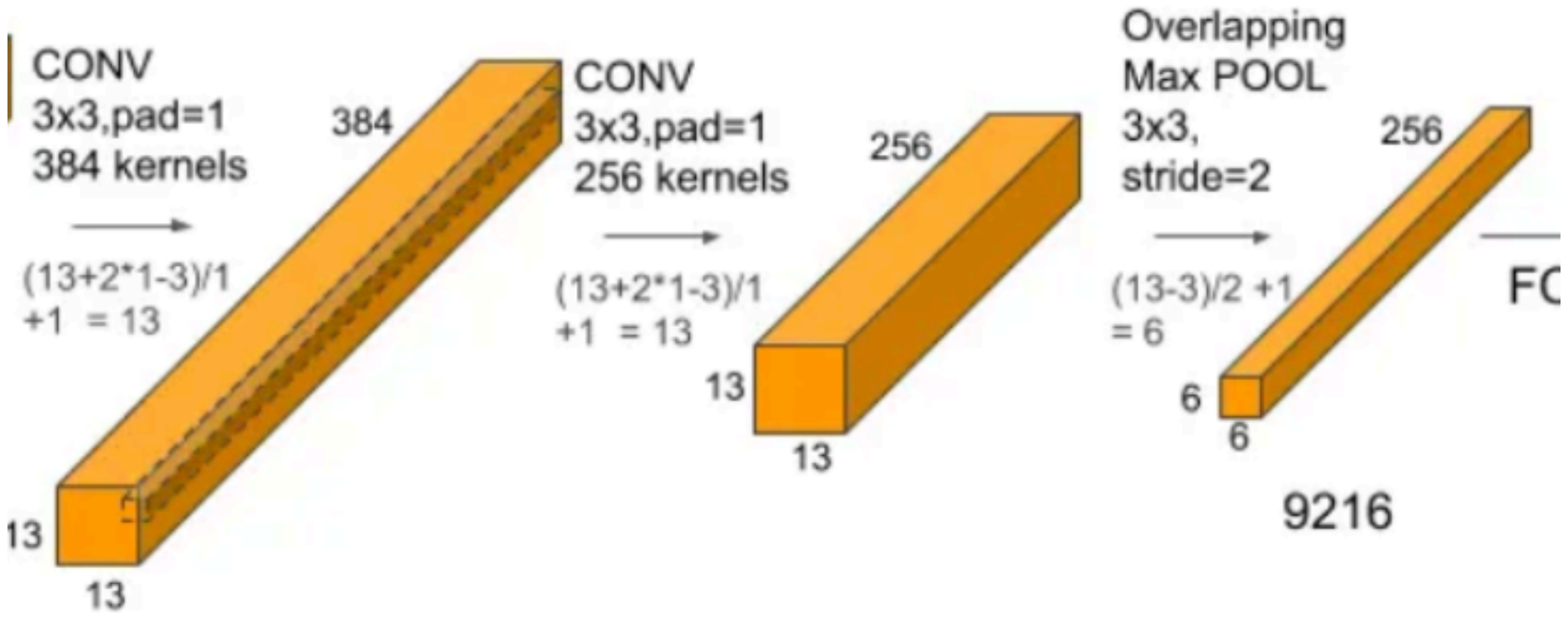
AlexNet-Block 3,4

- 2d Convolution Layer: 384*(3*3), s=1, p=1
  - Input Chanels: 256; Input Size: 13*13
  - Output Shape: ?
- ReLU



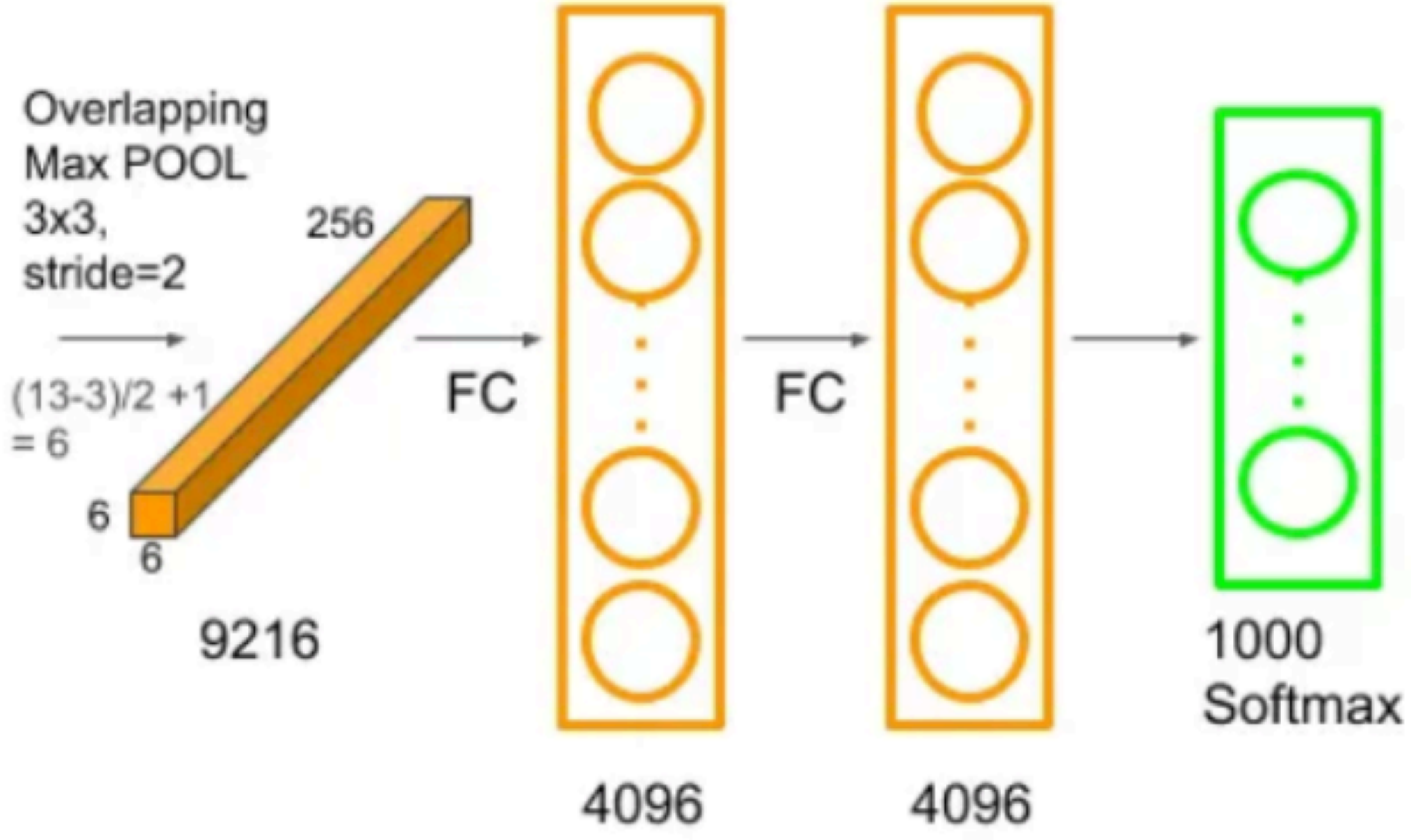
AlexNet-Block 5

- 2d Convolution Layer: 256*(3*3), s=1, p=1
  - Input Chanels: 384; Input Size: 13*13
  - Output Shape: ?
- ReLU
- MaxPooling



AlexNet-Full Connected Layer

- Flatten (256*6*6=9216)
- Linear: (9216,4096)
- ReLU
- Linear: (4096,1000)
- Softmax



VGG-11

VGG-11

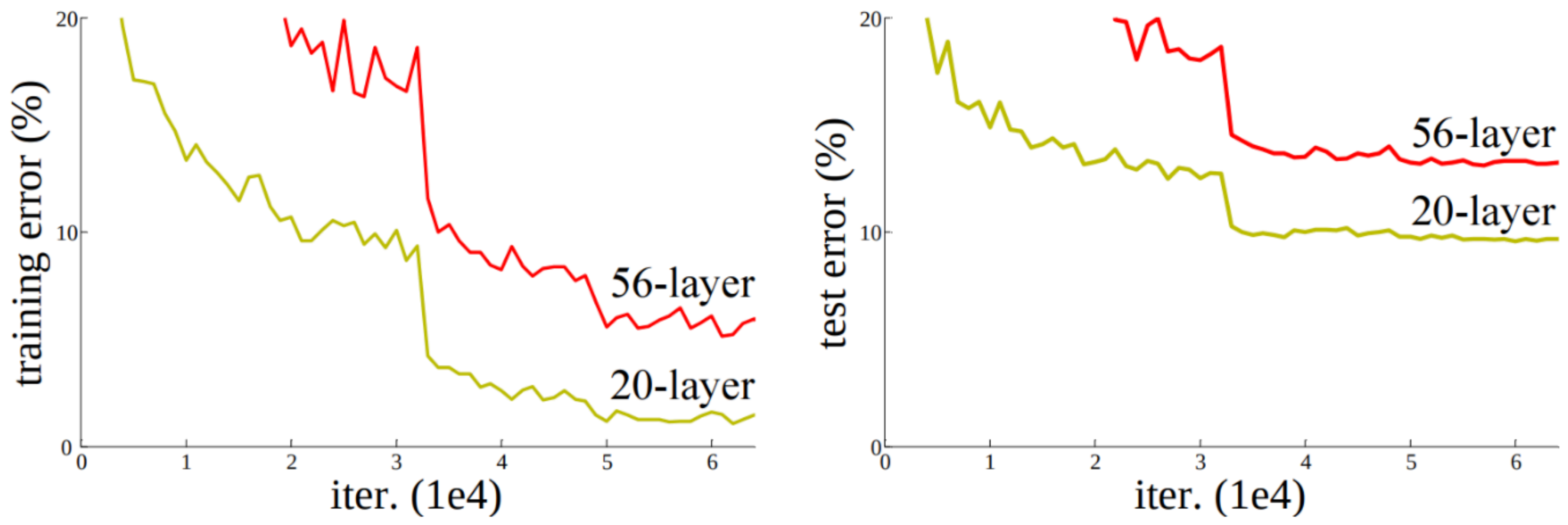
- VGG is also a popular CNN with a number of versions which are VGG-11, VGG-16 and VGG-19.
- In this class we are gonna build the VGG-11 according to the following diagram:

VGG 11			
		Input 224 x 224 x3	Input 32 x 32 x 3
conv3-64 + ReLU	In	224 x 224 x3	32 x 32 x 3
	Out	224 x 224 x64	32 x 32 x 64
MaxPool	In	224 x 224 x 64	32 x 32 x 64
	Out	112 x 112 x 64	16 x 16 x 64
conv3-128 + ReLU	In	112 x 112 x 64	16 x 16 x 64
	Out	112 x 112 x 128	16 x 16 x 128
MaxPool	In	112 x 112 x 128	16 x 16 x 128
	Out	56 x 56 x 128	8 x 8 x 128
conv3-256 + ReLU	In	56 x 56 x 128	8 x 8 x 128
	Out	56 x 56 x 256	8 x 8 x 256
conv3-256 + ReLU	In	56 x56 x 256	8 x 8 x 256
	Out	56 x 56 x 256	8 x 8 x 256
MaxPool	In	56 x 56 x 256	8 x 8 x 256
	Out	28 x 28 x 256	4 x 4 x 256
conv3-512 + ReLU	In	28 x 28 x 256	4 x 4 x 256
	Out	28 x 28 x 512	4 x 4 x 512
conv3-512 + ReLU	In	28 x 28 x 512	4 x 4 x 512
	Out	28 x 28 x 512	4 x 4 x 512
MaxPool	In	28 x28 x 512	4 x 4 x 512
	Out	14 x 14 x 512	2 x 2 x 512
conv3-512 + ReLU	In	14x14 x 512	2 x 2 x 512
	Out	14 x 14 x 512	2 x 2 x 512
conv3-512 + ReLU	In	14x14 x 512	2 x 2 x 512
	Out	14 x 14 x 512	2 x 2 x 512
MaxPool	In	14 x 14 x 512	2 x 2 x 512
	Out	7 x 7 x 512	1 x 1 x 512
FC	In	25088	512
	Out	4096	2048
FC	In	4096	2048
	Out	4096	2048
FC	In	4096	2048
	Out	1000	10
SoftMax			

ResNet

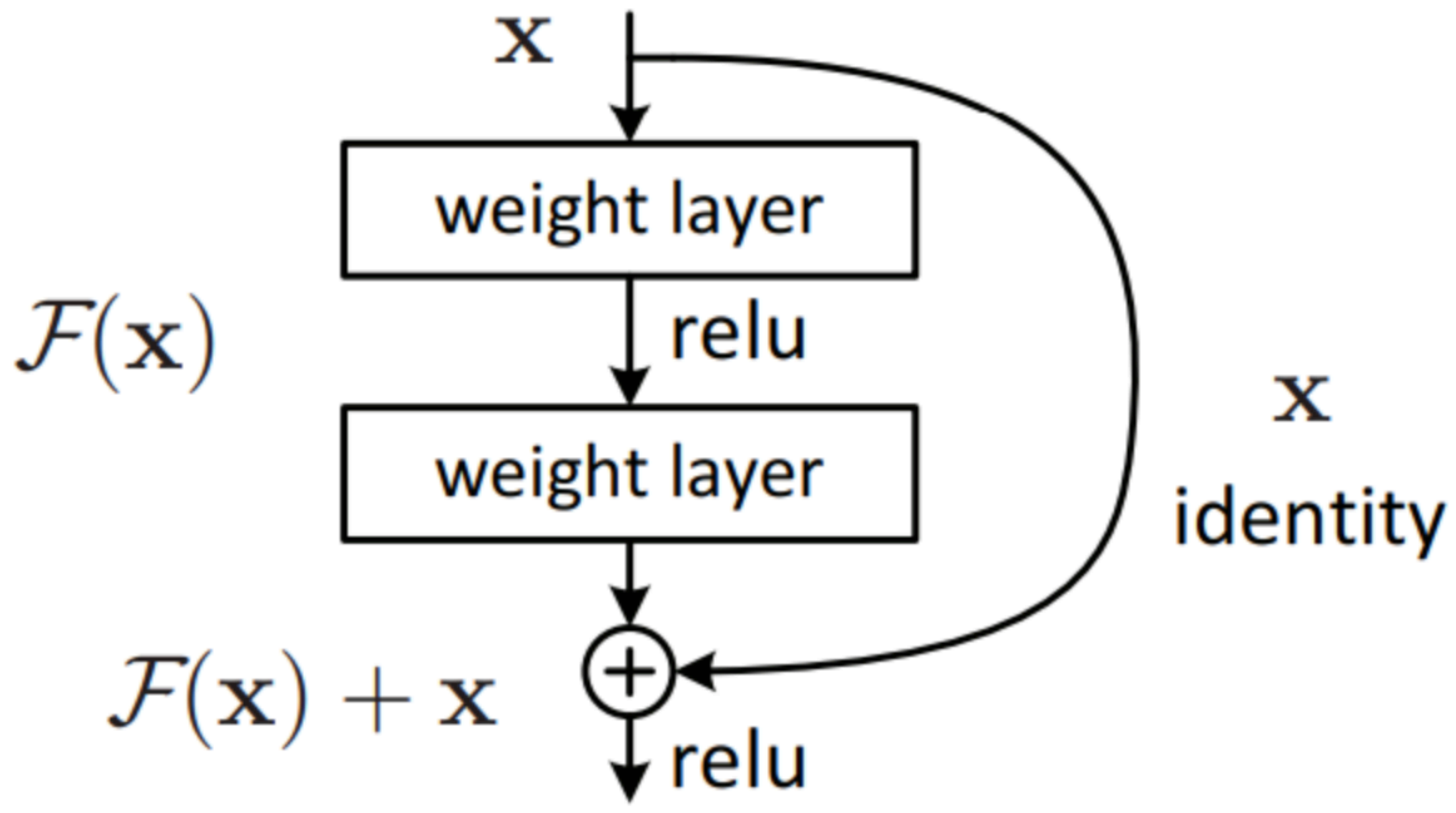
ResNet

- Existing Problems
    - People all realize that deeper network means better results. However, it is not the whole story
- Reason
    - **Gradient vanishing**: gradient disappeared at very early layer, while very strong in the last layers.
    - **Saturation**: (Observed in the Resnet paper) Stacking more layers without gradient vanishing also have gradient vanishing problem.



ResNet

- Skip Connection
- Intuition
  - If $F(x)$ is a saturated factor, $F(x)$ is optimized to 0. This will reduce the depth of the network. (saturation problem)
  - Strengthen signal from x. Which helps the gradient signals toward x is stronger. (gradient vanishing)
- Means:
  - Reduce the depth of the network if saturation
  - Reduce gradient vanishing



ResNet

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Code

Code

- ./materials/Week6_CNN_Architectures/Week6_CNN_Architectures.ipynb
- ./ResNet/Models/resnet.py
- ./ResNet/train_utils.py: line32
- ./ResNet/train.py: line203