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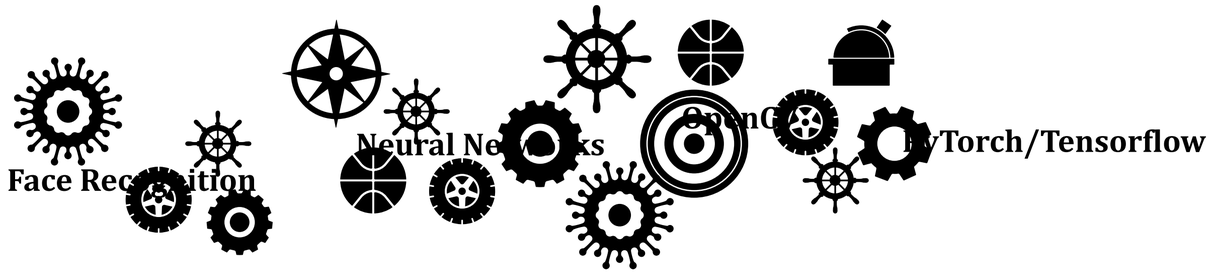
FOUNDATION FOR INNOVATION AND TECHNOLOGY TRANSFER
भारतीय प्रौद्योगिकी संस्थान दिल्ली
Indian Institute of Technology Delhi

Computer Vision



Deep Learning
Segmentation
Object Detection
Image Classification

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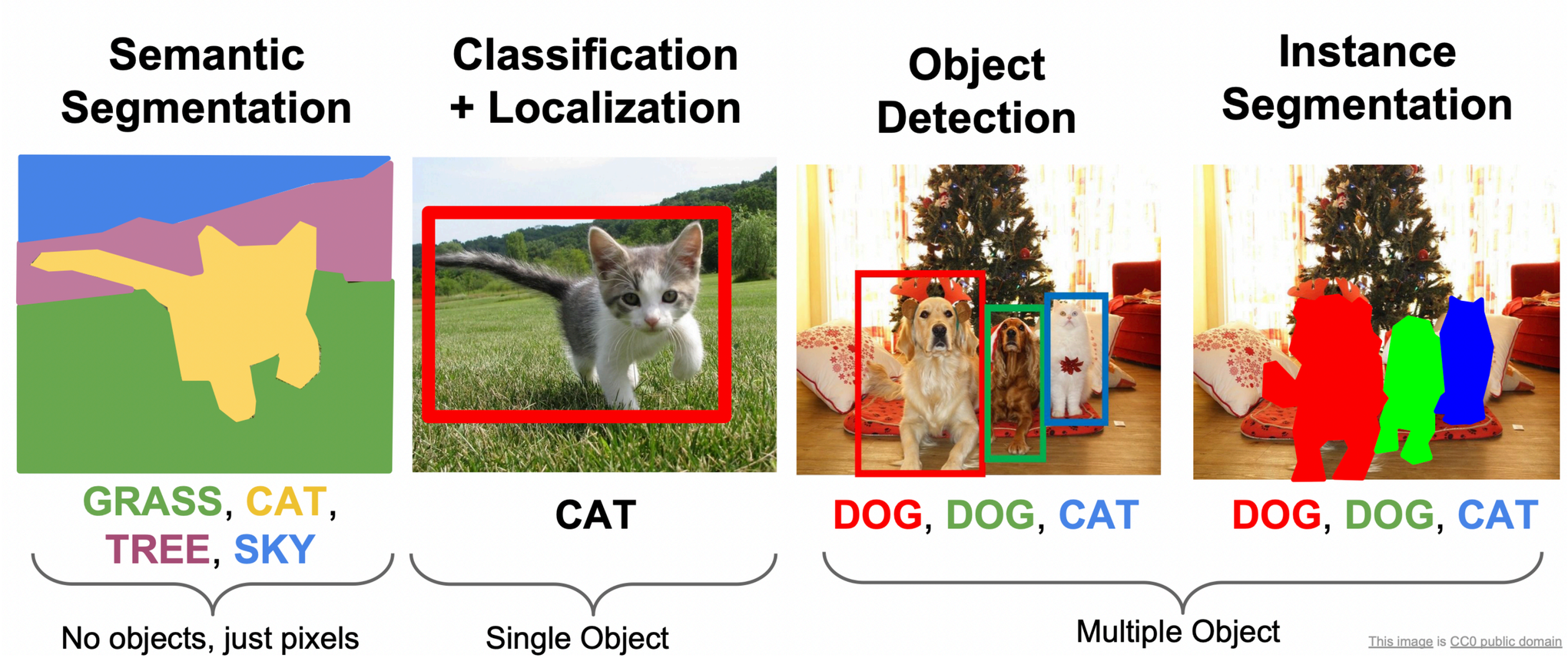
Semantic Segmentation



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Semantic Segmentation

Semantic Segmentation

Label each pixel in the image with a category label

Don’t differentiate instances, only care about pixels

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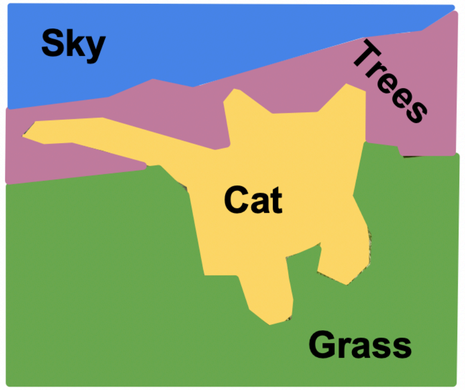

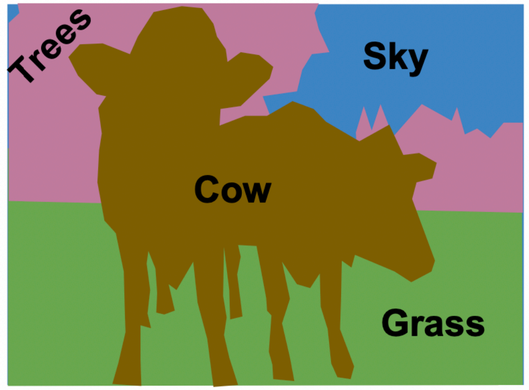

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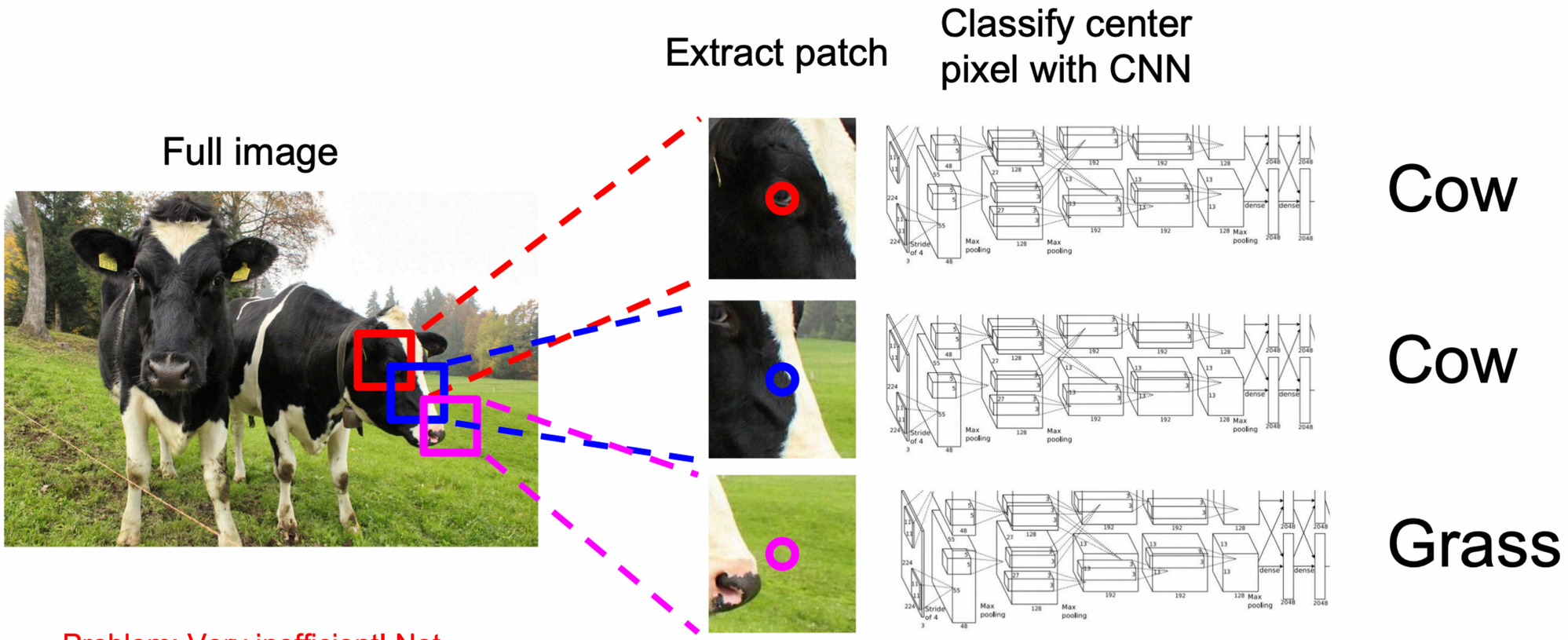
Semantic Segmentation Idea: Sliding Window



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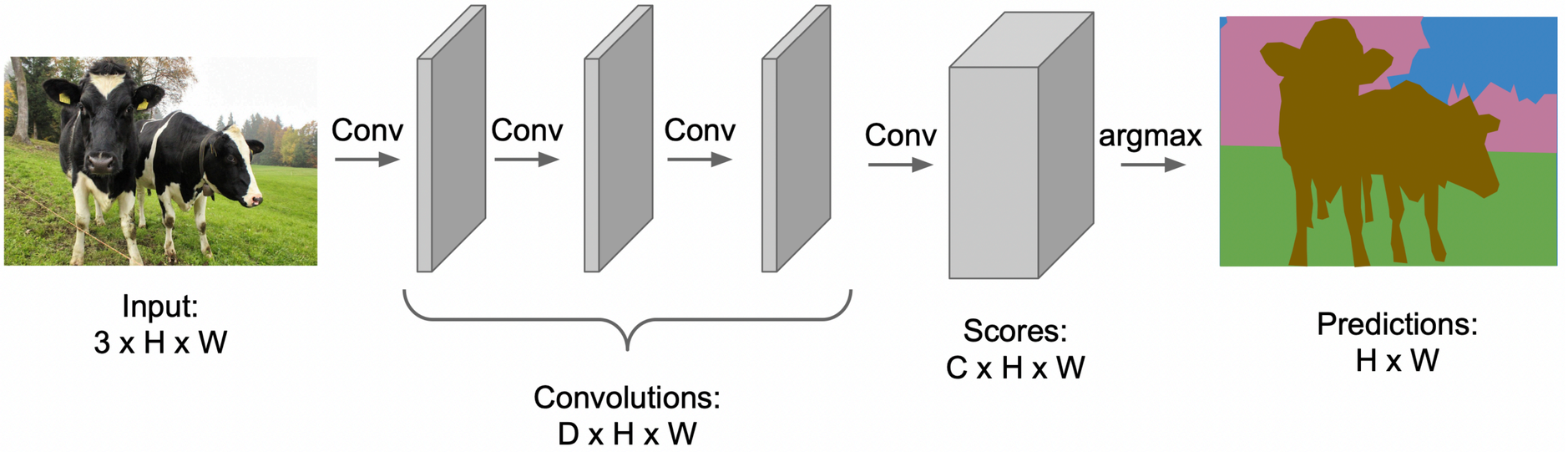
Semantic Segmentation

Semantic Segmentation Idea: Fully Convolutional

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



Problem: convolutions at original image resolution will be very expensive ...

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Semantic Segmentation

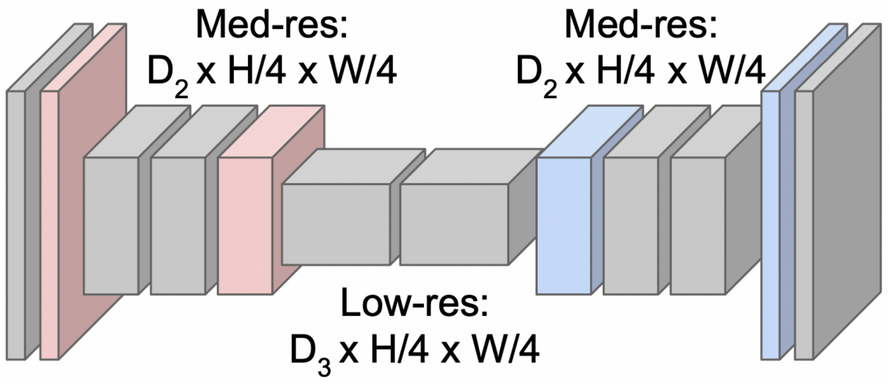
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution

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

Upsampling:
???

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

High-res:
D_1 x H/2 x W/2

Predictions:
H x W

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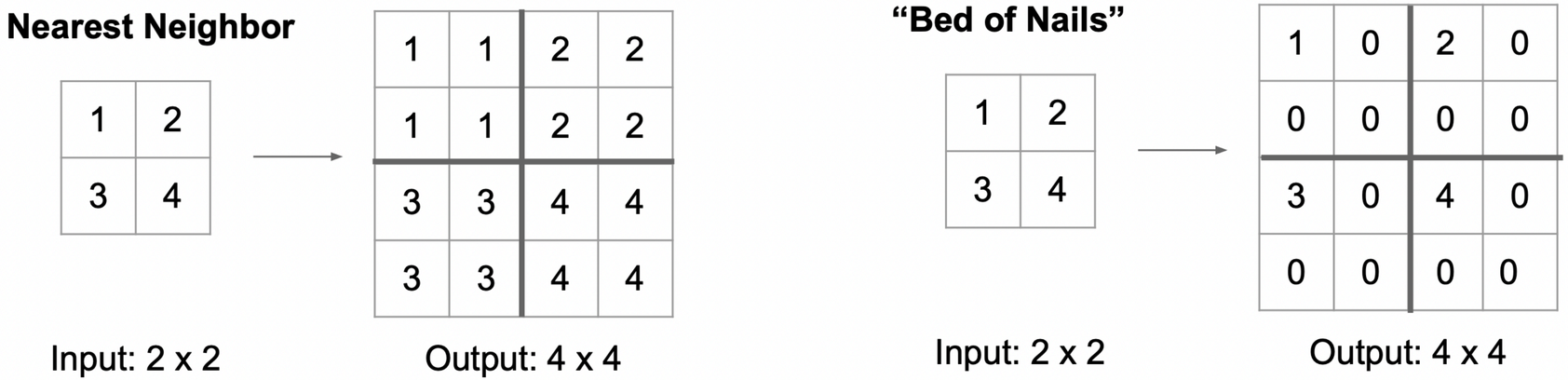
Semantic Segmentation

In-Network upsampling: “Unpooling”



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Semantic Segmentation

In-Network upsampling: “Max Unpooling”

Max Pooling
Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

Rest of the network

Max Unpooling
Use positions from pooling layer

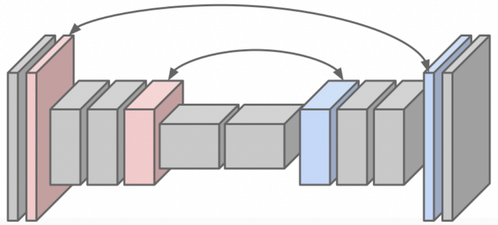
1	2
3	4

Input: 2 x 2

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

Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers



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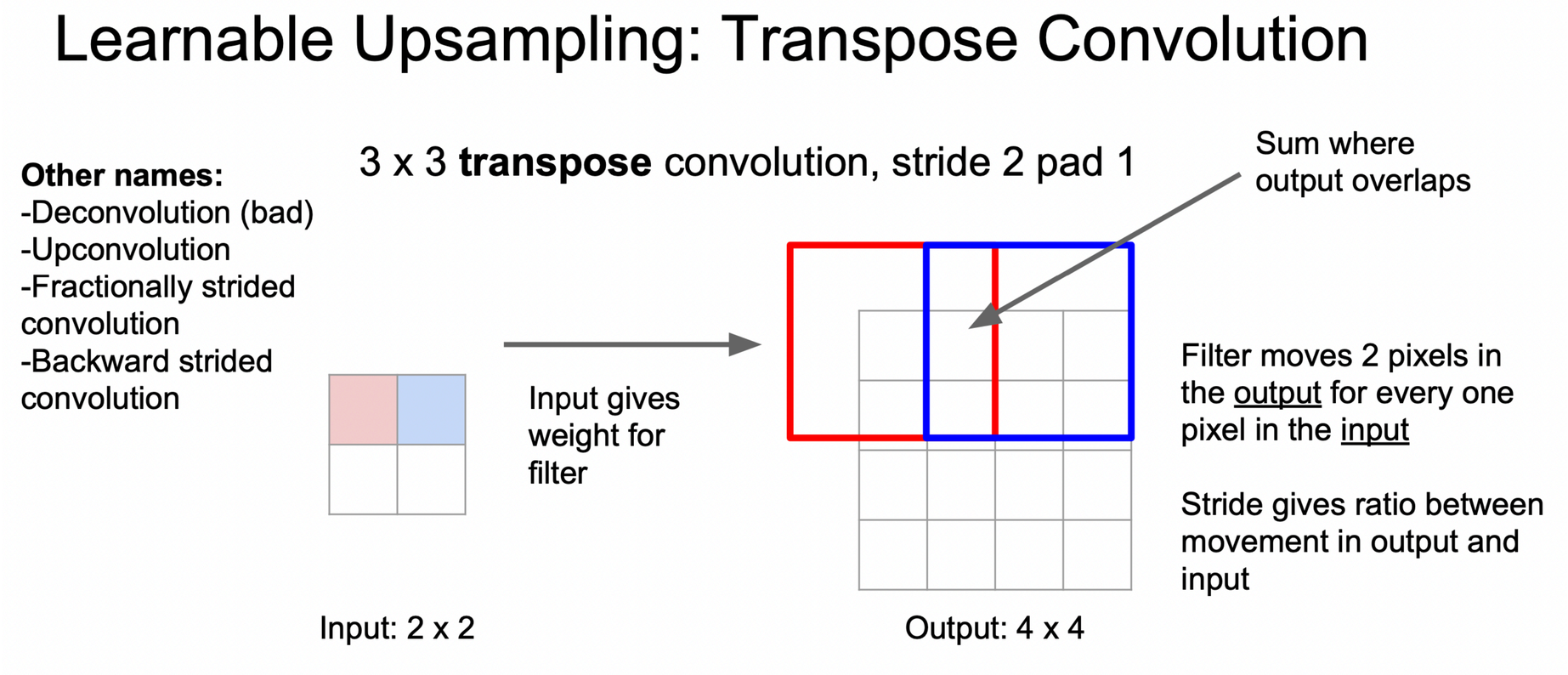
Semantic Segmentation



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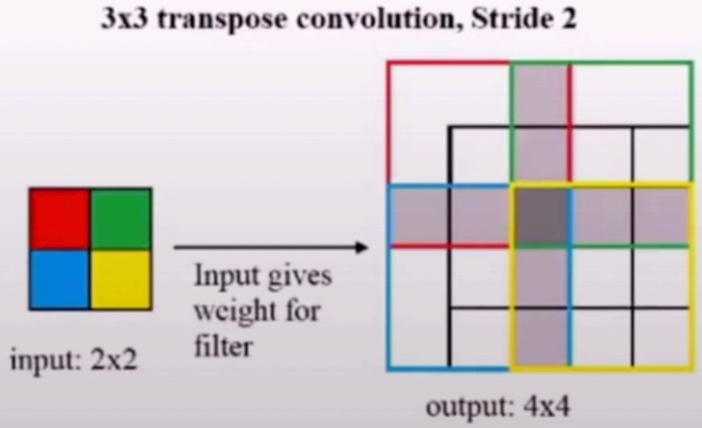
Semantic Segmentation

Upsampling Techniques: Checkerboard Artifacts

- Transpose convolution has uneven overlap when the kernel size is not divisible by the stride
- The uneven overlaps on the two axes multiply, creating a characteristic checkerboard artifact
- In principle, network could learn weights to avoid this but ...
- ... in practice, networks struggle to avoid it completely



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Semantic Segmentation

Checkerboard Artifacts

How to avoid

- Choose appropriate kernel size: use a kernel size that is divisible by the stride, avoiding the overlap issue
- Separate upsampling from convolution to compute features
- For example:
  - Resize the image (e.g., using NN or bilinear interpolation)
  - Add a convolutional layer

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Semantic Segmentation

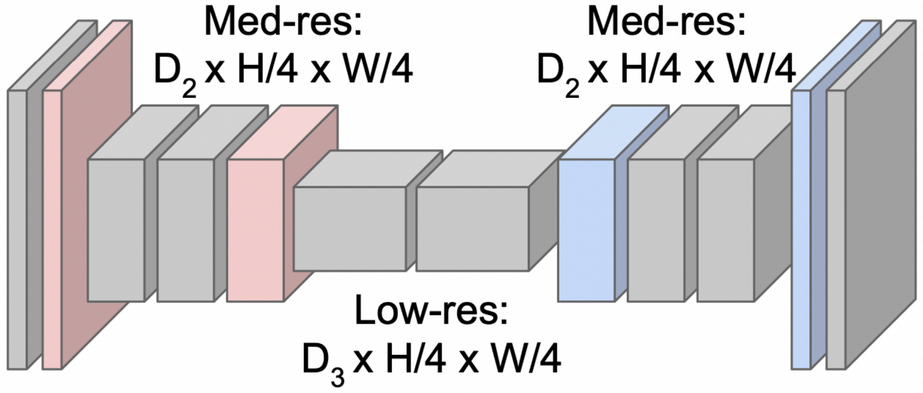
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution

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

Upsampling:
Unpooling or strided transpose convolution

Input:
3 x H x W



High-res:
D1 x H/2 x W/2

High-res:
D1 x H/2 x W/2

Predictions:
H x W

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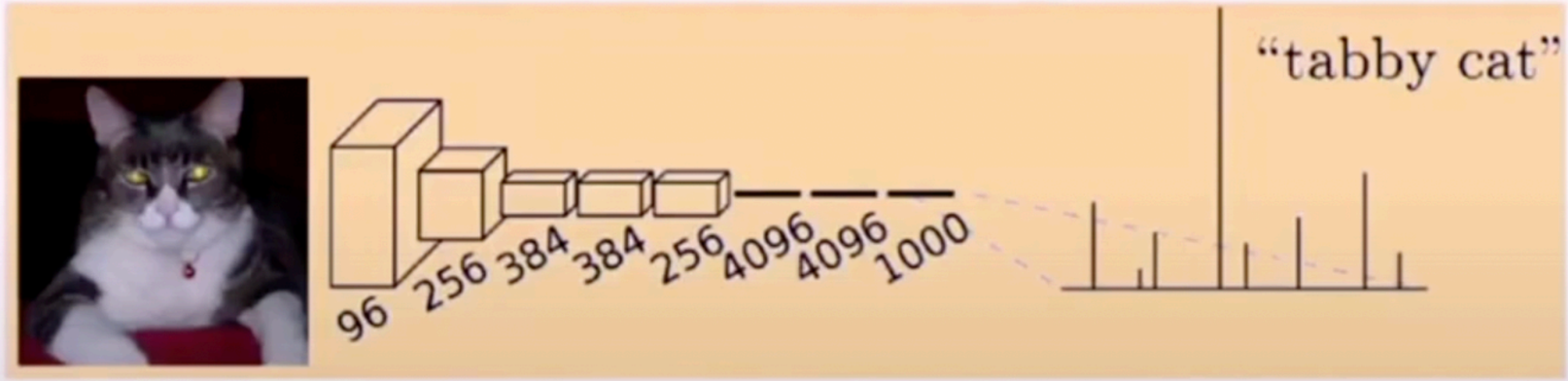
Semantic Segmentation

- Convolutional neural networks with **fully connected layers** used for classification:
  - CNN layers for feature extraction
  - Output dimensions reduced because of subsampling
  - **Fully connected layers** have fixed inputs and remove spatial information
  - Output: vector encoding class probabilities



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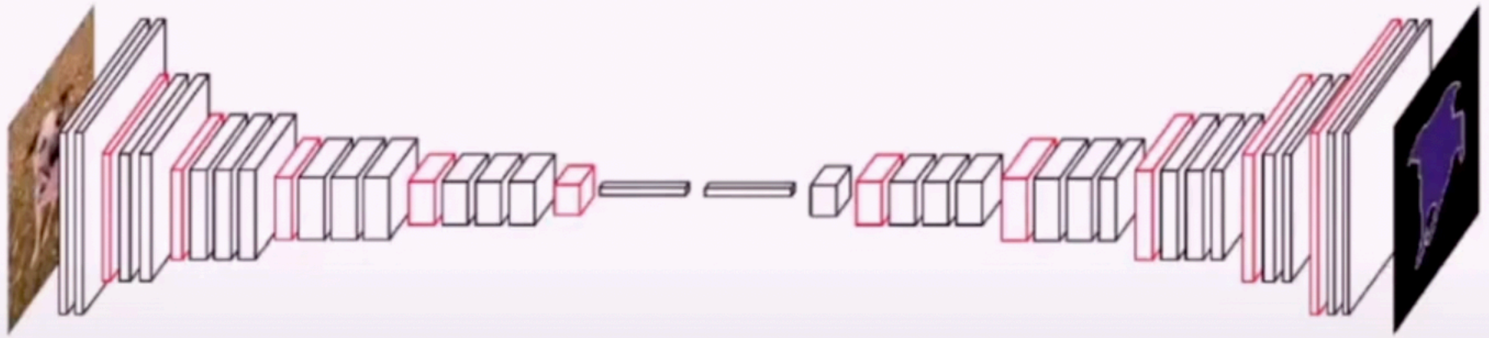
Semantic Segmentation

Encoder and Decoder

- Most methods use a classification network as basis

➔ If it can pickup the class, it should be able to learn the correct features



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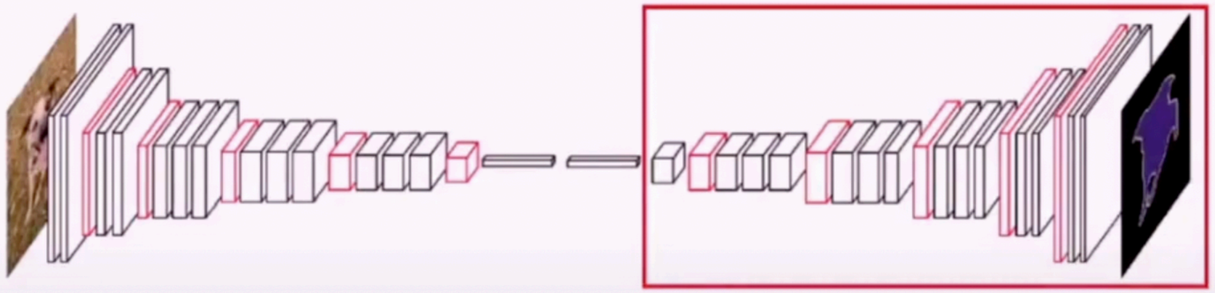
Semantic Segmentation

Encoder and Decoder (cont.)

- Network has to learn to **decode** (map) the output of the encoder to pixel-wise predictions
- Decoder part of the network



Example networks with different decoders:

- Long et al.'s Fully Convolutional Networks [13]
- SegNet [1]
- U-net [21]

Source: modified from: Long et al. 2015

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Semantic Segmentation

Integrating Context Knowledge: Combining Where and What

- Semantic segmentation requires integration of information from various spatial scales

→ Need to balance local and global information

- Local information crucial to achieve good pixel-level accuracy
- Global context of the image enables to resolve local ambiguities
- CNNs struggle with this balance

→ Different approaches to integrate local & global information

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Semantic Segmentation

Long et al.'s Fully Convolutional Networks [13]

- Upsampling using learnable transposed convolutions
- Idea: Add links combining the final prediction and previous (lower) layers with finer strides
- Additional 1×1 convolution after pooling layer, predictions are added up

→ Make local predictions with global structure

- Network topology is a directed acyclic graph (DAG), with **"skip connections"** from lower to higher layers
- Refinement of coarse segmentation

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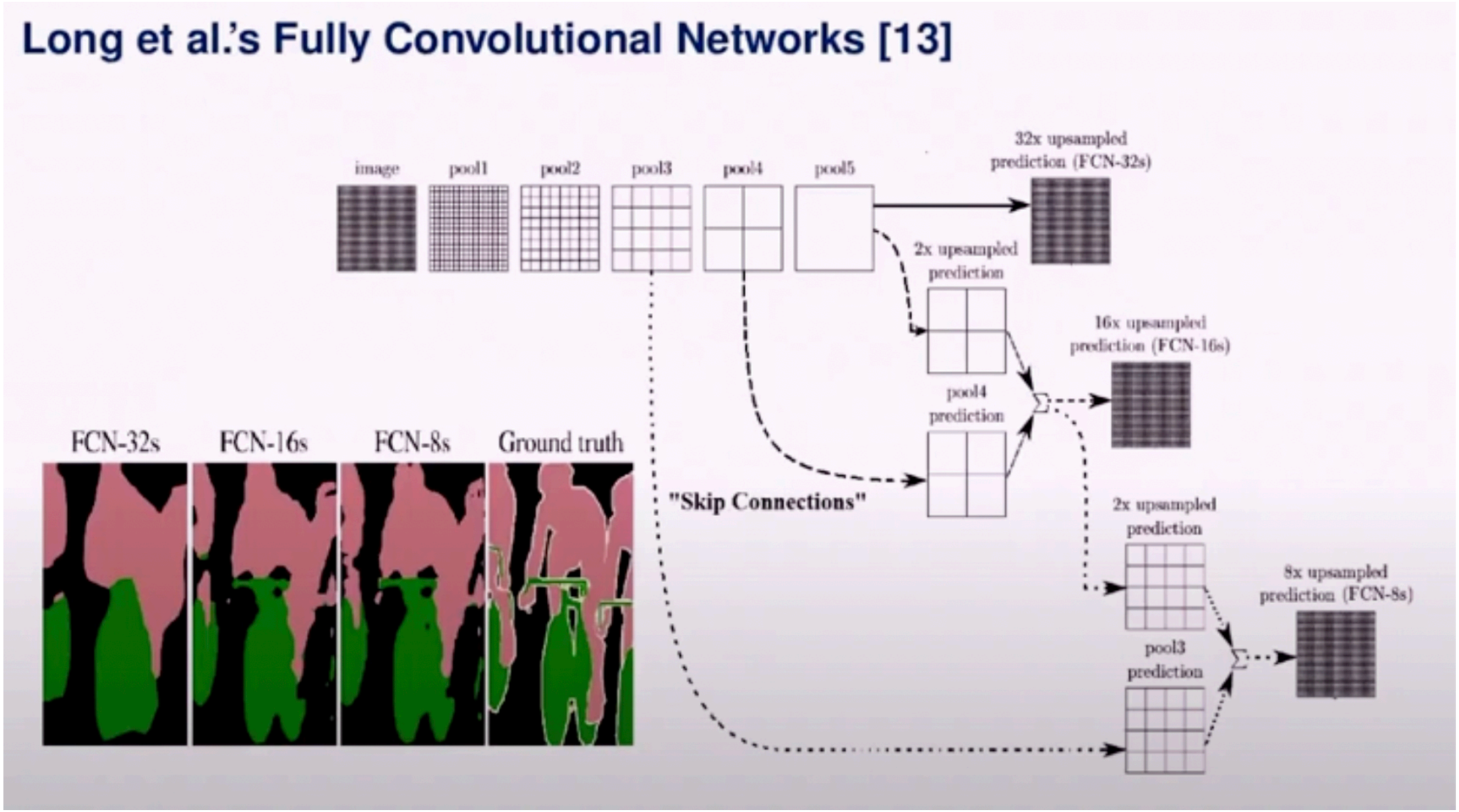
Semantic Segmentation



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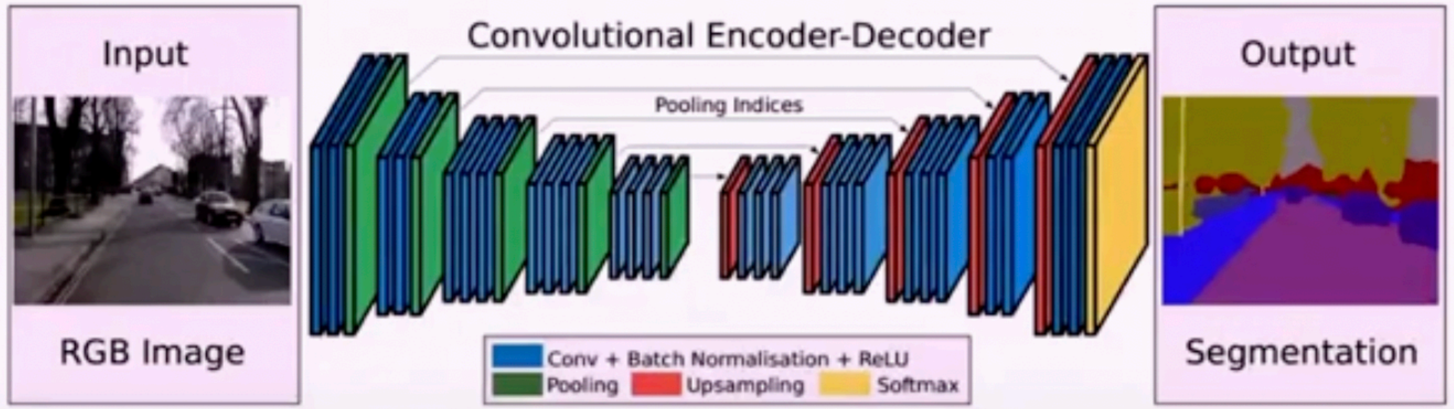
Semantic Segmentation

SegNet [1]:



- Decoder: Upsampling & convolution layers followed by softmax
- Each upsampling layer corresponds to a **max-pooling layer** in encoder
- Upsampling reuses max-pooling indices from feature maps in encoder

→ provides context information

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Semantic Segmentation

U-Net [21]

- The network consists of:
  - Encoder: A contracting path to capture context
  - Decoder: A **symmetric** expansion path for localization (decoder)
- Encoder follows typical architecture of a CNN
- Decoder (expansion path) consists of
  - **Upsampling of feature maps** followed by a 2×2 convolution that halves the number of feature channels.
  - **Concatenation** with the corresponding cropped feature map from the contracting path
- The training strategy relies on use of data augmentation
  - Non-rigid deformation
  - Rotation & translation

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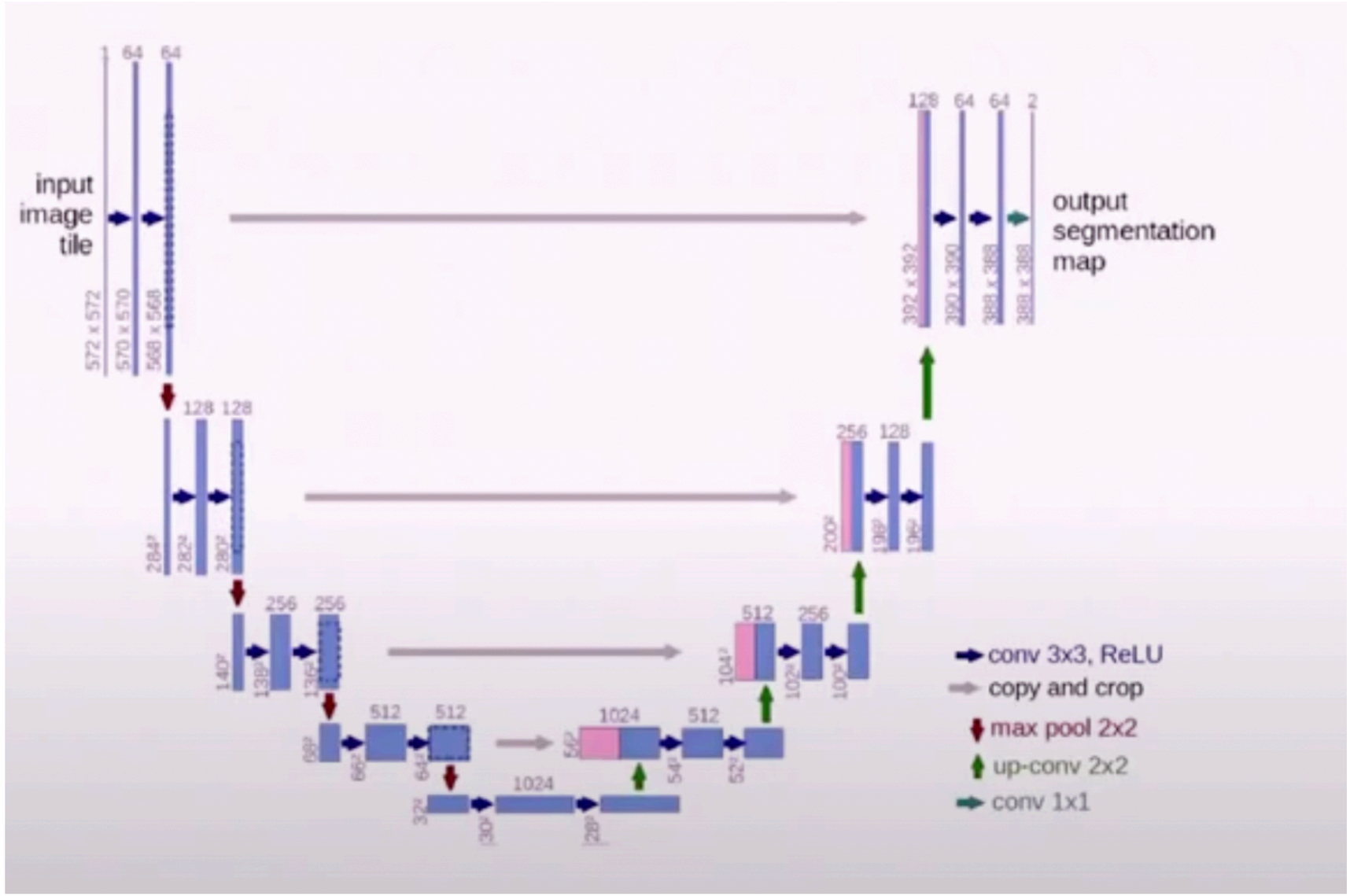
Semantic Segmentation



Semantic Segmentation

So far: Combination of feature maps from different levels + upsampling

Alternatives & extensions:

- Dilated convolutions
- Network stacks
- Multi-scale networks
- Defer context modeling to another network, e.g. an RNN
- Refinement as a post-processing step with Conditional Random Fields (CRFs)

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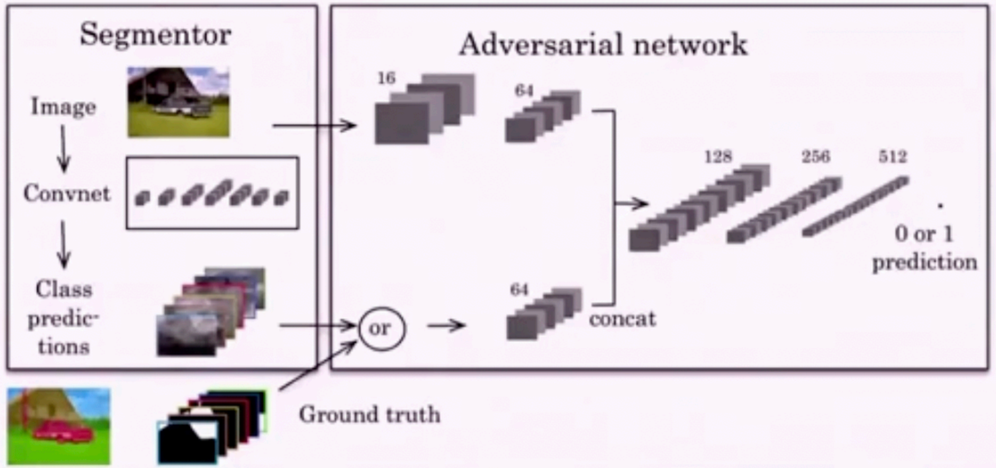
Semantic Segmentation

Adversarial Networks for Segmentation [14]



Source: Luc et al., 2016

Optimize Segmentor with hybrid loss function with two terms:

1.) Usual pixel-wise multi-class cross-entropy for semantic segmentation

2.) Loss based on min-max game with Discriminator

Semantic Segmentation

- Given a data set of N training images $\mathbf{x}_n$ and a corresponding label maps $\mathbf{y}_n$ the loss function defined as:

$$l(\theta_s, \theta_a) = \sum_{n=1}^{N} \underbrace{l_{mce}(s(\mathbf{x}_n), \mathbf{y}_n)}_{\text{multi-class cross-entropy}} - \lambda \underbrace{\left[l_{bce}(a(\mathbf{x}_n, \mathbf{y}_n), 1) + l_{bce}(a(\mathbf{x}_n, s(\mathbf{x}_n)), 0)\right]}_{\text{adverserial loss} \rightarrow \text{binary classification}}$$

- $(\mathbf{x}_n, \mathbf{y}_n), n \in \{1, \ldots, N\}$: Data set with ground truth labels
- θ_s: Parameters of the Segmentor $s(\mathbf{x}, \mathbf{y})$
- θ_a: Parameters of the Discriminator $a(\mathbf{x}, \mathbf{y})$

→ Segmentor is trained both on the segmentation and on fooling the discriminator

→ **Multi-task learning** with adversarial task