

# 파이썬 뽀수기

DeconvNet, SegNet

2020.10.28

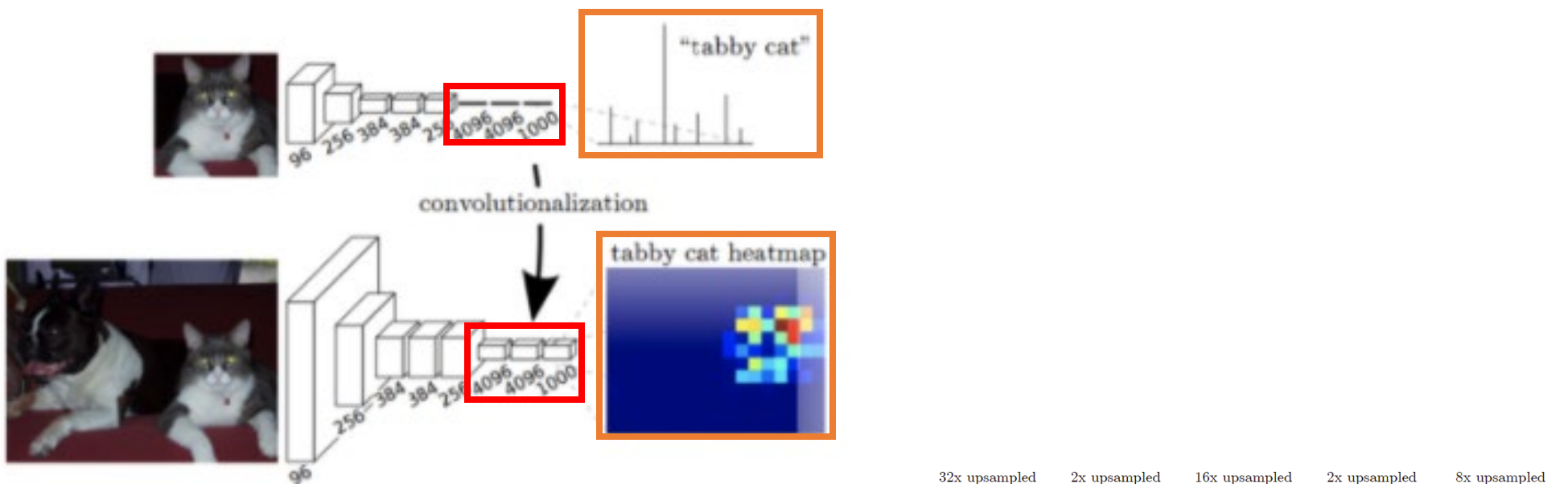
김현우

## 1

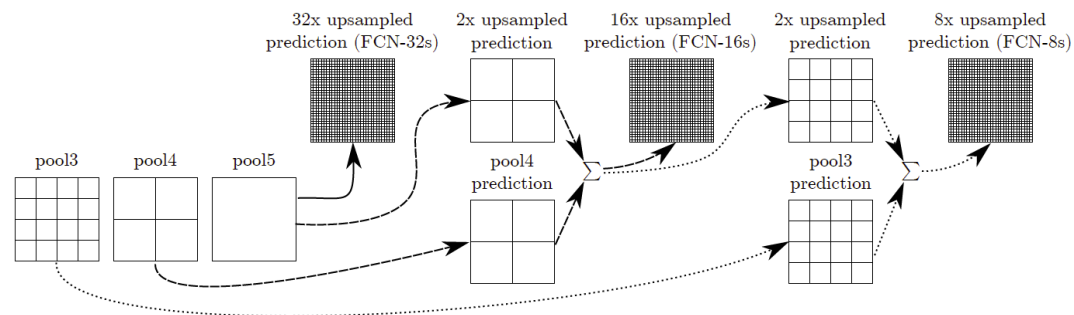
# Fully Convolutional Network

## ✓ Fully Convolutional Network 요약

### 1. Fully Connected Layer를 Fully Convolutional Layer로 변경



### 2. Residual Connection 기법을 이용

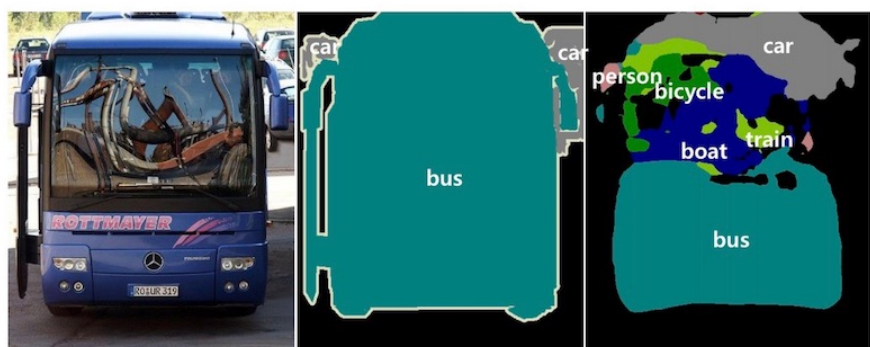


## 2

# Deconvolution Network

✓ FCN의 단점 (전반적인 Segmentation 문제)

1. Object의 크기에 약함



(a) Inconsistent labels due to large object size



(b) Missing labels due to small object size

2. Detail한 부분을 맞추지 못함



(a) Input image

(b) FCN-8s

(c) Ours

## 2

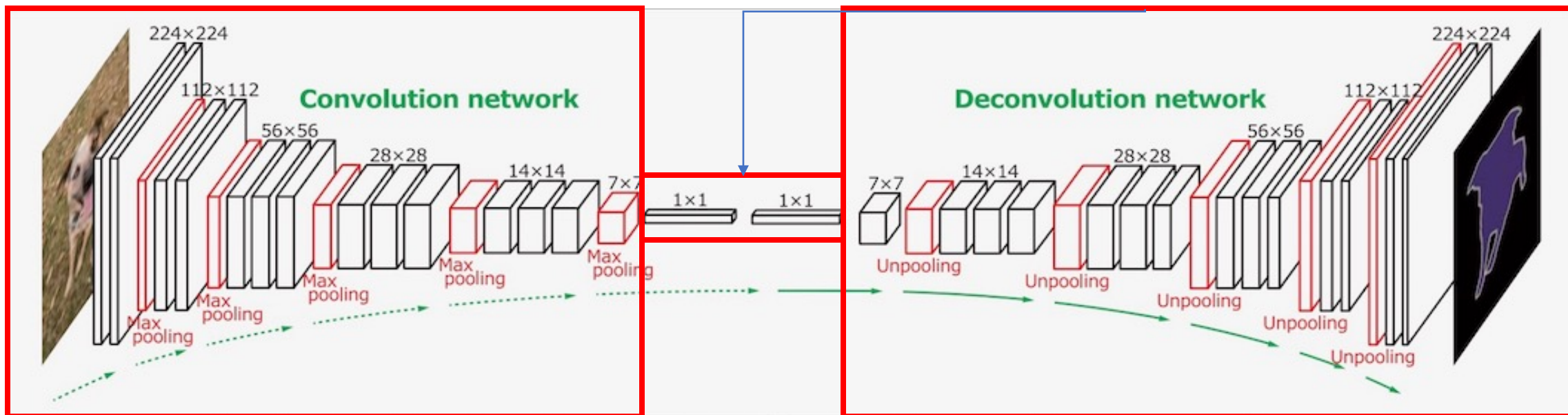
# Deconvolution Network

## 문제를 해결하는 방법

Layer를 더 깊게 쌓자 !!!

### 1x1 Convolution (Fully Connected Layer)

- Fully Connected Layer라는 표현을 사용했지만, Convolution을 이용했음



VGG 네트워크

VGG 네트워크 대칭



## 2

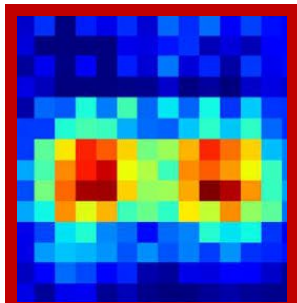
## Deconvolution Network

### ✓ Pooling 방법

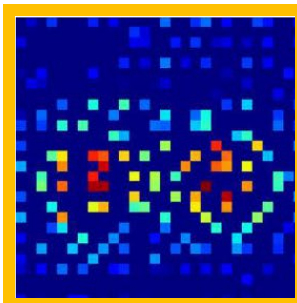
- Unpooling: 이미지의 디테일한 경계를 학습
- Deconvolution: 이미지의 전반적인 부분을 학습
- > 이미지의 Detail한 부분을 해결



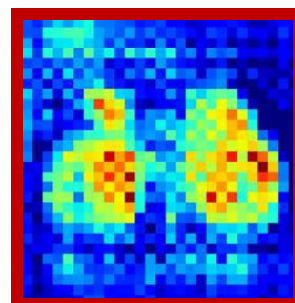
(a)



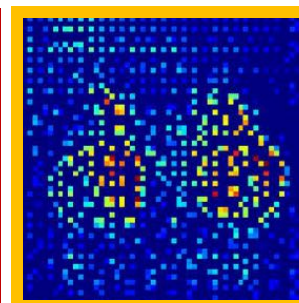
(b)



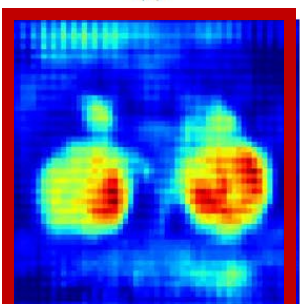
(c)



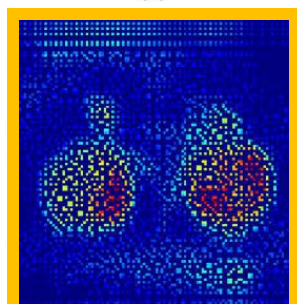
(d)



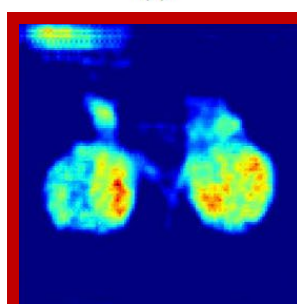
(e)



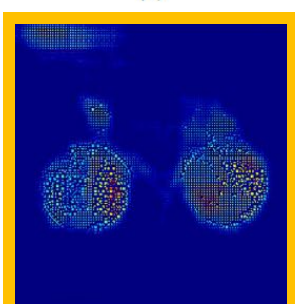
(f)



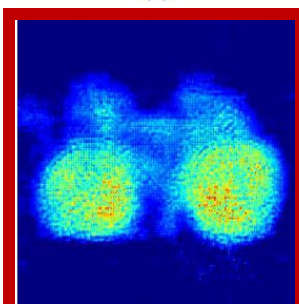
(g)



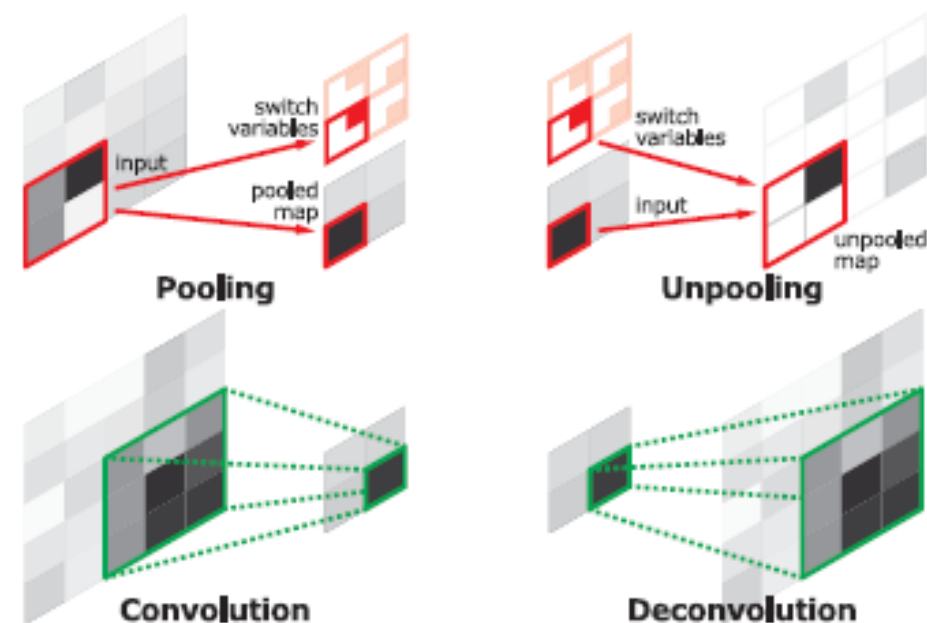
(h)



(i)



(j)



Convolution with trainable decoder filters

a	0	0	0
0	0	b	0
0	0	0	d
c	0	0	0

Max-pooling Indices

a	b
c	d

Deconvolution for upsampling

a	b
c	d

Dimensionality reduction

$x_1$	$x_2$	$x_3$	$x_4$	$y_1$	$y_2$	$y_3$	$y_4$
$x_5$	$x_6$	$x_7$	$x_8$	$y_5$	$y_6$	$y_7$	$y_8$
$x_9$	$x_{10}$	$x_{11}$	$x_{12}$	$y_9$	$y_{10}$	$y_{11}$	$y_{12}$
$x_{13}$	$x_{14}$	$x_{15}$	$x_{16}$	$y_{13}$	$y_{14}$	$y_{15}$	$y_{16}$

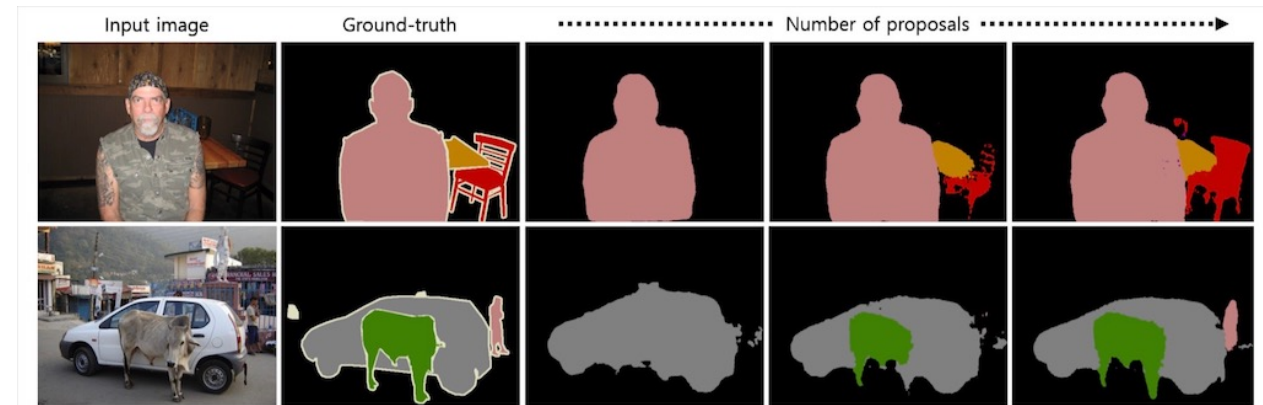
Encoder feature map

## Two-Stage Training

1. First Stage Training (Edge-box Object Proposal)
  - 객체가 있을 영역을 다양한 크기의 상자로 확인
  - 학습시에는 우선 실제 정답이 상자의 가운데에 들어가도록 이미지를 Crop
2. Second Stage Training
  - 1차 학습 후, IoU가 일정 값 이상인 이미지로 2차 학습 진행
  - 이렇게 학습한 edge-box를 추론 시에도 적용(edge-box의 수가 늘수록 성능 상승)

### Learning Details

- Batch Normalization
- VGGNet weight로 ConvNet을 initialized
- DeconvNet은 zero-mean Gaussians으로 initialized
- 64 Batch Size

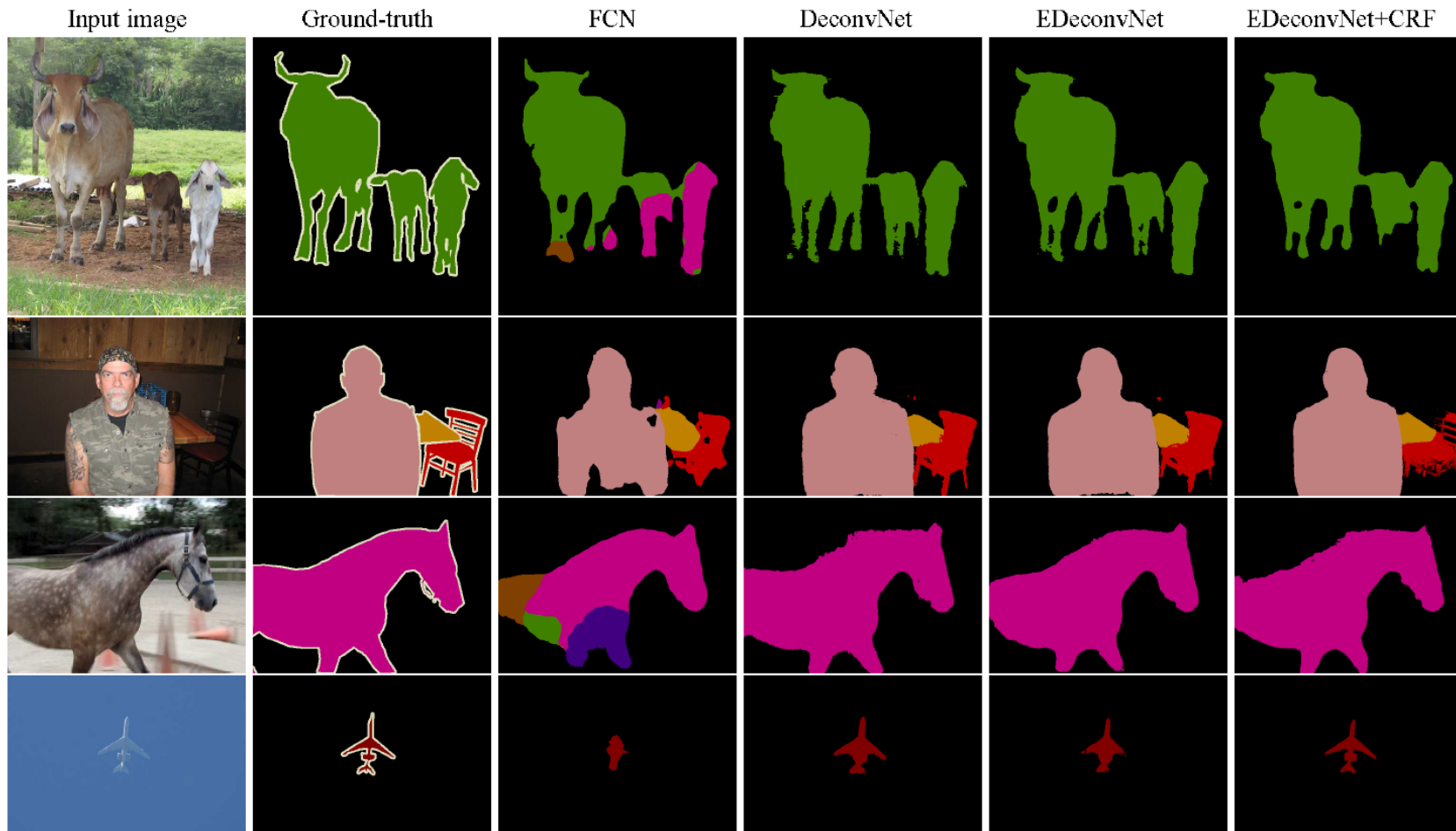


## 2

## Deconvolution Network



## Results



## ✓ Abstract

1. Encoder – Decoder으로 구성된 Pixel Wise Segmentation 방법
2. Upsampling 방법을 이용한 보간 방법
3. 메모리와 계산시간의 효율적인 방법
  - VGG16의 네트워크를 사용하고, Fully Connected Layer을 제거
  - Upsampling시에 Maxpooling에서 사용한 index를 가져옴 (Unpooling)



## ✓ Purpose

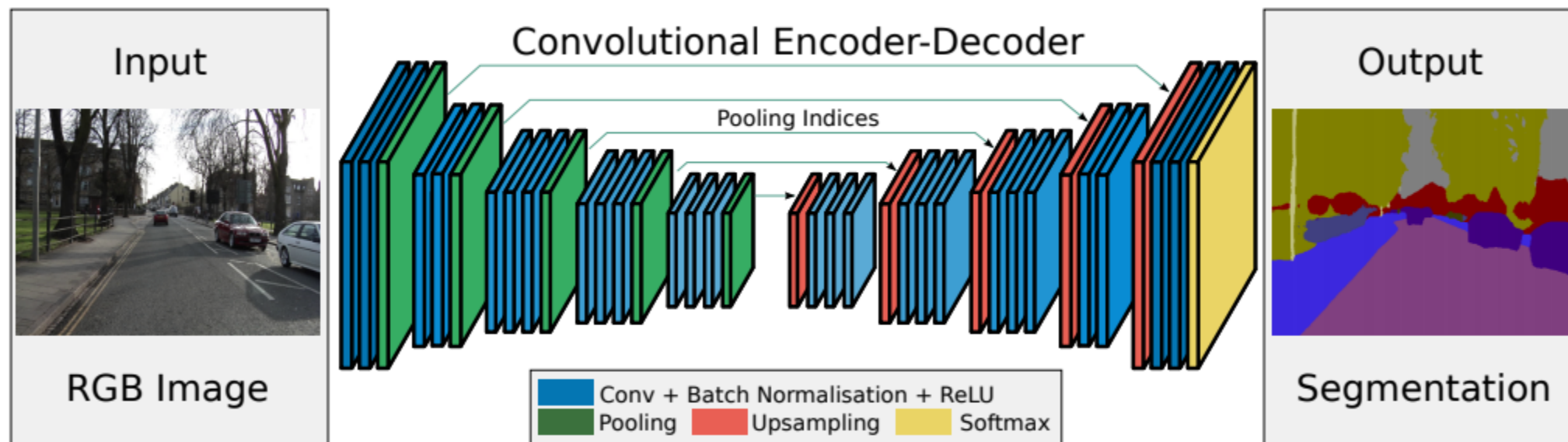
1. 자율주행과 관련된 구조들을 pixel-wise segmentation 하기 위해 설계된 모델



2. Object간의 관계가 있다는게 중요한 포인트
  - (차, 도로), (나무, 잔디), (차, 차), (보행자, 횡단보도), 등등

## ✓ Network

### 1. Encoder – Decode 형태의 네트워크 구성



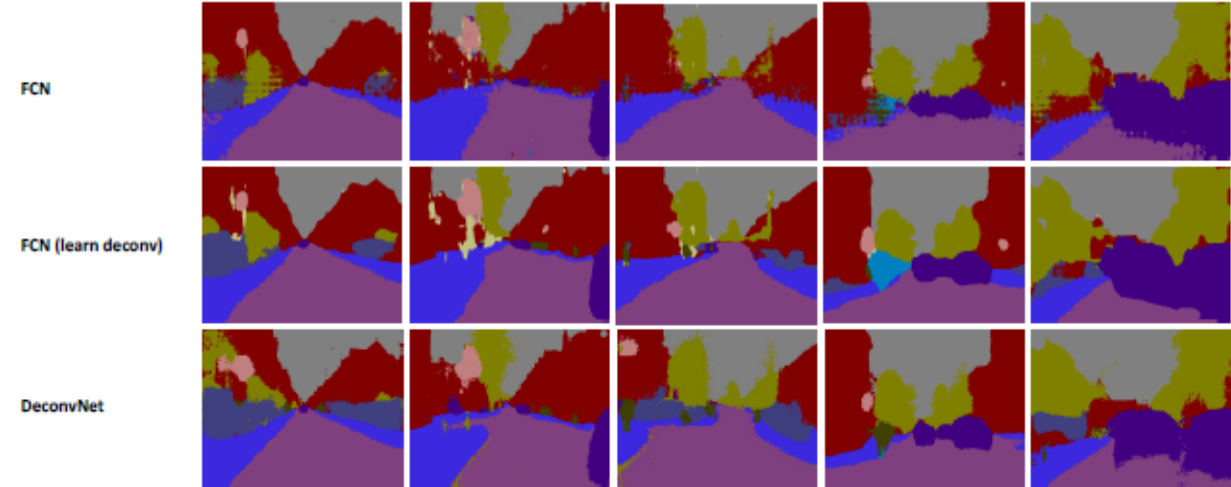
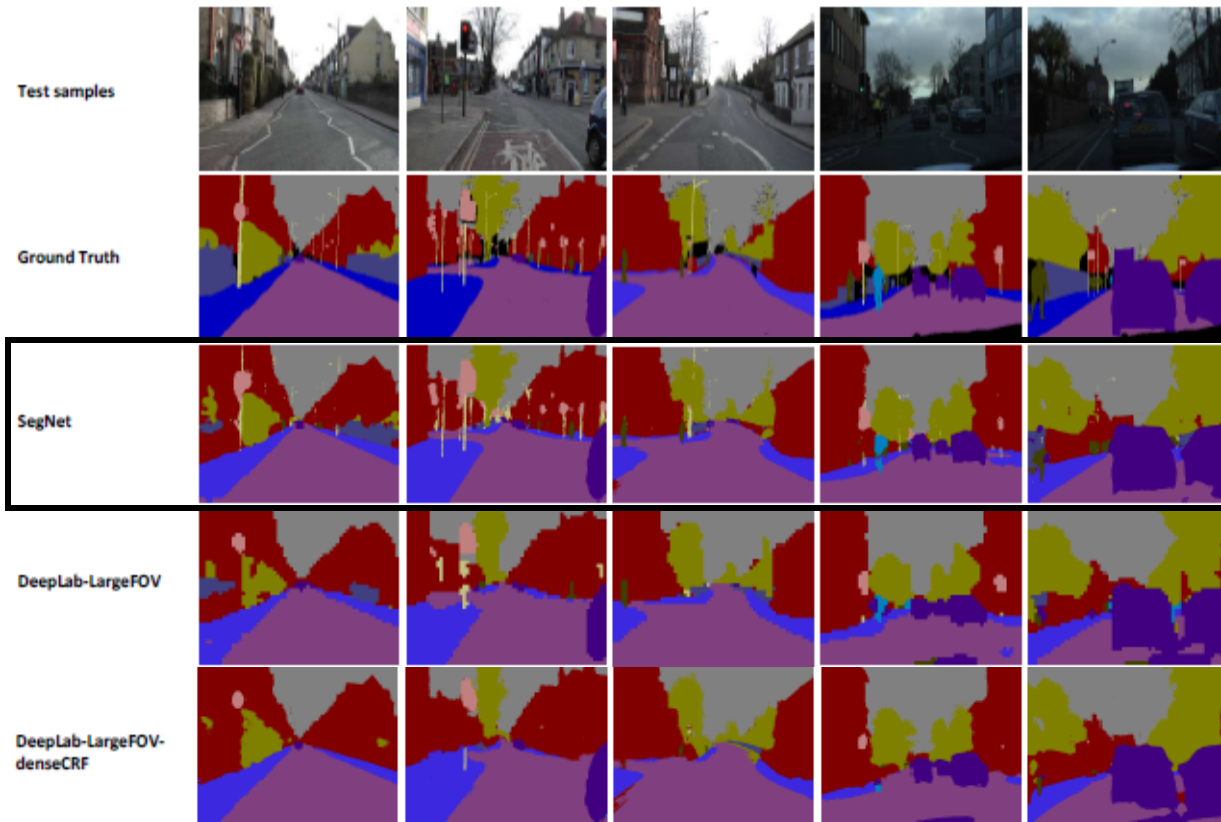
2. Upsampling시에 Pooling Indices 사용 -> 파라미터 수가 줄어서 속도 향상 및 이전의 정보 활용
3. Fully Connected Layer 제거 -> 속도 향상

## 3

## SegNet



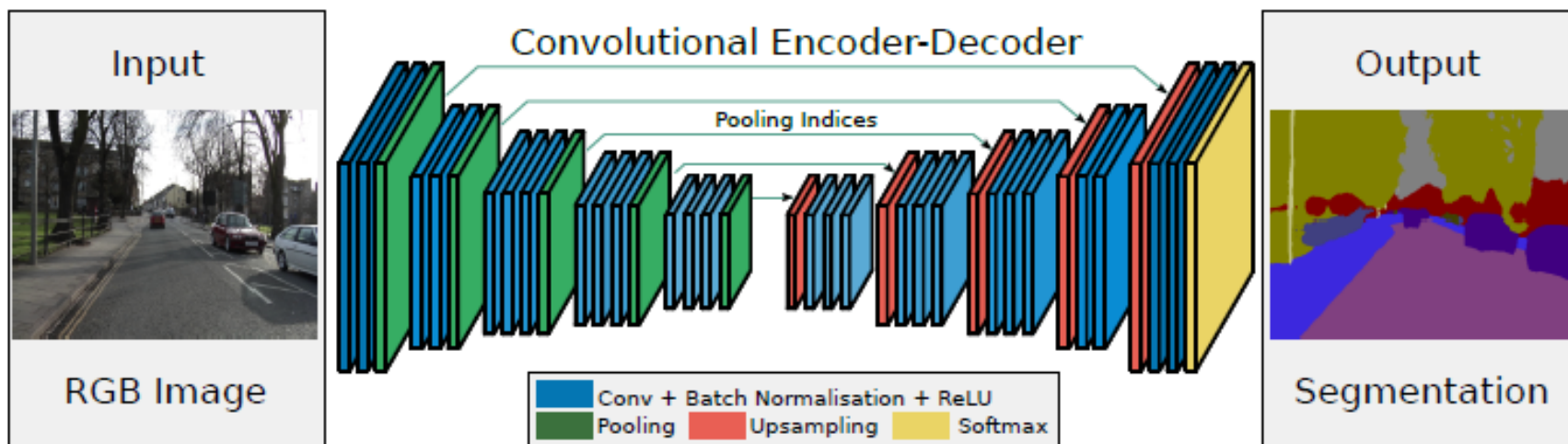
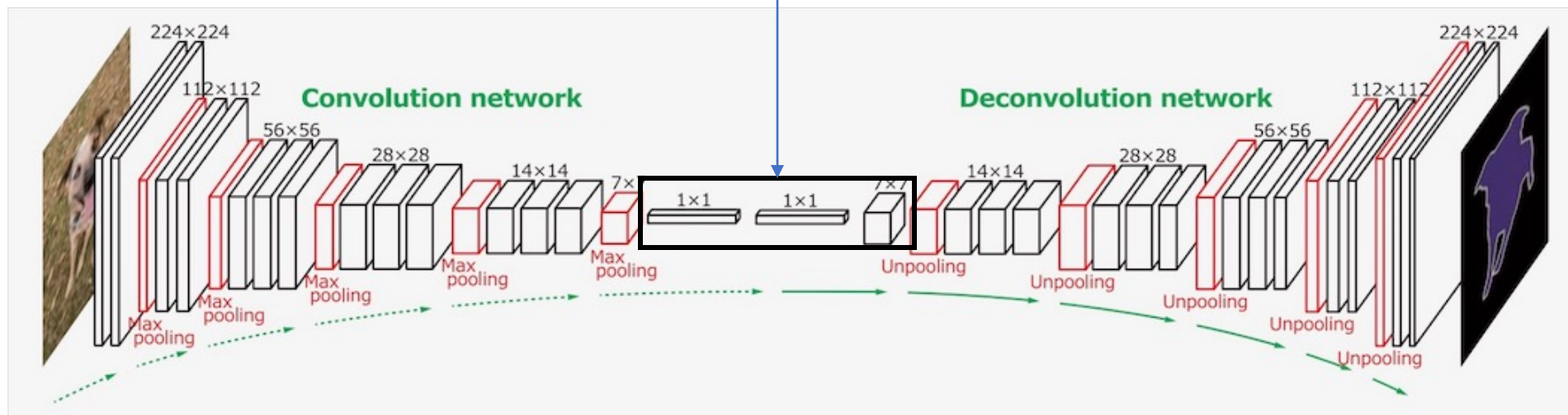
## Results





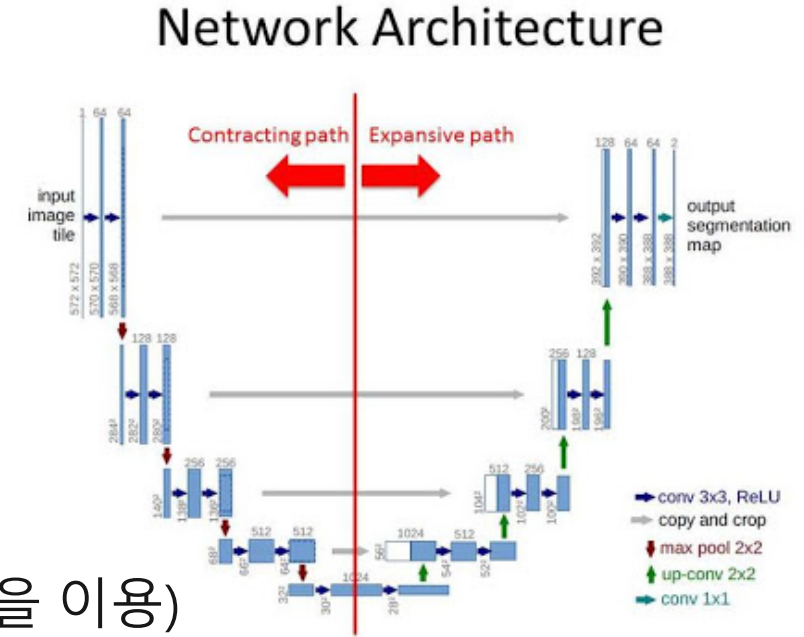
## DeconvNet vs SegNet

Fully Connected Layer의 존재  
-> Memory와 속도의 차이가 발생



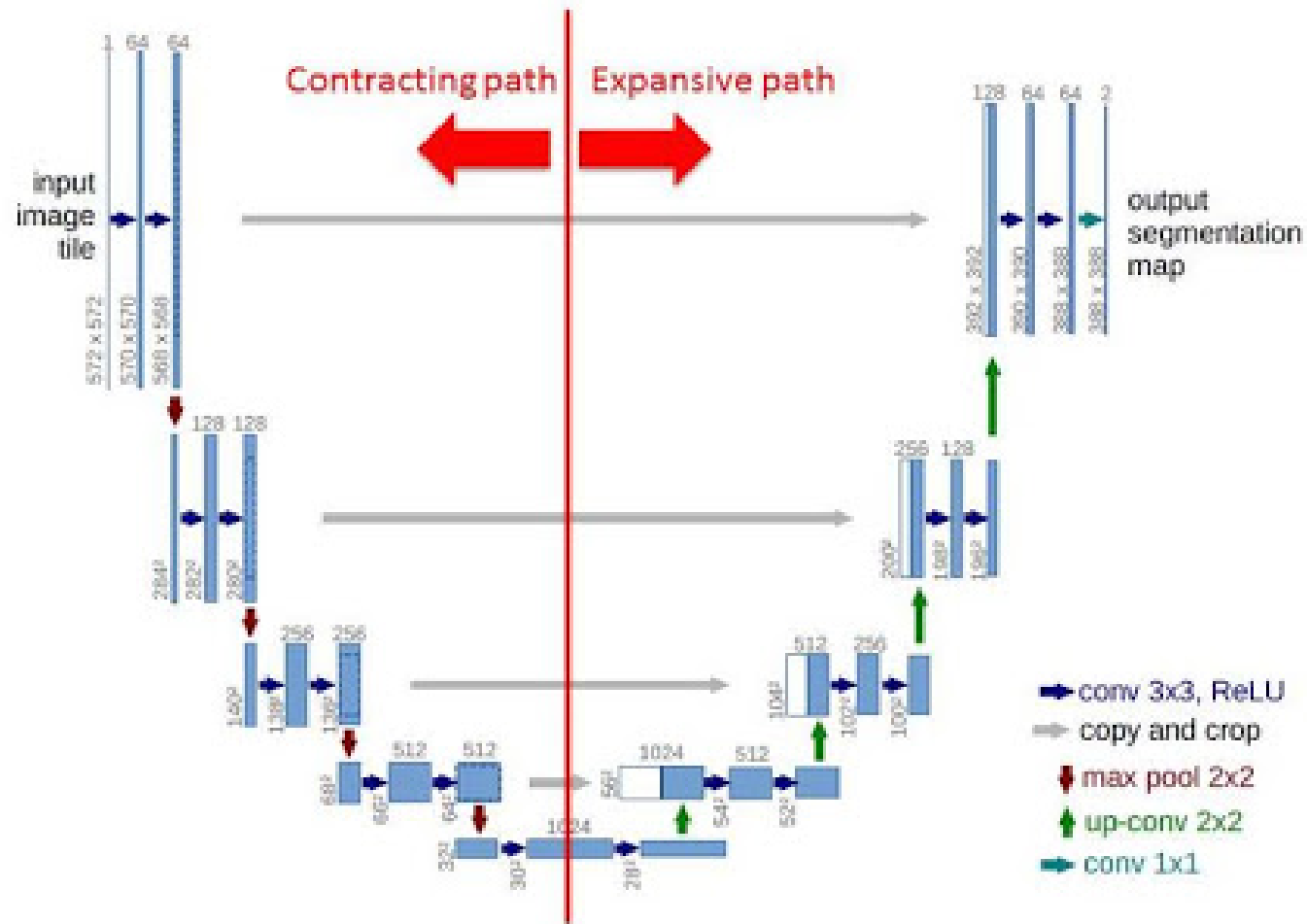
## ✓ SegNet vs UNet

1. UNet은 Bio 이미지에서 주로 사용되는 방법
2. UNet은 Unpooling 방법을 사용하지 않음 (Convolution을 이용)
3. 기본적으로 네트워크가 더 많은 메모리를 사용





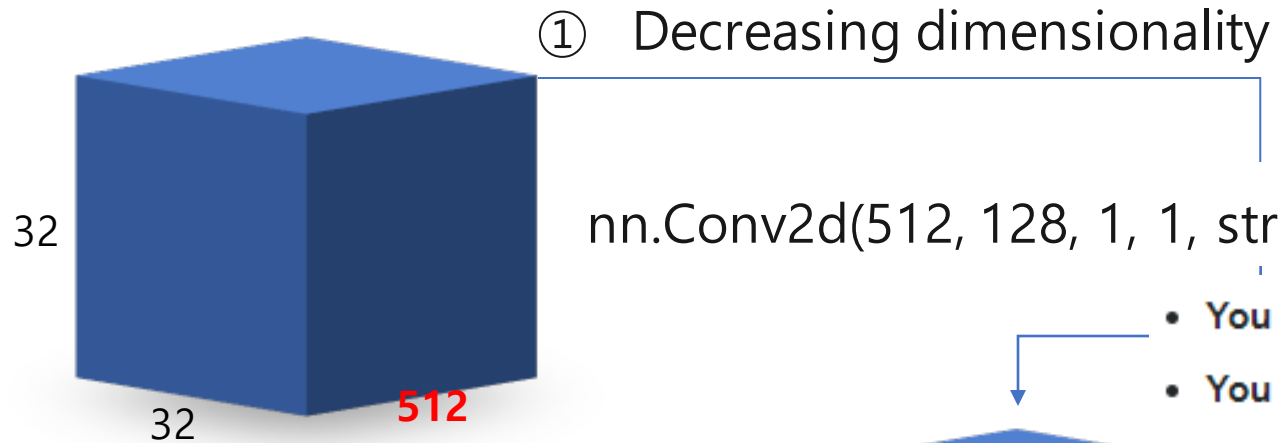
# Network Architecture



## 4

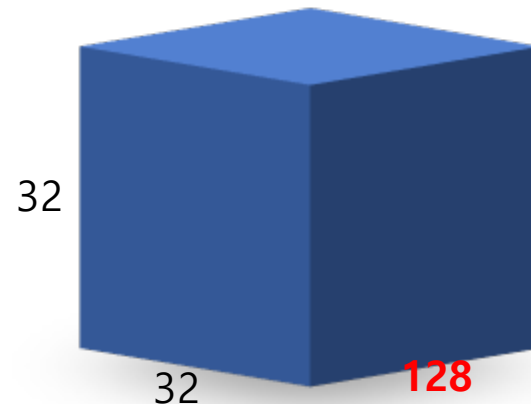
## Appendix

## ✓ 1x1 Convolution



```
nn.Conv2d(512, 128, 1, 1, stride=1, zero_padding=1)
```

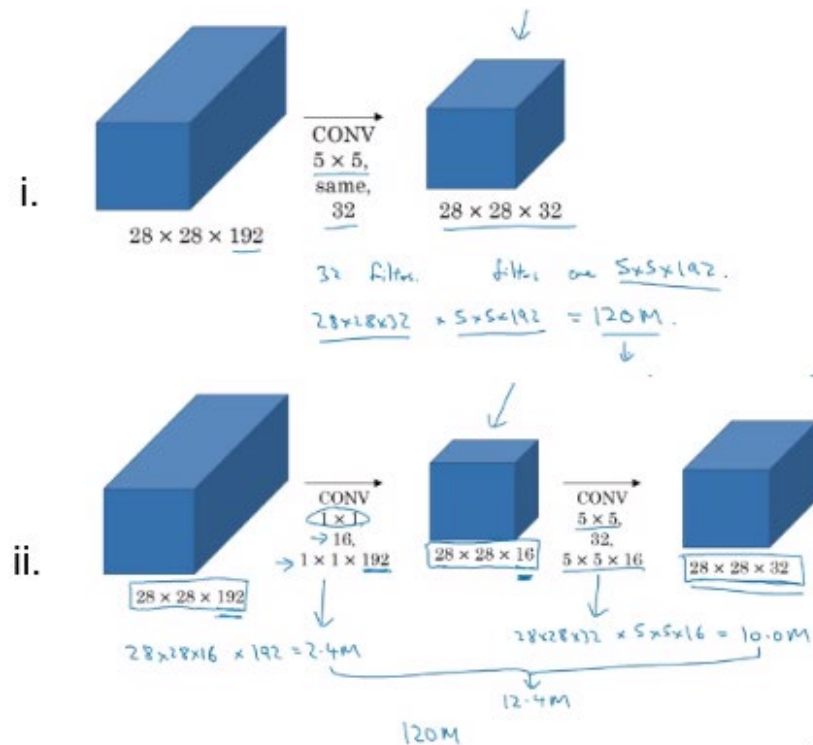
- You can use a 1x1 convolutional layer to reduce  $n_C$  but not  $n_H, n_W$ .
- You can use a pooling layer to reduce  $n_H, n_W$ , and  $n_C$ .



## ✓ 1x1 Convolution ② Reduce Number of Parameter -> More Faster

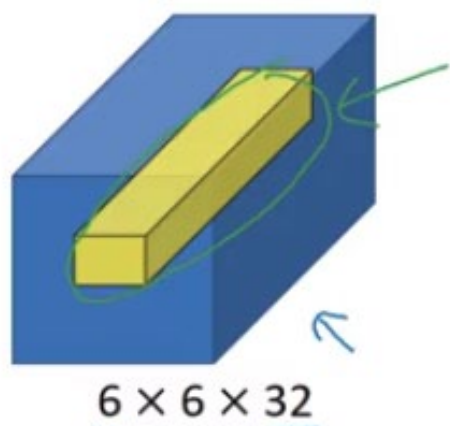
input (256 depth) -> 1x1 convolution (64 depth) -> 4x4 convolution (256 depth)

input (256 depth) -> 4x4 convolution (256 depth)

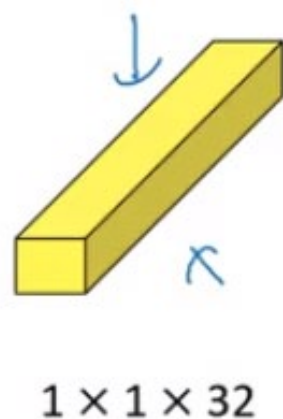


## ✓ 1x1 Convolution

③ Remember the position information



\*



=

ReLU

