Lecture 10:
Semantic Segmentation

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2. Segmentation as clustering: k-means, mean-shift
3. Upsampling
4. FCN, U-Net, Tiramisu
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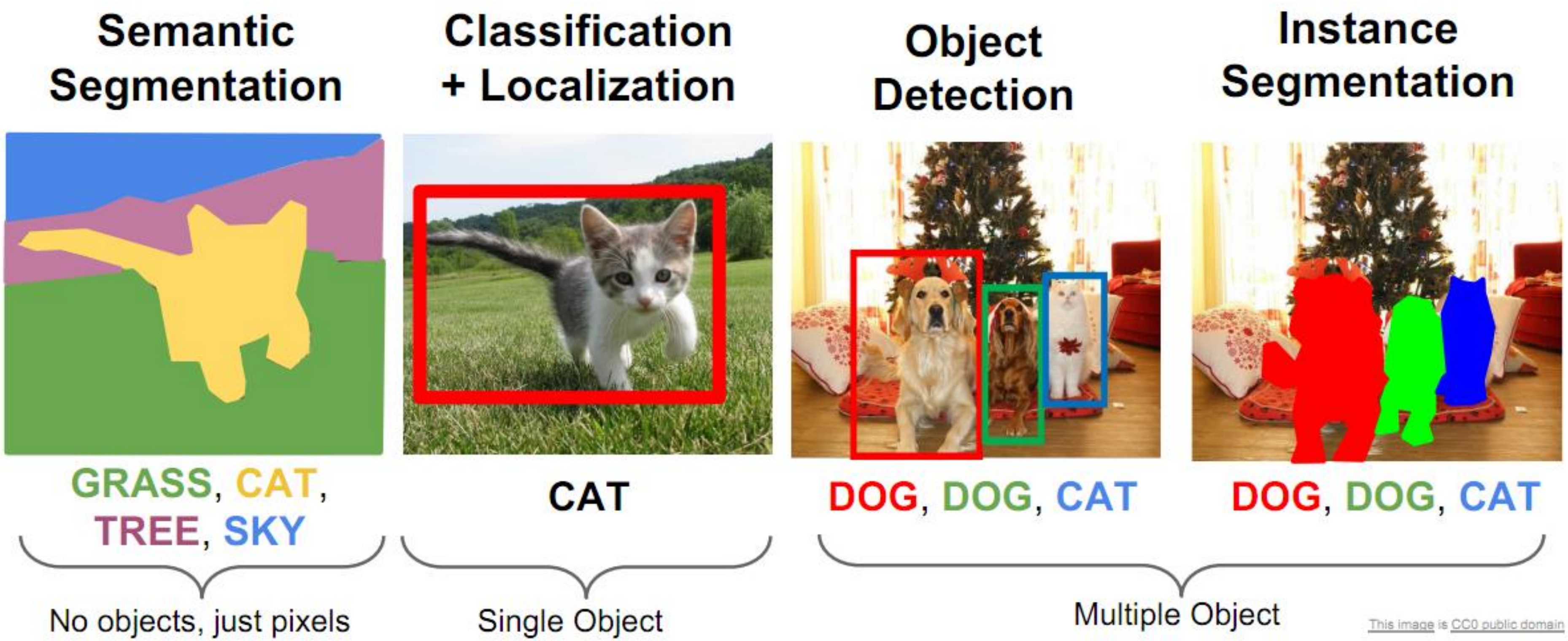
Computer Vision Tasks

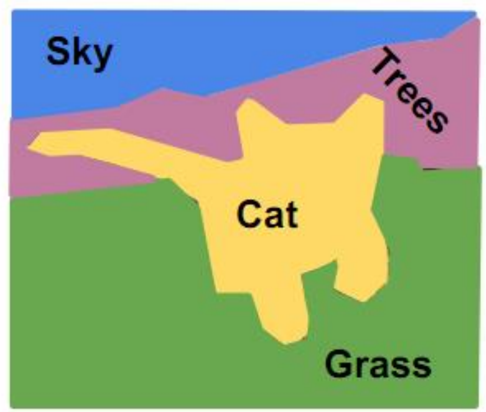


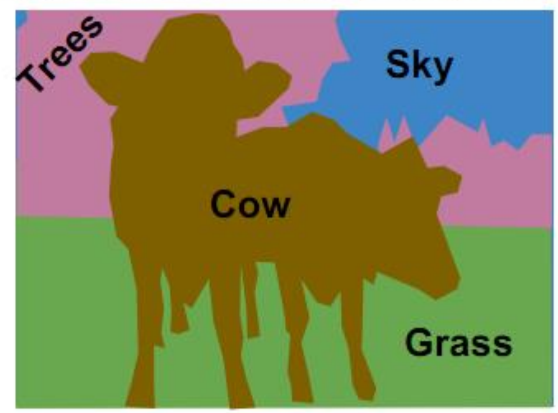
Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

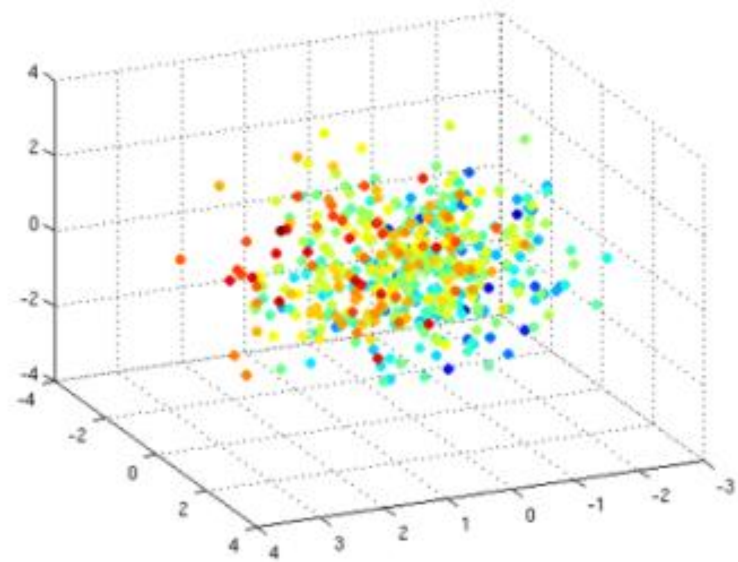
This image is CC0 public domain





Segmentation as Clustering

- Pixels are points in a high-dimensional space
  - color: 3d
  - color + location: 5d
- Cluster pixels into segments



Clustering: K-Means

Algorithm:

1. Randomly initialize the cluster centers, $c_1, \ldots, c_K$
2. Given cluster centers, determine points in each cluster
   - For each point p, find the closest c_i. Put p into cluster i
3. Given points in each cluster, solve for c_i
   - Set c_i to be the mean of points in cluster i
4. If c_i have changed, repeat Step 2

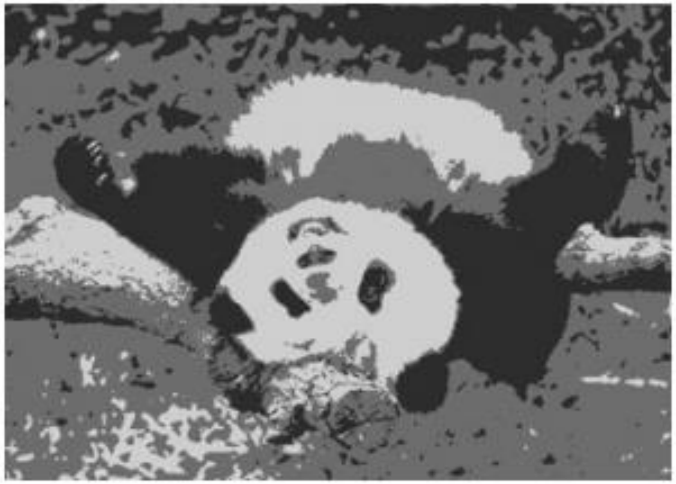
- Properties
  - Will always converge to some solution
  - Can be a "local minimum"
    - Does not always find the global minimum of objective function:

$$\sum_{i=1}^{k} \sum_{x \in C_i} \|x - c_i\|^2$$

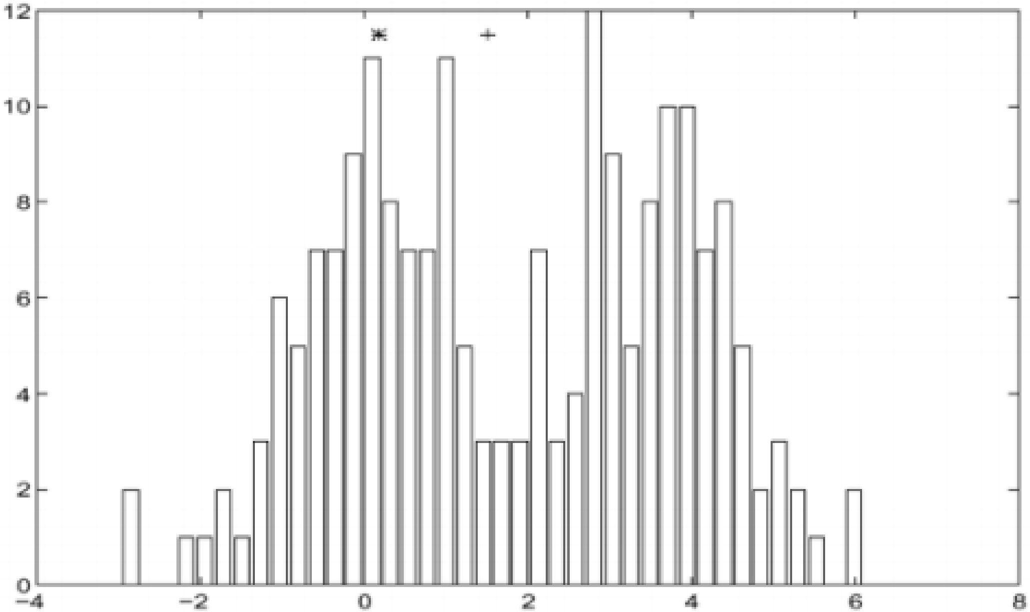
Clustering: K-Means

k=2

k=3



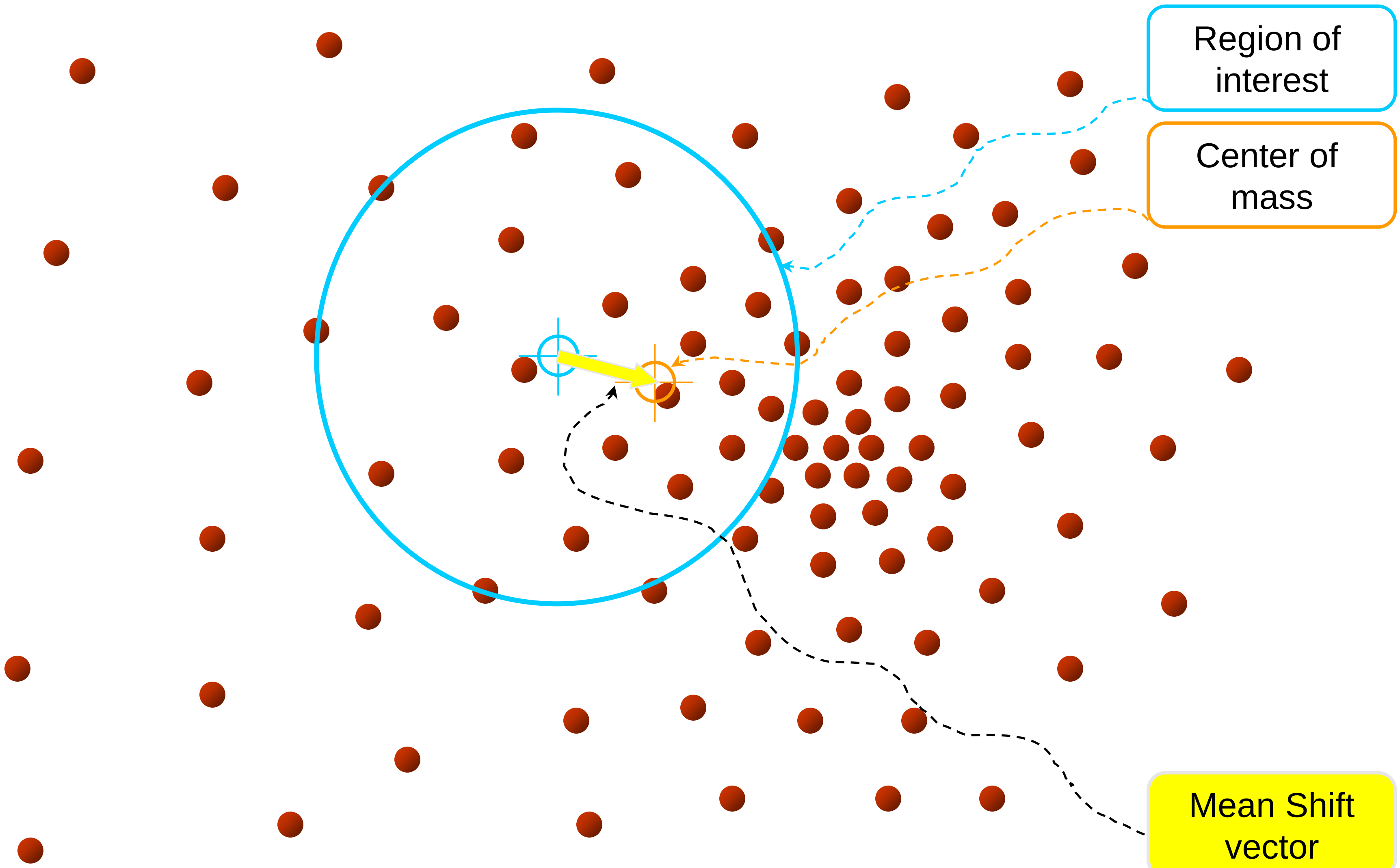
Clustering: Mean-shift



1. Initialize random seed, and window W
2. Calculate center of gravity (the "mean") of W: $\frac{1}{|W|}\sum_{x \in W} x$
   - Can generalize to arbitrary windows/kernels
3. Shift the search window to the mean
4. Repeat Step 2 until convergence

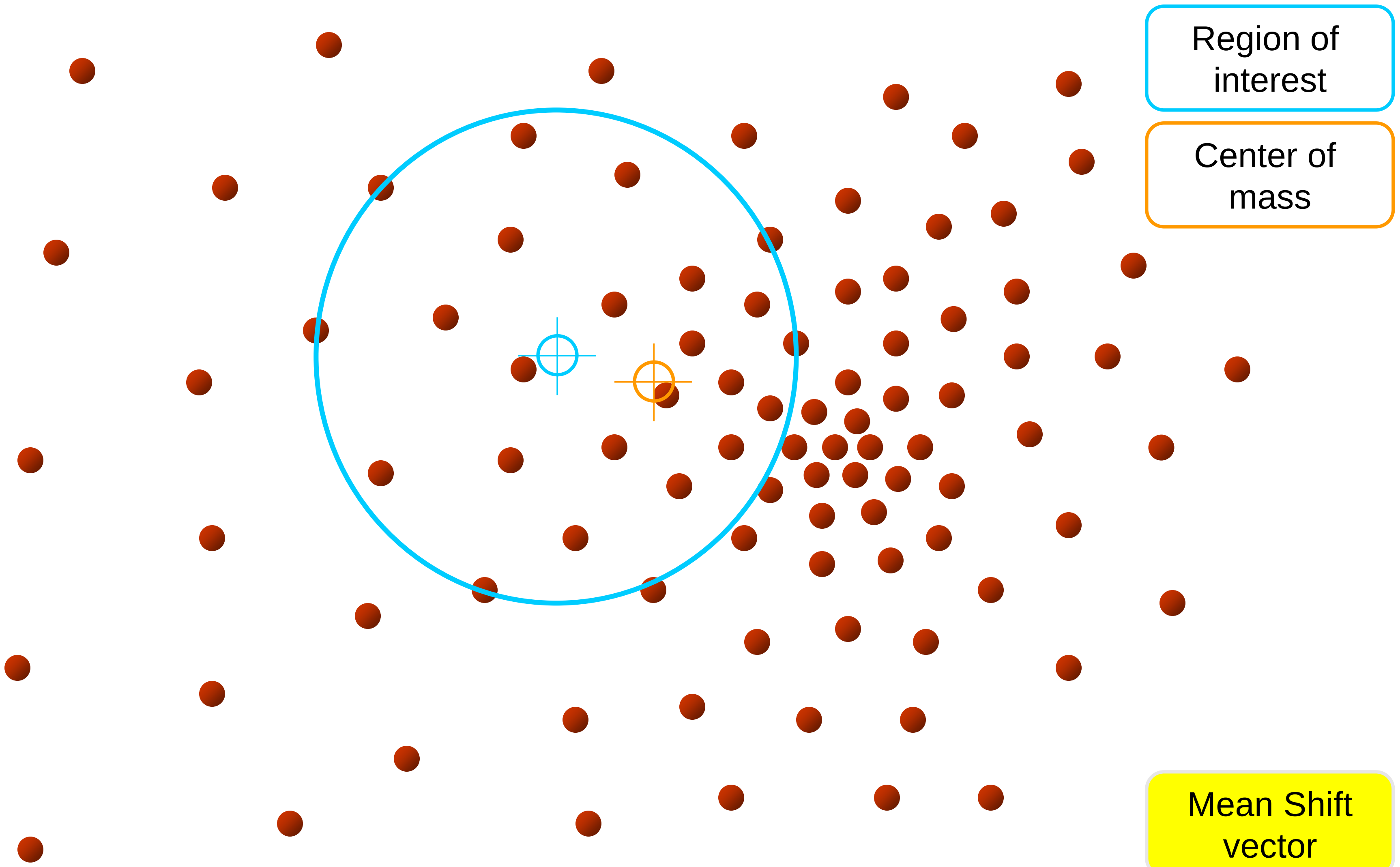
Only parameter: window size

Mean-Shift



Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



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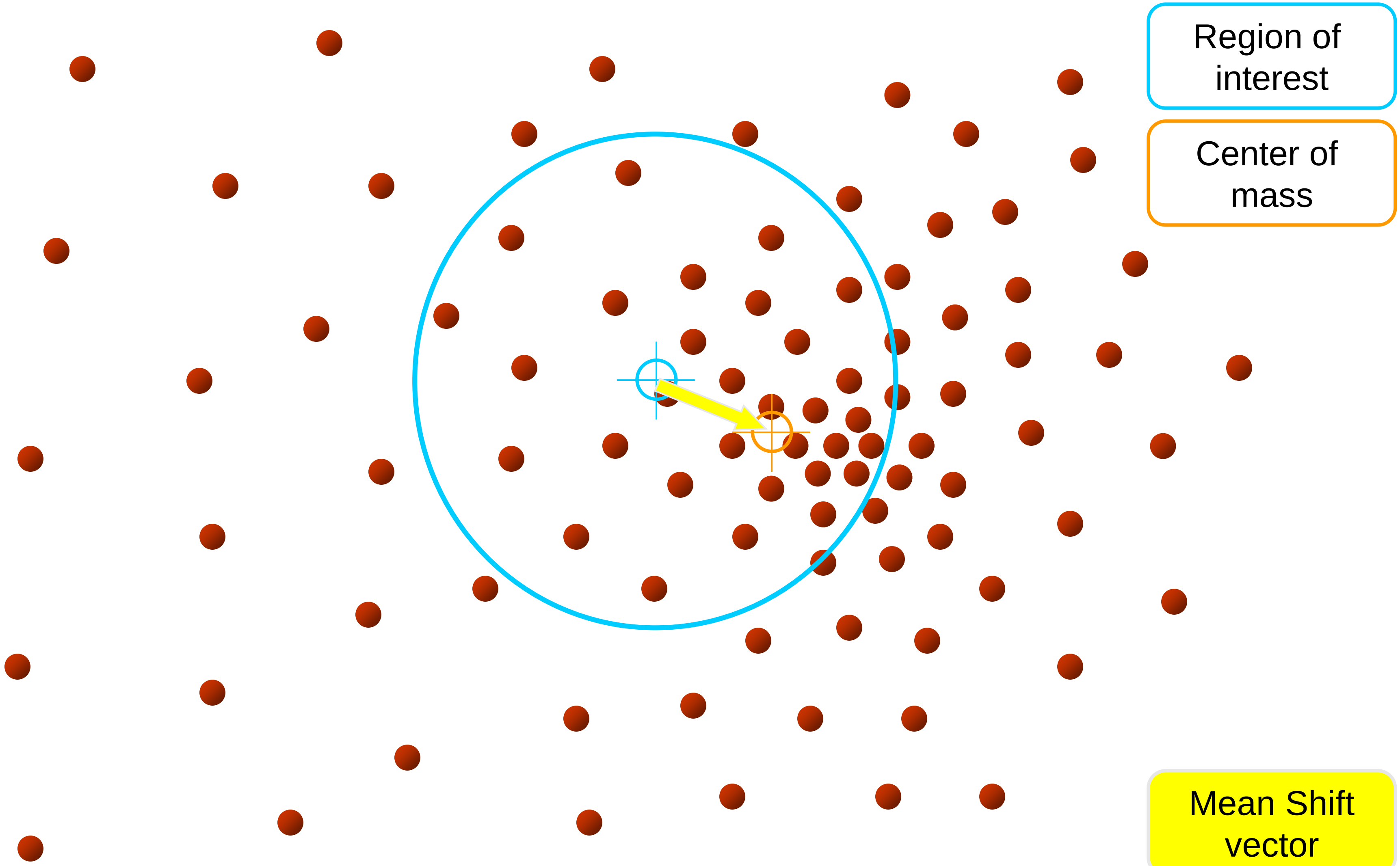
Mean-Shift



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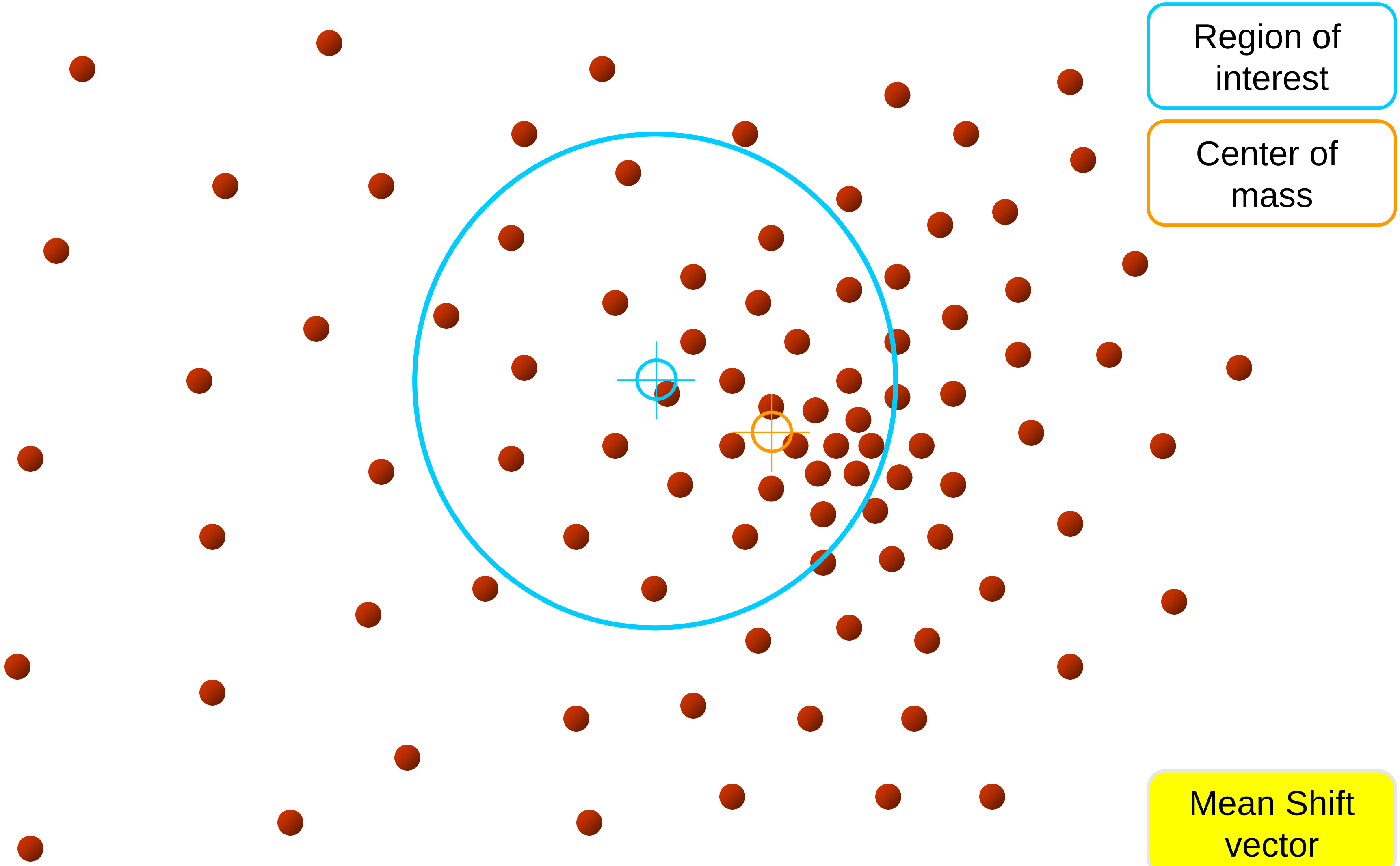
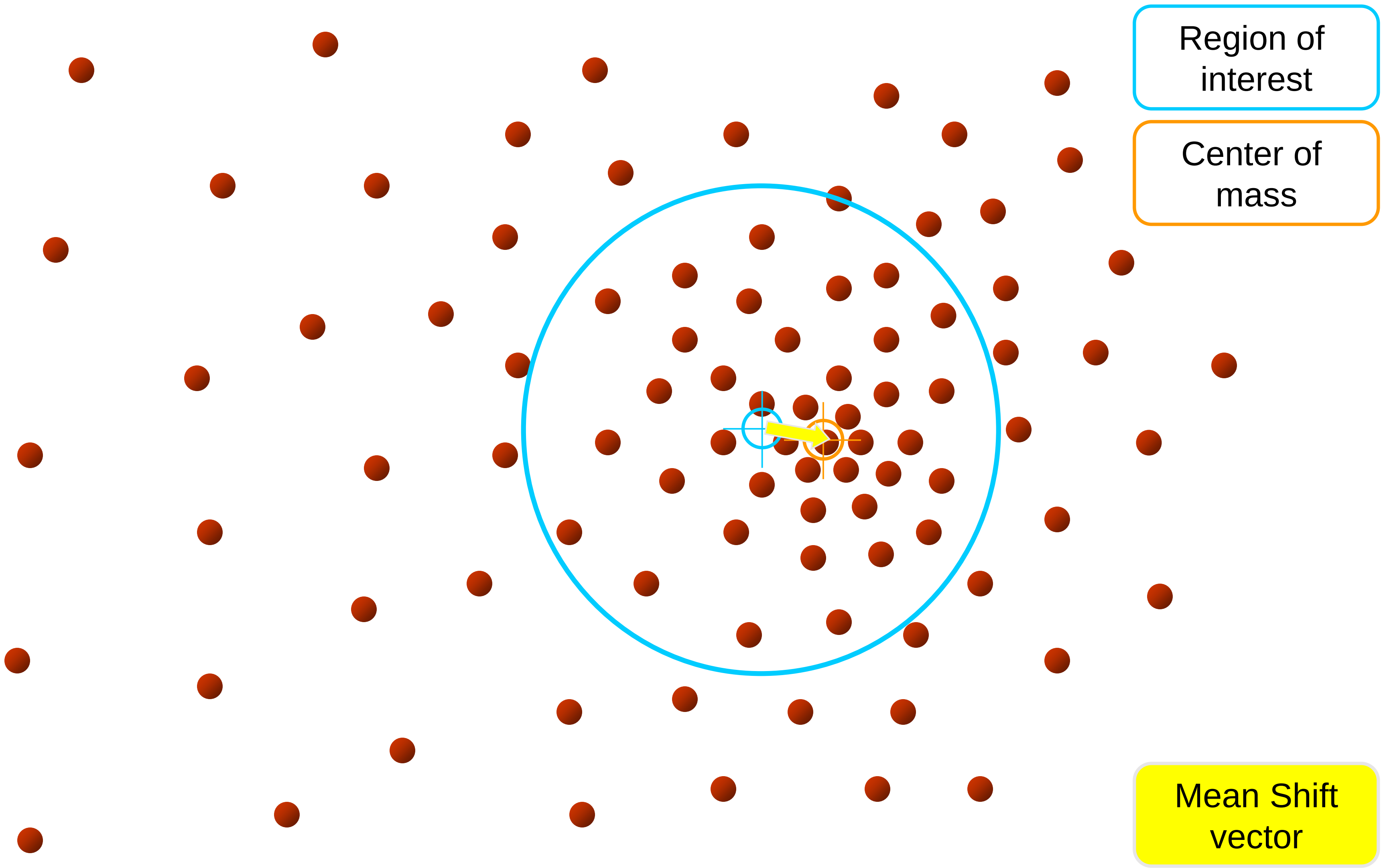
Mean-Shift



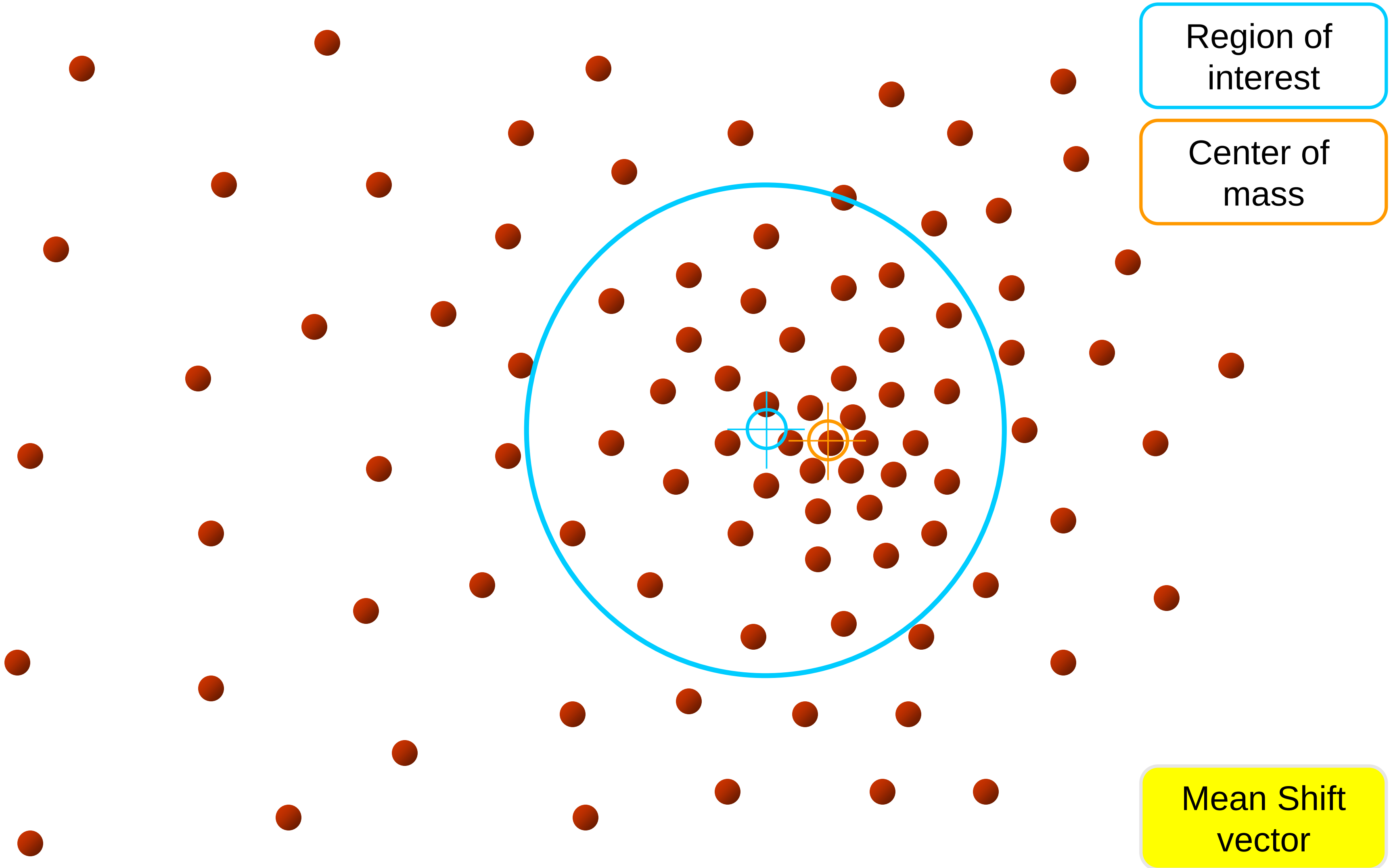
Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



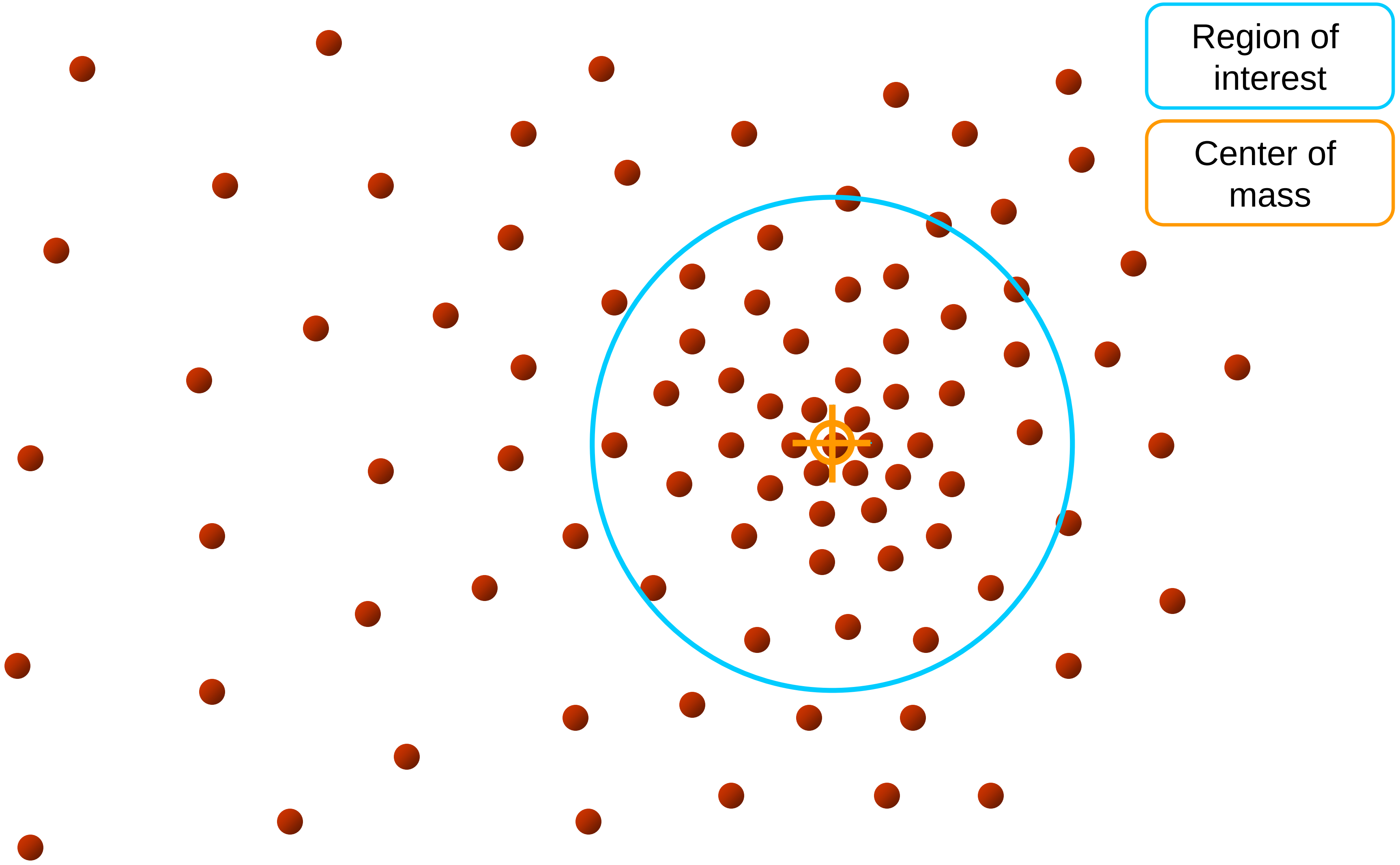
Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



Slide by Y. Ukrainitz & B. Sarel

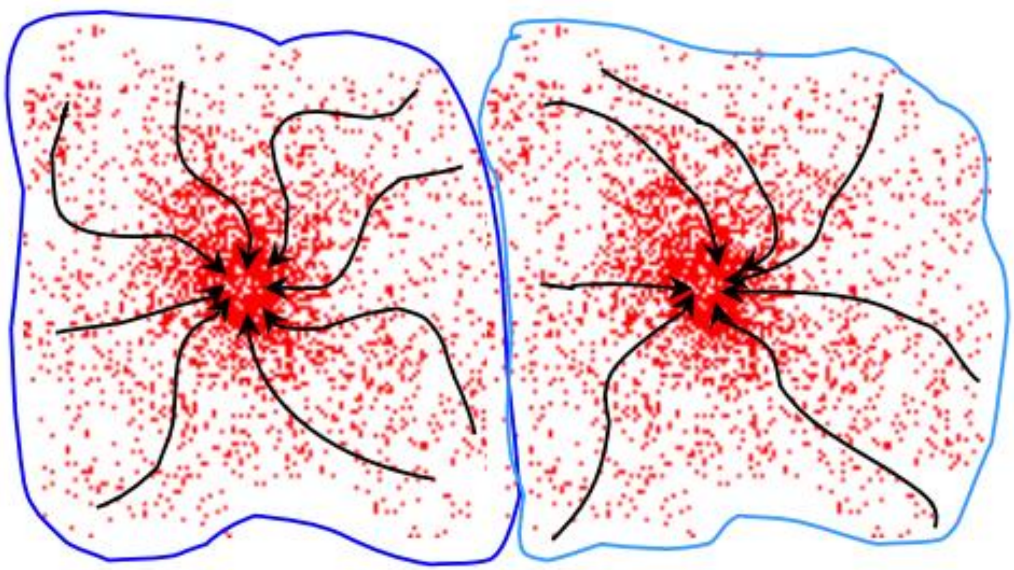
Mean-Shift



Slide by Y. Ukrainitz & B. Sarel

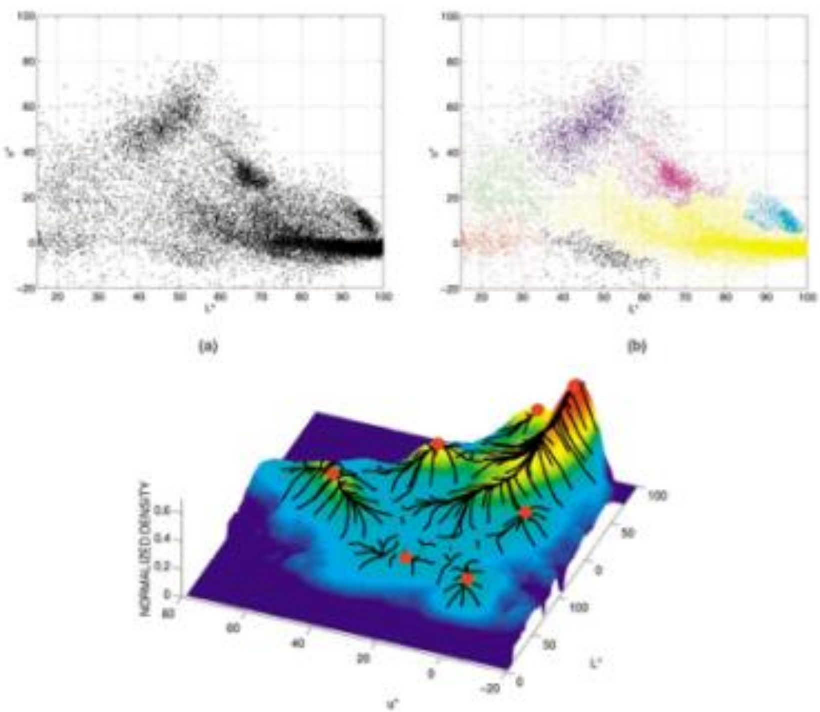
Mean-Shift

- Cluster: all data points in the attraction basin of a mode
- Attraction basin: the region for which all trajectories lead to the same mode

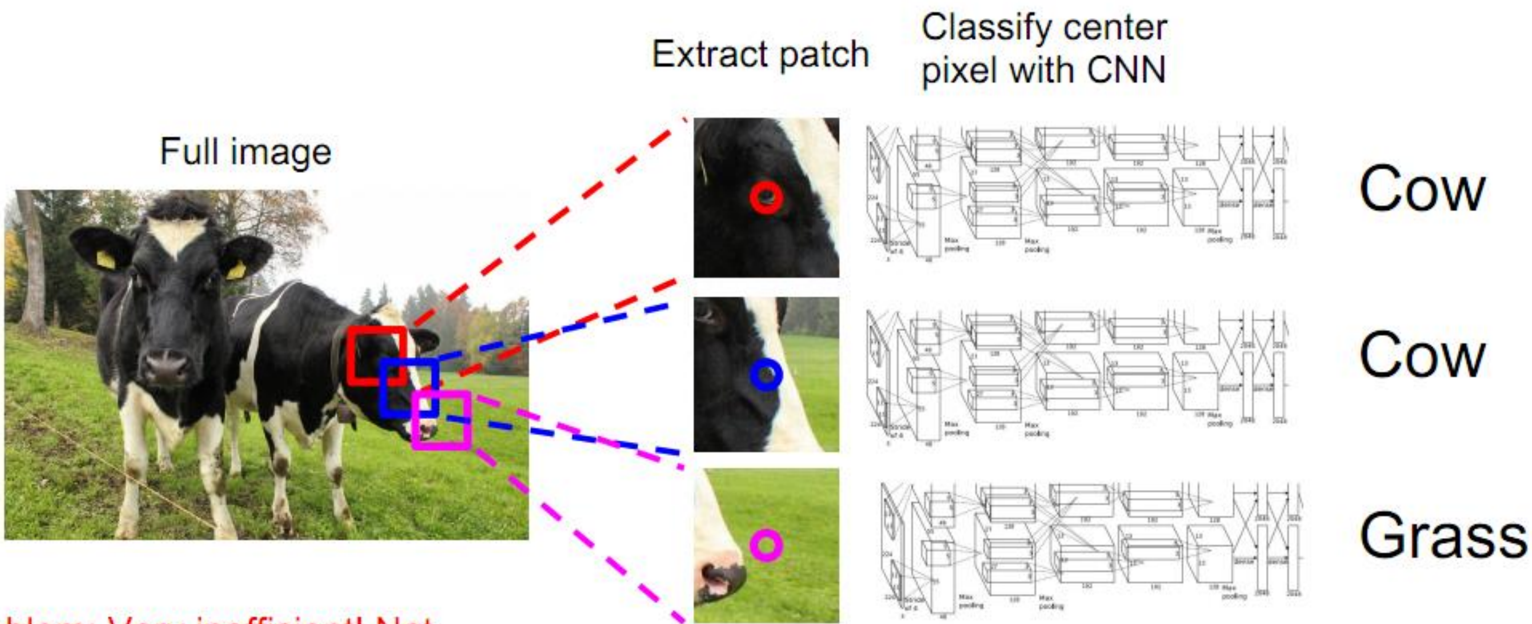


Mean-Shift for segmentation

- Find features (color, gradients, texture, etc)
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode



Semantic Segmentation: Sliding Window

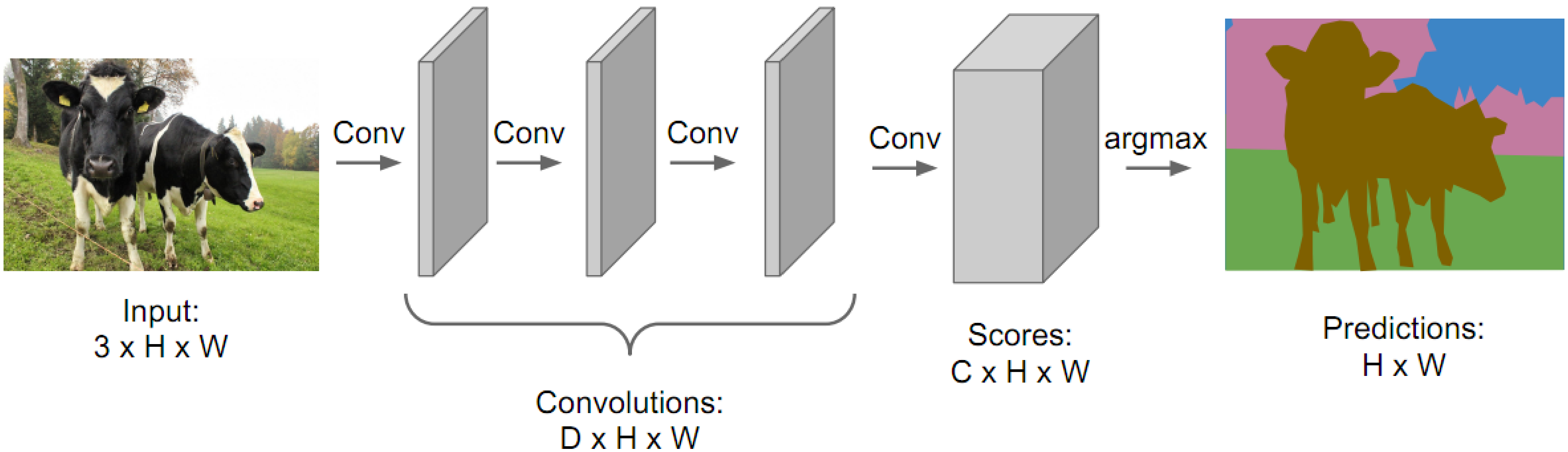


Problem: Very inefficient! Not reusing shared features between overlapping patches

Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

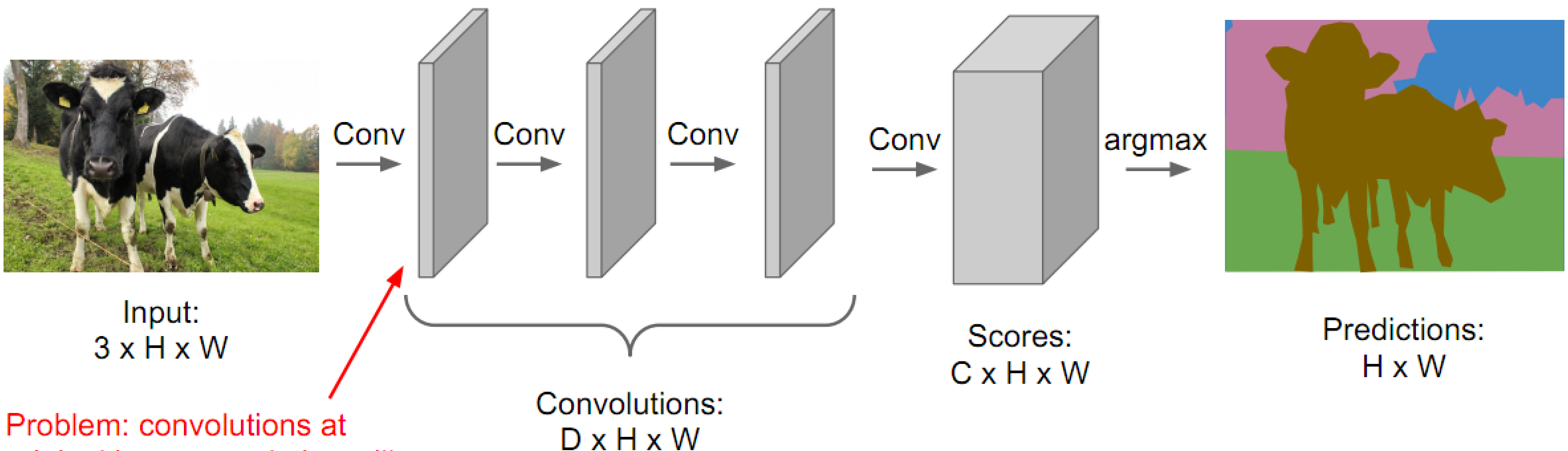
Semantic Segmentation Idea: Fully Convolutional

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



Semantic Segmentation Idea: Fully Convolutional

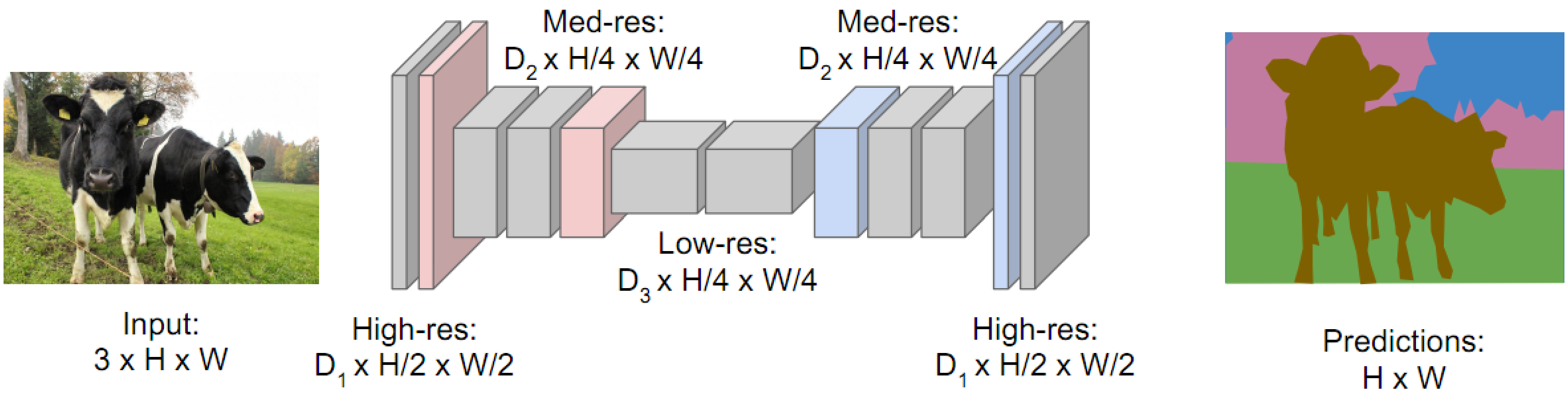
Design a network as a bunch of convolutional layers
to make predictions for pixels all at once!



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

Semantic Segmentation Idea: Fully Convolutional

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



Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

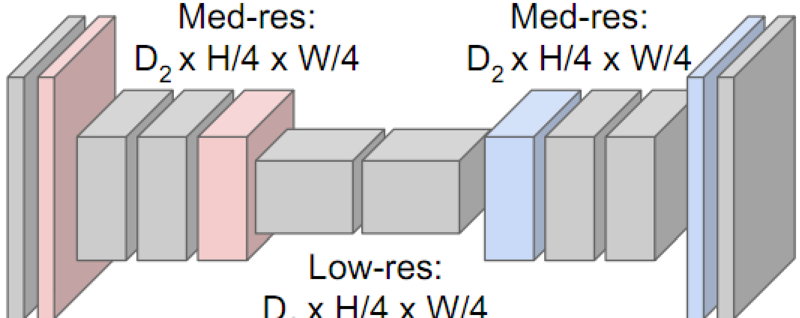
Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

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

Upsampling: ???

Input:
$3 \times H \times W$



Predictions:
$H \times W$

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

In-Network upsampling: “Unpooling”

Nearest Neighbor

1	2
3	4

Input: 2 x 2

→

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

Output: 4 x 4

“Bed of Nails”

1	2
3	4

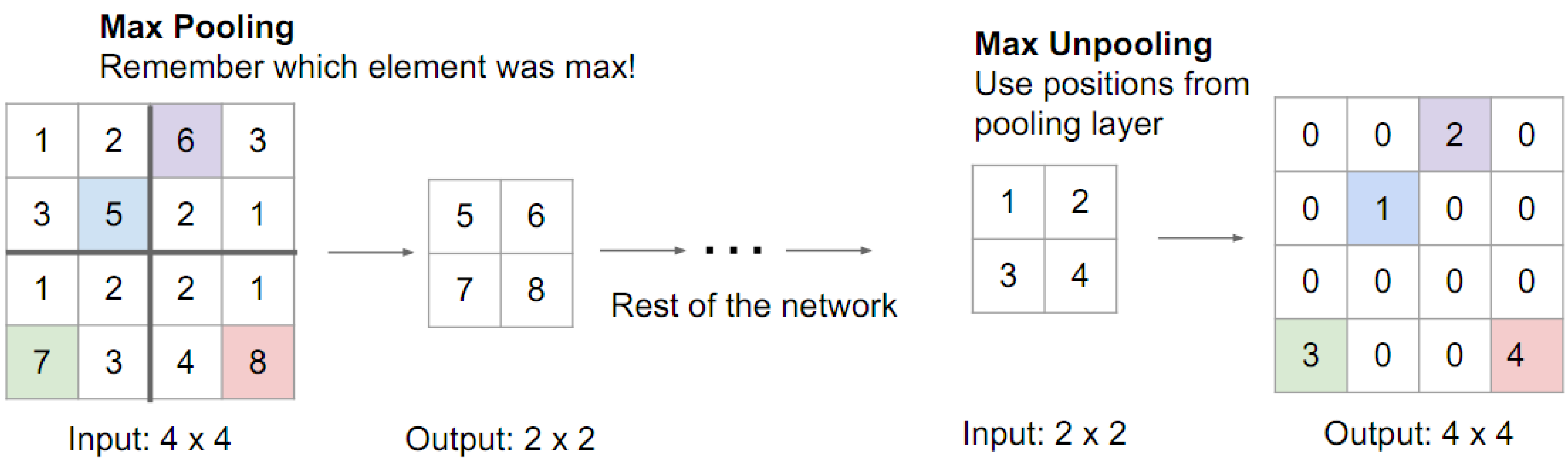
Input: 2 x 2

→

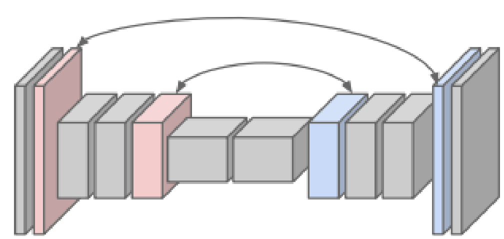
1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

Output: 4 x 4

In-Network upsampling: “Max Unpooling”

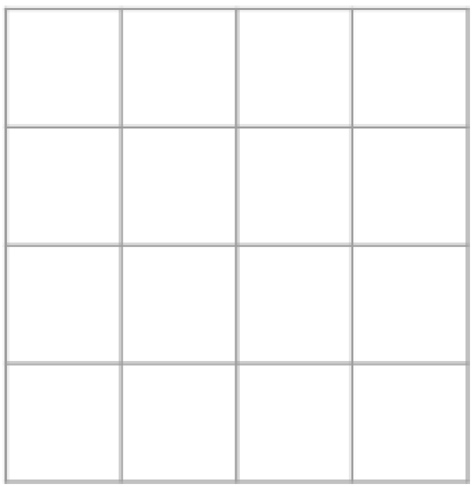


Corresponding pairs of downsampling and upsampling layers

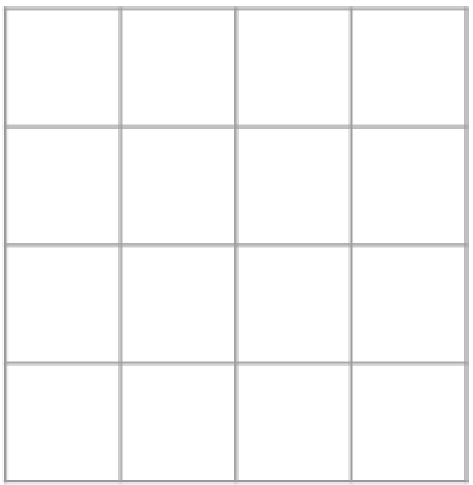


Learnable Upsampling: Transpose Convolution

Recall: Typical 3 x 3 convolution, stride 1 pad 1



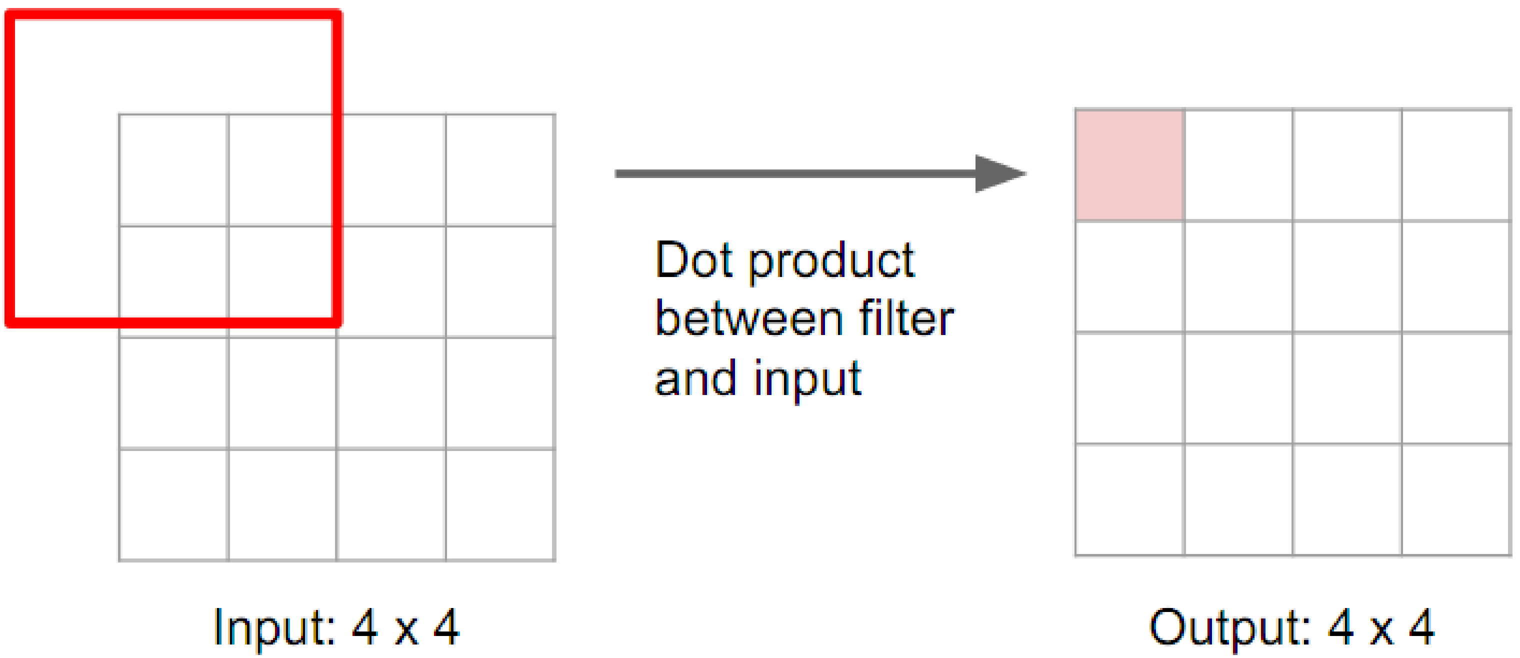
Input: 4 x 4



Output: 4 x 4

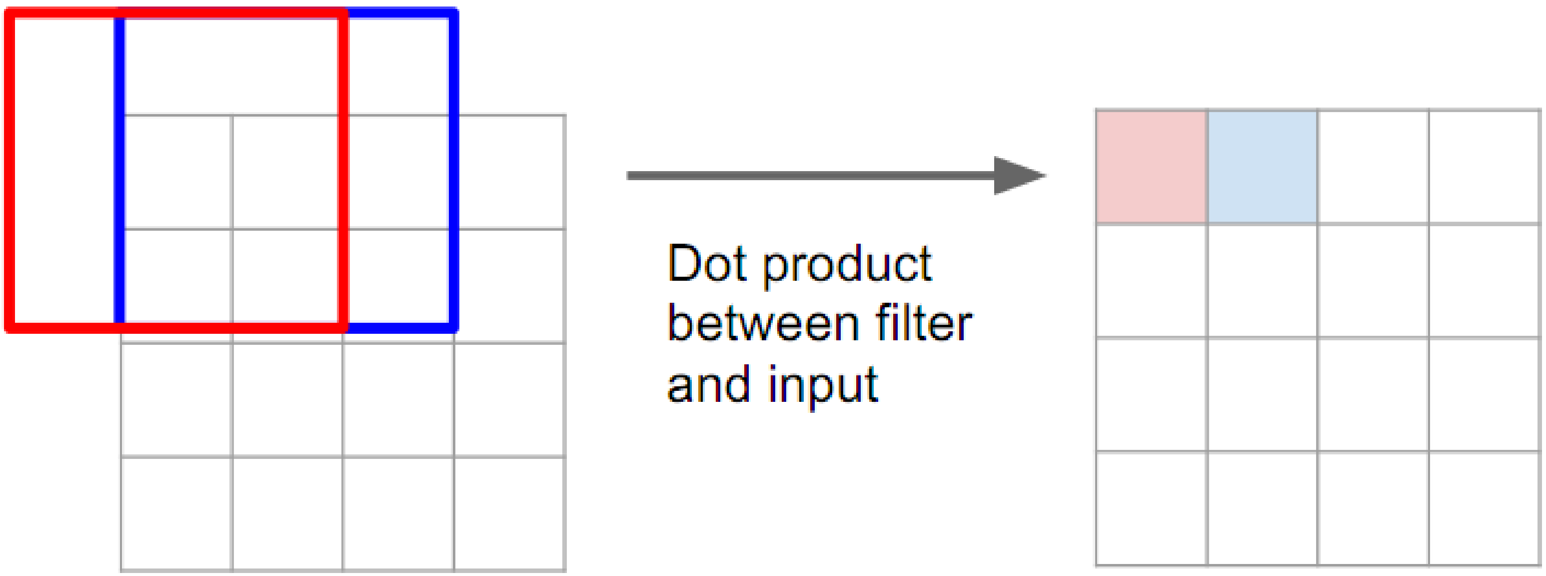
Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 1 pad 1



Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 1 pad 1

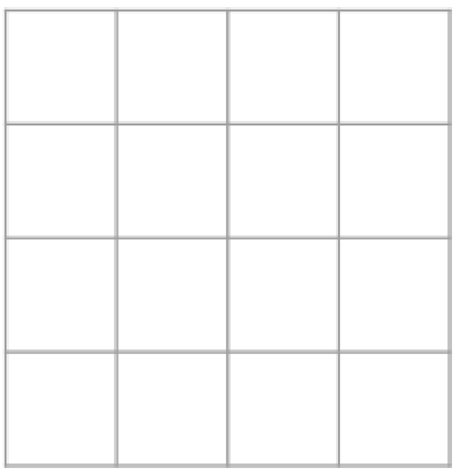


Input: 4 x 4

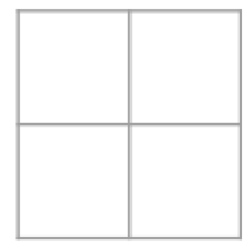
Output: 4 x 4

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



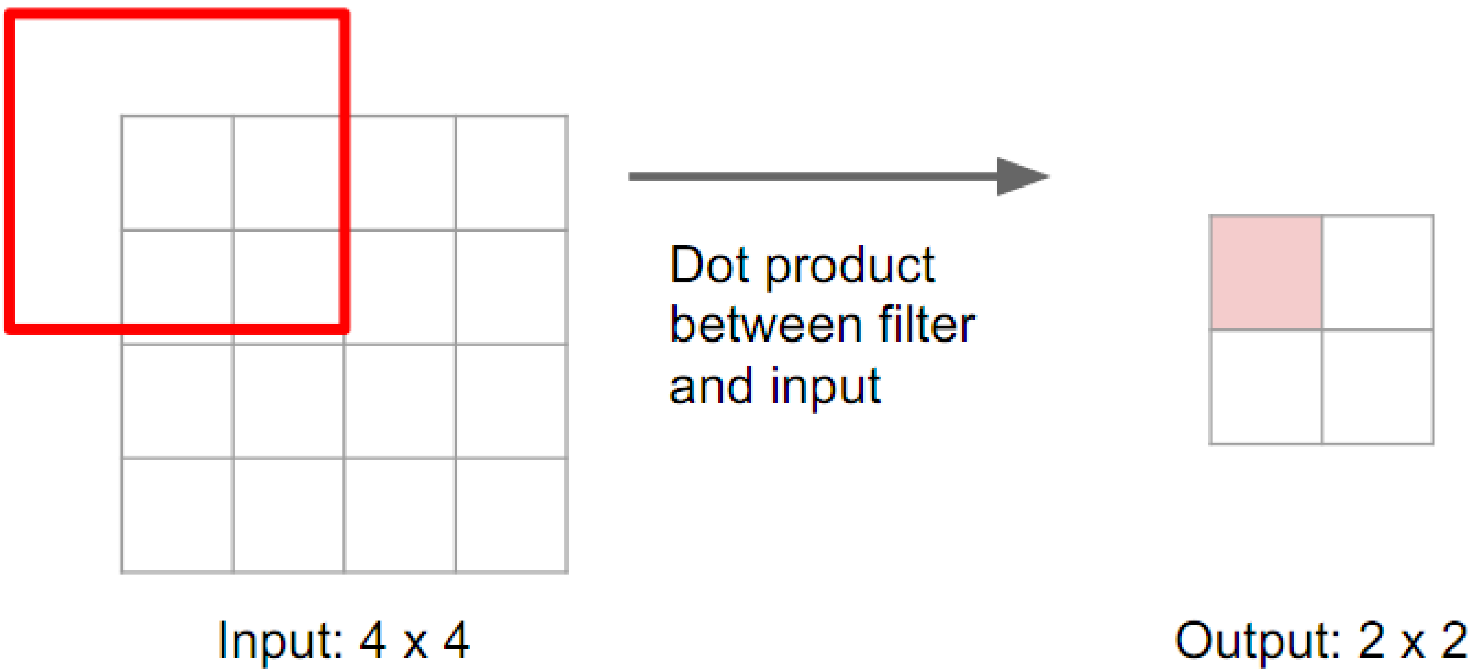
Input: 4 x 4



Output: 2 x 2

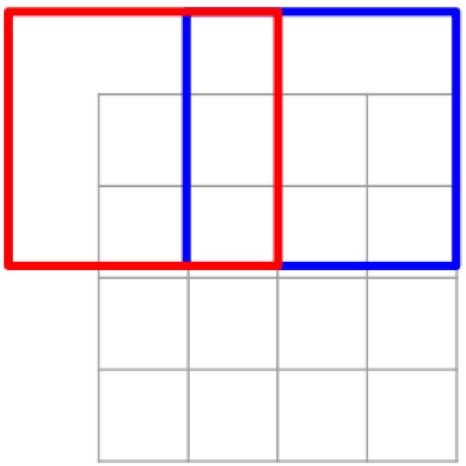
Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



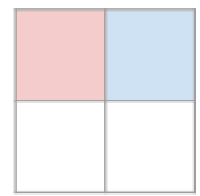
Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, <u>stride 2</u> pad 1



Input: 4 x 4

Dot product between filter and input



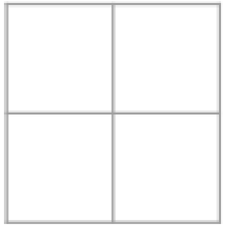
Output: 2 x 2

Filter moves 2 pixels in the input for every one pixel in the output

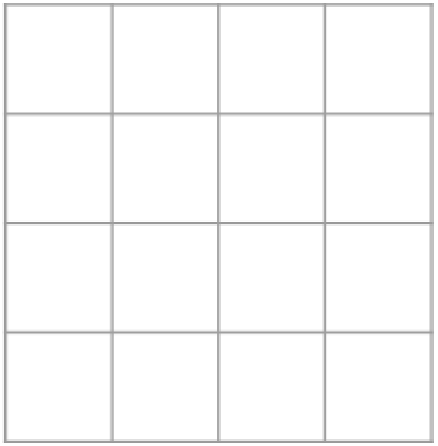
Stride gives ratio between movement in input and output

Learnable Upsampling: Transpose Convolution

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

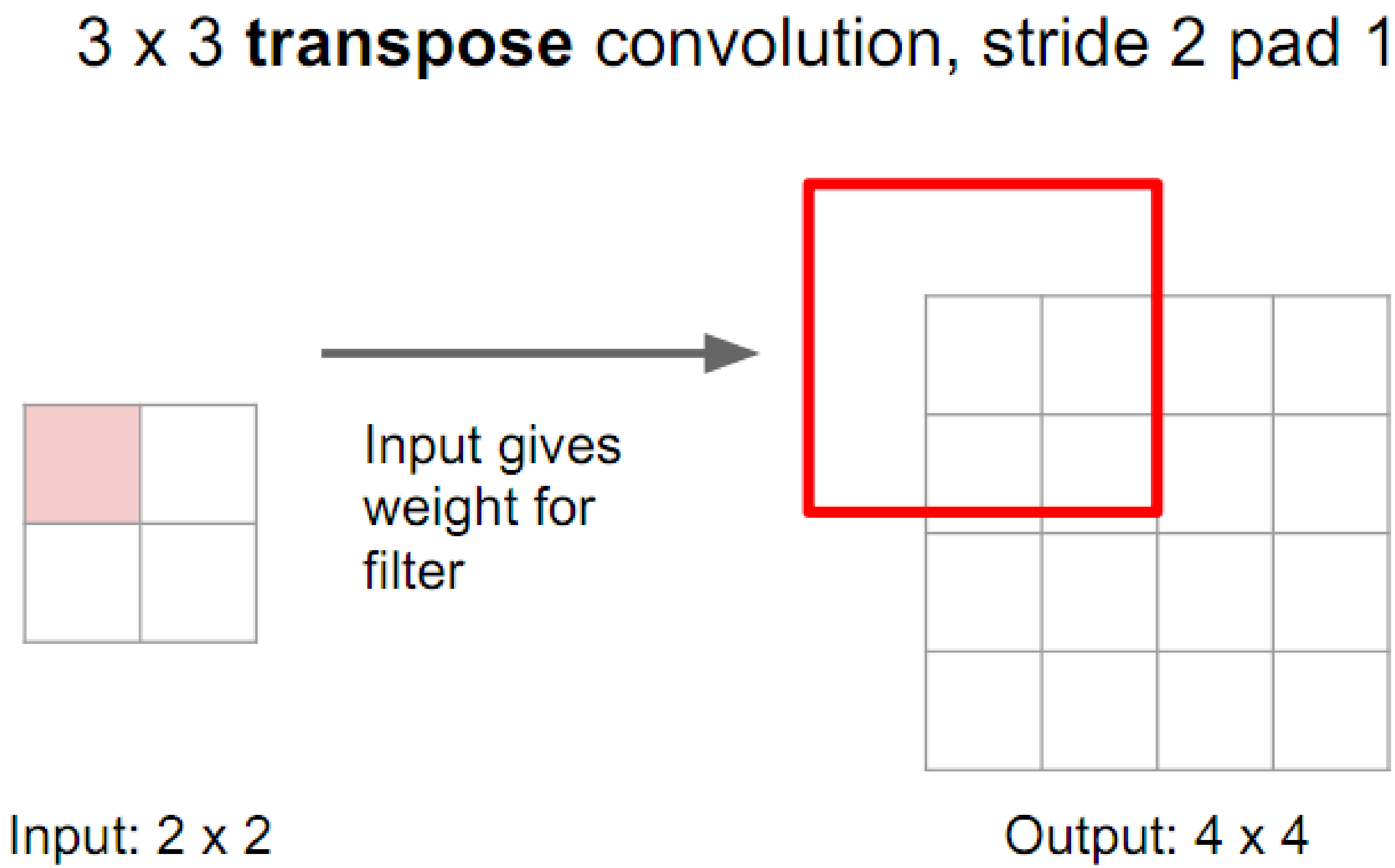


Input: 2 x 2



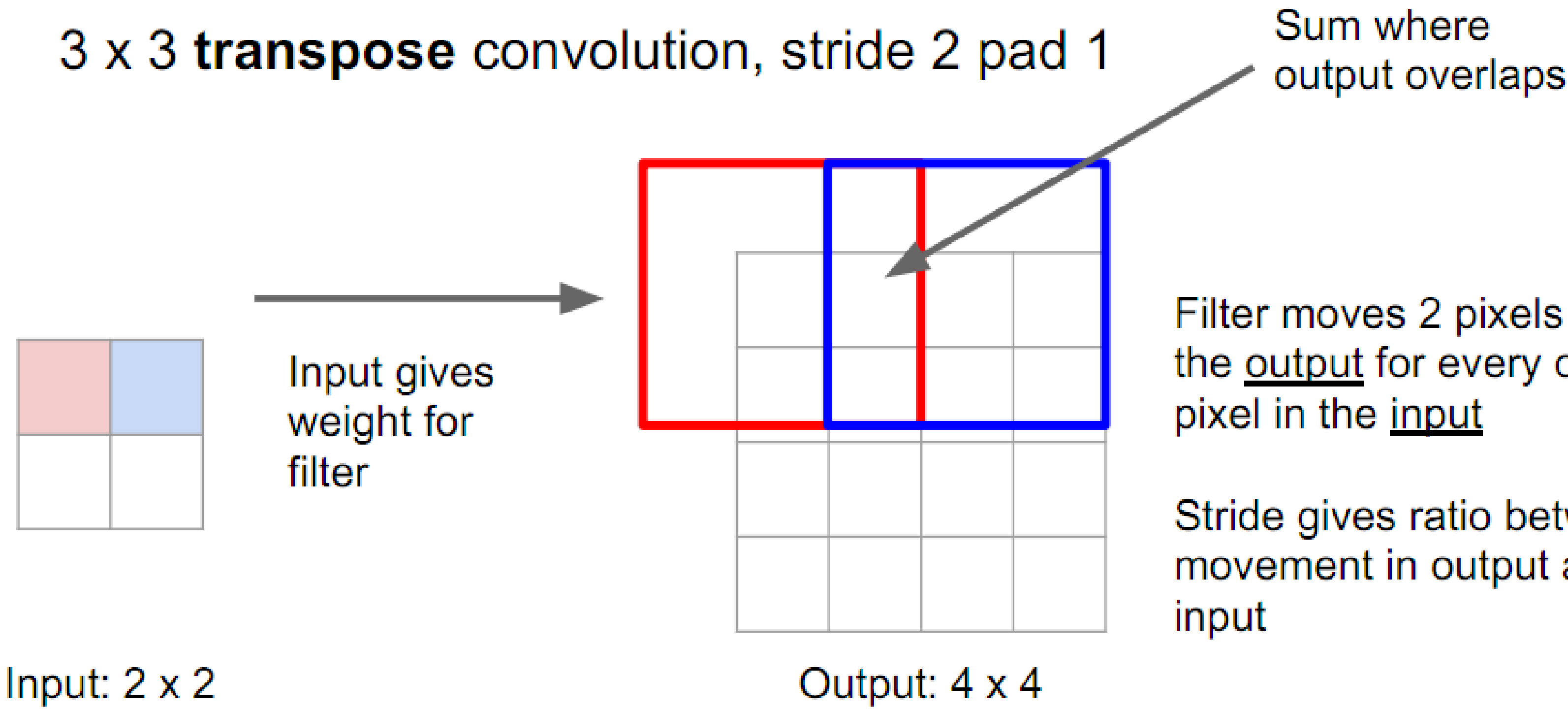
Output: 4 x 4

Learnable Upsampling: Transpose Convolution



Learnable Upsampling: Transpose Convolution

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



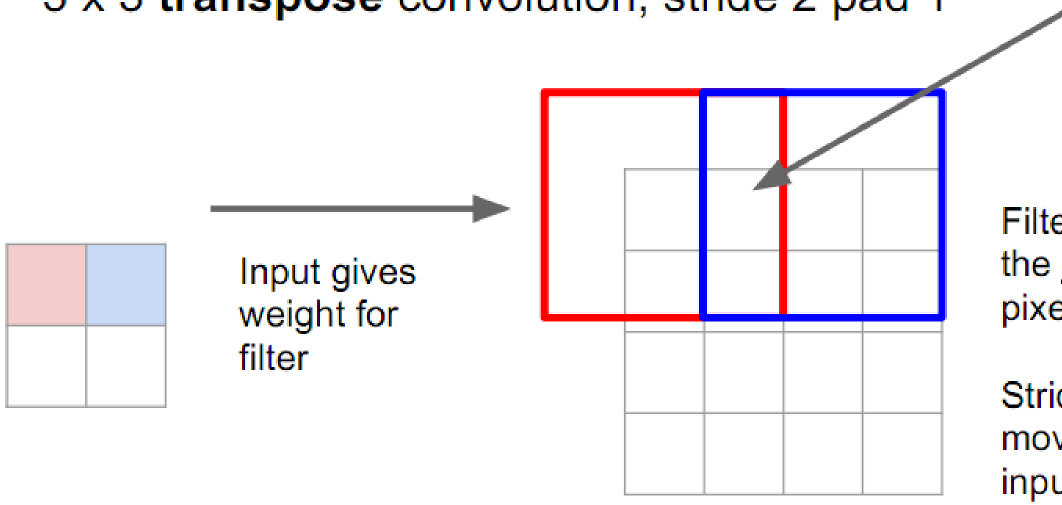
Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Learnable Upsampling: Transpose Convolution

Other names:
-Deconvolution (bad)
-Upconvolution
-Fractionally strided convolution
-Backward strided convolution

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



Input: 2 x 2

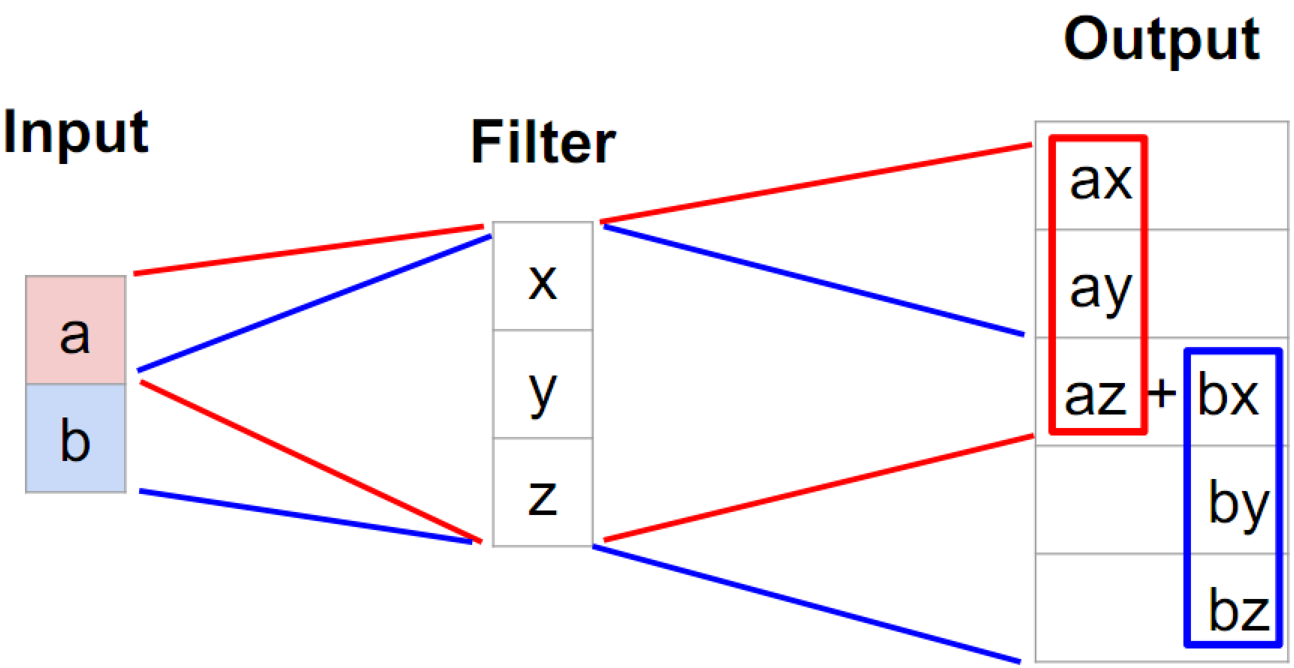
Output: 4 x 4

Sum where output overlaps

Filter moves 2 pixels in the <u>output</u> for every one pixel in the <u>input</u>

Stride gives ratio between movement in output and input

Learnable Upsampling: 1D Example



Output contains copies of the filter weighted by the input, summing at where at overlaps in the output

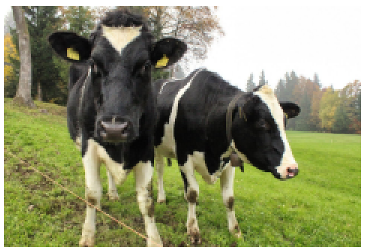
Need to crop one pixel from output to make output exactly 2x input

Semantic Segmentation Idea: Fully Convolutional

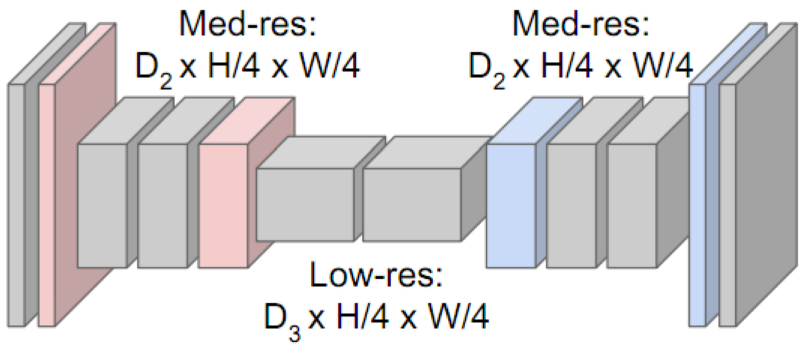
Downsampling:
Pooling, strided
convolution

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

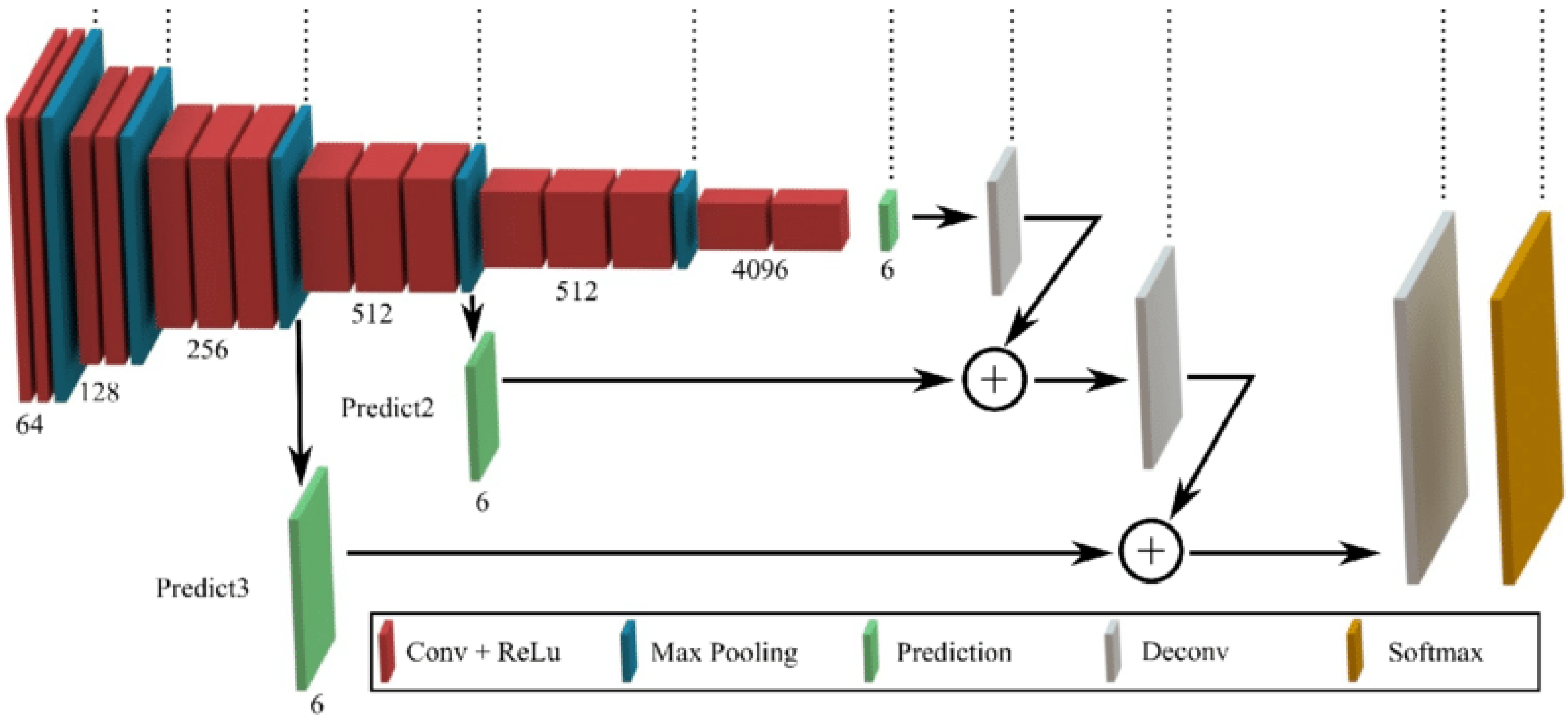


High-res:
D_1 x H/2 x W/2

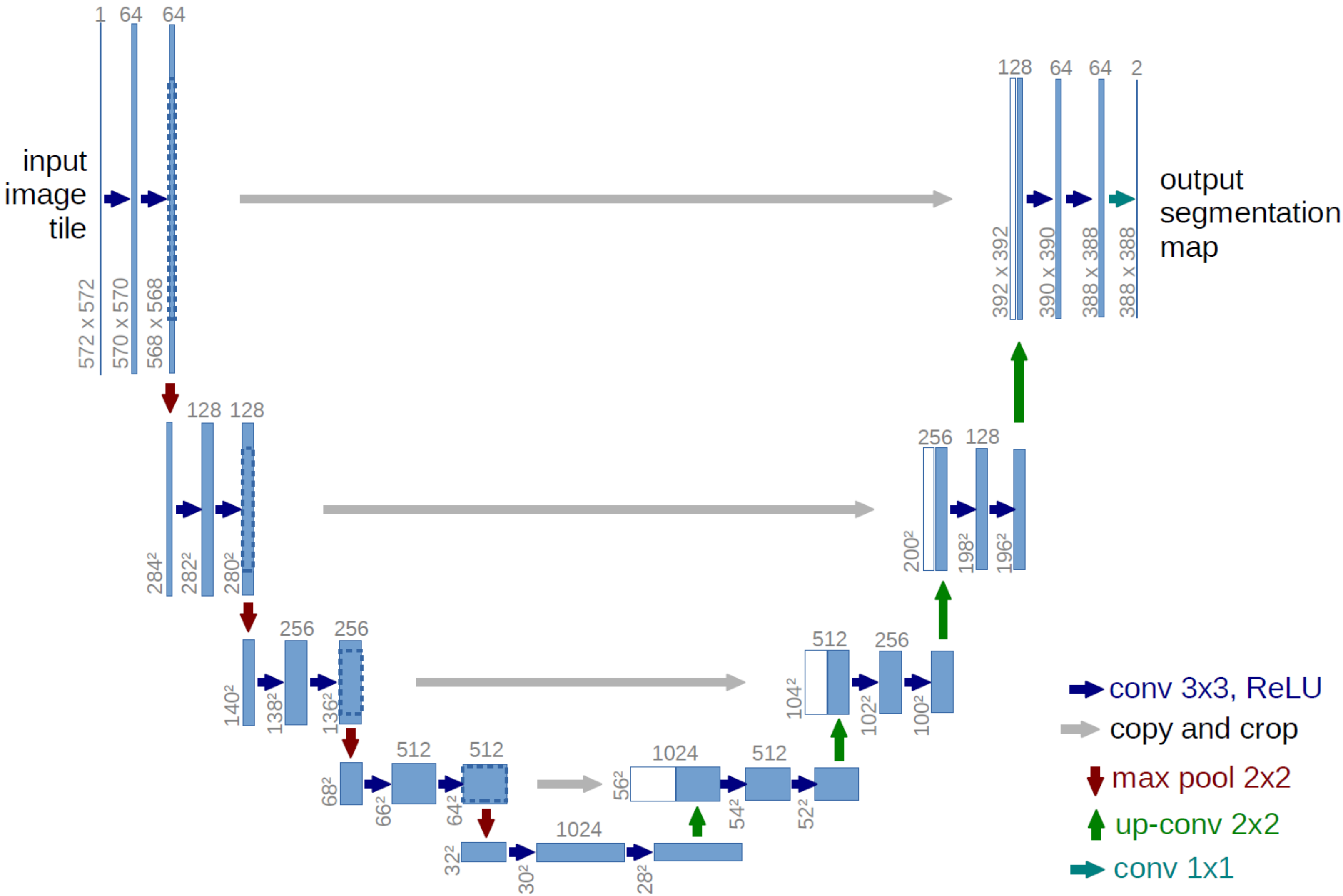
High-res:
D_1 x H/2 x W/2

Predictions:
H x W

FCN with 2 skip connections

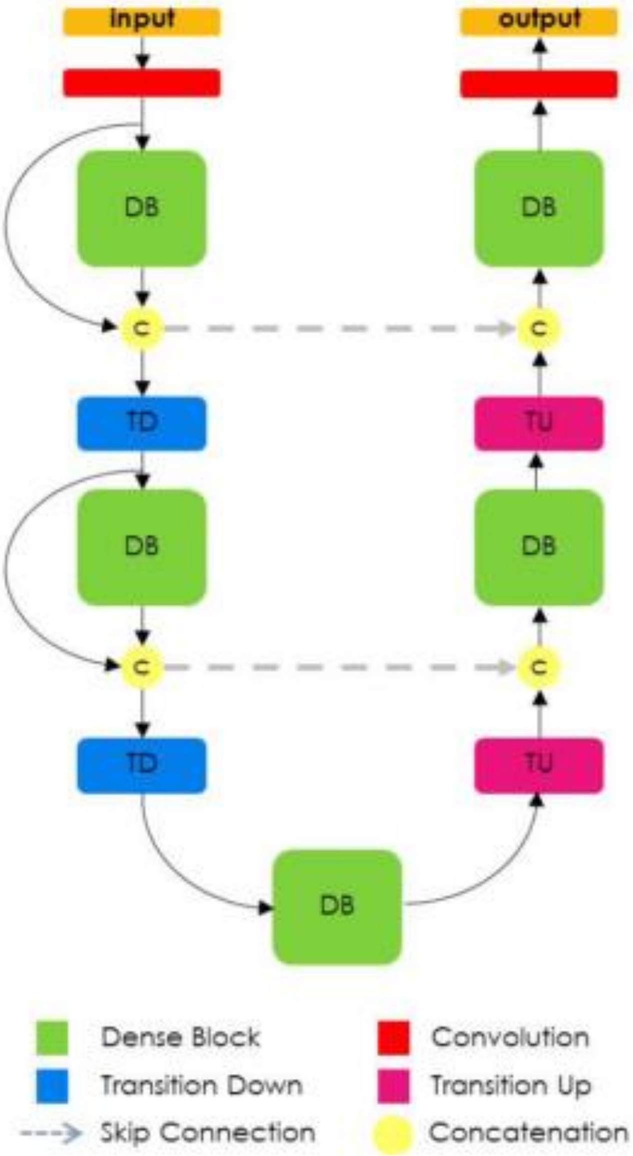


U-Net

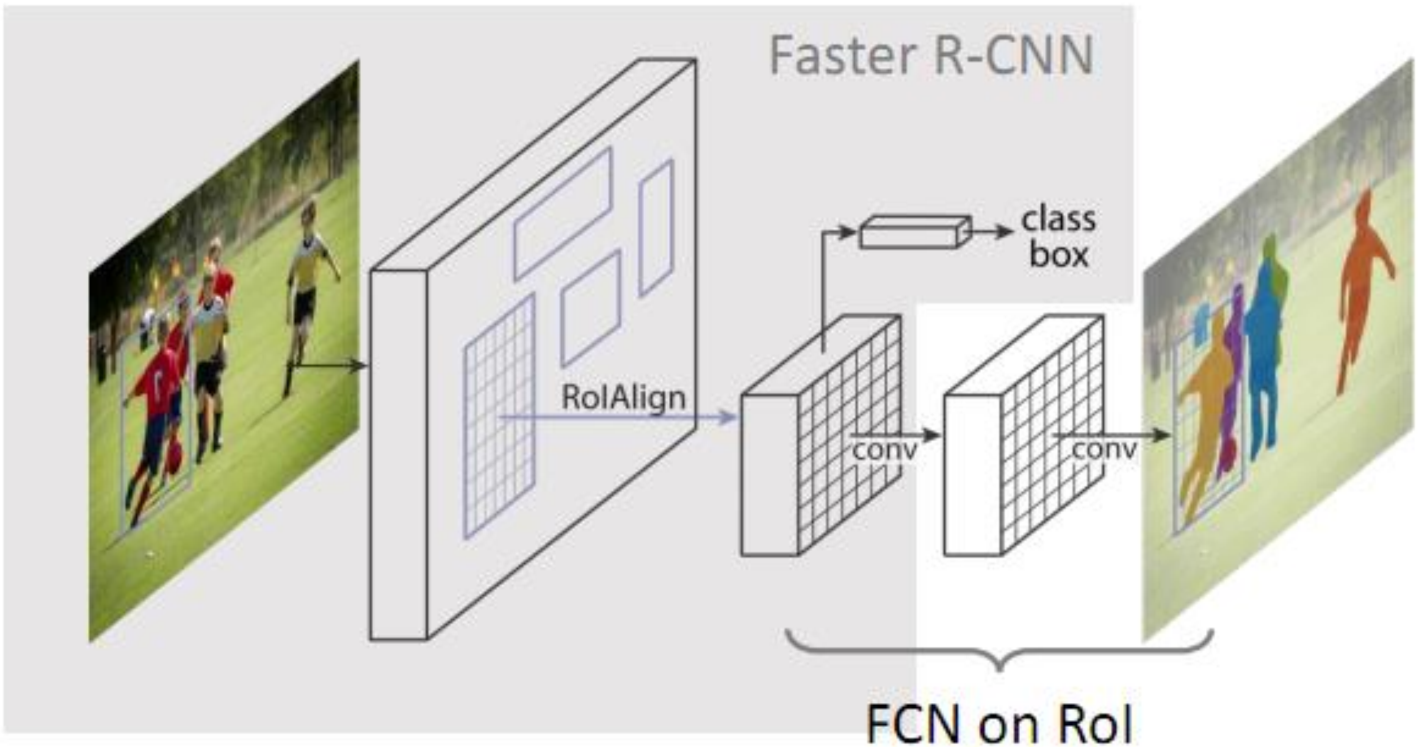


1
64
64
input image tile
572 x 572
570 x 570
568 x 568
128
128
284²
282²
280²
256
256
140²
138²
136²
512
512
68²
66²
64²
1024
32²
30²
28²
1024
512
56²
54²
52²
512
256
104²
102²
100²
256
128
200²
198²
196²
128
64
64
2
392 x 392
390 x 390
388 x 388
388 x 388
output segmentation map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

Tiramisu: Fully Convolutional DenseNets



Mask R-CNN



Mask RCNN =
- 1. Object detector using Faster RCNN +
- 2. fully convolutional network (FCN) on region of interest (RoI)