11 - Object detection

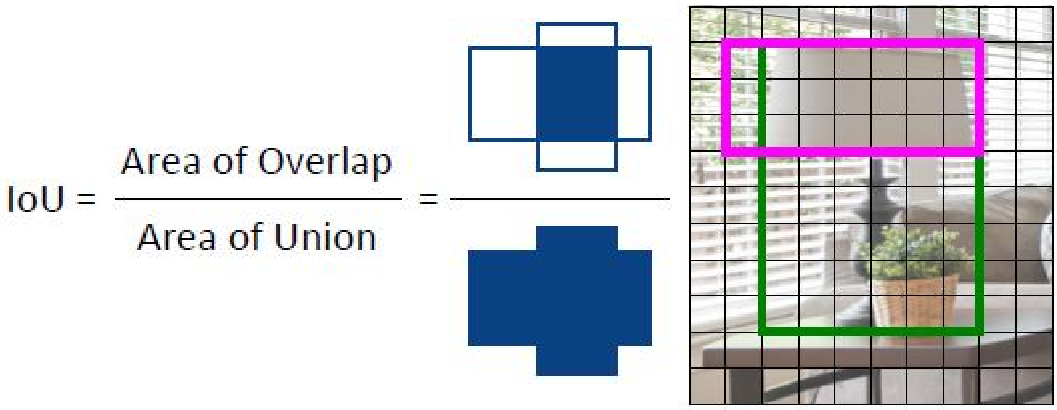
Object detection basics

Classification vs. Detection

- Object detection = locate objects in an image
    - Classification: “Is this a (class label)?”
    - Detection: “Where is the (class label)?”
- Object detection is usually modelled as a classification task performed within patches of an image
    - Detection: For every patch, “Is this a (class label)?”

Sliding window approach L11.1 P8

- Free parameters
    - Stride
    - Scale (size of window)
    - Shape (aspect ratio)
- Generally object dimensions are unknown, so a range of scales/shapes will be required
- Another parameter: Threshold for detection
    - Windows over the threshold will be considered “target”
    - Note that this makes evaluation tricky L11.2 P12
- Window evaluation: IoU L11.2 P13
    - Common method to evaluate a window result is **Intersection over Union** (IoU) between true bounding box and detection window



Summary

- Object detection is generally modelled as image classification within small regions of an image
- Windows over some threshold = “detections,” can be evaluated using IoU with ground truth
- Problems:
    - Very large number of possible windows (slow, increases probability of false detections)

- Overall evaluation of images with multiple targets can be complicated (multiple targets, multiple detection windows, different IoUs)

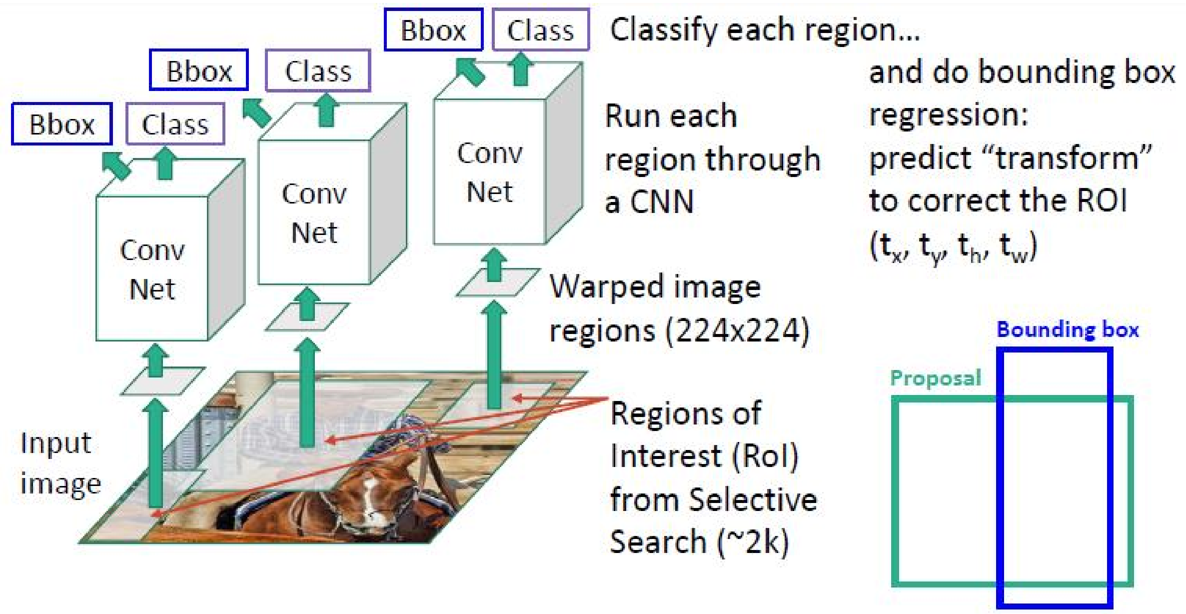
R-CNN

Sliding window classification

- Very large number of windows per image (C scales x S shapes x N locations)
- Even in a neural network, classifying all possible boxes may be slow (may also increase false alarms)
- Solution: Focus on boxes most likely to be objects

R-CNN

- R CNN = Region-based convolutional neural network
- Given an image, identify a small number of windows for object detection ("region proposals" or "regions of interest (ROIs)")
- Generating region proposals
    - R-CNN uses **Selective Search** to generate ROIs
    - Selective Search algorithm:
        - Oversegment image into superpixels
        - Iteratively combine adjacent superpixels based on similarity in colour + texture, size, and compactness



Bounding box computation

- Original region proposal = (p_x, p_y, p_h, p_w)
- Transform = (t_x, t_y, t_h, t_w)
- Goal: compute bounding box = (b_x, b_y, b_h, b_w)
- Step 1. Translate

$$b_x = p_x + p_w t_x \qquad b_y = p_y + p_h t_y$$

- Step 2. Scale

$$b_w = p_w \exp(t_w) \qquad b_h = p_h \exp(t_h)$$

R-CNN training

- CNN pretrained on ImageNet
- Last layer (1x1000) is replaced with a new classification layer of size 1x(N+1)
  - N+1 = N object classes + “background” class
  - CNN is retrained on (N+1)-way detection, using regions with IoU >=0.5 as ground truth "objects"
  - Sample regions so 75% of training set is “background”
- CNN features are used as input to:
  - Label classification model (1 vs all linear SVM)
  - Bounding box model (class specific linear regression)

R-CNN testing

- Input test image
- Compute region proposals (Selective Search)
- Each region: run through CNN to predict class labels and bounding box transforms
- “Detections” = regions with highest class confidence scores
  - Based on a threshold, or top k?
  - Overall, or per-category?

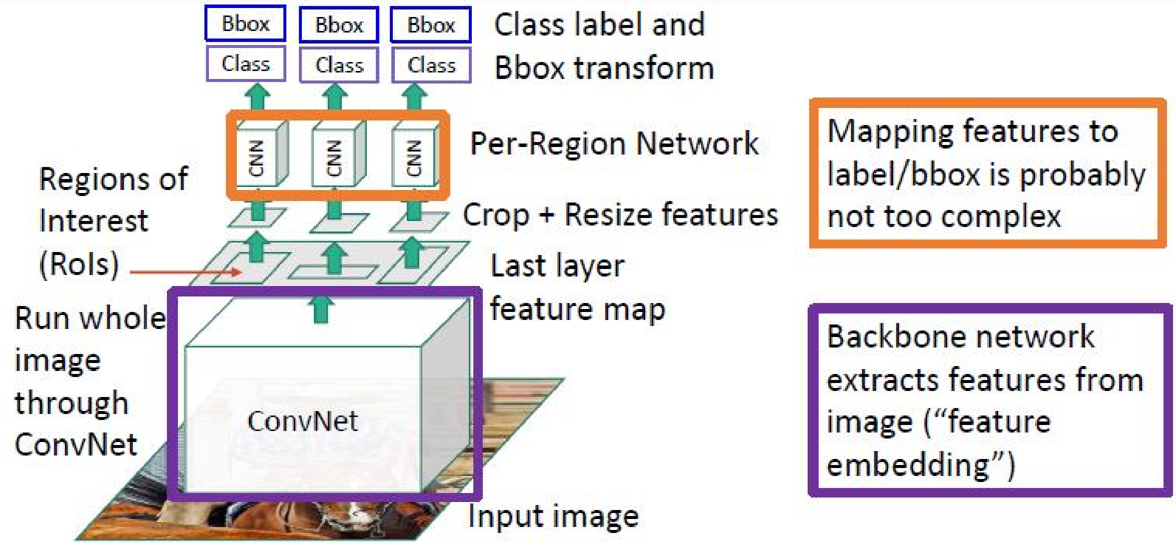
R-CNN results L11.1 P30, 31

Summary - R-CNN

- R-CNN (Region-based convolutional neural network) does classification in parallel over a set of region proposals
- Output: class labels and bounding box transforms
- Advantage: Much more efficient than classifying every window
- Disadvantages
  - Still requires classifying many windows (e.g., 2000)
  - Region proposal step could miss some objects

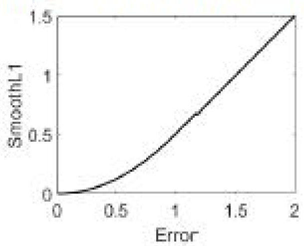
Fast R-CNN L11.1 P34

- Major change: run the whole image through a fully convolutional neural network
- Take region proposals from last convolutional layer
- Crop / resize features L11.1 P39



Fast R-CNN training

- Train on R regions sampled from N images
  - For efficiency, N is small (1-2) and R is large (e.g., 64)
  - Sample regions so 75% of training set is “background”
- Train with a multi-task loss: $L = L_{cls} + L_{loc}$
  - L_{cls} = cross-entropy loss over labels
  - L_{loc} = SmoothL1 of abs(true-predicted bbox parameter)
- L_{loc} computed for object classes only



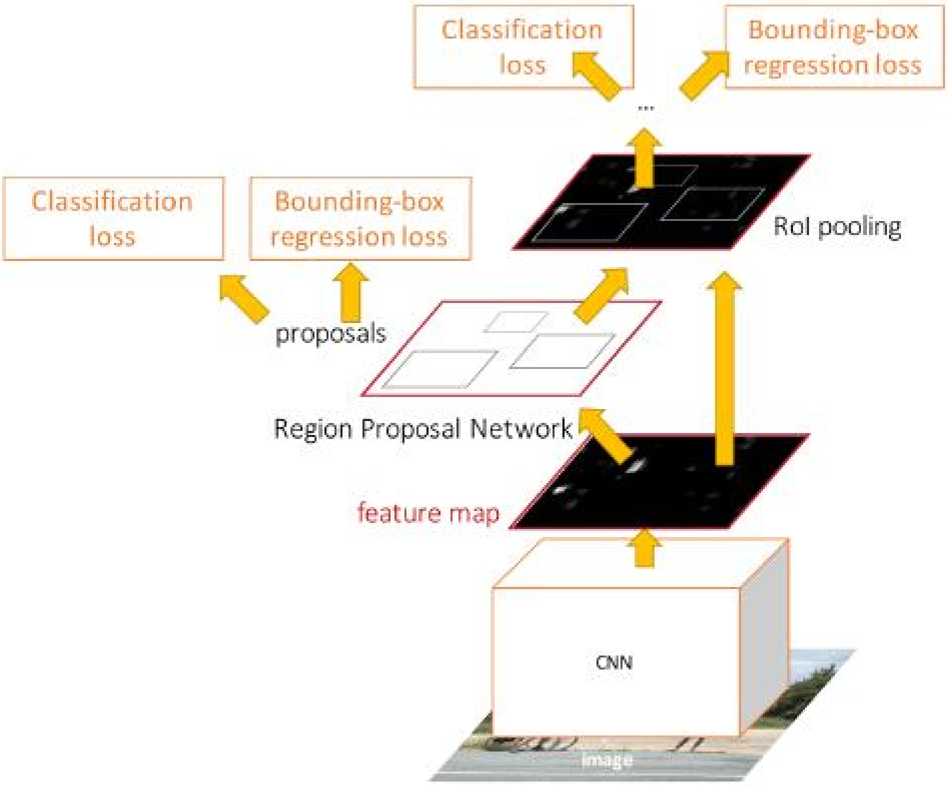
Summary - Fast R-CNN

- End-to-end region based convolutional neural network
- Advantages
  - Faster than R CNN (~9x faster training, ~140x faster test)
  - Slightly more accurate than R-CNN
- Disadvantages
  - ROIs aren’t learned; region proposal step could miss some objects

Faster R-CNN L11.1 P50

- Major change: network learns region proposals, instead of using Selective Search
- Region proposal network (RPN)
  - An “anchor point” is placed at each column in the feature map

    - Each anchor point generates k regions of fixed size and aspect ratio
- For each region:
    - Crop & resize features
    - Predict object class and bounding box transform
- For each image:
    - Run backbone CNN to get feature map
    - Compute region proposals from RPN



Faster R-CNN training

- RPN loss is weighted sum of:
    - Classification loss: binary cross entropy loss (any object vs. background)
    - Regression loss: SmoothL1 between true and predicted bbox parameters
- As in Fast R CNN, training samples R regions (anchors) from N images (R = 256, N = 1)
    - Anchors are sampled so up to 50% are objects
- Full network is RPN + Fast R-CNN (sharing a backbone)
    - Various ways to train this, but original method alternates between training RPN and Fast R CNN

Summary - Faster R-CNN

- Faster R-CNN is similar to Fast R-CNN but learns the region proposals with a region proposal network (RPN)
- Even faster than fast R-CNN (~10x faster test)
- Modular approach - variations on Faster R-CNN with deep backbone tend to be quite accurate
    - Speed-accuracy trade off: deeper networks are also slower

Summary I

- Object detection = classification of image regions
- Exhaustive search is slow; most methods use only a subset of regions ("region proposals" or "regions of interest (ROIs)")
- Many parameters to consider:
  - What counts as a true detection / true rejection (IoU threshold)?
  - How to select region proposals?
  - How to deal with class imbalance? ("background" is most common class)

Object detection II

Single-stage object detectors

YOLO (You Only Look Once) v1 L11.2 P13

- Main idea: instead of going through multiple steps (region proposals, region classification), just predict a heatmap for each class directly in a CNN
- Output is a set of N class probability maps + M bounding box parameter maps
- Loss is sum-squared error between true and predicted maps, with some weighting:
  - Bbox location parameters get higher weight in the loss
  - Grid cells that don't contain objects don't contribute to classification loss
  - Bbox parameters are penalised based on their confidence, encouraging the M bboxes to specialise for different objects
- Advantages:
  - Fast
  - Accurate, for a real time object detector
- Disadvantage:
  - Limited spatial precision
  - Generally less accurate than slower detectors
- There have been multiple versions of this algorithm that have improved on the original method

SSD: Single shot multibox detector L11.2 P18

- Similar to YOLO: instead of generating region proposals, directly predict a set of class+bbox heatmaps
  - For each anchor point: k bboxes * (N class confidences * 4 bbox parameters)
- Major change: anchor points in multiple convolutional layers, allowing for detection at different scales
- Faster than region proposal methods like Faster R-CNN
- Generally less accurate than region-proposal methods
- Anchor points in early layers helps with spatial prediction and detection of small objects

Alternatives to bounding boxed L11.2 P22

Summary - Single-stage object detectors

- Single-stage detectors skip the region proposal step and predict object classes/bounding boxes directly
- Single-stage methods tend to be faster but less accurate than two stage methods like Faster R-CNN
- Some recent methods simplify the prediction by predicting single points instead of bounding boxes

Instance segmentation

Common method:

- Instance segmentation can be modelled as object detection followed by binary segmentation (foreground/background)
- Run object detector, extract bounding boxes and labels
- Do binary (foreground/background) segmentation within each bounding box
- Common architecture is Mask R-CNN, which is a modification of Faster R CNN

Mask R-CNN L11.2 P28

- Basically just an extra step on Faster R-CNN - each patch runs through a fully convolutional network that predicts a binary segmentation mask
- Patch loss becomes: $L = L_{cls} + L_{box} + L_{mask}$

Evaluating object detectors

Object detection result

- Typically, object detectors will return many overlapping detections
  - Can be different objects, or the same object detected at multiple scales / positions
- Treat as multiple detections? Or select one as the final prediction?
  - Typical approach: Non-max suppression (NMS)
    - Starting with the highest scoring bounding box...
    - Drop bounding boxes with lower score that overlap with this box above some IoU threshold (e.g., 0.7)
    - Repeat with next highest scoring bounding box
  - Often done separately within each object class
  - Example   L11.2 P35
  - NMS can drop some correct detections when objects are highly overlapping
  - But generally this is preferable to counting the same object many times

Evaluation

- How to evaluate, given that there may be multiple objects/detections per image?
- Commonly used method:
  - Run detection on entire test set
  - Run NMS to remove overlapping detections
  - For each object category, compute **Average Precision (AP)** = area under precision recall (P-R) curve

    - Example   L11.2 P40
    - Mean Average Precision (mAP)   L11.2 P50
        - "COCO mAP ": Compute mAP for multiple IoU thresholds (0.5, 0.55. 0.6, ... 0.95) and average
- Common metric for evaluating object detectors is mAP (or COCO mAP)
- Both NMS and P-R steps require IoU thresholds; different thresholds can change results
- Object detection is complex - one number is not very informative
    - How accurate is the object classification?
    - How accurate are the bounding boxes?
    - What kinds of errors is the model making (misses, false alarms)?

Beyond patches

Scene priors

Object detection in context

- Scene context provides both global and local priors:
    - Global prior: likelihood of the object appearing at all
    - Local: likelihood of the object in given location
- Including these priors can help reduce false detections

Summary II

- Object detection is typically modelled as a patch classification problem
- Various ways to approach the classification problem: two-stage region proposal detectors, single-stage detectors
- However, this is not the only way to approach object detection - information outside the patch (scene context) can also be used to predict object presence / location