CSE 252D: Advanced Computer Vision

Manmohan Chandraker

Lecture 12: Semantic Segmentation

Virtual classrooms

- Virtual lectures on Zoom
  - Only host shares the screen
  - Keep video off and microphone muted
  - But please do speak up (remember to unmute!)
  - Slides uploaded on webpage just before class
- Virtual interactions on Zoom
  - Ask and answer plenty of questions
  - “Raise hand” feature on Zoom when you wish to speak
  - Post questions on chat window
  - Happy to try other suggestions!
- Lectures recorded and upload on Canvas
  - Available under “My Media” on Canvas

Overall goals for the course

- Introduce the state-of-the-art in computer vision
- Study principles that make them possible
- Get understanding of tools that drive computer vision
- Enable one or all of several such outcomes
  - Pursue higher studies in computer vision
  - Join industry to do cutting-edge work in computer vision
  - Gain appreciation of modern computer vision technologies
- This is a great time to study computer vision!

Papers for Wed, May 12

- Deep High-Resolution Representation Learning for Human Pose Estimation
  - https://arxiv.org/abs/1902.09212
- Simple Baselines for Human Pose Estimation and Tracking
  - https://arxiv.org/abs/1804.06208
- OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields
  - https://arxiv.org/abs/1812.08008
- End-to-end Recovery of Human Shape and Pose
  - https://arxiv.org/abs/1712.06584

Papers for Fri, May 14

- ENet: A Deep Neural Network Architecture for Real-Time Semantic Segmentation
  - https://arxiv.org/abs/1606.02147
- ERFNet: Efficient Residual Factorized ConvNet for Real-Time Semantic Segmentation
  - https://ieeexplore.ieee.org/abstract/document/8063438
- Fast-SCNN: Fast Semantic Segmentation Network
  - https://arxiv.org/abs/1902.04502
- Decoupled Deep Neural Network for Semi-supervised Semantic Segmentation
  - https://arxiv.org/abs/1506.04924

Papers for Wed, May 19

- Context Encoding for Semantic Segmentation
  - https://arxiv.org/abs/1803.08904
- Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation
  - https://arxiv.org/abs/1802.02611
- High-Resolution Representations for Labeling Pixels and Regions
  - https://arxiv.org/abs/1904.04514
- MSeg: A Composite Dataset for Multi-Domain Semantic Segmentation
  - https://ieeexplore.ieee.org/document/9157628

Recap

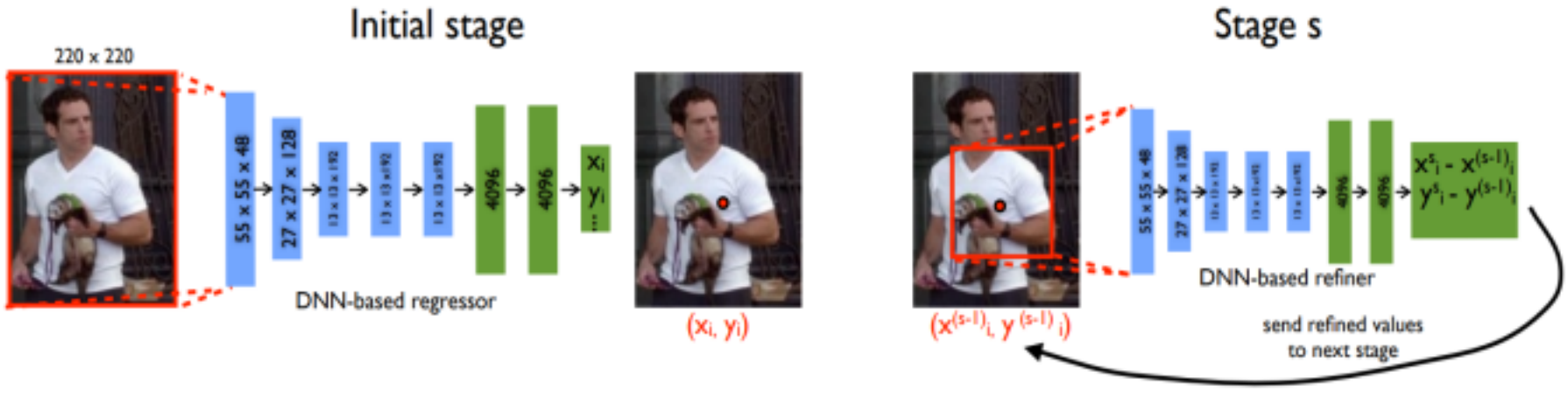
Local and Global Needed for Pose Estimation

- Local part-based detectors are not sufficient for pose estimation

Cascade of Regressors

- Advantages:
  - Simple, yet holistic
  - No need to define losses that capture interactions
  - Instead, all hidden layers are shared by joint regressors
  - Increasingly detailed prediction along cascade stages

- Disadvantages:
  - ~~Limited ability to consider details~~
  - ~~One prediction per image, no candidates~~
  - ~~Depends on quality of initial prediction~~



[Toshev and Szegedy, DeepPose]

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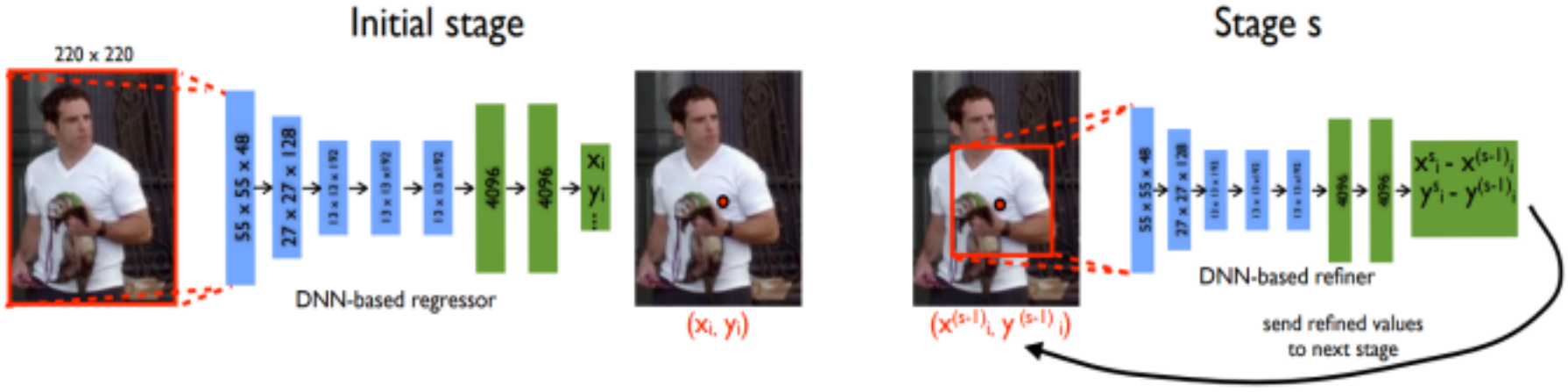

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Cascade of Heat Maps

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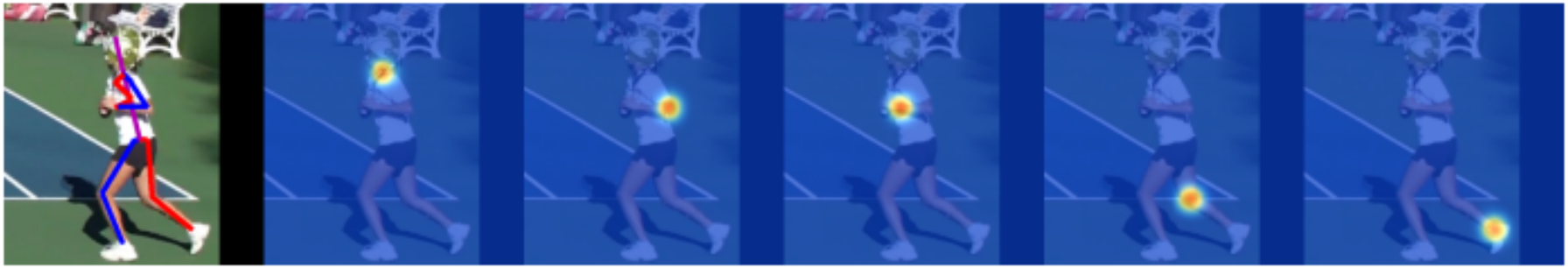
  - ~~Not enough modeling of spatial structure~~
  - ~~Cannot reason about occluded parts, or those outside window~~



[Tompson et al., Efficient Object Localization]

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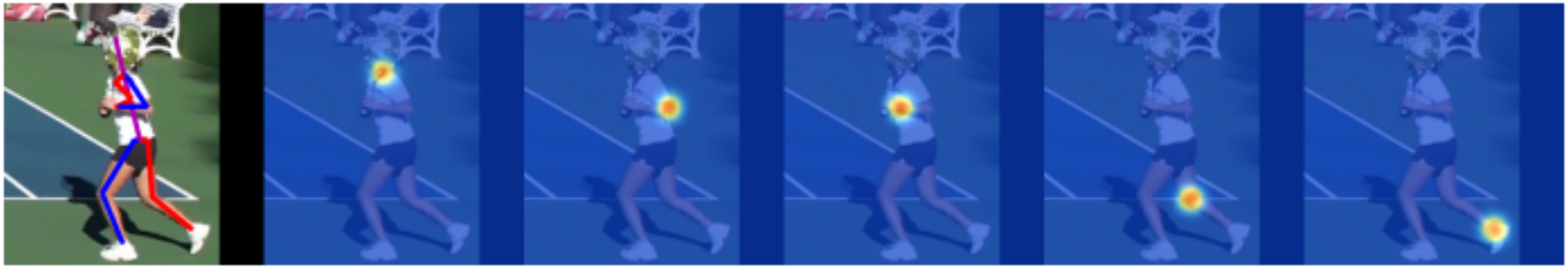

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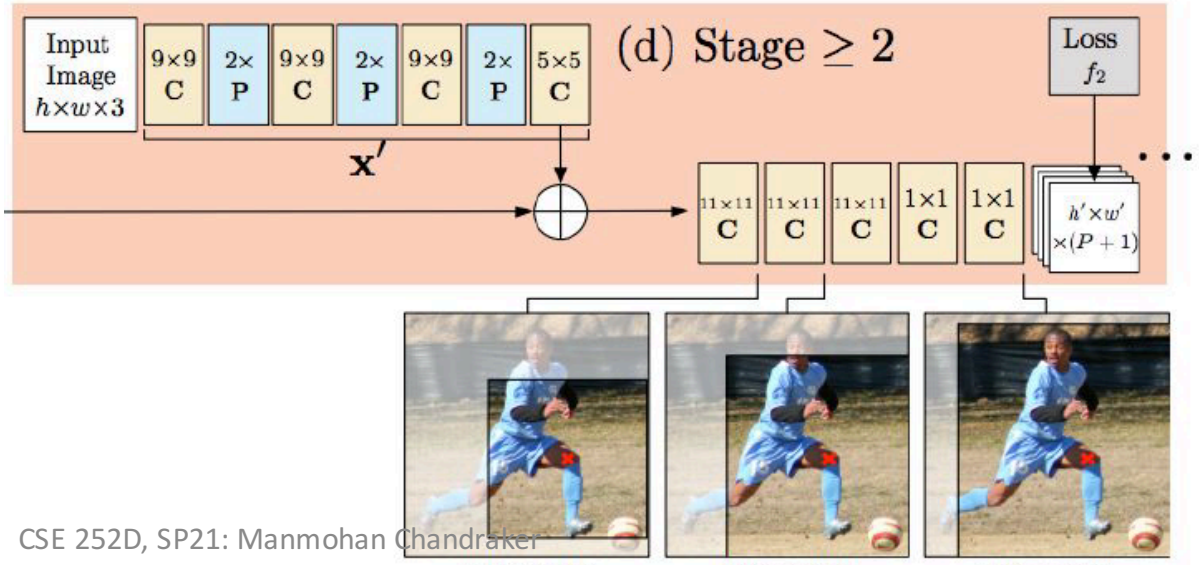
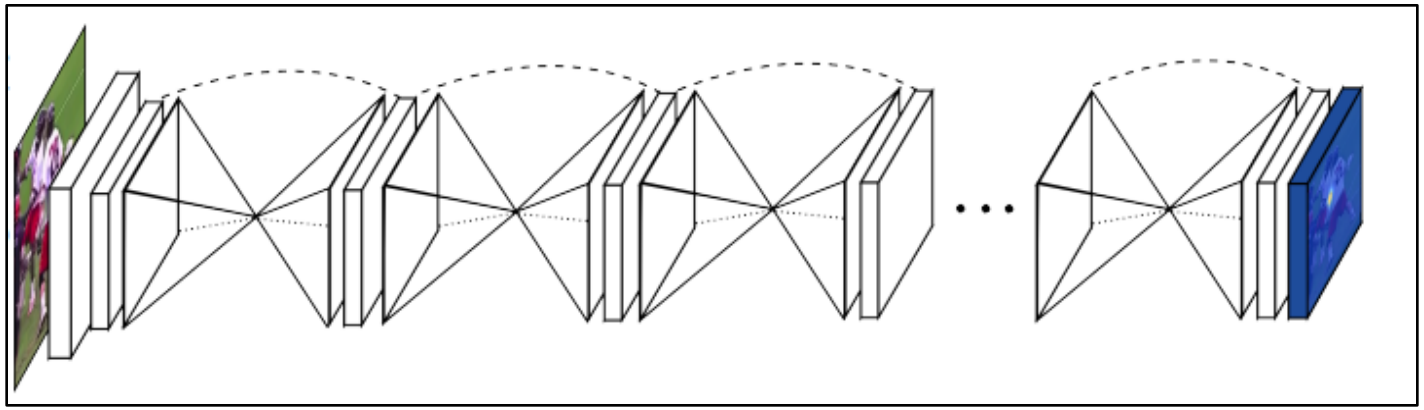
Convolutional Pose Machines: Next Stages

- Image features **x'** from the previous stage
- Context function ψ encodes landscape of belief maps around part locations
  - In practice, ψ is just the receptive field
  - Network decides how to combine features and learn higher relations
  - Previously: hand-defined potential functions in graphical model
- Three ways to increase size of receptive field
  - More pooling: lose local details
  - Larger filters: increase number of parameters
  - More layers: vanishing gradients ⇨ Intermediate supervision



Stacked Hourglass Network

- Multiple iterative stages allow refinement
- Each stage does full bottom-up and top-down processing (no weights shared)
- Repeated inference, with intermediate supervision for each stage
  - Network has had a chance to reason both locally and globally
  - Subsequent hourglass modules can reassess high-order spatial relations
  - Ask network to repeatedly reason across scales
- Intermediate supervision not straightforward for single hourglass module
  - Cannot apply before pooling since only local information available
  - After upsampling, cannot re-evaluate features globally



Recipes for Human Pose Estimation

- Local appearance: needed for accurate part detection
- Global reasoning: orientation of body, limb arrangement, part relationships

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- CNNs are inherently well-suited for this task
  - Multiscale feature extraction
  - Shared hidden layers capture part interactions

- But mechanisms needed to coax local and global performance out of CNNs

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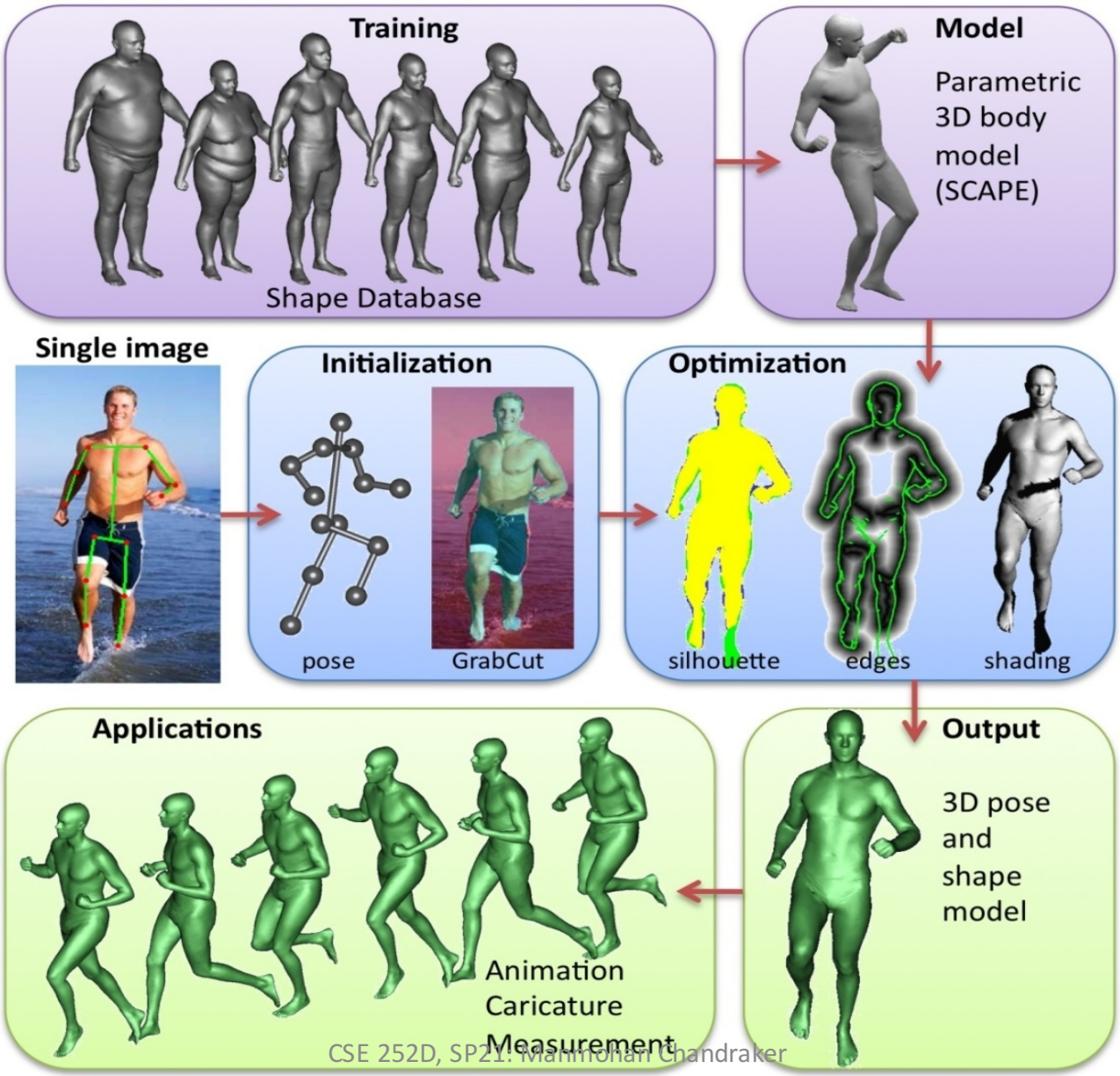
- Heat maps
  - Predict probability of joint appearing at a pixel

- Cascades
  - Iteratively refine predictions for fine localization
  - Long-range interactions through wider receptive fields

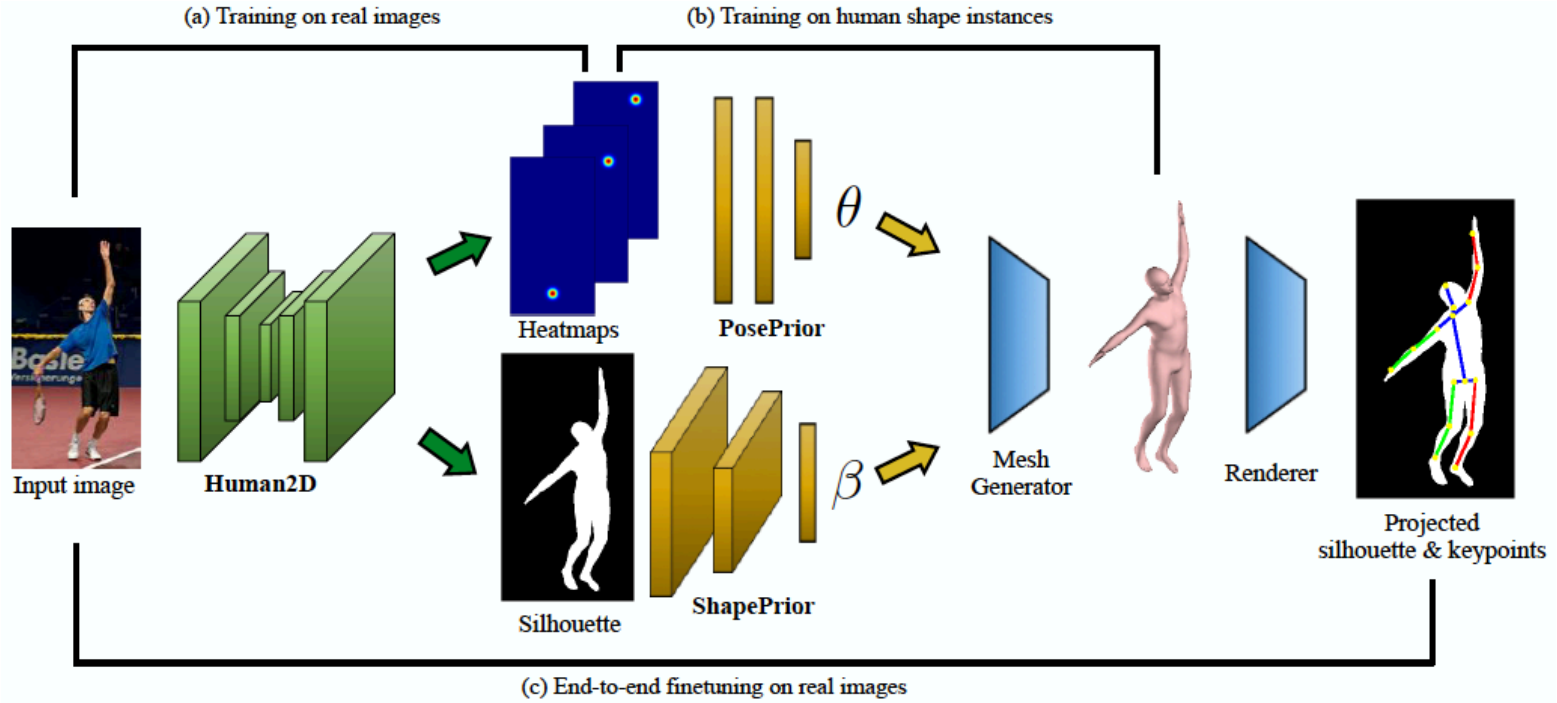
- Intermediate supervision
  - Prevent vanishing gradients through cascade stages
  - Allow cascade to repeatedly assess local and global information

Shape Fitting Pipeline



Predicting 3D Human Shape and Pose

- Use data-driven priors from deep network to avoid optimization difficulties
- Large-scale data exists for 2D keypoints and silhouettes
- Train a multi-task stacked hourglass network for heat maps and silhouette

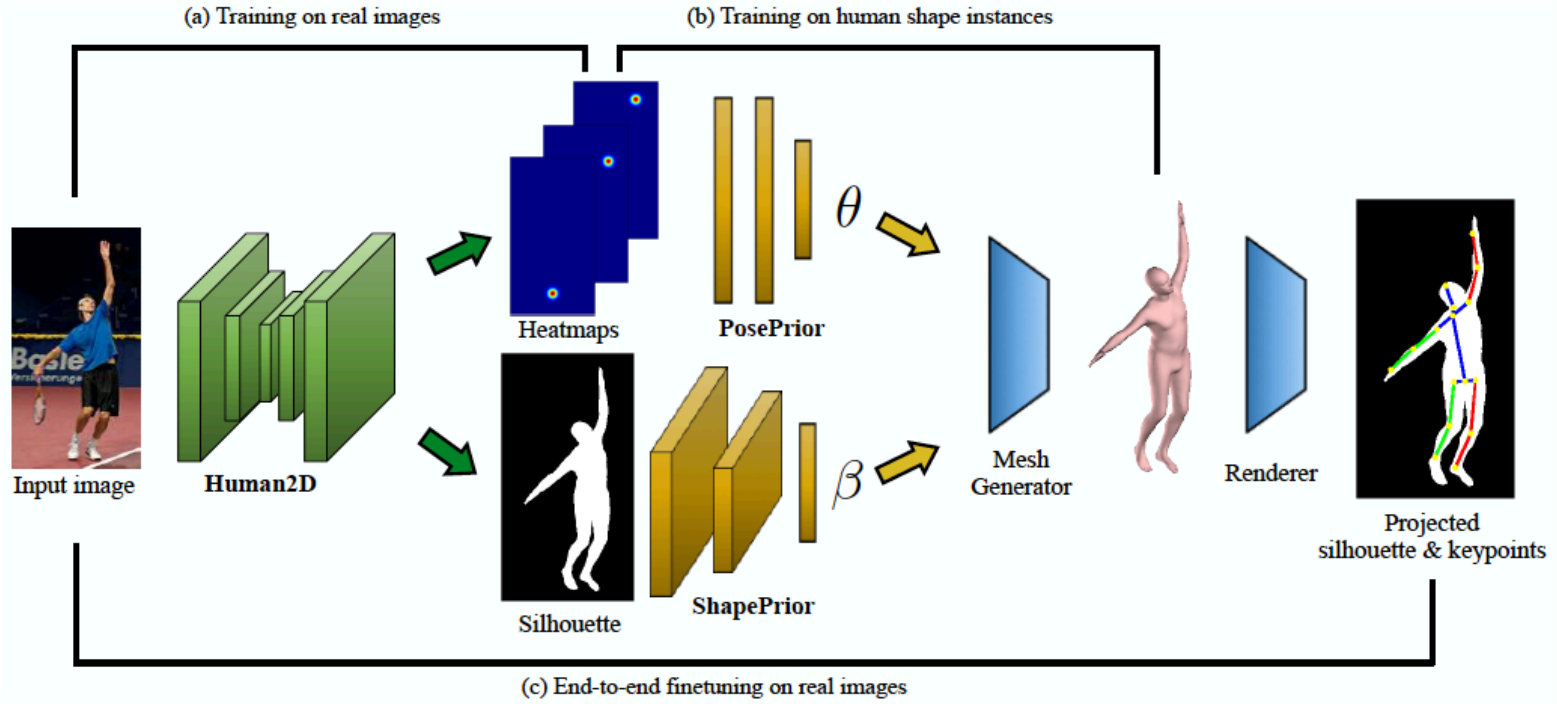


[Pavlakos et al., Learning to Estimate 3D Human Pose]

Predicting 3D Human Shape and Pose

- Use heat maps to predict pose, silhouette to predict shape parameters in SMPL
- Ignore inter-dependence, in favor of disentanglement
- Train based on data rendered from ground truth SMPL instances
- Objectives: 3D vertex loss and joint loss

$$\mathcal{L}_{\mathcal{M}} = \sum_{i=1}^{N} \|\hat{P}_i - P_i\|_2^2, \qquad \mathcal{L}_{\mathcal{J}} = \sum_{i=1}^{M} \|\hat{J}_i - J_i\|_2^2.$$



[Pavlakos et al., Learning to Estimate 3D Human Pose]

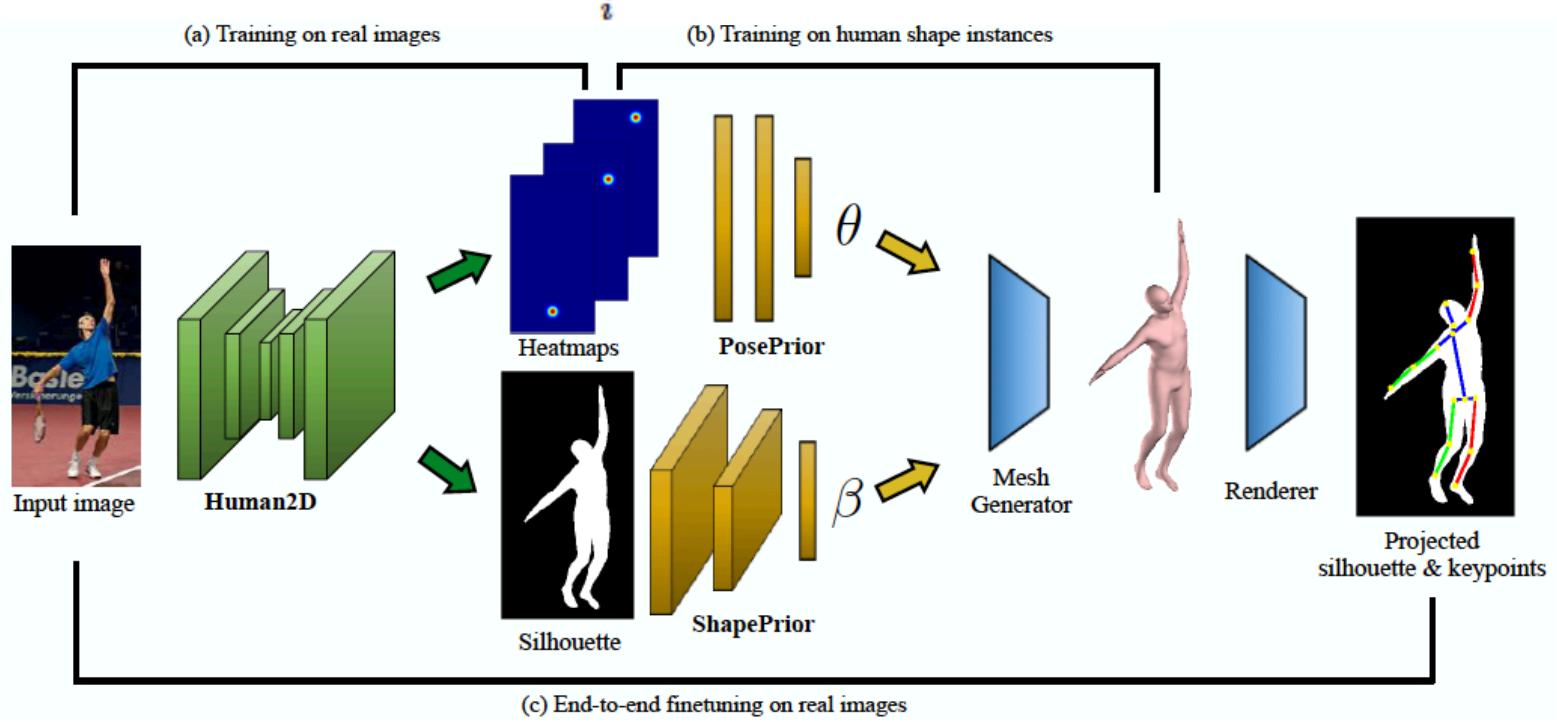
Predicting 3D Human Shape and Pose

- Fine-tune end-to-end using differentiable rendering
- Project vertex estimates to obtain silhouette, joint estimates for keypoints

$$\Pi(\hat{\boldsymbol{P}}) = \hat{\boldsymbol{S}}, \quad \Pi(\hat{\boldsymbol{J}}) = \hat{\boldsymbol{W}} \in \mathbb{R}^{M\times 2}.$$

- Supervised loss to minimize reprojection error:

$$\mathcal{L}_{\Pi} = \mu \sum_{i}^{M} \|\hat{W}_i - W_i\|_2^2 + \|\hat{S} - S\|_2^2$$



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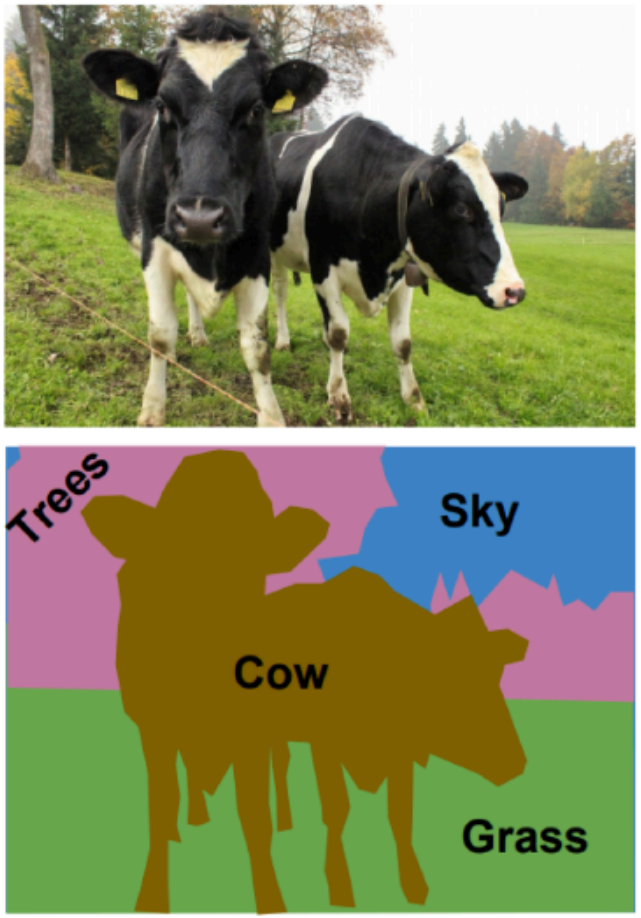
Predicting 3D Human Shape and Pose

Semantic Segmentation

Semantic Segmentation

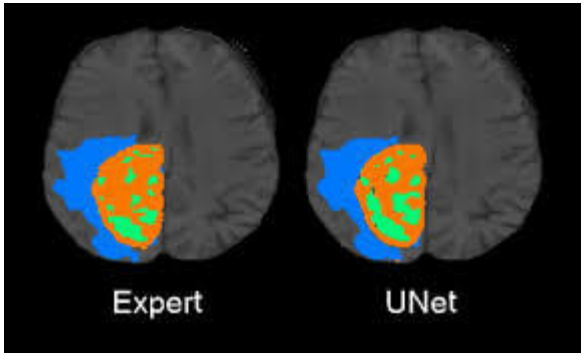
- Task: Assign each image pixel a class label

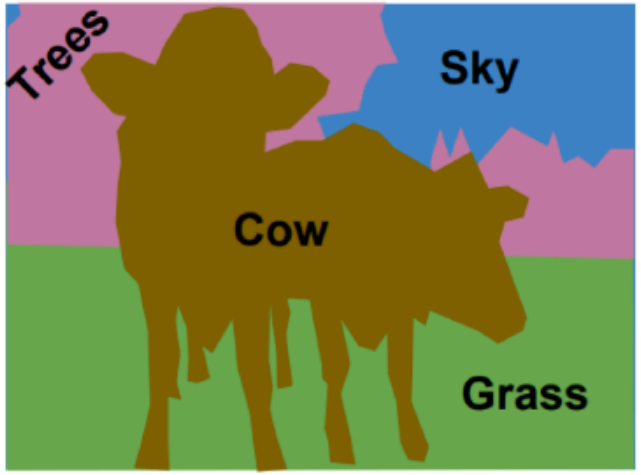


Semantic Segmentation

- Task: Assign each image pixel a class label

- Important applications:
  - Medicine
  - Self-driving





Semantic Segmentation

- Task: Assign each image pixel a class label

- Important applications:
  - Medicine
  - Self-driving
  - Selfies!!

[Bazarevsky and Tkachenka, Google AI blog]

Semantic Segmentation

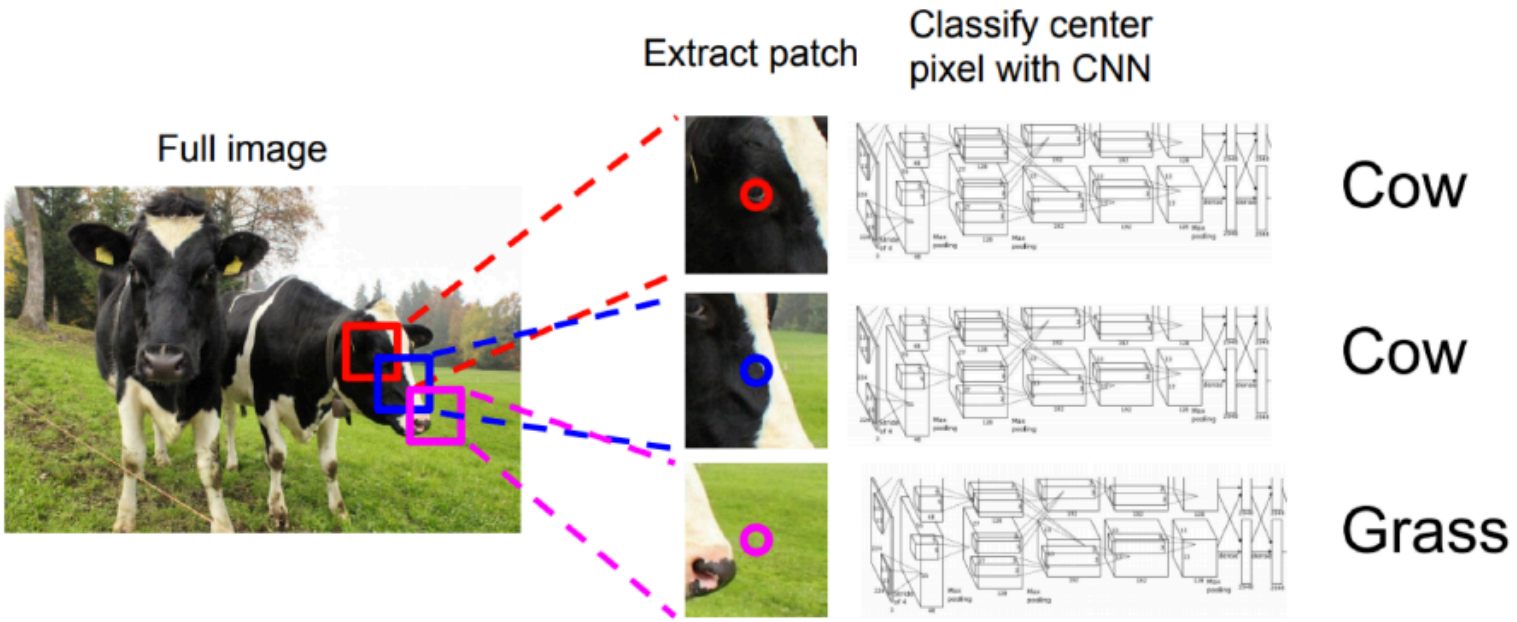
Global Reasoning ⟷ Locally accurate Boundaries

Figure from CityScapes Dataset

Per-Pixel Classification for Semantic Segmentation

Approaches

What could be a Problem?



Per-Pixel Classification for Semantic Segmentation

Approaches

What could be a Problem?
-Very inefficient
-No shared computation between overlapping patches

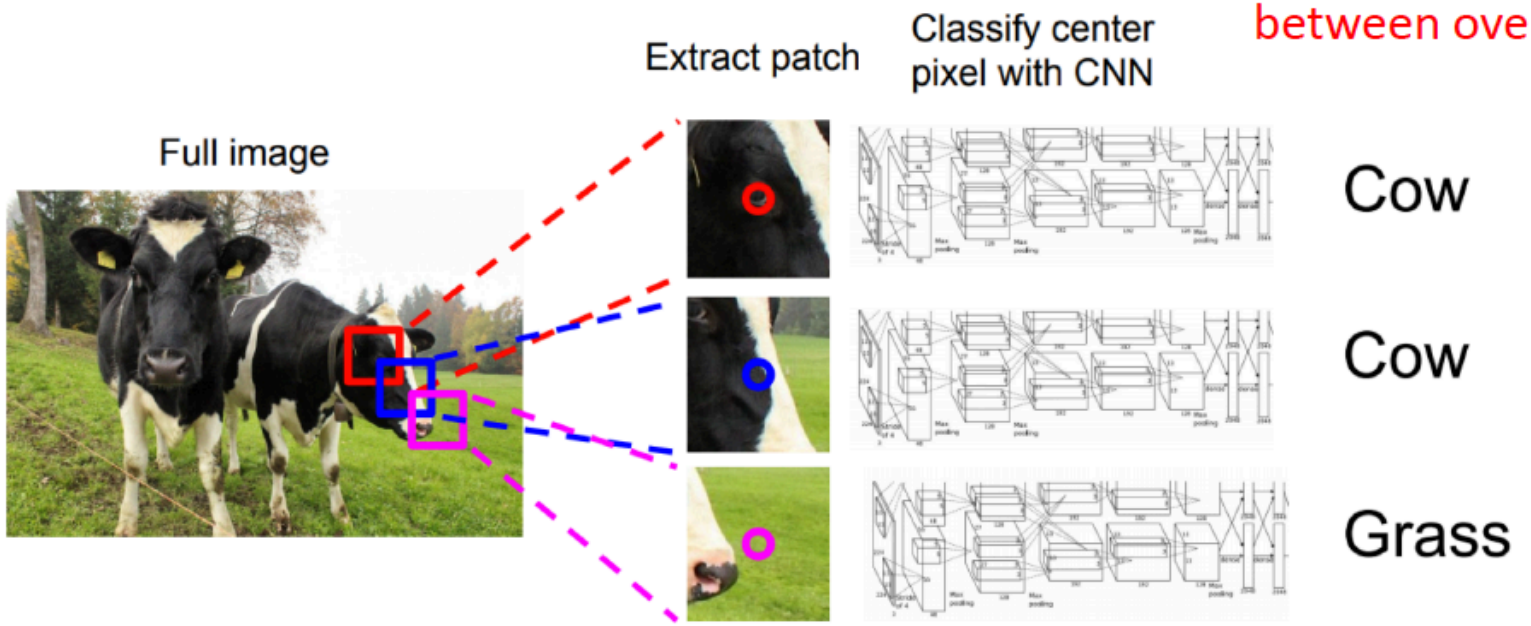
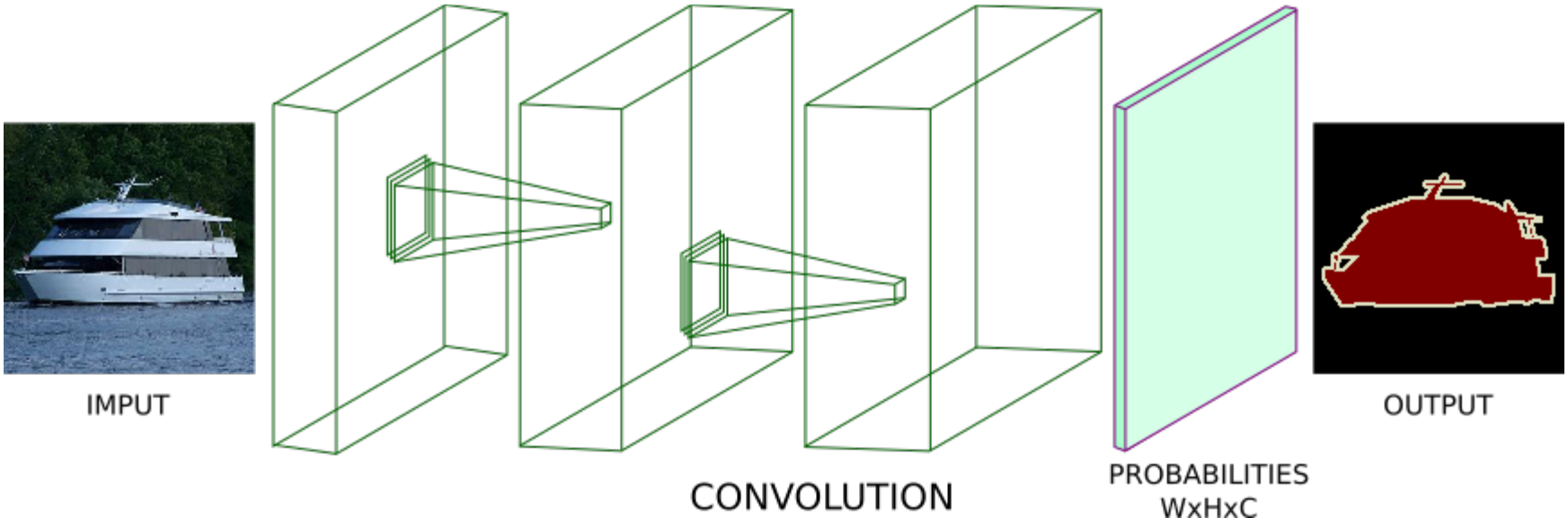


Image Resolution Convolutions



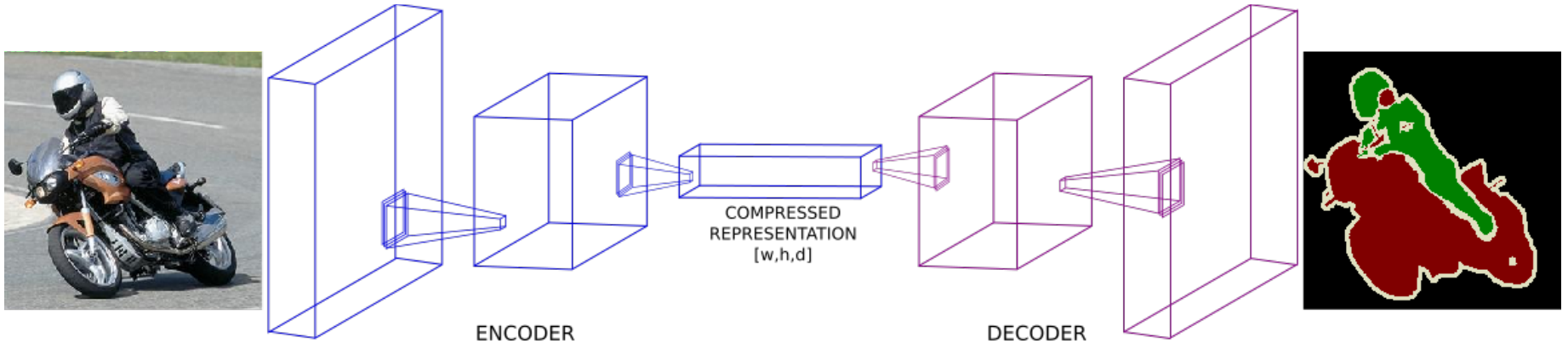
- Purely convolutions with stride 1, no pooling
- Maintains image resolution

- Drawbacks:
  - Expensive in memory and computation
  - Insufficient global reasoning

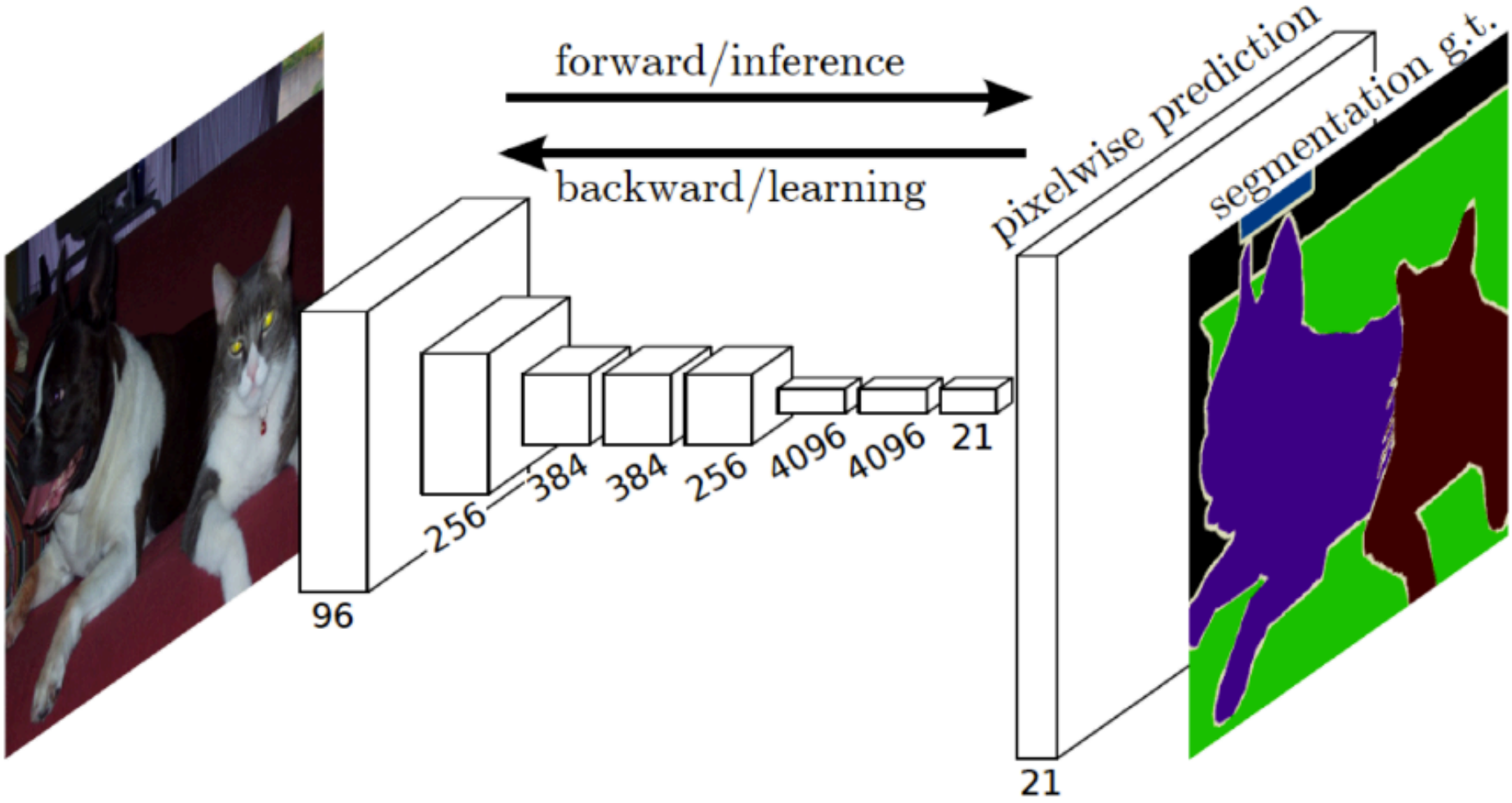
General Form of Segmentation Networks

- Most networks have similar encoders (inspired by classification networks)
  - Pooling and striding to downsample
  - Goal: do deeper convolutions without memory concerns

- Differences usually in decoder
  - Interpolation, transposed convolution, unpooling
  - Goal: recover spatial detail



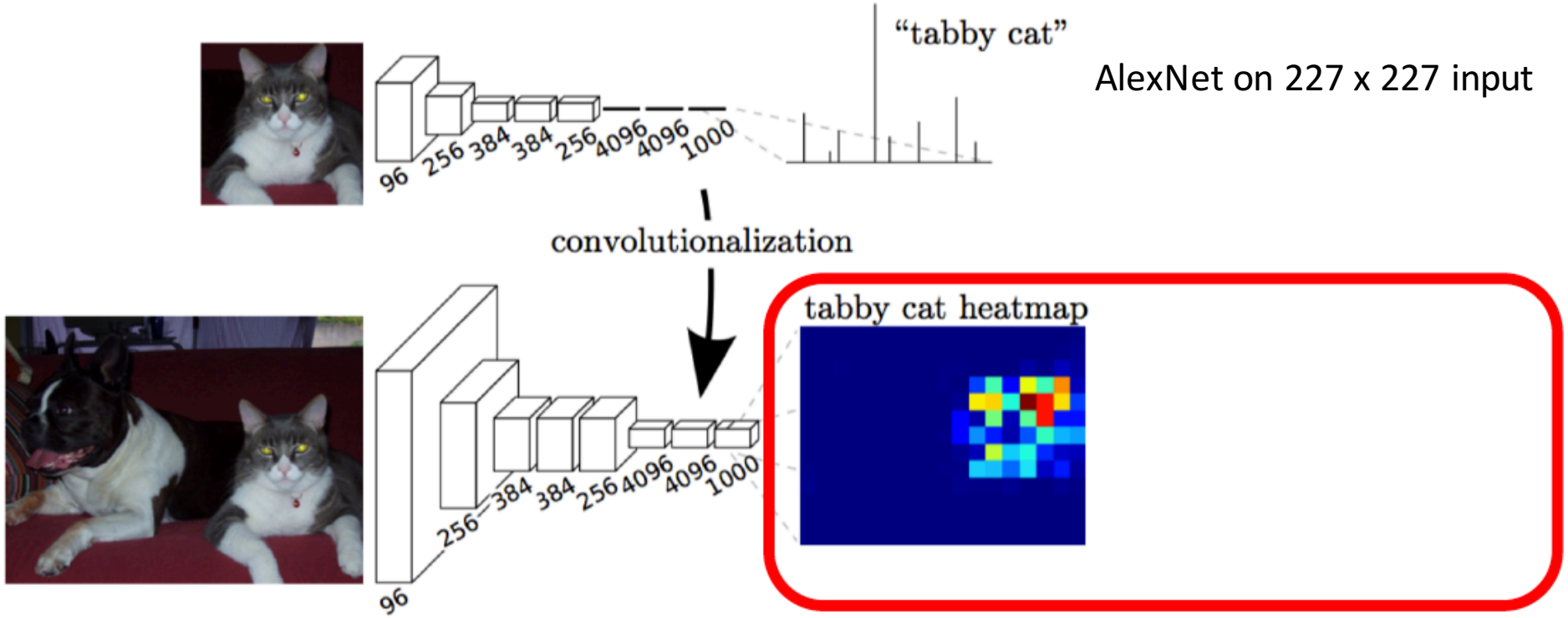
Fully Convolutional Network



[Long et al., FCNs for Semantic Segmentation]

Converting to Fully Convolutional Network

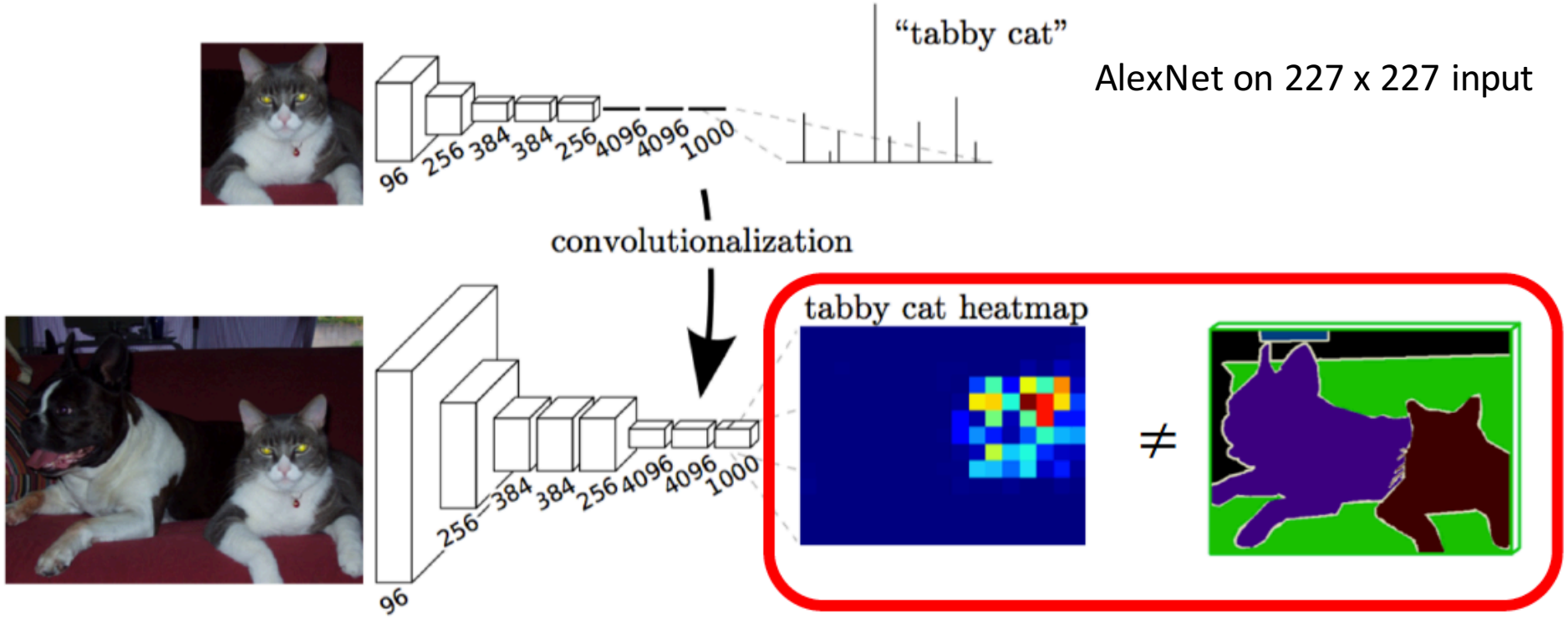
Fully-connected layer with *k* units = Convolution layer with *k* filters of size that covers input



Given 500 x 500 image, slide FCN with stride 32 to get 10 x 10 output.

Coarse Predictions

Fully-connected layer with *k* units = Convolution layer with *k* filters of size that covers input



AlexNet on 227 x 227 input

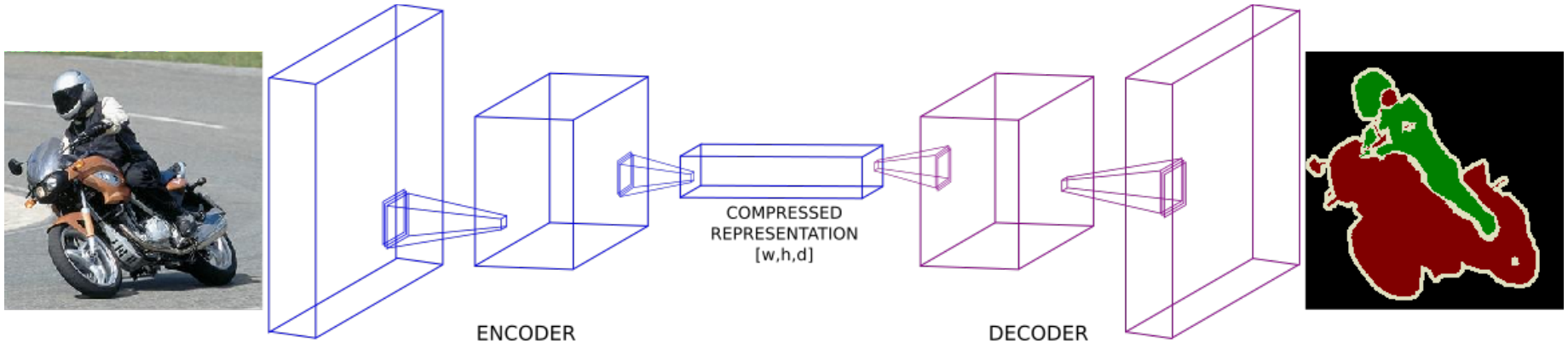
Given 500 x 500 image, slide FCN with stride 32 to get 10 x 10 output.

We want a segmentation output at image resolution.

Output Going to Image Resolution

- Encoder aggressively pools and subsamples image
- Necessary to capture context information which is necessary for segmentation
- But spatial detail is also necessary

- Goal for decoder: obtain output at image *resolution*
- Goal for decoder: recover *detail* in encoder feature maps before subsampling



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- Option 1
  - Use transposed convolution to upsample to image resolution

Normal Convolutions

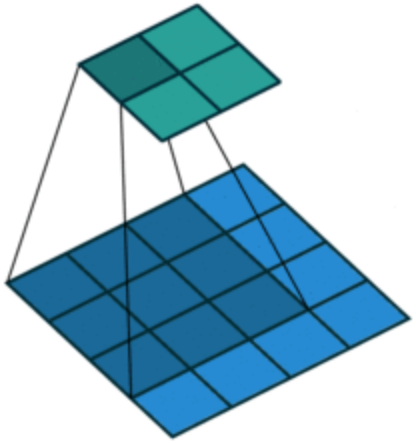
1	2
3	4

☆

1	2	3
4	5	6
7	8	9

=

37	47
67	77



Filter, a

Input, x

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

A

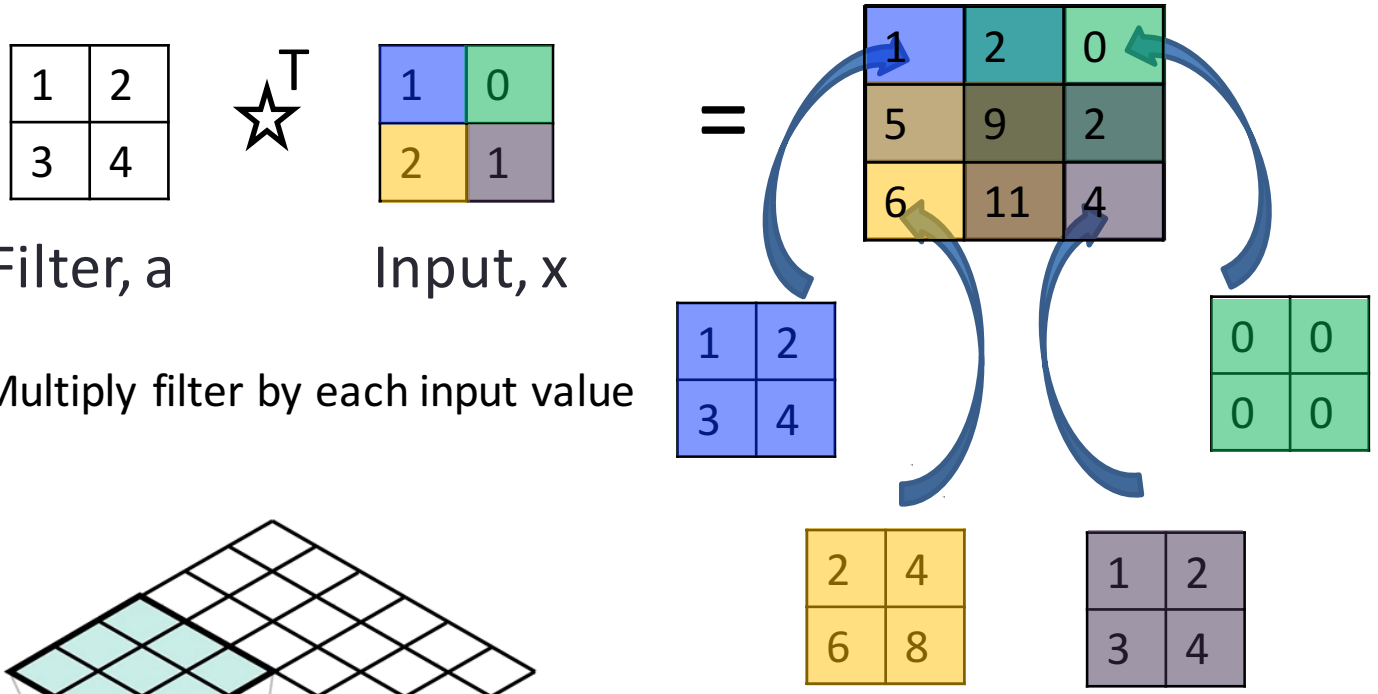
1
2
3
4
5
6
7
8
9

X

=

37
47
67
77

Transposed Convolutions

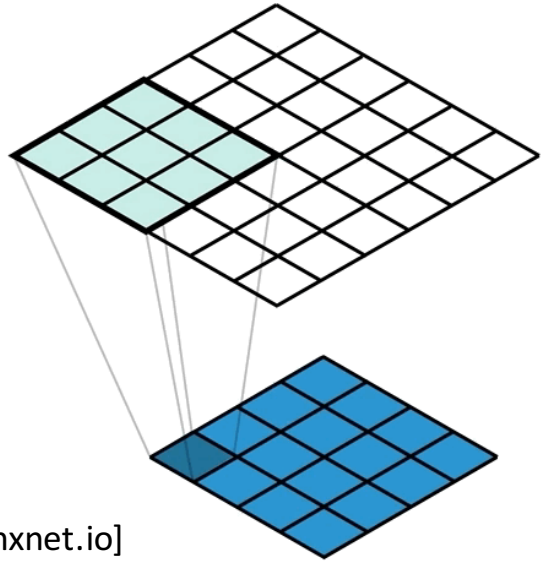


Filter, a

Input, x

Multiply filter by each input value

Tile the scaled filter at output locations
Add overlapping values



[Thom Lane, mxnet.io]

Transposed Convolutions

1	2
3	4

Filter, a

$\overset{T}{\star}$

1	0
2	1

Input, x

$=$

1	2	0
5	9	2
6	11	4

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

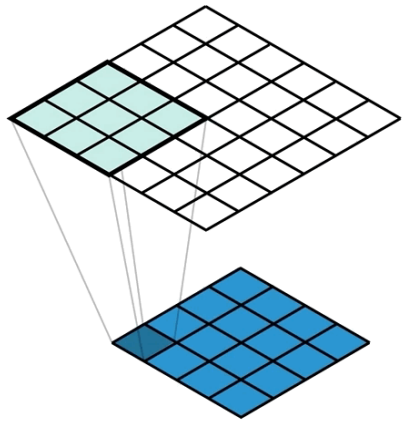
A^T

X

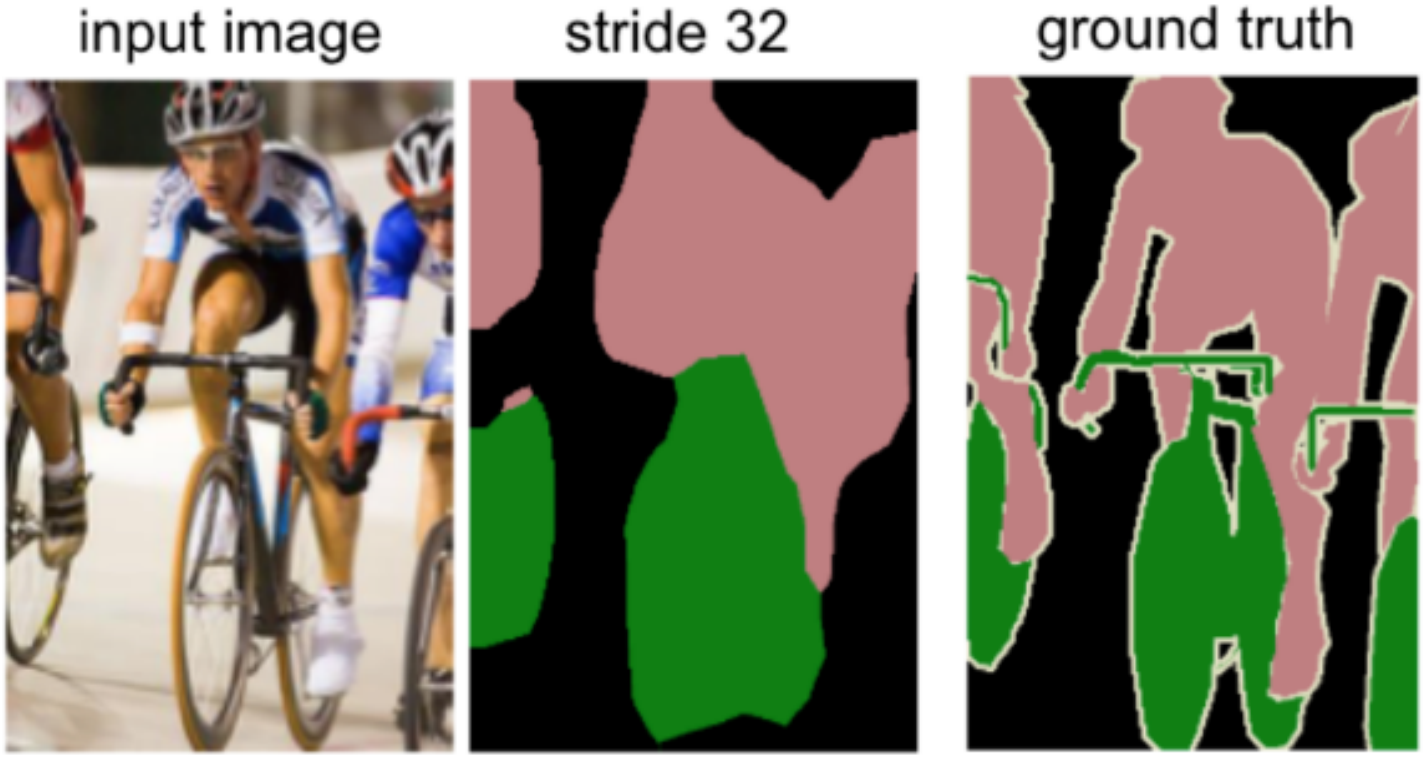
1
0
2
1

$=$

1
2
0
5
9
2
6
11
4



Output Going to Image Resolution



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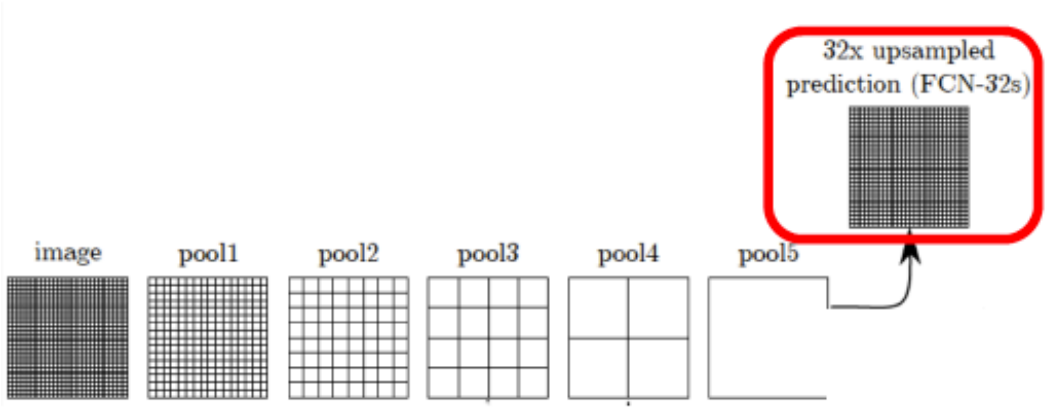
- Option 1
  - Use transposed convolution to upsample to image resolution
  - Concatenate encoder features to upsampled features during decoding

Combine Global and Local Information



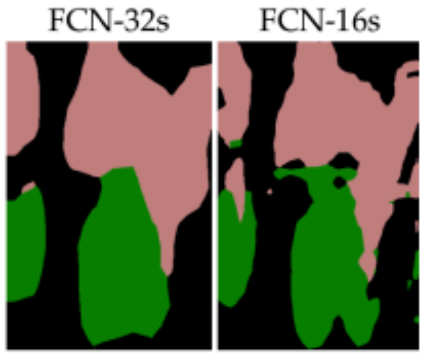
Combine Global and Local Information

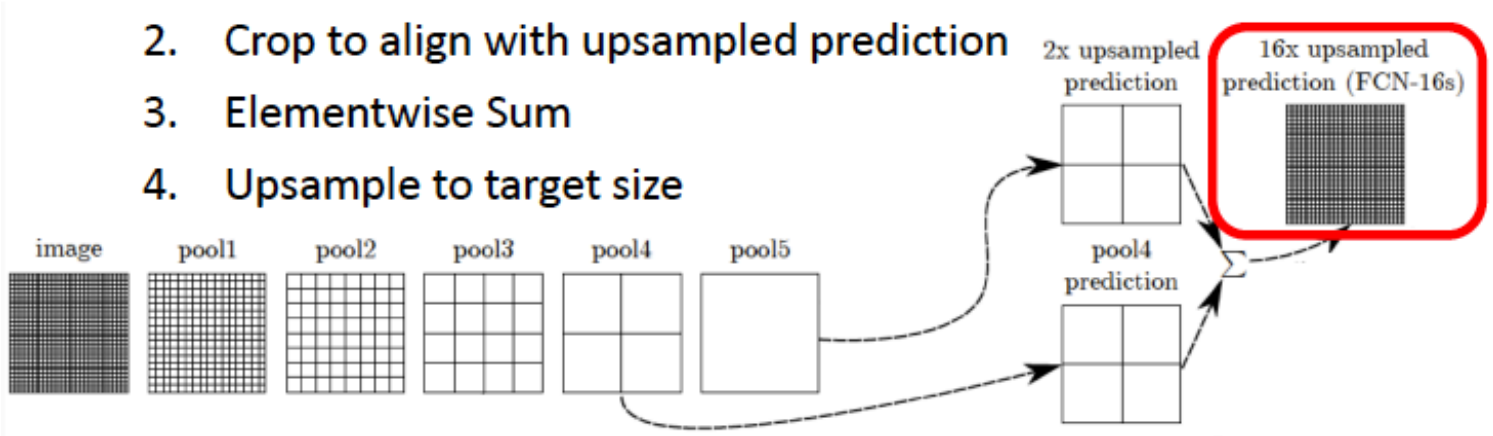
Fuse coarse semantic information with local appearance

Similar to: skip connections.

Process:

1. 1x1 Convolution on pool4 output
2. Crop to align with upsampled prediction
3. Elementwise Sum
4. Upsample to target size





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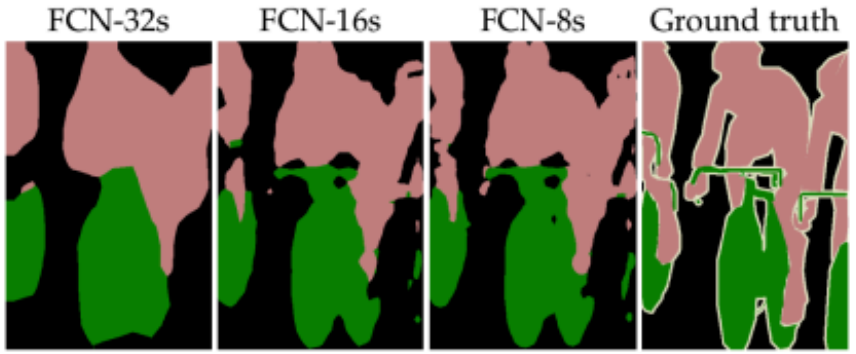
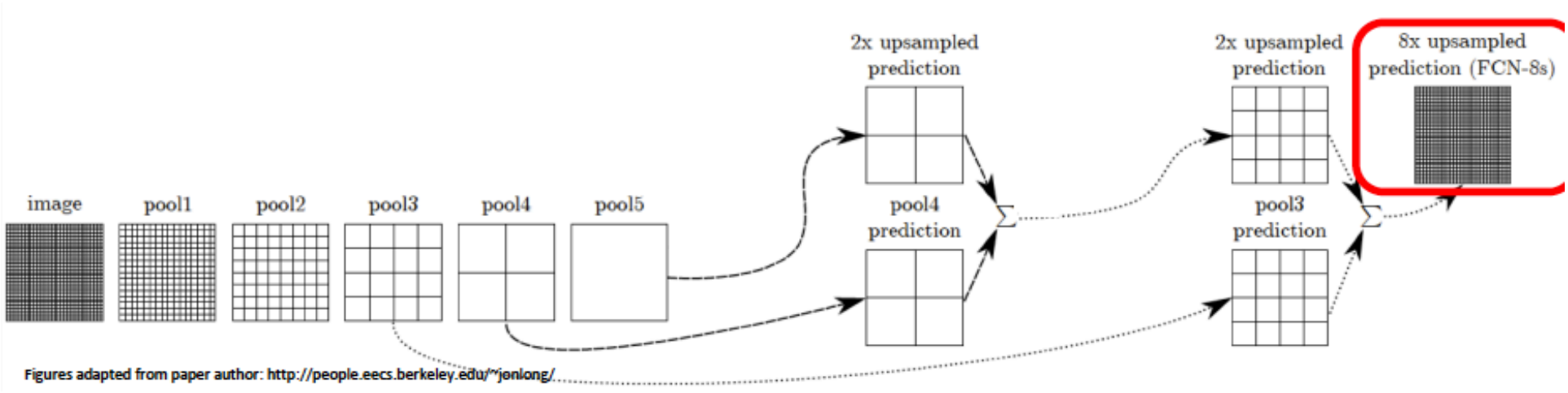
Similar to: skip connections.





Output Going to Image Resolution

- Encoder aggressively pools and subsamples image
- Necessary to capture context information which is necessary for segmentation
- But spatial detail is also necessary

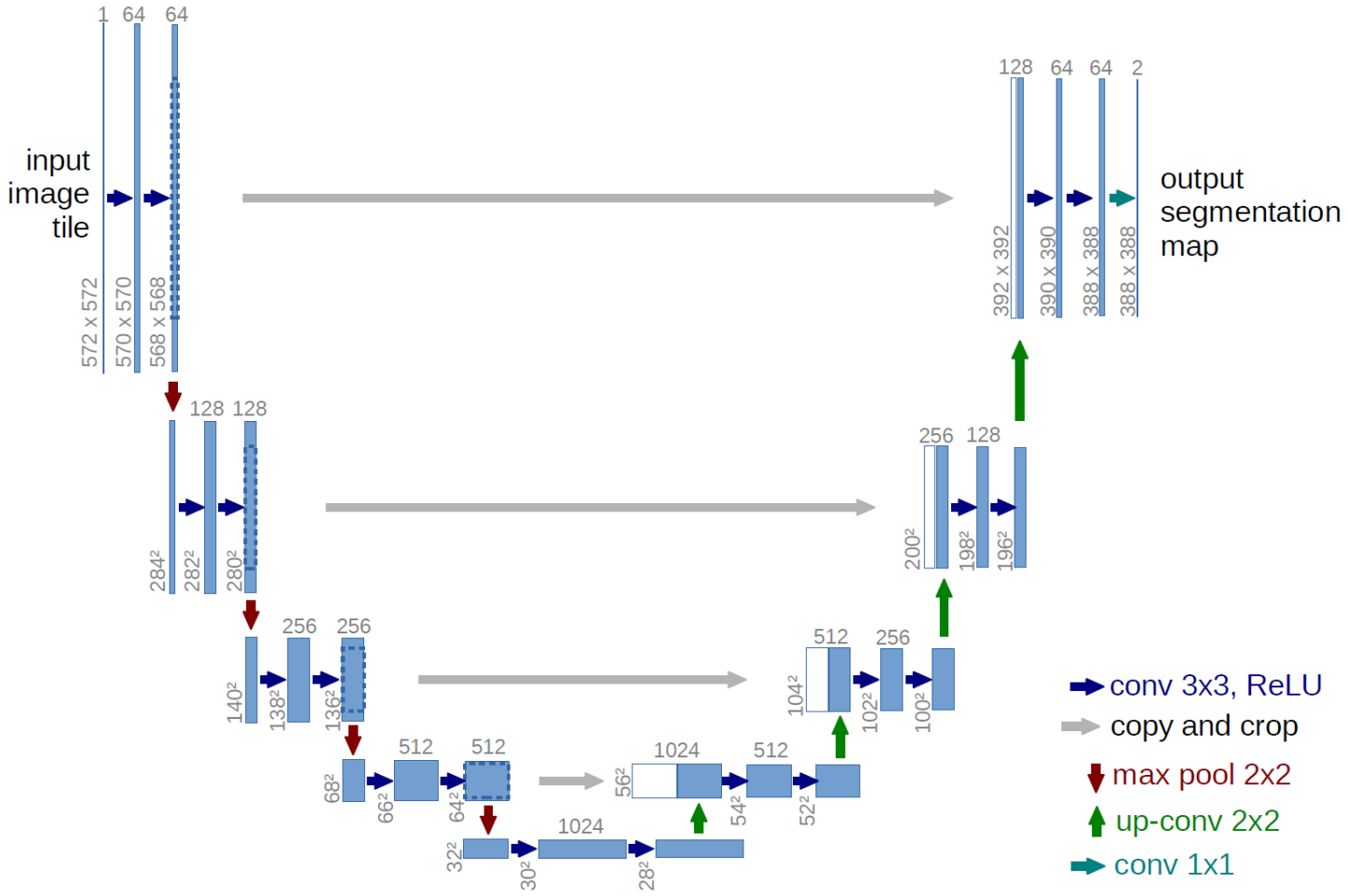
- Goal for decoder: obtain output at image *resolution*
- Goal for decoder: recover *detail* in encoder feature maps before subsampling

- Option 1
  - Use transposed convolution to upsample to image resolution
  - Concatenate encoder features to upsampled features during decoding

- Option 2
  - Similar as above, but more symmetric upsampling to image resolution

U-Net

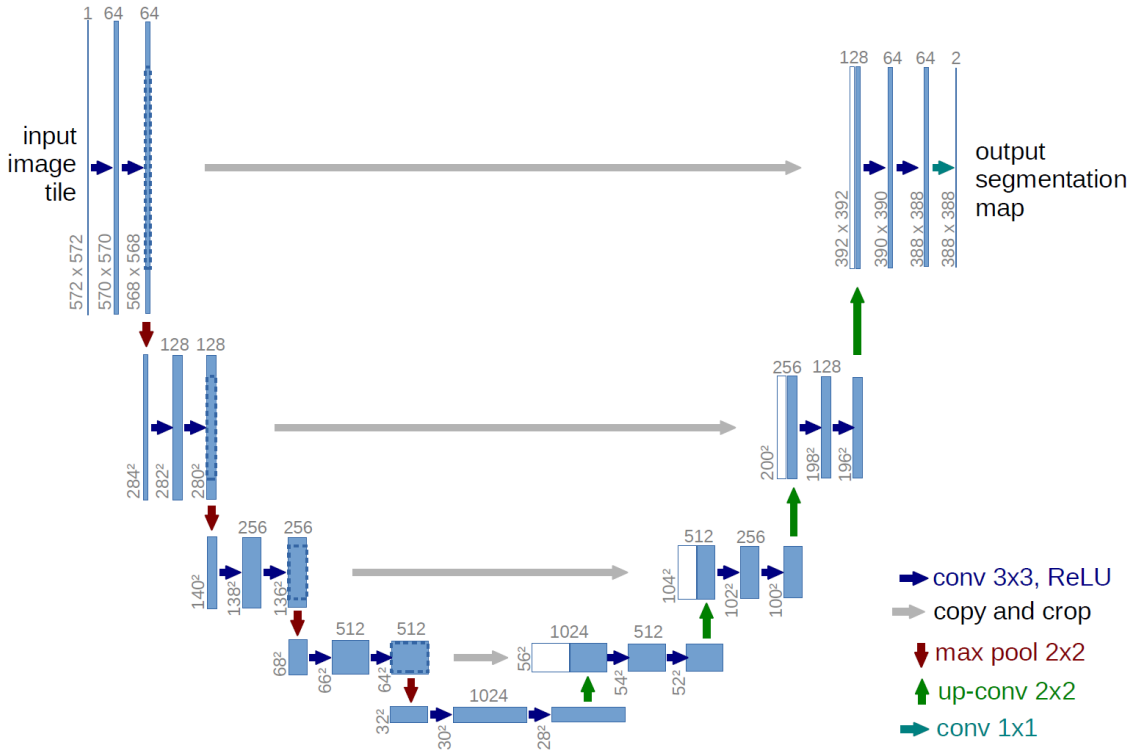
- Similar to FCN, but symmetric architecture



[Ronneberger et al., U-Net]

U-Net

- Encoder: Modules of two 3x3 convolution, followed by 2x2 pooling
- Decoder:
  - Upsample with 2x2 transposed convolution
  - Concatenate feature map from corresponding encoder level
  - Two 3x3 convolutions



[Ronneberger et al., U-Net]

Output Going to Image Resolution

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- Option 2
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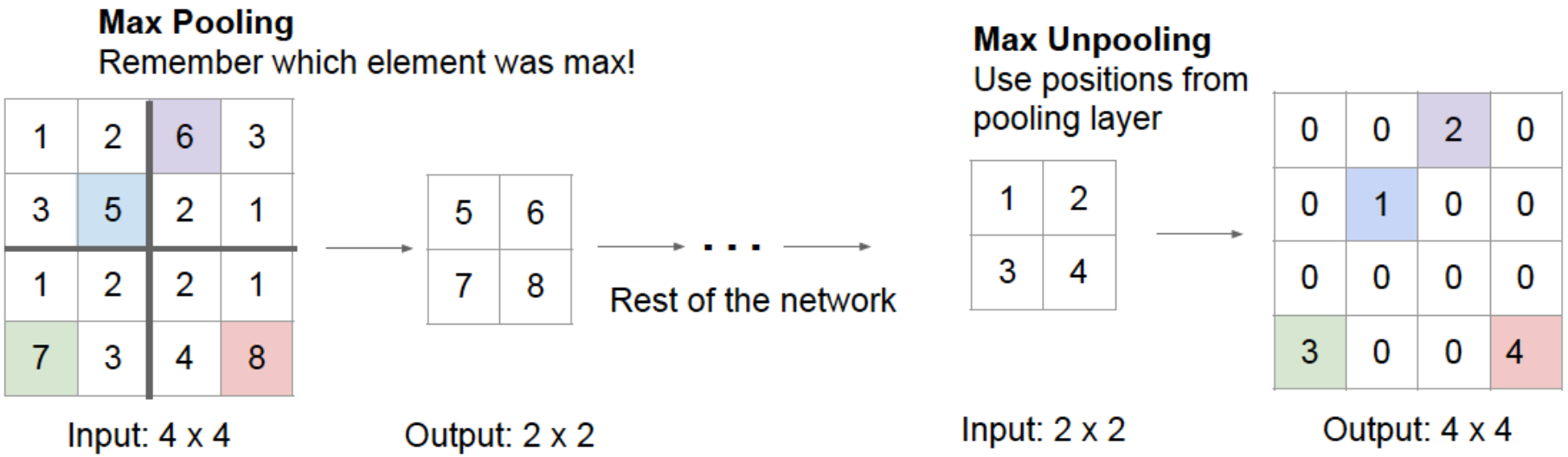
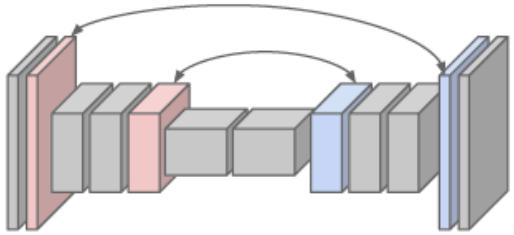
- Option 3
  - Unpool based on encoder locations and convolve to densify

Refinement: Unpooling followed by convolution

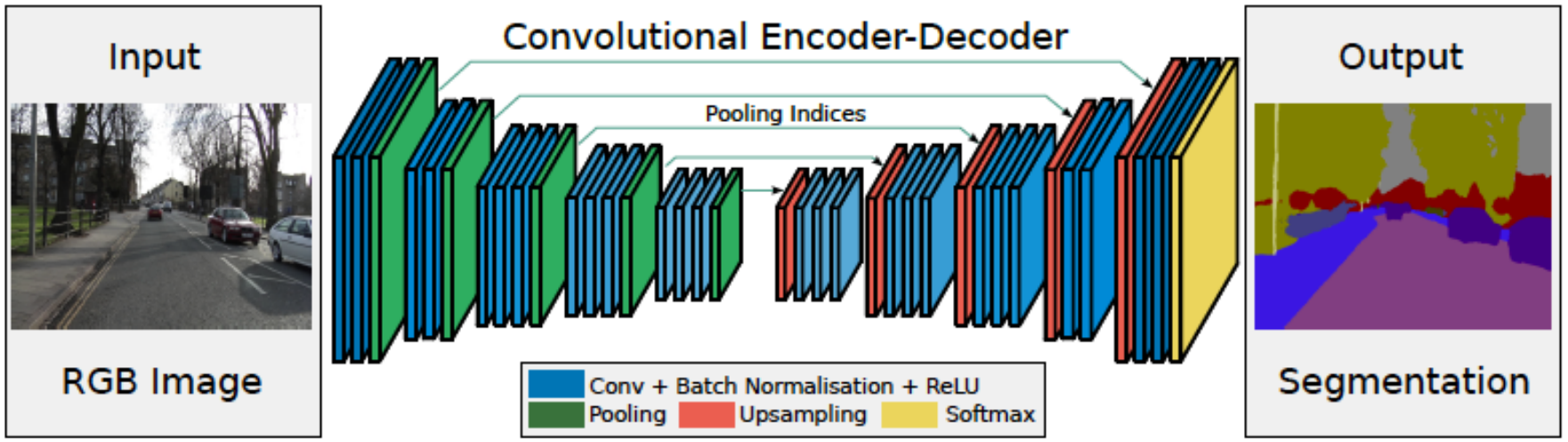


Corresponding pairs of downsampling and upsampling layers



[Figure from: L. Fei-Fei et al., CS 231n]

Output Going to Image Resolution

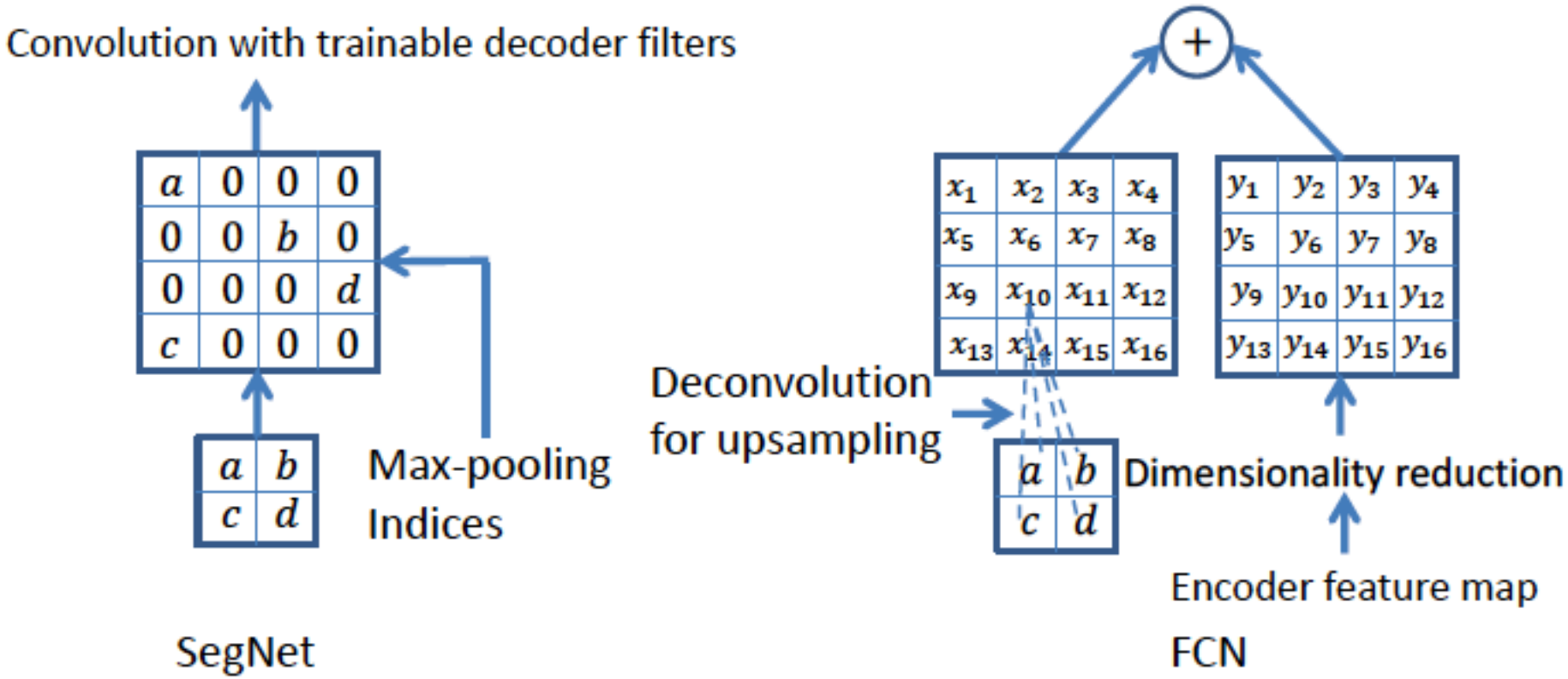


- In U-Net, encoder feature maps need to be stored in memory for concatenation
- In SegNet, only store the indices where max-pool is active
- Store 2x2 pooling index with 2 bits, as opposed to floating point feature map

- Significant memory reduction at inference time

[Badrinarayanan et al., SegNet]

Comparison of two approaches to upsample



[Badrinarayanan et al., SegNet]