Deep Learning MSDS 631

Object Detection (and other tasks)

Michael Ruddy

Questions?

- From last lecture?
- From the homework?

More Imaging Tasks

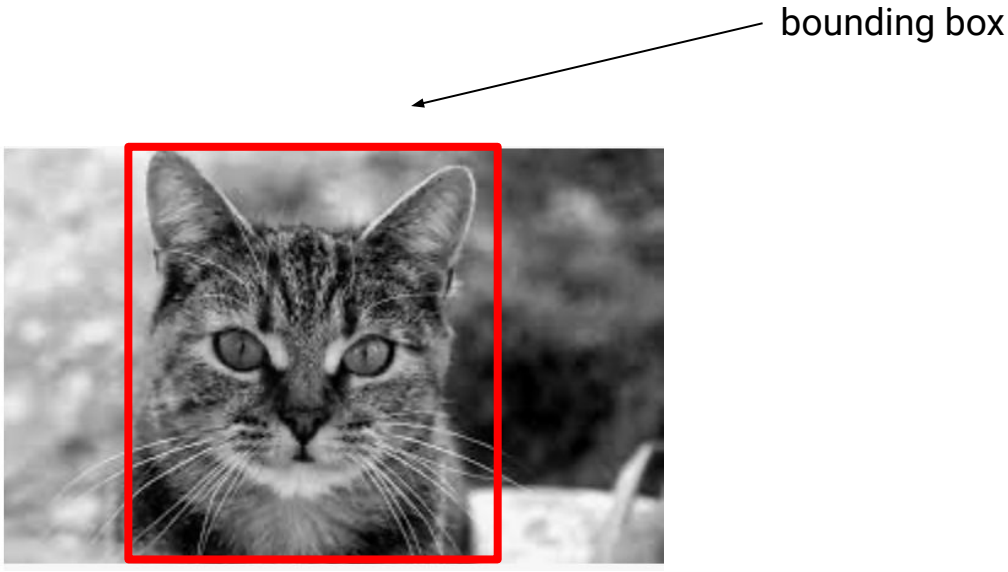
- Classification
- Objects
  - Object Localization
  - Object Detection
- Keypoint detection
  - Human pose detection
  - Facial recognition
- Segmentation
  - Instance/Scene segmentation
  - Medical imaging

Object Localization

- Where is an object in the image?

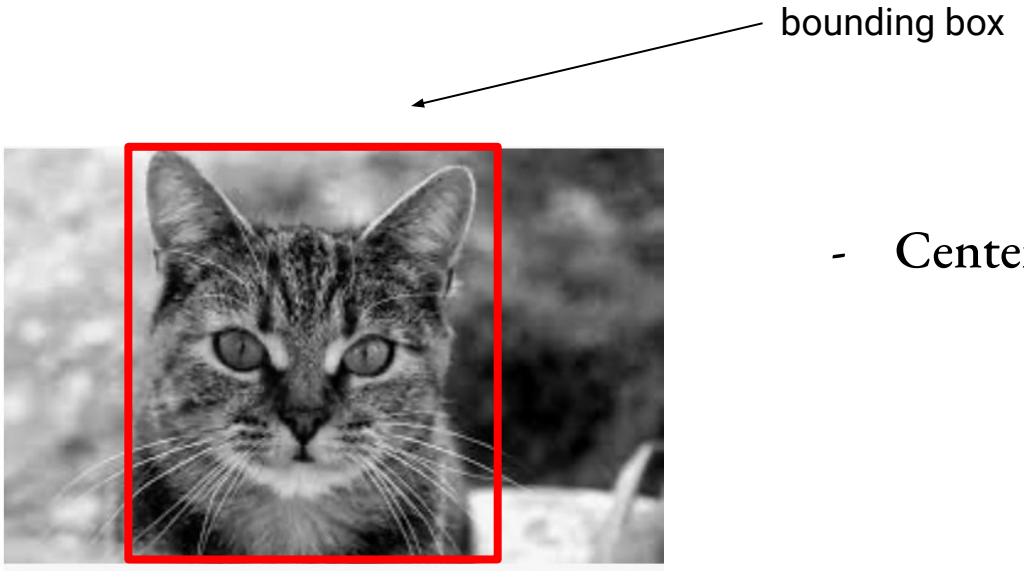
Object Localization

- Where is an object in the image?
  - Input: image of a cat
  - Label: location of cat



Object Localization

- Where is an object in the image?
  - Input: image of a cat
  - Label: bounding box coordinates



  - Center/Dimensions: (x, y, w, h)

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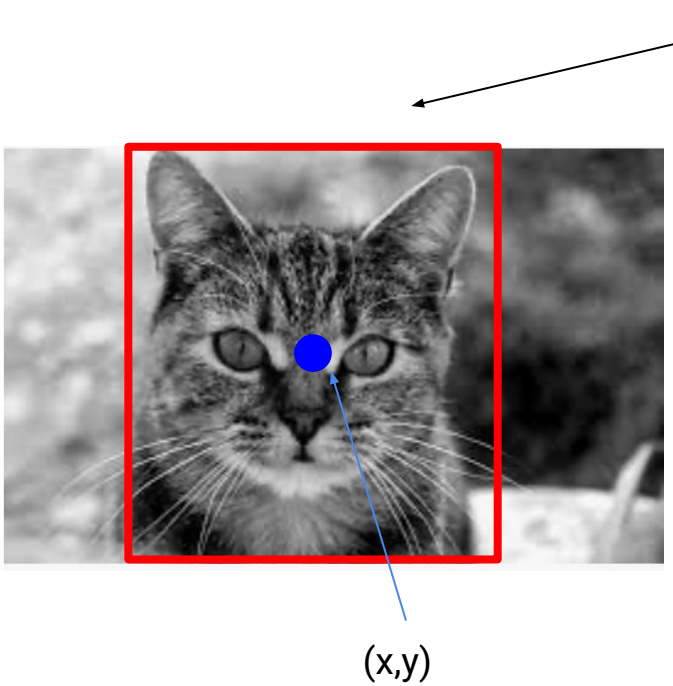

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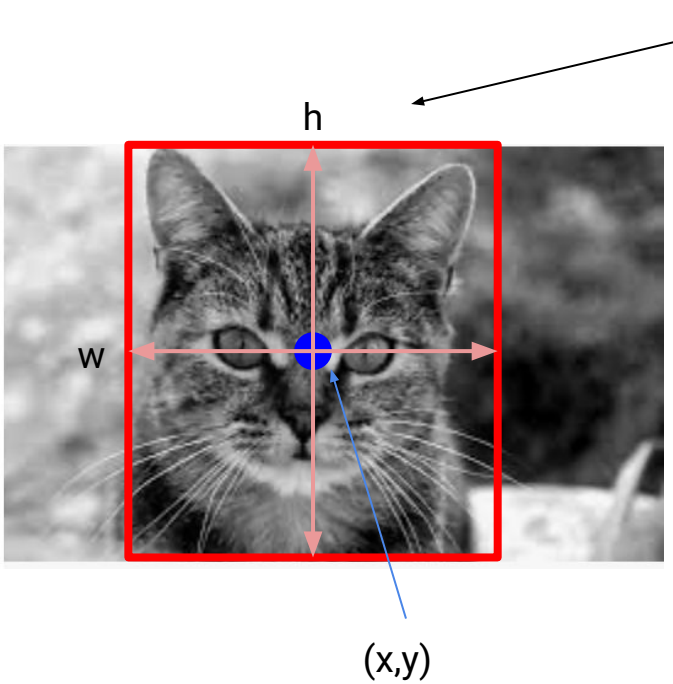

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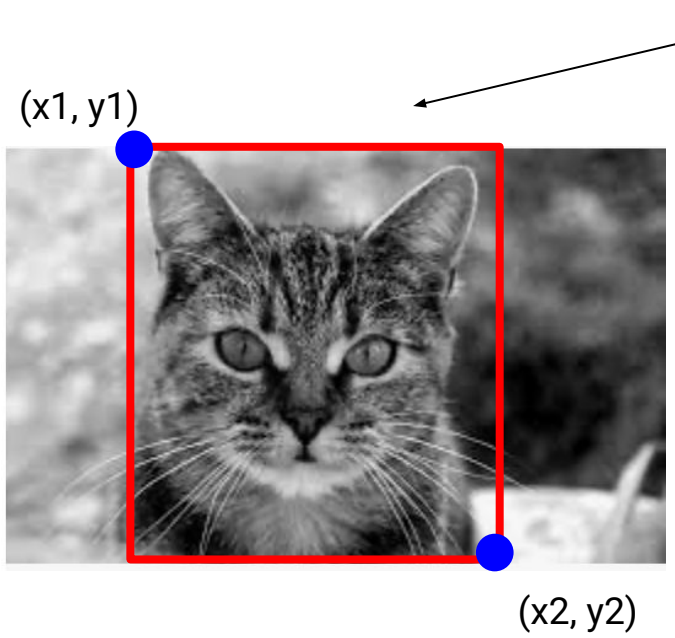

- Center/Dimensions: (x, y, w, h)
- Two corners: (x1, y1, x2, y2)

Object Localization

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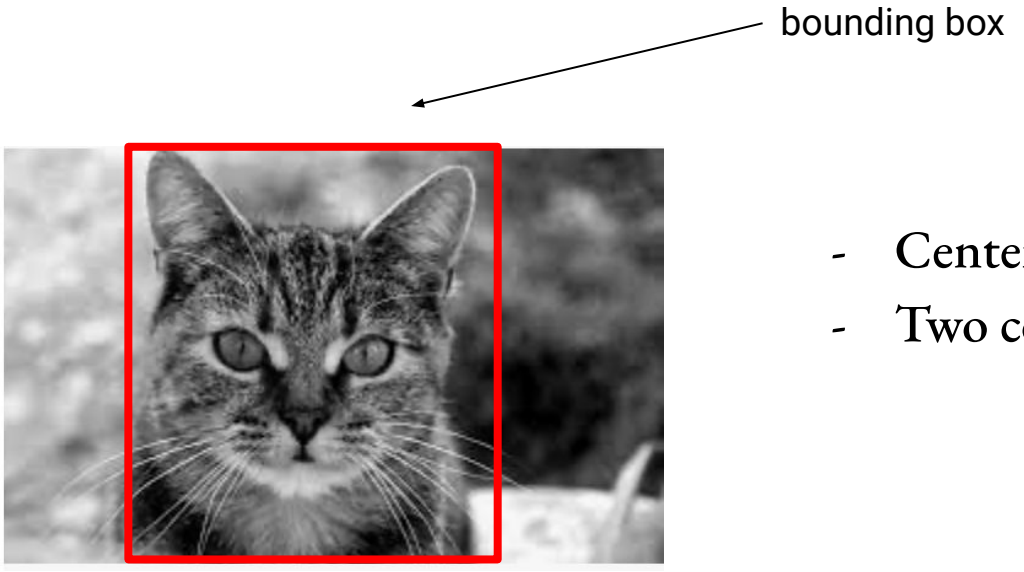

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bounding box

regression

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Classification + Localization

- Simultaneously answer:
  - Does this photo contain a cat?
  - If so where is the cat?

cat

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(1, 150, 175, 50, 70) <-> (class, x, y, w, h)

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Classification: BCELoss(predicted class, true class)

Localization: MSELoss(predicted coords, true coords)

Classification + Localization

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Class label

$$Loss = BCELoss + Y * MSELoss$$

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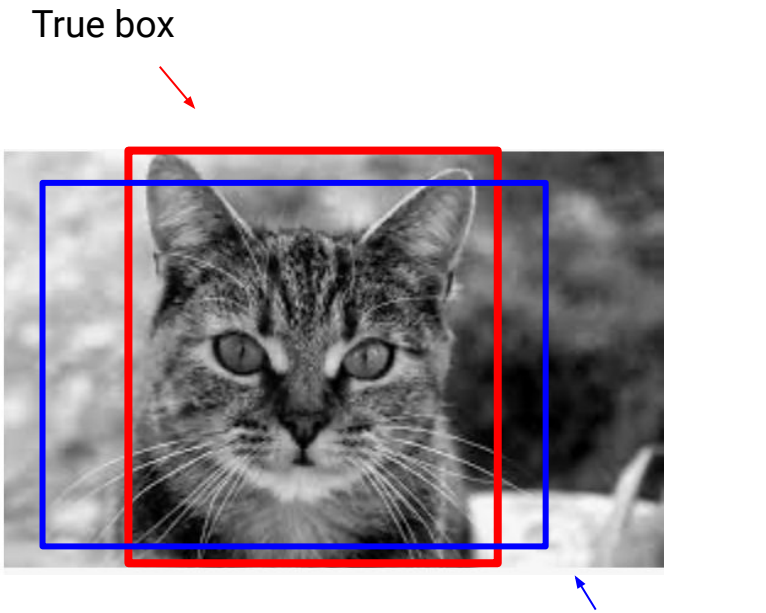
Intersection over Union for Localization



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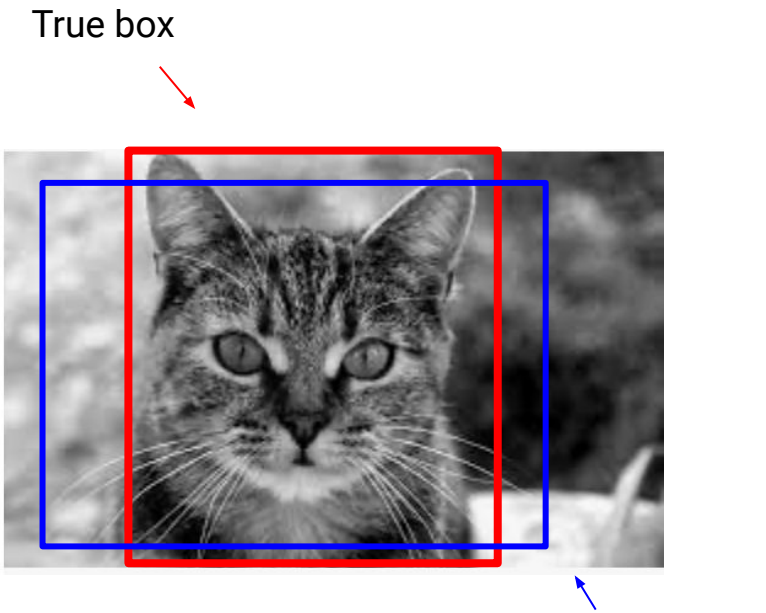
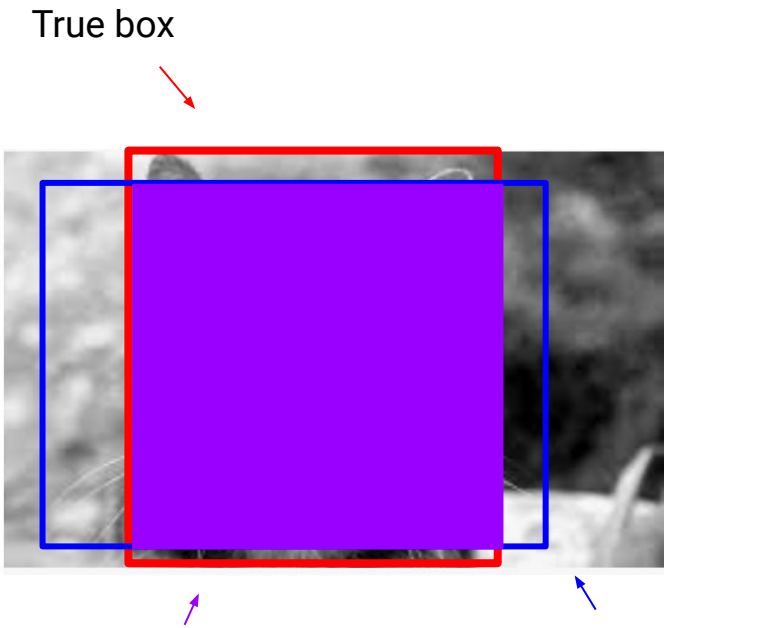


IoU: $\frac{Intersection\ Area}{Union\ Area}$

- Score from 0 to 1
- Higher is better

Intersection over Union for Localization



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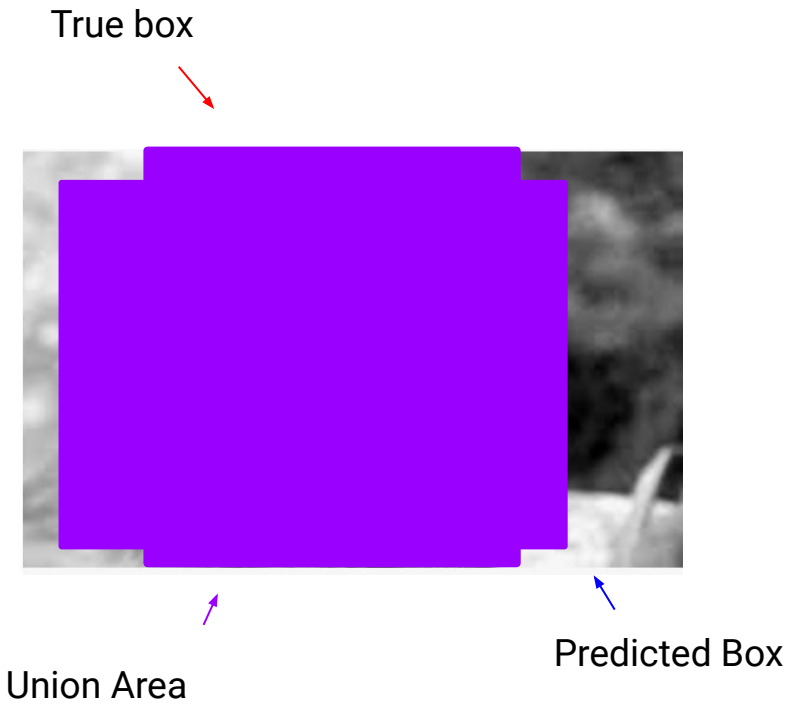

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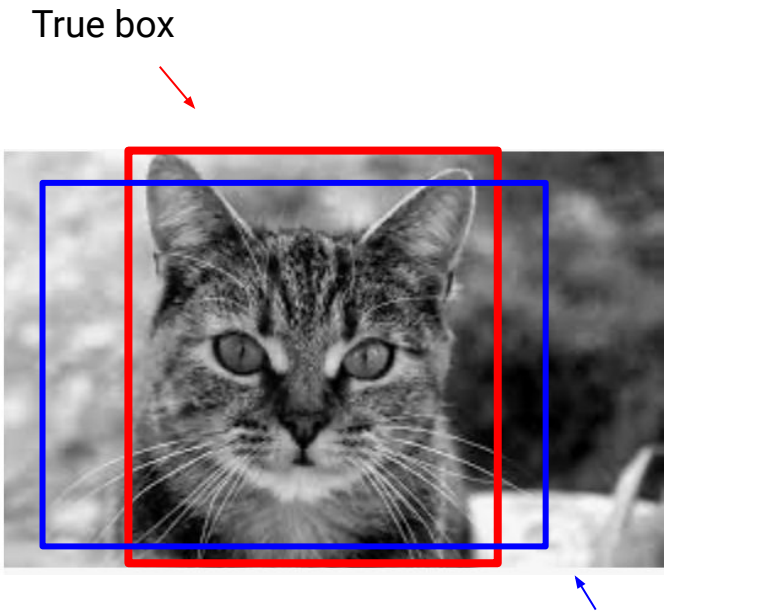

IoU: $\frac{Intersection\ Area}{Union\ Area}$

- Score from 0 to 1
- Higher is better
- Areas can be computed from box coordinates
- Union given by

Box1 Area + Box2 Area - Intersection Area

Multi-Label Classification + Localization

- What about multiple classes in the same photo?

Multi-Label Classification + Localization

- What about multiple classes in the same photo?
- k classes -> k binary classification tasks + localization

Classes
- Pedestrian
- Stop sign
- Car
- Traffic Light

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Label

$(0, 0, 0, 0, 0)$

$(1, 200, 300, 10, 10)$

$(1, 400, 100, 300, 100)$

$(0, 0, 0, 0, 0)$

Multi-Label Classification + Localization

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Label

classes

$$\begin{matrix}(0, & 0, & 0, & 0, & 0) \\ (1, & 200, & 300, & 10, & 10) \\ (1, & 400, & 100, & 300, & 100) \\ (0, & 0, & 0, & 0, & 0)\end{matrix}$$

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Label

Bounding box coordinates

classes

$$\begin{matrix}(0, & 0, 0, 0, 0) \\ (1, & 200, 300, 10, 10) \\ (1, & 400, 100, 300, 100) \\ (0, & 0, 0, 0, 0)\end{matrix}$$

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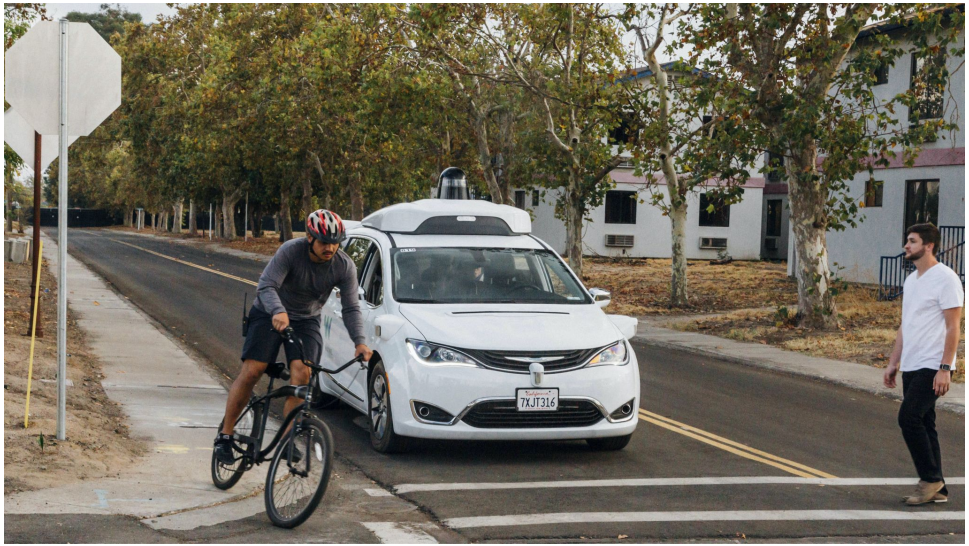

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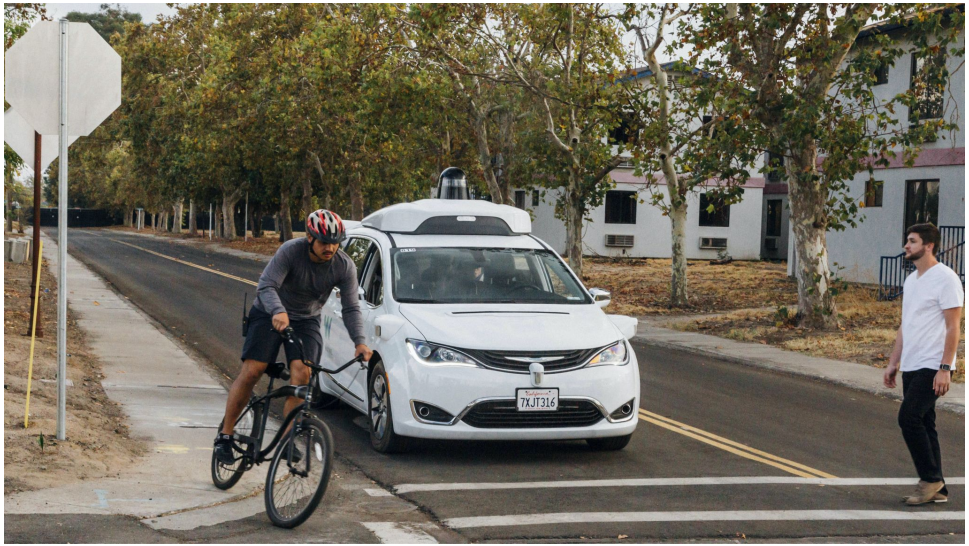

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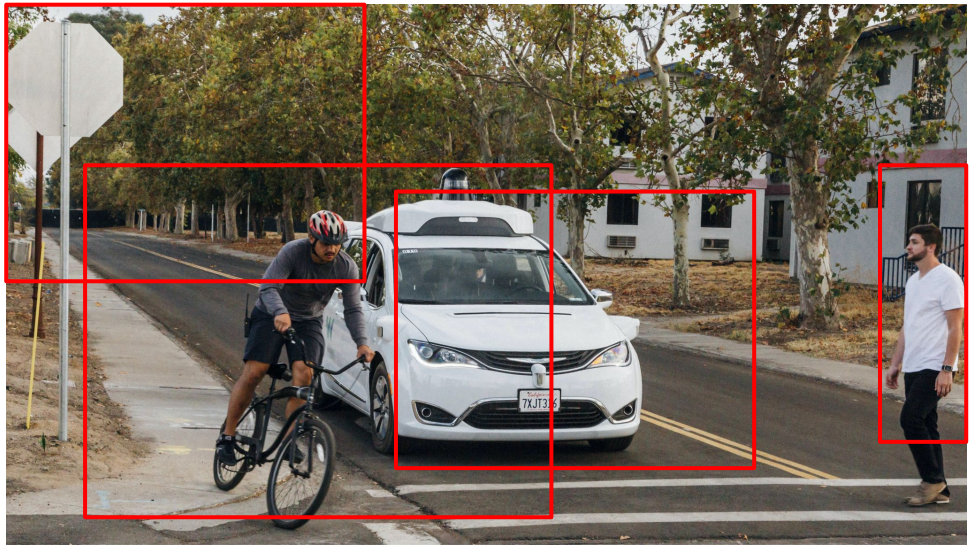

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Object Detection

- Classify and locate all objects in an image
- Region Proposals (RCNNs)
- You Only Look Once (YOLO)
  1. Sort each bounding box label into various “anchor boxes”
  2. Divide Image into a grid
  3. For each grid square predict whether the center of a bounding box appears in the grid square (for each anchor box)

YOLO

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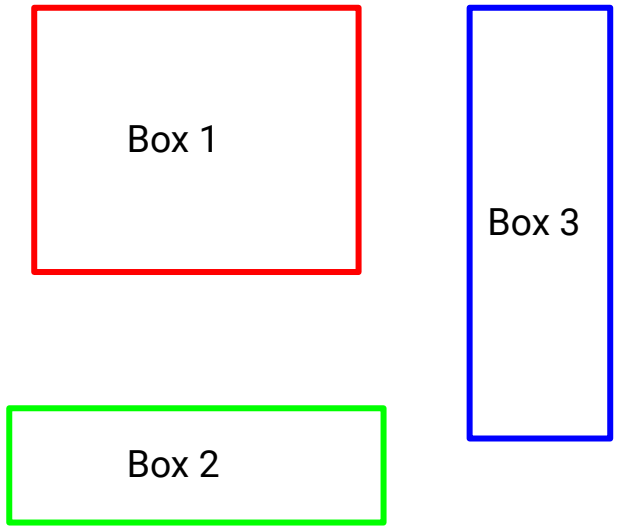

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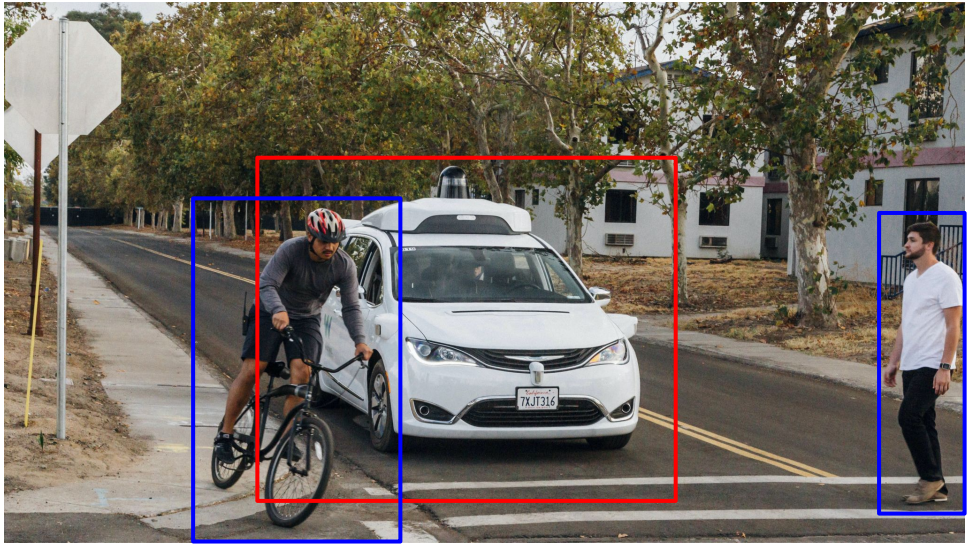

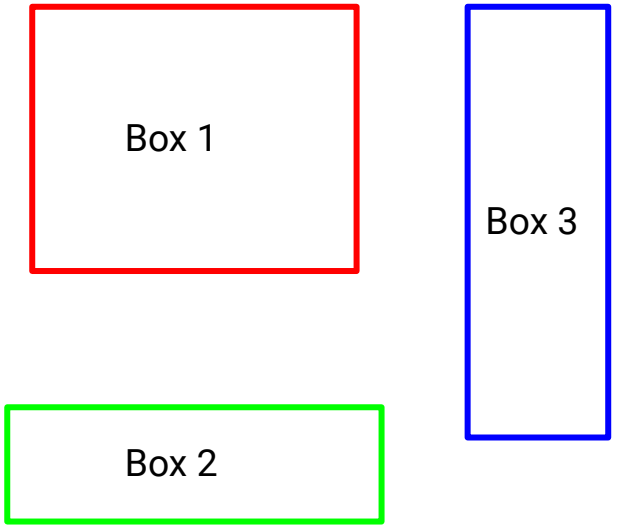

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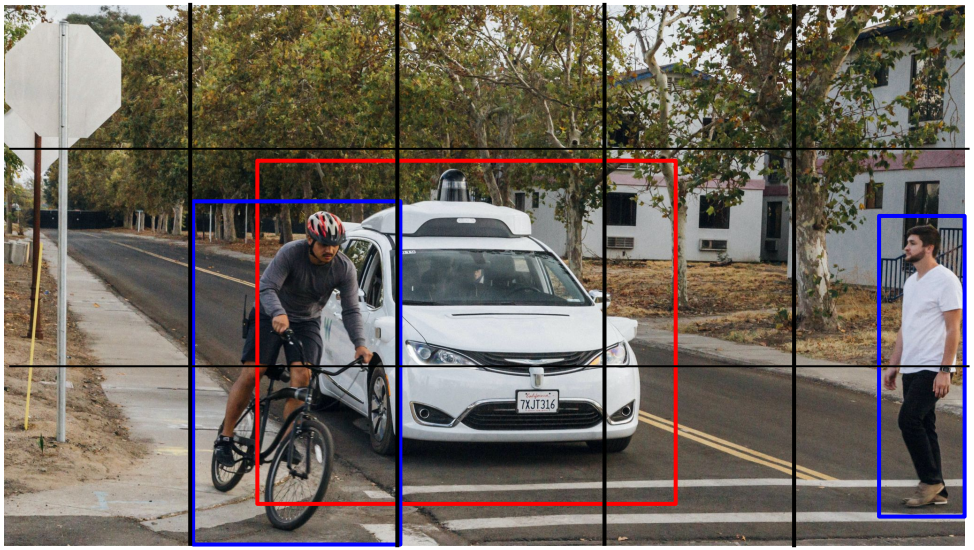

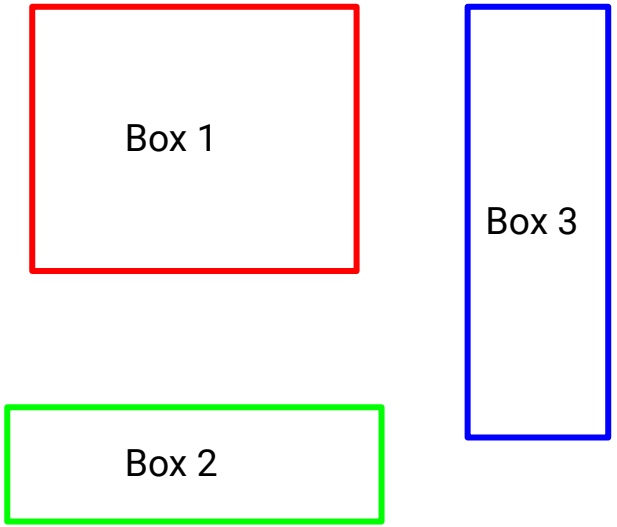

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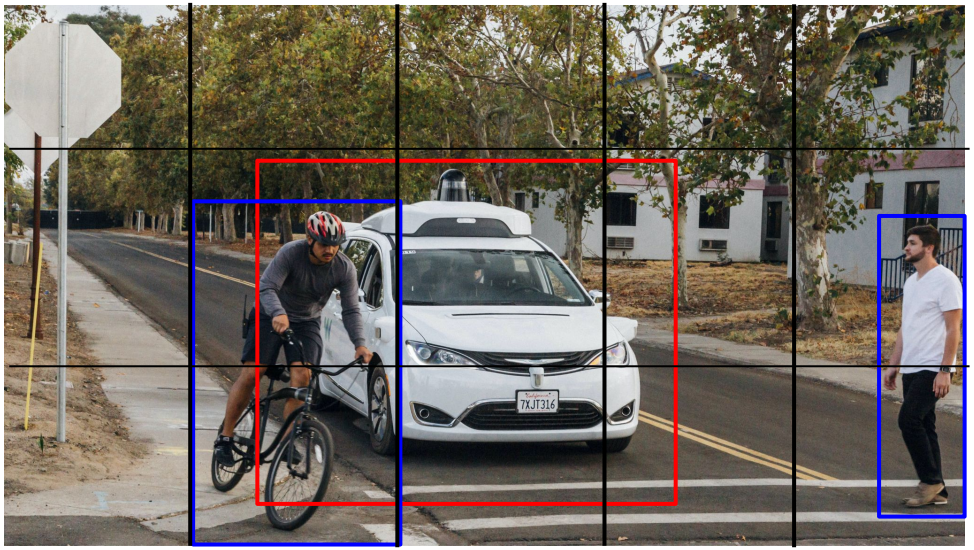

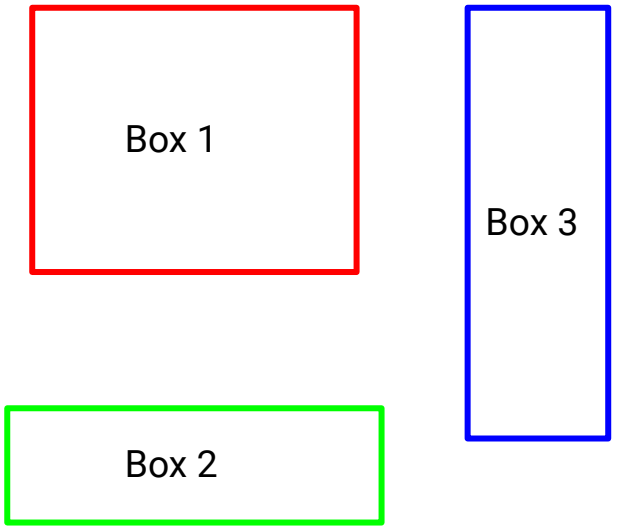

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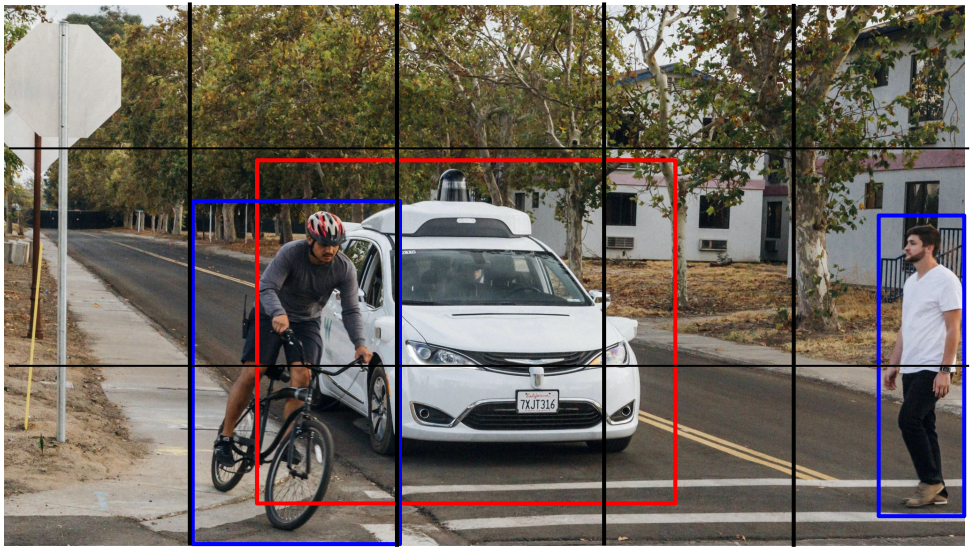


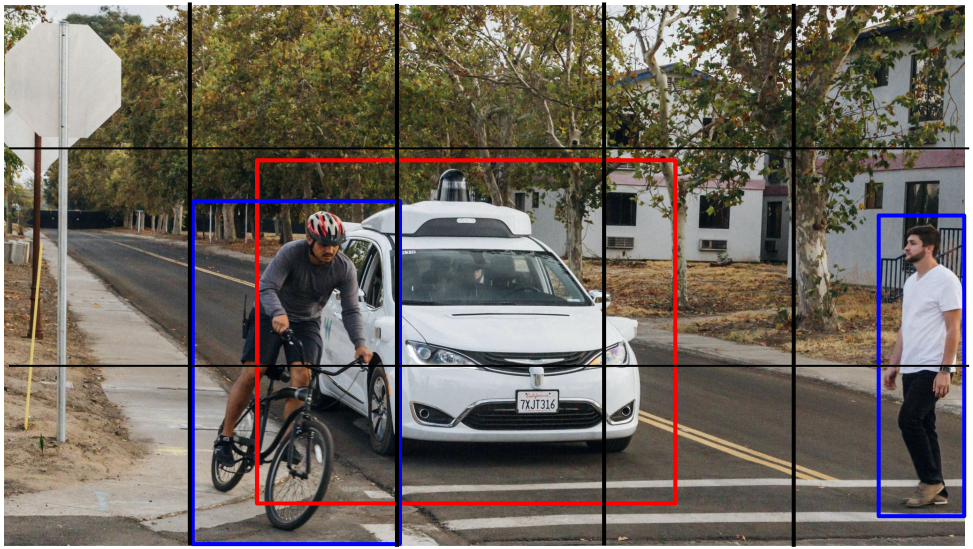
$$
\begin{bmatrix}
p_c^1 \\ c_1^1 \\ c_2^1 \\ \vdots \\ c_k^1 \\ x^1 \\ y^1 \\ w^1 \\ h^1 \\
p_c^2 \\ c_1^2 \\ c_2^2 \\ \vdots \\ c_k^2 \\ x^2 \\ y^2 \\ w^2 \\ h^2 \\
p_c^3 \\ c_1^3 \\ c_2^3 \\ \vdots \\ c_k^3 \\ x^3 \\ y^3 \\ w^3 \\ h^3
\end{bmatrix}
$$

Probability an object appears matching anchor box 1

Class predictions for this box

Bounding box coords for this box

YOLO



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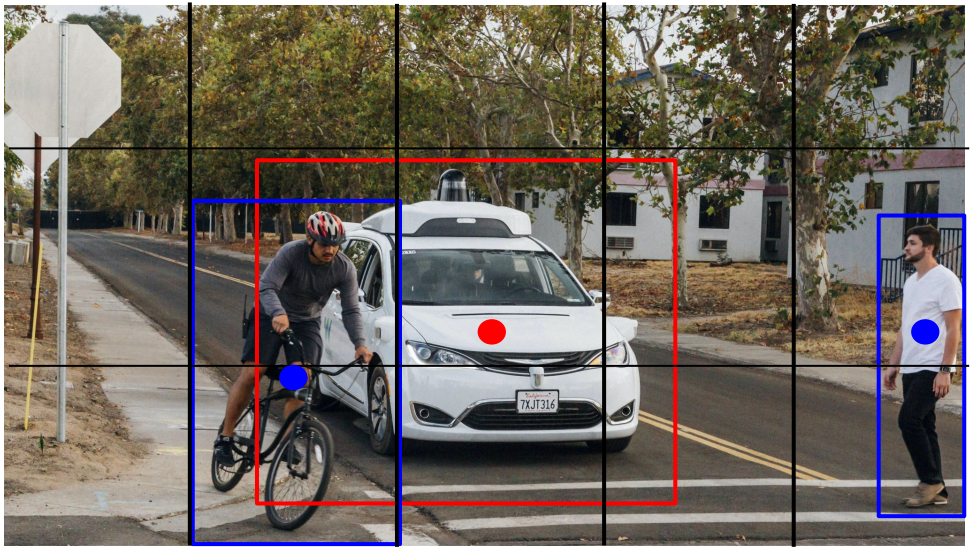
p_c^3 \\ c_1^3 \\ c_2^3 \\ \vdots \\ c_k^3 \\ x^3 \\ y^3 \\ w^3 \\ h^3
\end{bmatrix}
$$

Probability an object appears matching anchor box 2

Class predictions for this box

Bounding box coords for this box

YOLO



$$
\begin{bmatrix}
(p_c^1)^1 & \dots & (p_c^1)^N \\
(c_1^1)^1 & & (c_1^1)^N \\
c_2^1)^1 & & (c_2^1)^N \\
\vdots & & \vdots \\
(c_k^1)^1 & & (c_k^1)^N \\
(x^1)^1 & & (x^1)^N \\
(y^1)^1 & & (y^1)^N \\
(w^1)^1 & & (w^1)^N \\
(h^1)^1 & & (h^1)^N \\
(p_c^2)^1 & & (p_c^2)^N \\
(c_1^2)^1 & & (c_1^2)^N \\
(c_2^2)^1 & & (c_1^2)^N \\
\vdots & & \vdots \\
(c_k^2)^1 & & (c_k^2)^N \\
(x^2)^1 & & (x^2)^N \\
(y^2)^1 & & (y^2)^N \\
(w^2)^1 & & (w^2)^N \\
(h^2)^1 & & (h^2)^N \\
(p_c^3)^1 & & (p_c^3)^N \\
(c_1^3)^1 & & (c_1^3)^N \\
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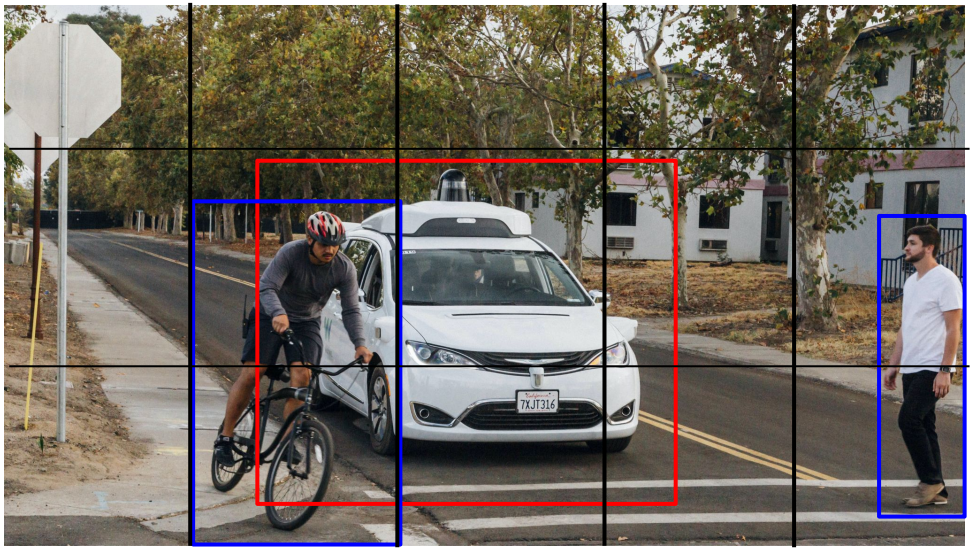
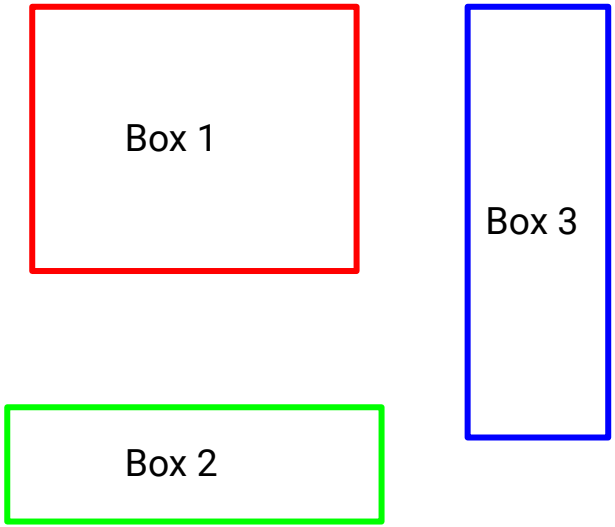
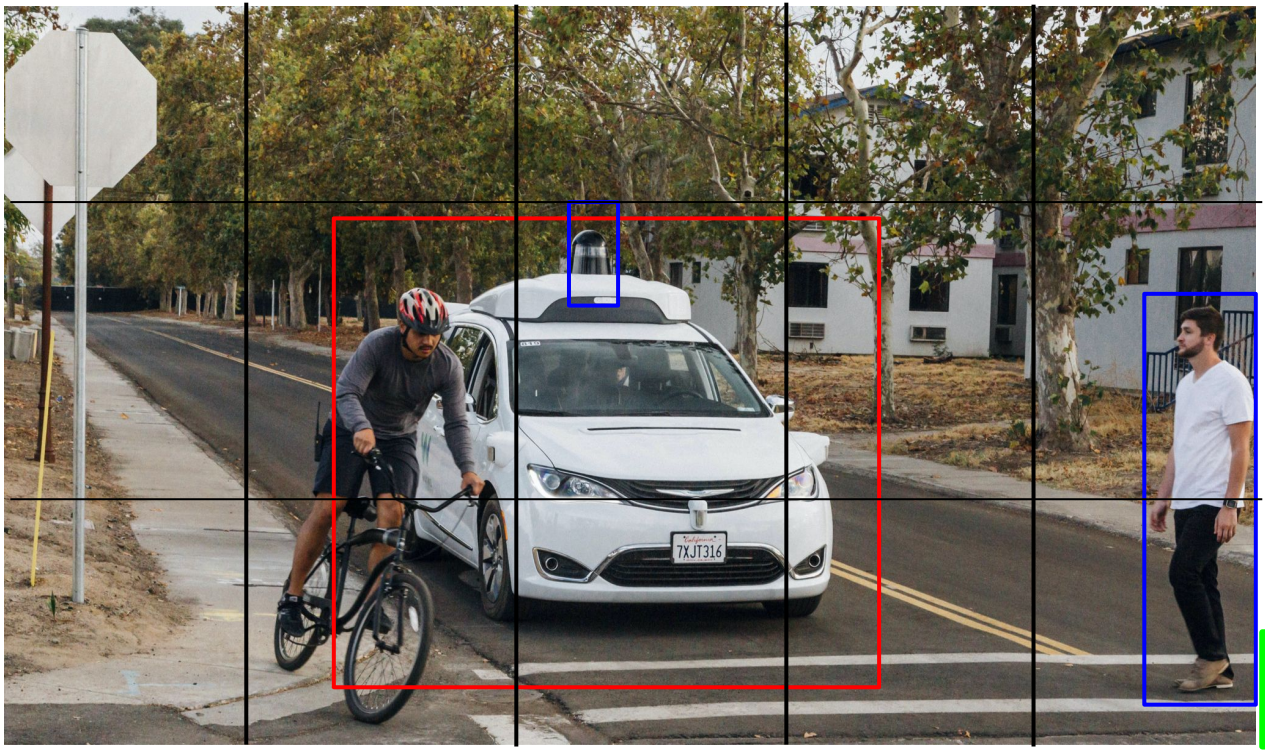






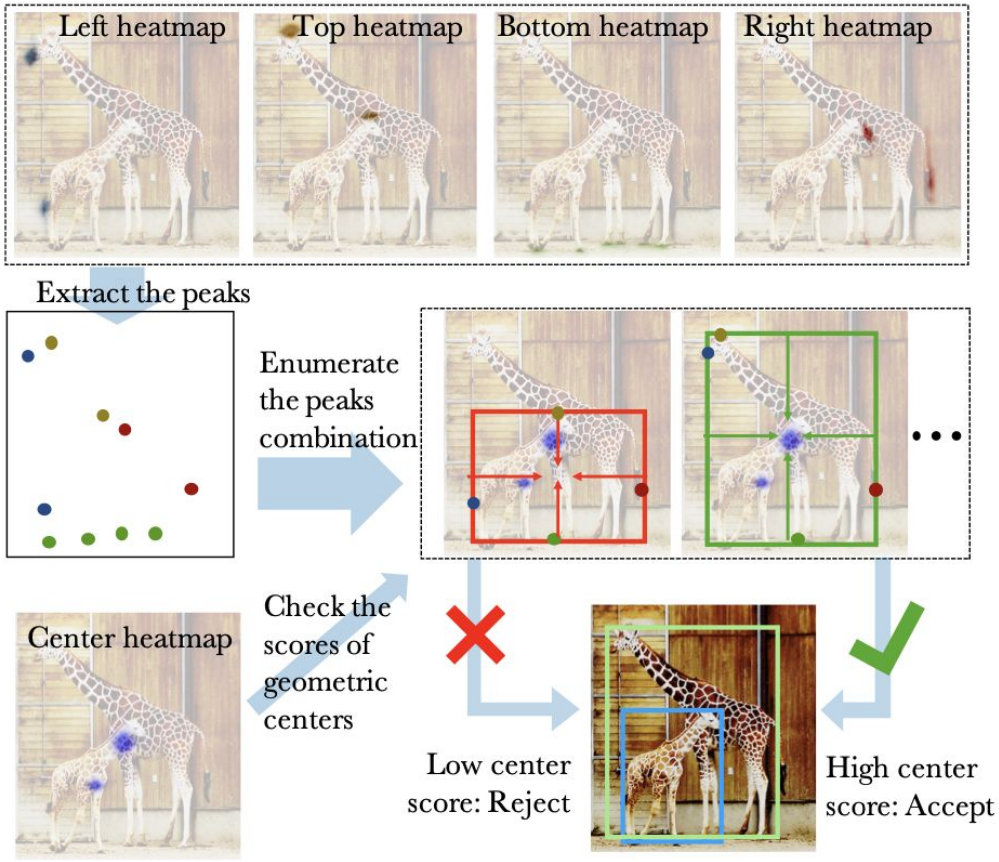
Box 1

Box 2

Box 3

Other Methods

- Some methods output a “heatmap” or series of heatmaps
- Probability each pixel is a keypoint of the bounding box and its class
- Examples
  - CenterNet
  - ExtremeNet



Bottom-up Object Detection by Grouping Extreme and Center Points

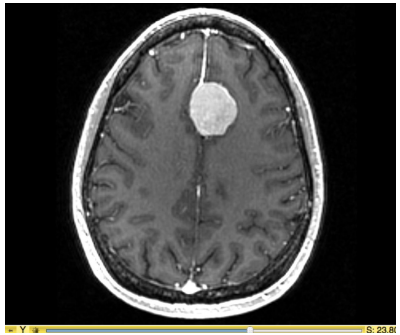
by X. Zhou, J. Zhuo, P. Krähenbühl

Segmentation

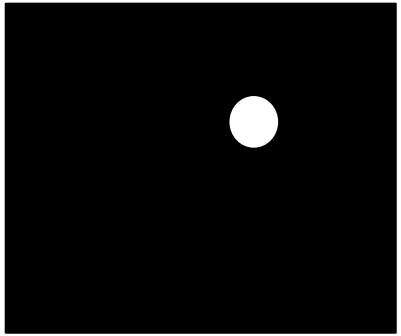
- Instance or Scene Segmentation
- More sophisticated labels
- Output/Labels are masks or series of masks (same size as image)

Segmentation

- Medical Imaging



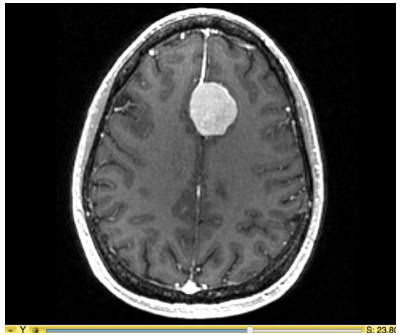
Input



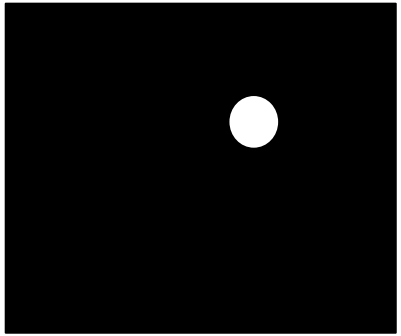
Label

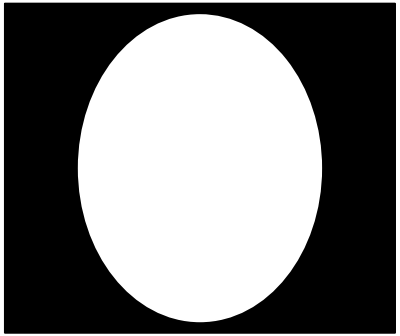
Segmentation

- Medical Imaging



Input

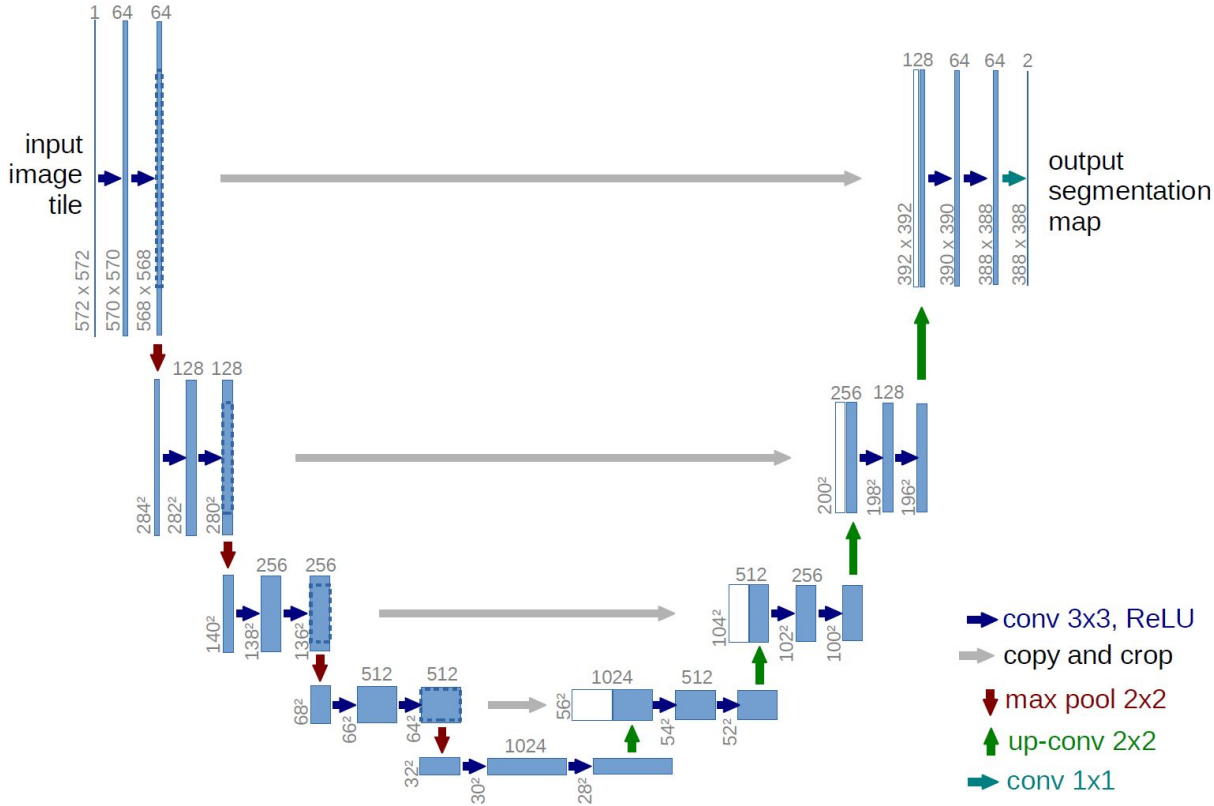




labels

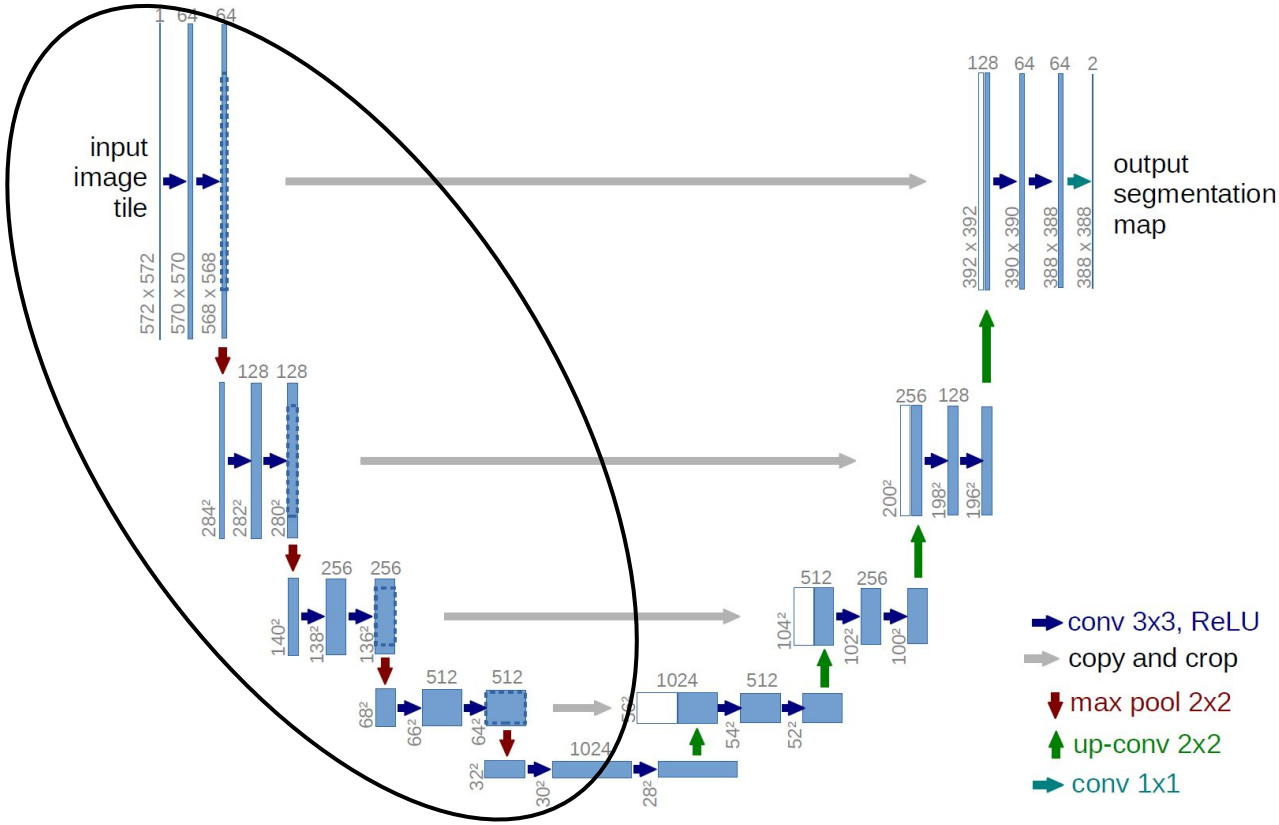
Segmentation

- UNet-like Architecture



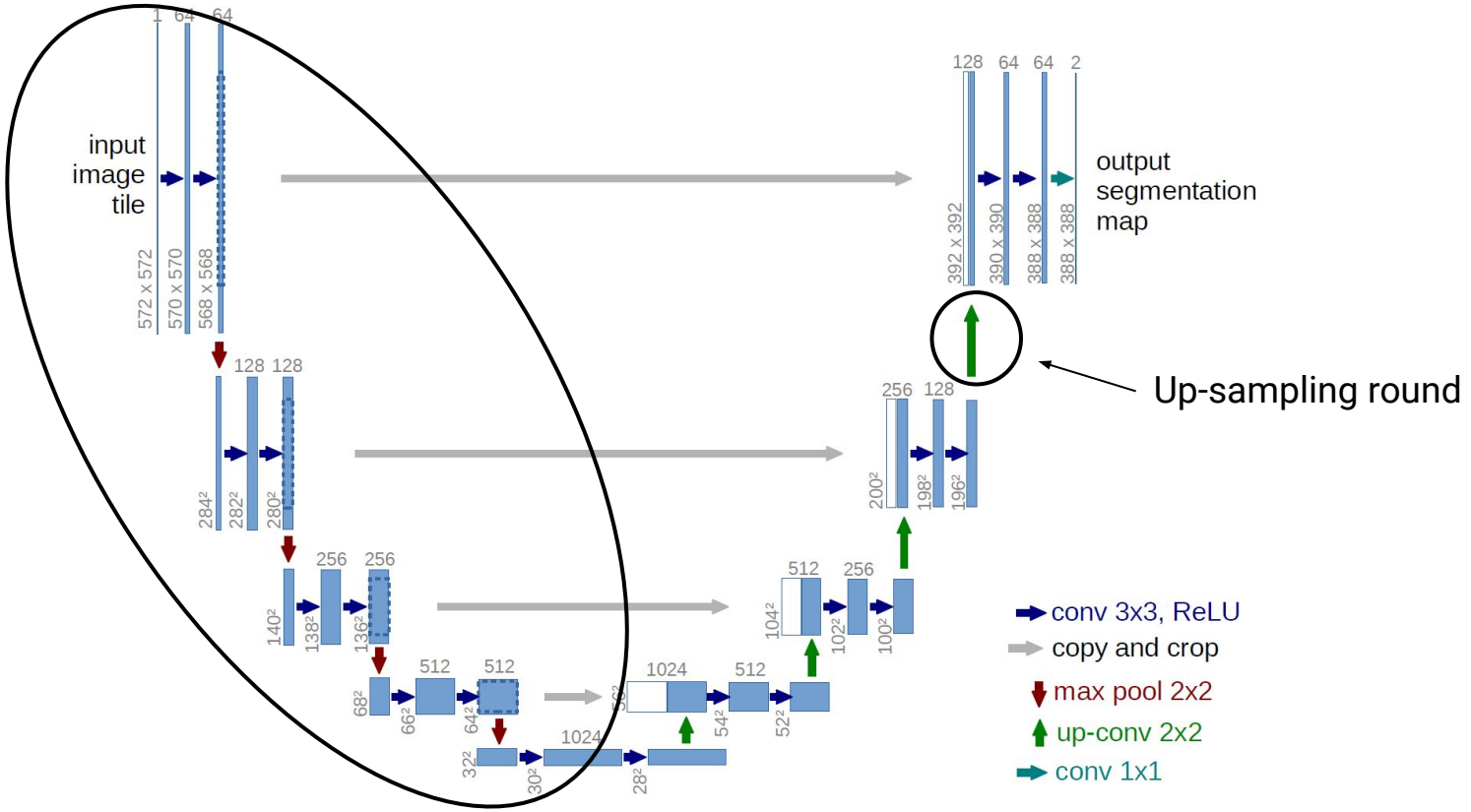
Segmentation

- UNet-like Architecture



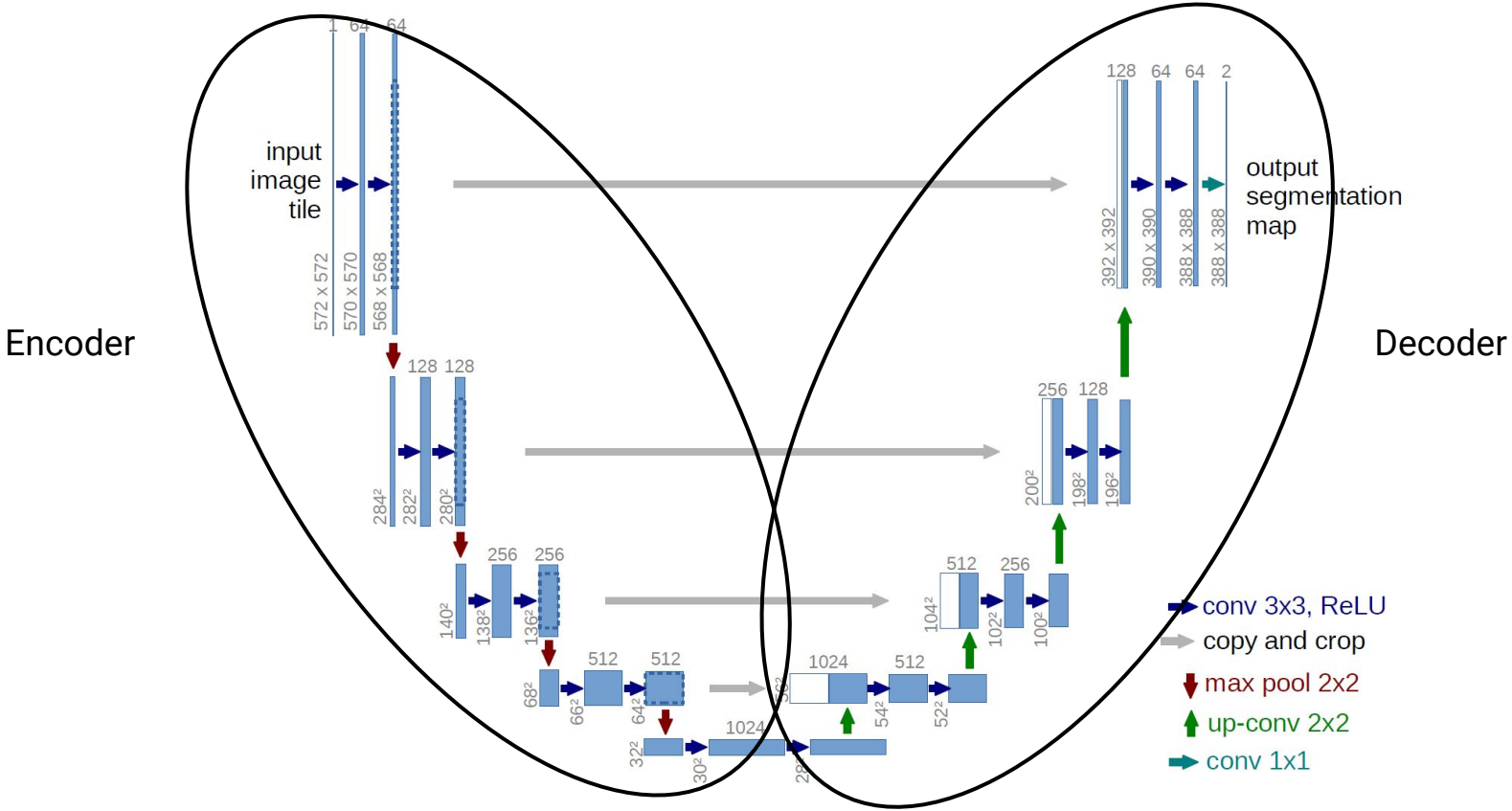
Segmentation

- UNet-like Architecture



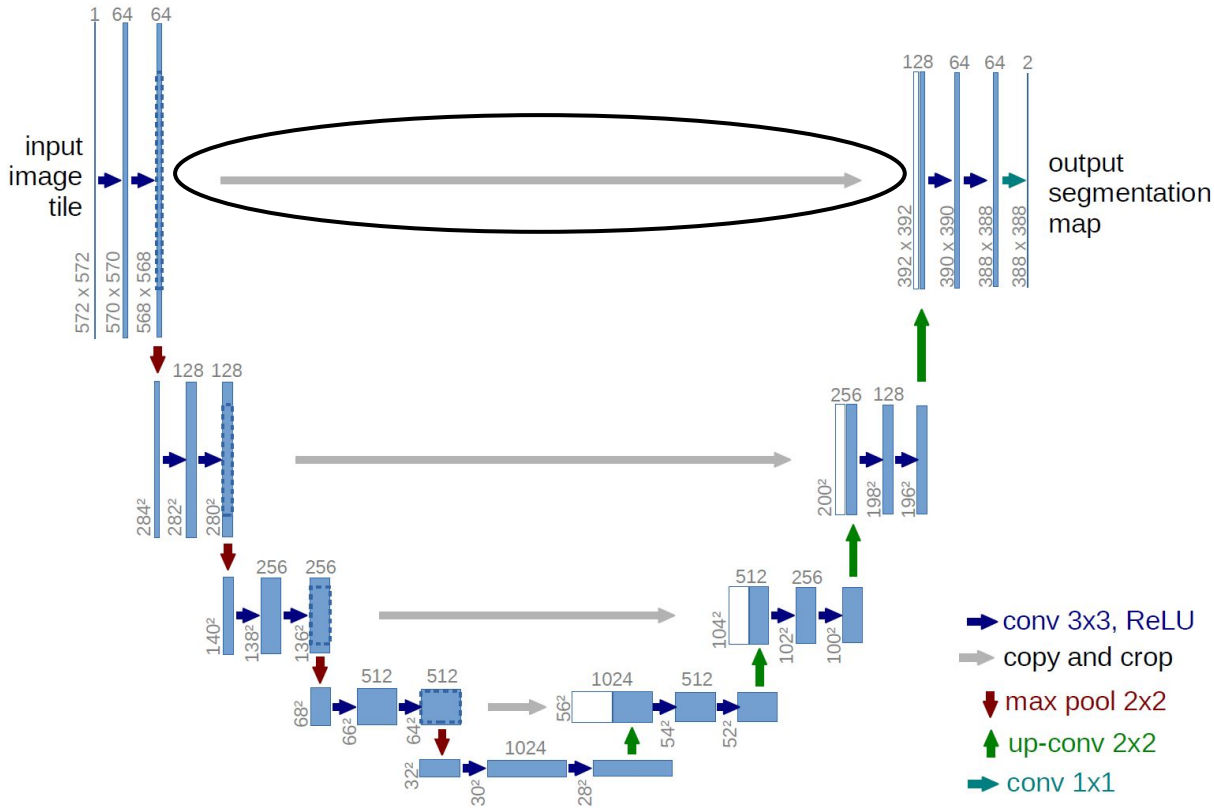
Segmentation

- UNet-like Architecture



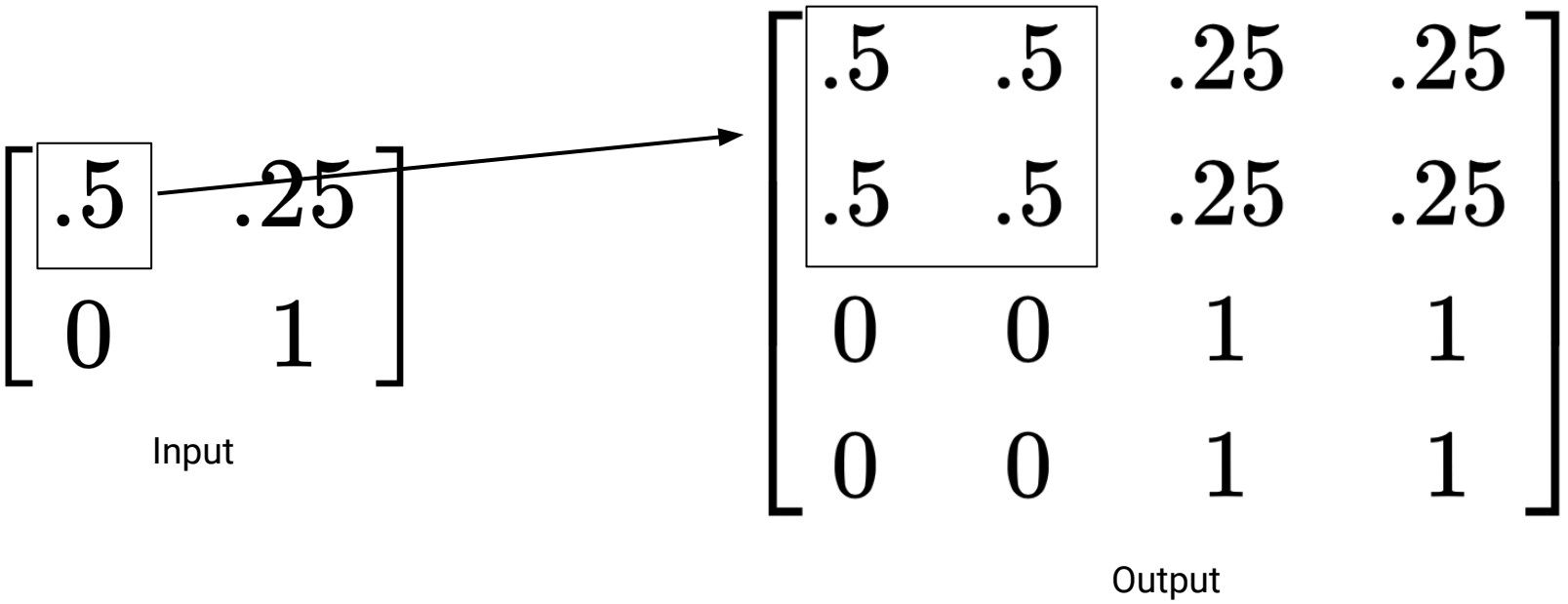
Segmentation

- UNet-like Architecture



Up-Sampling

- Increase resolution of the feature map
- Simplest: Un-pooling



Up-Sampling

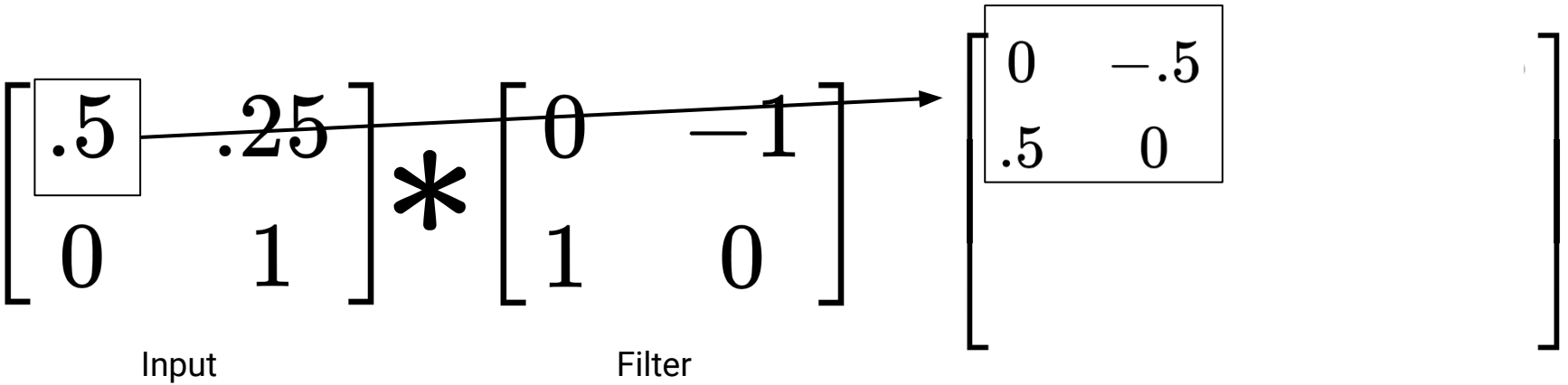
- Increase resolution of the feature map
- Simplest: Un-pooling
- Up-Convolution

$$\begin{bmatrix} .5 & .25 \\ 0 & 1 \end{bmatrix} * \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

Input Filter

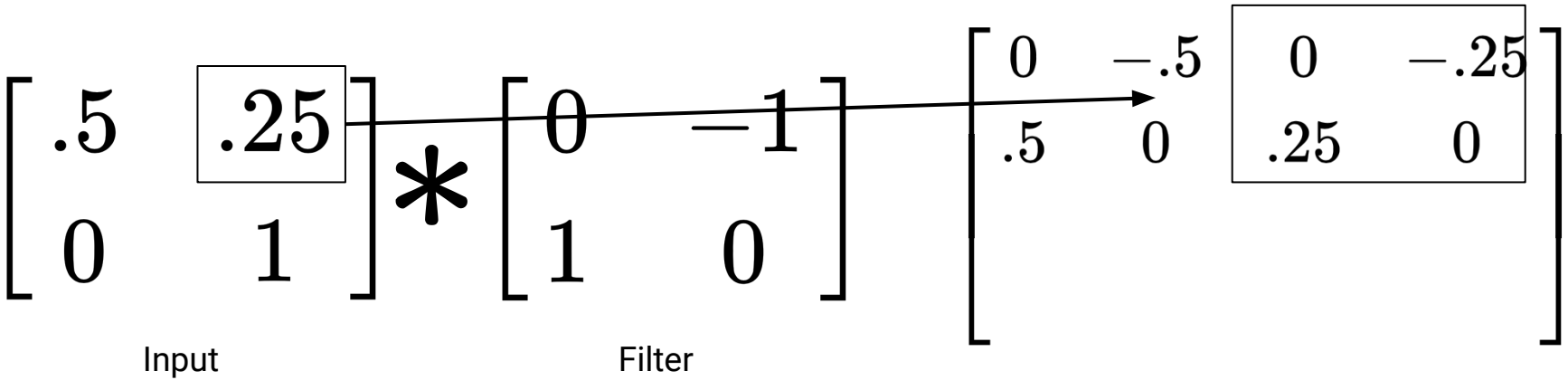
Up-Sampling

- Increase resolution of the feature map
- Simplest: Un-pooling
- Up-Convolution



Up-Sampling

- Increase resolution of the feature map
- Simplest: Un-pooling
- Up-Convolution



Up-Sampling

- Increase resolution of the feature map
- Simplest: Un-pooling
- Up-Convolution

$$\begin{bmatrix} .5 & .25 \\ 0 & 1 \end{bmatrix} * \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \longrightarrow \begin{bmatrix} 0 & -.5 & 0 & -.25 \\ .5 & 0 & .25 & 0 \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Input Filter

Up-Sampling

- Increase resolution of the feature map
- Simplest: Un-pooling
- Up-Convolution

$$\begin{bmatrix} .5 & .25 \\ 0 & 1 \end{bmatrix} * \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} \longrightarrow \begin{bmatrix} 0 & -.5 & 0 & -.25 \\ .5 & 0 & .25 & 0 \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Input Filter