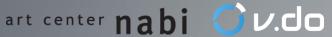
아티스트를 위한 머신러닝 & 딥러닝

# 텐서플로를 활용한 딥러닝#4

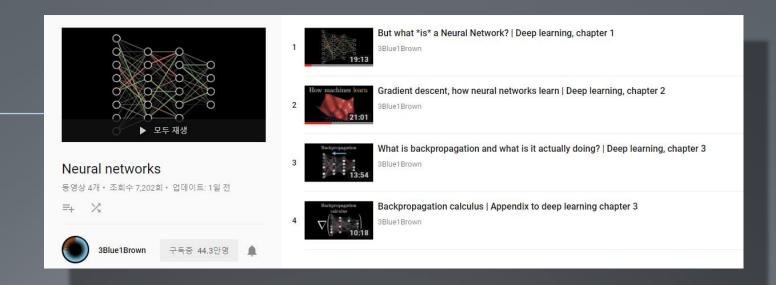
서울대학교 & V.DO / 김대식



# Recap

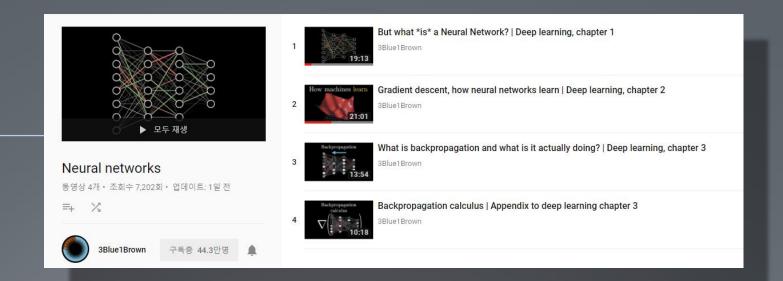


## What is a Neural network?

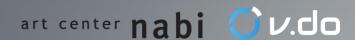


https://youtu.be/aircAruvnKk

## Gradient descent



https://youtu.be/IHZwWFHWa-w



# 컨볼루션 신경망 (Convolution Neural Network)

#### CS231n: Convolutional Neural Networks for Visual Recognition Spring 2017



#### Course Description

Computer Vision has become ubiquitous in our society, with applications in search, image understanding, apps, mapping, medicine, drones, and self-driving cars. Core to many of these applications are visual recognition tasks such as image classification, localization and detection. Recent developments in neural network (aka "deep learning") approaches have greatly advanced the performance of these state-of-the-art visual recognition systems. This course is a deep dive into details of the deep learning architectures with a focus on learning end-to-end models for these tasks, particularly image classification. During the 10-week course, students will learn to implement, train and debug their own neural networks and gain a detailed understanding of cutting-edge research in computer vision. The final assignment will involve training a multi-million parameter convolutional neural network and applying it on the largest image classification dataset (ImageNet). We will focus on teaching how to set up the problem of image recognition, the learning algorithms (e.g. backpropagation), practical engineering tricks for training and fine-tuning the networks and guide the students through hands-on assignments and a final course project. Much of the background and materials of this course will be drawn from the ImageNet Challenge.

#### Instructors



#### Teaching Assistants



Albert Ha



Rishi Bedi



Shyamal Buch



Zhao (Joe) Chen



Timnit Gebr

http://cs231n.stanford.edu/

# Next: Convolutional Neural Networks Image Maps Output Convolutions Subsampling Mustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

# ImageNet Classification with Deep Convolutional Neural Networks

[Krizhevsky, Sutskever, Hinton, 2012]

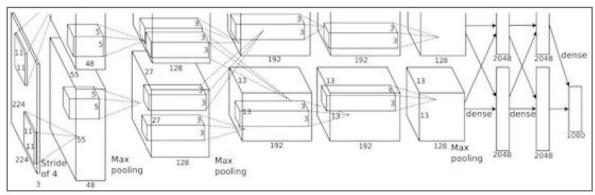
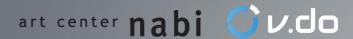
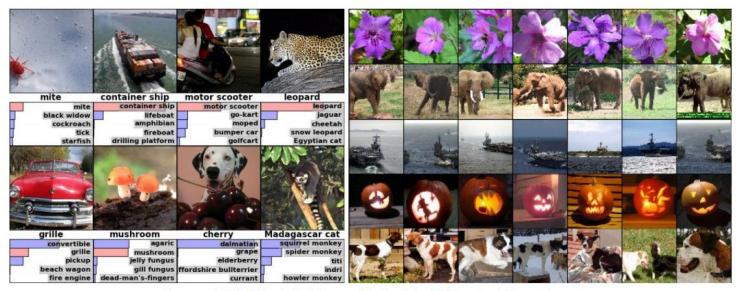


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

"AlexNet"

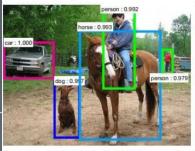


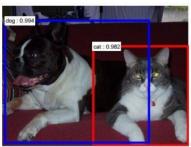
Classification Retrieval

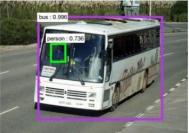


Figures copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

#### Detection









Figures copyright Shaoqing Ren, Kaiming He, Ross Girschick, Jian Sun, 2015. Reproduced with permission.

[Faster R-CNN: Ren, He, Girshick, Sun 2015]

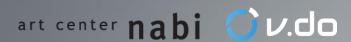
#### Segmentation

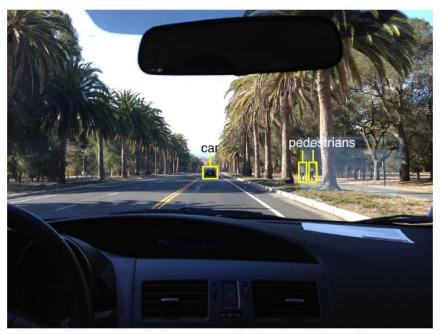




Figures copyright Clement Farabet, 2012. Reproduced with permission.

[Farabet et al., 2012]





self-driving cars

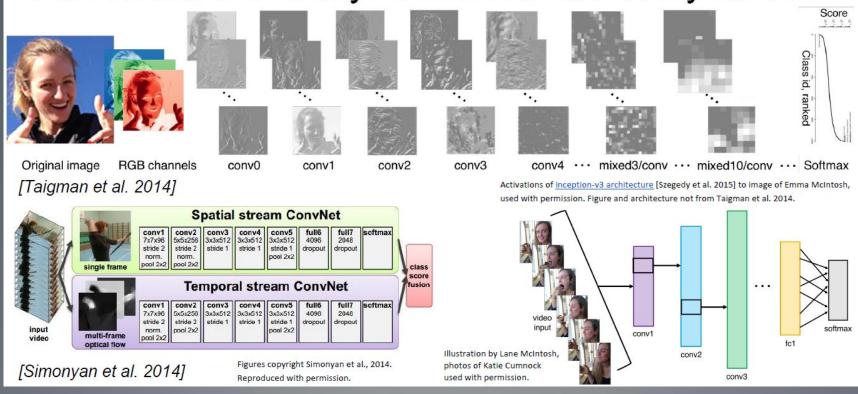
Photo by Lane McIntosh. Copyright CS231n 2017.



#### **NVIDIA** Tesla line

(these are the GPUs on rye01.stanford.edu)

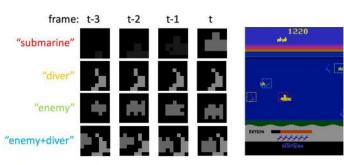
Note that for embedded systems a typical setup would involve NVIDIA Tegras, with integrated GPU and ARM-based CPU cores.





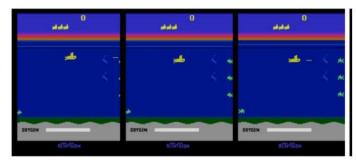
[Toshev, Szegedy 2014]

Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

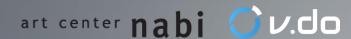


[Guo et al. 2014]





Figures copyright Xiaoxiao Guo, Satinder Singh, Honglak Lee, Richard Lewis, and Xiaoshi Wang, 2014. Reproduced with permission.



#### No errors



A white teddy bear sitting in the grass



A man riding a wave on top of a surfboard

#### Minor errors



A man in a baseball uniform throwing a ball



A cat sitting on a suitcase on the floor

#### Somewhat related



A woman is holding a cat in her hand



A woman standing on a beach holding a surfboard

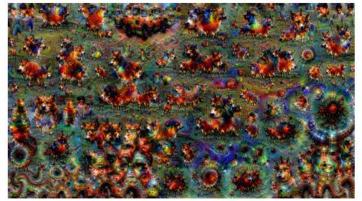
# Image Captioning

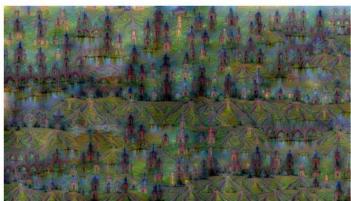
[Vinyals et al., 2015] [Karpathy and Fei-Fei, 2015]

All images are CC0 Public domain:

https://pixabay.com/en/lugqage-antique-cat-1643010/ https://pixabay.com/en/teddy-plush-bears-cute-teddy-bear-162343 https://pixabay.com/en/surf-wave-summer-sport-litoral-1668716/ https://pixabay.com/en/woman-female-model-portrait-adult-98396/ https://pixabay.com/en/handstand-lake-meditation-496008/ https://pixabay.com/en/baseball-player-shortstop-infield-1045263/

Captions generated by Justin Johnson using Neuraltalk2





Figures copyright Justin Johnson, 2015. Reproduced with permission. Generated using the Inceptionism approach from a blog post by Google Research.



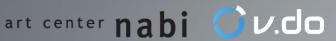








Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016 Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017



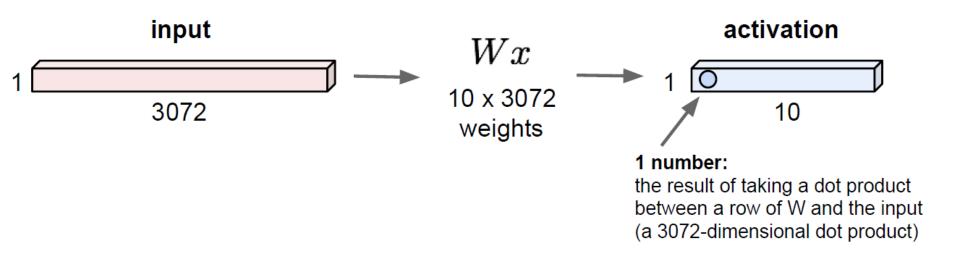
# 컨볼루션 비디오

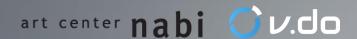
https://www.youtube.com/watch?v=KiftWz 544 8



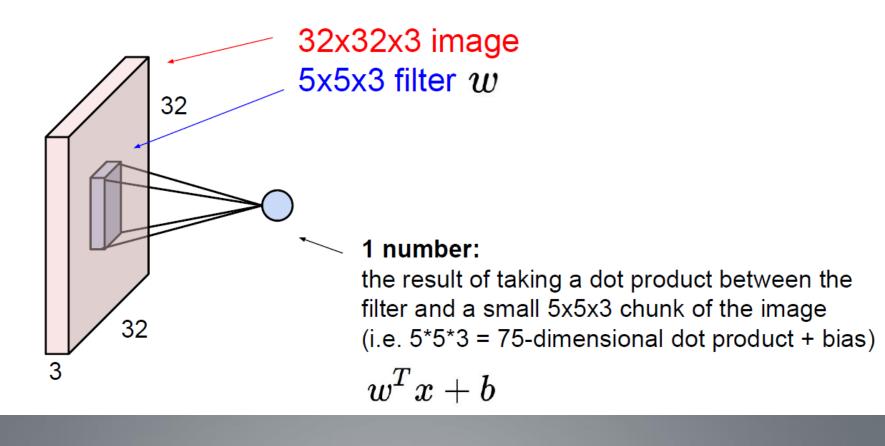
# Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



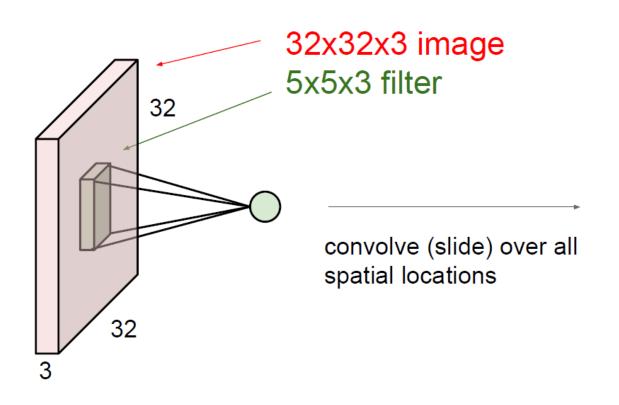


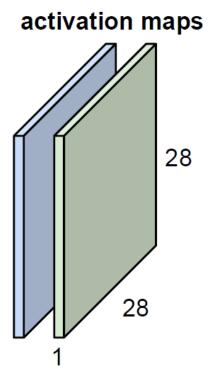
#### Convolution Layer



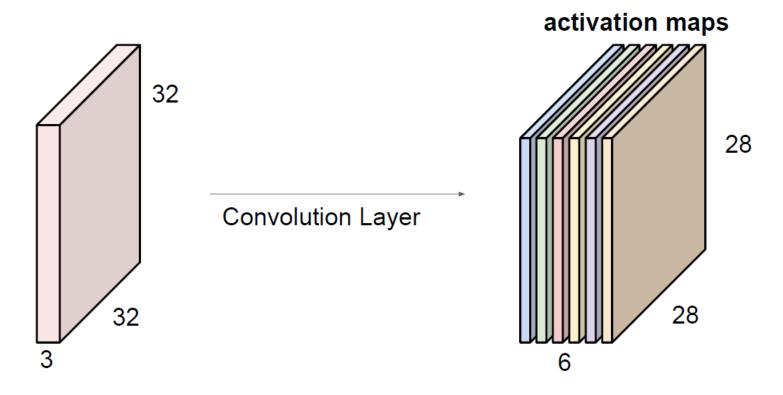
#### **Convolution Layer**

#### consider a second, green filter



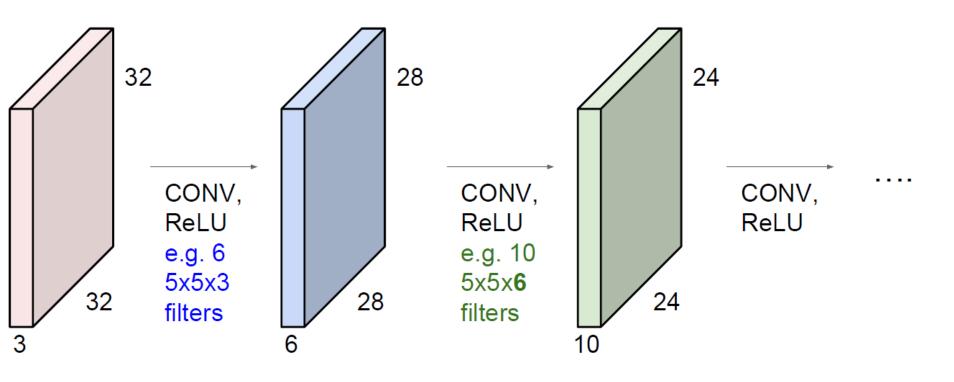


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

**Preview:** ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



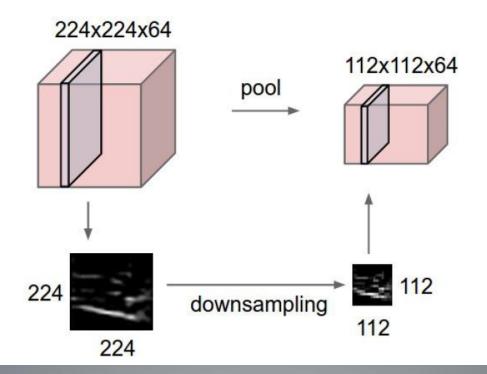
# 풀링 비디오

https://www.youtube.com/watch?v=mW3K **yFZDNIQ** 



### Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently:



#### MAX POOLING

Single depth slice

 1
 1
 2
 4

 5
 6
 7
 8

 3
 2
 1
 0

 1
 2
 3
 4

max pool with 2x2 filters and stride 2

6	8
3	4

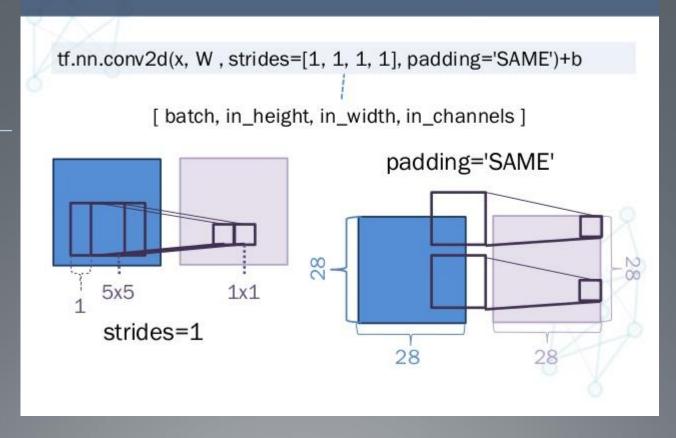
У

# 텐서플로 실습



## 컨볼루션 in 텐서플로

## Convolutional Layer

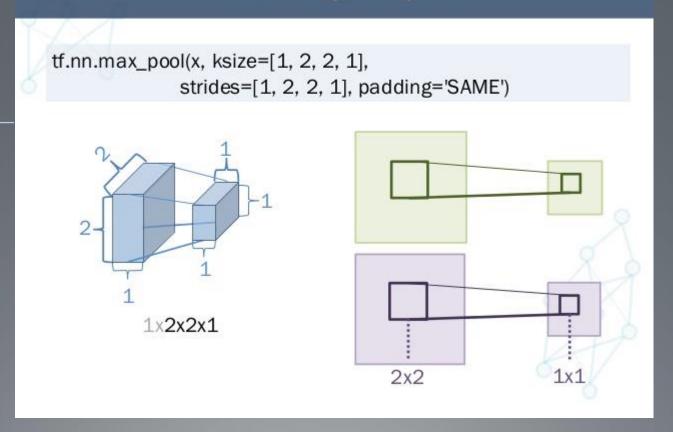


## <u> 컨볼루션 in 텐서플로</u>

```
def createNetwork():
    # network weights
    W conv1 = weight variable([3, 3, 4, 32])
    b conv1 = bias variable([32])
    W conv2 = weight variable([3, 3, 32, 64])
    b conv2 = bias variable([64])
    W \text{ conv3} = \text{weight variable}([3, 3, 64, 64])
    b conv3 = bias variable([64])
    W fc1 = weight variable([6400, 512])
    b fc1 = bias variable([512])
    W fc2 = weight variable([512, ACTIONS])
    b fc2 = bias variable([ACTIONS])
    # input laver
    s = tf.placeholder("float", [None, 80, 80, 4])
    # hidden lavers
    h conv1 = tf.nn.relu(conv2d(s, W conv1, 1) + b conv1)
    h_pool1 = max_pool_2x2(h_conv1)
    h conv2 = tf.nn.relu(conv2d(h pool1, W conv2, 1) + b conv2)
    h pool2 = max pool 2x2(h conv2)
    h_conv3 = tf.nn.relu(conv2d(h_pool2, W_conv3, 1) + b_conv3)
    h pool3 = max pool 2x2(h conv3)
    \#h pool3 flat = tf.reshape(h pool3, [-1, 256])
    h conv3 flat = tf.reshape(h pool3, [-1, 6400])
    h_fc1 = tf.nn.relu(tf.matmul(h_conv3 flat, W fc1) + b fc1)
```

## 맥스풀링 in 텐서플로

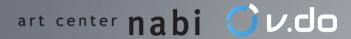
## Pooling Layer



## CIFAR-10

#### CIFAR-10 Model

airplane			
automobile	ar 🤝 🎏 📻 🚐		
bird		A & S	
cat			
deer			
dog	W. A. 40 11 15 15		
frog			
horse		MAR AND THE REAL PROPERTY.	
ship			
truck			
Data Sets	data_sets.train	50000 images & labels	
	data_sets.validation	1000 images & labels	
	data_sets.test	10000 images & labels	
Source: http://www.cs.toranto.edu/~kriz/cifar.html			



# 웹버전 실습

http://cs.stanford.edu/people/karpathy/con vnetjs/demo/cifar10.html



## Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

[227x227x3] INPUT

[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0

[27x27x96] MAX POOL1: 3x3 filters at stride 2

[27x27x96] NORM1: Normalization layer

[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2

[13x13x256] MAX POOL2: 3x3 filters at stride 2

[13x13x256] NORM2: Normalization layer

[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1

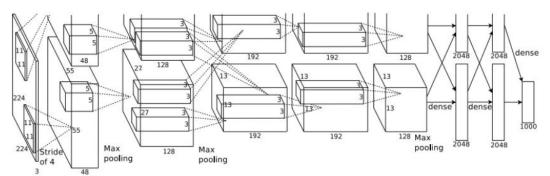
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1

[6x6x256] MAX POOL3: 3x3 filters at stride 2

[4096] FC6: 4096 neurons [4096] FC7: 4096 neurons

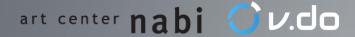
[1000] FC8: 1000 neurons (class scores)



#### **Details/Retrospectives:**

- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.



#### ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

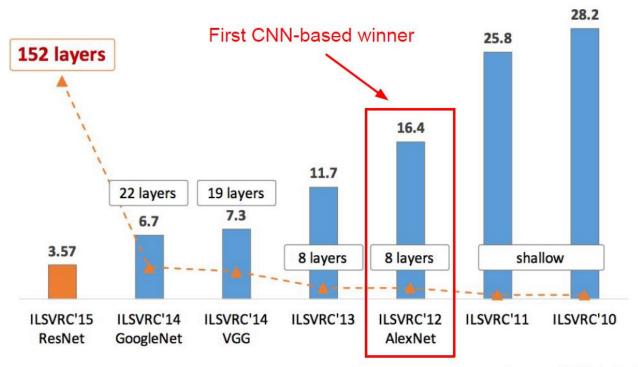
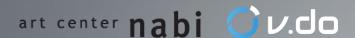


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#### ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

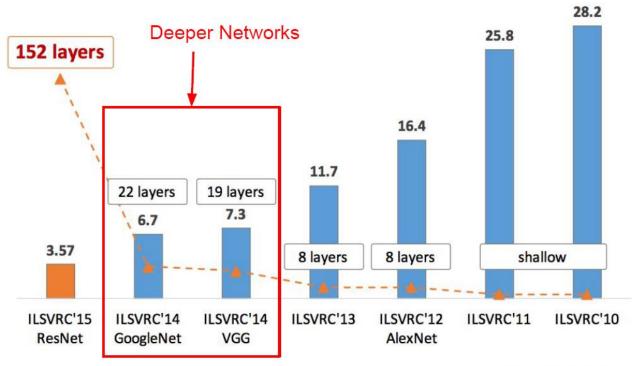
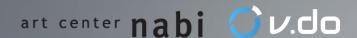


Figure copyright Kaiming He, 2016. Reproduced with permission.



## Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

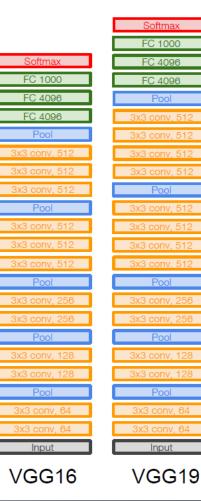
8 layers (AlexNet)
-> 16 - 19 layers (VGG16Net)

Only 3x3 CONV stride 1, pad 1 and 2x2 MAX POOL stride 2

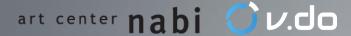
11.7% top 5 error in ILSVRC'13 (ZFNet)

-> 7.3% top 5 error in ILSVRC'14





```
(not counting biases)
INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
                                                                                                          fc8
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
                                                                                               FC 4096
                                                                                                          fc7
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
                                                                                               FC 4096
                                                                                                          fc6
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
                                                                                                         conv5-3
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
                                                                                                         conv5-2
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
                                                                                                         conv5-1
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
                                                                                                         conv4-3
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
                                                                                                         conv4-2
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
                                                                                              3x3 conv, 512
                                                                                                         conv4-1
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
                                                                                                         conv3-2
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
                                                                                                        conv3-1
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
                                                                                                Pool
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512=2,359,296
                                                                                                        conv2-2
                                                                                                        conv2-1
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512=2,359,296
                                                                                               Pool
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512=2,359,296
                                                                                                         conv1-2
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
                                                                                                        conv1-1
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
                                                                                                Input
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16.777.216
                                                                                             VGG16
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000
TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
                                                                                            Common names
```



TOTAL params: 138M parameters

#### ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

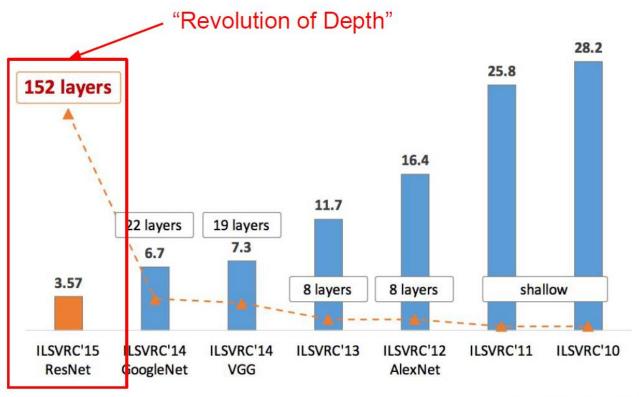
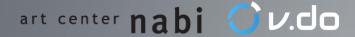


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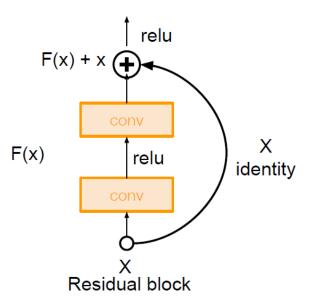


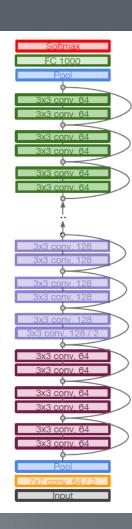
#### Case Study: ResNet

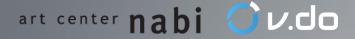
[He et al., 2015]

# Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!







# 감사합니다

