

2018.10.13

NEURAL NETWORK (2)

3기 천용희

CONTENTS

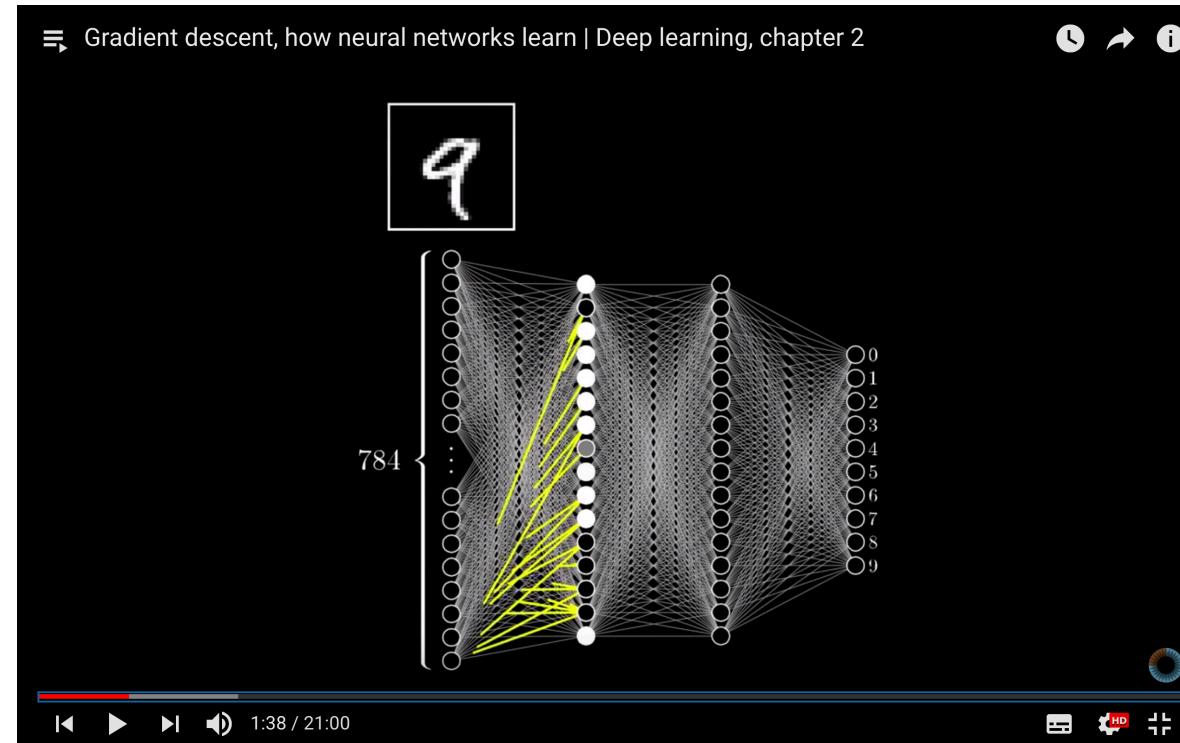
1. 머신러닝 복습 및 딥러닝 이해
2. 합성곱 신경망
3. 실전 활용을 위한 툴
4. PyTorch를 이용한 딥러닝 튜토리얼

Chapter 1

머신러닝 복습 및 딥러닝 이해

Chapter 1.1 | What is a Neural Network?

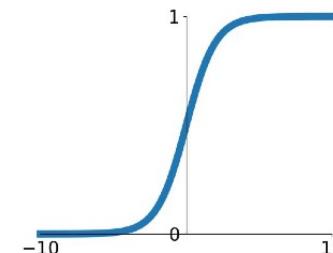
3Blue1Brown Video



Chapter 1.2 | 활성화 함수의 종류

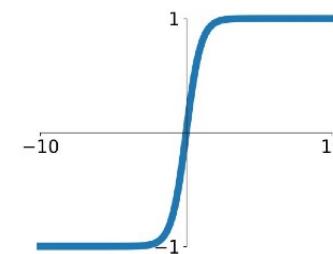
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



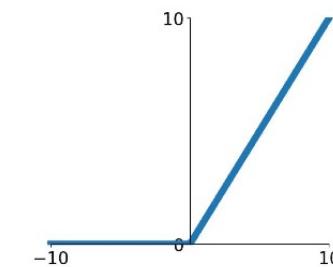
tanh

$$\tanh(x)$$



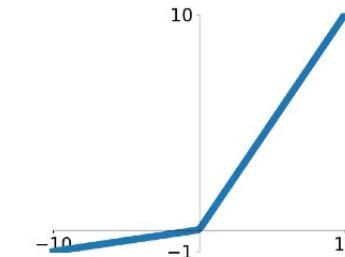
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

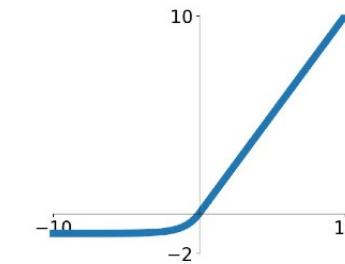


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

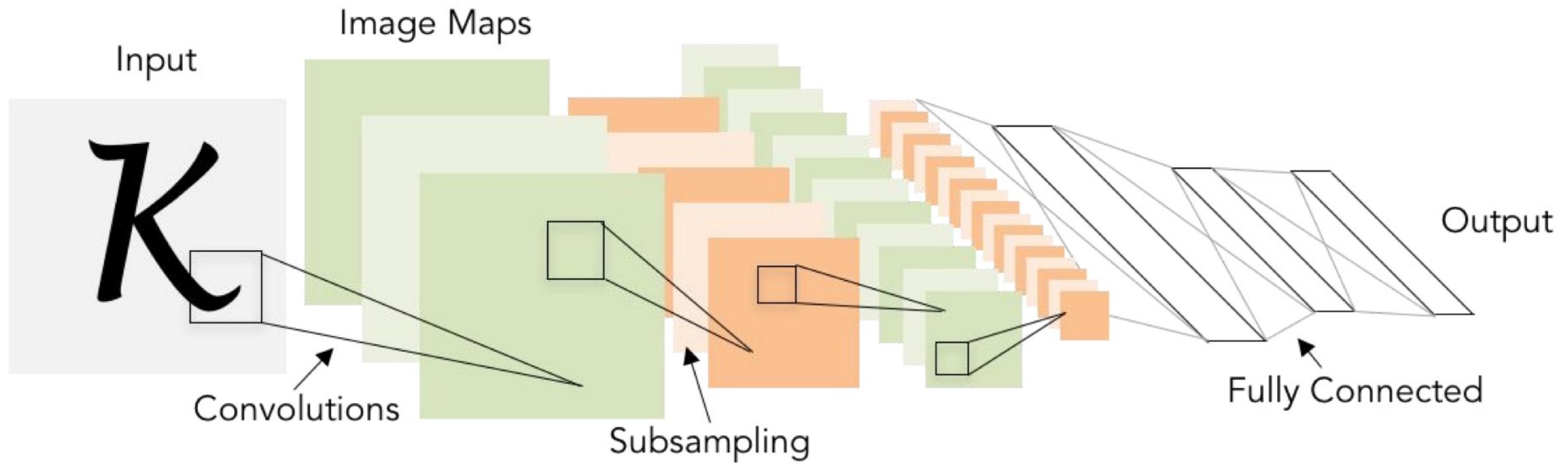


Chapter 2

합성곱 신경망

Convolutional Neural Networks

Chapter 2.1 | CNN의 아키텍쳐

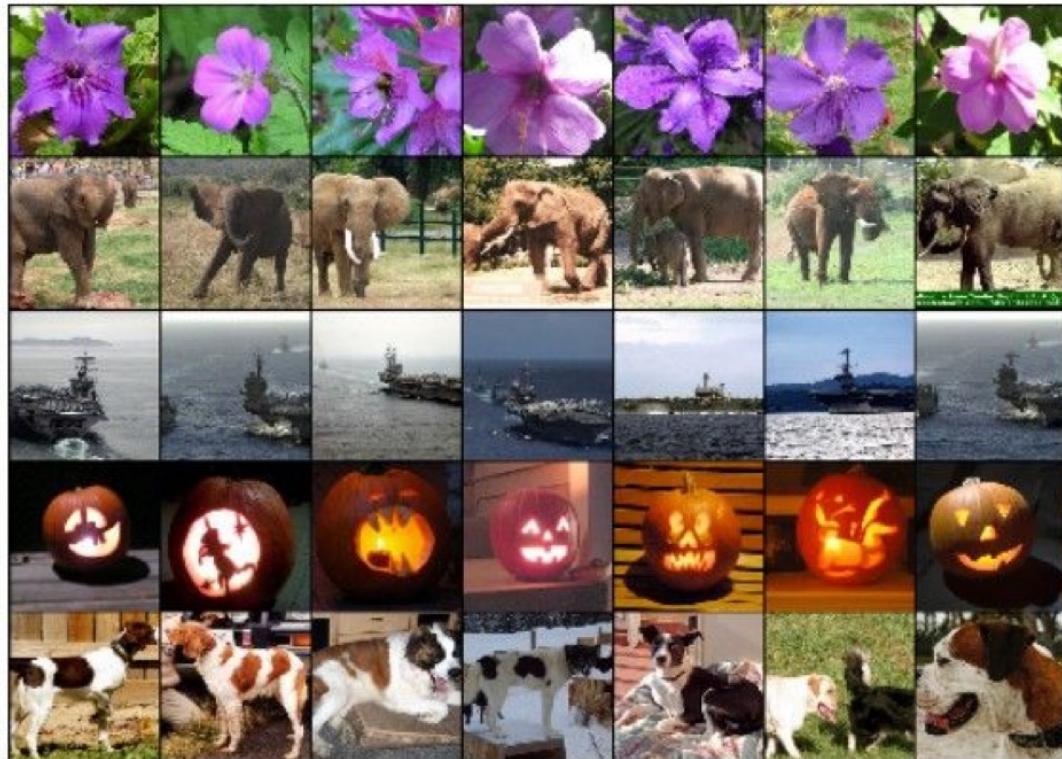


Chapter 2.2 | CNN 활용 예시

Classification

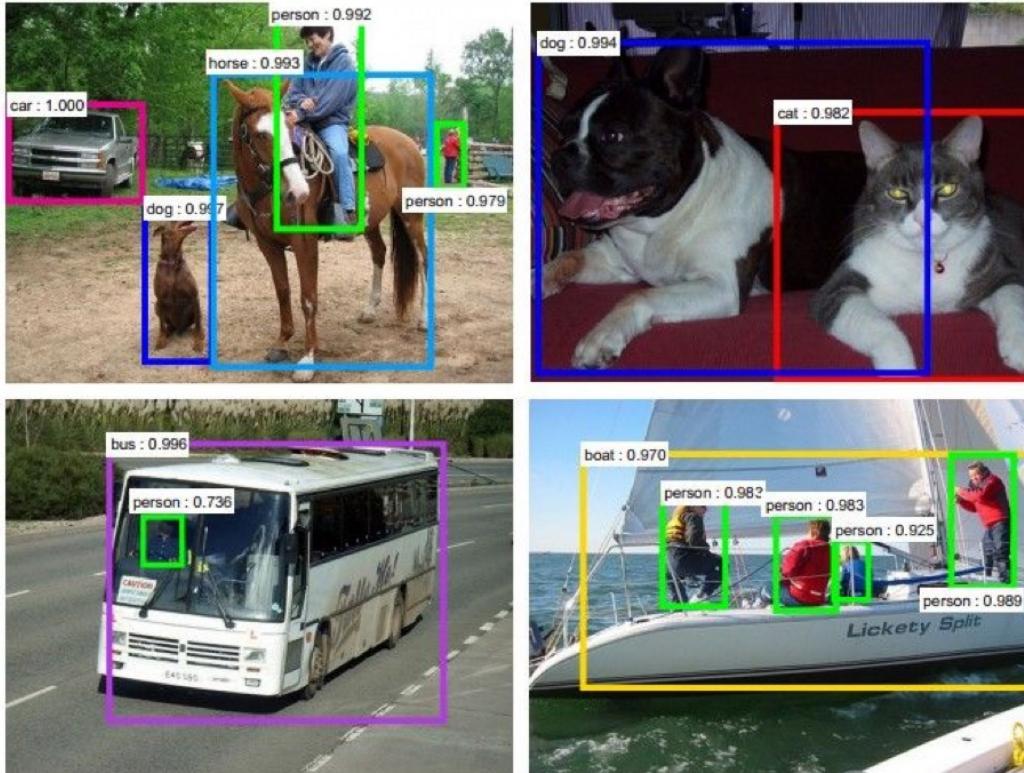


Clustering



Chapter 2.2 | CNN 활용 예시

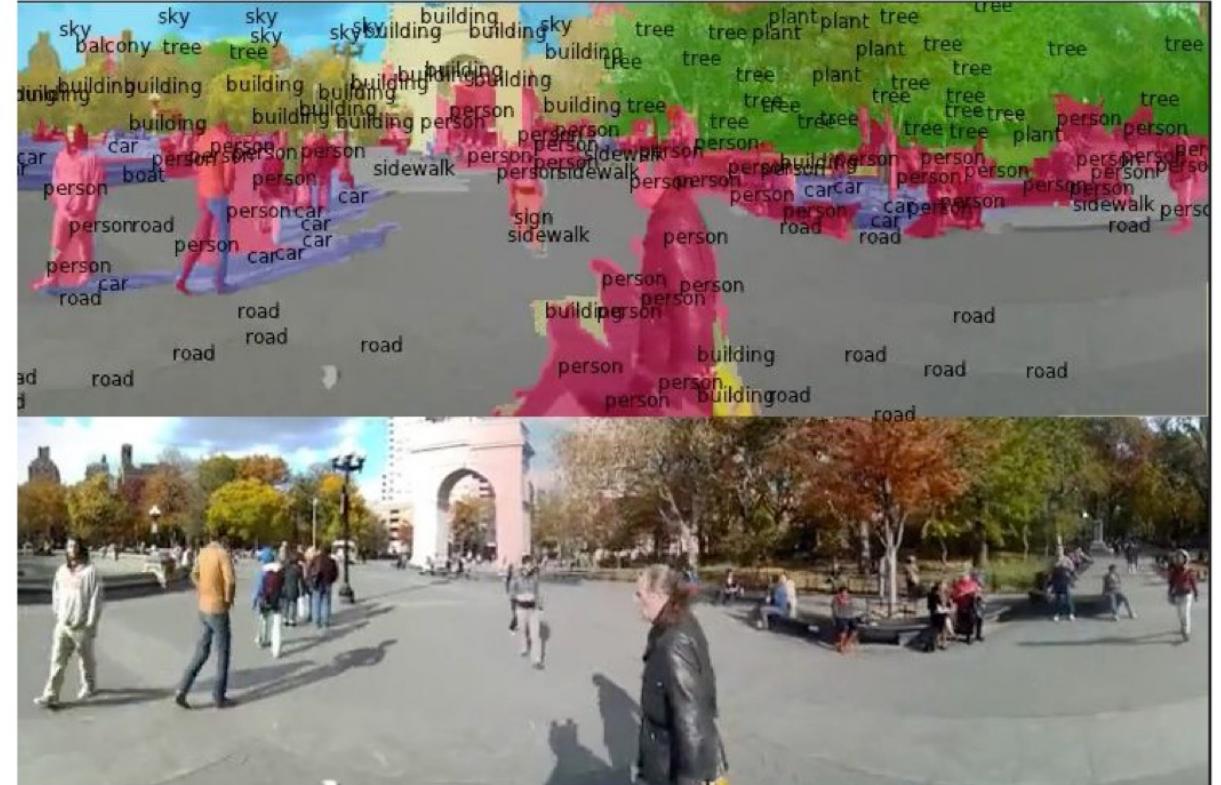
Detection



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

Segmentation



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[Farabet et al., 2012]

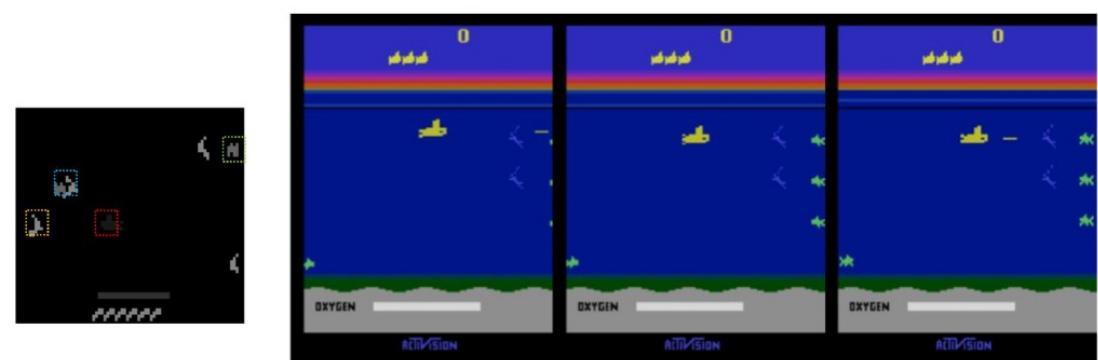
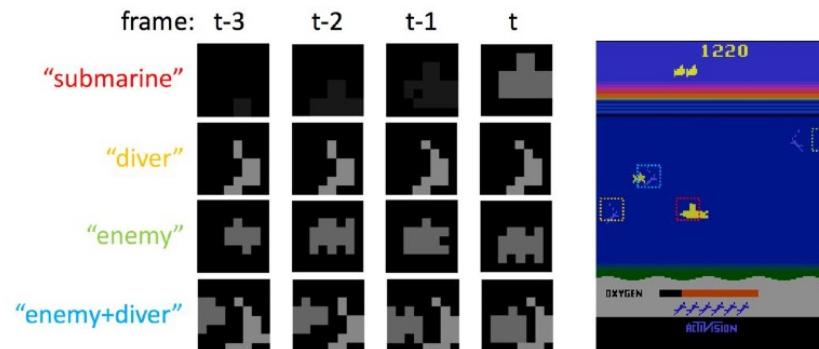
Growth Hackers

Chapter 2.2 | CNN 활용 예시



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

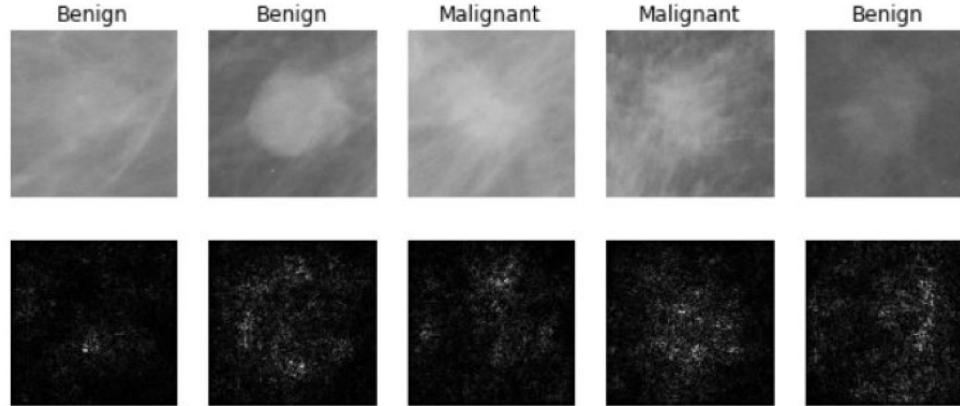
[Toshev, Szegedy 2014]



[Guo et al. 2014]

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

Chapter 2.2 | CNN 활용 예시



[Levy et al. 2016]



[Dieleman et al. 2014]

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[Sermanet et al. 2011]
[Ciresan et al.]

Photos by Lane McIntosh.
Copyright CS231n 2017.

Chapter 2.2 | CNN 활용 예시

[This image](#) by Christin Khan is in the public domain
and originally came from the U.S. NOAA.



Whale recognition, Kaggle Challenge

Photo and figure by Lane McIntosh; not actual example from Mnih and Hinton, 2010 paper.



Mnih and Hinton, 2010

Chapter 2.2 | CNN 활용 예시

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

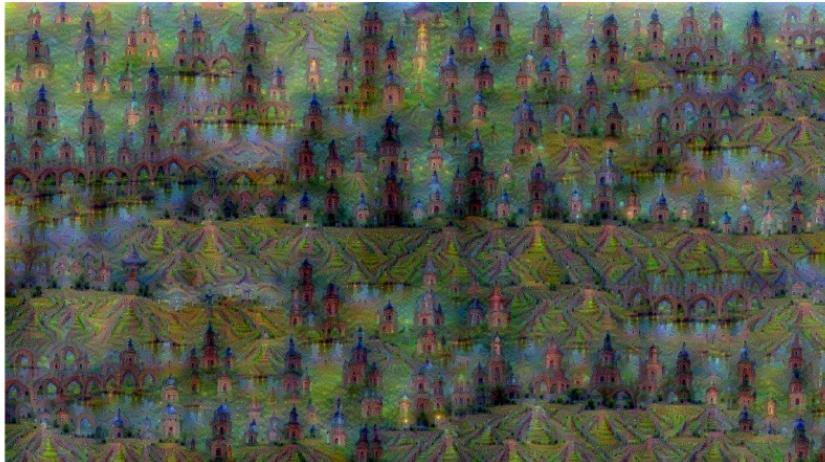
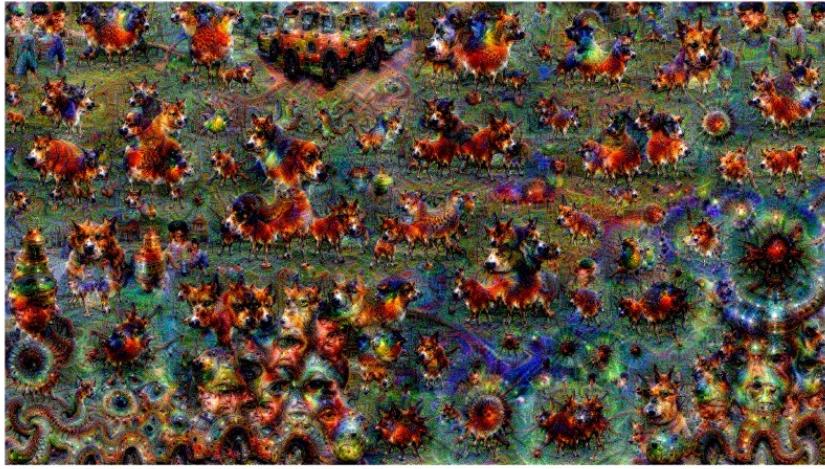
Image Captioning

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

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<https://pixabay.com/en/teddy-plush-bears-cute-teddy-bear-1623436/>
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<https://pixabay.com/en/handstand-lake-meditation-496008/>
<https://pixabay.com/en/baseball-player-shortstop-infield-1045263/>

Captions generated by Justin Johnson using [Neuraltalk2](#)

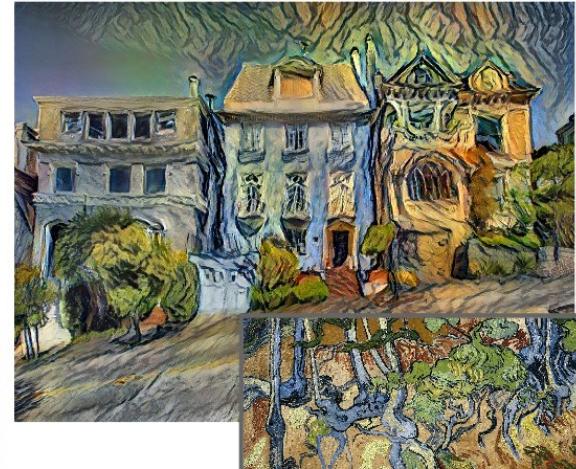
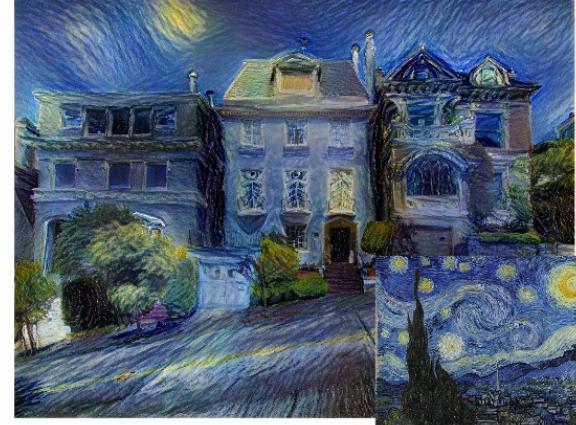
Chapter 2.2 | CNN 활용 예시



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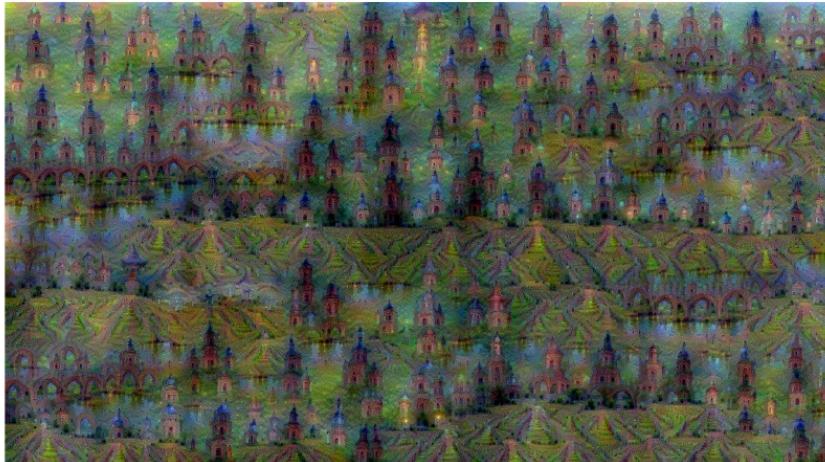
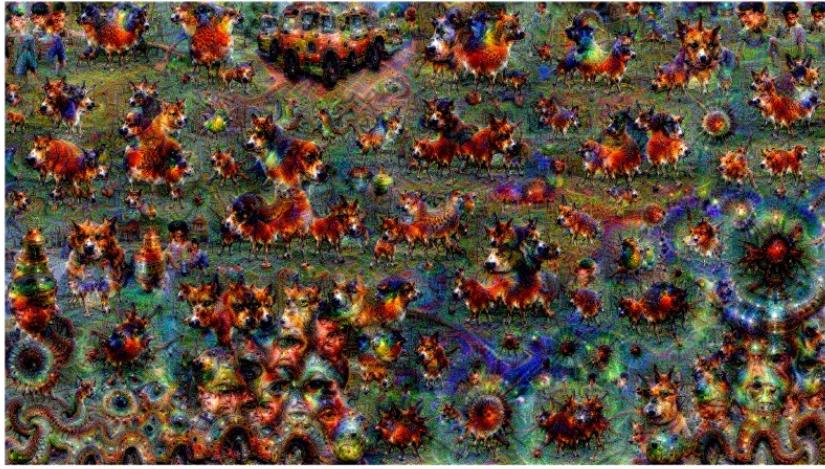


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Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016
Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

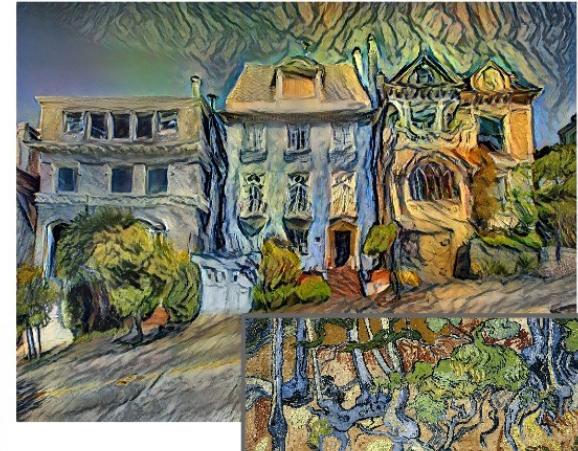
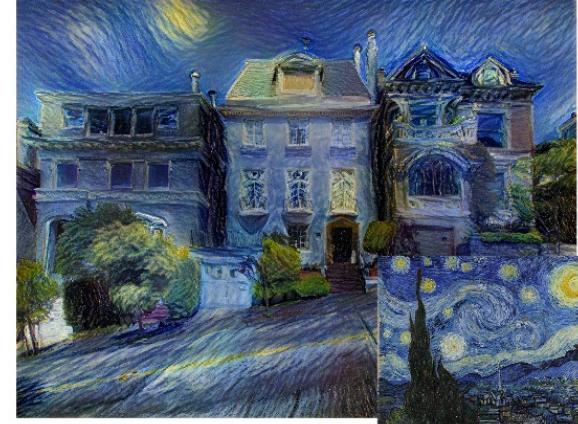
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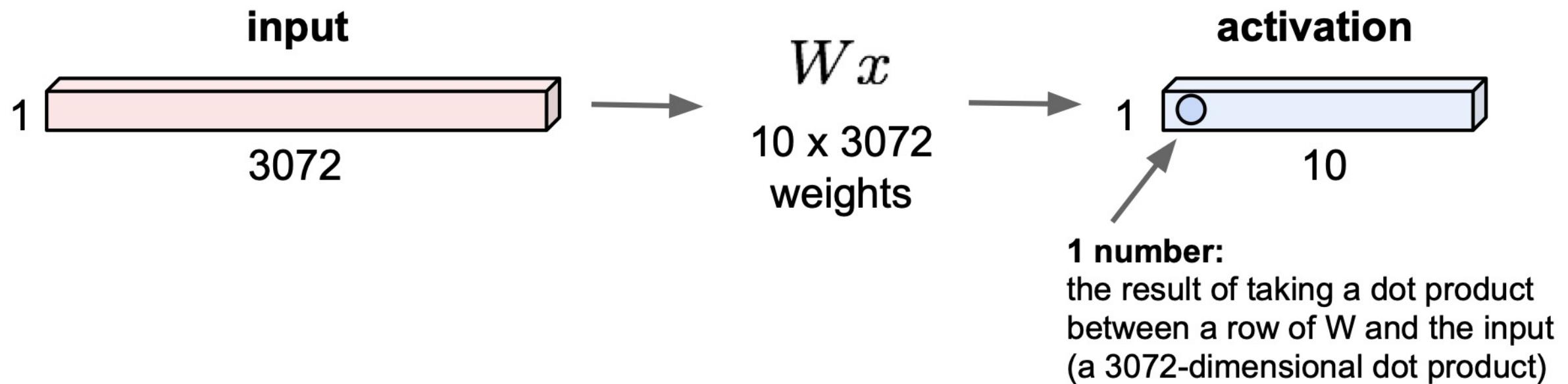
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Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016
Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

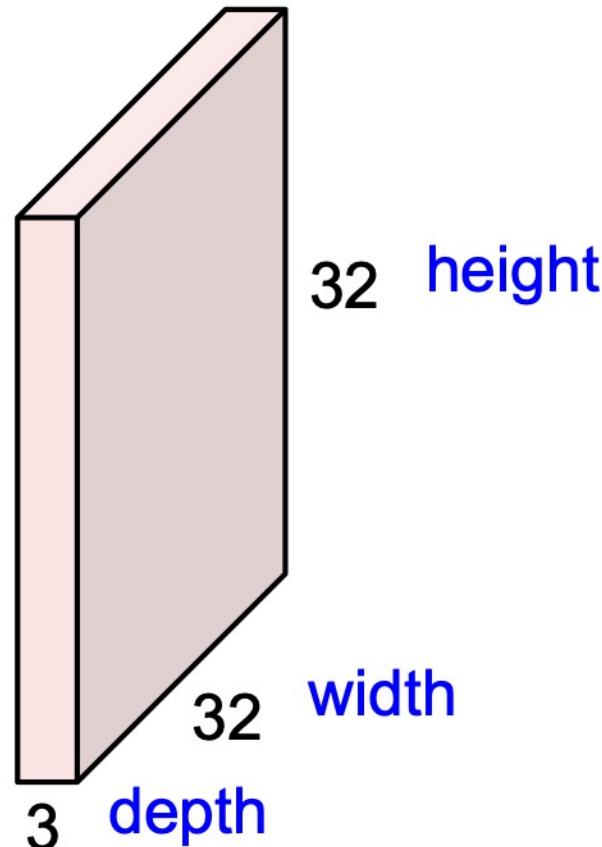
Chapter 2.3.1 | Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



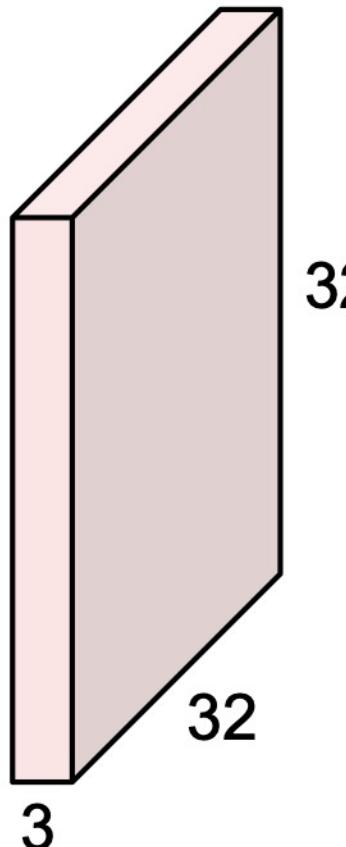
Chapter 2.3.2 | Convolutional Layer

32x32x3 image -> preserve spatial structure



Chapter 2.3.2 | Convolutional Layer

32x32x3 image

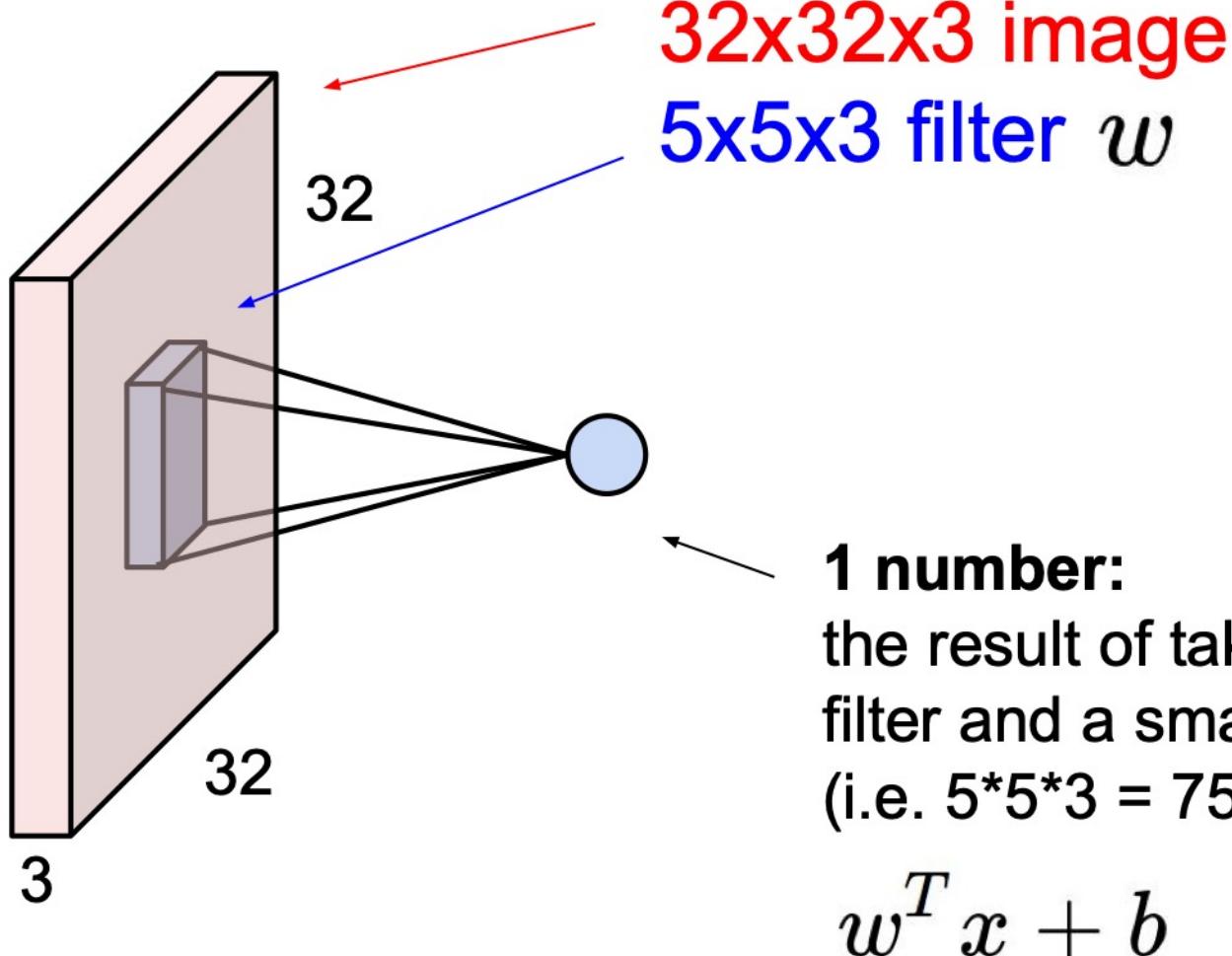


5x5x3 filter

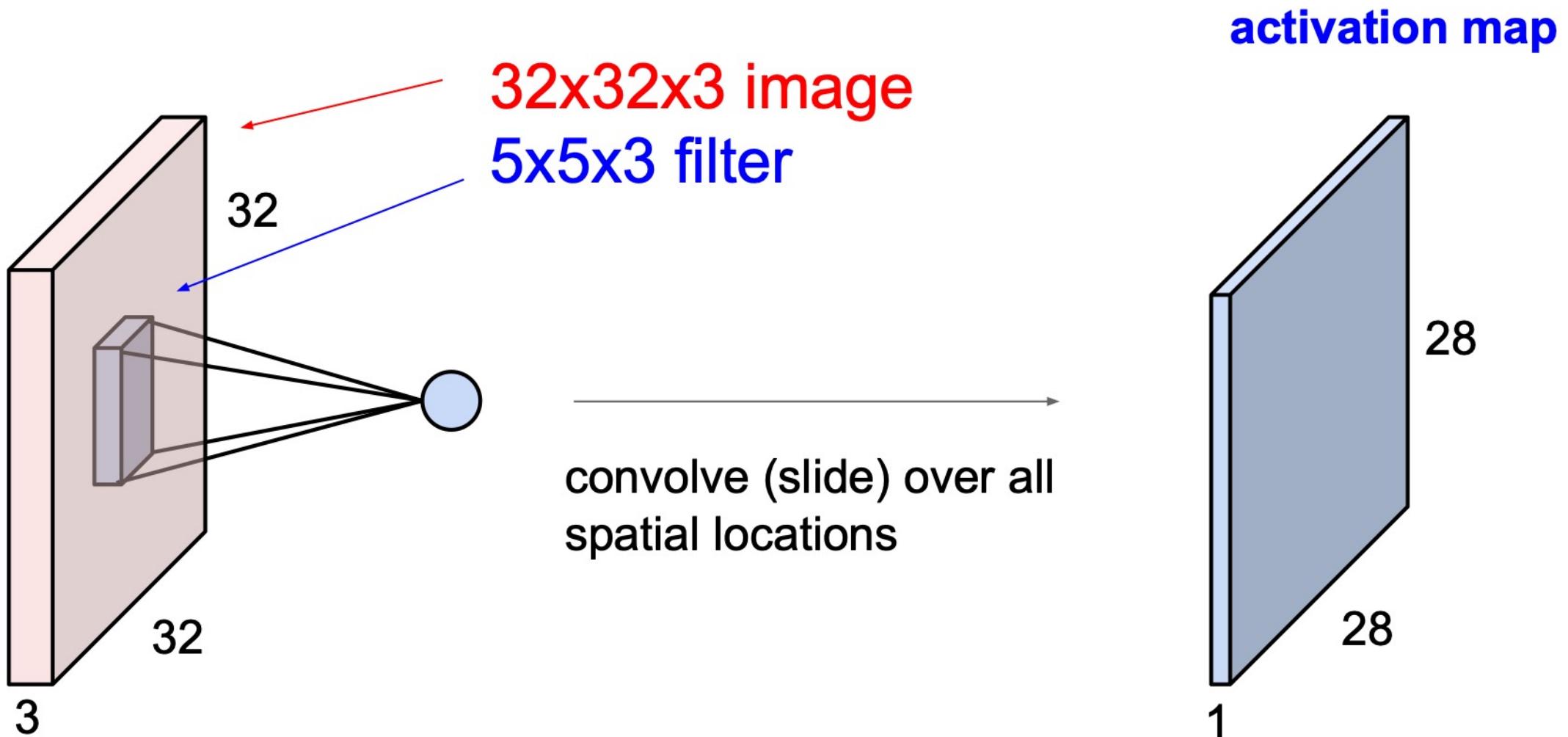


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Chapter 2.3.2 | Convolutional Layer



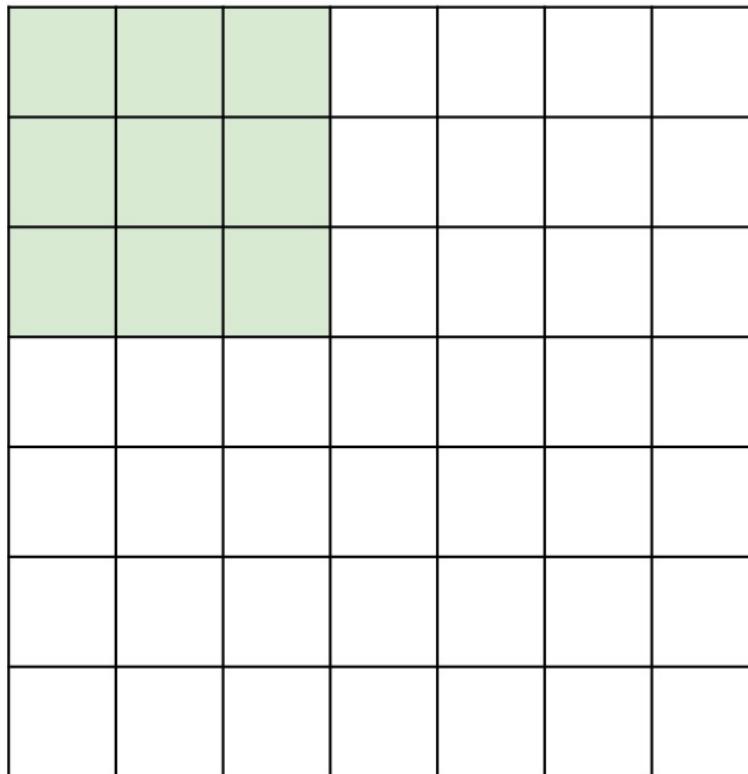
Chapter 2.3.3 | Activation Map



Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

7



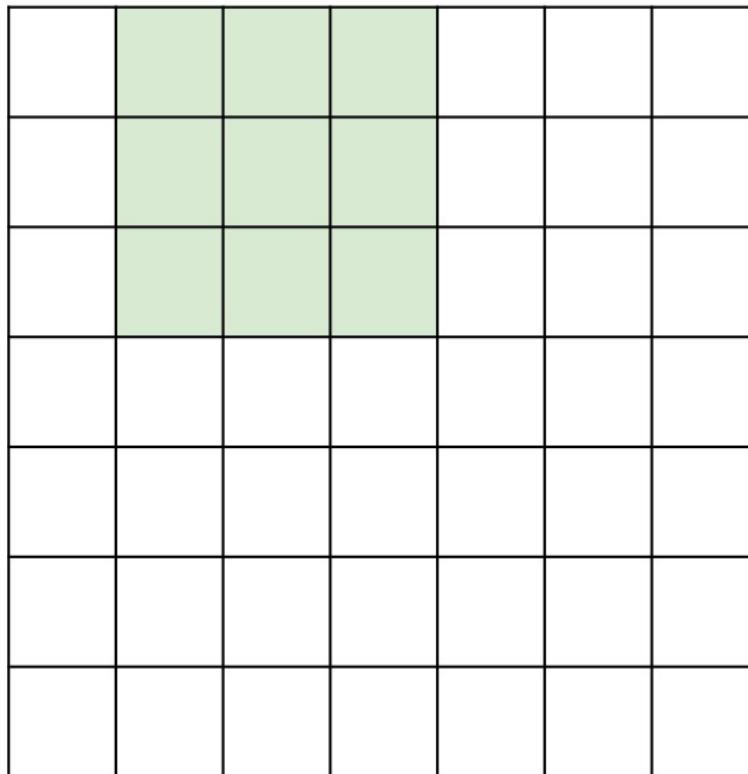
7x7 input (spatially)
assume 3x3 filter

7

Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

7



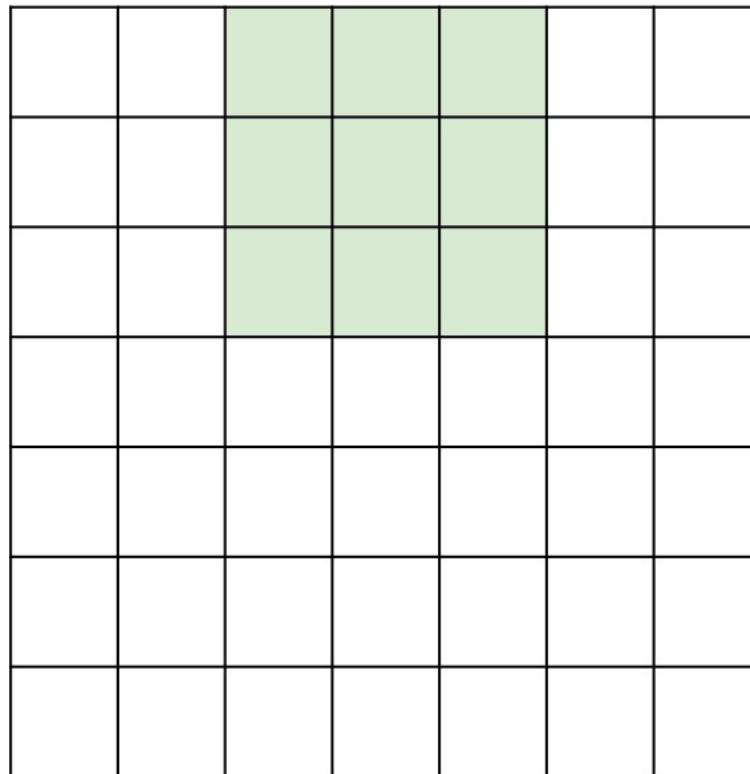
7x7 input (spatially)
assume 3x3 filter

7

Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

7



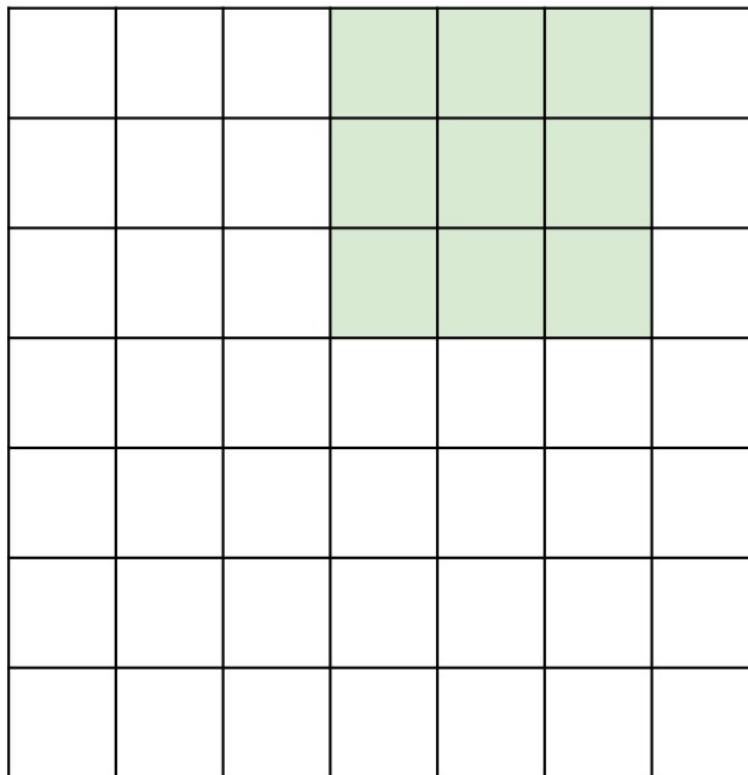
7x7 input (spatially)
assume 3x3 filter

7

Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

7

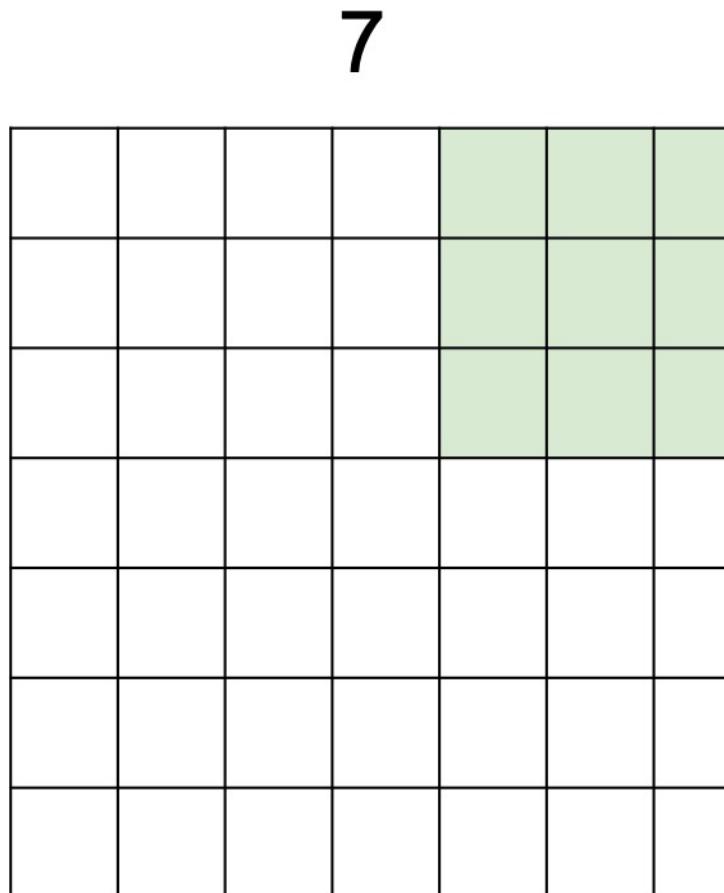


7x7 input (spatially)
assume 3x3 filter

7

Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

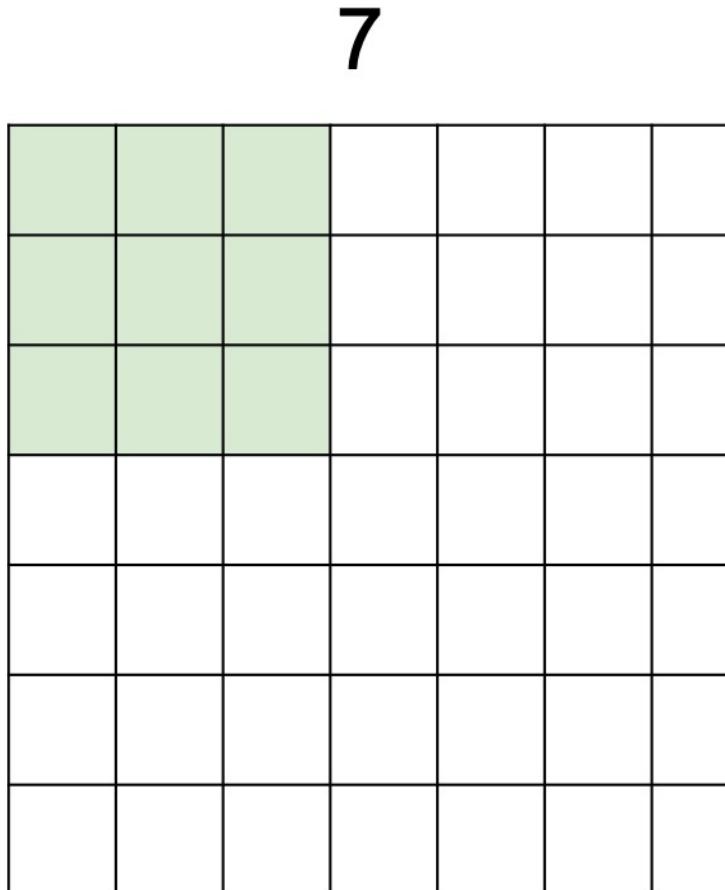


7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

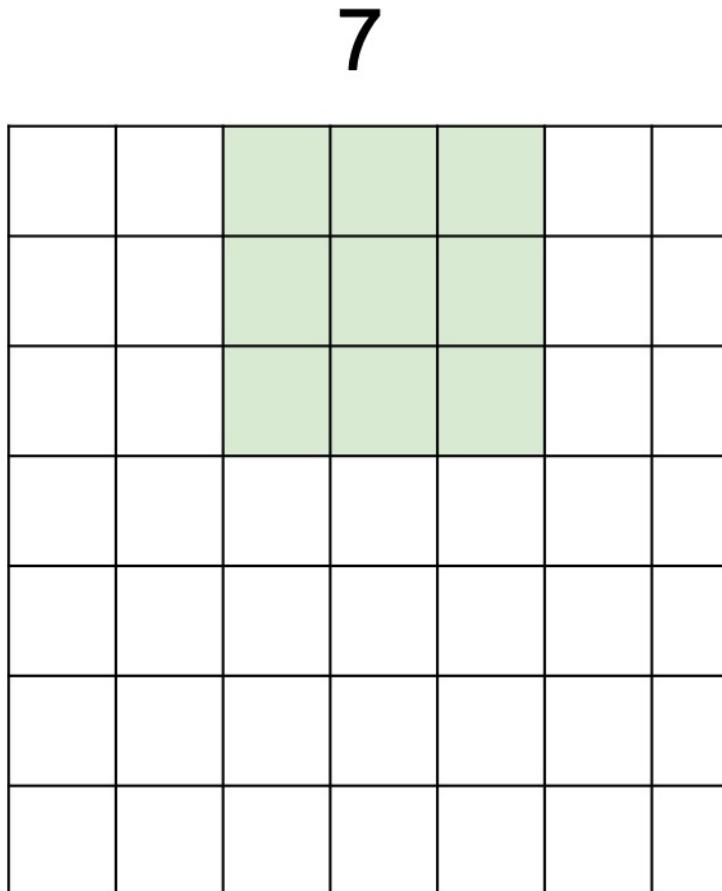


7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

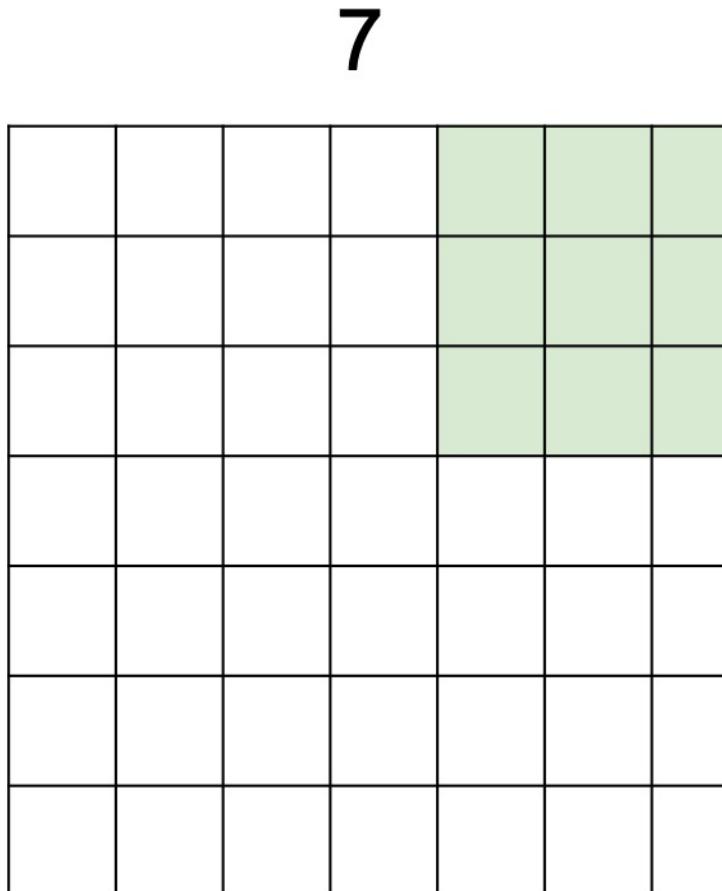


7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

Chapter 2.3.3.1 | Activation Map in Toy Example

A closer look at spatial dimensions:

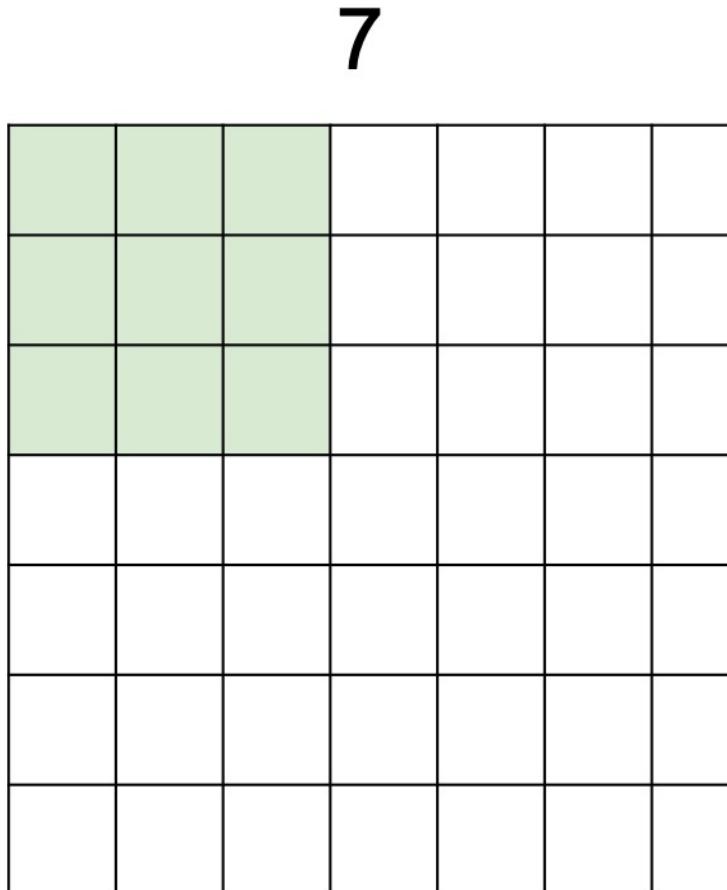


7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

Chapter 2.3.3.1 | Activation Map in Toy Example

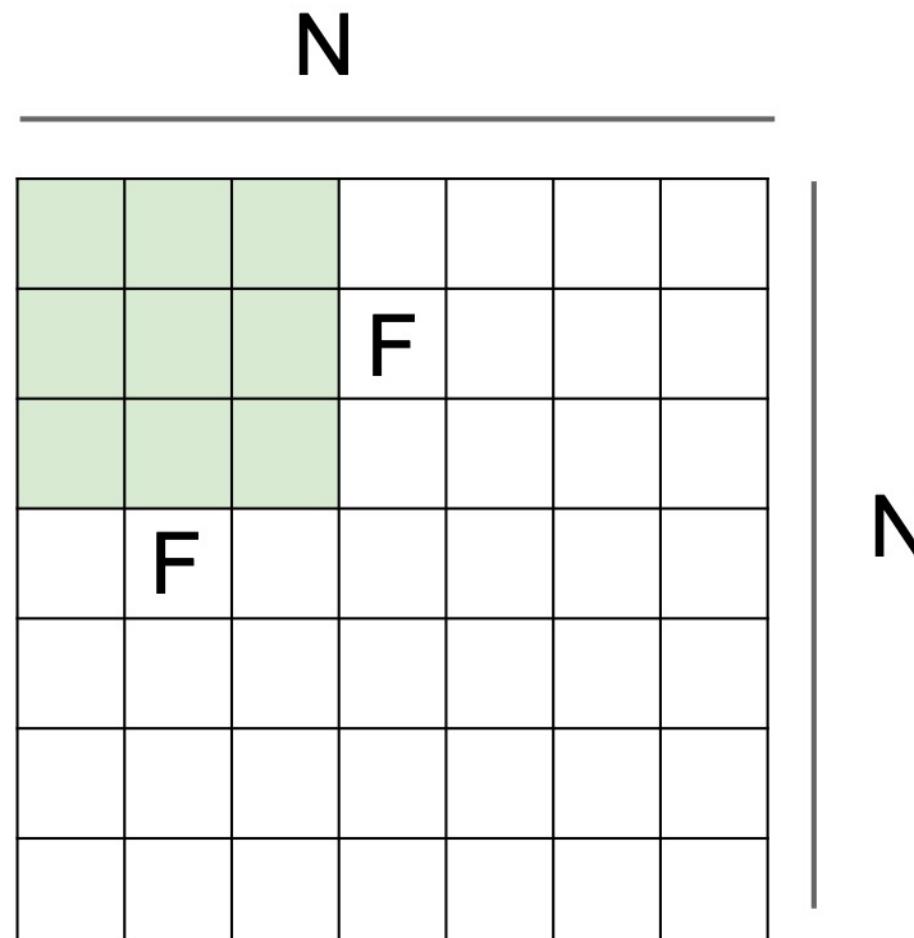
A closer look at spatial dimensions:



7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

Chapter 2.3.3.1 | Activation Map in Toy Example



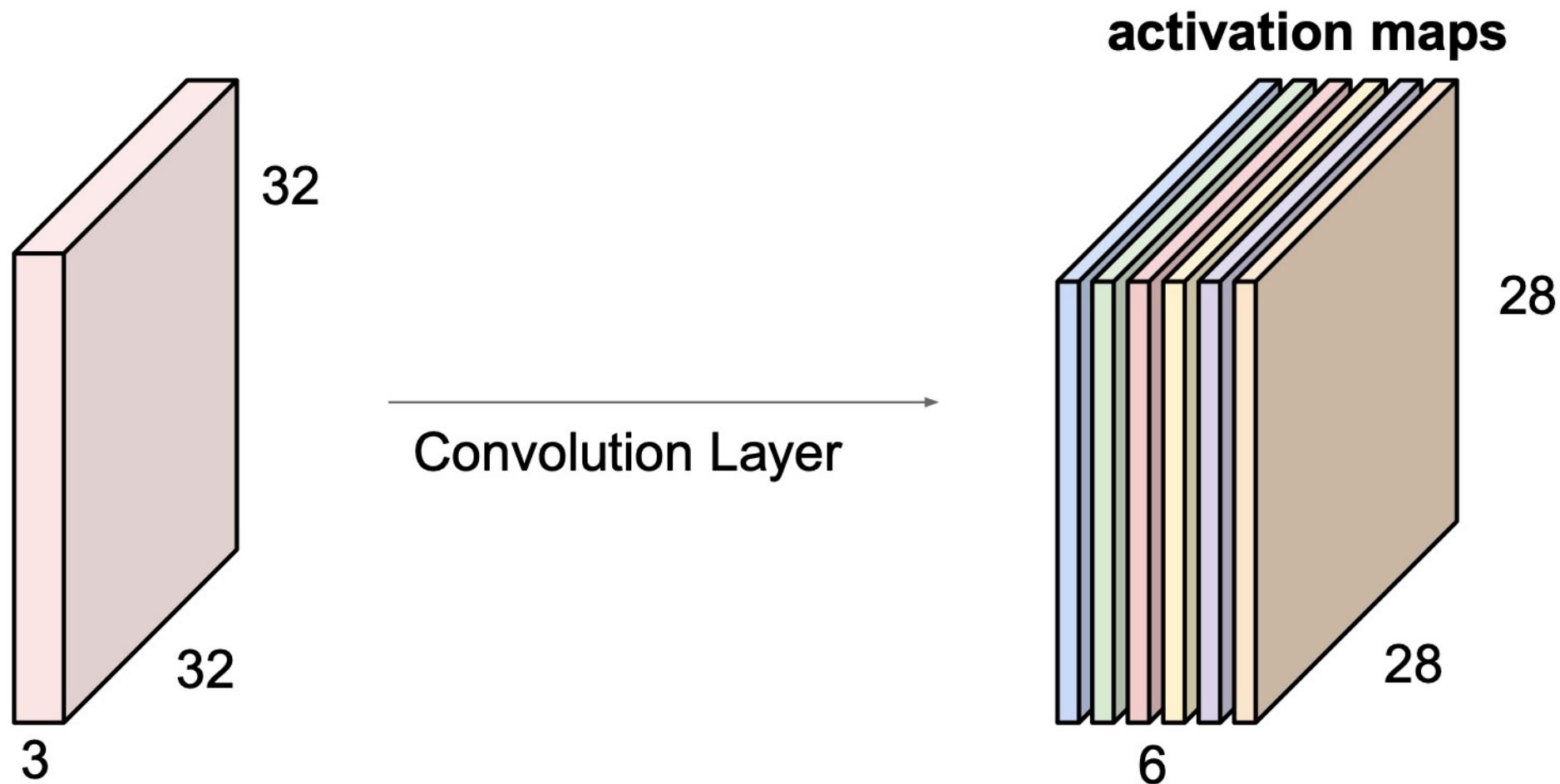
Output size:
(N - F) / stride + 1

e.g. $N = 7, F = 3$:
stride 1 => $(7 - 3)/1 + 1 = 5$
stride 2 => $(7 - 3)/2 + 1 = 3$
stride 3 => $(7 - 3)/3 + 1 = 2.33$:\

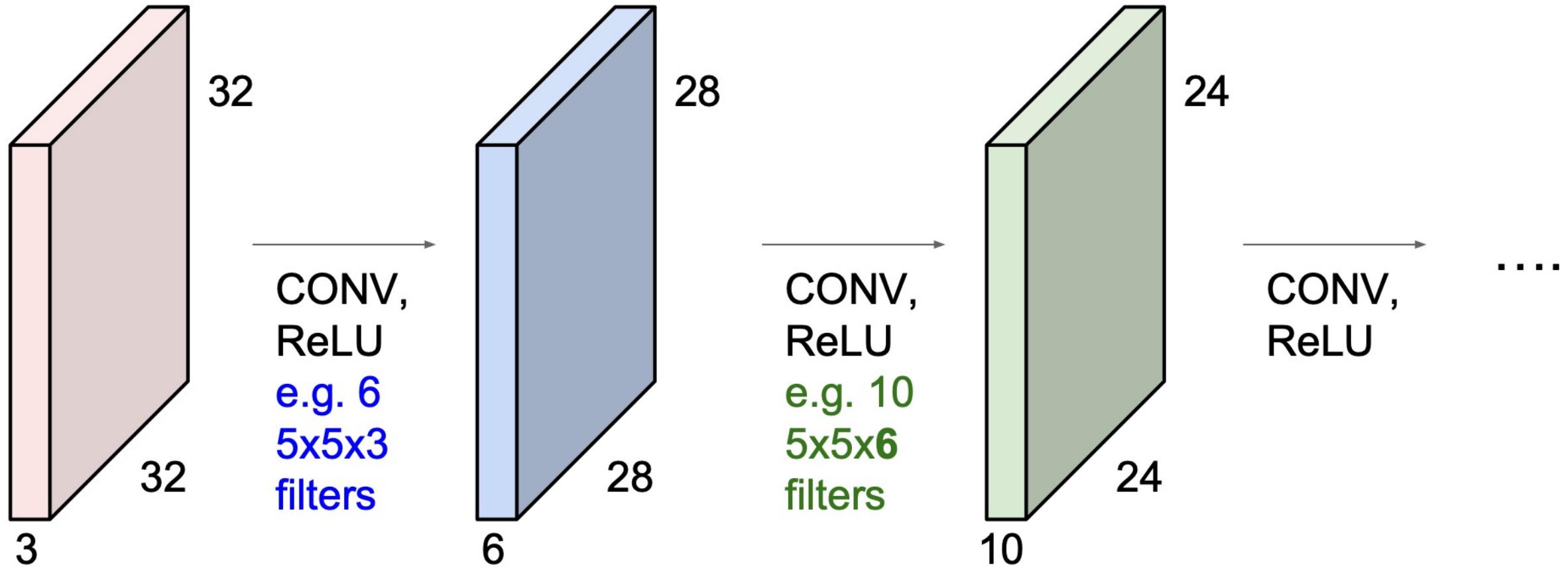
Chapter 2.3.3 | Activation Map



Chapter 2.3.3 | Activation Map



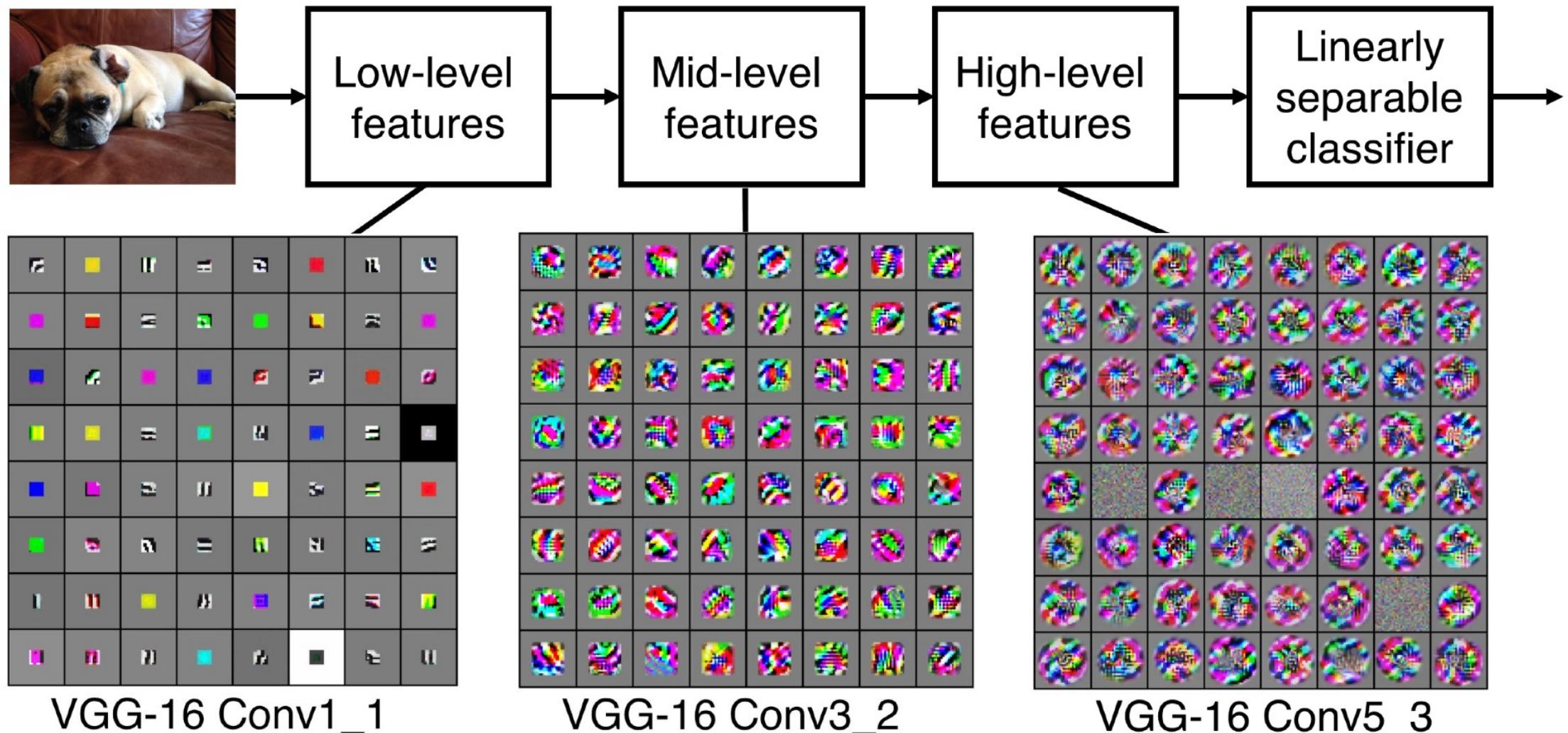
Chapter 2.4 | Convnet 구조



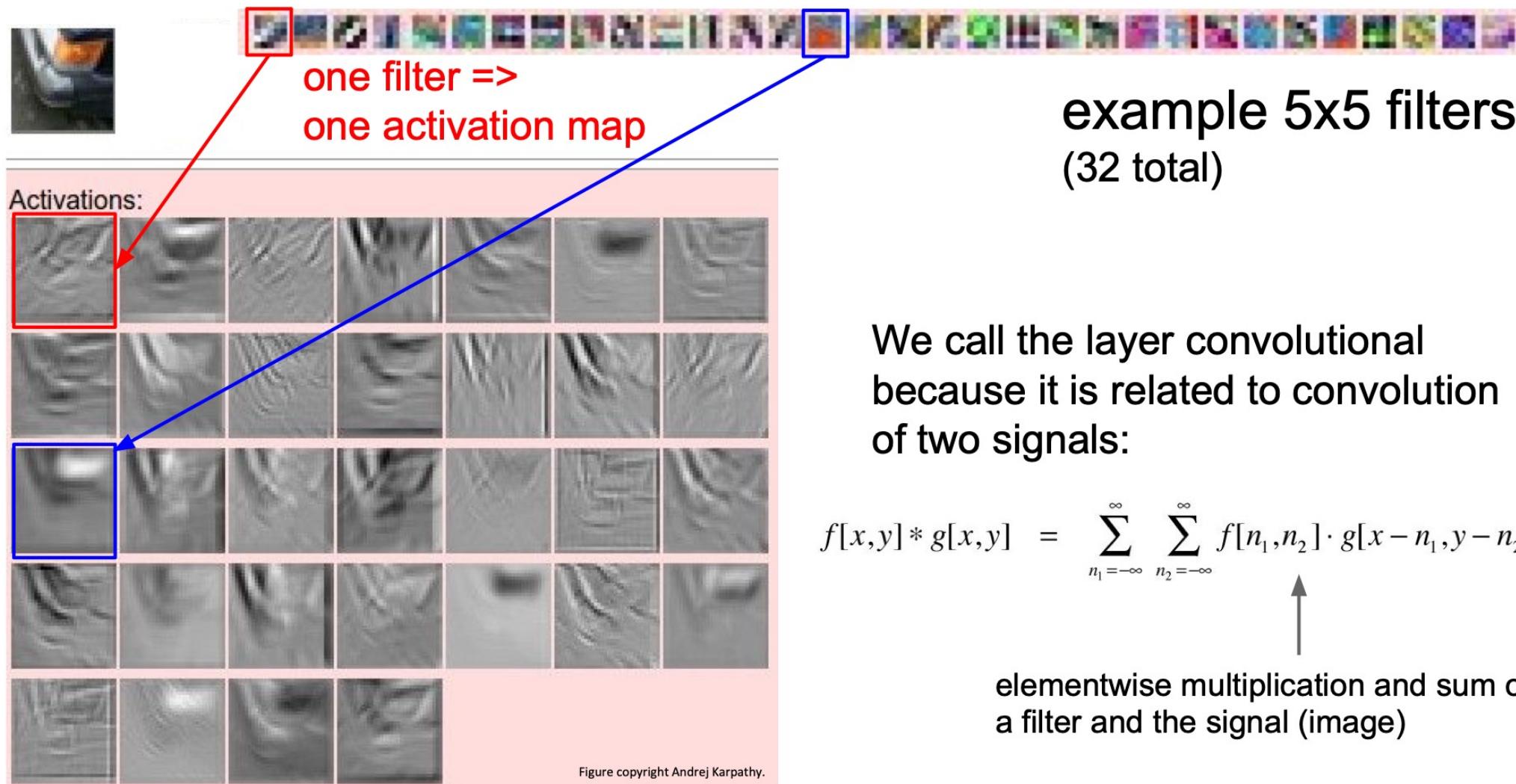
Chapter 2.4 | Convnet 구조



Chapter 2.4 | Convnet 구조

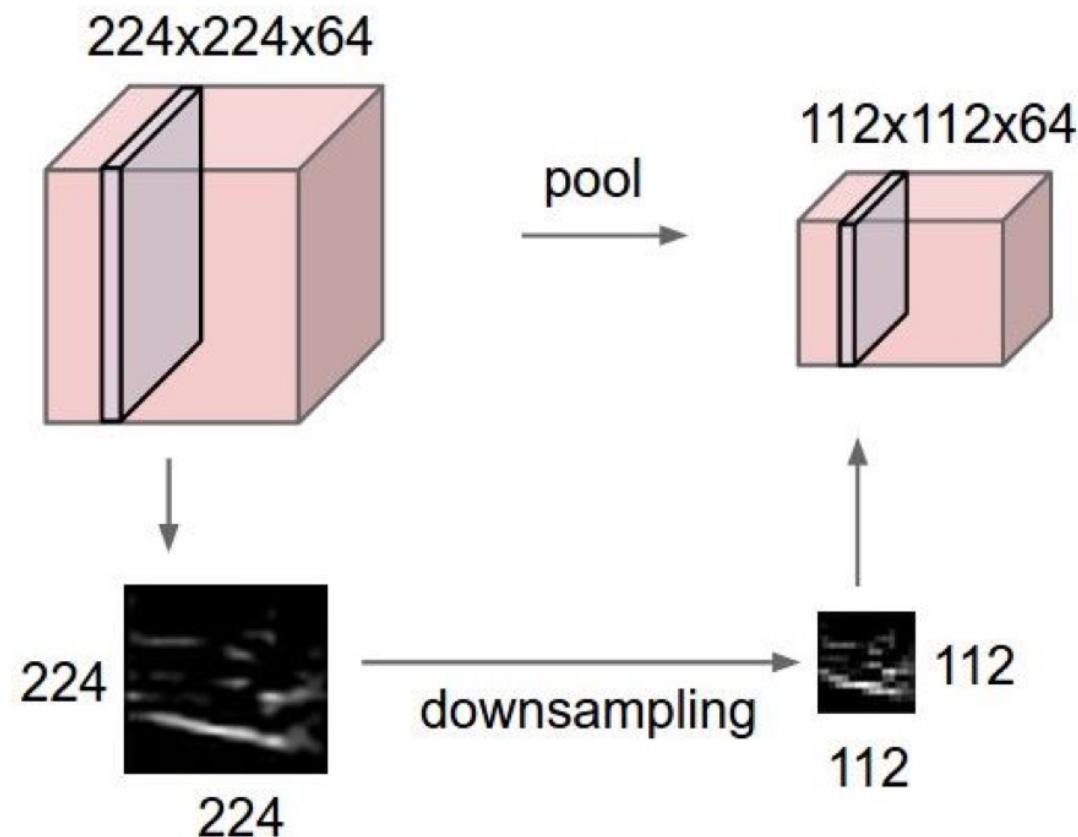


Chapter 2.5 | Activation Preview

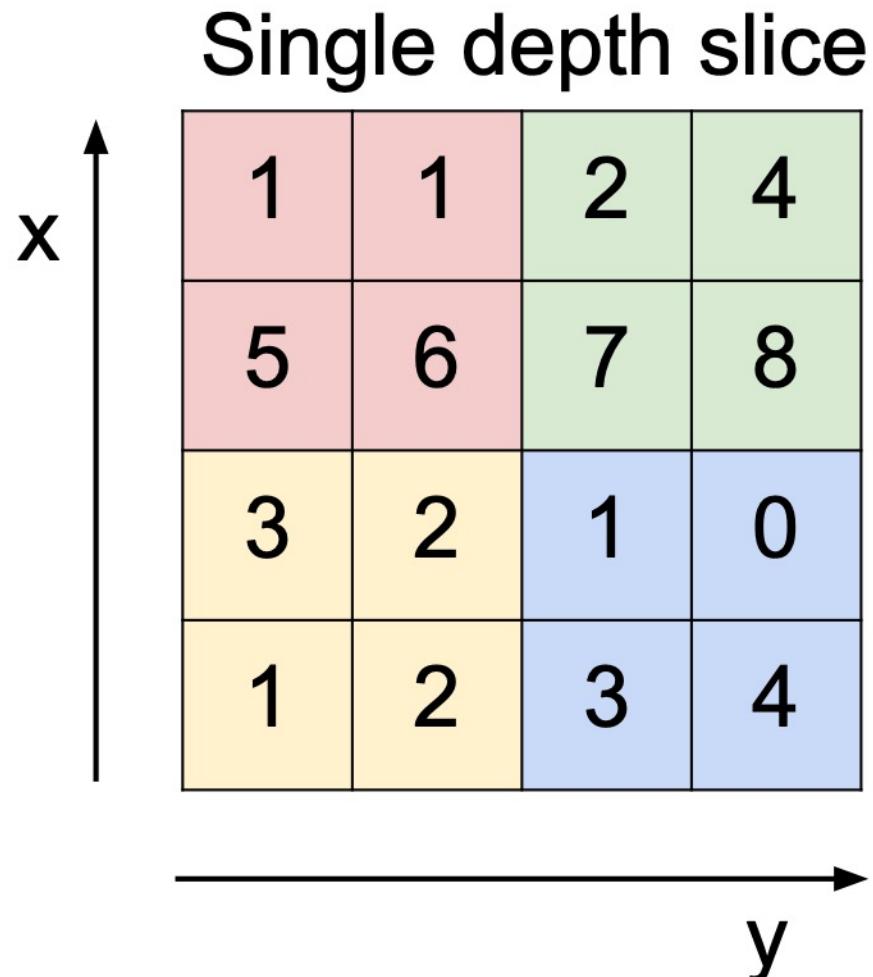


Chapter 2.6.1 | Pooling

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



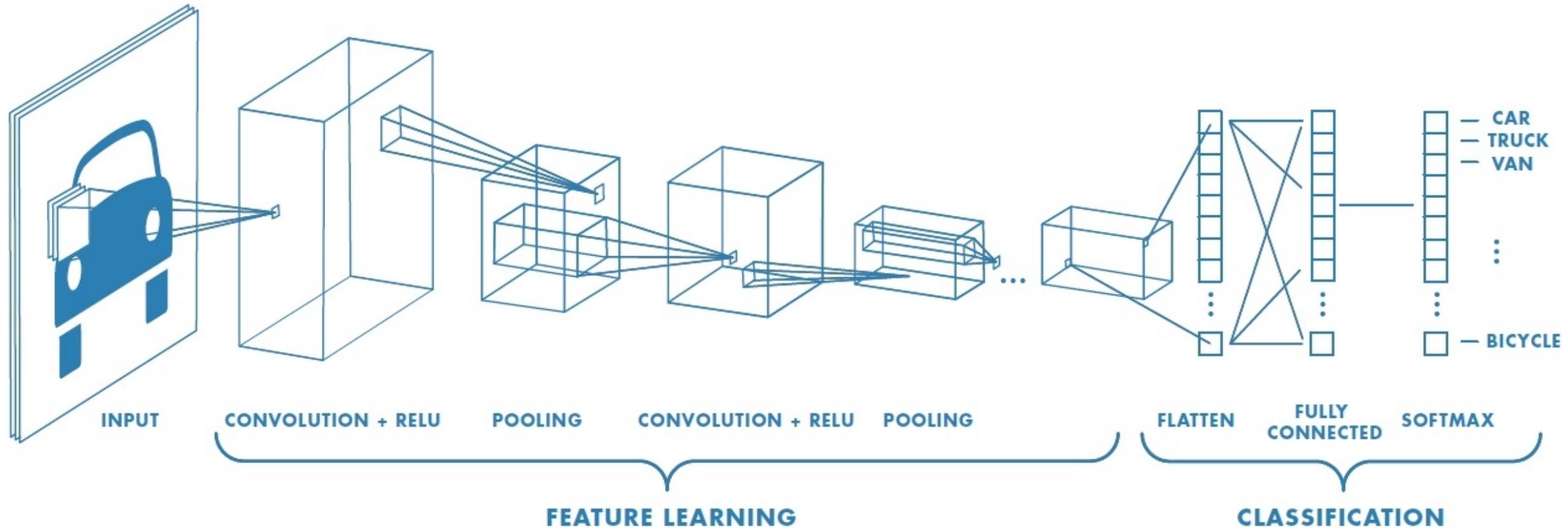
Chapter 2.6.2 | Max Pooling



max pool with 2x2 filters
and stride 2

6	8
3	4

Chapter 2.7 | Convnet 전체 과정



Chapter 3

실전 툴

Chapter 3.1 | 딥러닝 툴 발전 개요 (2016)

Caffe
(UC Berkeley)

Torch
(NYU / Facebook)

Theano
(U Montreal) → **TensorFlow**
(Google)

Chapter 3.1 | 딥러닝 툴 발전 개요 (2018)

Caffe
(UC Berkeley)



Caffe2
(Facebook)

Torch
(NYU / Facebook)



PyTorch
(Facebook)

Theano
(U Montreal)



TensorFlow
(Google)

CNTK
(Microsoft)

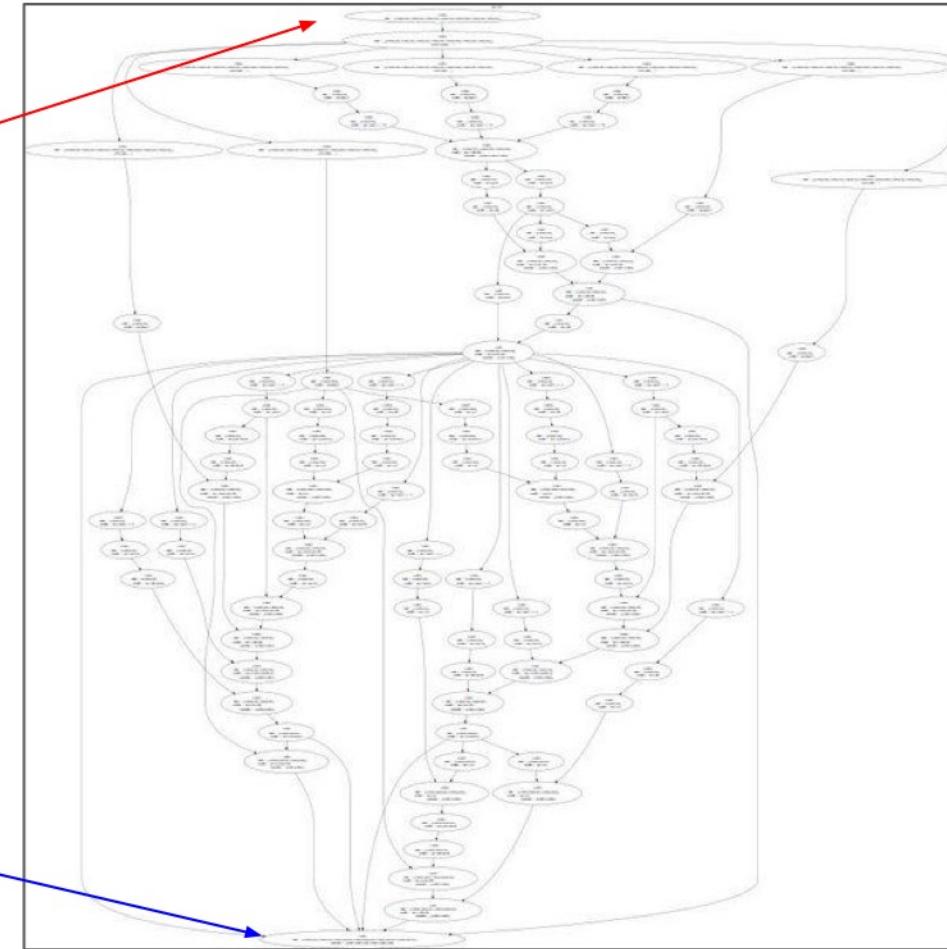
MXNet
(Amazon)

Developed by U Washington, CMU, MIT,
Hong Kong U, etc but main framework of
choice at AWS

Chapter 3.2 | Computational Graph 표현

input image

loss



Chapter 3.3 | Numpy

Numpy

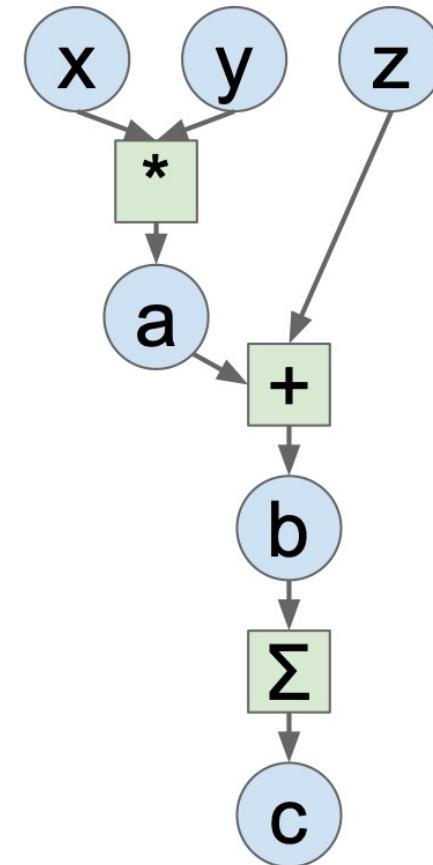
```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```



Chapter 3.3 | Numpy

Numpy

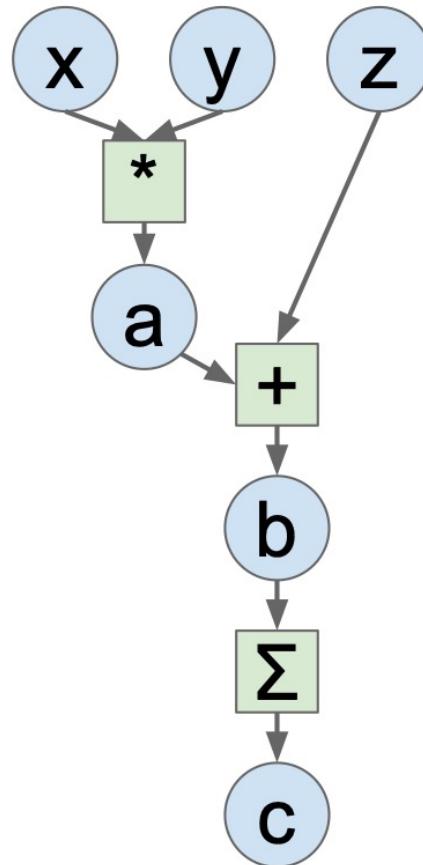
```
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

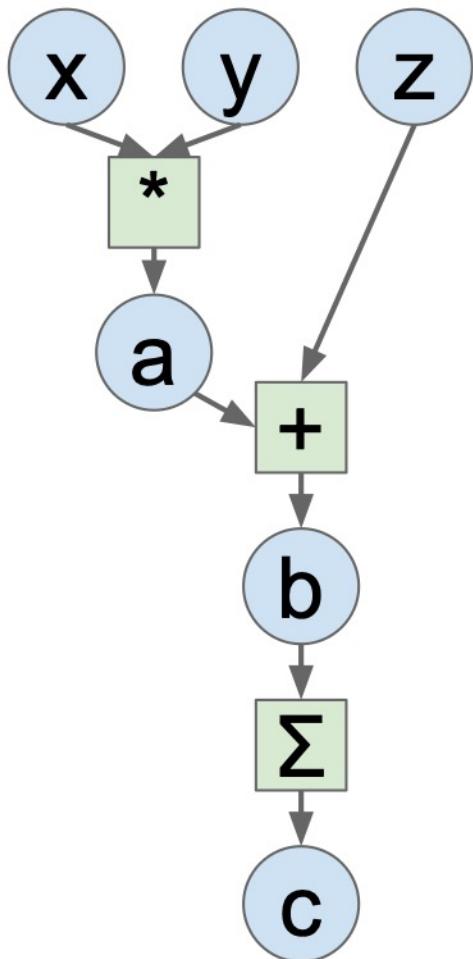
grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```



Problems:

- Can't run on GPU
- Have to compute our own gradients

Chapter 3.4 | PyTorch



Define **Variables** to start building a computational graph

```
import torch
from torch.autograd import Variable

N, D = 3, 4

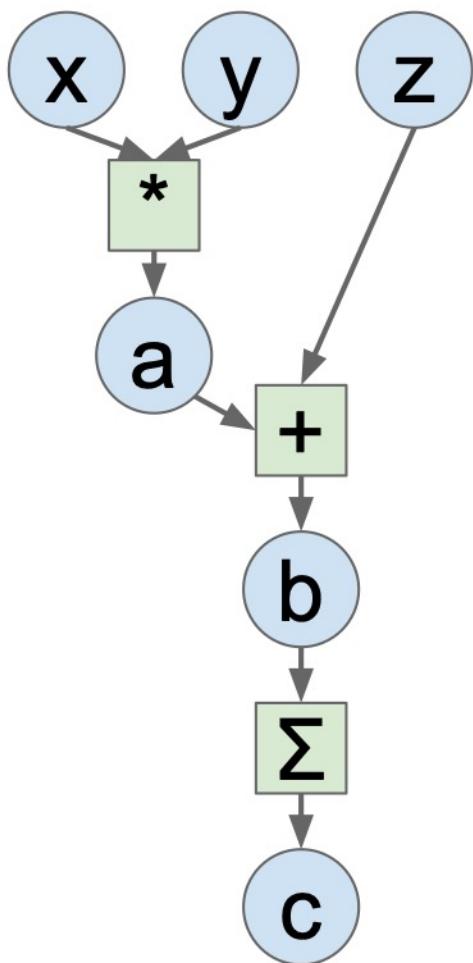
x = Variable(torch.randn(N, D),
             requires_grad=True)
y = Variable(torch.randn(N, D),
             requires_grad=True)
z = Variable(torch.randn(N, D),
             requires_grad=True)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()

print(x.grad.data)
print(y.grad.data)
print(z.grad.data)
```

Chapter 3.4 | PyTorch



Forward pass
looks just like
numpy

```
import torch
from torch.autograd import Variable

N, D = 3, 4

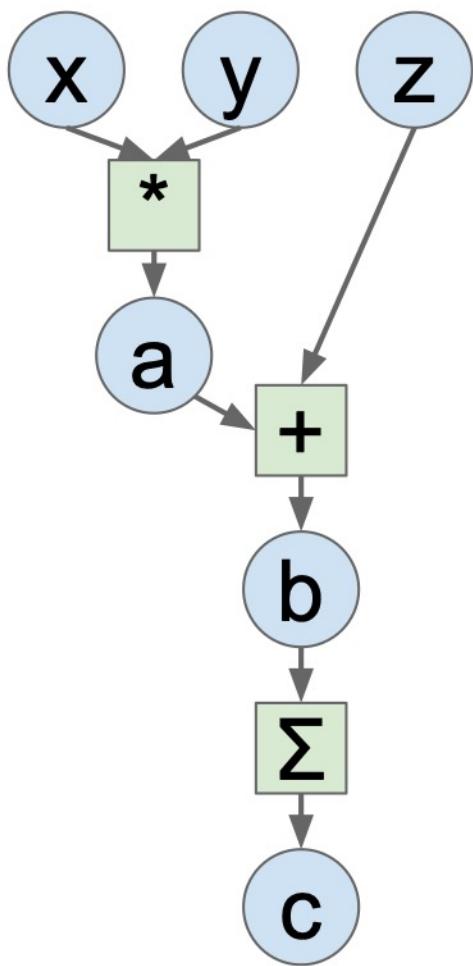
x = Variable(torch.randn(N, D),
             requires_grad=True)
y = Variable(torch.randn(N, D),
             requires_grad=True)
z = Variable(torch.randn(N, D),
             requires_grad=True)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()

print(x.grad.data)
print(y.grad.data)
print(z.grad.data)
```

Chapter 3.4 | PyTorch



Calling `c.backward()` computes all gradients

```
import torch
from torch.autograd import Variable

N, D = 3, 4

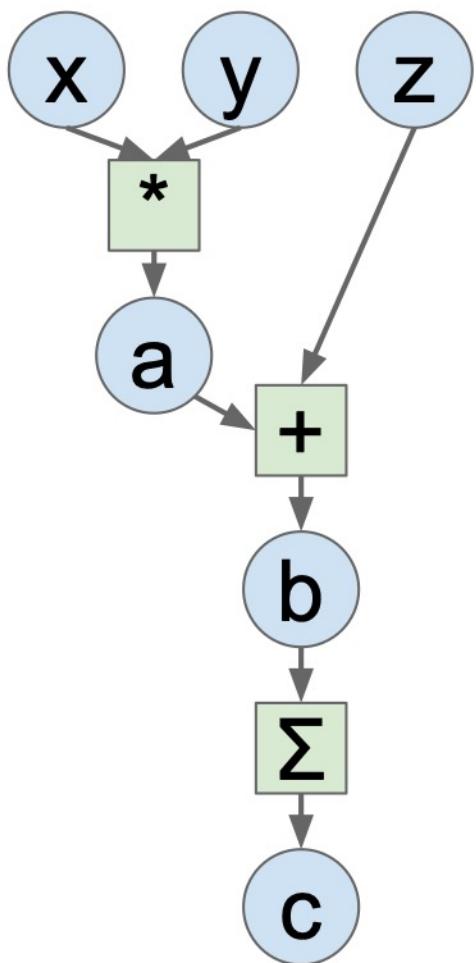
x = Variable(torch.randn(N, D),
             requires_grad=True)
y = Variable(torch.randn(N, D),
             requires_grad=True)
z = Variable(torch.randn(N, D),
             requires_grad=True)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()

print(x.grad.data)
print(y.grad.data)
print(z.grad.data)
```

Chapter 3.4 | PyTorch



Run on GPU by
casting to .cuda()

```
import torch
from torch.autograd import Variable

N, D = 3, 4

x = Variable(torch.randn(N, D).cuda(),
             requires_grad=True)
y = Variable(torch.randn(N, D).cuda(),
             requires_grad=True)
z = Variable(torch.randn(N, D).cuda(),
             requires_grad=True)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()

print(x.grad.data)
print(y.grad.data)
print(z.grad.data)
```

Chapter 4

코딩 (ipynb 활용)



E.O.D