SEGMENTATION AND OBJECT DETECTION

IN5400 — Machine Learning for Image Analysis

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Messages

- Weekly exercises will be uploaded soon
- PhD-students: Remainder about essay
  - Coordinate topics with Anne
  - Deadline for topic selection: 01.04.2019
  - Deadline for submission: 01.05.2019
- ML-servers has been down due to change of GPU. This should be resolved now.

Outline

- Introduction and motivation
- Performance evaluation metrics
- Object detection
- Image segmentation

INTRODUCTION AND MOTIVATION

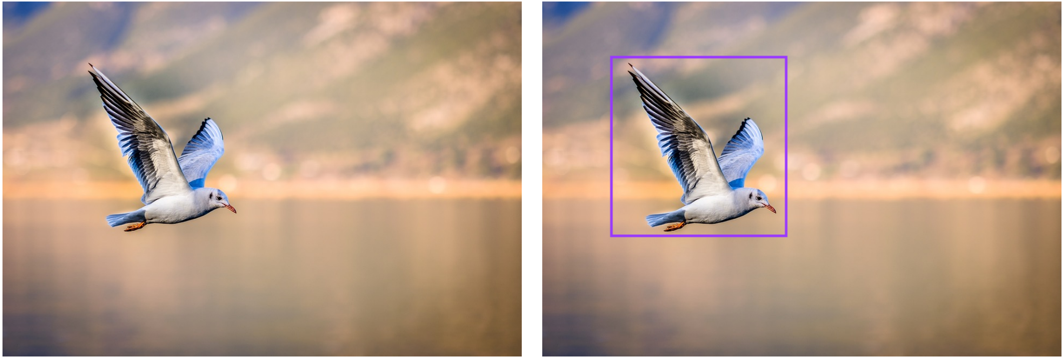


Figure 1: Seagull. Image source: https://www.pixabay.com

Object detection — Multiple instances

Figure 2: Rooster, cat, dog, donkey. Image source: https://www.pixabay.com

SEMANTIC SEGMENTATION

Figure 3: Left: Original. Right: Segmented. Image source: https://www.pexels.com

Figure 4: Left: Original. Right: Segmented. Image source: https://www.pexels.com

Learning outcome

- We will see a lot of different approaches
- Not expected to know every algorithm inside-out
- Most important that you are educated about the possibilities
- Curriculum (exam-relevant), will be decided well in time before the exam

PERFORMANCE EVALUATION METRICS

Evaluation metrics

- Sensitivity
- Specificity
- Precision
- Accuracy
- Jaccard index
- Mean average precision

Dichotomous partition

- Let B_R be the set of pixels enclosed by the *reference* bounding box
- Let B_P be the set of pixels enclosed by the *predicted* bounding box
- True positive: $TP = |B_R \cap B_P|$
- False negative: $FN = |B_R \setminus B_P|$ (*Type I error*)
- False positive: $FP = |B_P \setminus B_R|$ (*Type II error*)
- True negative: $TN = |(B_R \cup B_P)^c|$
- Where, for sets $A, B \subseteq C$
  - $A \cap B = \{x : x \in A, x \in B\}$ is the *intersection* of A and B
  - $A \setminus B = \{x : x \in A, x \notin B\}$ is the *set difference* between A and B
  - $(A \cup B)^c = \{x : x \notin A, x \notin B, x \in C\}$ is the *complement* of $(A \cup B)$

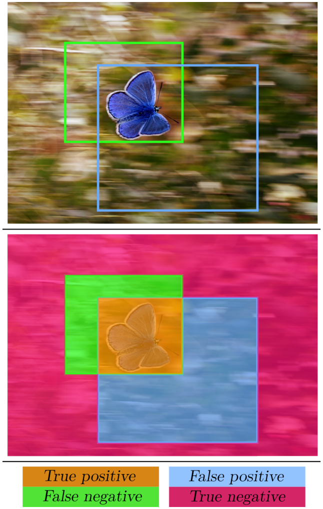


Figure 5: Top: reference (green), prediction (blue). Bottom: TP (orange), FN (green), FP (blue), TN (red). Image source: https://www.pixabay.com

Sensitivity

- Proportion of positive reference instances labelled as positive by the predicted method

$$tpr = \frac{TP}{TP + FN} = \frac{|B_R \cap B_P|}{|B_R|}$$

- Also known as
  - *true positive rate* (tpr)
  - *recall*
- Example on the right is pixel classification, but it also applies to object instances

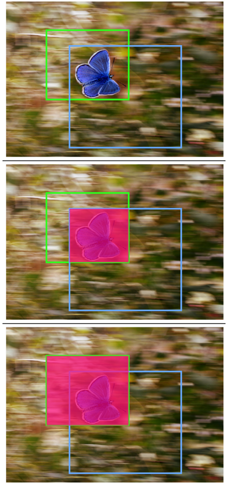


Figure 6: Top: reference (green), prediction (blue). Middle: True positive (red). Bottom: Reference positive (red). Image source: https://www.pixabay.com

- Proportion of negative reference instances labelled as negative by the predicted method

$$tnr = \frac{TN}{TN + FP} = \frac{|(B_R \cap B_P)^c|}{|B_R^c|}$$

- Also known as *true negative rate* (tnr)

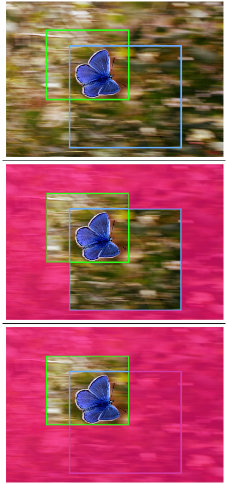


Figure 7: Top: reference (green), prediction (blue). Middle: True negative (red). Bottom: Reference negative (red). Image source: https://www.pixabay.com

Precision

- Proportion of predicted positive instances that are also labeled positive by the reference

$$ppv = \frac{TP}{TP + FP}$$
$$= \frac{|B_R \cap B_P|}{|B_P|}$$

- Also known as *positive predictive value* (ppv)
- Example on the right is pixel classification, but it also applies to object instances

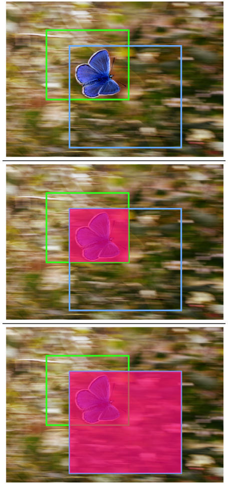


Figure 8: Top: reference (green), prediction (blue). Middle: True positive (red). Bottom: predicted positive (red). Image source: https://www.pixabay.com

Accuracy

The proportion of correctly classified instances, relative to all instances (N)

$$acc = \frac{TP + TN}{TP + TN + FP + FN} \\ = \frac{|B_R \cap B_P| + |(B_R \cup B_P)^c|}{|N|}$$

Unsuited when class prevalence is unbalanced

	First attempt	Second attempt
TP	5	0
FP	22	0
FN	10	15
TN	563	585
acc	$\frac{5+563}{600} \approx 0.946$	$\frac{0+585}{600} = 0.975$

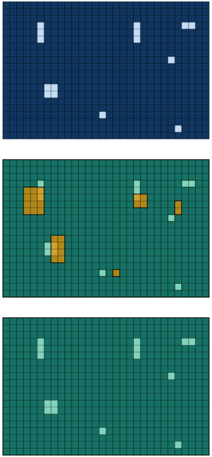


Figure 9: Dark blue: reference background. Light blue: reference foreground. Green: Predicted background. Orange: Predicted foreground. Top: reference. Middle: First attempt. Bottom: Second attempt

Balanced accuracy

Weighted accuracy where the weight of an instance is equal to the inverse prevalence of its true class. In the dichotomous case

$$bac = \frac{1}{2}(tpr + tnr)$$

Often more suited than the raw accuracy

	First attempt	Second attempt
TP	5	0
FP	22	0
FN	10	15
TN	563	585
bac	$\frac{1}{2}(\frac{5}{5+10} + \frac{563}{563+22}) \approx 0.648$	$\frac{1}{2}(0 + \frac{585}{585+15}) \approx 0.488$

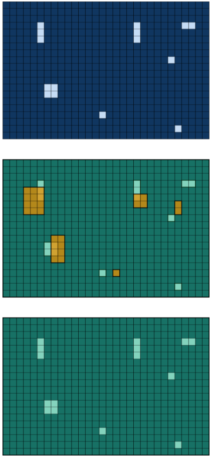


Figure 10: Dark blue: reference background. Light blue: reference foreground. Green: Predicted background. Orange: Predicted foreground. Top: reference. Middle: First attempt. Bottom: Second attempt

- The proportion of all instances classified as positive by the reference and/or the prediction method, that are classified as positive by both the reference and the prediction method

$$
\begin{aligned}
iou &= \frac{TP}{TP + FN + FP} \\
&= \frac{|B_R \cap B_P|}{|B_R \cup B_P|}
\end{aligned}
$$

- Also known as
  - Intersection over Union (IoU)
  - Tanimoto index
- Example on the right is pixel classification, but it also applies to object instances

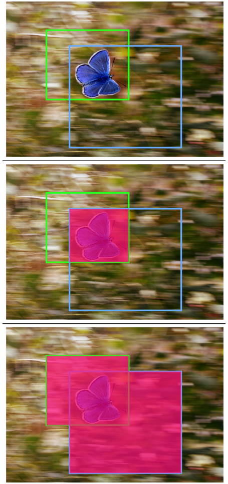
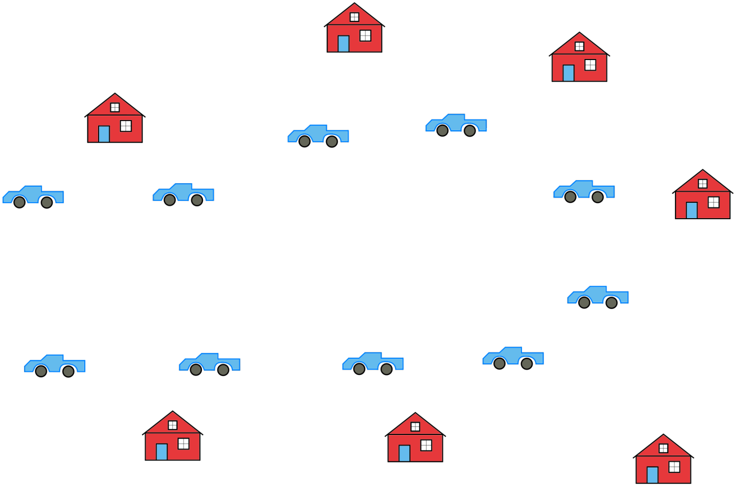
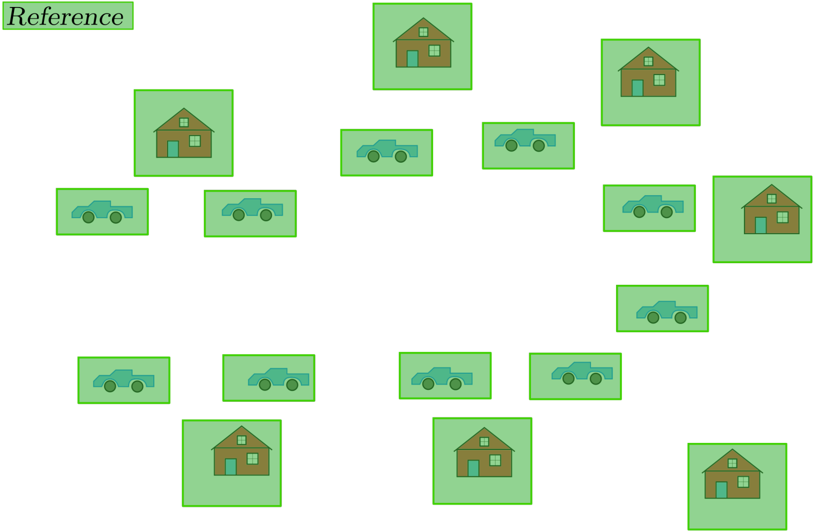


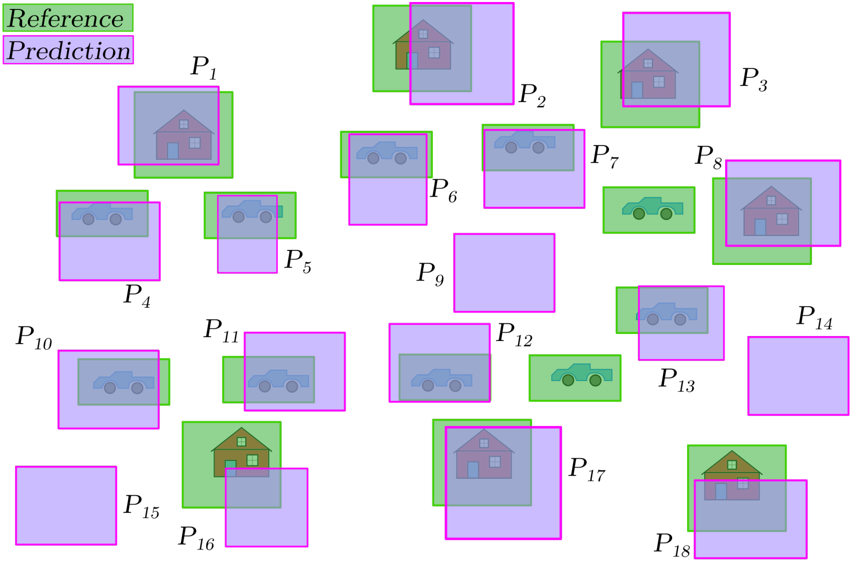
Figure 11: Top: reference (green), prediction (blue). Middle: Intersection (red). Bottom: Union (red). Image source: https://www.pixabay.com

- Mean average precision (mAP) is a common evaluation metric in object detection
- Each detected region (a bounding box) has a confidence score for each class
- Set all detected regions with an $IoU < T$ to be a false positive region, no matter the confidence score
- Common threshold values are $T = 0.5$
- For each class, compute the *Average Precision* (AP)
    - Sort detections by decreasing confidence
    - Compute precision and recall cumulatively as you “walk” from high confidence to low confidence
    - Average all computed precision values by some method (will be discussed more in detail later)
- Average the computed average precision scores over all classes

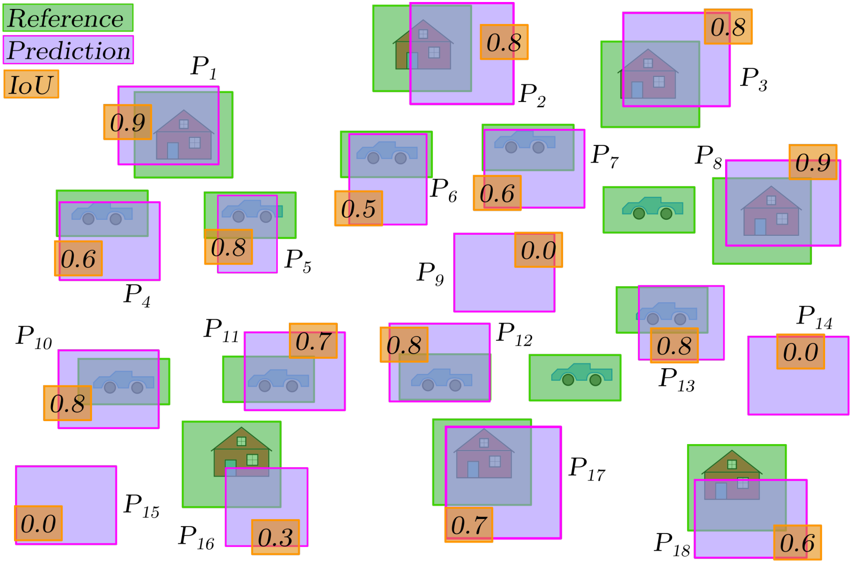
Mean average precision example — initial image




Reference


Reference
Prediction
P_1
P_2
P_3
P_4
P_5
P_6
P_7
P_8
P_9
P_{10}
P_{11}
P_{12}
P_{13}
P_{14}
P_{15}
P_{16}
P_{17}
P_{18}

Mean average precision example — Intersection over Union



Mean average precision example — class confidences

	P confidence		R confidence		$IoU \geq 0.5$
	Car	House	Car	House	
P_1	0.1	0.9	0	1	✓
P_2	0.3	0.7	0	1	✓
P_3	0.3	0.7	0	1	✓
P_4	0.6	0.4	1	0	✓
P_5	0.7	0.3	1	0	✓
P_6	0.5	0.5	1	0	✓
P_7	0.8	0.2	1	0	✓
—	—	—	1	0	✗
P_8	0.1	0.9	0	1	✓
P_9	0.4	0.6	—	—	✗
P_{10}	0.8	0.2	1	0	✓
P_{11}	0.6	0.4	1	0	✓
P_{12}	0.9	0.1	1	0	✓
—	—	—	1	0	✗
P_{13}	0.7	0.3	1	0	✓
P_{14}	0.6	0.4	—	—	✗
P_{15}	0.5	0.5	—	—	✗
P_{16}	0.7	0.3	0	1	✗
P_{17}	0.2	0.8	0	1	✓
P_{18}	0.4	0.6	0	1	✓

Mean average precision — Precision / recall

- We compute the precision and recall (sensitivity) for each class independently
- First, we sort the predictions by decreasing confidence
- Then, we compute the precision and recall for the different confidence levels
- The recall at a confidence level is the number of true positive predictions at this confidence level and above, divided by all reference positive instances
- The precision at a confidence level is the number of true positive predictions at this confidence level and above, divided by all predicted positive instances at this confidence level and above

	P car confidence	R car	$IoU \geq 0.5$	Recall	Precision
P_{12}	0.9	1	✓	$\frac{1}{10}$	$\frac{1}{1}$
P_{10}	0.8	1	✓	$\frac{2}{10}$	$\frac{2}{2}$
P_7	0.8	1	✓	$\frac{3}{10}$	$\frac{3}{3}$
P_{16}	0.7	0	✗	$\frac{3}{10}$	$\frac{3}{4}$
P_{13}	0.7	1	✓	$\frac{4}{10}$	$\frac{4}{5}$
P_5	0.7	1	✓	$\frac{5}{10}$	$\frac{5}{6}$
P_{14}	0.6	—	✗	$\frac{5}{10}$	$\frac{5}{7}$
P_{11}	0.6	1	✓	$\frac{6}{10}$	$\frac{6}{8}$
P_4	0.6	1	✓	$\frac{7}{10}$	$\frac{7}{9}$
P_{15}	0.5	—	✗	$\frac{7}{10}$	$\frac{7}{10}$
P_6	0.5	1	✓	$\frac{8}{10}$	$\frac{8}{11}$
P_{18}	0.4	0	✓	$\frac{8}{10}$	$\frac{8}{12}$
P_9	0.4	—	✗	$\frac{8}{10}$	$\frac{8}{13}$
P_3	0.3	0	✓	$\frac{8}{10}$	$\frac{8}{14}$
P_2	0.3	0	✓	$\frac{8}{10}$	$\frac{8}{15}$
P_{17}	0.2	0	✓	$\frac{8}{10}$	$\frac{8}{16}$
P_8	0.1	0	✓	$\frac{8}{10}$	$\frac{8}{17}$
P_1	0.1	0	✓	$\frac{8}{10}$	$\frac{8}{18}$

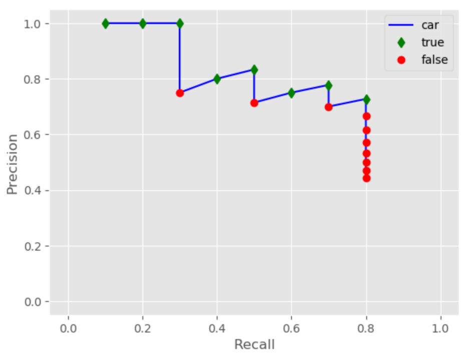


Figure 12: Left: Car predictions sorted by decreaseing confidence. Right: Corresponding precision-recall plot.

Mean average precision example — Precision / recall for house

	P house confidence	R house	$IoU \geq 0.5$	Recall	Precision
P_1	0.9	1	✓	$\frac{1}{7}$	$\frac{1}{1}$
P_8	0.9	1	✓	$\frac{2}{7}$	$\frac{2}{2}$
P_{17}	0.8	1	✓	$\frac{3}{7}$	$\frac{3}{3}$
P_2	0.7	1	✓	$\frac{4}{7}$	$\frac{4}{4}$
P_3	0.7	1	✓	$\frac{5}{7}$	$\frac{5}{5}$
P_9	0.6	—	✗	$\frac{5}{7}$	$\frac{5}{6}$
P_{18}	0.6	1	✓	$\frac{6}{7}$	$\frac{6}{7}$
P_6	0.5	0	✓	$\frac{6}{7}$	$\frac{6}{8}$
P_{15}	0.5	—	✗	$\frac{6}{7}$	$\frac{6}{9}$
P_4	0.4	0	✓	$\frac{6}{7}$	$\frac{6}{10}$
P_{11}	0.4	0	✓	$\frac{6}{7}$	$\frac{6}{11}$
P_{14}	0.4	—	✗	$\frac{6}{7}$	$\frac{6}{12}$
P_5	0.3	0	✓	$\frac{6}{7}$	$\frac{6}{13}$
P_{16}	0.3	1	✗	$\frac{6}{7}$	$\frac{6}{14}$
P_{13}	0.3	0	✓	$\frac{6}{7}$	$\frac{6}{15}$
P_7	0.2	0	✓	$\frac{6}{7}$	$\frac{6}{16}$
P_{10}	0.2	0	✓	$\frac{6}{7}$	$\frac{6}{17}$
P_{12}	0.1	0	✓	$\frac{6}{7}$	$\frac{6}{18}$

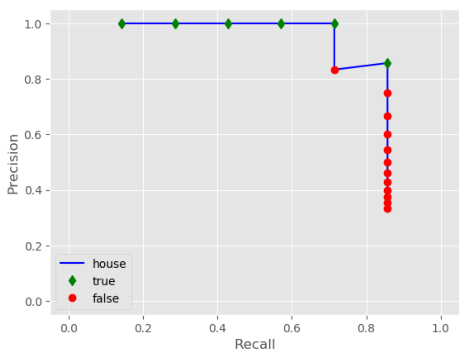
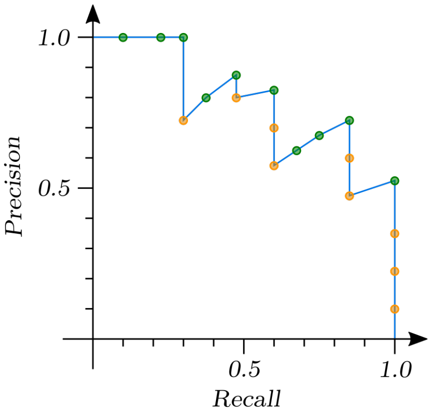


Figure 13: Left: House predictions sorted by decreaseing confidence. Right: Corresponding precision-recall plot.

Mean average precision — Averaging

- We get the mean average precision by averaging the *Average Precision* (AP) over all classes
- The average precision is usually related to the area under the curve (AUC) made by graphing the true positive rate versus the false positive rate.
- Some common definitions of AP:
    - The area under the precision / recall curve
    - The area under the *interpolated* precision / recall curve
- See e.g. [Everingham et al., 2015] for more info



- Interpolate the precision / recall curve

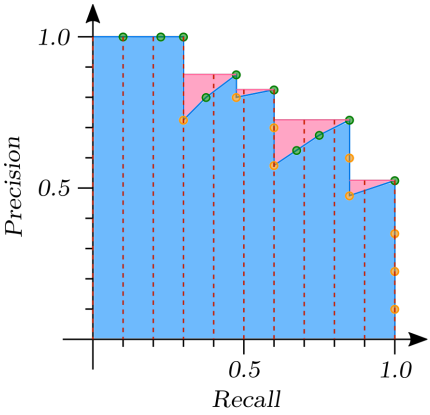
$$p_{\text{interp}}(r) = \max_{\hat{r}:\hat{r}\geq r} p(\hat{r})$$

where $p(\hat{r})$ is the precision at recall $\hat{r}$.

- Take the average of the interpolated precision at evenly sampled recall values

$$AP = \frac{1}{11} \sum_{r\in\{0.0,0.1,\dots,1.0\}} p_{\text{interp}}(r)$$

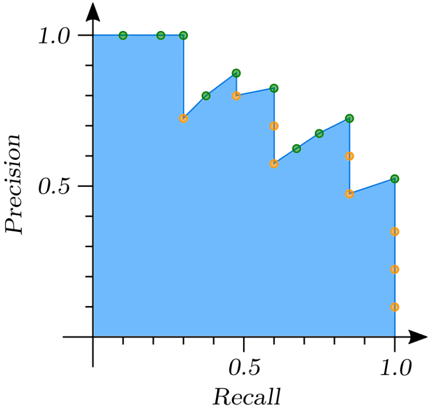
- Used in the PASCAL VOC object detection challenge up until 2009
- Intended to reduce the impact of “wiggles” in the precision / recall curve
- Downside: Can be too crude



- Compute the true area under the precision / recall curve
- Area of the blue region in the figure to the right
- E.g. used in the PASCAL VOC object detection competition from 2010 and onwards
- Common to use the trapezoidal rule to compute the area
- Can also use a simpler estimate (e.g. in `sklearn.metrics.average_precision_score`)

$$AP = \sum_{n=2}^{N} (r_n - r_{n-1}) p_n \tag{1}$$

for (precision, recall) entries $\{(p_1, r_1), (p_2, r_2), \ldots, (p_N, r_N)\}$



Mean average precision example — Averaging over classes

- Using eq. (1) to compute AP, we get
  - Car class: $AP_{\text{car}} \approx 0.5888$
  - House class: $AP_{\text{car}} \approx 0.6939$
- The mean of the two is then $mAP \approx 0.6414$

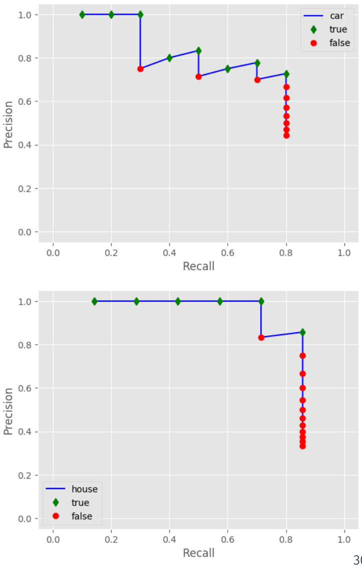


IMAGE CLASSIFICATION AND LOCALIZATION

- Classify an image with a single object
- Draw a bounding box around the object

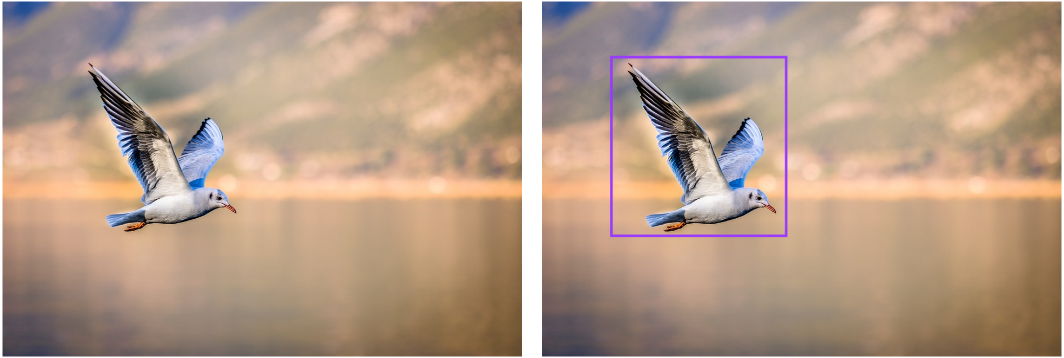


Figure 15: Seagull. Image source: https://www.pixabay.com

Label vector

- Add object/no object indicator c_0
- Interpret c_0 as
  $c_0 = \Pr(\text{there is an object in this box})$
- c_0 is often referred to as the *objectness*, but can also be thought of as a "catch-all" background class indicator
- Standard category probabilities from classification $(c_1, c_2, \ldots, c_{N_c})$
- Interpret c_i as $c_i = \Pr(\text{class}_i | c_0 = 1)$, $i = 1, \ldots, n$
- Add bounding box location specifiers
  - b_r: Center row coordinate
  - b_c: Center column coordinate
  - b_h: Box height
  - b_w: Box width

$$y = \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ \vdots \\ c_{N_c} \\ b_r \\ b_c \\ b_h \\ b_w \end{bmatrix}$$

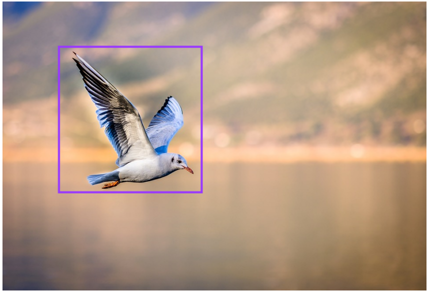
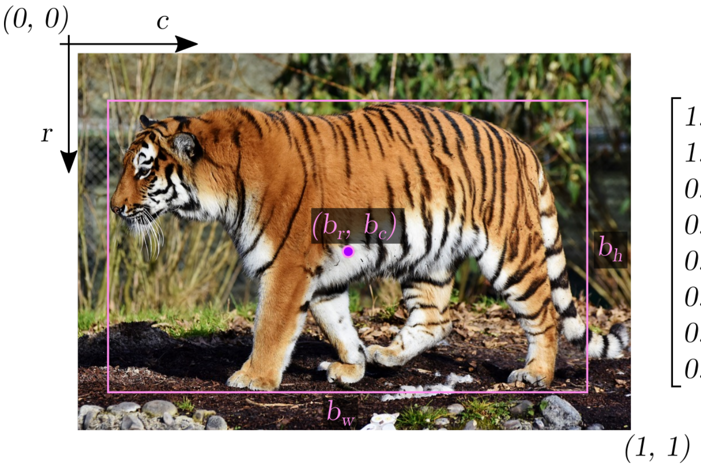


Figure 16: Seagull. Image source: `https://www.pixabay.com`

Example: Big cats

- c_1: Tiger
- c_2: Leopard
- c_3: Lion

$$y = \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \\ b_r \\ b_c \\ b_h \\ b_w \end{bmatrix}$$



$$\begin{bmatrix} 1.0 \\ 1.0 \\ 0.0 \\ 0.0 \\ 0.55 \\ 0.45 \\ 0.80 \\ 0.90 \end{bmatrix}$$

Figure 17: Tiger. Image source: `https://www.pixabay.com`

Example: Big cats

- c_1: Tiger
- c_2: Leopard
- c_3: Lion

$$y = \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \\ b_r \\ b_c \\ b_h \\ b_w \end{bmatrix}$$

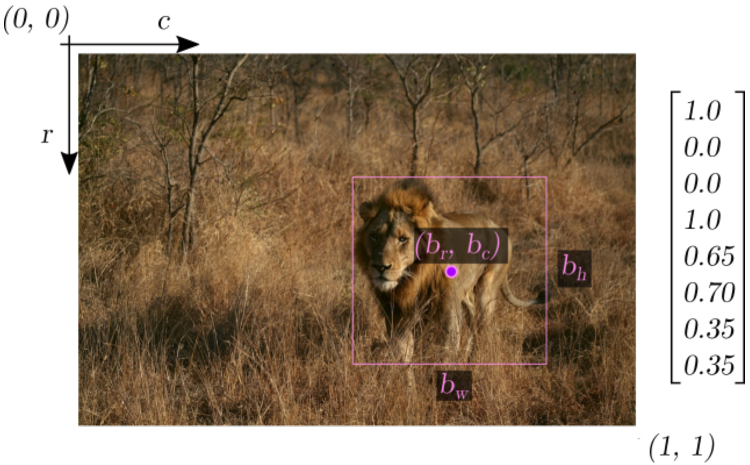


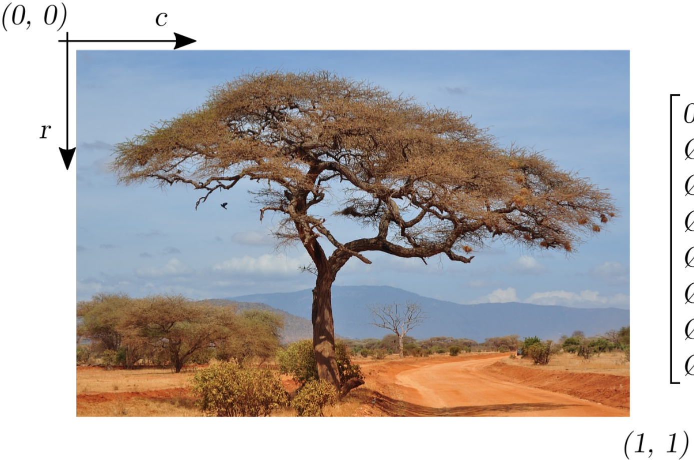
Figure 18: Lion. Image source: https://www.pixabay.com

Example: Big cats

- c_1: Tiger
- c_2: Leopard
- c_3: Lion

$$y = \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \\ b_r \\ b_c \\ b_h \\ b_w \end{bmatrix}$$

Note that $c_0 = 0$, so we do not care about the rest, symbolized by $\emptyset$.



$$\begin{bmatrix} 0.0 \\ \emptyset \\ \emptyset \\ \emptyset \\ \emptyset \\ \emptyset \\ \emptyset \\ \emptyset \end{bmatrix}$$

Figure 19: Savannah. Image source: `https://www.pixabay.com`

- We could use a conditioned L_2 loss for all elements

$$L(y, \hat{y}) = \begin{cases} \sum_{i=1}^{|y|} (y_i - \hat{y}_i)^2, & \text{if } y_1 = 1 \\ (y_1 - \hat{y}_1)^2, & \text{if } y_1 = 0 \end{cases}$$

- where
  - y is the reference (ground truth) label vector
  - $\hat{y}$ is the predicted label vector

Multi-task loss function

- Partition y into $y = [c, b]$, with
  - $c = [c_0, c_1, \ldots, c_{N_c}]$
  - $b = [b_r, b_c, b_h, b_w]$
- L_2 loss for object bounding box location b

$$L_b(b, \hat{b}) = \sum_{i \in \{x,y,h,w\}} (b_i - \hat{b}_i)^2$$

- Cross entropy loss for object categories c

$$L_c(c, \hat{c}) = -\sum_{i=1}^{n} \hat{c}_i \log c_i$$

- The total loss can be written as

$$L(y, \hat{y}) = L_c + [c_0 = 1] L_b$$

- Only compare bounding box if there is an object

OBJECT DETECTION

OD: Objectness detection

- Detect all objects in an image
- Does not care about category

SOD: Salient object detection

- Inspired by human visual attention system
- Focus on a few informative image regions

COD: Category-specific object detection

- Detect objects from predefined categories
- Detect and classify object
- This is the focus in this lecture

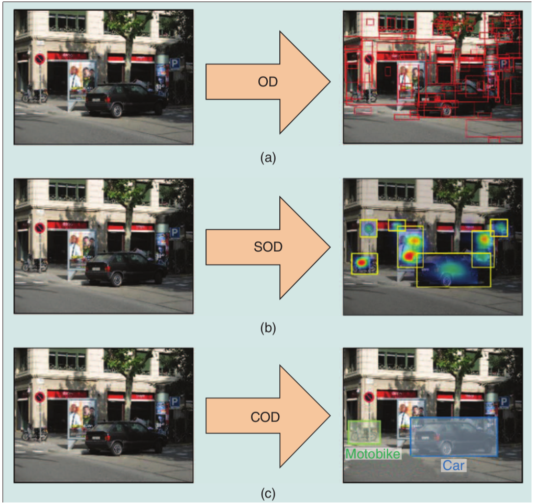


Figure 20: Source: [Han et al., 2018]

Bounding box regression for object detection

- Impractical to encode a bounding box $b = [b_x, b_y, b_h, b_w]$ for every instance and class
- Every image would need a custom number of outputs

Figure 21: Image source: https://www.pixabay.com

- Train a classification net on images tightly cropped around objects
- Slide a window (of multiple sizes) over the image you want to detect objects in
- Give each pixel a score based on the trained classification net on each window
- Ok for cheap classification methods
- Very slow for CNN classification

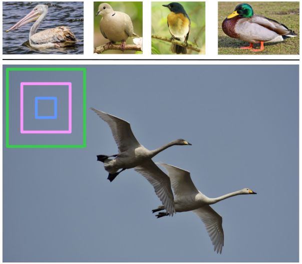


Figure 22: Image source: https://www.pixabay.com

- Convolutional implementation can fix the efficiency problem (see e.g. OverFeat method)
- Still not very precise bounding boxes

- A subclass of object detection methods
- Use a separate method to find candidate regions
- Filter out regions without an object, or redundant, overlapping regions with an object
- Classify these regions and refine region boundary

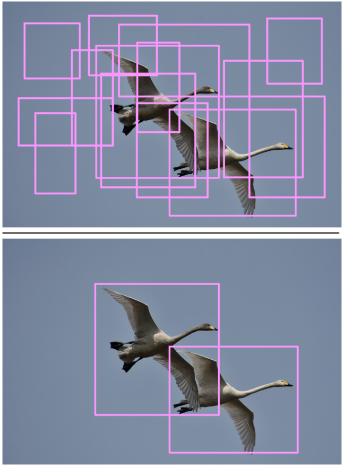


Figure 23: Image source: https://www.pixabay.com

- Originally proposed in [Girshick et al., 2014]
- Combines region proposals and convolutional neural networks
- Consists of three modules:
  - For each image, propose a set of category-independent regions
  - Extract a fixed-length feature vector from each region using a CNN
  - Classify the feature vectors with a class-specific linear SVM

Figure 24: Image source: https://www.pixabay.com

R-CNN

- Propose regions (~ 2000)
  - In the original publication they use *selective search* [Uijlings et al., 2013]

Figure 25: Image source: `https://www.pixabay.com`

R-CNN

- Propose regions (~ 2000)
    - In the original publication they use *selective search* [Uijlings et al., 2013]
- Warp the regions (regardless of shape) to a fixed size

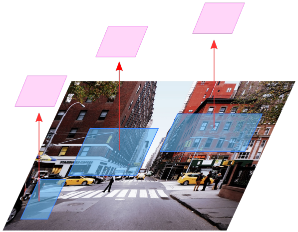


Figure 26: Image source: https://www.pixabay.com

R-CNN

- Propose regions (~ 2000)
  - In the original publication they use *selective search* [Uijlings et al., 2013]
- Warp the regions (regardless of shape) to a fixed size
- Feature extraction
  - Feed the warped regions into a pretrained CNN[1]
  - Output a 4096-dimensional feature vector

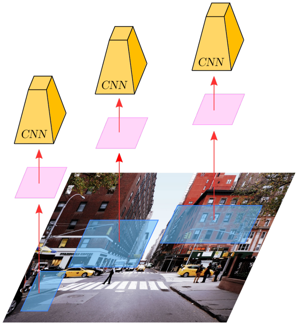


Figure 27: Image source: https://www.pixabay.com

[1] Pretrained on ImageNet, finetuned to Pascal VOC, see paper for details

R-CNN

- Propose regions (~ 2000)
  - In the original publication they use *selective search* [Uijlings et al., 2013]
- Warp the regions (regardless of shape) to a fixed size
- Feature extraction
  - Feed the warped regions into a pretrained CNN[1]
  - Output a 4096-dimensional feature vector
- A pretrained SVM scores each region
- Reject regions with non-maximum suppression
- Tune bounding boxes with a pretrained regression model

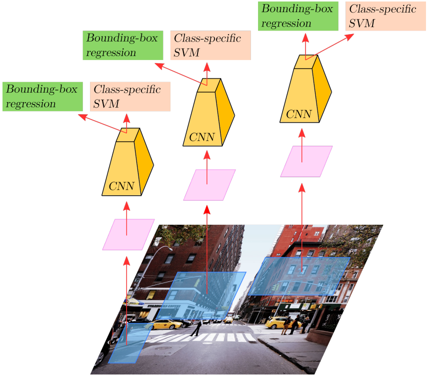


Figure 28: Image source: `https://www.pixabay.com`

[1]Pretrained on ImageNet, finetuned to Pascal VOC, see paper for details

Non-max suppression

- Important step in several object detection algorithms
- Remove all boxes with associate objectness c_0 smaller than some threshold, say $c_0 < 0.5$
- For each class $i = 1, 2, \ldots, n$
  - Create a list of unseen regions U_i that contains all the regions in the image
  - Create an empty list of regions to keep K_i
  - While there are regions left in U_i
    - Find the most probable region $R_{\max}$
    - $R_{\max}$ can be the region with highest value of $c_0 c_i$ (or some similar criterion)
    - Remove all regions that overlaps with $R_{\max}$ (e.g. with $iou > 0.5$), from U_i
    - Move $R_{\max}$ from U_i to K_i

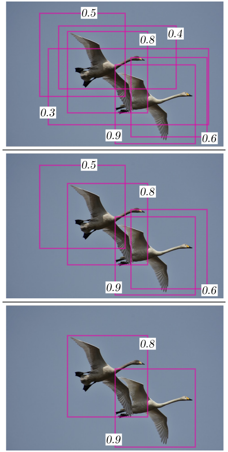


Figure 29: Top: Original. Middle: Too low c_0 removed. Bottom: $iou > 0.5$ removed. Image source: https://www.pixabay.com

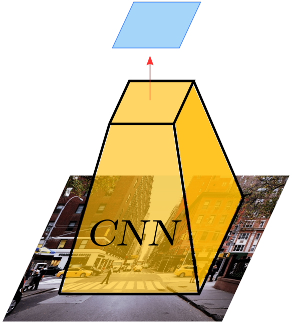
- Publication: [Girshick, 2015]
- The original R-CNN is slow and expencive:
  - Multi-stage pipeline
  - Classify each predicted region with a CNN
  - Intermediate feature maps are stored, takes a lot of space
- Fast R-CNN manages to save computation by first feeding the entire image into a CNN

Fast R-CNN

- Get region proposals (as in R-CNN)

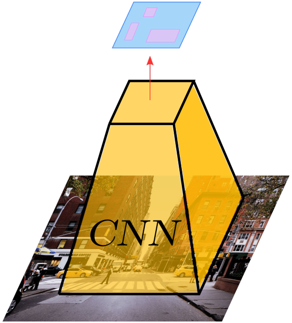
Fast R-CNN

- Get region proposals (as in R-CNN)
- Run a CNN on the entire image



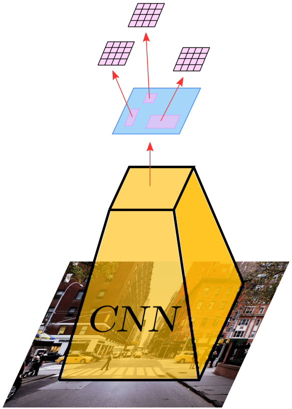
Fast R-CNN

- Get region proposals (as in R-CNN)
- Run a CNN on the entire image
- Project region proposals (ROIs) onto output CNN feature map



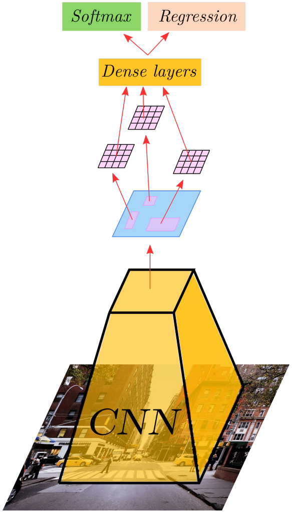
Fast R-CNN

- Get region proposals (as in R-CNN)
- Run a CNN on the entire image
- Project region proposals (ROIs) onto output CNN feature map
- ROI pooling layer



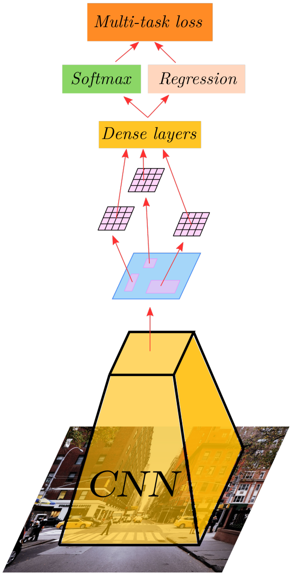
Fast R-CNN

- Get region proposals (as in R-CNN)
- Run a CNN on the entire image
- Project region proposals (ROIs) onto output CNN feature map
- ROI pooling layer
- Feed the fixed-sized pooled region to fully connected layers
- One softmax output for class prediction
- One regression output for the bounding box prediction



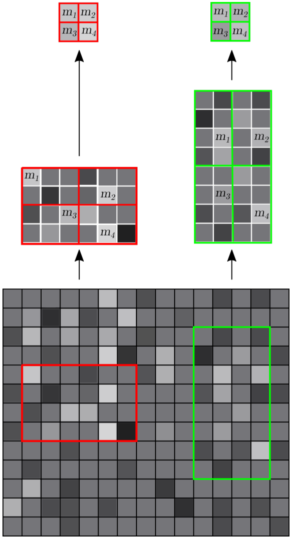
Fast R-CNN

- Get region proposals (as in R-CNN)
- Run a CNN on the entire image
- Project region proposals (ROIs) onto output CNN feature map
- ROI pooling layer
- Feed the fixed-sized pooled region to fully connected layers
- One softmax output for class prediction
- One regression output for the bounding box prediction
- Multi-task loss



Region of Interest (ROI) pooling

- Max-pooling on input of non-uniform size
- Often used when extracting features for regions
- One list of region descriptors: (b_r, b_c, b_h, b_w) for every region
- One, shared feature map
- ROI-pooling partitions the box region into a $S \times S$ grid
- Extracts the max in each grid cell
- This results in a $S \times S$ matrix, no matter the input shape

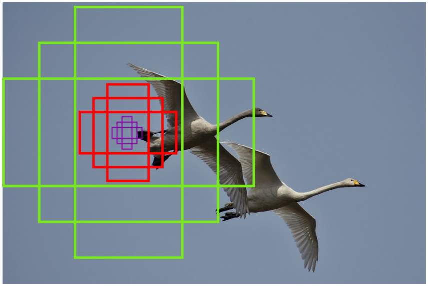


Faster R-CNN

- Publication: [Ren et al., 2016]
- With Fast R-CNN, the region proposal is the bottleneck
- Faster R-CNN introduces a Region Proposal Network (RPN)
- Consists of two modules:
    - A fully convolutional RPN
    - The Fast R-CNN detection network
- The RPN "tells Fast R-CNN where to look"
- The RPN and the detection network share layers

Anchor boxes

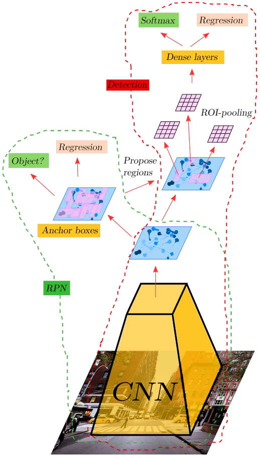
- A location have multiple boxes in different sizes and shapes
- Spread these anchor locations around an image
- Anchor shapes can be task-specific
- Training/labeling: Every anchor box is labeled as containing an object or not
- The overlap between the anchor box and reference box determines the label



Region proposal network (RPN)

- A small network that scans the anchor boxes
- Predicts if an anchor box contain an object
- Refines the anchor box region boundary
- The regions with highest confidence of containing an object is kept
- Non-maximum suppression handles overlap
- These proposal regions go on to the next stage

- The CNN extracts features
- Features are used by the RPN
- The RPN proposes regions to a detection network (like Fast-RCN)
- The detection network uses the same features as the RPN
- Training:
  - Alternate between RPN and detection network training
  - Or, train them jointly



YOLO

- Publication: [Redmon et al., 2016]
- You Only Look Once
- Very fast (about $100\times$ faster than Fast R-CNN)
- Not as accurate as the most accurate methods

- Partition image into $S \times S$ grid
- A grid cell is responsible for detecting an object with center point in that grid cell
- Each grid cell predicts B bounding boxes, and a confidence score for each box
- Confidence: $c_0 \cdot iou($reference box, predicted box$)$ (zero if there is no reference box in that cell)

Figure 30: Image source: https://www.pixabay.com

YOLO — PREDICTION VECTOR

- The target vector has then the shape $(S, S, 5 \cdot B + N_c)$
- For each cell:
  - One set of parameters $(c_0, b_r, b_c, b_h, b_w)$, for every bounding box
  - A set of class parameters $(c_1, c_2, \ldots, n_c)$
- Can train against the target vector with a conventional CNN
- Limitation: One cell can predict B objects of the *same* class
- Extension: Use multiple anchor boxes, each with an associated class

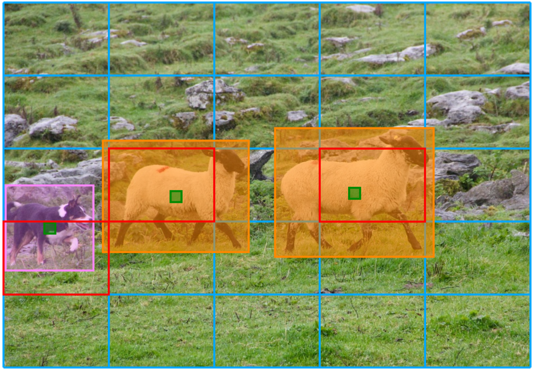


Figure 31: Image source: `https://www.pixabay.com`

Object detection — summary

- A challenging problem
- Impressive progress the last few years
- More recent methods
  - R-FCN
  - SSD

SEMANTIC SEGMENTATION

- Classify every pixel in an image
- Differentiate between classes
- Do not differentiate between multiple instances of the same class

Figure 32: Left: Original. Right: Segmented. Image source: https://www.pexels.com

Sliding window classification

- Select a small window
- Classify this image
- Assign the center pixel of this window the most probable class
- Repeat for all pixels in the image
- Very inefficient
- Misses larger image context

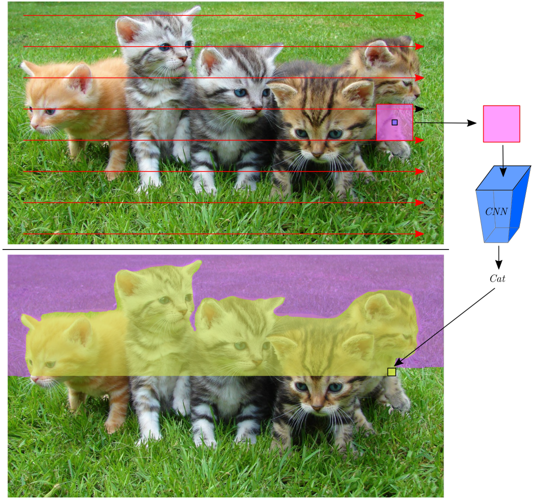


Figure 33: Top: Original. Bottom: Partially segmented. Image source: https://www.pexels.com

CNN MULTIPLE PIXEL CLASSIFICATION

- Segment image all at once
- Input image shape: $H \times W \times C$
- Output layer shape: $H \times W \times N_c$, where N_c: number of classes
- Pixel-wise cross entropy loss
    - Softmax over channels at a pixel location
    - Repeat, and average over all pixels
- Very expensive on computation and memory

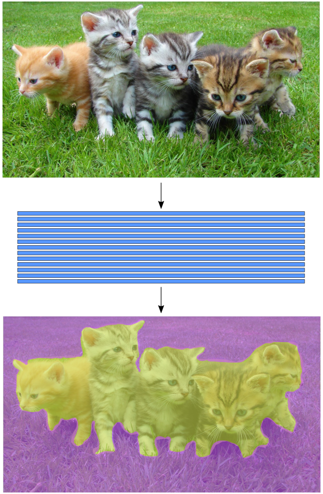


Figure 34: Top: Original. Bottom: Segmented. Image source: https://www.pexels.com

Downsampling and upsampling

- Segment image all at once
- Input image shape: $H \times W \times C$
- Output layer shape: $H \times W \times N_c$, where N_c: number of classes
- Spatial downsampling followed by upsampling (encoding, decoding)
- Pixel-wise cross entropy loss
    - Softmax over channels at a pixel location
    - Repeat, and average over all pixels
- Different upsampling techniques

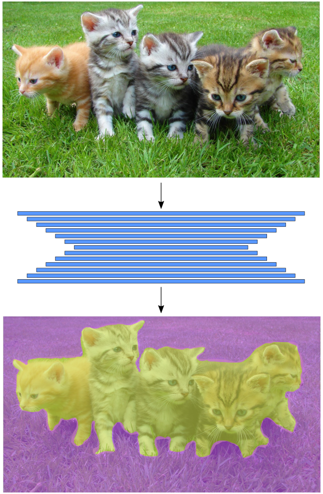
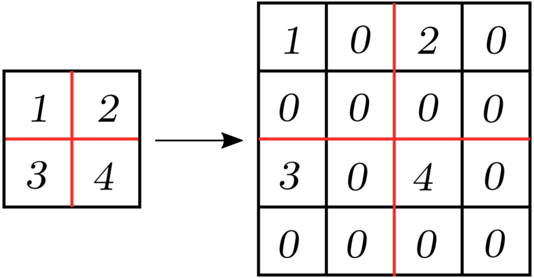
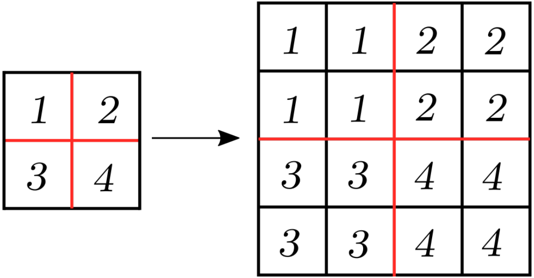


Figure 35: Top: Original. Bottom: Segmented. Image source: https://www.pexels.com

Fill with zeros

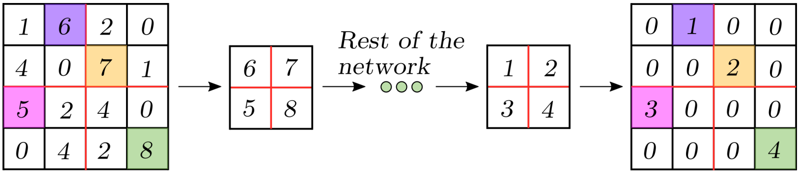


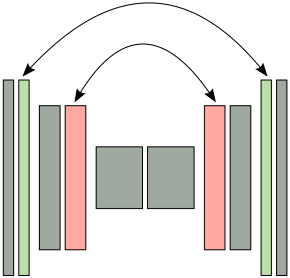
Fill with same

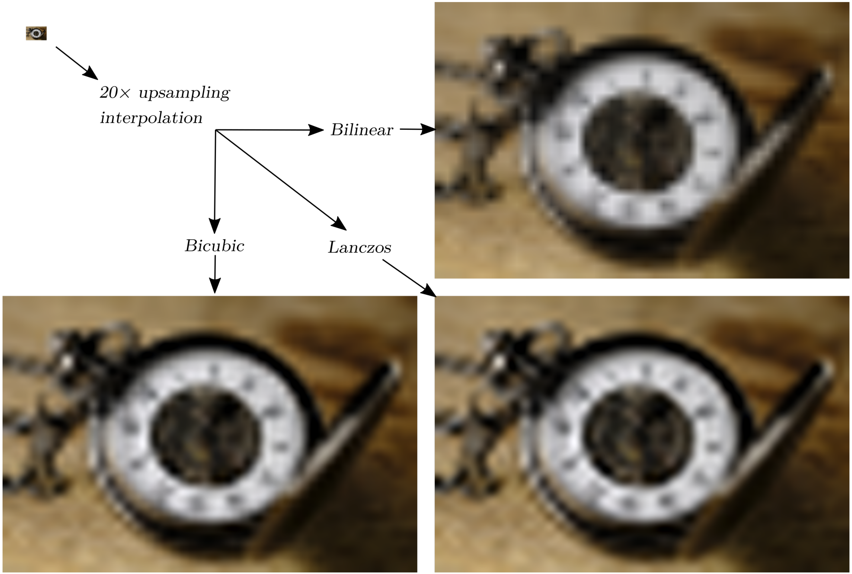


Max unpooling

Remember max locations from max pool downsampling. Reverse this on the “opposite” layer



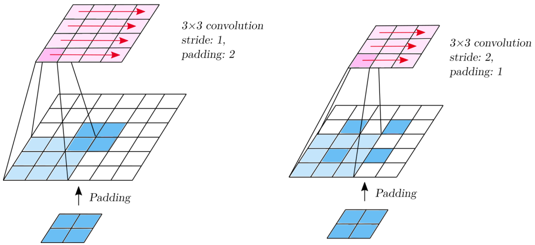



20× upsampling
interpolation
Bilinear
Bicubic
Lanczos

Trainable upsampling

- Upsampling convolution
- In depth convolution tutorial here
- Can learn kernel parameters as with regular convolution

- Can view convolution as a matrix-matrix multiplication
- Transposed convolution gets its name by transposing this operation
- Also called
  - fractionally strided convolution
  - deconvolution (this is a misnomer)



FCN

- Publication: [Long et al., 2014]
- Early adaptor of segmentation with end-to-end trained CNNs
- Uses learnable transposed convolution in upsampling

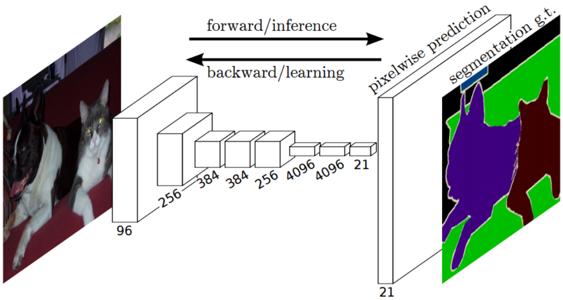


Figure 36: FCN architecture. Image source: [Long et al., 2014]

- Aggressive upsampling leads to course segmentation result
- Combine upsampling from different parts in the layer
- Each with different upscaling

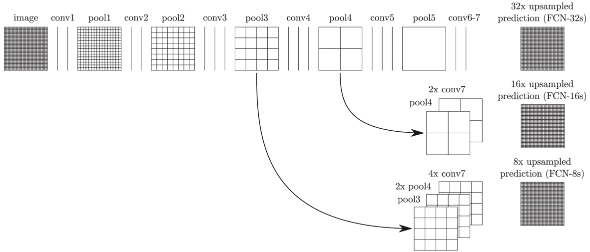
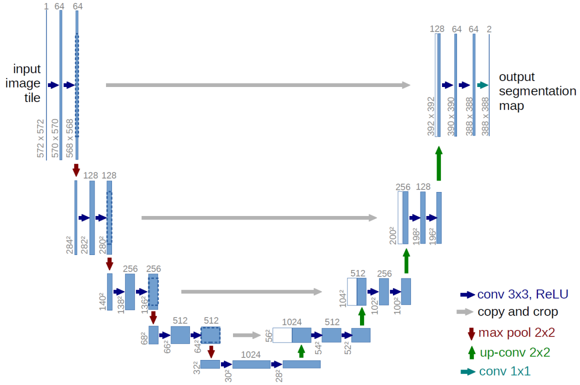


Figure 37: FCN architecture with different upsampling strategies. Image source: [Long et al., 2014]

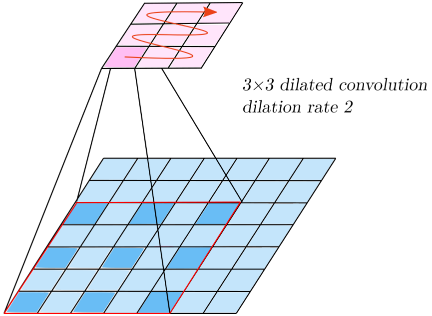
U-NET

- Publication: [Ronneberger et al., 2015]
- Contraction: Ordinary convolution and pooling layers
- Expansion: Concatenation of
  - Cropped feature maps from contraction phase (gray arrows)
  - Transposed convolution from previous layer



Dilated convolution

- Insert spacing between convolution kernel cells (dilation rate)
- Also called
  - convolution with holes
  - A-trous convolution (a trous is french for with holes)
- Increase field of view, without needing larger convolution kernel, or multiple chained convolutions



- Publication: [Chen et al., 2016]
- VGG16 or ResNet as base networks
- Employs dilated convolution in upsampling
- v3 currently holds top position on the PASCAL VOC segmentation leaderboard

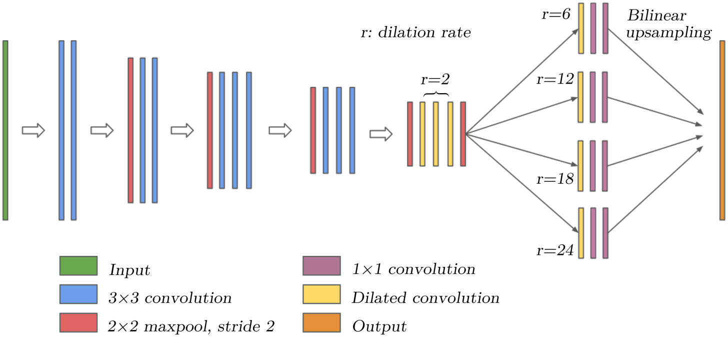
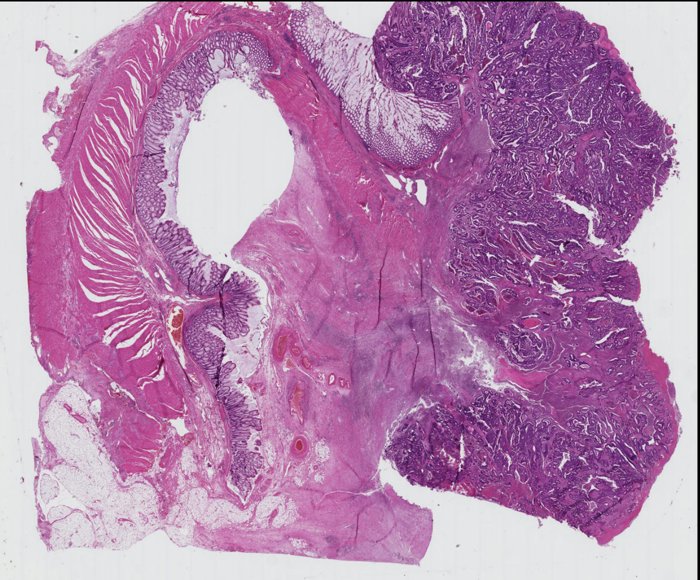
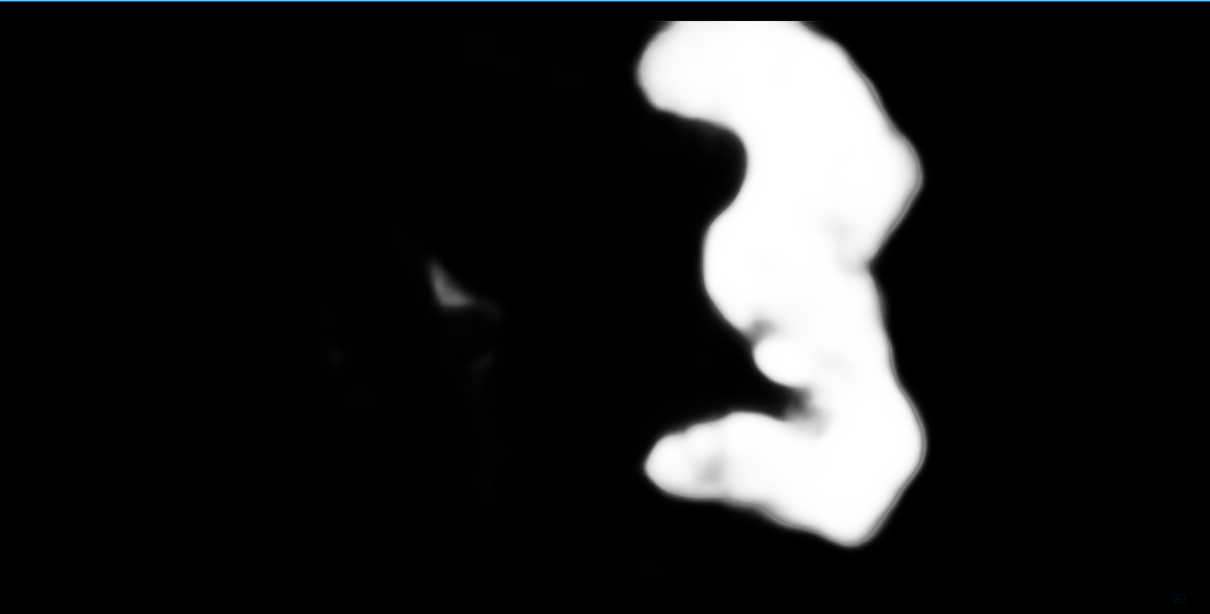


Figure 38: VGG16 version with atrous spatial pyramid pooling (ASPP)

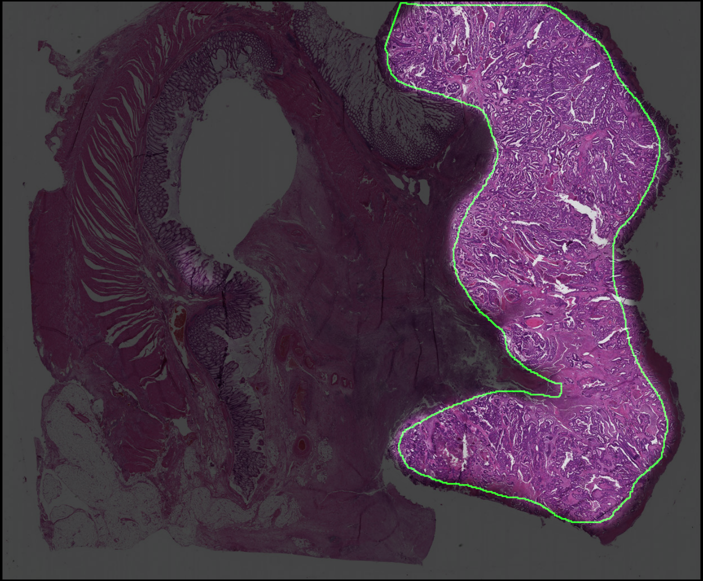
Example: Tumor segmentation — input



Example: Tumor segmentation — prediction



Example: Tumor segmentation — prediction and reference



Segmentation — argmax

- Normally, convnet-segmentation methods outputs a probability map for each class
- Need to assign *one* label to each pixel (segment the image)
- Could use arg-max over classes for each pixel
- Pros:
  - Simple
  - Fast
- Cons:
  - Ugly
  - Inaccurate
- Very common to use *Dense Conditional Random Fields*

- Fast implementation: Efficient Inference in Fully Connected CRFs with Gaussian Edge Potentials
- Use information from the output probability map
- Also takes into account features from the input image, such as color in neighbouring pixels

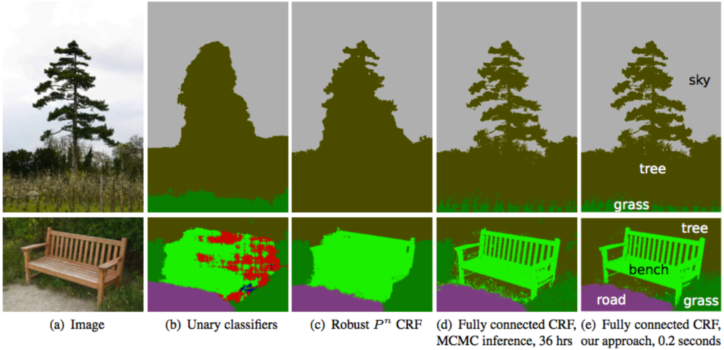
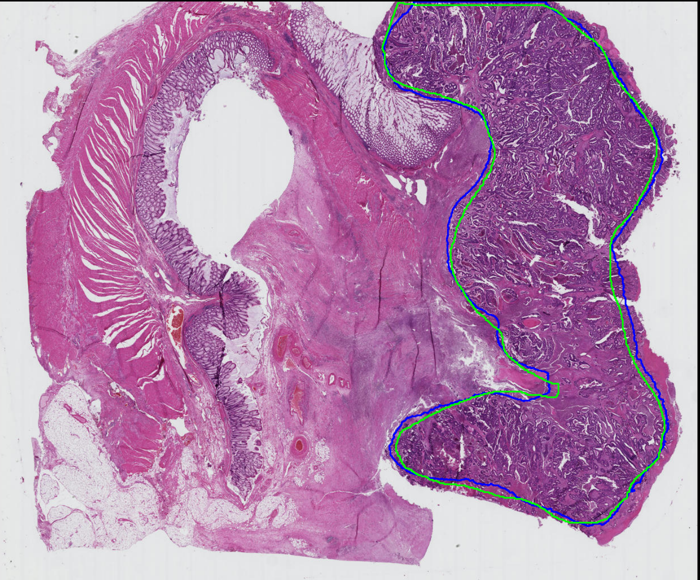


Figure 39: Source: [Krähenbühl and Koltun, 2011]

Example: Tumor segmentation — segmentation and reference



INSTANCE SEGMENTATION

- Image segmentation with discrimination between instances of the same class
- Combines object detection and semantic segmentation
- More difficult than standard semantic segmentation

Figure 40: Left: Original. Right: Segmented. Image source: https://www.pexels.com

Mask R-CNN

- Publication: [He and Girshick, 2017]
- Extends Faster R-CNN
- Faster R-CNN outputs a class label and a bounding box offset for each detected region
- Mask R-CNN in addition outputs one object mask for each class
- The object mask is produced by a small segmentation network (e.g. FCN)
- The segmentation is performed independently in each class
- Substitutes the ROI pooling with a location-preserving ROI alignment layer

Figure 41: Mask R-CNN results [He and Girshick, 2017]

Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *arXiv preprint*, pages 1–10, 2016.

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Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. *arXiv preprint*, pages 1–8, 2015.

J. Uijlings, K. van de Sande, T. Gevers, and A. Smeulders. Selective search for object recognition. *IJCV*, 2013.

QUESTIONS?