NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas

Department : E & ECE, IIT Kharagpur

Topic

Lecture 51: Face Recognition

CONCEPTS COVERED

Concepts Covered:

- ❑ Face Recognition System
- ❑ One shot learning
- ❑ FaceNet
- ❑ Triplet Loss
- ❑ Triplet Selection

Face Recognition System

Face recognition system has become a integral part of our modern day to day life. Various application of face recognition system are:

- Payments
- Access and security
- Criminal identification
- Advertising
- Healthcare

Face Recognition System

Challenges:

- Different illumination condition.
- Different Pose and orientation of image.
- Other variational conditions.
- Limited Dataset for training.

Image Source: Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 815-823. 2015.

One Shot learning

- One-shot learning is an object categorization problem, found mostly in computer vision.
- Most machine learning based object categorization algorithms require training on hundreds or thousands of samples/images and very large datasets,
- One-shot learning aims to learn information about object categories from one, or only a few, training samples/images.

One Shot learning

Face Recognition as a One shot Learning:

- ❑ Consider a facial recognition system which is used by a small organization for security purpose.
- ❑ It has one image of every person working in that company.
- ❑ The network needs to be train using those few images,
- ❑ It can identify a person who is not working in the company and also the verify who is working currently in the company.
- ❑ This problem becomes one shot or few shot learning problem.

FaceNet

FaceNet learns a embedding function $f(x)$; $\|f(x)\|_2 = 1)$

$$f: x \in R^{M \times N} \to R^d; \quad d < M \times N$$

Take two images x_i and x_j

$$\|f(x_i) - f(x_j)\|^2$$

Small if x_i and x_j are same person

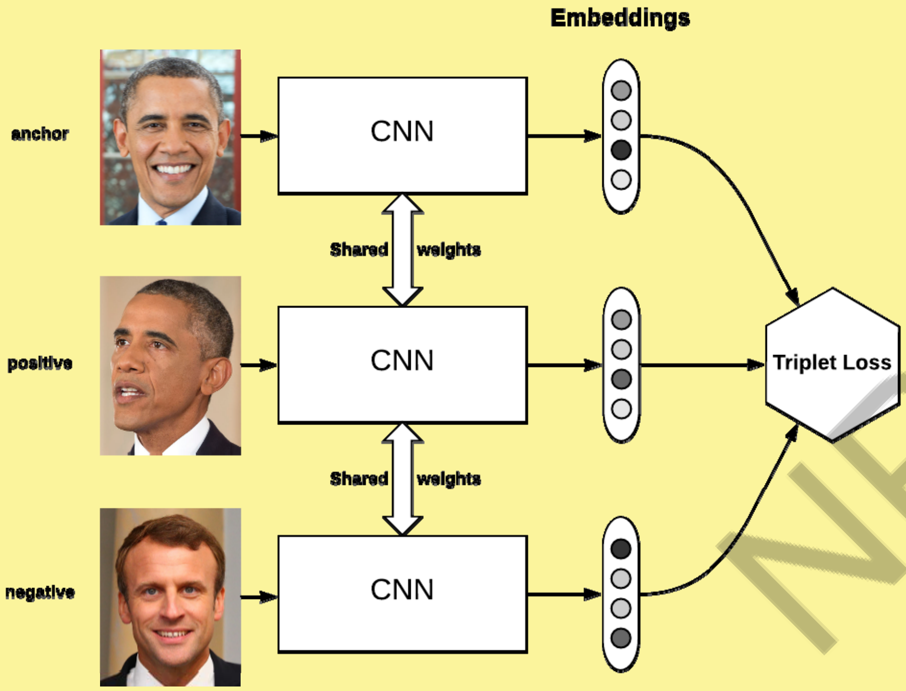
Large otherwise

FaceNet

- FaceNet uses a deep CNN model to learn the embedding function $f(x)$.
- It consists of a batch input layer and a deep CNN
- Followed by L2 normalization, which results in the face embedding.

Image Source: Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 815-823. 2015.

Training/Triplet Loss



- Minimize **triplet loss function** :-loss function using **three** images
- An anchor image A, a positive image P (same person as the anchor), and a negative image N (different person than the anchor).
- Distance d(f(A), f(P)) must be less than or equal to the distance d(f(A), f(N))

Image Source: https://omoindrot.github.io/triplet-loss

Triplet Loss

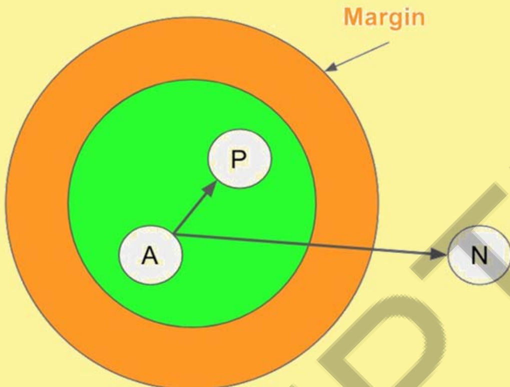
Desired:- $\|f(x^a) - f(x^p)\|_2^2 < \|f(x^a) - f(x^n)\|_2^2$

The problem:

- The model can learn to make the same encoding for different images of the same person.
- That makes $\|f(x^a) - f(x^p)\|_2 = 0$
- Unfortunately, it will satisfy the triplet loss function.
- Model stops learning.
- Solution: add a margin α to always have a gap between A and P versus A and N.

Triplet Loss

Thus : $\|f(x^a) - f(x^p)\|_2^2 + \alpha < \|f(x^a) - f(x^n)\|_2^2$

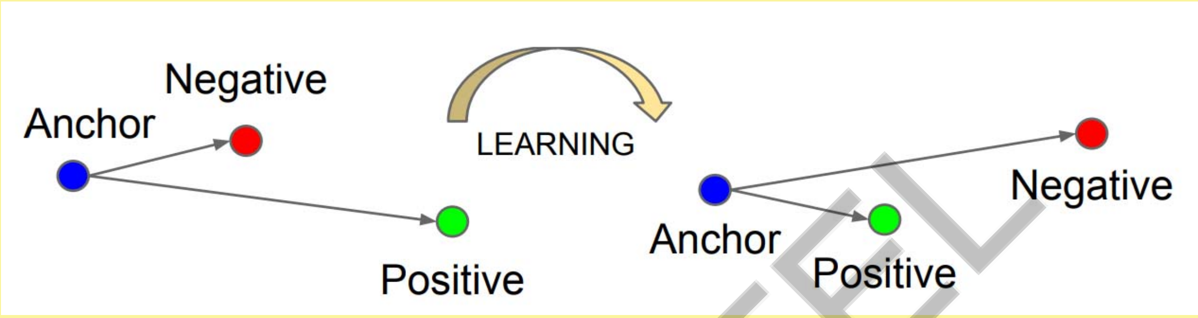


The loss that is being minimized is then

$$L = \sum_{i=1}^{N} [\|f(x^a) - f(x^p)\|_2^2 - \|f(x^a) - f(x^n)\|_2^2 + \alpha]$$

Image Source :https://medium.com/@ahmdtaha/facenet-a-unified-embedding-for-face-recognition-and-clustering-7d34abde9

Triplet Loss



- The Triplet Loss minimizes the distance between an anchor and a positive.
- Maximizes the distance between the anchor and a negative.
- Compact clusters of embedding of same person.
- Pictures of the same person become close to each other.
- Pictures of different persons are far from each other.

Image Source: Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 815-823. 2015.

Triplet Selection

- Selecting all possible triplets would result in many triplets that satisfy $\|f(x^a - x^p\|_2^2 + \alpha < \|f(x^a - x^n\|_2^2)$.
- These triplets would not contribute to the training and result in slower convergence, as they would still be passed through the network.
- It is crucial to select hard triplets, that are active and can therefore contribute to improving the model.

Image Source: https://omoindrot.github.io/triplet-loss

Triplet Selection

- In order to ensure fast convergence it is crucial to select triplets that violate the triplet constraint .
- This means that, given x_i^a , we want to select an x_i^p (hard positive) such that $argmax_{x_i^p} \left\| f(x_i^a) - f(x_i^p) \right\|_2^2$
- Similarly select x_i^n (hard negative) such that $argmin_{x_i^n} \| f(x_i^a) - f(x_i^n) \|_2^2$

Image Source: https://omoindrot.github.io/triplet-loss

Triplet Selection

- Selecting hardest negative may collapse the model: f(x)=0.
- Select semi-hard negative

$$\|f(x^a) - f(x^p)\|_2^2 < \|f(x^a) - f(x^n)\|_2^2$$

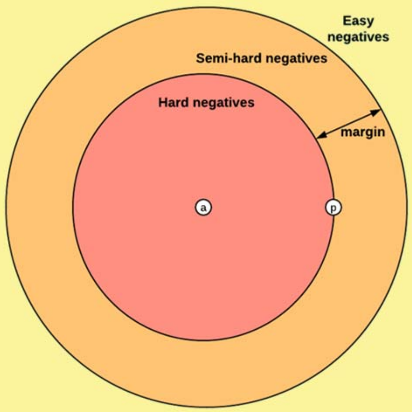


Image Source: https://omoindrot.github.io/triplet-loss

Face Verification

- Pass the reference image and the query image through the embedding network.
- Use the distance between them for verification.

$$d(reference, query) = \|f(refernce) - f(query)\|_2^2$$

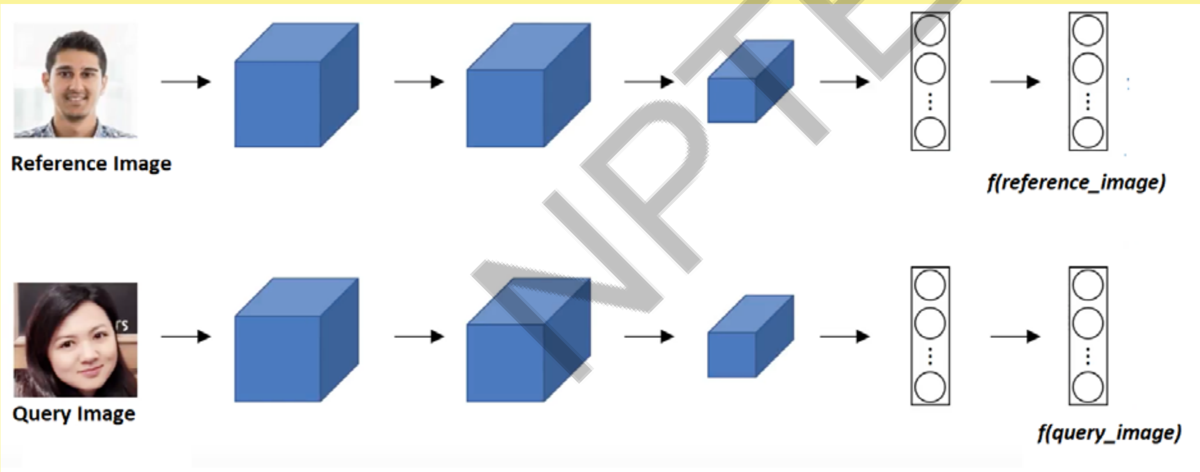


Image Source : https://www.coursera.org/learn/convolutional-neural-networks?specialization=deep-learning

References:

- Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 815-823. 2015.
- https://omoindrot.github.io/triplet-loss
- http://bamos.github.io/2016/01/19/openface-0.2.0/

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Topic

Lecture 52: Deconvolution/Upsampling

CONCEPTS COVERED

Concepts Covered:

- FaceNet
- Filtering/Semantic Segmentation
- Deconvolution
- Upsampling

Convolution/Deconvolution

X(0)	X(1)	X(2)
X(3)	X(4)	X(5)
X(6)	X(7)	X(B)

a	b	c
d	e	f
g	h	i

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Topic

Lecture 53: Semantic Segmentation

CONCEPTS COVERED

Concepts Covered:

- Deconvolution
- Upsampling
- Semantic Segmentation
- Fully Convolutional Network
- Deconvolutional Network

Image Segmentation

- Image segmentation is the task of partitioning an image into multiple Regions.
- Grouping pixels together on the basis of specific characteristic(s).
- Characteristics can often lead to different types of image segmentation, which we can divide into the following:

➢ Semantic Segmentation

➢ Instance Segmentation

Image Courtesy :
https://www.ntu.edu.sg/home/asjfcai/Benchmark_Website/benchmark_index.html

Semantic Segmentation

- Semantic segmentation refers to the process of linking each pixel in an image to a class label.
- We can think of semantic segmentation as image classification at a pixel level.
- In an image having many cars, segmentation will label all the objects as car objects.
- In the example image all the pixels belonging to different classes like; human, car, house and grass is labelled with different colours.

Image Courtesy : https://github.com/CSAILVision/semantic-segmentation-pytorch

Instance Segmentation

Instance segmentation includes identification of boundaries of the objects at the detailed pixel level. Following example shows the difference between semantic segmentation and instance segmentation.

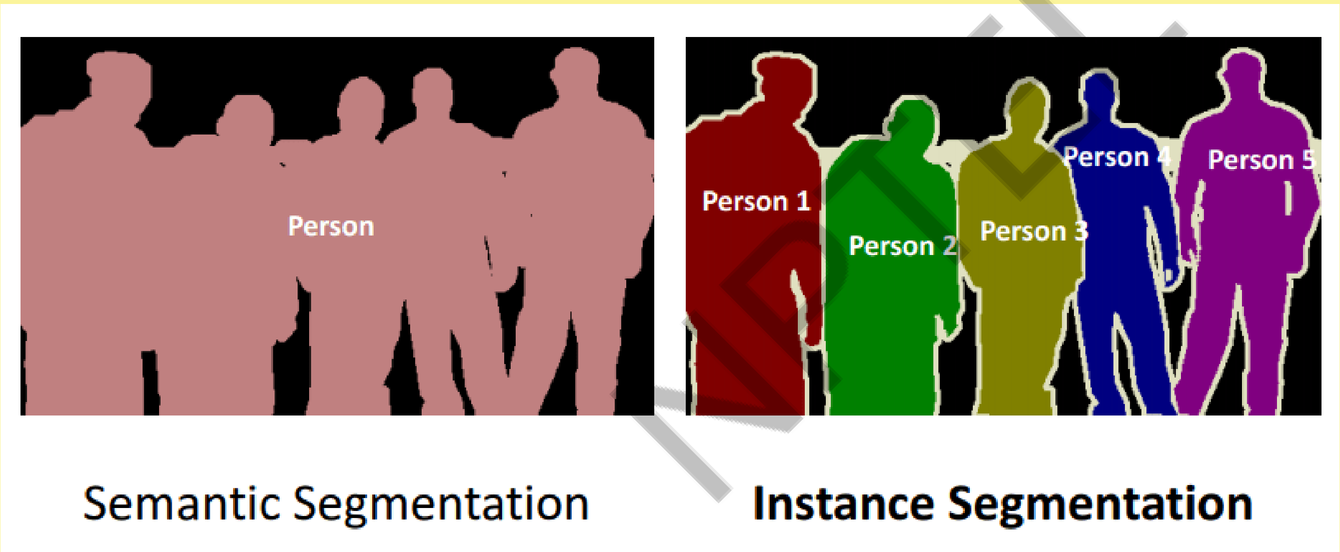
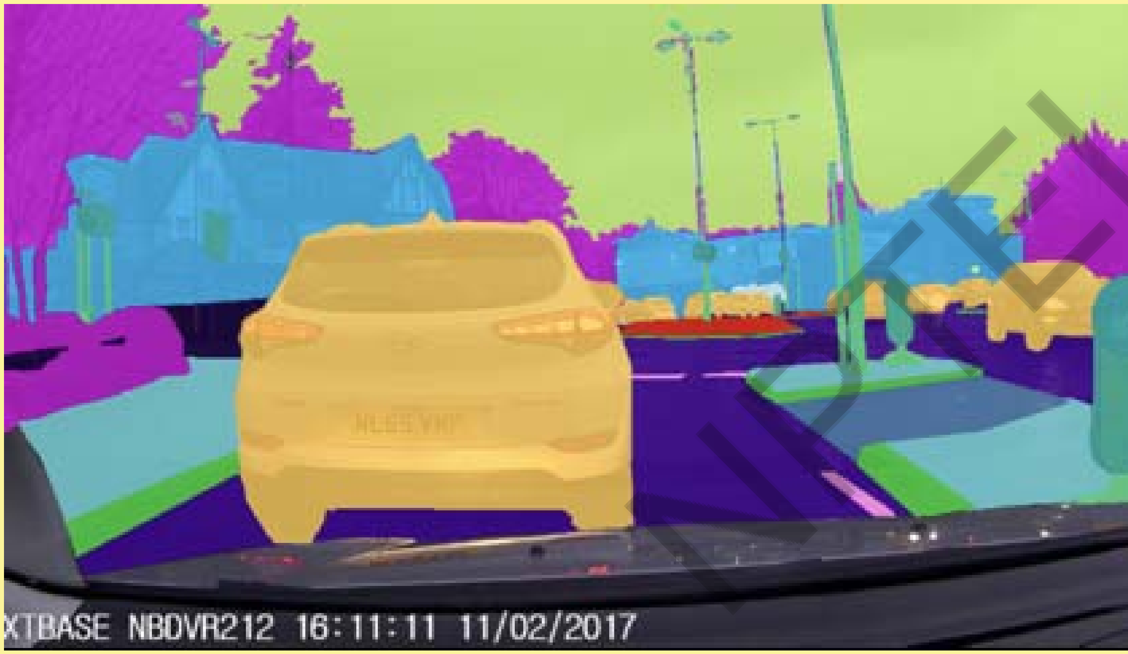


Image Source:
https://www.analyticsvidhya.com/blog/2019/02/tutorial-semantic-segmentation-google-deeplab/

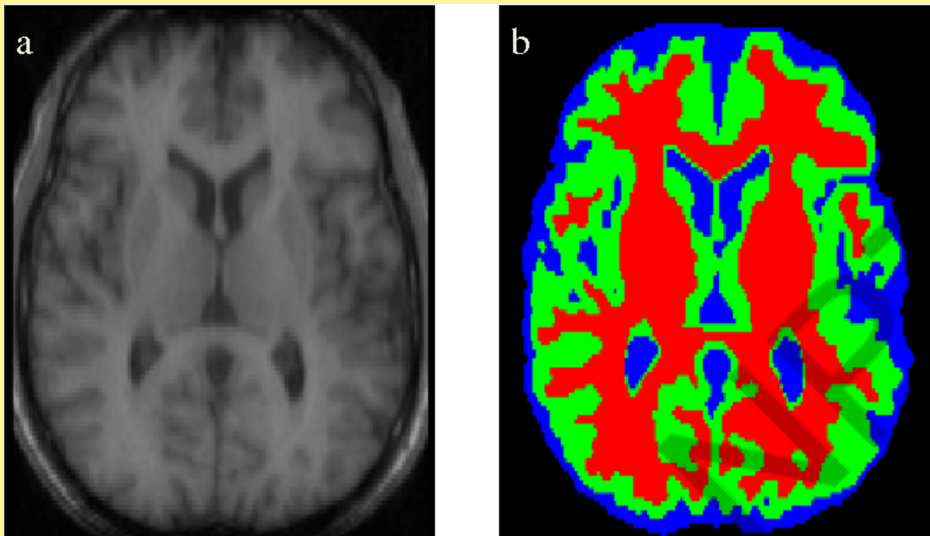
Use of Semantic Segmentation



For Autonomous driving

Image Source: https://blog.playment.io/semantic-segmentation/

Use of Semantic Segmentation



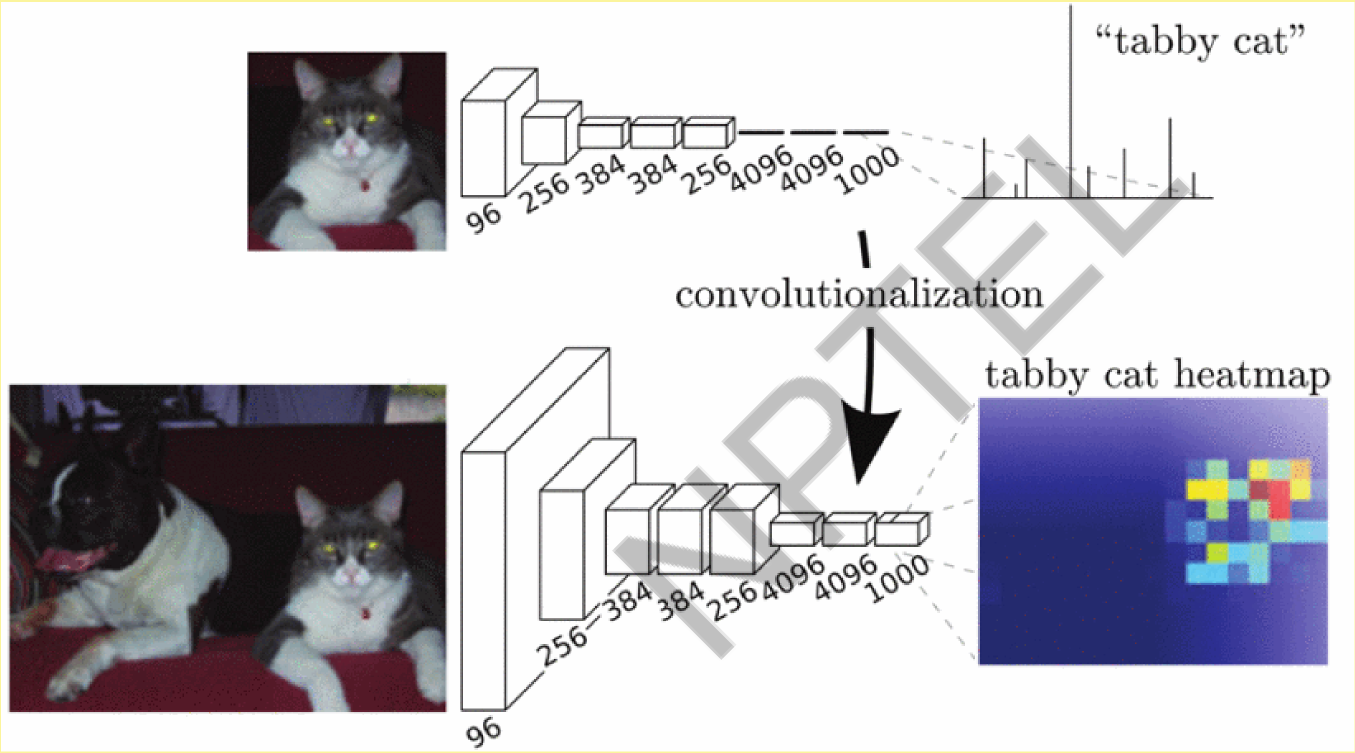
For Medical Applications

Segmentation of white matter, grey matter and Cerebrospinal fluid from brain MRI image.

Withey, Daniel J., and Zoltan J. Koles. "A review of medical image segmentation: methods and available software." *International Journal of Bioelectromagnetism* 10, no. 3 (2008): 125-148.

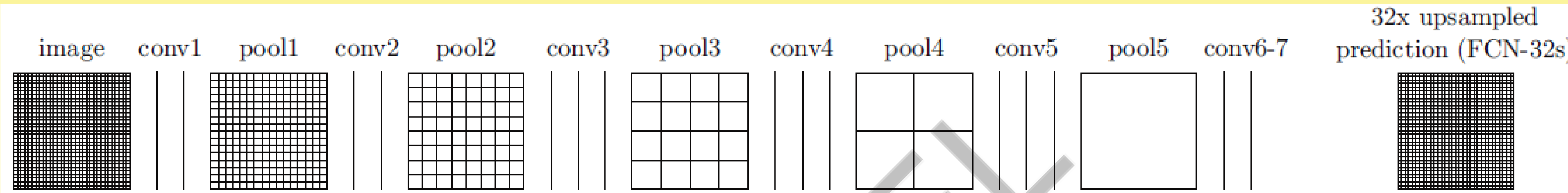
Fully Convolutional Network for Semantic Segmentation

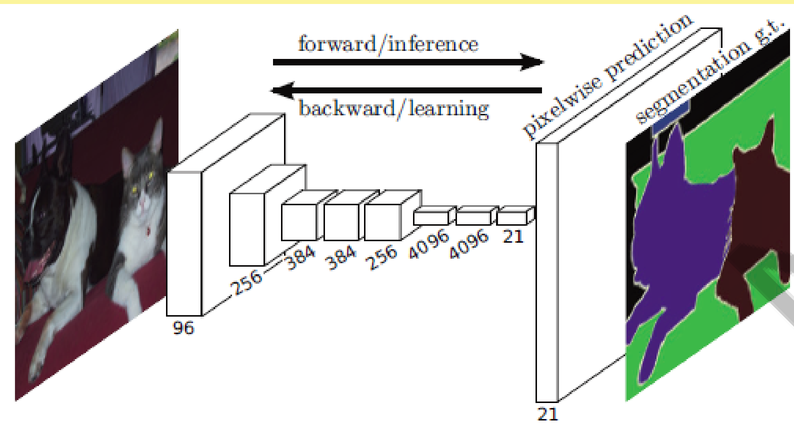
Fully Convolutional Network



Jonathan Long, Evan Shelhamer, Trevor Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Fully Convolutional Network

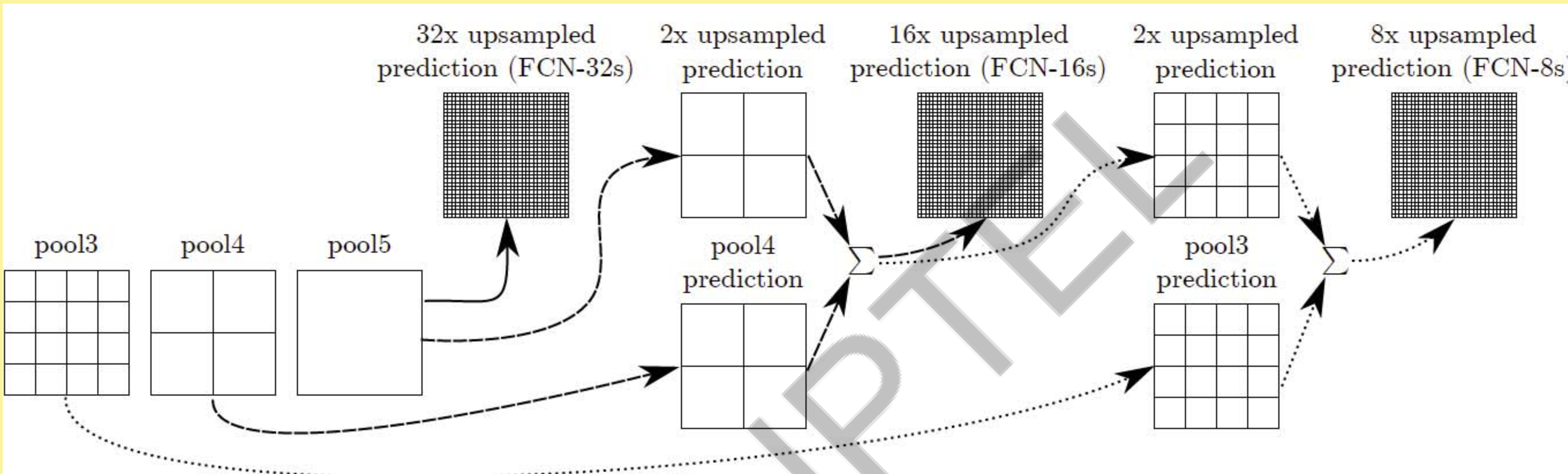




- After going through conv7 the output size 1/32.
- 32× upsampling is done to make the output have the same size of input image.
- But makes the output label map sparse.
- It is called **FCN-32s**.

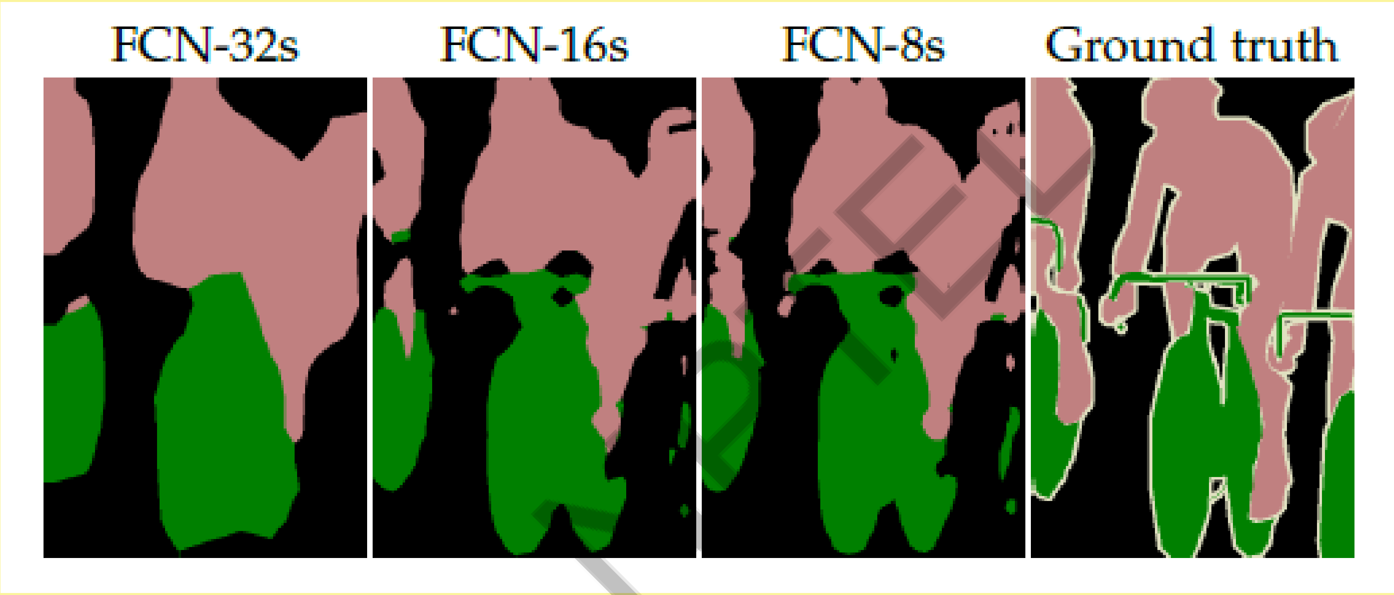
Jonathan Long, Evan Shelhamer, Trevor Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Fully Convolutional Network



Jonathan Long, Evan Shelhamer, Trevor Darrell,
"Fully Convolutional Networks for Semantic
Segmentation", CVPR 2015

Fully Convolutional Network



Jonathan Long, Evan Shelhamer, Trevor Darrell, “Fully Convolutional Networks for Semantic Segmentation”, CVPR 2015

References

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- http://cs231n.stanford.edu/
- Xu, Li, Jimmy SJ Ren, Ce Liu, and Jiaya Jia. "Deep convolutional neural network for image deconvolution." In *Advances in neural information processing systems*, pp. 1790-1798. 2014.
- Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3431-3440. 2015.
- Milletari, Fausto, Nassir Navab, and Seyed-Ahmad Ahmadi. "V-net: Fully convolutional neural networks for volumetric medical image segmentation." In *2016 Fourth International Conference on 3D Vision (3DV)*, pp. 565-571. IEEE, 2016.

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Topic

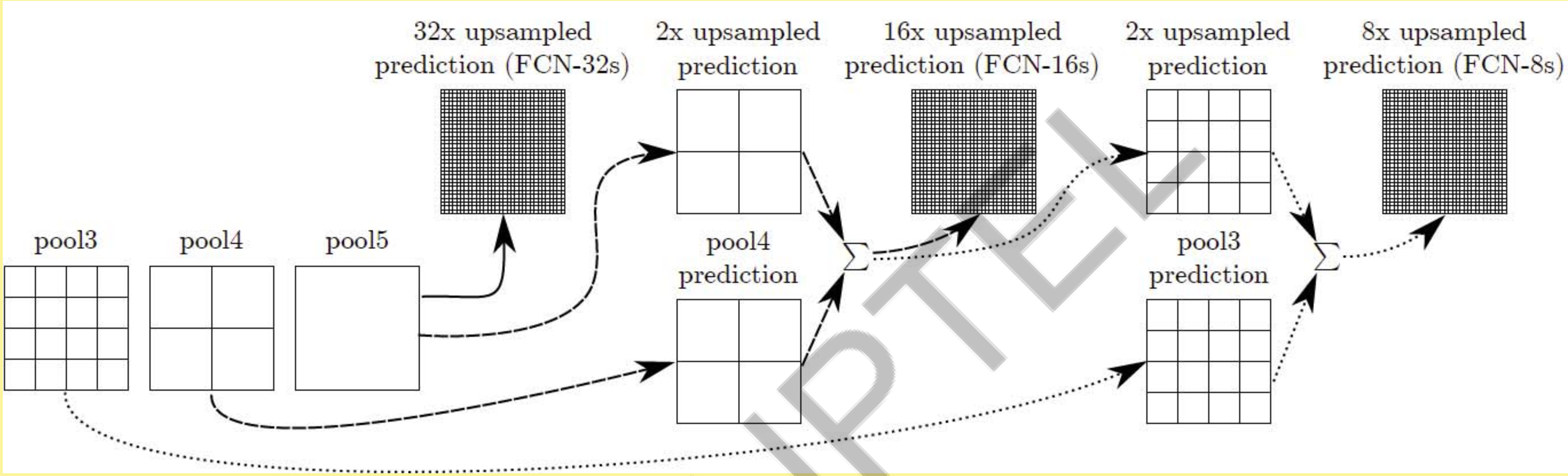
Lecture 54: Semantic Segmentation - II

CONCEPTS COVERED

Concepts Covered:

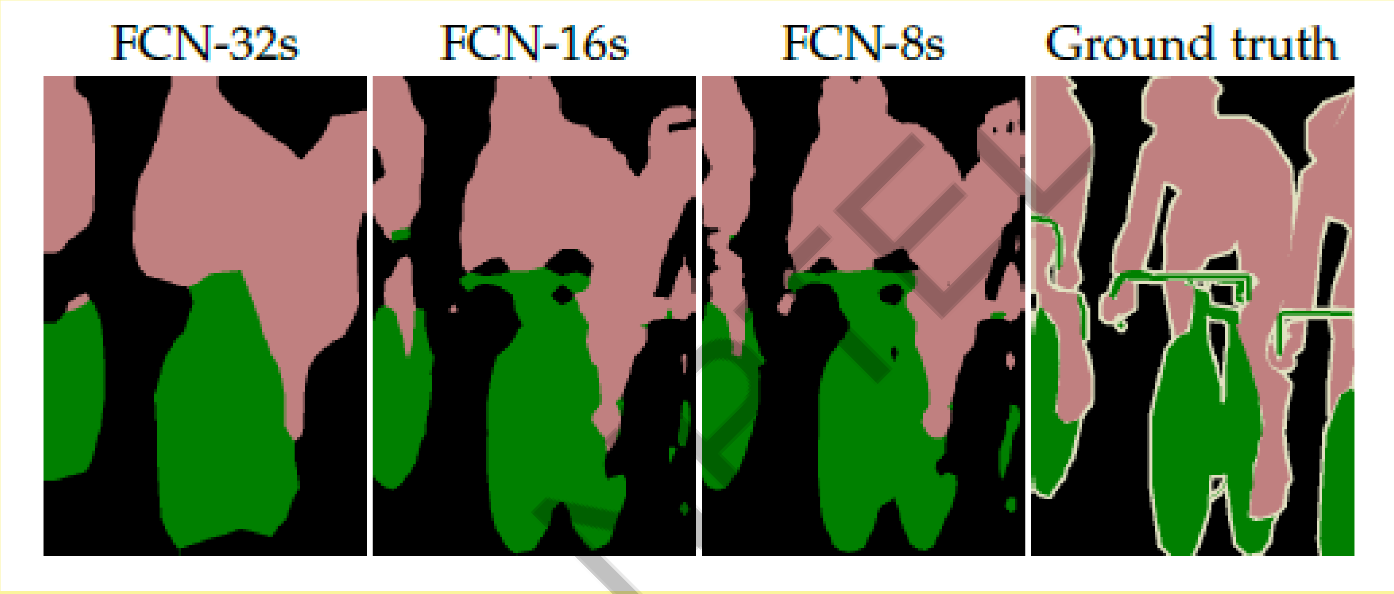
- ❑ Semantic Segmentation
- ❑ Fully Convolutional Network
- ❑ Deconvolutional Network

Fully Convolutional Network



Jonathan Long, Evan Shelhamer, Trevor Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Fully Convolutional Network



Jonathan Long, Evan Shelhamer, Trevor Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Deconvolution Network for Semantic Segmentation

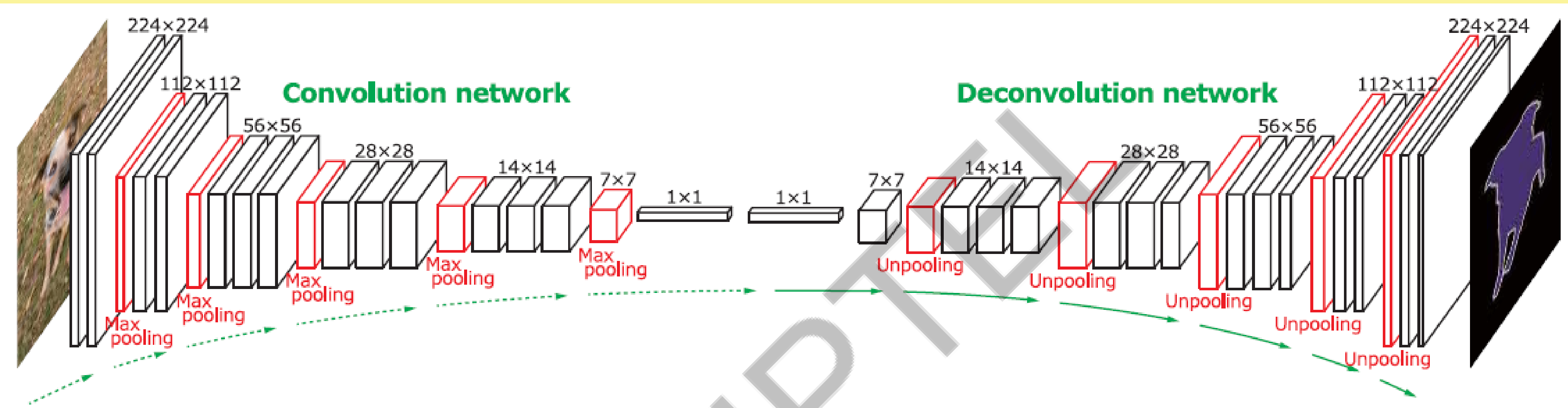
Deconvolution Network

(a) Inconsistent labels due to large object size

(b) Missing labels due to small object size

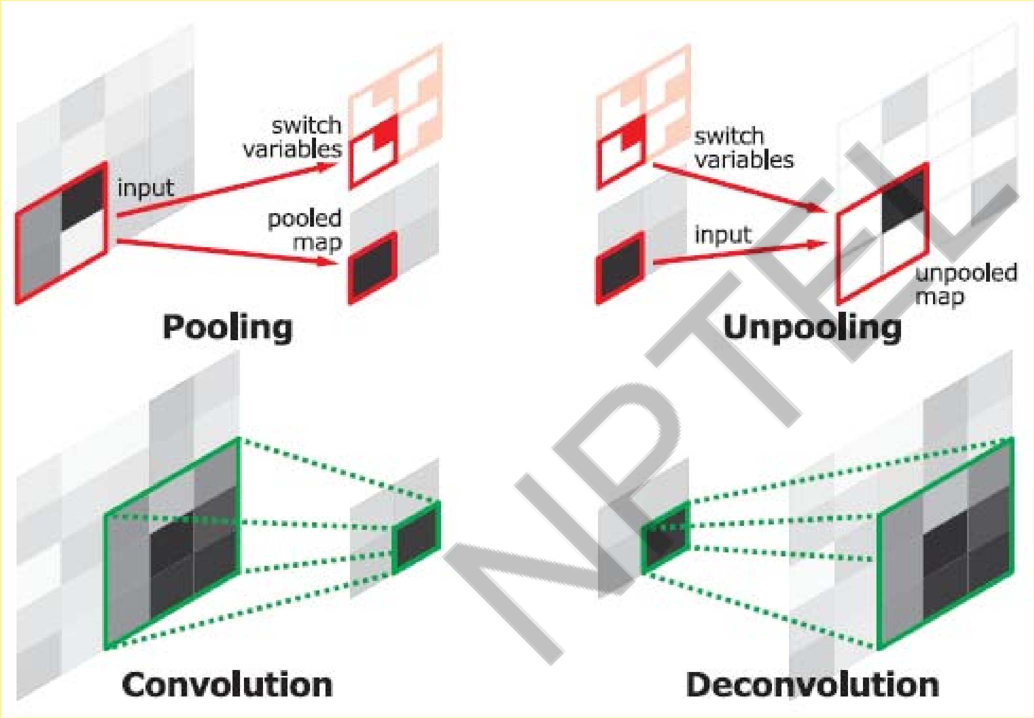
Hyeonwoo Noh, Seunghoon Hong, Bohyung Han, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Deconvolution Network



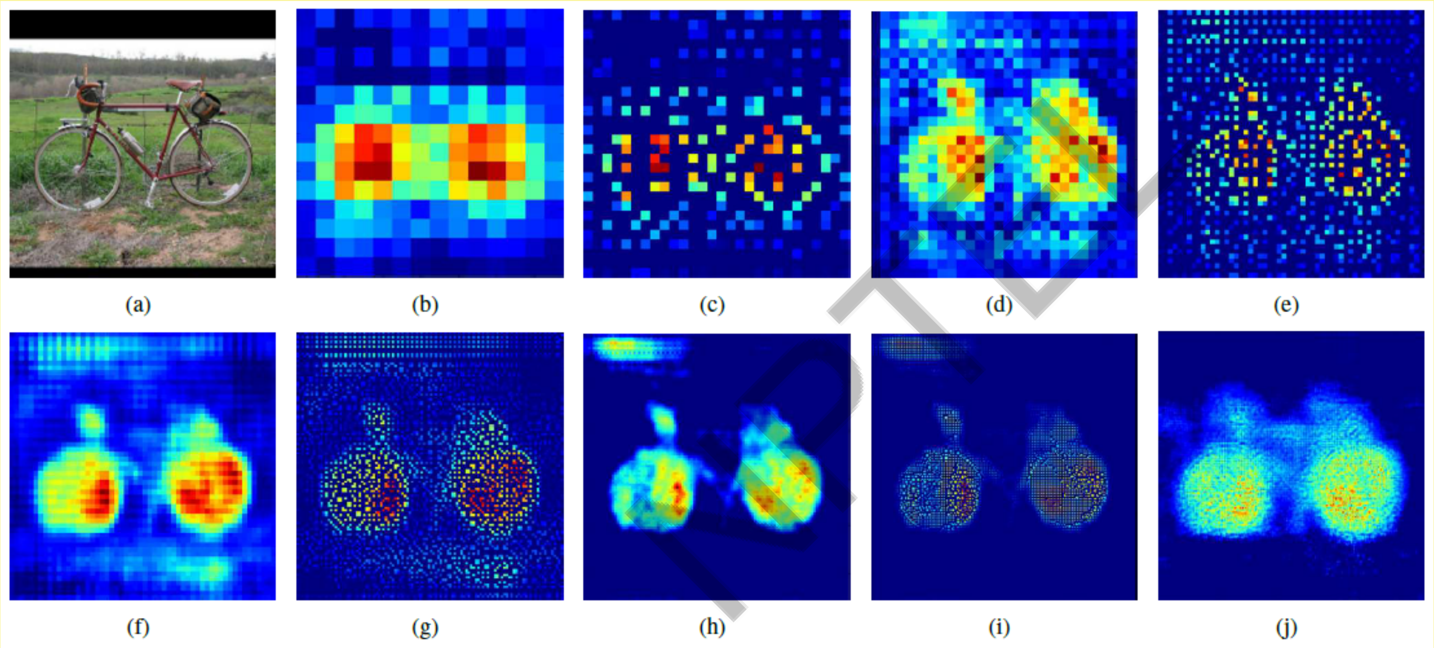
Hyeonwoo Noh, Seunghoon Hong, Bohyung Han, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Deconvolution/Upsampling



Hyeonwoo Noh, Seunghoon Hong, Bohyung Han, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

Deconvolution/Upsampling



Hyeonwoo Noh, Seunghoon Hong, Bohyung Han, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

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Topic

Lecture 55: Network Training for Semantic Segmentation

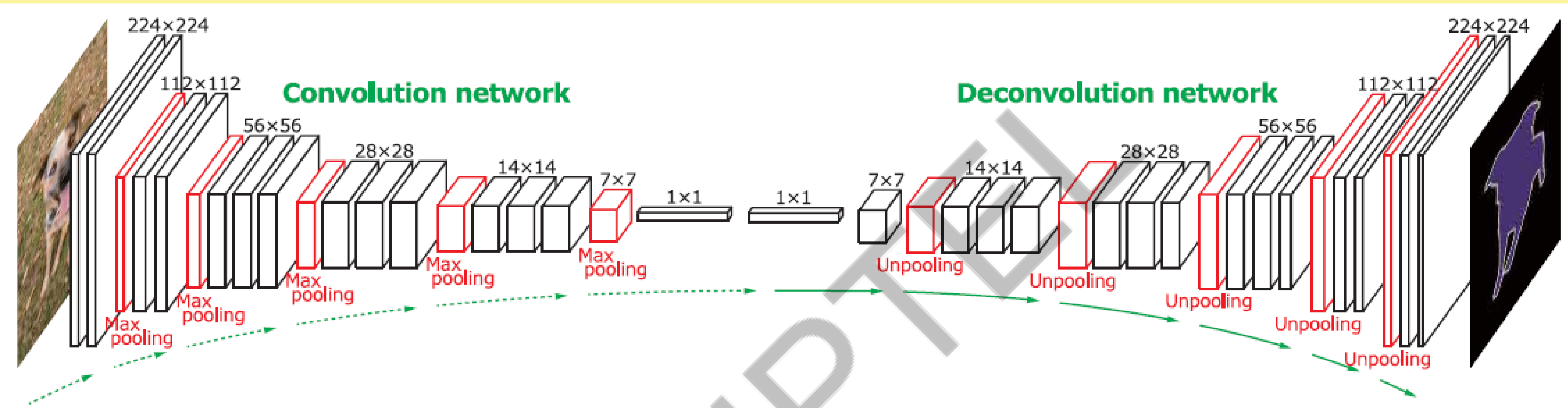
CONCEPTS COVERED

Concepts Covered:

- ❑ Semantic Segmentation
- ❑ Fully Convolutional Network
- ❑ Deconvolutional Network
- ❑ Network Training
- ❑ Cross Entropy Loss
- ❑ Dice Loss

Network Training for Semantic Segmentation

Deconvolution Network



Hyeonwoo Noh, Seunghoon Hong, Bohyung Han, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

Fully Convolutional Network

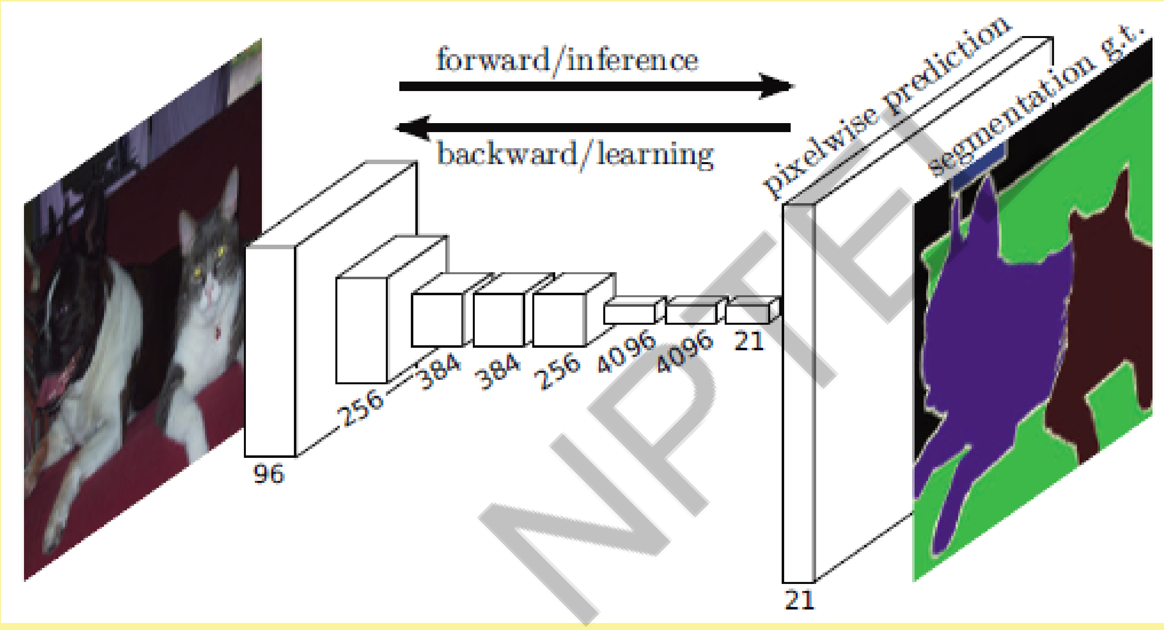


Image Source: Jonathan Long, Evan Shelhamer, Trevor Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Training Ground Truth

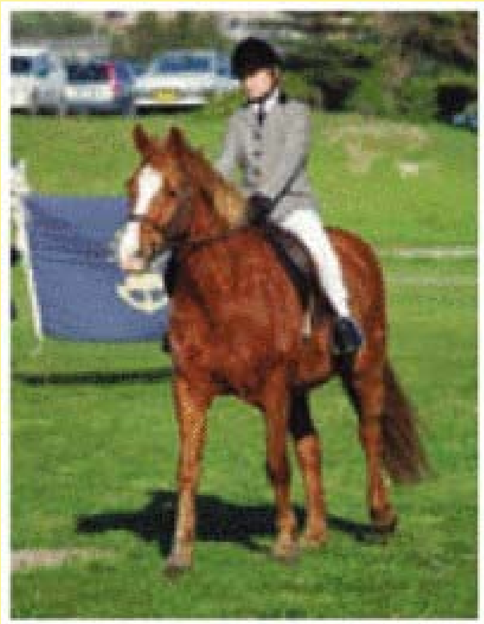
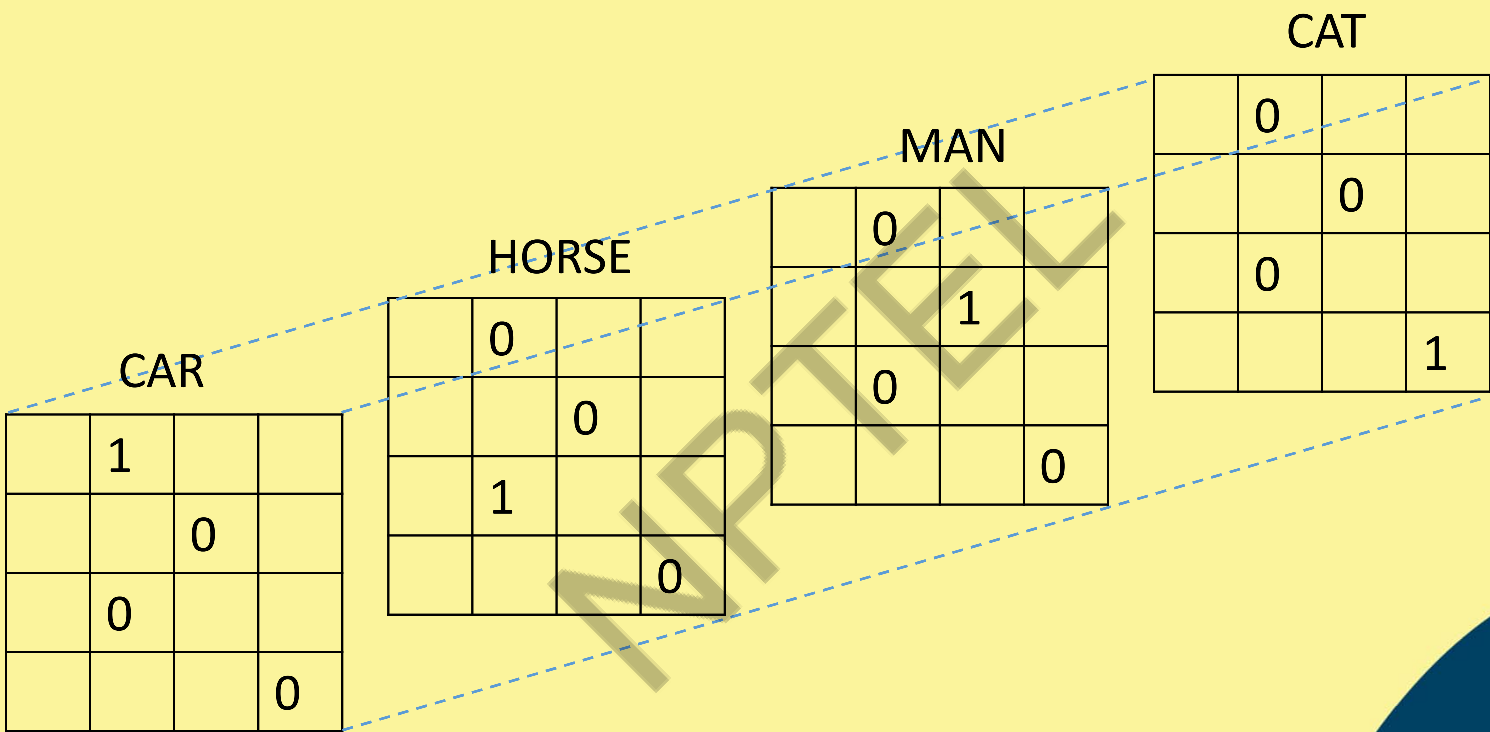
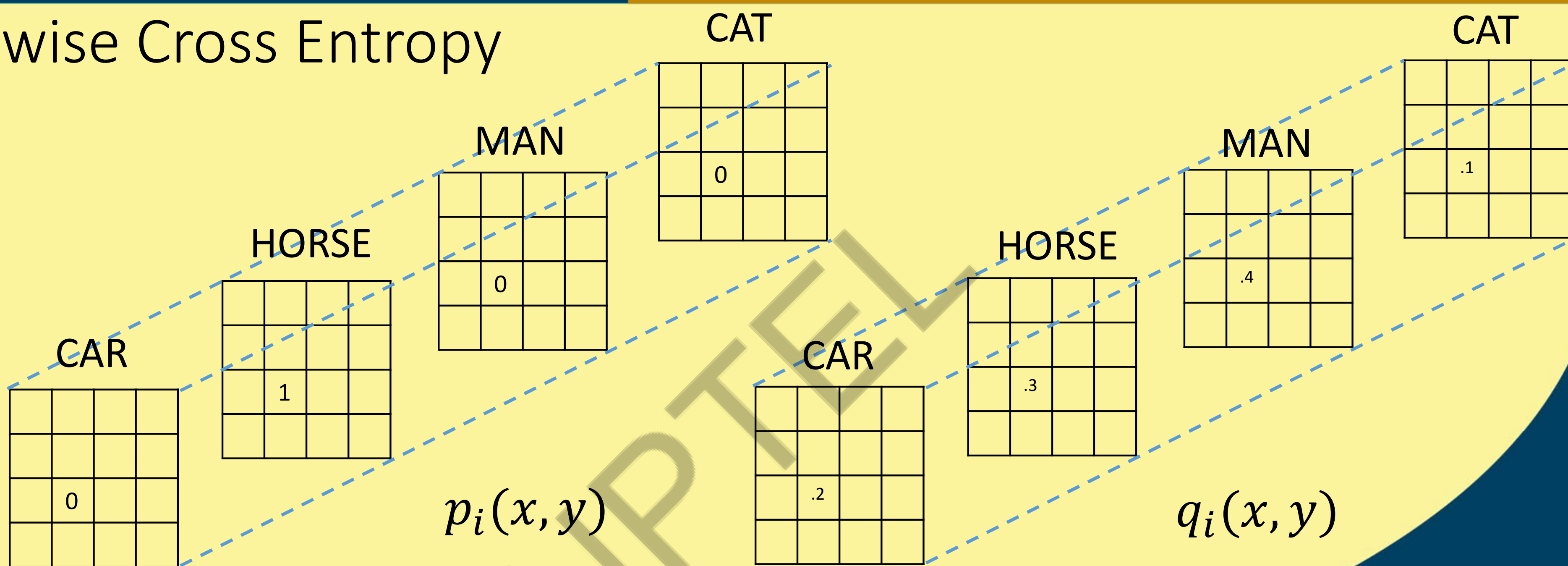


Image Source: Jonathan Long, Evan Shelhamer, Trevor Darrell, “Fully Convolutional Networks for Semantic Segmentation”, CVPR 2015

Training for Sem Segmentation



Pixel wise Cross Entropy



$$L = -\frac{1}{N}\sum_{N}\sum_{x,y} p_i(x,y).\,log q_i(x,y)$$

Semantic Segmentation

CAR (1)

0.2				
		.05		

HORSE(3)

0.1				
		0.6		

MAN (2)

0.5				
		.25		

CAT (4)

0.1				
		0.1		

2				
		3		

SEGMENTATION

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