12기 정규세션 ToBig's 11기 임채빈

Convolutional Neural Networks

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Unit 01 | intro : Applications of CNN
Unit 02 | CNN
Unit 03 | Convolution Layer
Unit 04 | Sub-sampling
Unit 05 | Summary
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Applications of cnn

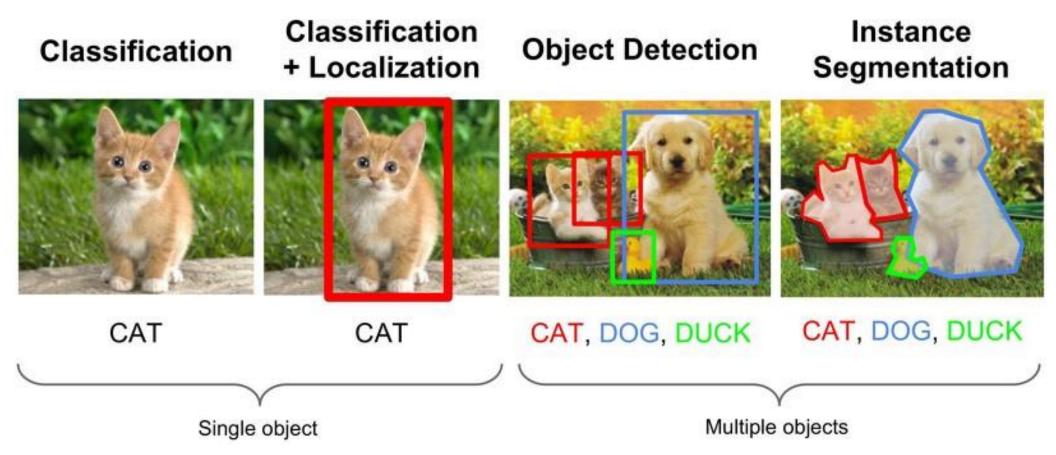


Image Caption Generation



† a living room with a couch and a television

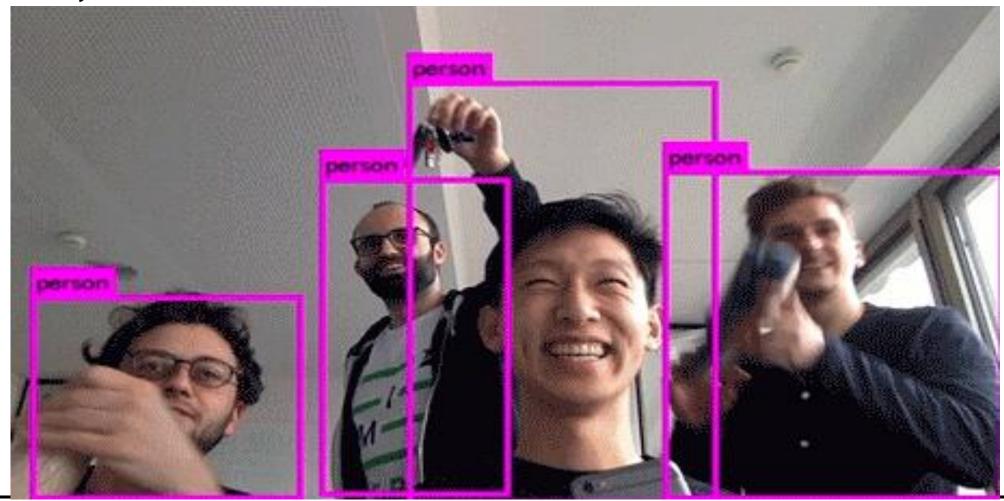


1 a man riding a bike on a beach



a man is walking down the street with a suitcase /

Real Time Object Detection



Real Time Pose Estimation

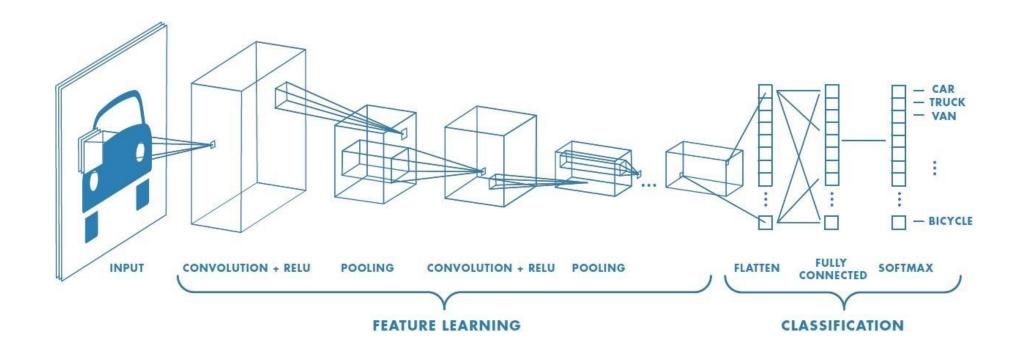


GAN

Tobig Studio

맞춤형 취업사진 생성



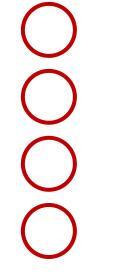


- Convolution Layer + Subsampling Layer + Fully Connected Layer
- Feature extraction : Convolution Layer + Pooling Layer
- Classification : Fully Connected Layer

Conventional Neural Network



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Conventional Neural Network

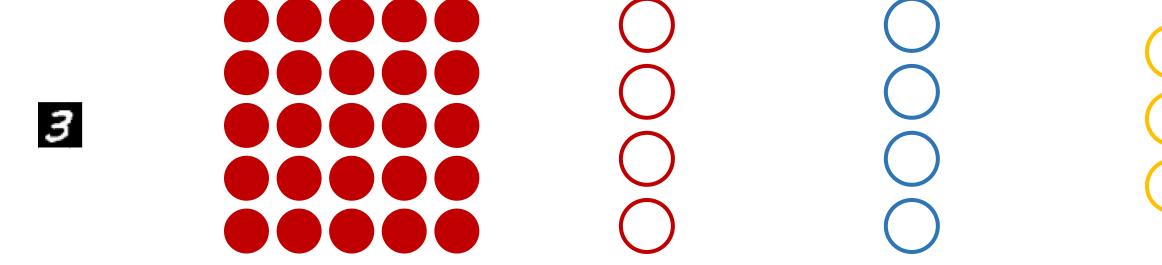
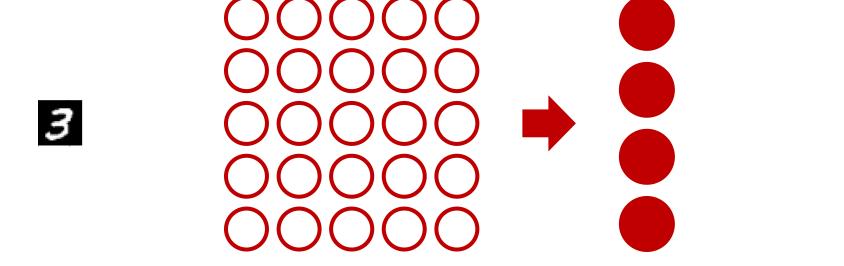


Image pixel (5x5)

Conventional Neural Network

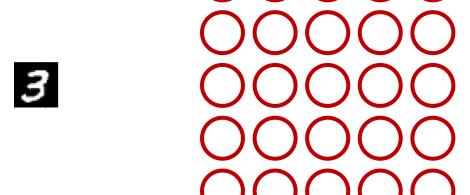


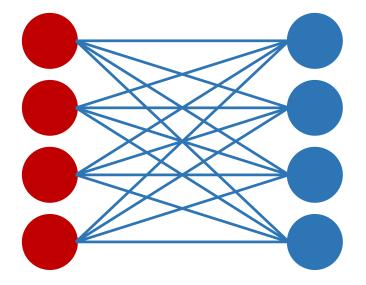




Flatten (1 x 25)

Conventional Neural Network



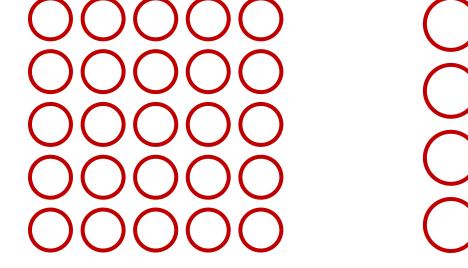


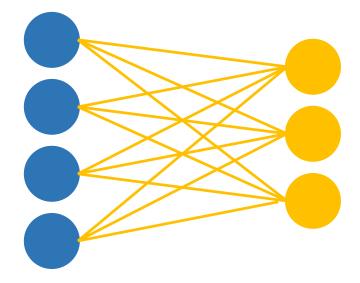


FC + Activation function

Conventional Neural Network

3





FC+ Classifier

Convolutional Neural Network

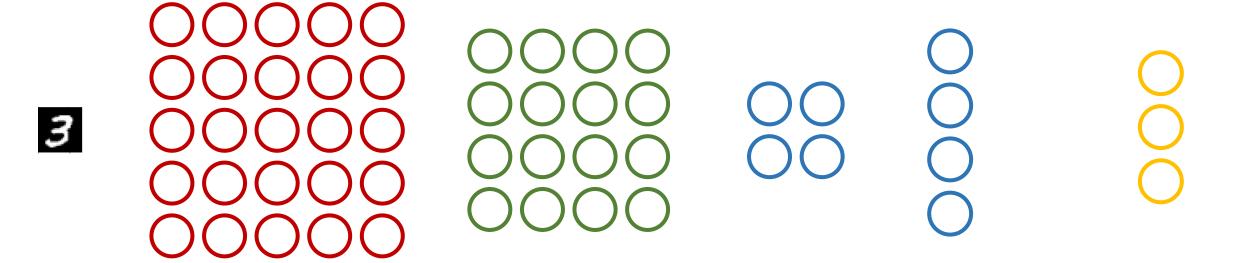
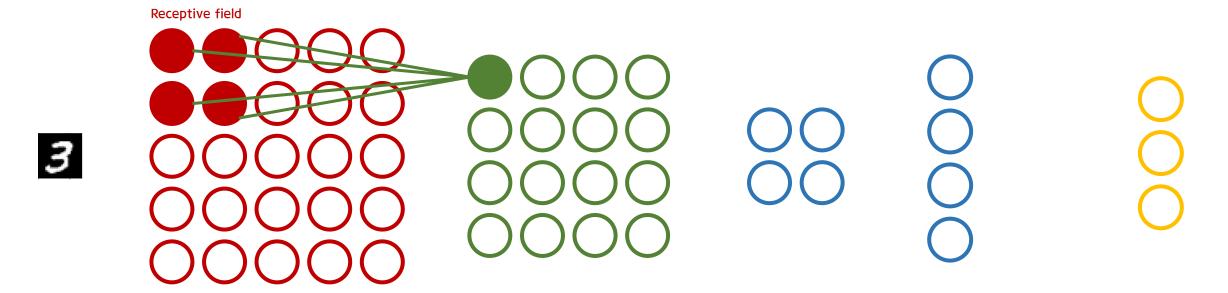
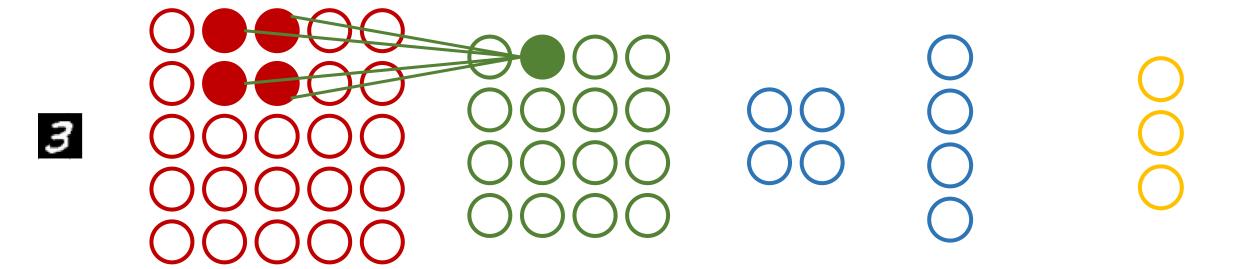


Image pixel (5x5)

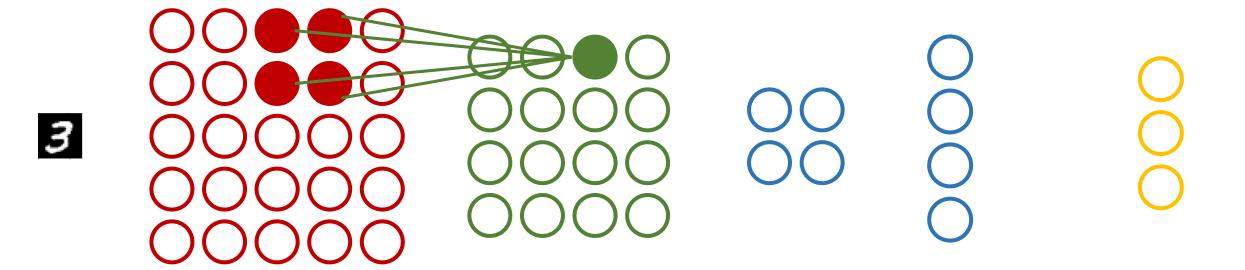
- Convolutional Neural Network
 - Receptive field : 출력 레이어의 뉴런 하나에 영향을 미치는 입력 뉴련들의 공간



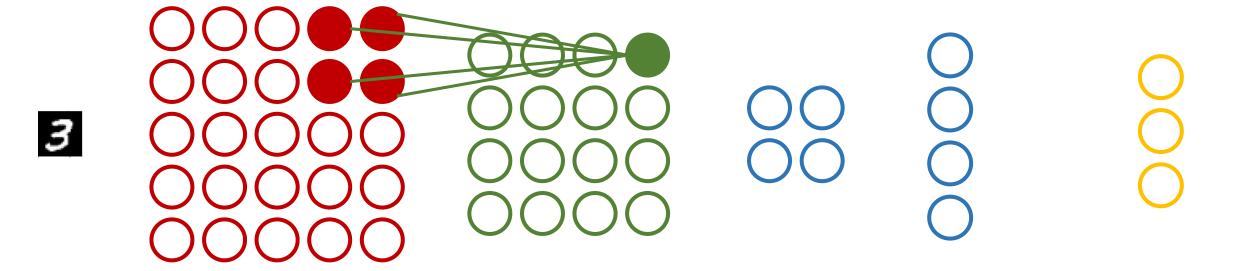
Convolutional Neural Network



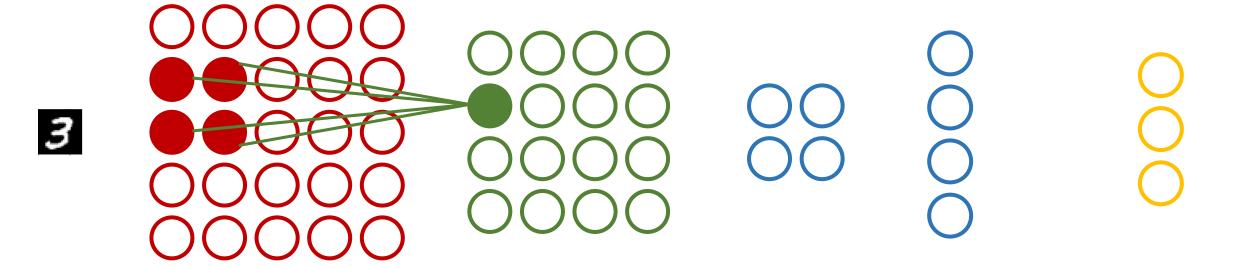
Convolutional Neural Network



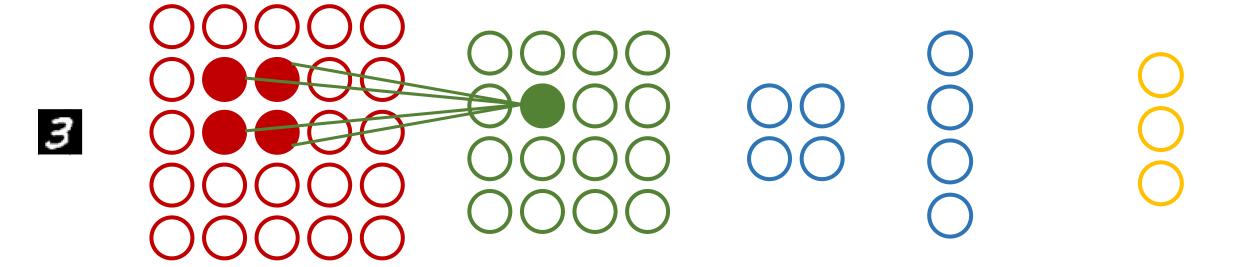
Convolutional Neural Network



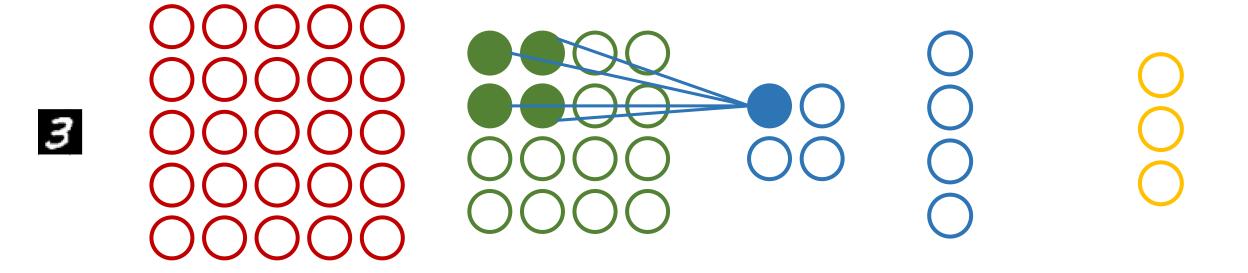
Convolutional Neural Network



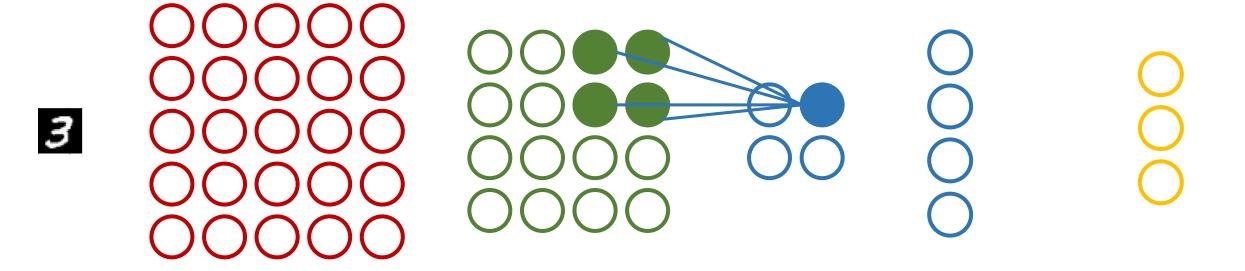
Convolutional Neural Network



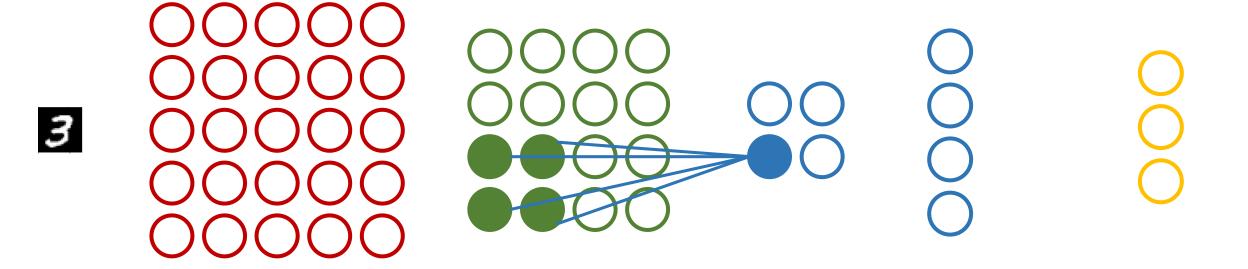
Convolutional Neural Network



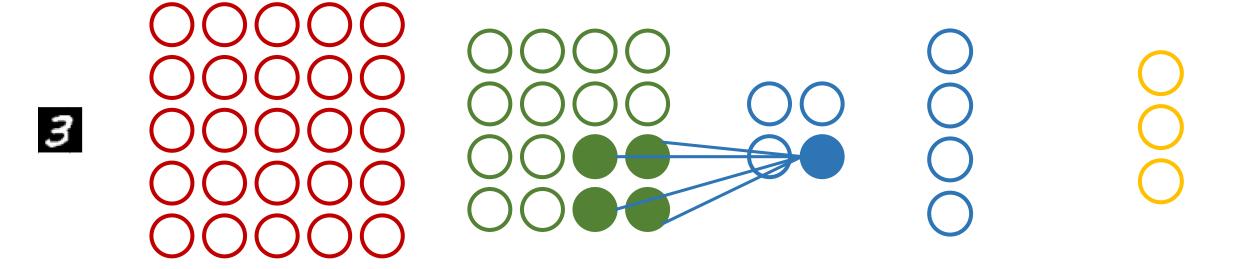
Convolutional Neural Network



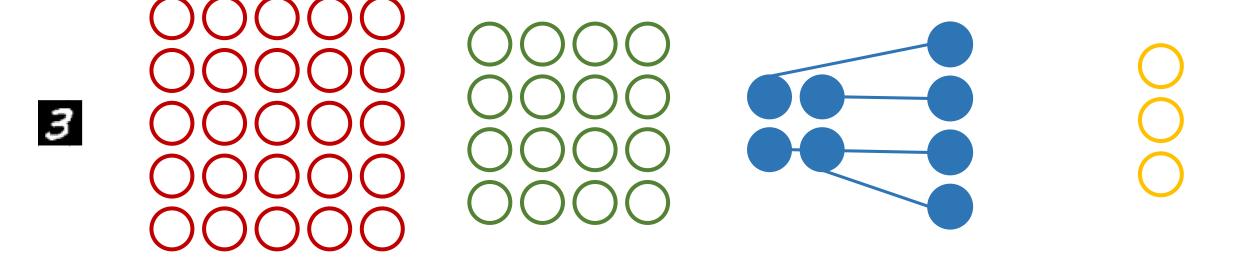
Convolutional Neural Network



Convolutional Neural Network

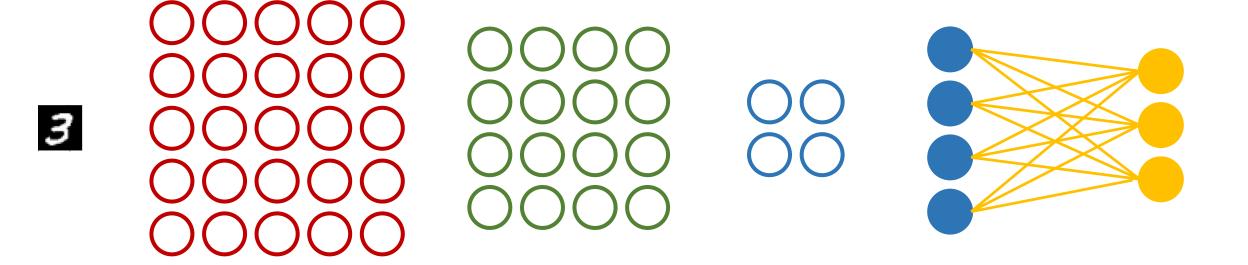


Convolutional Neural Network



Flatten

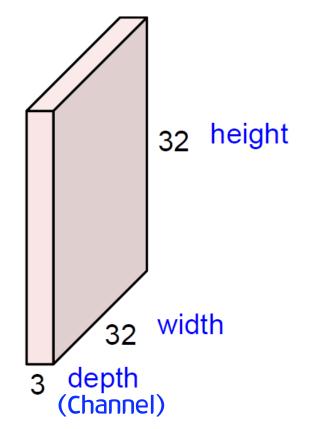
Convolutional Neural Network



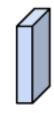
FC + Classifier

Convolution

32x32x3 image -> preserve spatial structure



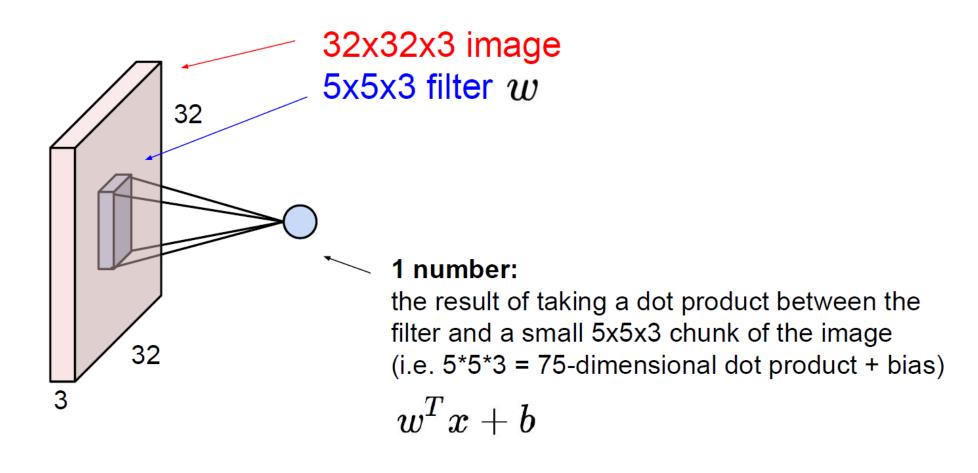
5x5x3 filter (Shared Weight)



· Image와 filter의 channel은 항상 같다.

Ex) RGB = 3 channel, grayscale = 1channel

Convolution



Convolution

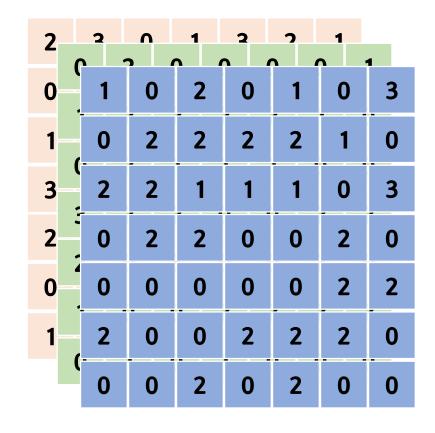
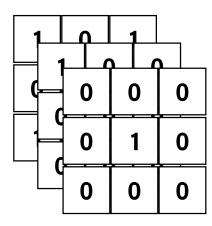


Image 7x7x3



filter 3x3x3

Convolution

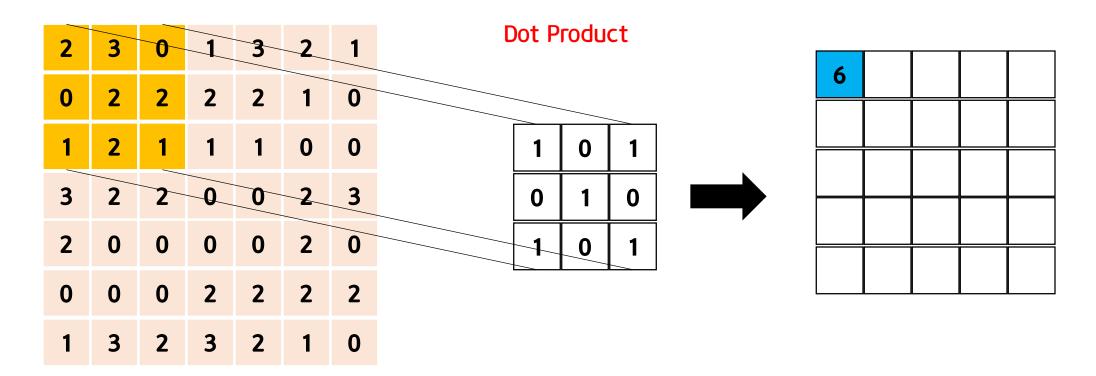
2	3	0	1	3	2	1
0	2	2	2	2	1	0
1	2	1	1	1	0	0
3	2	2	0	0	2	3
2	0	0	0	0	2	0
0	0	0	2	2	2	2
1	3	2	3	2	1	0

1	0	1
0	1	0
1	0	1

Input Volumn (7x7)

Filter (3 x 3)

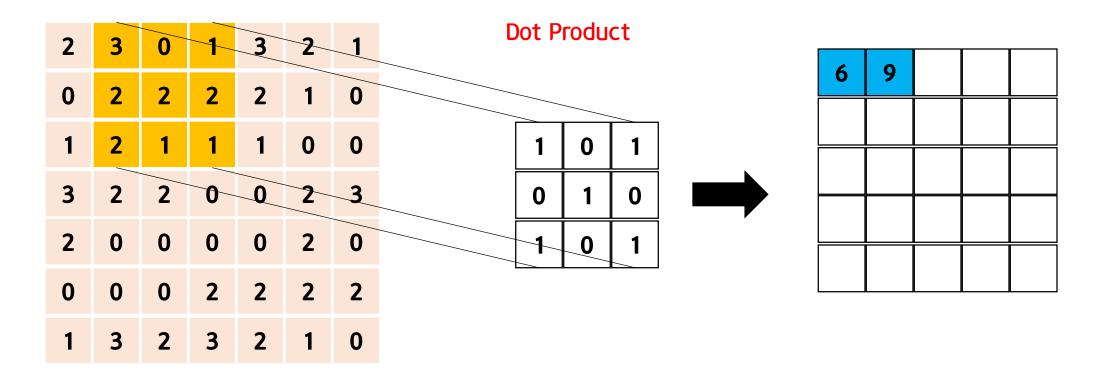
Convolution



Input Volumn (7x7)

Filter (3 x 3)

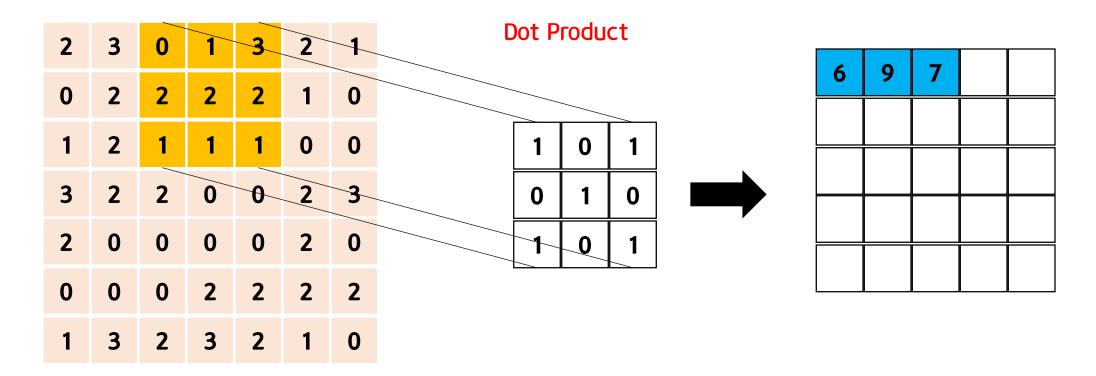
Convolution



Input Volumn (7x7)

Filter (3 x 3)

Convolution



Input Volumn (7x7)

Filter (3 x 3)

Convolution

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

1	0	1	
0	1	0	
1	0	1	

6	9	7	6	6
9	7	7	6	5
6	5	2	3	3
5	4	4	6	9
5	6	6	8	4

Input Volumn (7x7)

Filter (3 x 3)

Convolution

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

1	0	0	
0	0	0	
0	0	0	

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

Input Volumn (7x7)

Filter (3 x 3)

Convolution

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

0	0	0	
0	1	0	
0	0	0	

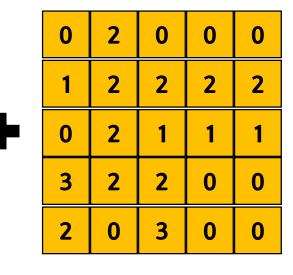
2	2	2	2	1
2	1	1	1	0
2	2	0	0	2
0	0	0	0	2
0	0	2	2	2

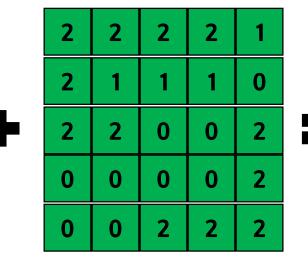
Input Volumn (7x7)

Filter (3 x 3)

Convolution

6	9	7	6	6
9	7	7	6	5
6	5	2	3	3
5	4	4	6	9
5	6	6	8	4

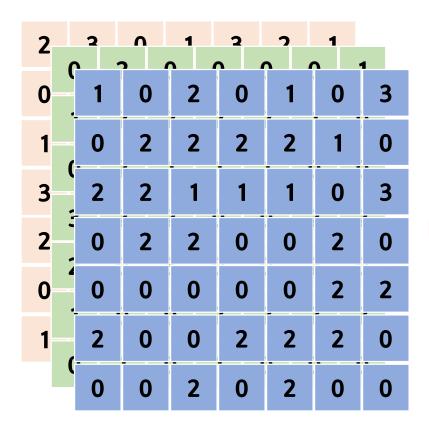




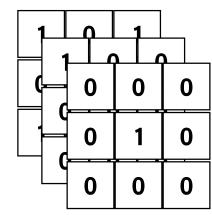
New feature map

8	13	9	8	7
12	10	10	9	7
8	9	3	4	6
8	6	6	6	11
7	6	11	10	6

Convolution



Dot Product



New feature map

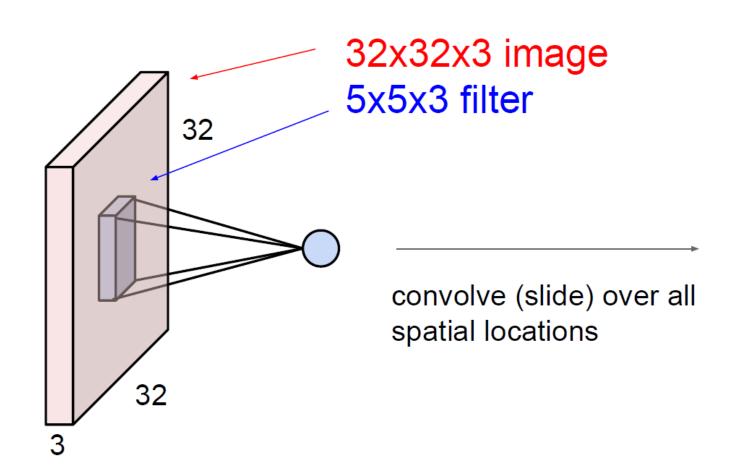
8	13	9	8	7
12	10	10	9	7
8	9	3	4	6
8	6	6	6	11
7	6	11	10	6

Image 7x7x3

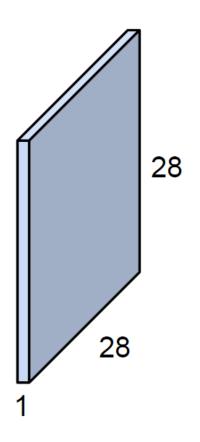
filter 3x3x3

Feature map 5x5x1

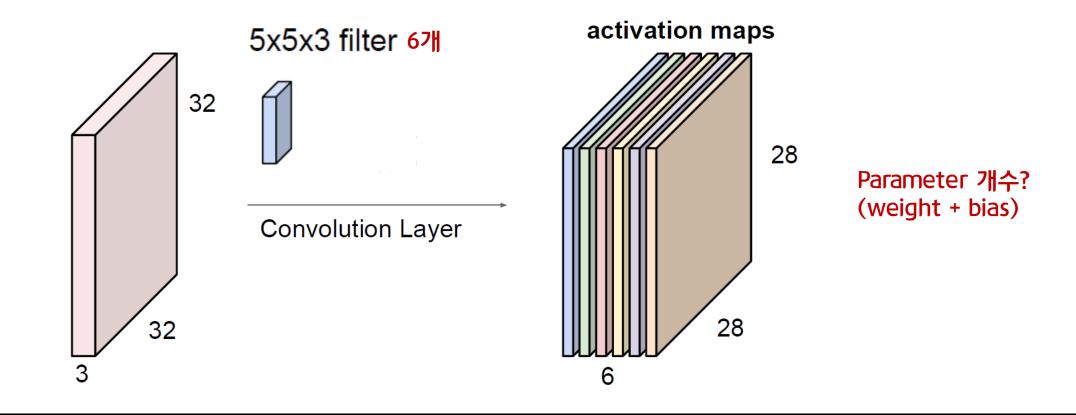
Convolution



activation map

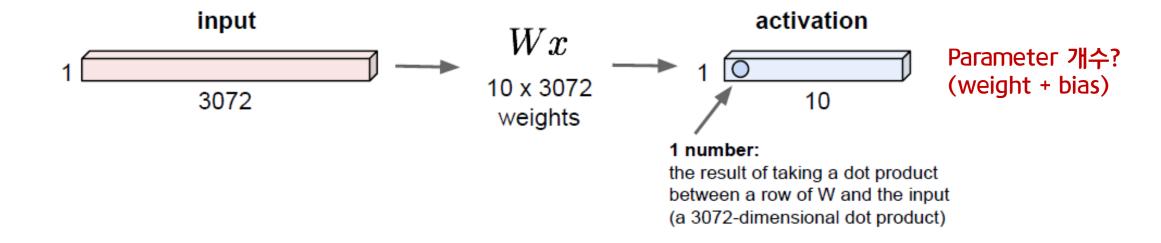


- Convolution
 - Filter 수가 6개라면 6개의 새로운 feature map이 생성됨. (hyper parameter)
 - 6개의 feature map을 stack up하여 28x28x6의 새로운 데이터 생성



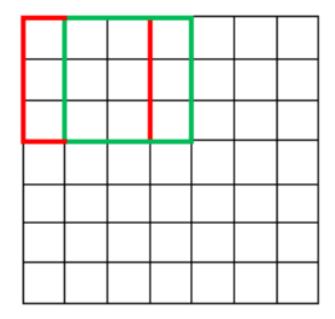
- Convolution
 - 각각의 pixel을 하나의 channel로 flatten 후 1x1x3072 filter 10개를 사용
 - FC?

32x32x3 image -> stretch to 3072 x 1

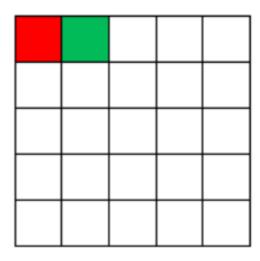


- Stride
 - Filter가 이동하는 거리

7 x 7 Input Volume

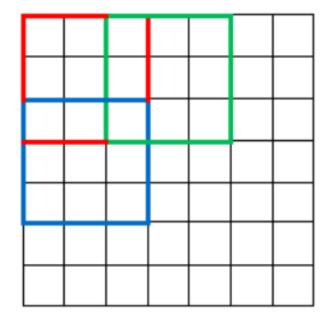


5 x 5 Output Volume

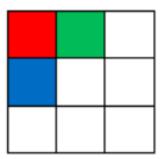


- Stride
 - Filter가 이동하는 거리

7 x 7 Input Volume

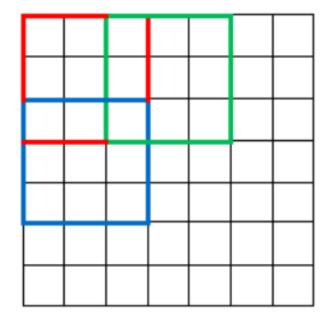


3 x 3 Output Volume

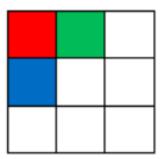


- Stride
 - Filter가 이동하는 거리

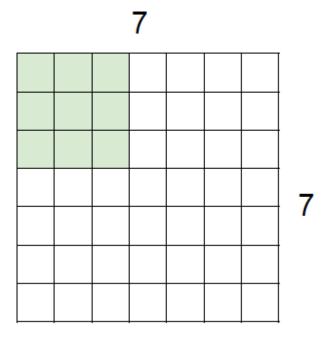
7 x 7 Input Volume



3 x 3 Output Volume



- Stride
 - Filter가 이동하는 거리



Stride = 3?

- Stride
 - Filter가 이동하는 거리
 - Output의 volume이 integer가 되도록 stride 설정 7

7

doesn't fit!

Stride = 3?

- Stride
 - Filter가 이동하는 거리
 - Output의 volume이 integer가 되도록 stride 설정

 N											
		F									
F											
Г											

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 => $(7 - 3)/3 + 1 = 2.33$ Fraction!

- Stride
 - Filter가 이동하는 거리
 - Output의 volume이 integer가 되도록 stride 설정

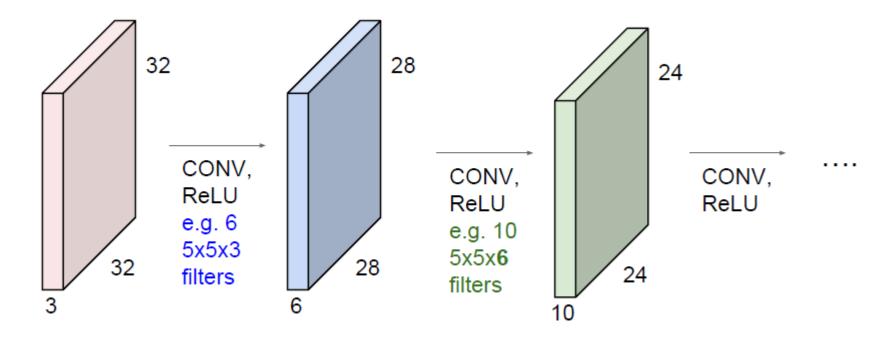
 N											
		F									
F											
Г											

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 => $(7 - 3)/3 + 1 = 2.33$ Fraction!

- Padding
 - Convolution layer 층이 깊어질 수록 data의 size가 줄어든다.
 - Data size가 너무 빠르게 줄어들면 잘 작동하지 않음!



- Padding
 - 데이터 테두리에 zero-padding을 더해 크기 손실 방지

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

- Padding
 - 데이터 테두리에 zero-padding을 더해 크기 손실 방지

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

- Padding
 - 데이터 테두리에 zero-padding을 더해 크기 손실 방지

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

- Padding
 - 데이터 테두리에 zero-padding을 더해 크기 손실 방지

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

- Padding
 - 데이터 테두리에 zero-padding을 더해 크기 손실 방지

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

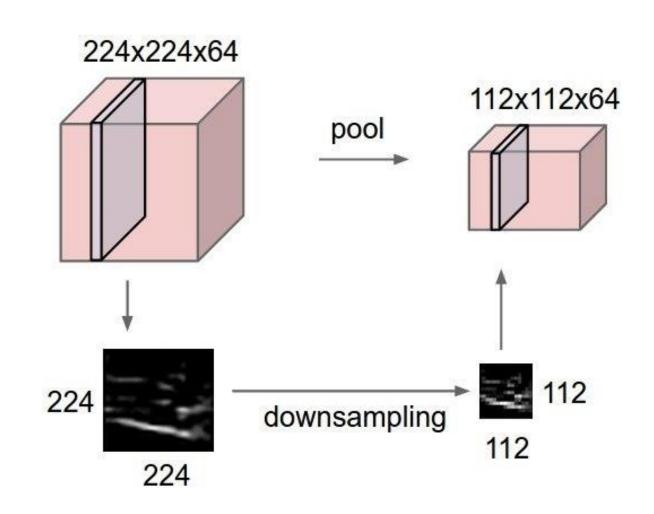
Example

Input volume: 32x32x3 10 5x5 filters with stride 1, pad 2

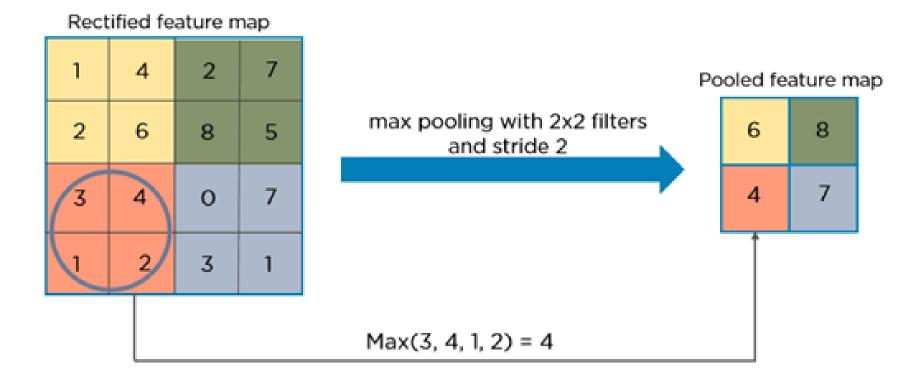
- 1. Output volume size: ?
- 2. Number of parameters in this layer : ?

- Sub Sampling
 - 이미지의 특성은 유지
 - 사이즈를 줄여 관리하기 쉽게 만듬
 - 각 feature map마다 독립적으로 작용

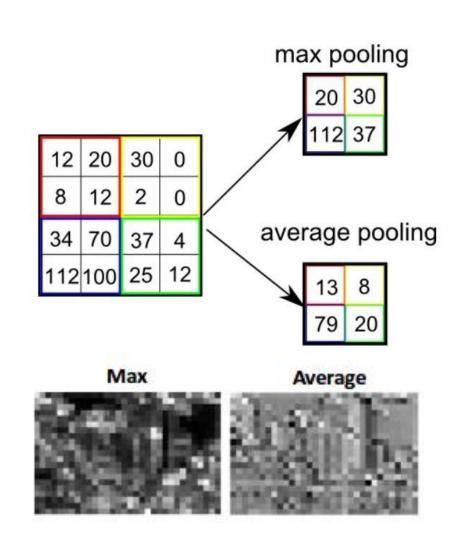
But 기기의 성능 향상으로 사이즈를 줄일 필요가 적어지면서 성능을 위해 잘 사용하지 않는 추세



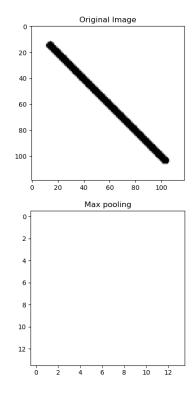
- Sub Sampling
 - Max pooling
 - Filter size와 stride 존재

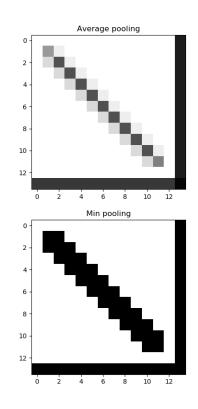


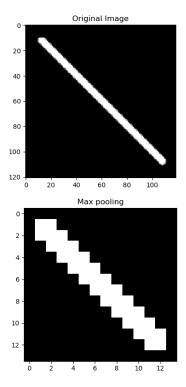
- Max pooling vs Average pooling
 - Max pooling
 해당 window의 max값을 추출
 - Average pooling
 해당 window의 평균 값 추출 (smoothing 됨)

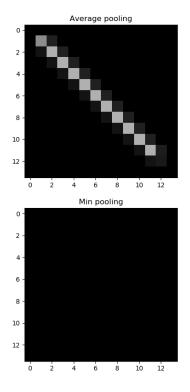


- Max pooling vs Average pooling
 - Most important features를 뽑는다는 관점에서 일반적으로 Max pooling을 사용

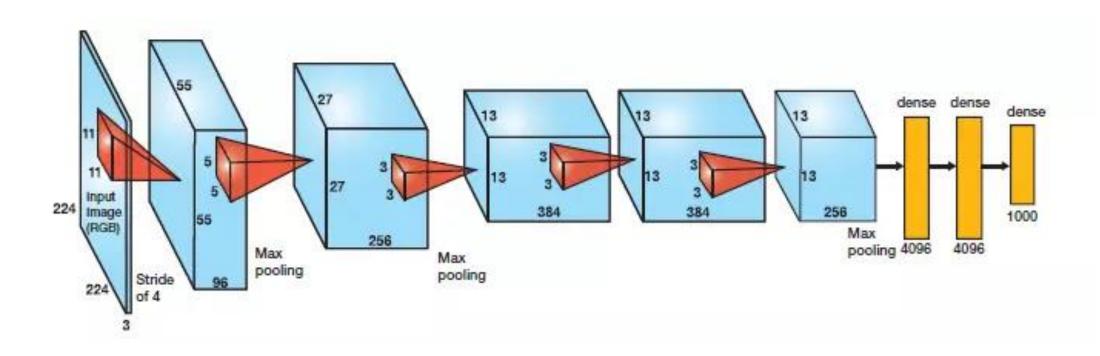




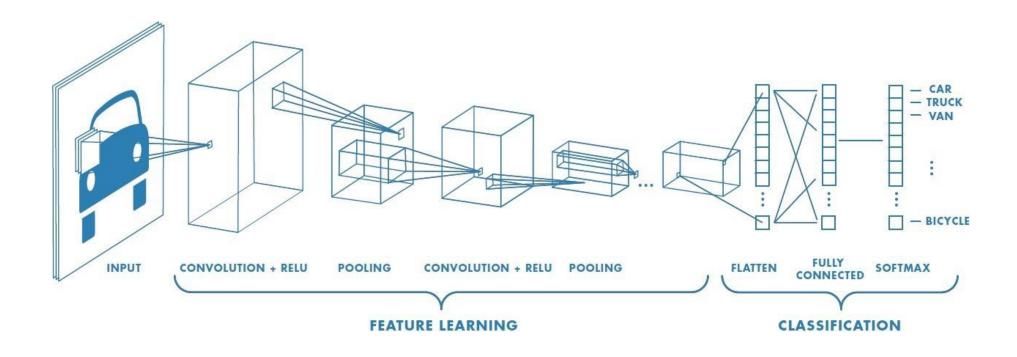




pretty much everything of 'CNN' (AlexNet)



Unit 05 | Summary



- Convolution Layer + Subsampling Layer + Fully Connected Layer
- Feature extraction : Convolution Layer + Pooling Layer
- Classification : Fully Connected Layer

Unit 02 | Layers in CNN

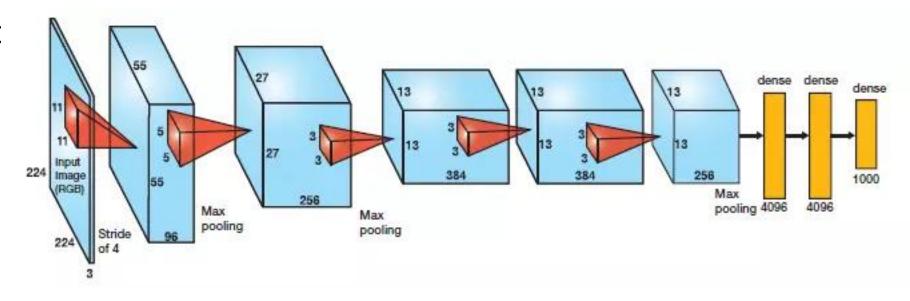
- Convolutional Neural Network
 - Local connectivity(receptive field)
 - 지역적으로 뉴런을 연결하여 다양한 local feature 추출 가능
 - Shared Weights and Biases (topology invariance)
 - Filter의 weight을 공유하여 parameter를 획기적으로 줄일 수 있다.
 - 찾고자 하는 특징이 이미지 어디에 위치해도 알 수 있다.
 - Compositionality
 - 저레벨 특징을 고레벨 특징으로 compose함
 - ex) 눈의 특징, 귀의 특징, 코의 특징 등등이 결합하여 사람의 얼굴의 특징으로 귀결

Unit 05 | Summary

- 용어 정리
 - Convolution(합성곱)
 - 채널(Channel)
 - 필터(Filter) = 커널(Kernel)
 - 스트라이드(Stride)
 - 패딩(Padding), zero-Padding
 - 피처 맵(Feature Map) = 액티베이션 맵(Activation Map)
 - 풀링(Pooling) 레이어
 - receptive field(수용공간)

Assignment

AlexNet



- 과제 1. assignment_1.ipynb 물음표 채우기
- 과제 2. AlexNet model 구현 (프레임워크 자유)
 - -모델 구현 후 summary로 전체 모델 구조 보이고 주석을 통해 간단한 설명 (각 프레임워크 별 summary 방법 구글링)

Q&A

들어주셔서 감사합니다.

Appendix

- 참고자료
- # 10기 박성진님 강의

http://www.datamarket.kr/xe/index.php?mid=board_jPWY12&page=2&document_srl=52335

Stanford cs231n 강의

http://cs231n.stanford.edu/syllabus.html

towards data science

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

케라스 창시자에게 배우는 딥러닝

https://github.com/gilbutlTbook/006975