

Review

CNN Architectures

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Practice

model

Review



Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

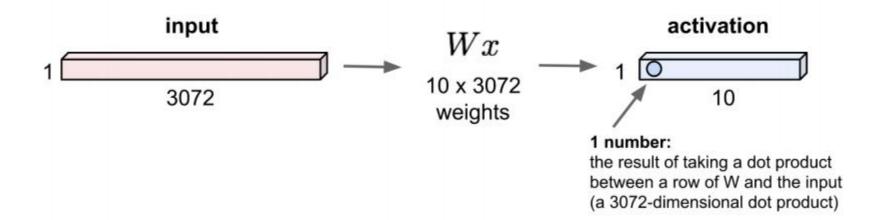
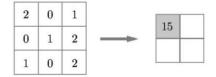




그림 7-4 합성곱 연산의 계산 순서

1	2	3	0
0	1	2	3
3	0	1	2
2	3	0	1





	1	2	3	0
	0	1	2	3
Ì	3	0	1	2
	2	3	0	1



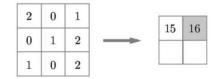


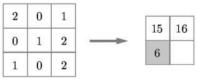


그림 7-5 합성곱 연산의 편향: 필터를 적용한 원소에 고정값(편향)을 더한다.

ဥ	J력 (레이	터			필터						편향		출력 [베이트
2	3	0	1		1	U									
0	U	1			1	0	2		0	19		A		9	18
3	0	1	2	*	0	1	2		6	15	+	3		0	10
0	1	4	3	*	0	-	0	100	15	16		0	0222	18	19
Λ	1	0	2		2	0	1		15	10				10	10
1	2	3	0												







1	2	3	0
0	1	2	3
3	0	1	2
2	3	0	1



2	0	1		
_			 15	16
0	1	2	 6	15
1	0	2		10



In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7
3x3 filter, applied with stride 1
pad with 1 pixel border => what is the output?

7x7 output!



$$(OH, OW) = \left(\frac{H + 2P - FH}{S} + 1, \frac{W + 2P - FW}{S} + 1\right)$$

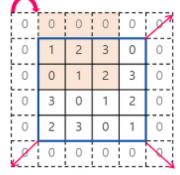
(H, W): 입력크기

(FH, FW): 필터크기

(OH, OW): 출력크기

P: 패딩
 S: 스트라이드







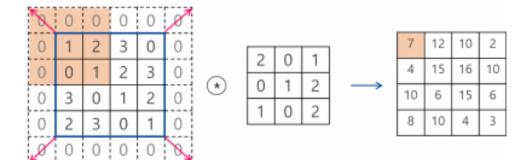
	7	12	10	2	
	4	15	16	10	
>	10	6	15	6	
	8	10	4	3	

$$(OH, OW) = \left(\frac{4+2*1-3}{1}+1, \frac{4+2*1-3}{1}+1\right) = (4,4)$$



그림 7-6 합성곱 연산의 패딩 처리 : 입력 데이터 주위에 0을 채운다(패딩은 점선으로 표시했으며 그 안의 값 '0'은 생략했다).

	0								_	10	10	0
1	2	3	0		0	0	1		7	12	10	2
0	1	2	3		2	0	1		4	15	16	10
3	0	1		*	0	1	2	\longrightarrow	10	6	15	6
2	3	0	177.7		1	0	2		8	10	4	3
						(3, 3	1			14	4)	
-1-1	(4, 4)								(4, 4)			
입력 [입력 데이터(패딩 : 1)					필터			출력 데이터			

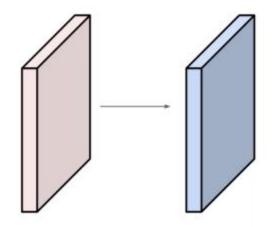




Examples time:

Input volume: 32x32x3

10 5x5 filters with stride 1, pad 2



Output volume size:

(32+2*2-5)/1+1 = 32 spatially, so

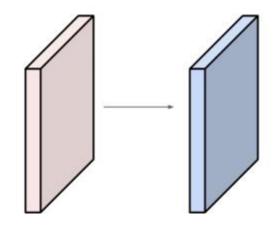
32x32x10



Examples time:

Input volume: 32x32x3

10 5x5 filters with stride 1, pad 2

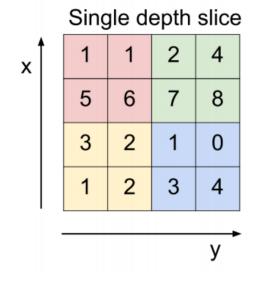


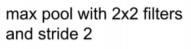
Number of parameters in this layer? each filter has 5*5*3 + 1 = 76 params => 76*10 = 760

(+1 for bias)



MAX POOLING





6	8
3	4

Pooling layer: summary

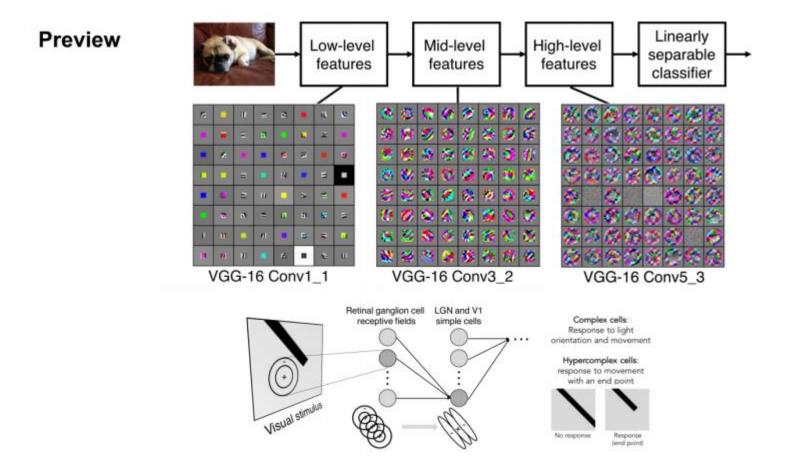
Let's assume input is W₁ x H₁ x C Conv layer needs 2 hyperparameters:

- The spatial extent F
- The stride **S**

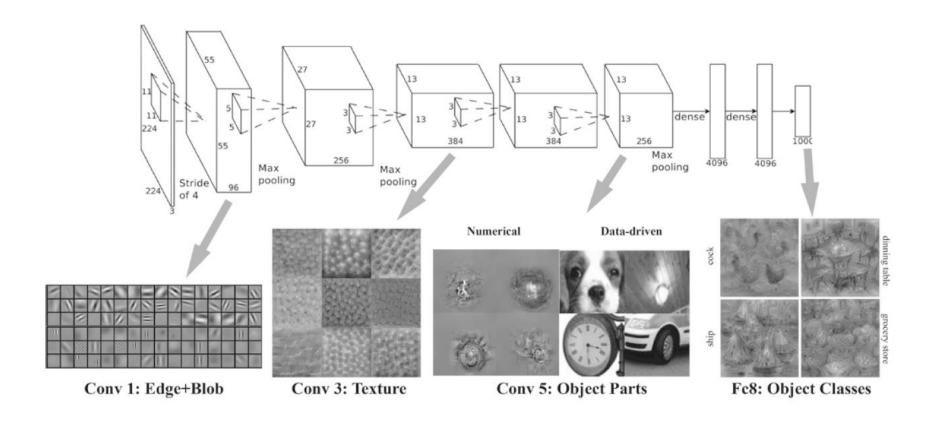
This will produce an output of $W_2 \times H_2 \times C$ where:

Number of parameters: 0





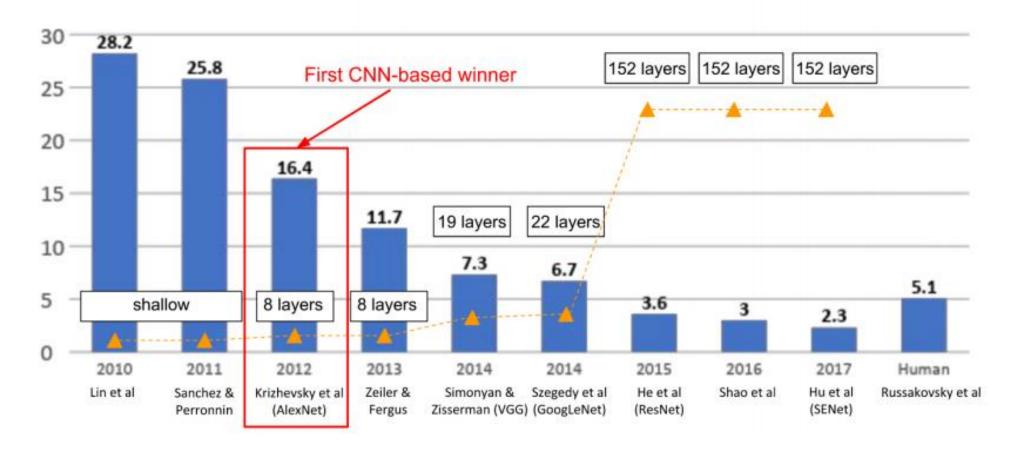








ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners





Case Study: AlexNet, VGGNet

Softmax
FC 1000
FC 4096
FC 4096
Pool
3x3 conv, 256
3x3 conv, 384
Pool
3x3 conv, 384
Pool
1x11 conv, 96
Input

AlexNet

FC 1000 Softmax FC 4096 FC 1000 FC 4096 FC 4096 FC 4096 Pool Pool 3x3 conv, 512 Pool Pool Pool Pool Input Input

VGG16 VGG19



TOTAL params: 138M parameters

```
(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
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
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
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
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
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000
TOTAL memory: 24M * 4 bytes ~= 96MB / image (for a forward pass)
```

Softmax FC 4096 FC 4096 Input

VGG16

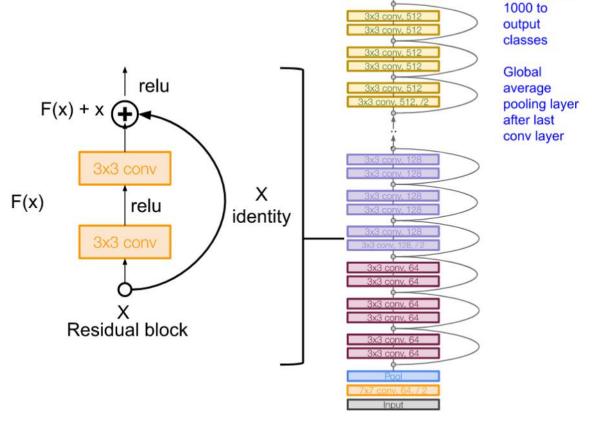


Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning (stem)
- No FC layers at the end (only FC 1000 to output classes)
- (In theory, you can train a ResNet with input image of variable sizes)





No FC layers besides FC

https://pytorch.org/docs/stable/torchvision/models.html
 TORCHVISION.MODELS

The models subpackage contains definitions of models for addressing different tasks, including: image classification, pixelwise semantic segmentation, object detection, instance segmentation, person keypoint detection and video classification.

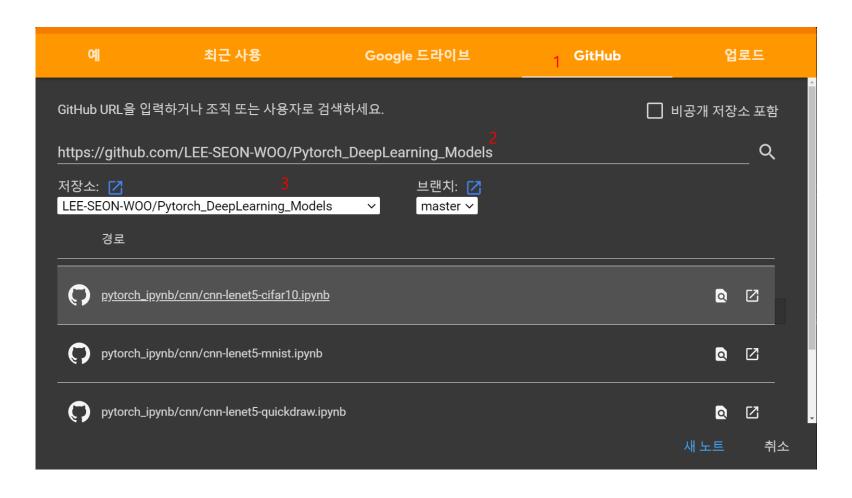
```
import torchvision.models as models
import torchvision.models as models
                                                  resnet18 = models.resnet18(pretrained=True)
resnet18 = models.resnet18()
                                                  alexnet = models.alexnet(pretrained=True)
alexnet = models.alexnet()
                                                  squeezenet = models.squeezenet1_0(pretrained=True)
vgg16 = models.vgg16()
                                                  vgg16 = models.vgg16(pretrained=True)
squeezenet = models.squeezenet1 0()
                                                  densenet = models.densenet161(pretrained=True)
densenet = models.densenet161()
                                                  inception = models.inception_v3(pretrained=True)
inception = models.inception v3()
                                                  googlenet = models.googlenet(pretrained=True)
googlenet = models.googlenet()
                                                  shufflenet = models.shufflenet_v2_x1_0(pretrained=True)
shufflenet = models.shufflenet v2 x1 0()
                                                  mobilenet = models.mobilenet_v2(pretrained=True)
mobilenet = models.mobilenet v2()
                                                  resnext50_32x4d = models.resnext50_32x4d(pretrained=True)
resnext50_32x4d = models.resnext50_32x4d()
wide_resnet50_2 = models.wide_resnet50_2()
                                                  wide_resnet50_2 = models.wide_resnet50_2(pretrained=True)
mnasnet = models.mnasnet1 0()
                                                  mnasnet = models.mnasnet1_0(pretrained=True)
```

3 Practice



CNN Tutorials

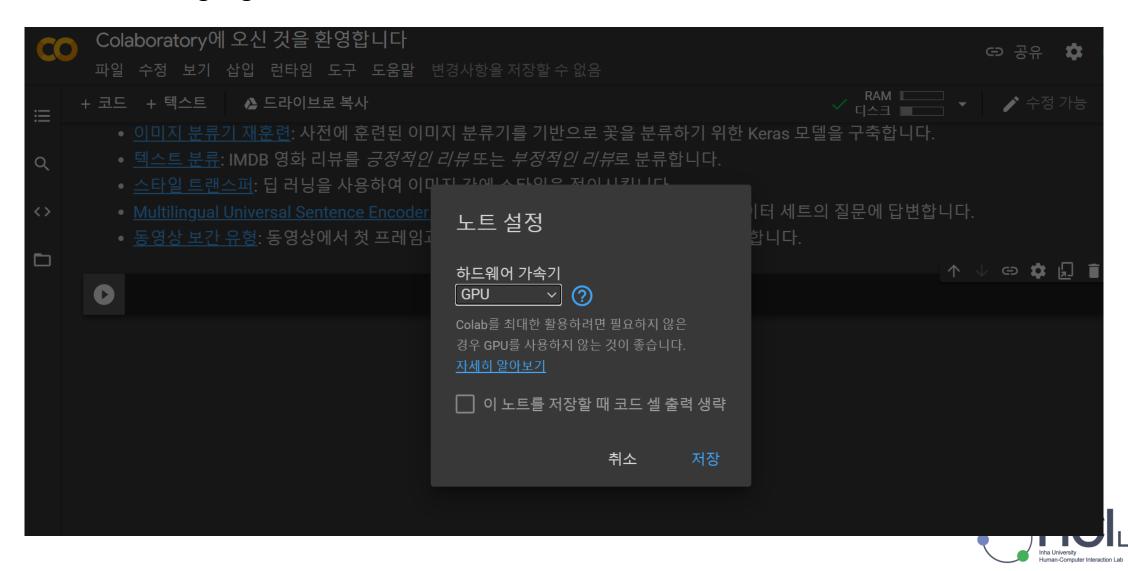
https://colab.research.google.com/





CNN Tutorials

https://colab.research.google.com/



Book

주교재

밑바닥부터 시작하는 딥러닝 1, 사이토 고키 지음, 개앞맨시 옮김 . (Deep Learning from Scratch의 번역서입니다 .)

부교재

Pytorch로 시작하는 딥러닝, 비슈누 수브라마니안 지음 김태완 옮김. (Deep Learning with PYTORCH 의 번역서입니다.)

O'REILLY'

파이썬으로 익하는 딥러닝 이론과 구현

