



CS231n Lecture 11

- ☑ BOAZ 10기 박성현
- ☑ BOAZ 11기 김태희
- ☑ BOAZ 11기 홍지민
- ☑ BOAZ 10기 김용규

차이점 : 몇 개의 object를 잡아낼 수 있는지

Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Classification + Localization



CAT

Single Object

Object Detection



DOG, DOG, CAT

Multiple Object

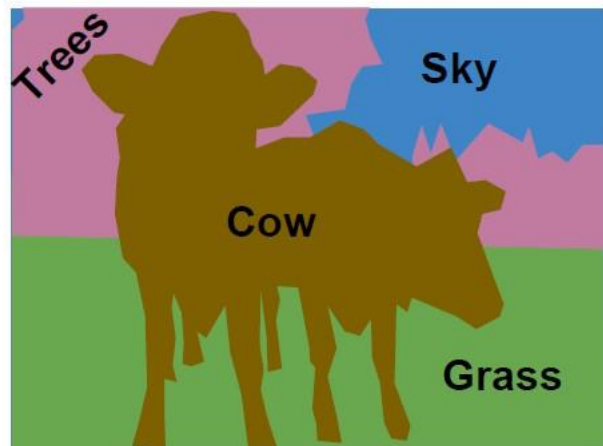
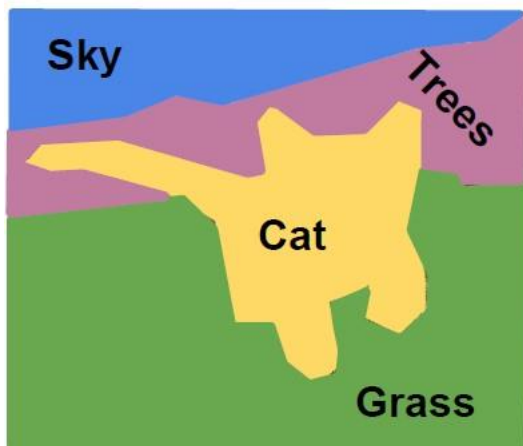
Instance Segmentation



DOG, DOG, CAT

This image is CC0 public domain



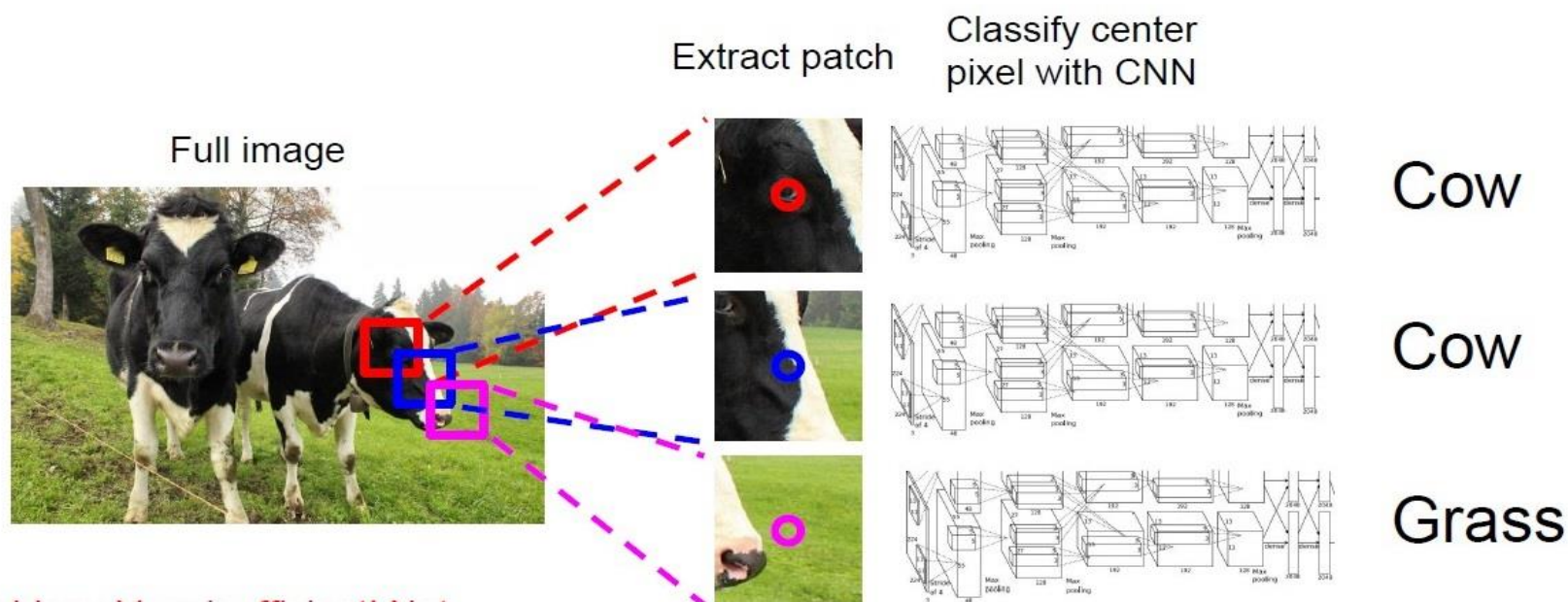


Classification : 하나의 사진 단위

Segmentation : 하나의 pixel 단위
Instance를 구분하는 게 아닌 pixel에 대해서
집중한다.



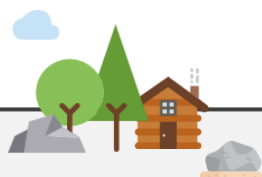
Semantic Segmentation Idea : Sliding Window



Problem: Very inefficient! Not reusing shared features between overlapping patches

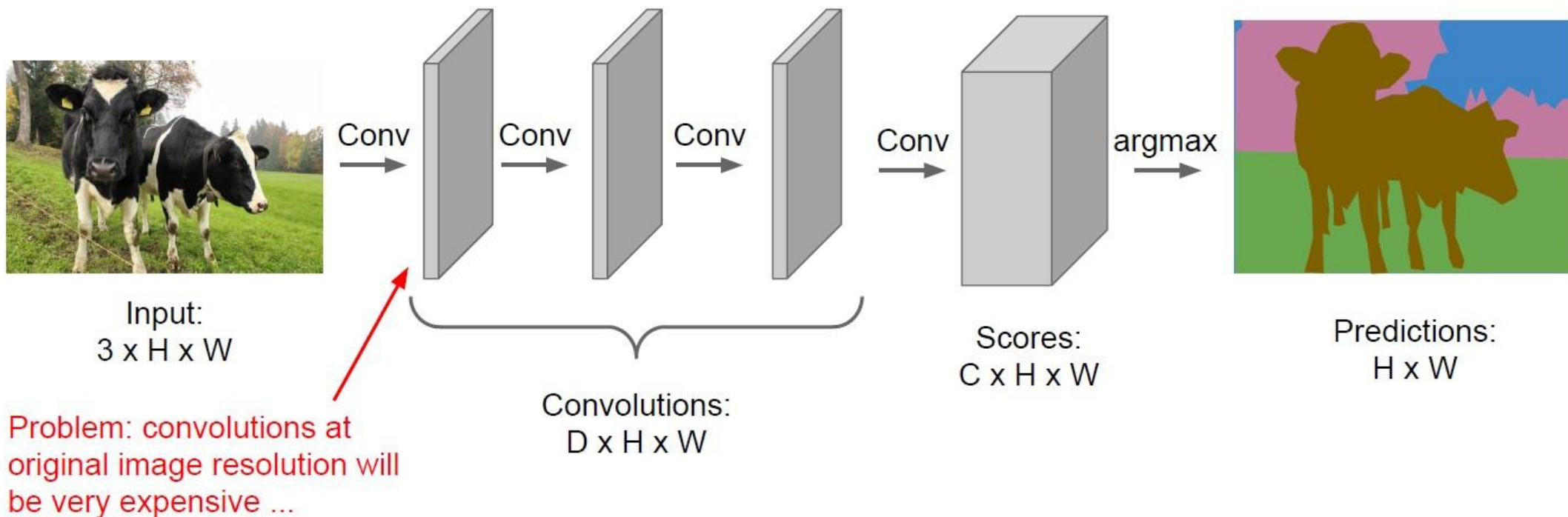
Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
 Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

1. 작은 patch들을 일일이 CNN의 input으로 사용하는 비효율성
2. 겹치는 patch들 사이에 shared feature를 재사용하지 않음



Semantic Segmentation Idea : Fully Convolutional

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!

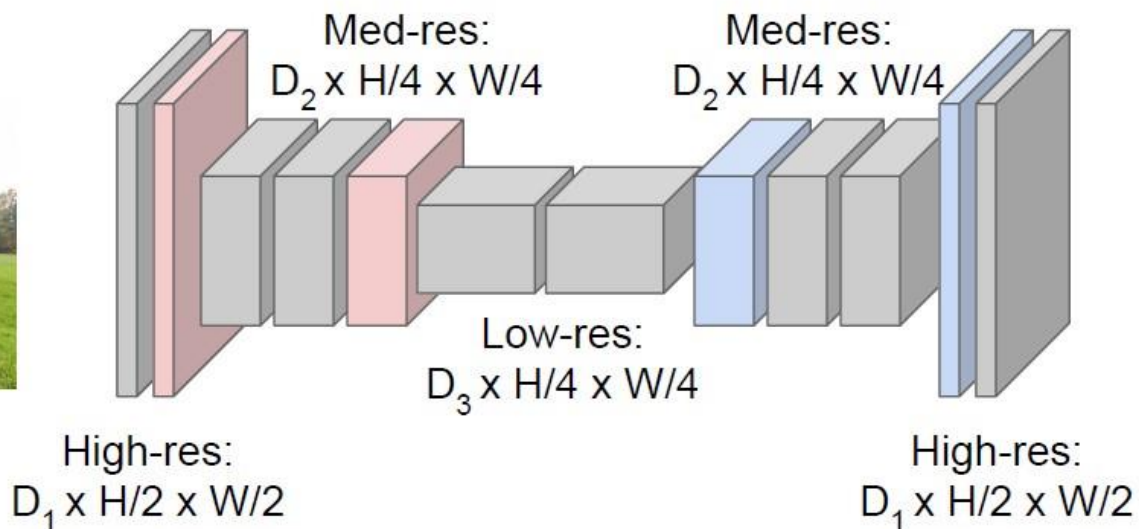


Semantic Segmentation Idea : Fully Convolutional

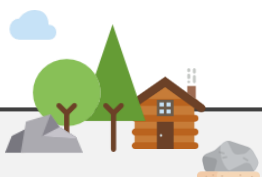
Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



Input:
 $3 \times H \times W$



Predictions:
 $H \times W$



In-Network upsampling : “Unpooling”

Nearest Neighbor

1	2
3	4



1	1	2	2
1	1	2	2
3	3	4	4
3	3	4	4

Input: 2 x 2

Output: 4 x 4

Nearest Neighbor
: 주변 값들을 모두 같은 수로 변경

“Bed of Nails”

1	2
3	4

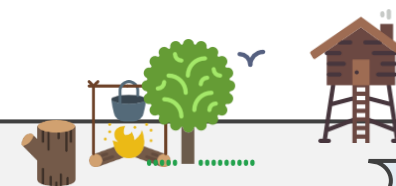


1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

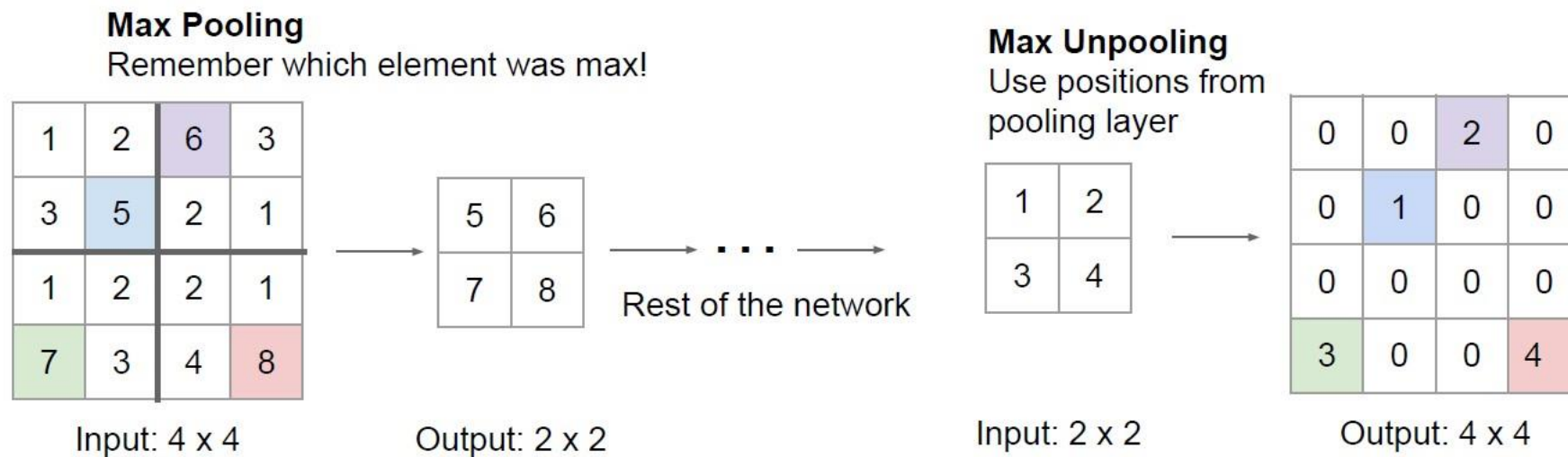
Input: 2 x 2

Output: 4 x 4

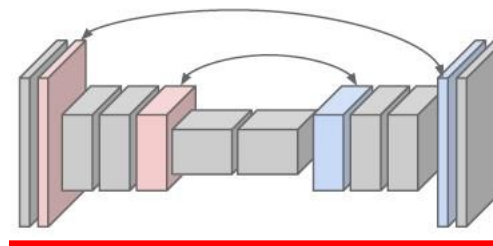
Bed of Nails
: 맨 왼쪽, 맨 위의 값만을 채움



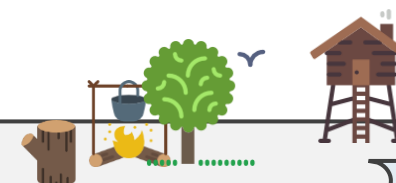
In-Network upsampling : “Max Unpooling”



Corresponding pairs of
downsampling and
upsampling layers



이전에 Max Pooling 자리를 기억
이를 이용해서 Max Unpooling

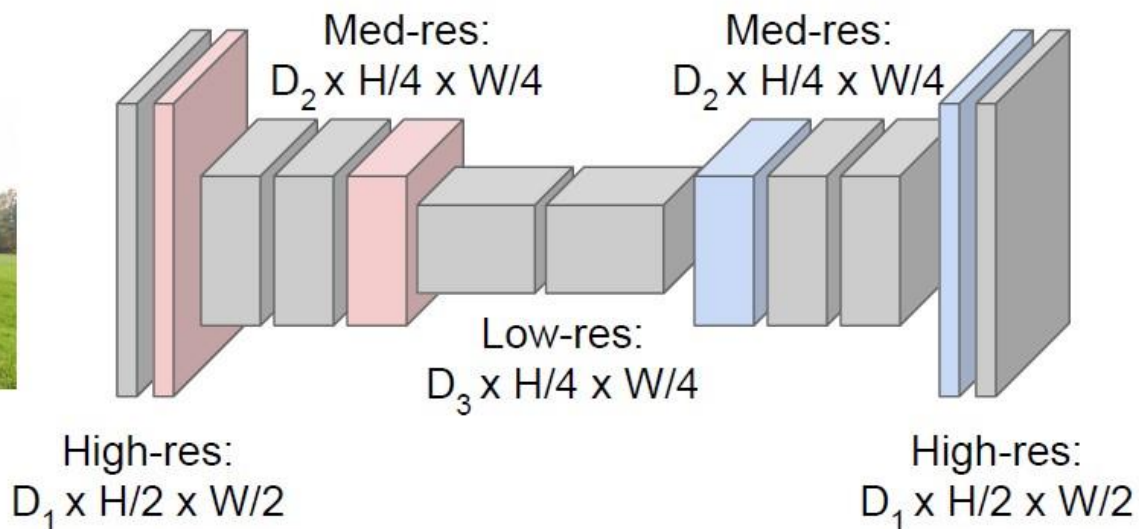


Semantic Segmentation Idea : Fully Convolutional

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



Input:
 $3 \times H \times W$

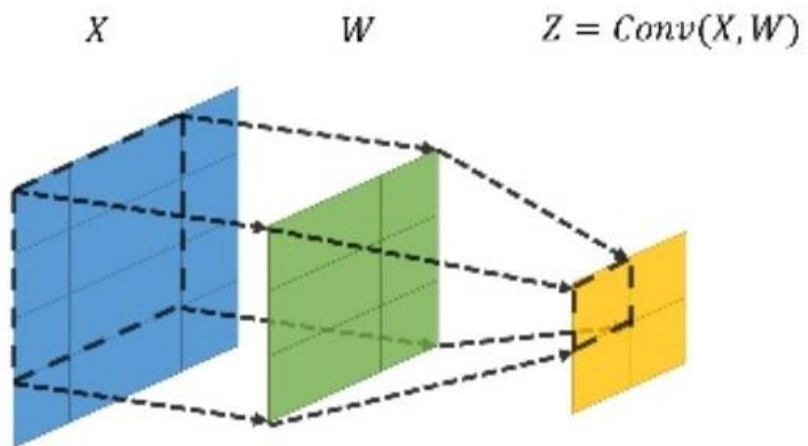


Predictions:
 $H \times W$



Convolution vs Transpose Convolution

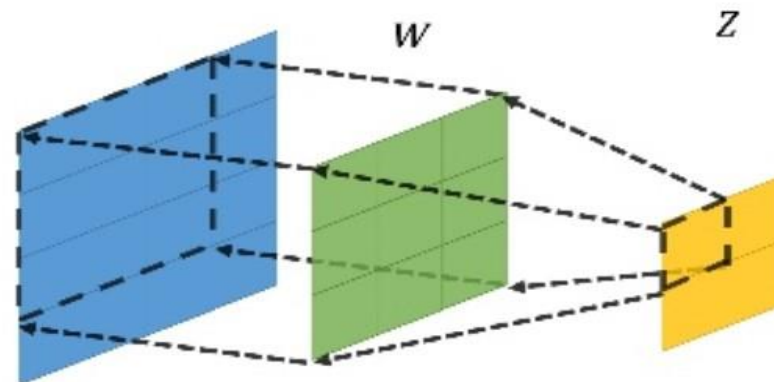
Convolution Network



X : image
 W : filter
 Z : feature

Transpose Convolution Network

$$X = \text{TransConv}(Z, W)$$



X : feature
 W : filter
 Z : input

Transpose convolution filter 또한 convolution filter의 특징을 가지고 있다.



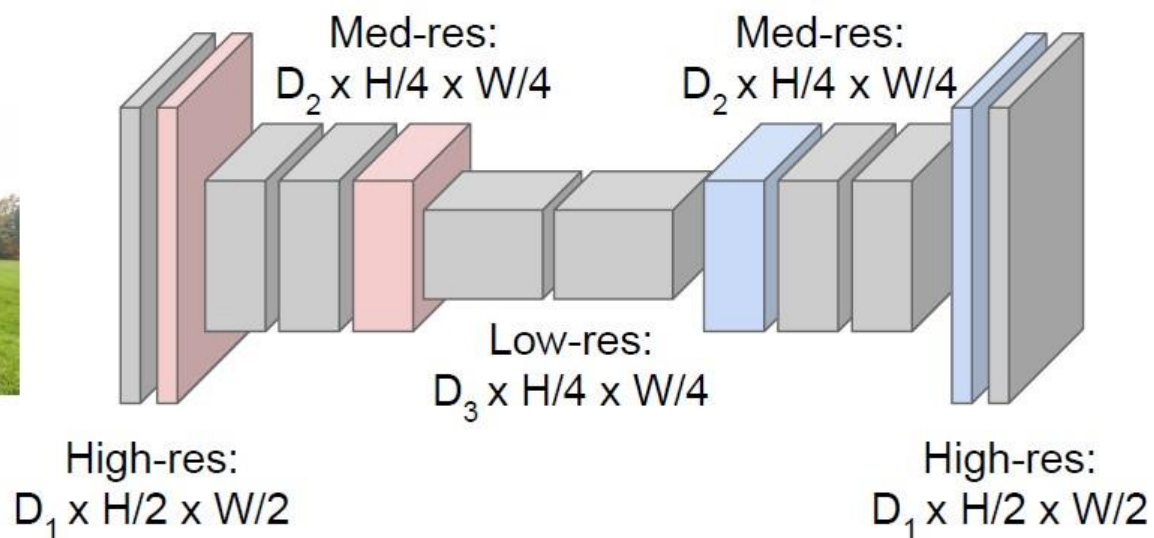
Semantic Segmentation Idea : Fully Convolutional

Downsampling:
Pooling, strided
convolution



Input:
 $3 \times H \times W$

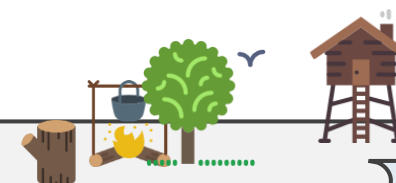
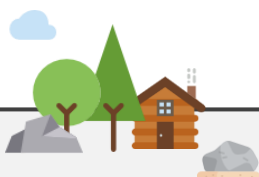
Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



Upsampling:
Unpooling or strided
transpose convolution

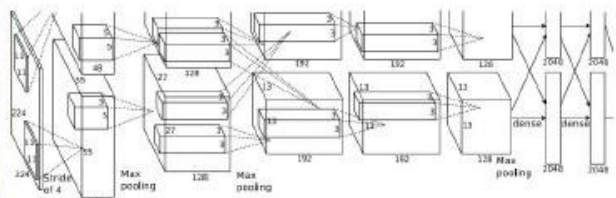


Predictions:
 $H \times W$





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Fully
Connected:
4096 to 1000

Class Scores

Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label:

Cat

**Softmax
Loss**

Multitask Loss

+

Loss

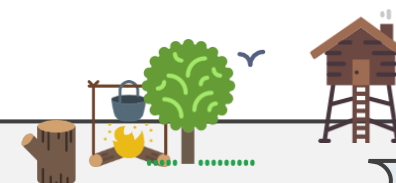
Vector:
4096
Fully
Connected:
4096 to 4

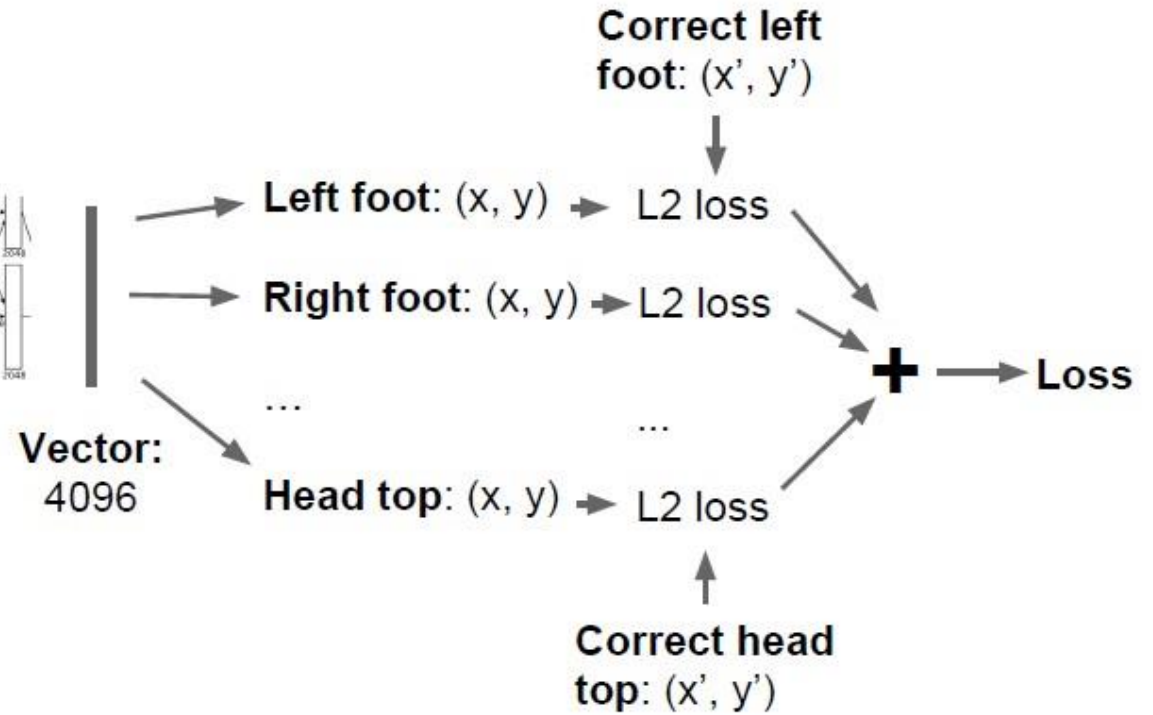
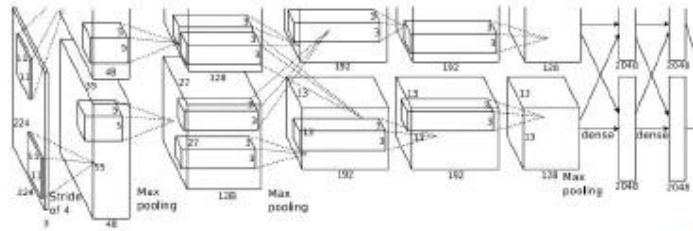
**Box
Coordinates**
(x, y, w, h)

L2 Loss

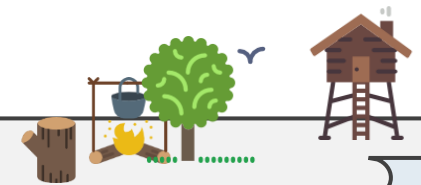
Correct box:
(x', y', w', h')

Treat localization as a
regression problem!





Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014



CS231n : <http://cs231n.stanford.edu/syllabus.html>

website : <https://www.slideshare.net/ssuserb208cc1/transposed-convolution>

