Insight
Centre for Data Analytics

DEEP LEARNING WORKSHOP

Dublin City University
27-28 April 2017

DCU

Day 2 Lecture 7

Object Segmentation

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UPC

Object Segmentation

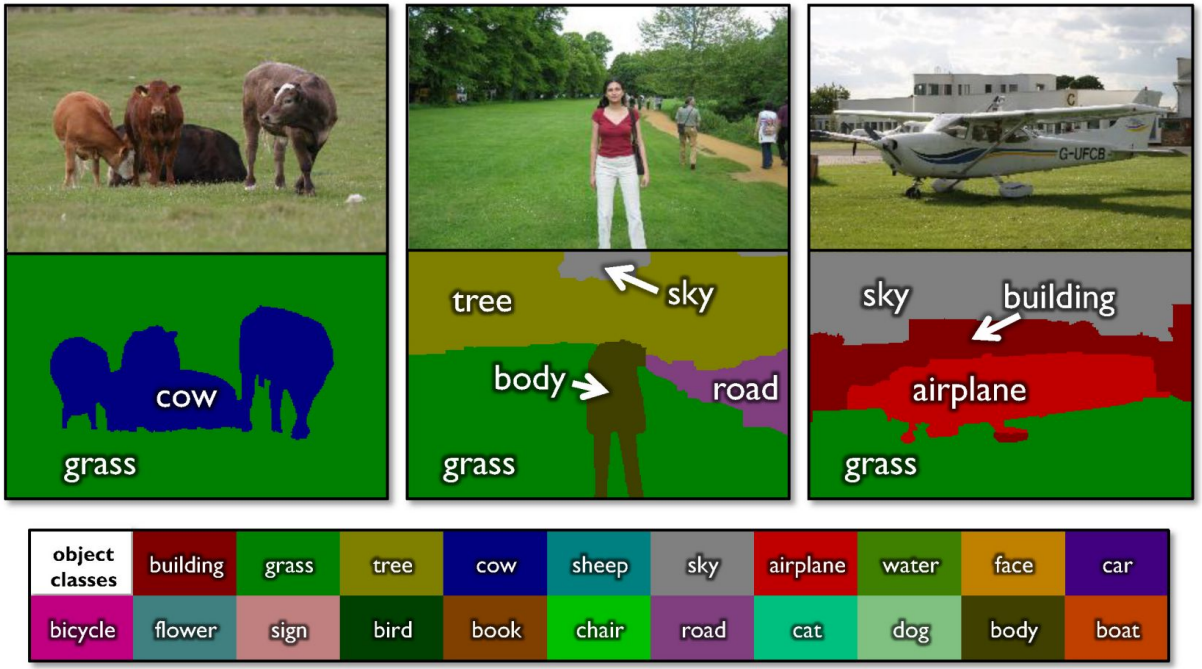
Define the accurate boundaries of all objects in an image

Semantic Segmentation

Label every pixel!

Don’t differentiate instances (cows)

Classic computer vision problem

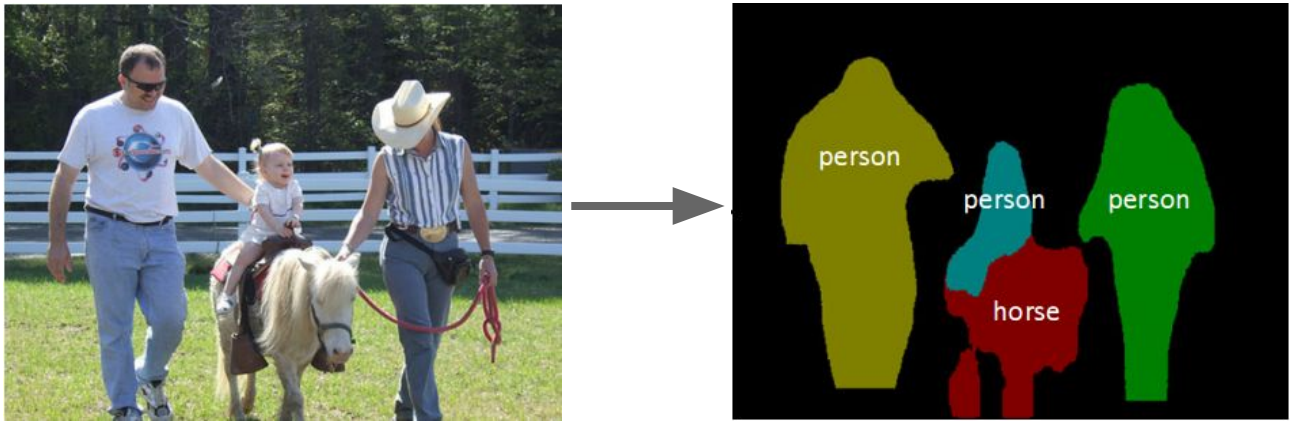


Slide Credit: CS231n

Instance Segmentation

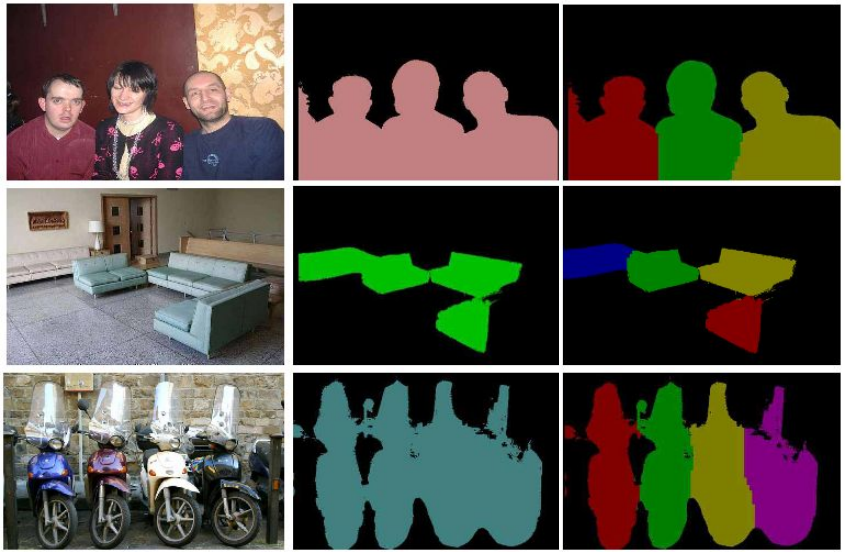
Detect instances, give category, label pixels

“simultaneous detection and segmentation” (SDS)



Slide Credit: CS231n

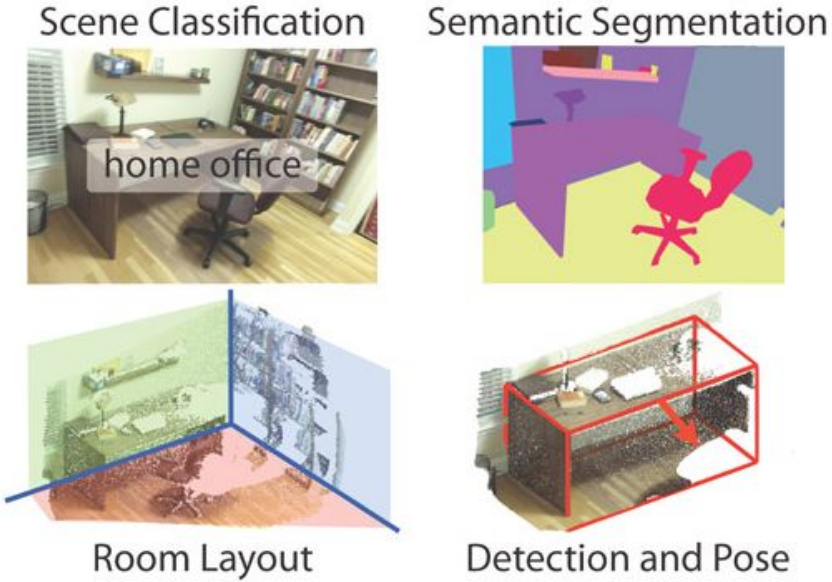
Object Segmentation: Datasets



[Pascal Visual Object Classes]
20 Classes
~ 5.000 images

[Pascal Context]
540 Classes
~ 10.000 images

Object Segmentation: Datasets

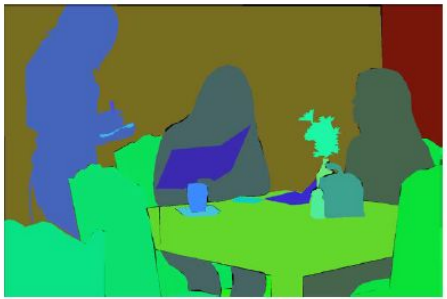


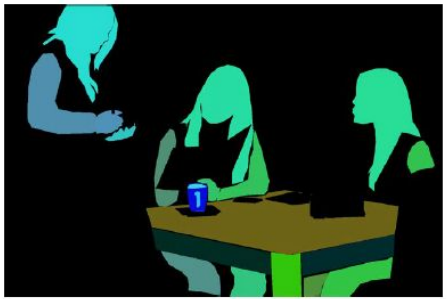
SUN RGB-D
19 Classes
~ 10.000 images

Microsoft COCO
80 Classes
~ 300.000 images

Object Segmentation: Datasets

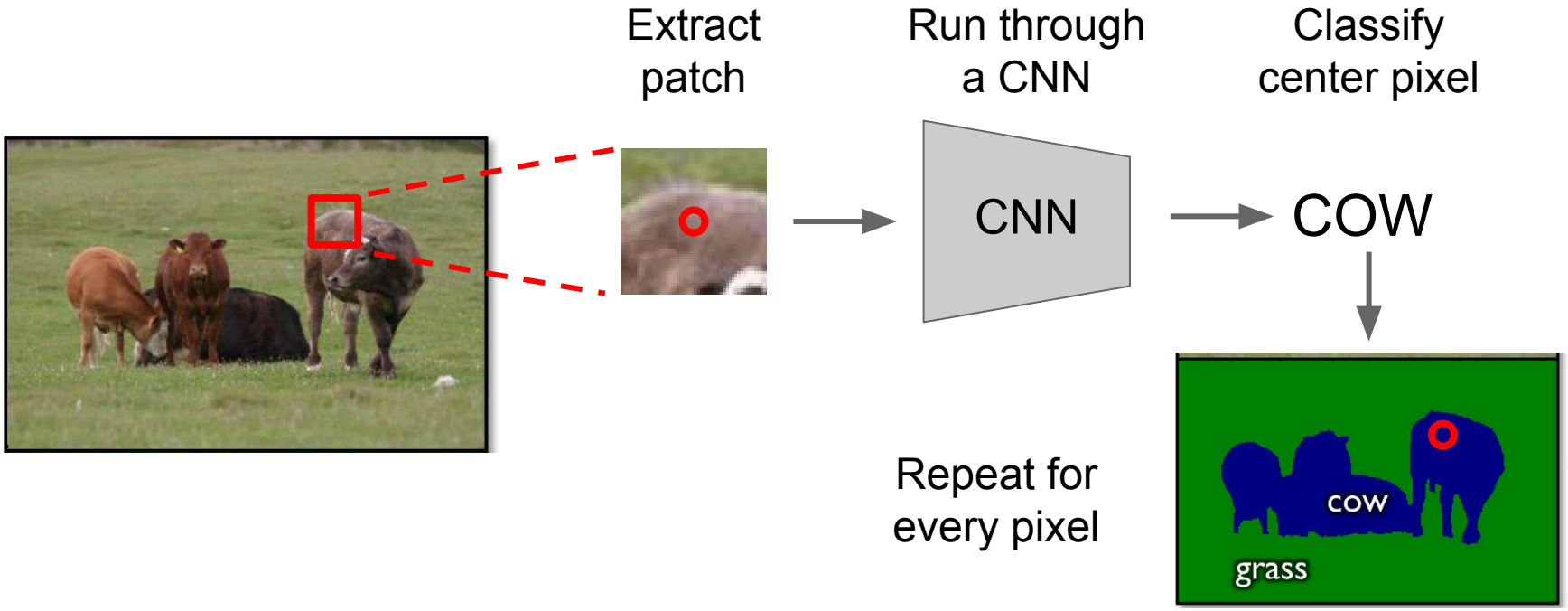
CityScapes
30 Classes
~ 25.000 images





ADE20K
>150 Classes
~ 22.000 images

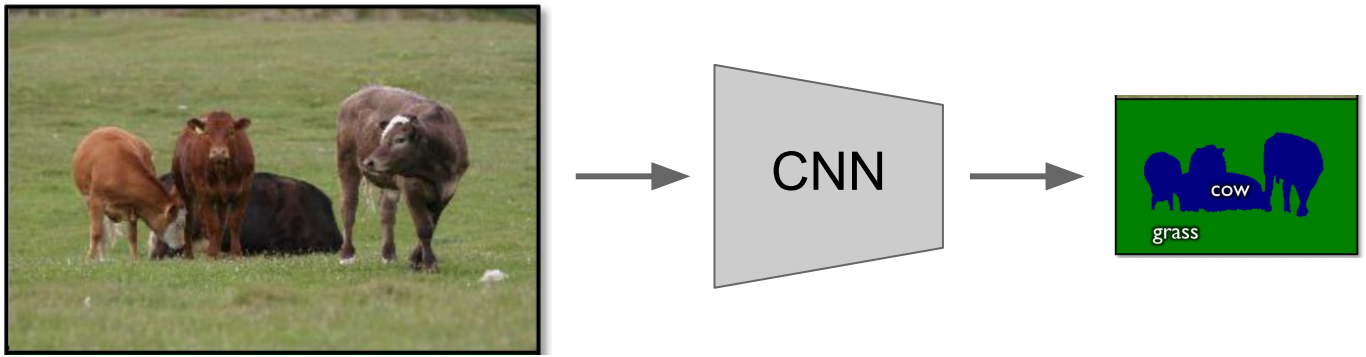
Semantic Segmentation



Slide Credit: CS231n

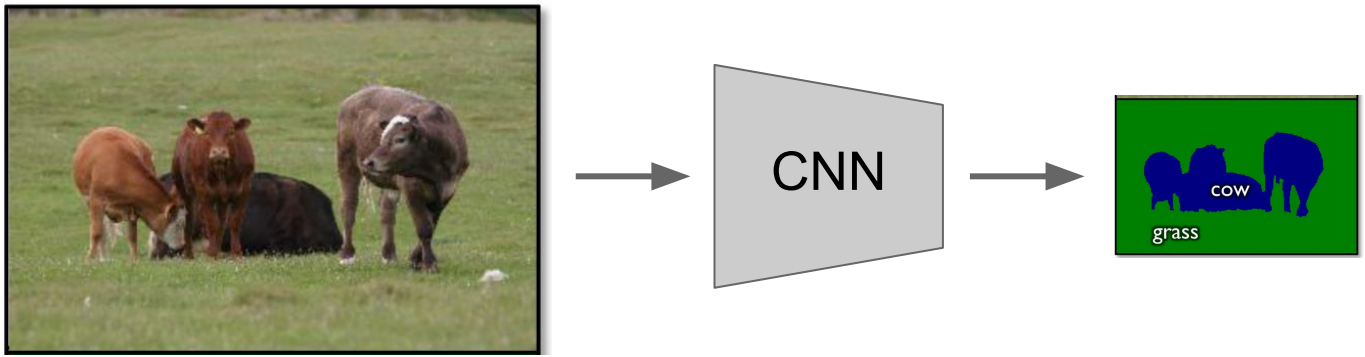
Semantic Segmentation

Run “fully convolutional” network
to get all pixels at once



Slide Credit: CS231n

Semantic Segmentation



Problem 1:

Smaller output due to pooling

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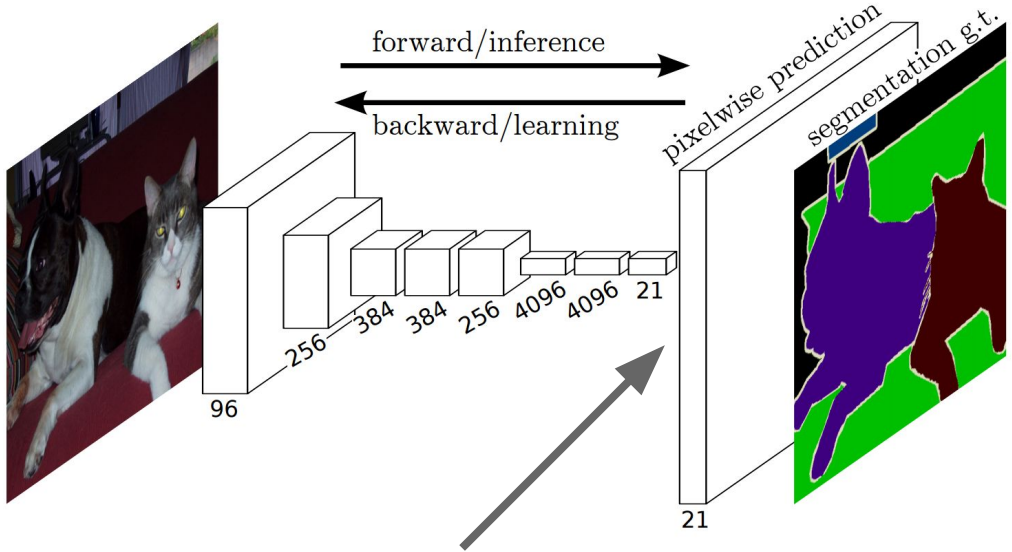
Learnable upsampling

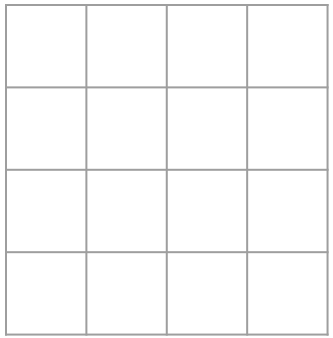


Long et al. Fully Convolutional Networks for Semantic Segmentation. CVPR 2015

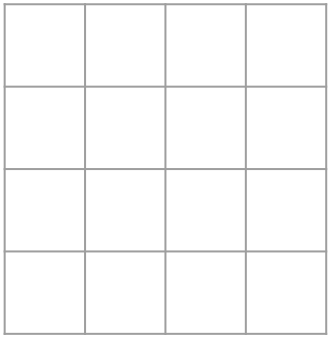
Slide Credit: CS231n

Reminder: Convolutional Layer

Typical 3 x 3 convolution, stride 1 pad 1



Input: 4 x 4

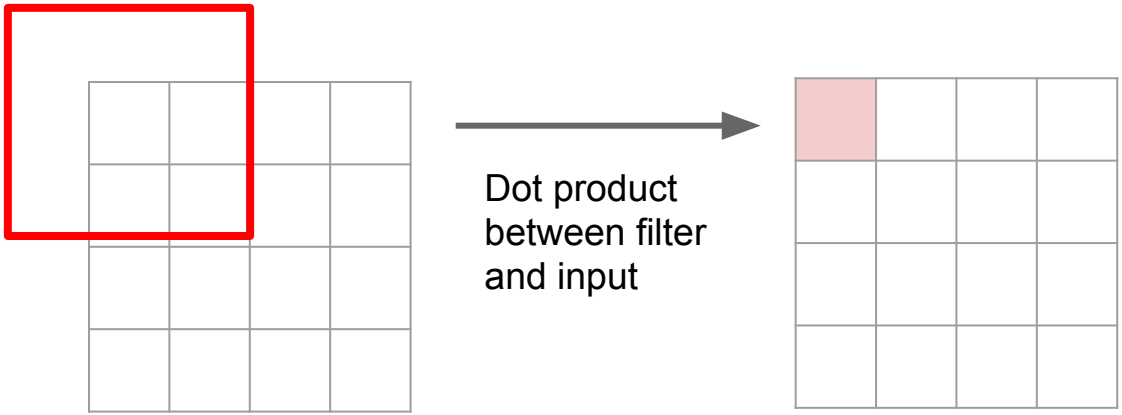


Output: 4 x 4

Slide Credit: CS231n

Reminder: Convolutional Layer

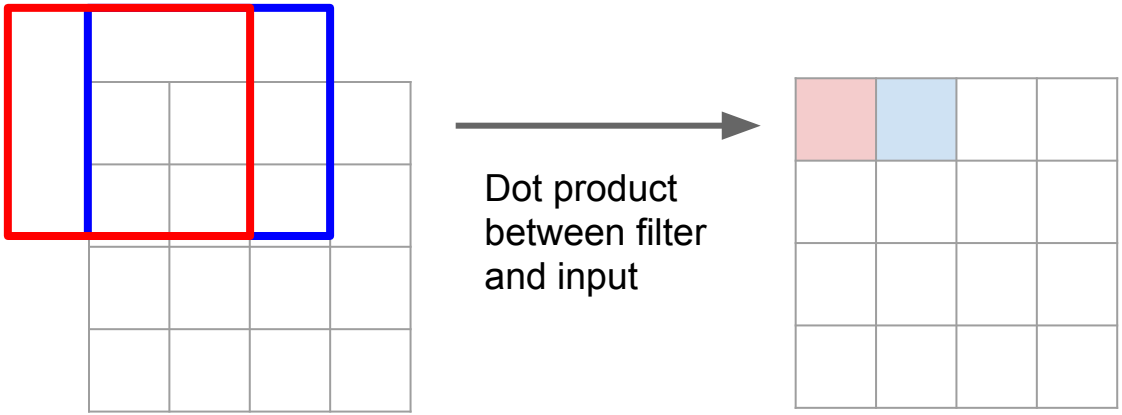
Typical 3 x 3 convolution, stride 1 pad 1



Slide Credit: CS231n

Reminder: Convolutional Layer

Typical 3 x 3 convolution, stride 1 pad 1



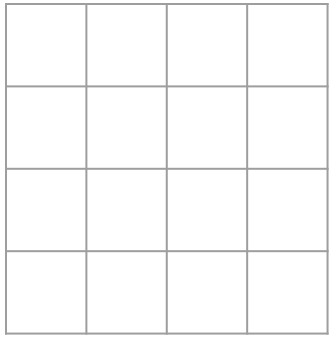
Input: 4 x 4

Output: 4 x 4

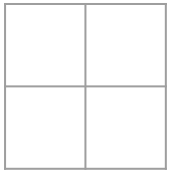
Slide Credit: CS231n

Reminder: Convolutional Layer

Typical 3 x 3 convolution, **stride 2** pad 1



Input: 4 x 4

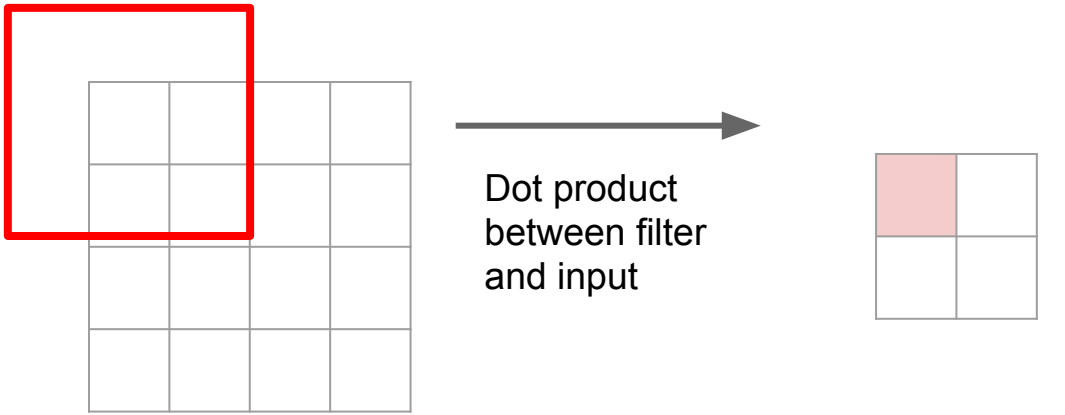


Output: 2 x 2

Slide Credit: CS231n

Reminder: Convolutional Layer

Typical 3 x 3 convolution, stride 2 pad 1



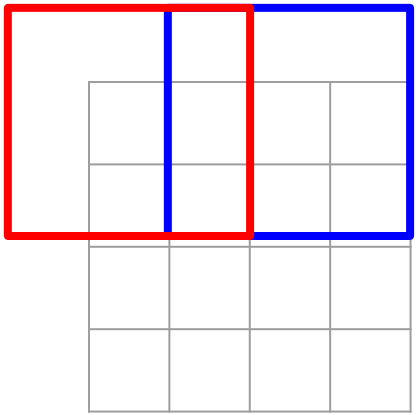
Input: 4 x 4

Output: 2 x 2

Slide Credit: CS231n

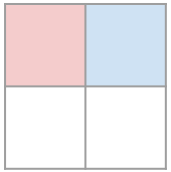
Reminder: Convolutional Layer

Typical 3 x 3 convolution, stride 2 pad 1



Input: 4 x 4

Dot product between filter and input

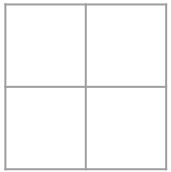


Output: 2 x 2

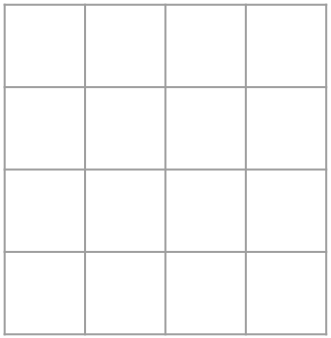
Slide Credit: CS231n

Learnable Upsample: Deconvolutional Layer

3 x 3 “deconvolution”, stride 2 pad 1



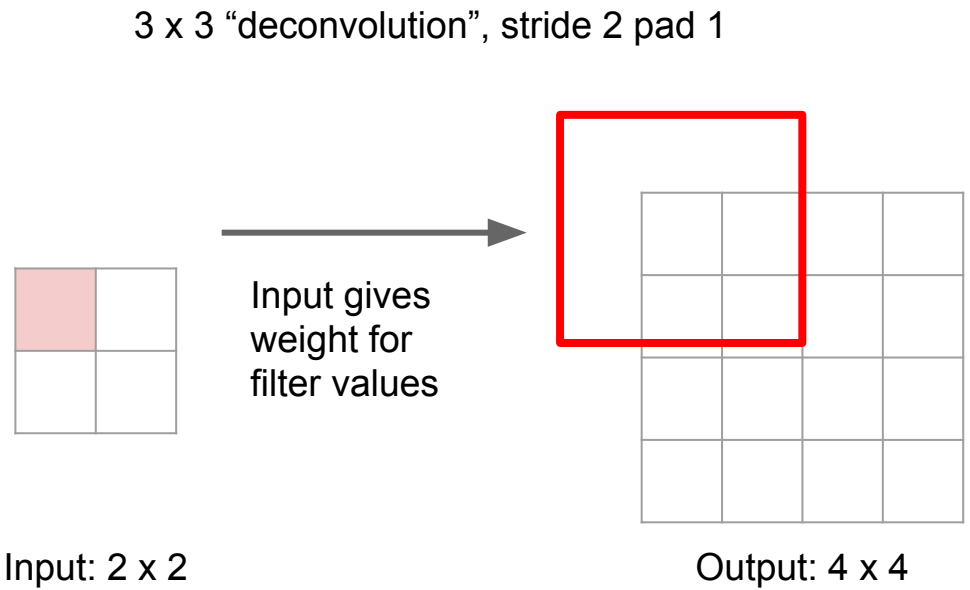
Input: 2 x 2



Output: 4 x 4

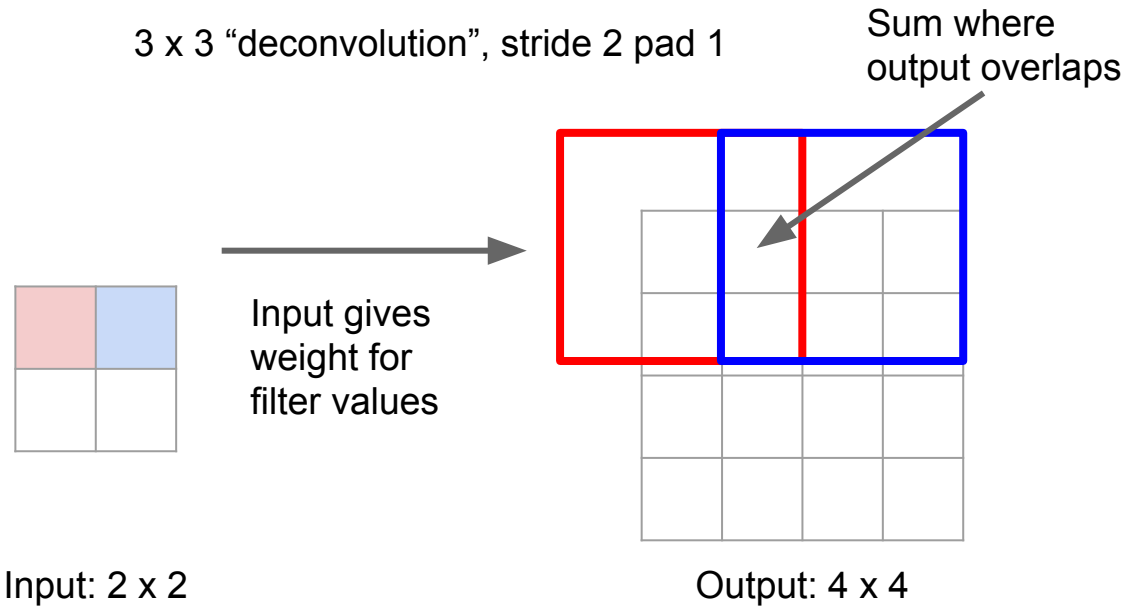
Slide Credit: CS231n

Learnable Upsample: Deconvolutional Layer



Slide Credit: CS231n

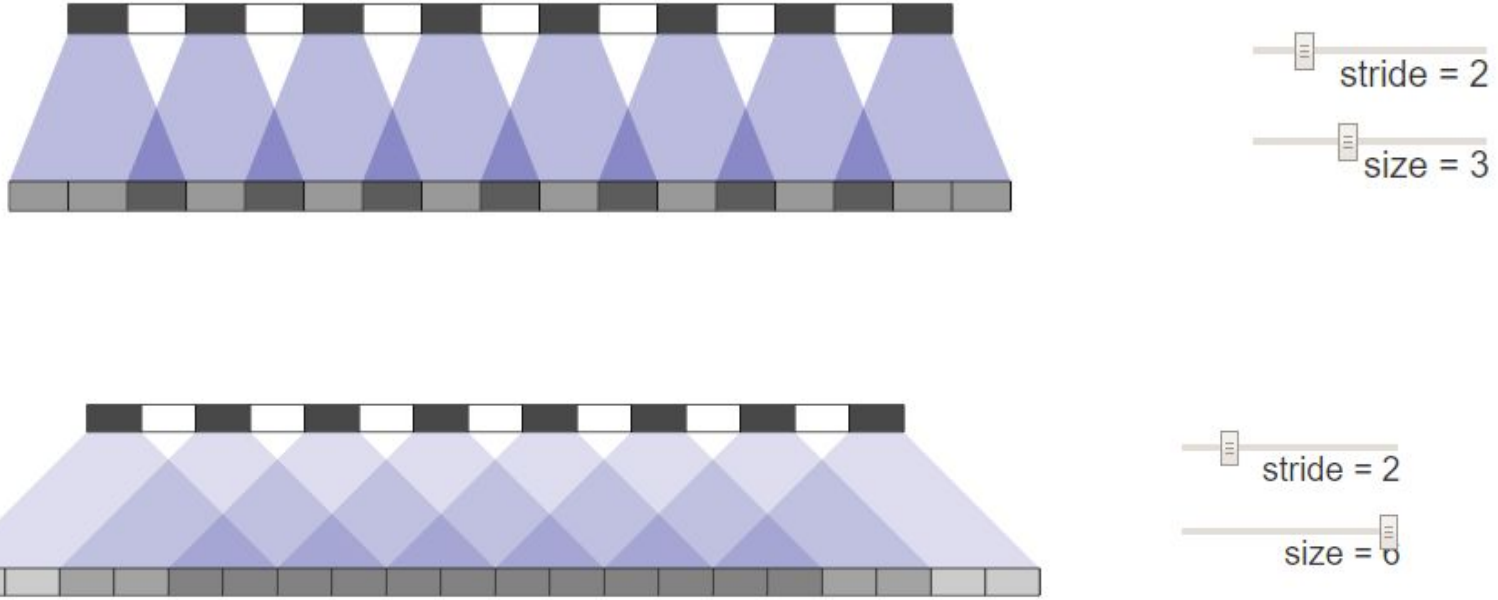
Learnable Upsample: Deconvolutional Layer



Slide Credit: CS231n

Learnable Upsample: Deconvolutional Layer

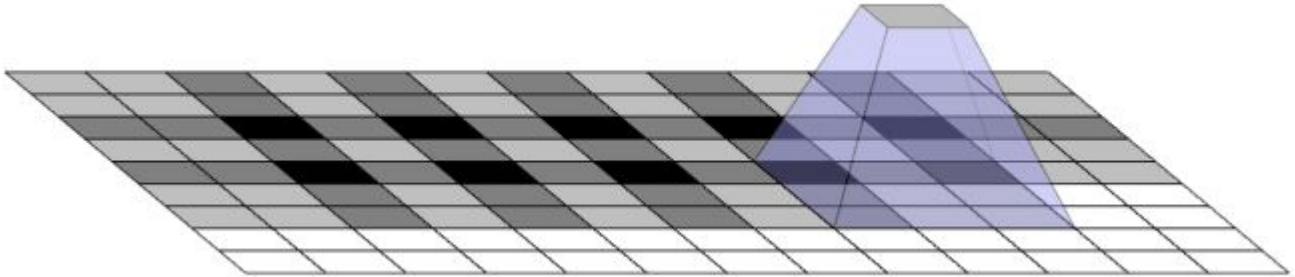
Warning: Checkerboard effect when kernel size is not divisible by the stride



Source: distill.pub

Learnable Upsample: Deconvolutional Layer

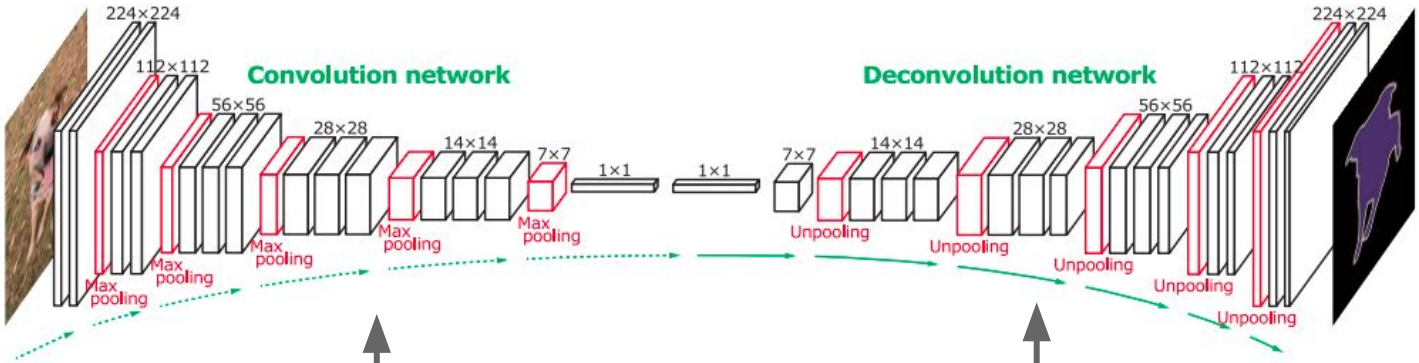
Warning: Checkerboard effect when kernel size is not divisible by the stride



stride = 2, kernel_size = 3

Source: distill.pub

Semantic Segmentation



“Regular” VGG

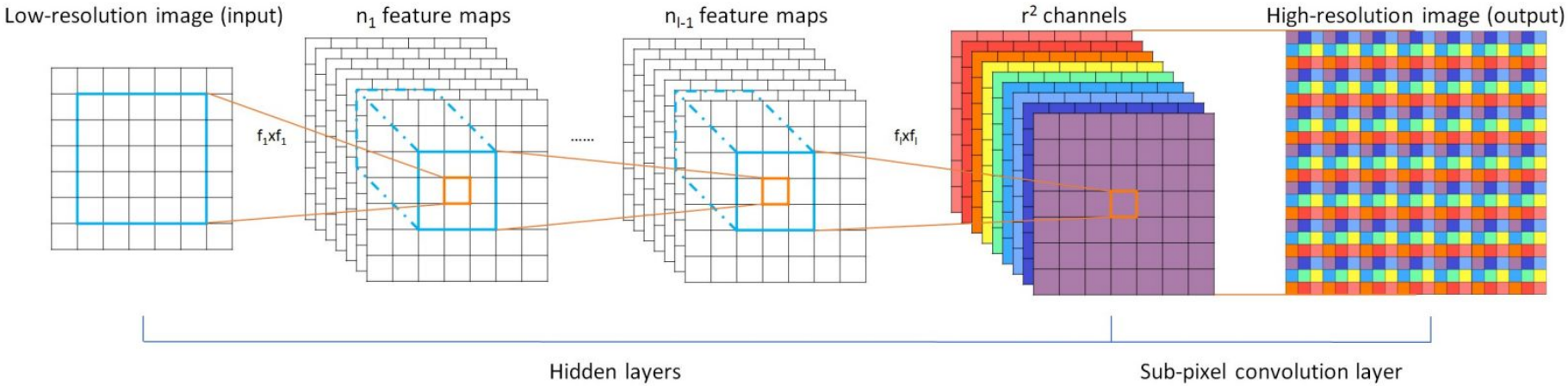
“Upside down” VGG

Noh et al. Learning Deconvolution Network for Semantic Segmentation. ICCV 2015

Slide Credit: CS231n

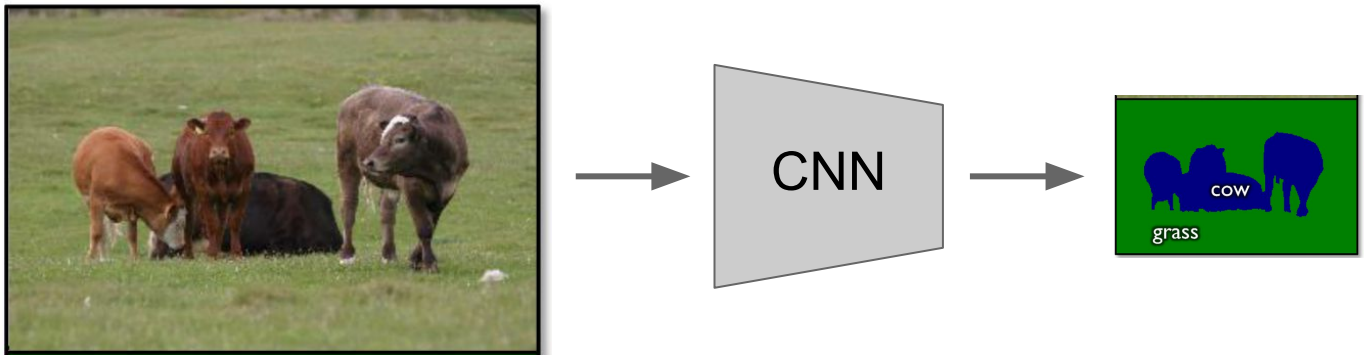
Better Upsampling: Subpixel

Re-arange features in previous convolutional layer to form a higher resolution output



Shi et al.[Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network](#).CVPR 2016

Semantic Segmentation



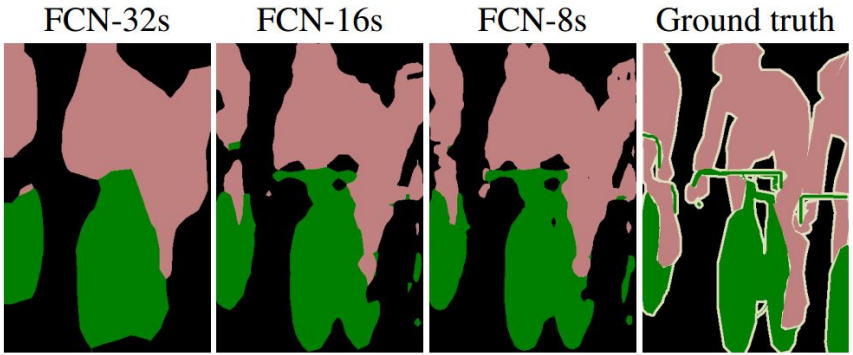
Problem 2:

Blobby-like segmentations

High-level features (e.g. conv5 layer) from a pretrained classification network are the input for the segmentation branch

Skip Connections

Recovering low level features from early layers



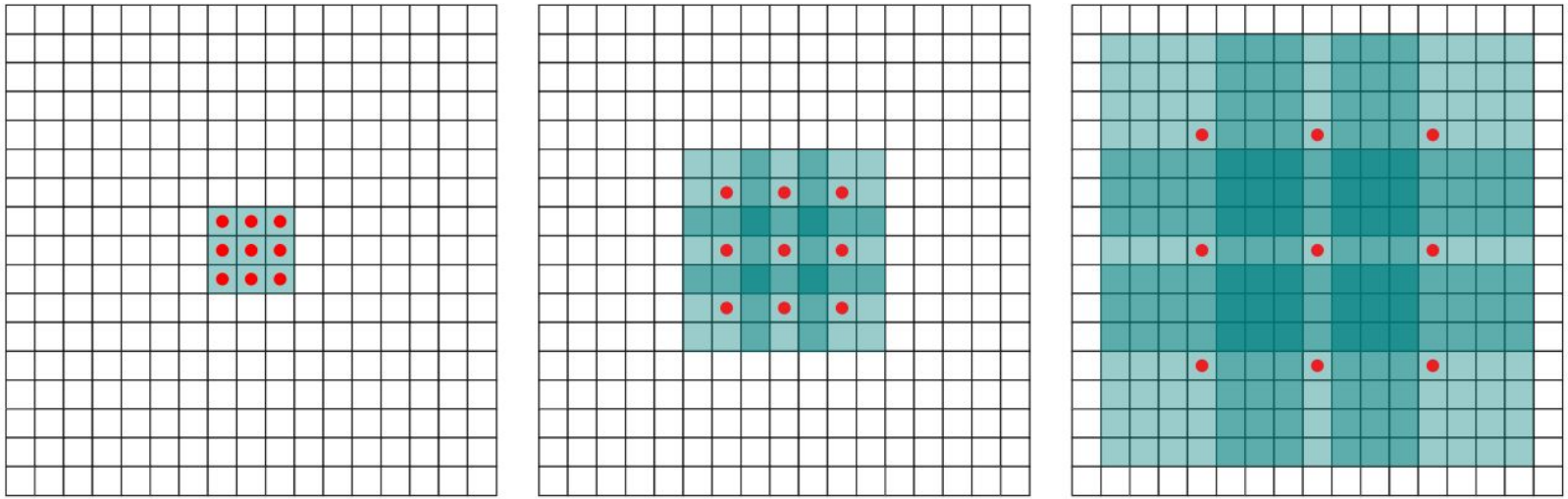
Skip connections = Better results

Long et al. Fully Convolutional Networks for Semantic Segmentation. CVPR 2015

Slide Credit: CS231n

Dilated Convolutions

Structural change in convolutional layers for dense prediction problems (e.g. image segmentation)



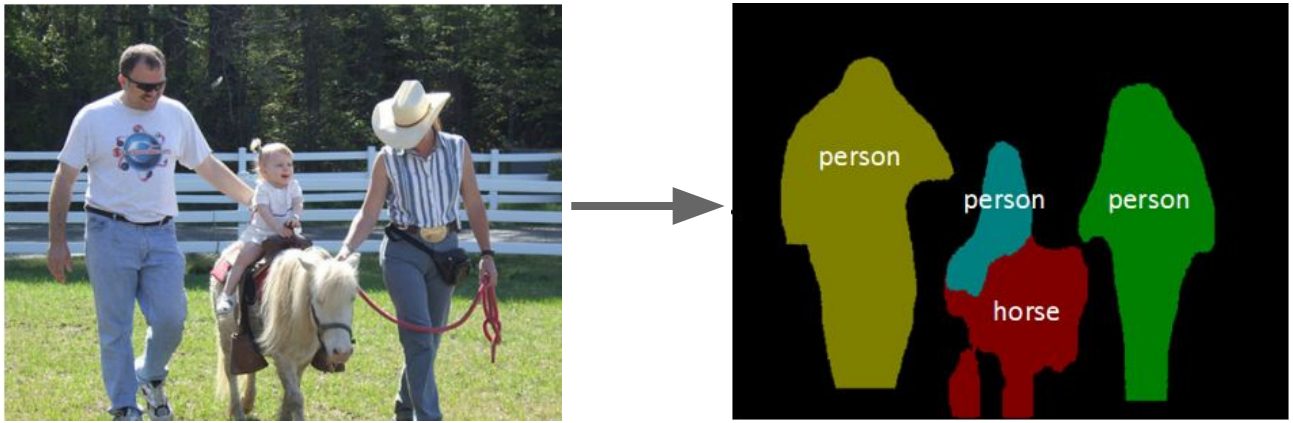
- The receptive field grows exponentially as you add more layers → more context information in deeper layers wrt regular convolutions
- Number of parameters increases linearly as you add more layers

Yu & Koltun. Multi-Scale Context Aggregation by Dilated Convolutions. ICLR 2016

Instance Segmentation

Detect instances, give category, label pixels

“simultaneous detection and segmentation” (SDS)



Slide Credit: CS231n

Instance Segmentation

More challenging than Semantic Segmentation

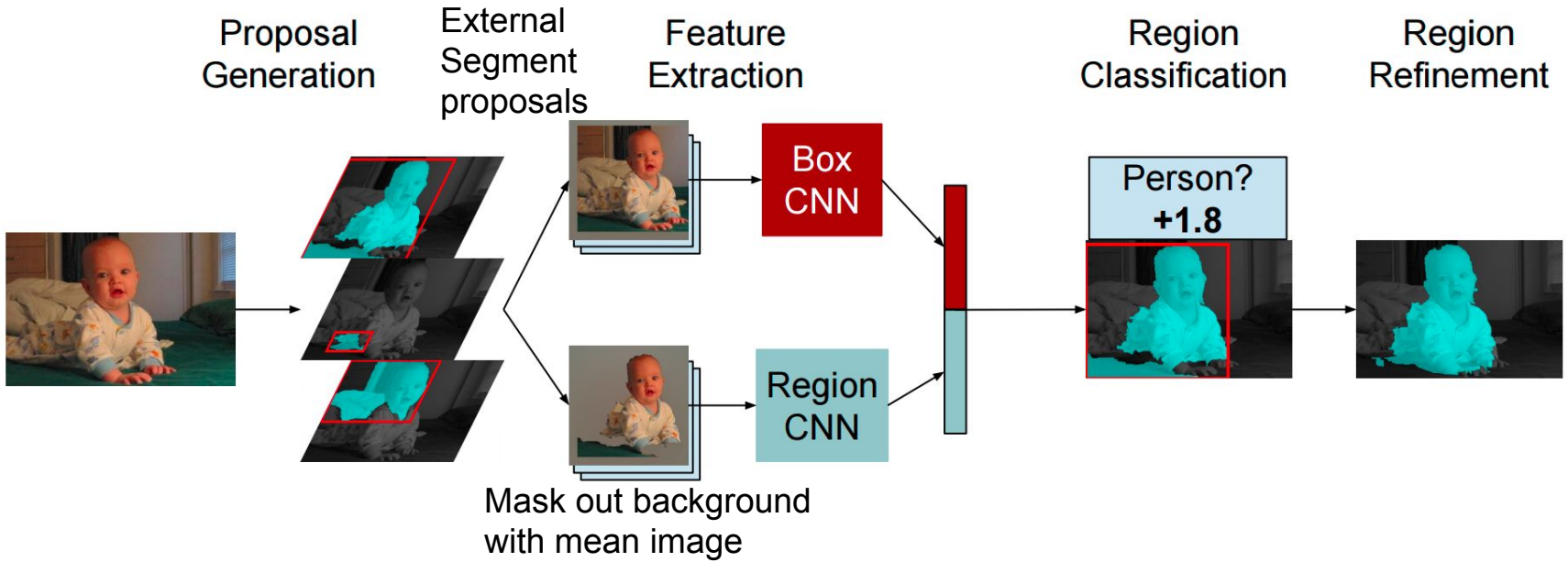
- Number of objects is variable
- No unique match between predicted and ground truth objects (cannot use instance IDs)

Several attack lines:

- Proposal-based methods
- Recurrent Neural Networks

Proposal-based

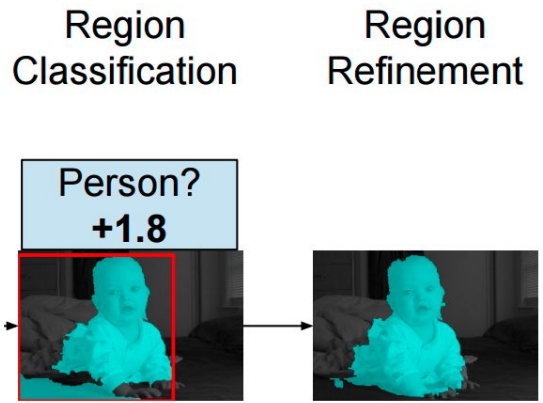
Similar to R-CNN, but with segment proposals

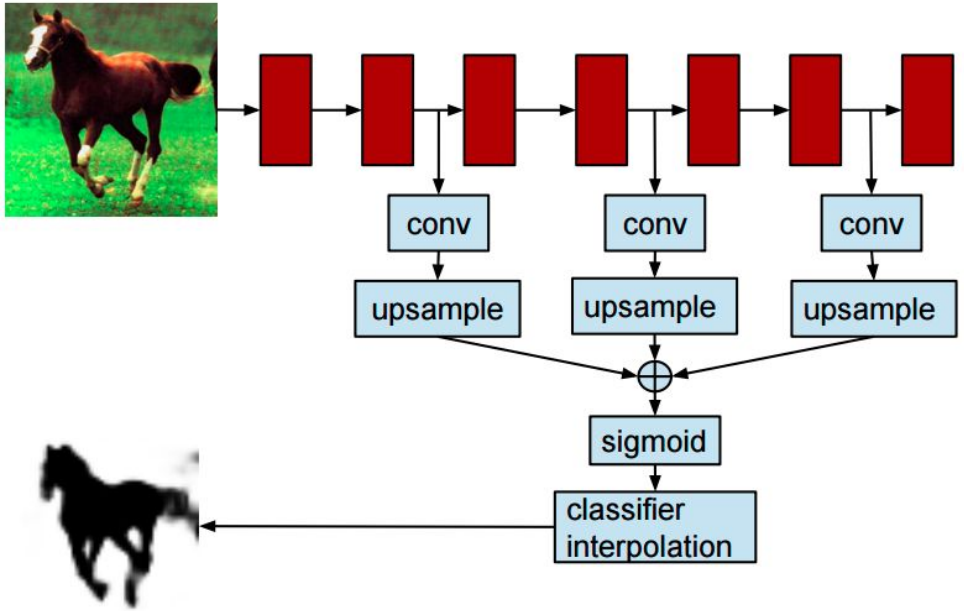


Hariharan et al. Simultaneous Detection and Segmentation. ECCV 2014

Slide Credit: CS231n

Proposal-based



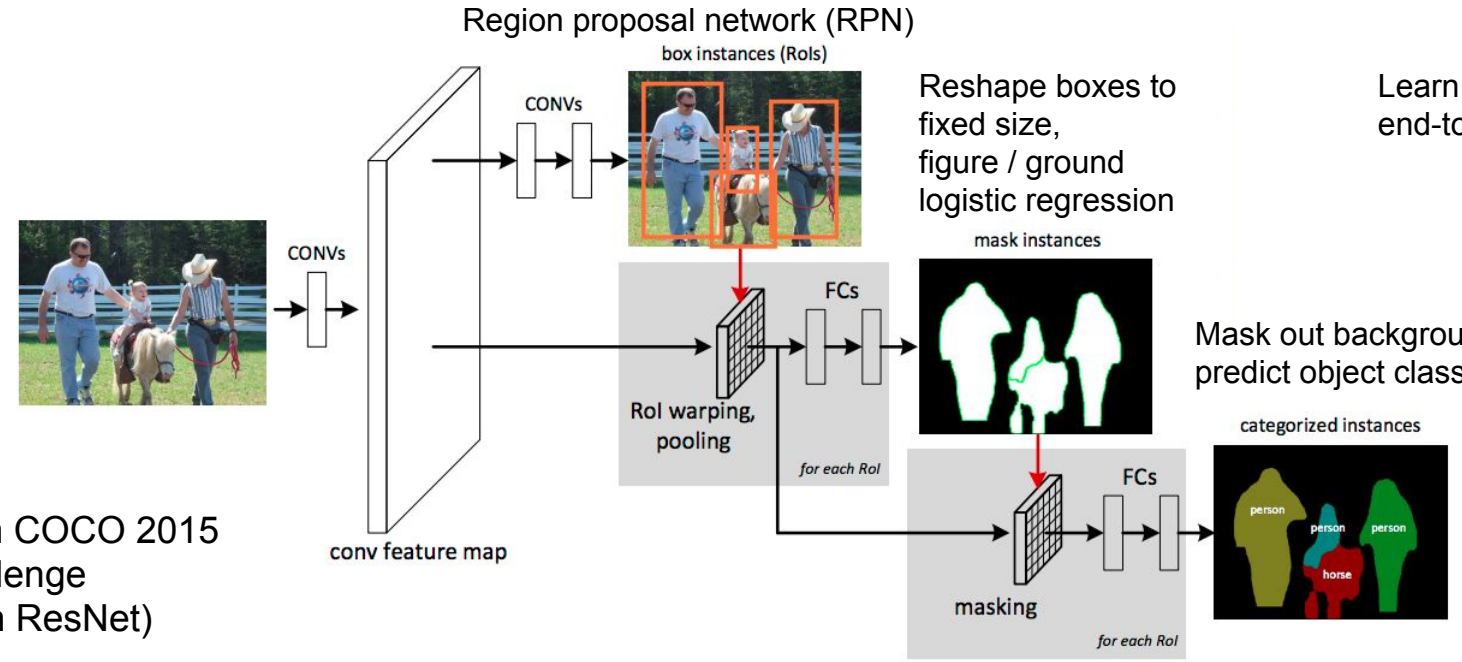


Hariharan et al. Hypercolumns for Object Segmentation and Fine-grained Localization. CVPR 2015

Slide Credit: CS231n

Proposal-based Instance Segmentation: MNC

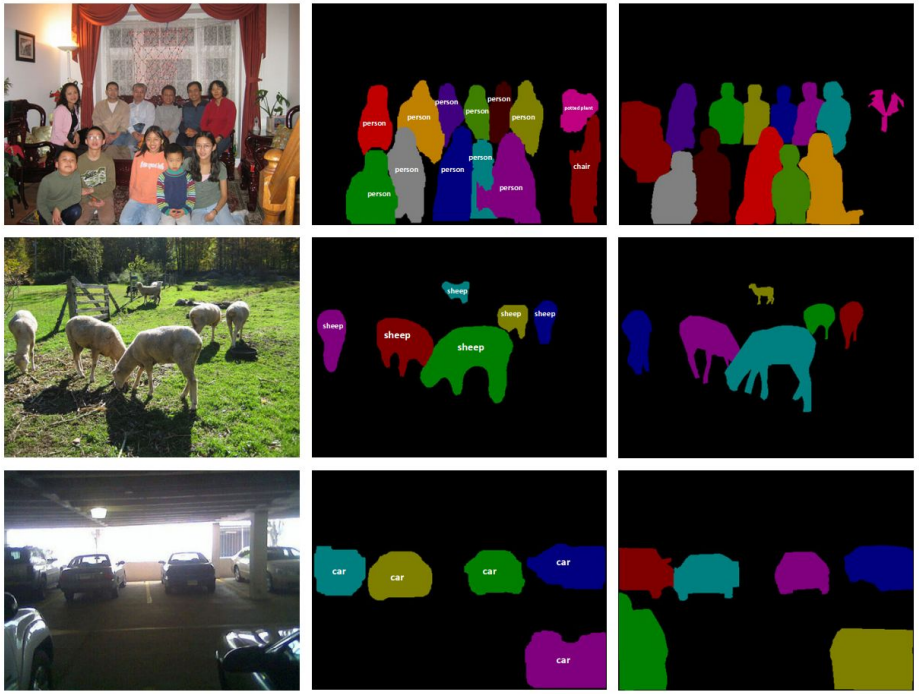
Faster R-CNN for Pixel Level Segmentation in a multi-stage cascade strategy



Won COCO 2015 challenge (with ResNet)

Dai et al. Instance-aware Semantic Segmentation via Multi-task Network Cascades. CVPR 2016

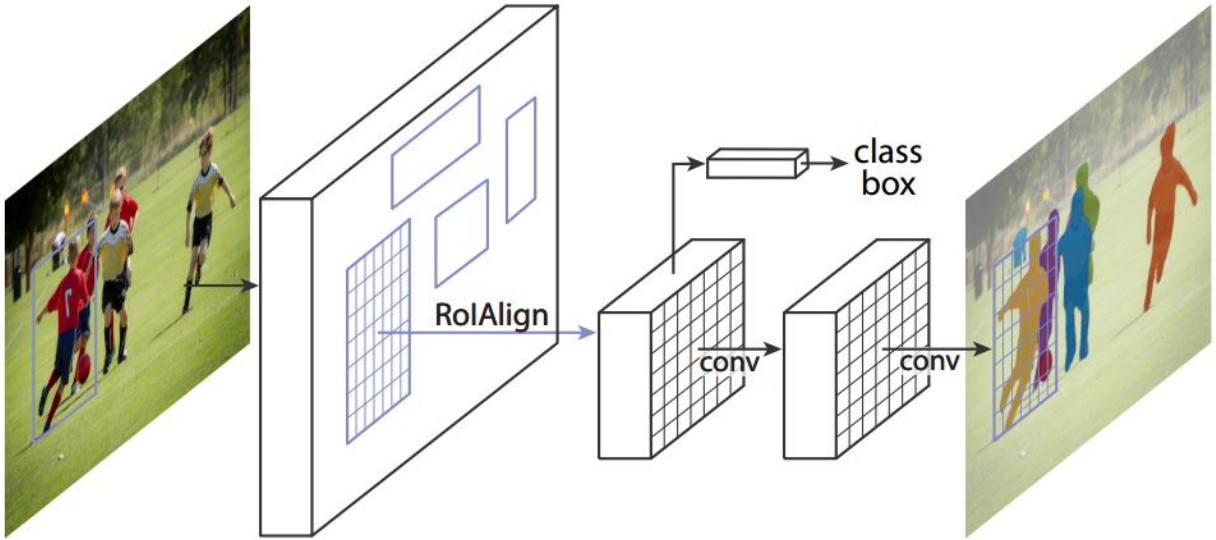
Proposal-based Instance Segmentation: MNC



Dai et al. Instance-aware Semantic Segmentation via Multi-task Network Cascades. CVPR 2016

Proposal-based Instance Segmentation: Mask R-CNN

Faster R-CNN for Pixel Level Segmentation as a **parallel prediction of masks and class labels**

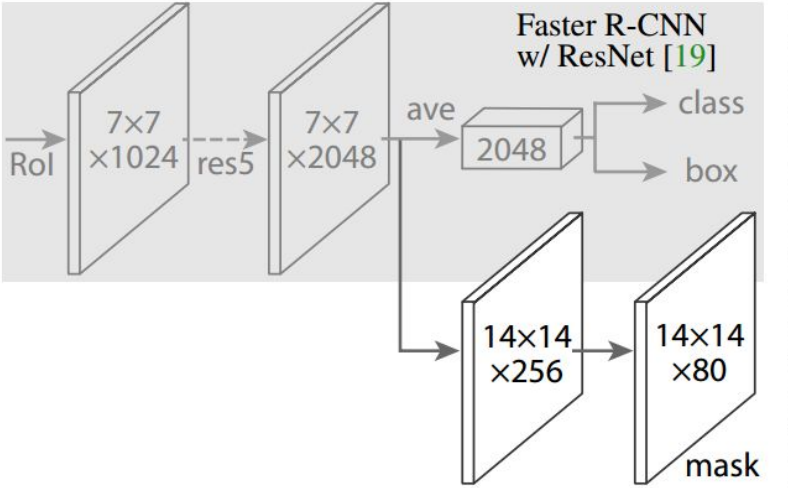


He et al. Mask R-CNN. arXiv Mar 2017

Mask R-CNN

- Classification & box detection losses are identical to those in Faster R-CNN
- Addition of a new loss term for mask prediction:

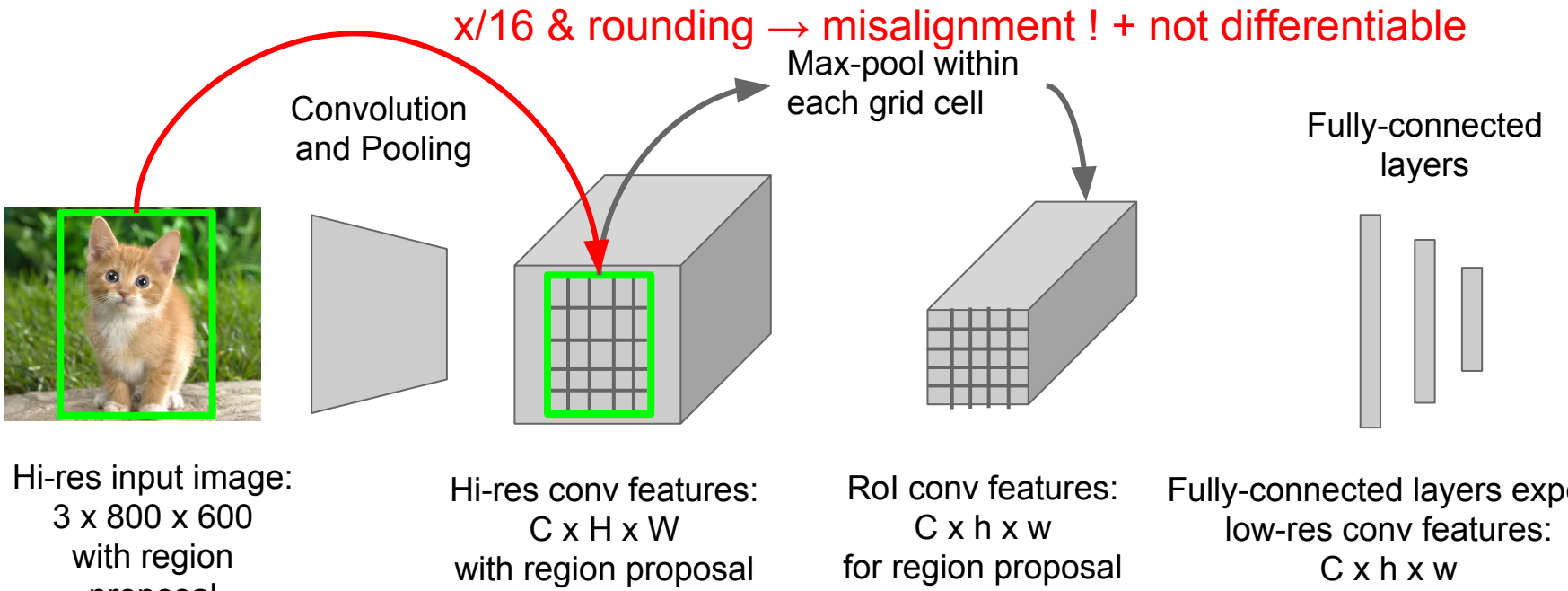
The network outputs a *K x m x m* volume for mask prediction, where *K* is the number of categories and *m* is the size of the mask (square)



He et al. Mask R-CNN. arXiv Mar 2017

Mask R-CNN: RoI Align

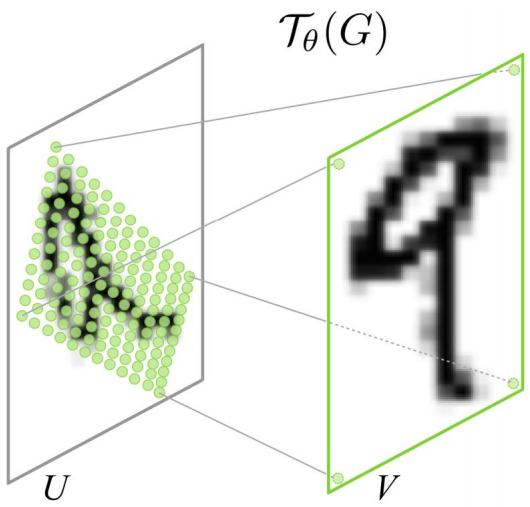
Reminder: RoI Pool from Fast R-CNN



He et al. Mask R-CNN. arXiv Mar 2017

Mask R-CNN: RoI Align

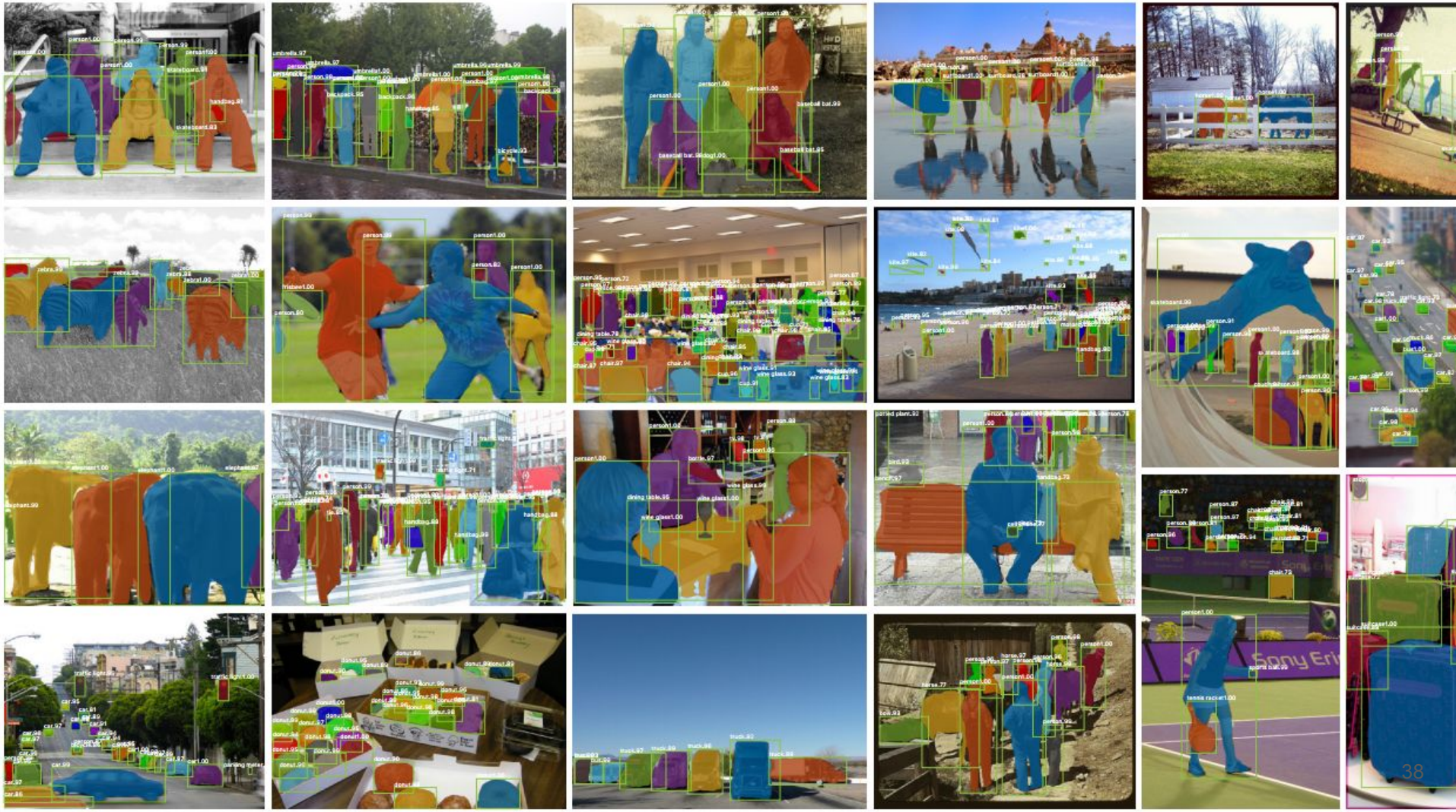
Use bilinear interpolation instead of cropping + maxpool



Mapping given by box coordinates
(θ_{12} and θ_{21} = 0 translation + scale)

$$\begin{pmatrix} x_i^s \\ y_i^s \end{pmatrix} = \begin{bmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \end{bmatrix} \begin{pmatrix} x_i^t \\ y_i^t \\ 1 \end{pmatrix}$$

Jaderberg et al. Spatial Transformer Networks. NIPS 2015



Mask R-CNN

Instance Segmentation

	backbone	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
MNC [10]	ResNet-101-C4	24.6	44.3	24.8	4.7	25.9	43.6
FCIS [26] +OHEM	ResNet-101-C5-dilated	29.2	49.5	-	7.1	31.3	50.0
FCIS+++ [26] +OHEM	ResNet-101-C5-dilated	33.6	54.5	-	-	-	-
Mask R-CNN	ResNet-101-C4	33.1	54.9	34.8	12.1	35.6	51.1
Mask R-CNN	ResNet-101-FPN	35.7	58.0	37.8	15.5	38.1	52.4
Mask R-CNN	ResNeXt-101-FPN	**37.1**	**60.0**	**39.4**	**16.9**	**39.9**	**53.5**

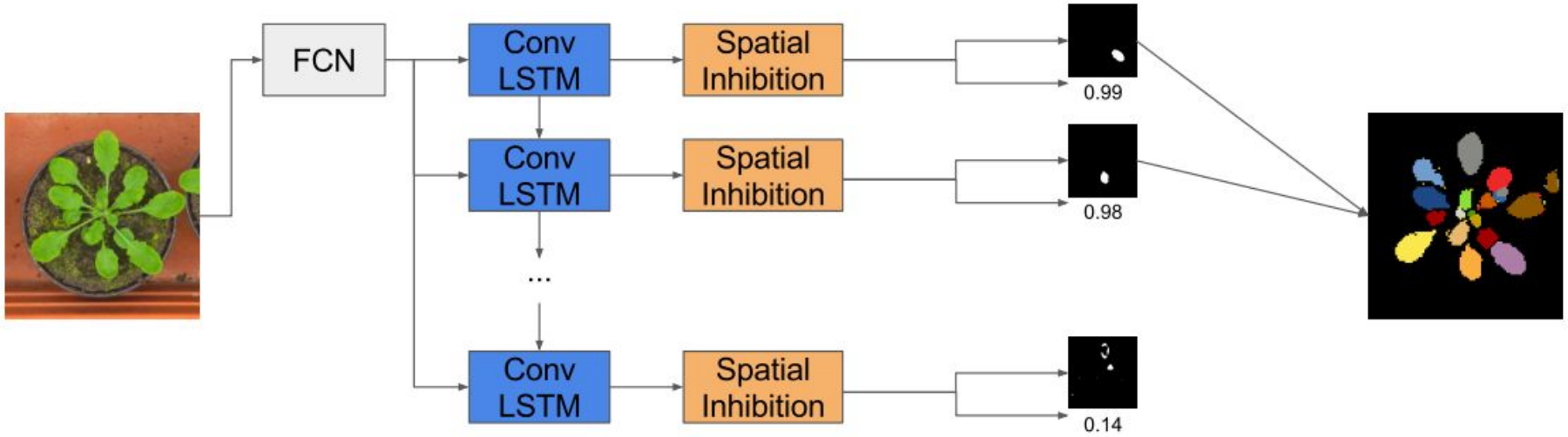
Object Detection

	backbone	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{bb}_S	AP^{bb}_M	AP^{bb}_L
Faster R-CNN+++ [19]	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN [27]	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI [21]	Inception-ResNet-v2 [37]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [36]	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
Faster R-CNN, RoIAlign	ResNet-101-FPN	37.3	59.6	40.3	19.8	40.2	48.8
Mask R-CNN	ResNet-101-FPN	38.2	60.3	41.7	20.1	41.1	50.2
Mask R-CNN	ResNeXt-101-FPN	**39.8**	**62.3**	**43.4**	**22.1**	**43.2**	51.2

He et al. Mask R-CNN. arXiv Mar 2017

Recurrent Instance Segmentation

Sequential mask generation



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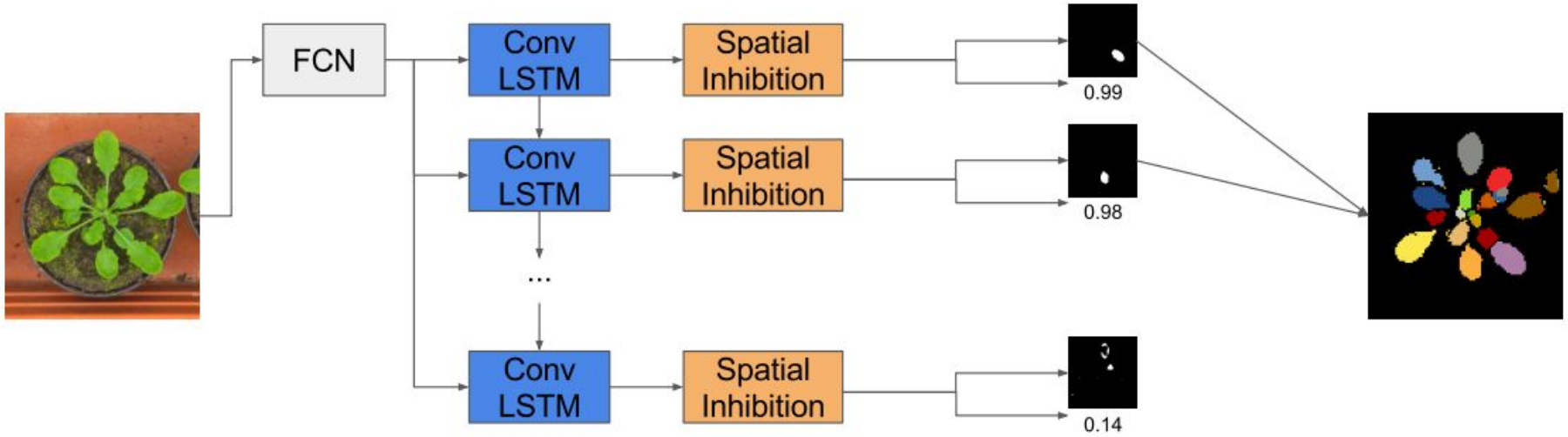
Recurrent Instance Segmentation

Mapping between ground truth and predicted masks ?



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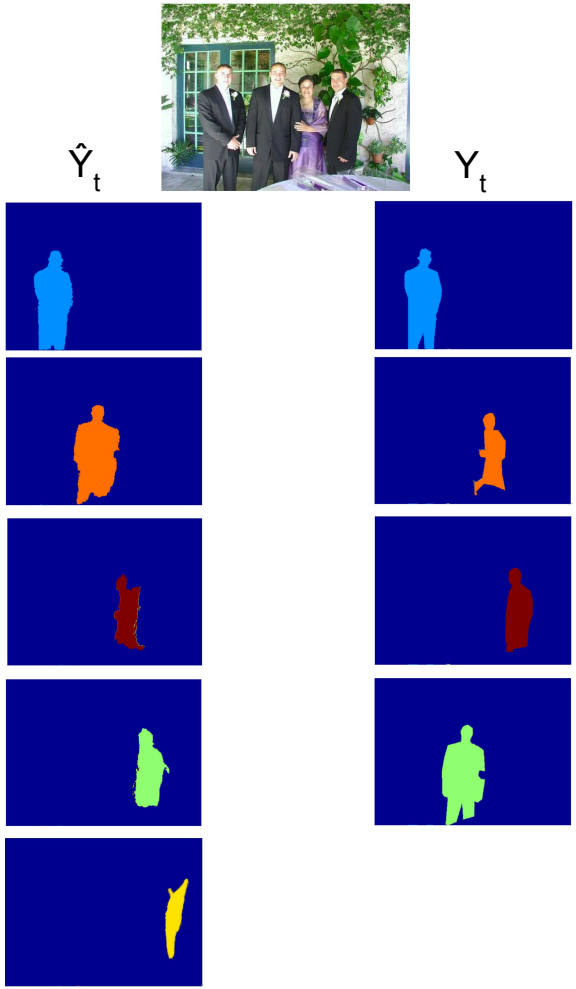
Recurrent Instance Segmentation:

Coverage Loss

1-Compute the IoU for all pairs of Predicted/GT masks

$$f_{IoU}(\hat{\mathbf{y}}, \mathbf{y}) = \frac{\langle \hat{\mathbf{y}}, \mathbf{y} \rangle}{\|\hat{\mathbf{y}}\|_1 + \|\mathbf{y}\|_1 - \langle \hat{\mathbf{y}}, \mathbf{y} \rangle}$$



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Recurrent Instance Segmentation:

Coverage Loss

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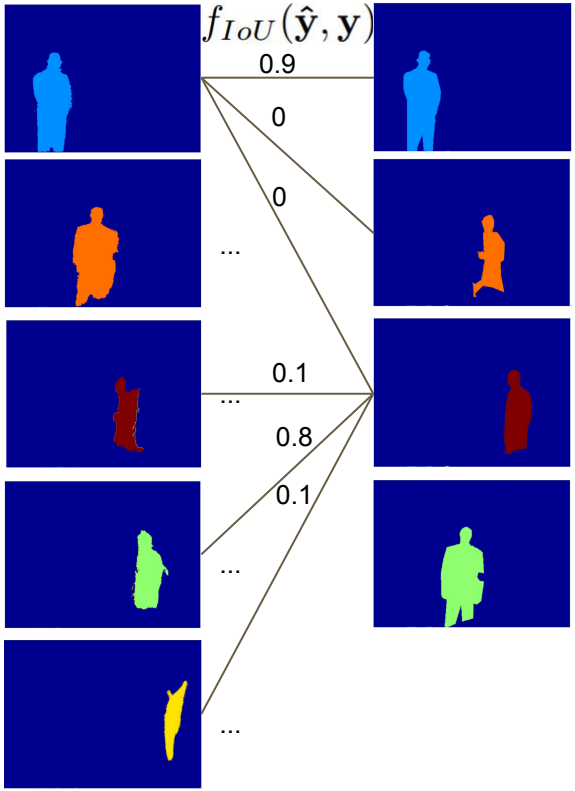
$$\begin{pmatrix} 0.9 & 0 & 0 & 0.08 \\ 0.12 & 0.14 & 0 & 0.87 \\ 0 & 0.68 & 0.1 & .0.7 \\ 0 & 0.1 & 0.8 & 0 \\ 0 & 0 & 0.1 & 0 \end{pmatrix}$$



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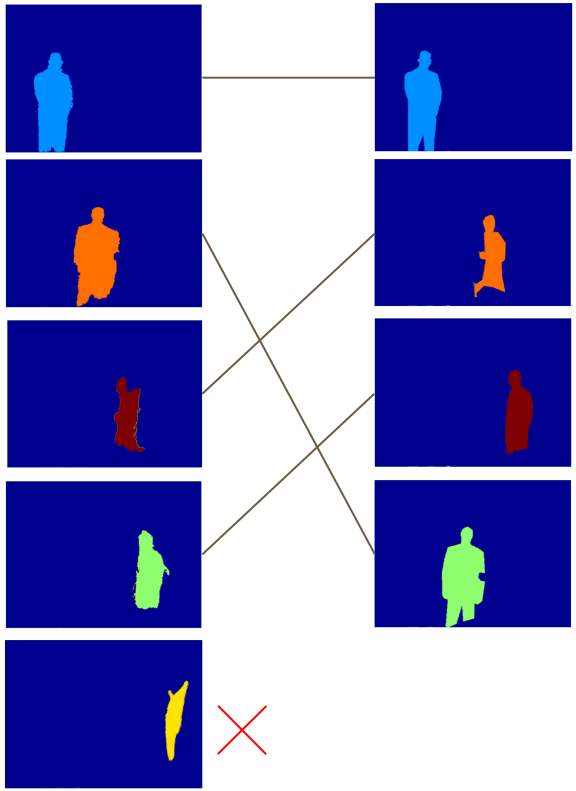
Recurrent Instance Segmentation:

Coverage Loss

2-Find best matching:

$$\begin{pmatrix} \underline{0.9} & 0 & 0 & 0.08 \\ 0.12 & 0.14 & 0 & \underline{0.87} \\ 0 & \underline{0.68} & 0.1 & .0.7 \\ 0 & 0.1 & \underline{0.8} & 0 \\ 0 & 0 & 0.1 & 0 \end{pmatrix}$$



Loss: Sum of the Intersections over the union for the best matching (*-1)

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Recurrent Instance Segmentation:

Coverage Loss

3-Also take into account the scores

$$\lambda \sum_{t=1}^{\hat{n}} f_{BCE}\left([t \leq n], s_t\right)$$

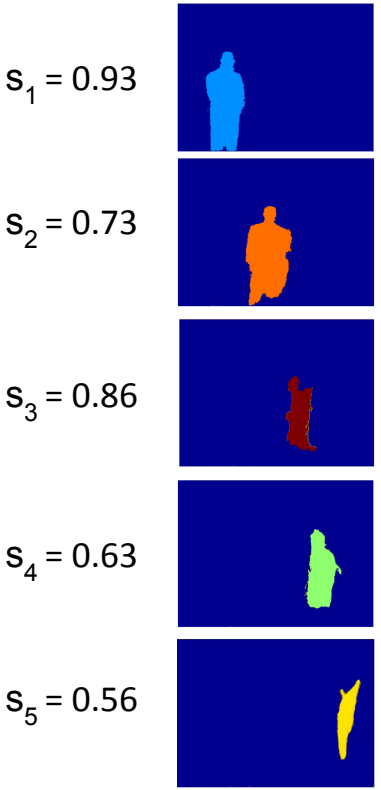
Where:

$f_{BCE}(a, b)$ is the binary cross entropy:

$f_{BCE}(a, b) = -\left(a\log(b) + (1-a)\log(1-b)\right)$

$[\cdot]$ is the Iverson bracket which:

Is 1 if the condition is true and 0 else



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Recurrent Instance Segmentation:

Coverage Loss

4-Add everything together

$$\ell(\hat{\mathbf{Y}}, \mathbf{s}, \mathbf{Y}) = \min_{\delta \in \mathcal{S}} - \sum_{\hat{t}=1}^{\hat{n}} \sum_{t=1}^{n} f_{IoU}\left(\hat{\mathbf{Y}}_{\hat{\mathbf{t}}}, \mathbf{Y}_{\mathbf{t}}\right) \delta_{\hat{t},t} + \lambda \sum_{t=1}^{\hat{n}} f_{BCE}\left([t \leq n], s_t\right)$$

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Recurrent Instance Segmentation

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Summary

Segmentation Datasets

Semantic Segmentation Methods

- Deconvolution
- Dilated Convolution
- Skip Connections

Instance Segmentation Methods

- Proposal-Based
- Recurrent

Questions ?