Fully Convolutional Netwoks for Semantic Segmentation

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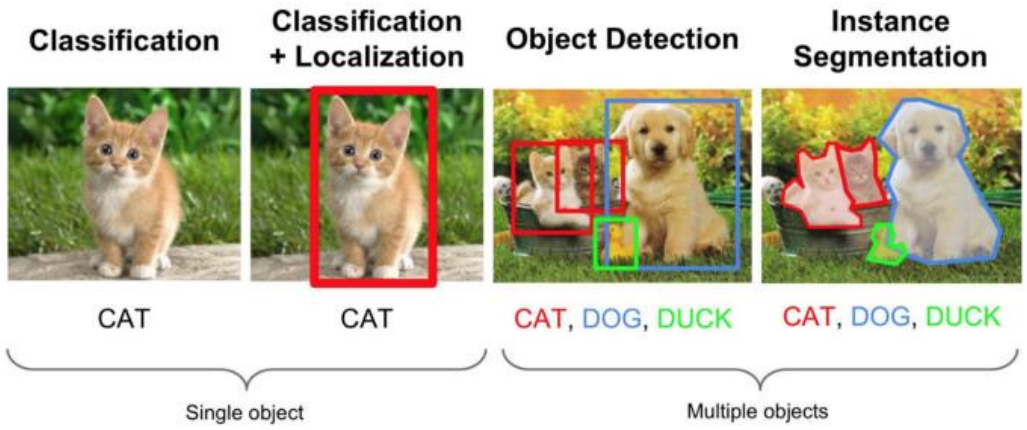
- Introduction to Semantic Segmentation
- Metric - IoU (Intersection over Union)
- Fully Convolutional Networks
- Encoder (Downsampling)
- Decoder (Upsampling)
- Results
- Key Points

Introduction to Semantic Segmentation

• **Classification** (분류): 인풋에 대해서 하나의 레이블을 예측하는 작업.
VGG, ResNet, Inception 등의 모델

• **Object Localization/Detection** (검출): 물체의 레이블을 예측하면서 그 물체가 어디에 있는지 정보를 제공. 물체가 있는 곳에 네모를 그리는 등으로 표현
YOLO, R-CNN 등의 모델

• **Segmentation** (분할): 모든 픽셀의 레이블을 예측
FCN, SegNet, DeepLab 등의 모델



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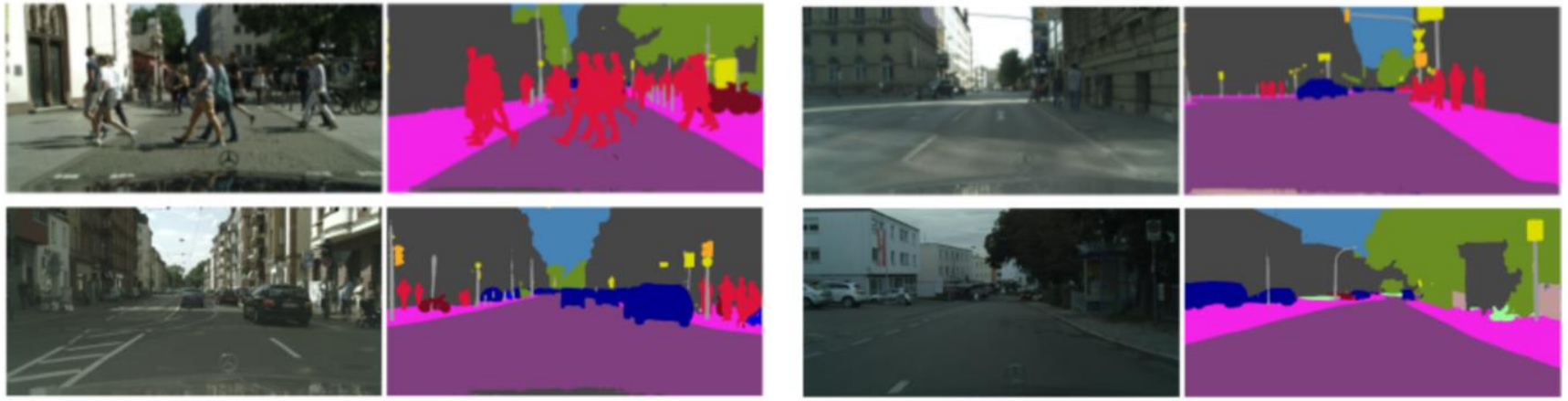
Introduction to Semantic Segmentation



Task Target : 사진 또는 영상의 모든 픽셀을 해당하는 Class로 분류하는 것

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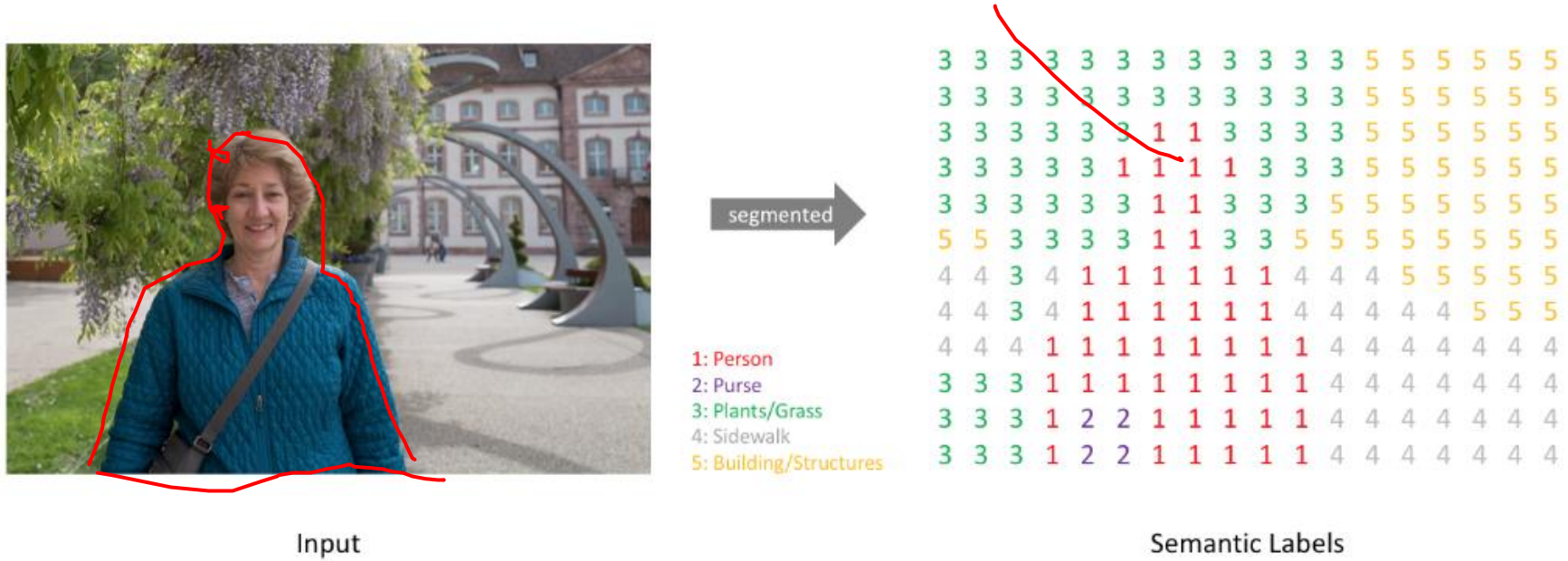
Introduction to Semantic Segmentation



Input : (Height X Width X 3) or (Height X Width X 1)

Output : Segmenatation Map

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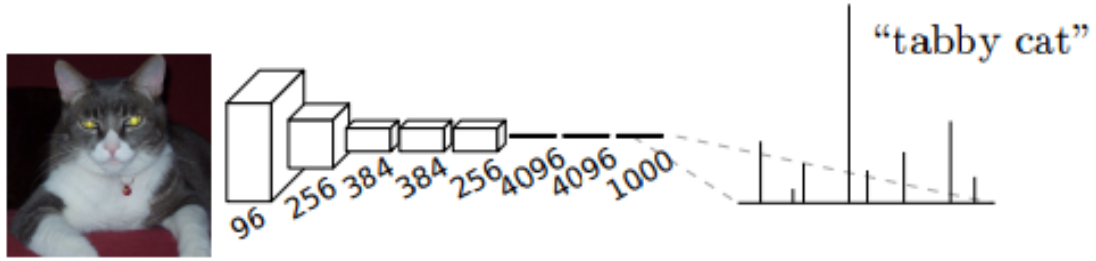
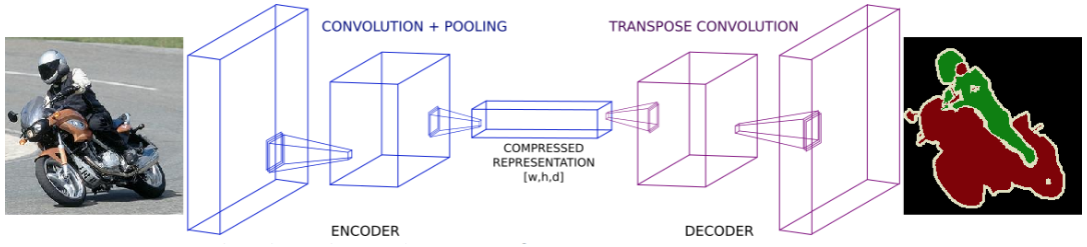
Introduction to Semantic Segmentation



일반적인 CNN의 구조
-> 마지막 Fully Connected Layer에 의해 위치정보를 잃음



Semantic Segmentation 모델들은 Encoder Decoder형태를 사용해 위치 정보를 잃지 않음

대부분의 Semantic Segmentation 방법론은
오늘 리뷰하는 FCN을 기반으로 함

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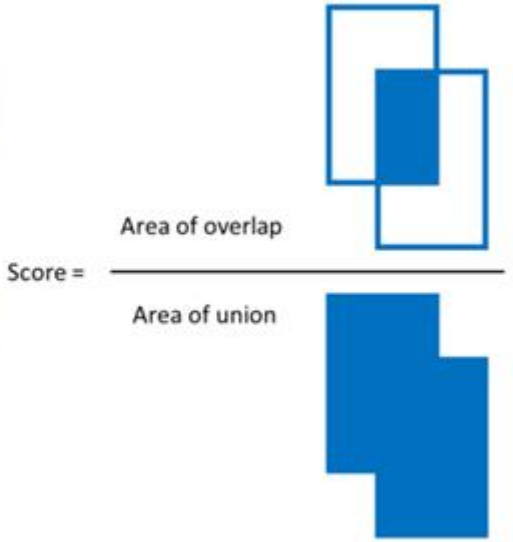
Metric - IoU (Intersection over Union)



- pixel accuracy: $\sum_i n_{ii} / \sum_i t_i$
- mean accuraccy: $(1/n_{\text{cl}}) \sum_i n_{ii}/t_i$
- mean IU: $(1/n_{\text{cl}}) \sum_i n_{ii} / \left(t_i + \sum_j n_{ji} - n_{ii}\right)$
- frequency weighted IU: $\left(\sum_k t_k\right)^{-1} \sum_i t_i n_{ii} / \left(t_i + \sum_j n_{ji} - n_{ii}\right)$

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Fully Convolutional Networks

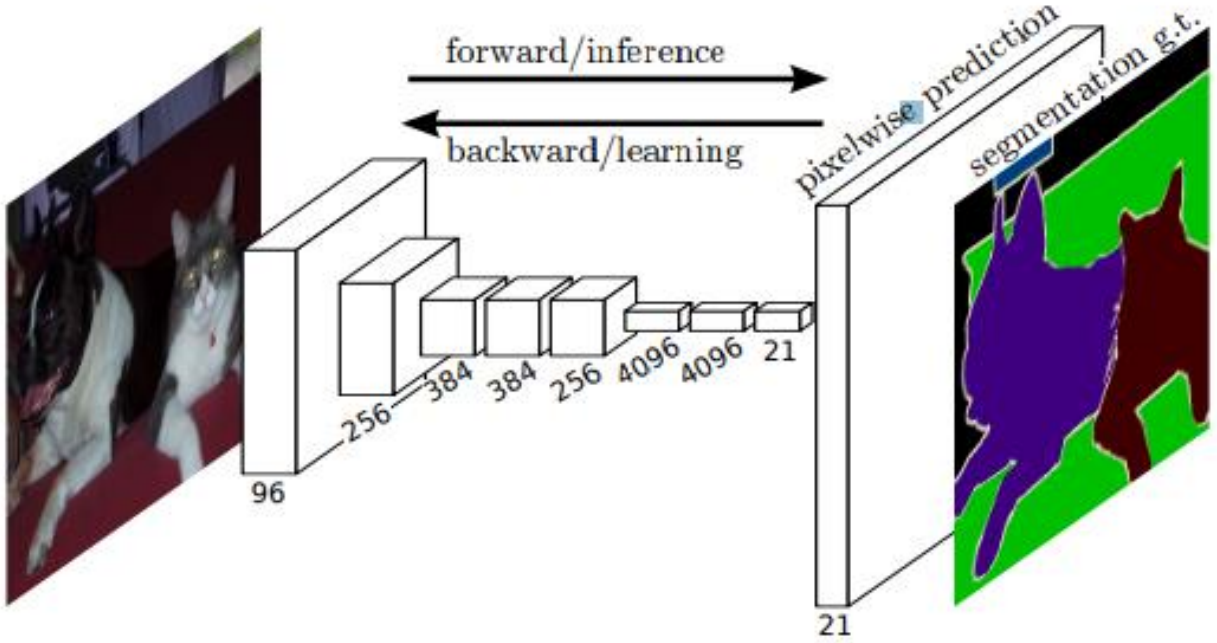

Figure 1. Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks like semantic segmentation.

FCN's Overall Network Structure

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Fully Convolutional Networks

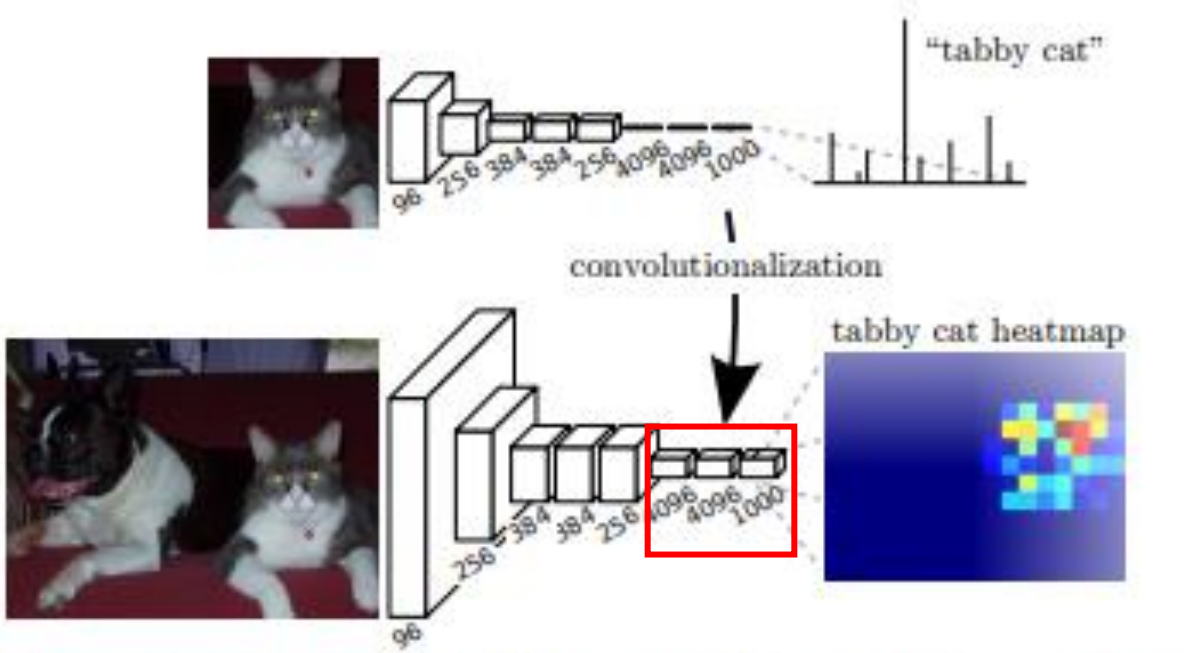

Figure 2. Transforming fully connected layers into convolution layers enables a classification net to output a heatmap. Adding layers and a spatial loss (as in Figure 1) produces an efficient machine for end-to-end dense learning.

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Encoder

Adapting classifiers for dense prediction

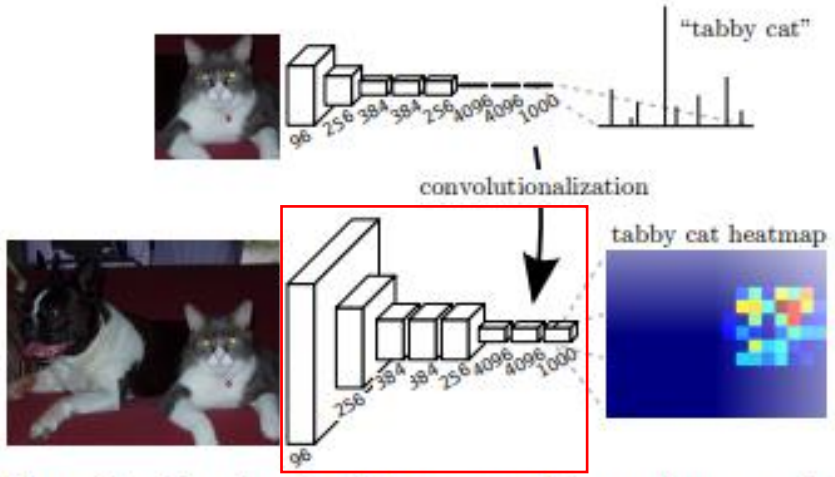

Figure 2. Transforming fully connected layers into convolution layers enables a classification net to output a heatmap. Adding layers and a spatial loss (as in Figure 1) produces an efficient machine for end-to-end dense learning.

	FCN-AlexNet	FCN-VGG16	FCN-GoogLeNet[4]
mean IU	39.8	**56.0**	42.5
forward time	50 ms	210 ms	59 ms
conv. layers	8	16	22
parameters	57M	134M	6M
rf size	355	404	907
max stride	32	32	32

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Decoder (Skip Architecture)

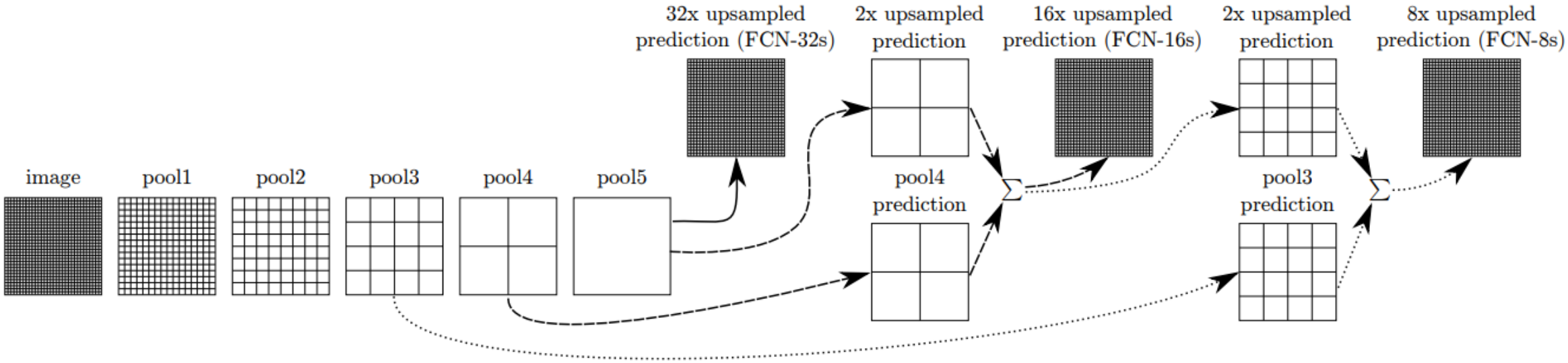

Table 2. Comparison of skip FCNs on a subset of PASCAL VOC2011 validation[7]. Learning is end-to-end, except for FCN-32s-fixed, where only the last layer is fine-tuned. Note that FCN-32s is FCN-VGG16, renamed to highlight stride.

	pixel acc.	mean acc.	mean IU	f.w. IU
FCN-32s-fixed	83.0	59.7	45.4	72.0
FCN-32s	89.1	73.3	59.4	81.4
FCN-16s	90.0	75.7	62.4	83.0
FCN-8s	**90.3**	**75.9**	**62.7**	**83.2**

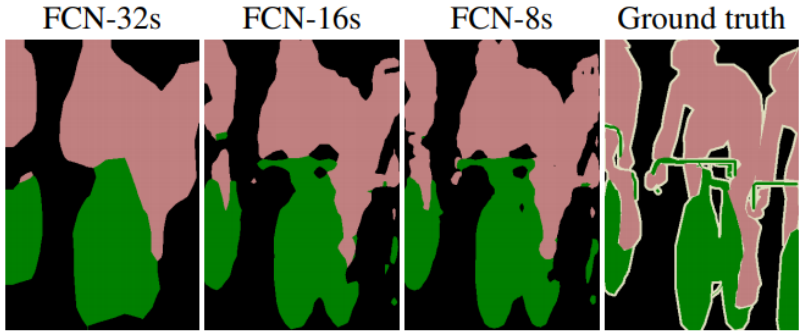

Figure 4. Refining fully convolutional nets by fusing information from layers with different strides improves segmentation detail. The first three images show the output from our 32, 16, and 8 pixel stride nets (see Figure 3).

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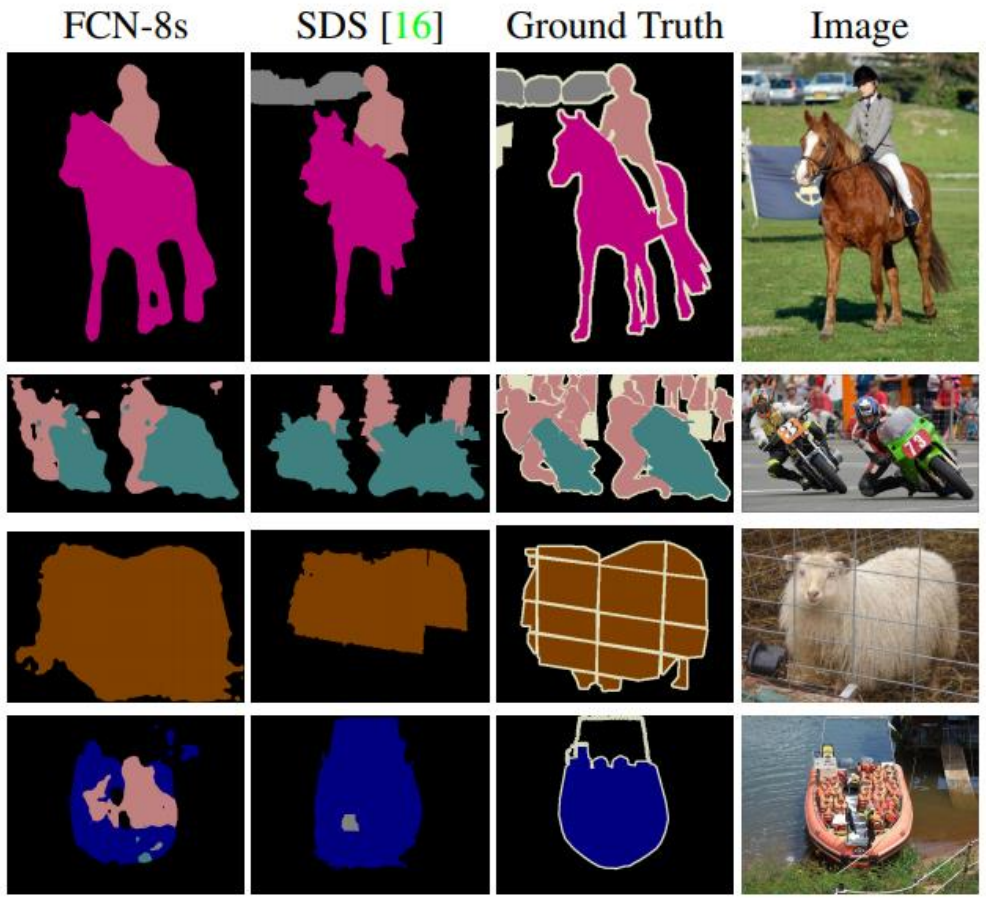
Results

PASCAL VOC

Table 3. Our fully convolutional net gives a 20% relative improvement over the state-of-the-art on the PASCAL VOC 2011 and 2012 test sets, and reduces inference time.

	mean IU VOC2011 test	mean IU VOC2012 test	inference time
R-CNN [12]	47.9	-	-
SDS [16]	52.6	51.6	~ 50 s
FCN-8s	**62.7**	**62.2**	~ **175 ms**



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Results

NYUDv2

Table 4. Results on NYUDv2. *RGBD* is early-fusion of the RGB and depth channels at the input. *HHA* is the depth embedding of [14] as horizontal disparity, height above ground, and the angle of the local surface normal with the inferred gravity direction. *RGB-HHA* is the jointly trained late fusion model that sums RGB and HHA predictions.

	pixel acc.	mean acc.	mean IU	f.w. IU
Gupta *et al.* [14]	60.3	-	28.6	47.0
FCN-32s RGB	60.0	42.2	29.2	43.9
FCN-32s RGBD	61.5	42.4	30.5	45.5
FCN-32s HHA	57.1	35.2	24.2	40.4
FCN-32s RGB-HHA	64.3	44.9	32.8	48.0
FCN-16s RGB-HHA	**65.4**	**46.1**	**34.0**	**49.5**

SIFT Flow

Table 5. Results on SIFT Flow[10] with class segmentation (center) and geometric segmentation (right). Tighe [33] is a non-parametric transfer method. Tighe 1 is an exemplar SVM while 2 is SVM + MRF. Farabet is a multi-scale convnet trained on class-balanced samples (1) or natural frequency samples (2). Pinheiro is a multi-scale, recurrent convnet, denoted RCNN$_3$ ($\circ^3$). The metric for geometry is pixel accuracy.

	pixel acc.	mean acc.	mean IU	f.w. IU	geom. acc.
Liu *et al.* [23]	76.7	-	-	-	-
Tighe *et al.* [33]	-	-	-	-	90.8
Tighe *et al.* [34] 1	75.6	41.1	-	-	-
Tighe *et al.* [34] 2	78.6	39.2	-	-	-
Farabet *et al.* [8] 1	72.3	50.8	-	-	-
Farabet *et al.* [8] 2	78.5	29.6	-	-	-
Pinheiro *et al.* [28]	77.7	29.8	-	-	-
FCN-16s	**85.2**	**51.7**	39.5	76.1	**94.3**

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Key Points

1. Adopting Fully Convolutional Layer instead of Fully Connected Layer
   -> to maintain corresponding spatial dimension of input data

2. Defined Novel Skip Architecture
   -> to combine deep, coarse, semantic information and shallow, fine, appearance information

Input

Ground truth

Prediction

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