Object Recognition Chapter 10

Object Detection with Deep Neural Networks

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Document History

Version Nr.	Date	Changes
1.0		Initial Version

Chapter 10: Object Detection with Deep Neural Networks

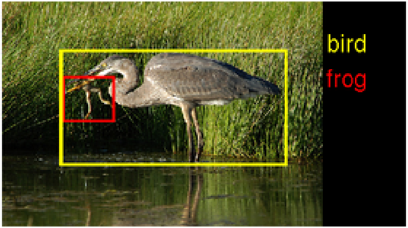
Goal of object Detection

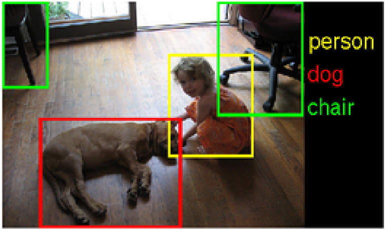
Object Detection Task

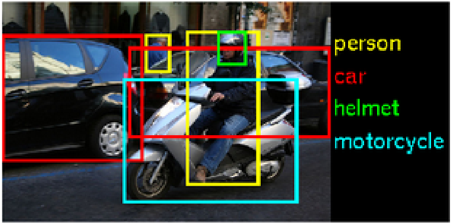
For a given image, determine:

- Which objects are in the image
- Where are these objects
- Confidence score of detection

Object Detection Examples





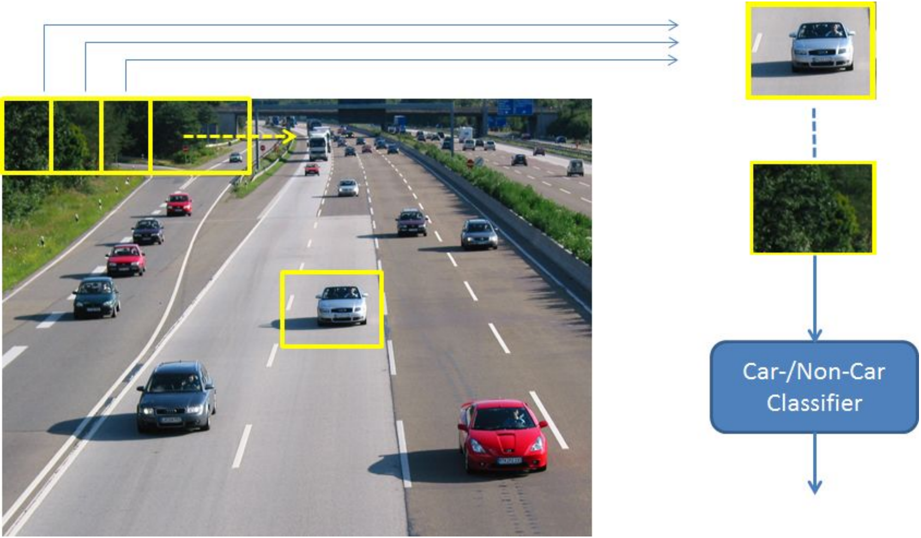


Source: http://image-net.org/challenges/LSVRC/2014/index

Object Detection: Approaches

- Sliding Window
- Overfeat: Train for each supported object category a CNN regressor-model, which predicts the coordinates of the bounding box
- In this lecture: Region Proposals and Deep Neural Networks:
    - R-CNN [Girshick et al., 2014]
    - Fast R-CNN
    - SPPnet
    - Yolo

Sliding Window Approach for Object Detection



Intersection over Union (IoU)

- If A is the set of detected pixels and B is the set of Groundtruth-pixel, their IoU is defined to be
$$IoU(A,B) = \frac{|A \cap B|}{|A \cup B|},$$
where $|X|$ is the number of pixels in set X.
- Usually two bounding boxes (pixel sets) are said to match, if their IoU is > 0.5.

Mean Average Precision (mAP)

- Calculate the average precision for each class.
- For determining TP,TN,FP and FN matches must be determined.
- Match: *detected object = groundtruth object* and *IoU of bounding boxes* > 0.5
- Average precision is related to the area under the precision-recall curve for a class:

$$AP = \frac{1}{11} \sum_{r \in \{0, 0.1, \ldots, 1\}} p_{interp}(r),$$

  where $p_{interp}(r)$ is the interpolated precision at recall r.
- The mean of these average individual-class-precisions is the Mean Average Precision
- More info: PASCAL VOC Challenge

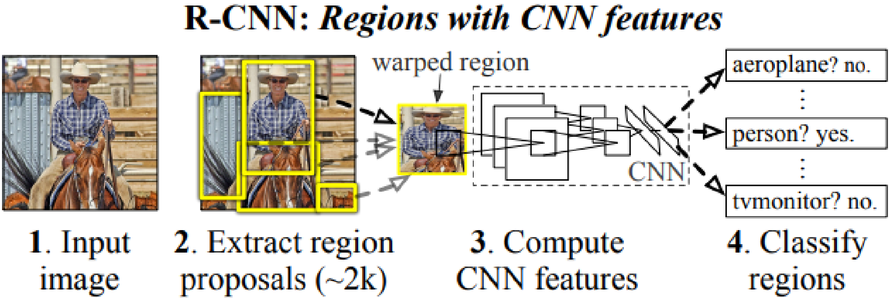
Region Proposals

- Goal: Given an input image find all possible places where objects can be located.
- Output: List of bounding boxes of likely positions of objects (= Region Proposals or Regions of Interest (ROI))
- Approach: Apply segmentation, e.g. hierarchical clustering, mean-shift clustering or graph-based segmentation
- Refine result from segmentation by e.g. selective search

R-CNN

- Published 2014 in [Girshick et al., 2014]
- Combines Region Proposals and CNN
- Region Proposals
  - are candidate boxes, which likely contain a object
  - can be computed by different algorithms, e.g. Selective Search
- mAP (mean Average Precision) of 53.7% on PASCAL VOC 2010- compared to 35.1% of an approach, which uses the same region proposals, but spatial pyramid matching + BoW
- mAP (mean Average Precision) of 33.4% on ILSVRC 2013 Detection benchmark- compared to 24.3% of the previous best result OverFeat [Sermanet et al.,]

R-CNN



Source: [Girshick et al., 2014]

R-CNN

Process:

1. Apply Selective Search for calculating about 2000 region proposals for the given image.
2. Warp each region proposal to a fixed size, since the CNN requires a fixed-size input.
3. Pass each warped region proposal through the CNN (modified AlexNet). Linear SVM-Classifier calculates a probability for each class.
4. Since the region proposals are not accurate, Bounding-Box Regression is applied to compute accurate bounding boxes. Input are coordinates of the region proposal. Output are the coordinates of the groundtruth bounding-box.

Training comprises:

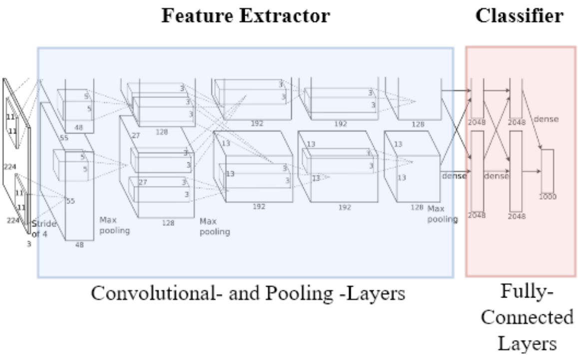
- Fine Tuning of CNN-Feature Extractor
- Train for each class a SVM Detector
- Train Bounding-Box regression (Ridge-Regression)

R-CNN

Drawback:

- 3 models must be learned
- Each of the $\sim$ 2000 region proposals must be passed through the entire CNN
- In particular for small regions the warping to a fixed size CNN-input is a waste of computational resources and yields slow detection
- $\Rightarrow \sim 13s/image$ on GPU

Why fixed size input to CNN?



- Convolutional- and pooling layer can easily cope with varying input-size.
- Fully connected layer require fixed-size input, because for this type varying size means varying number of weights.
- Idea: At the interface between Feature Extractor and Classifier: Find a method which can have variable size input but constant size output.

Spatial Pyramid Pooling in CNNs

- Published 2015 in [He et al., 2016]
- Integration of Spatial Pyramid Pooling ([Lazebnik et al., 2006]) into CNNs
- Applicable for classification and detection: ILSVRC 2014 rank in classification and rank 2 in detection task.
- As R-CNN based on region proposals
- No warping to fixed CNN-input size.
- Instead pass image only once through conv- and pool-layers of CNN.
- $24 - 102$ times faster than R-CNN in testing.

How SPPnet provides fixed-size representation to the classifier

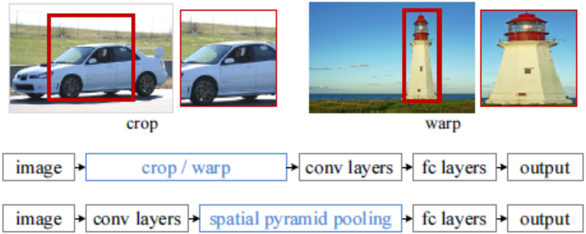
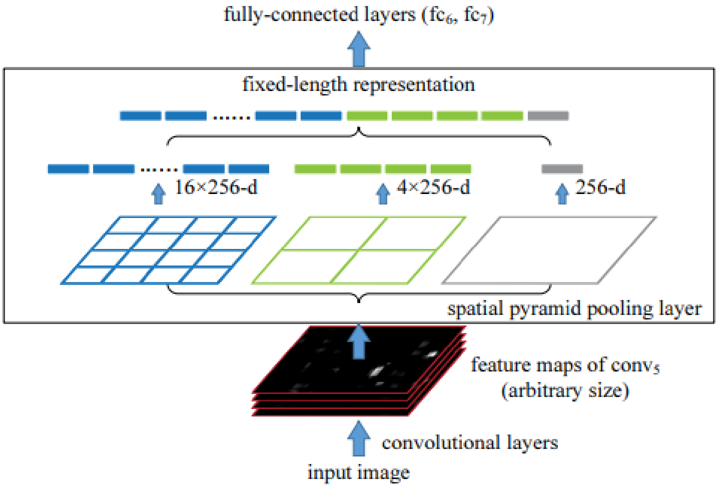


Figure 1: Top: cropping or warping to fit a fixed size. Middle: a conventional CNN. Bottom: our spatial pyramid pooling network structure.

Source: [He et al., 2016]

SPPnet



Source: [He et al., 2016]

SPPnet Process

Process:

1. Calculate Region Proposals
2. Pass image once and calculate feature maps for the entire image
3. Calculate the representation of each region proposal in the last conv-layer (before the fully-connected layers).
4. Crop the 256 feature maps in the last conv-layer to the size of the current region-proposal representation in this layer.
5. Apply spatial pyramid max-pooling (instead of simple max-pooling) on the cropped feature-maps of the last conv-layer and calculate fixed-size input to the fully-connected part of the CNN.
6. 4-level Pooling: $(1 \times 1, 2 \times 2, 3 \times 3, 6 \times 6)$
7. $\Rightarrow$: $1 + 4 + 9 + 36 = 50$ bins per feature map
8. $\Rightarrow$: $50 \cdot 256 = 12800$-length input to classifier.
9. Train binary linear SVM for each category.
10. Train Bounding-Box Regression

SPPnet Drawbacks

Drawback:

- As in R-CNN: 3 models must be trained
- Convolutional Layers that precede the spatial pyramid pooling can not be fine-tuned (because the gradients of the error function can not be passed efficiently through SPP). I.e. End-to-End training is not possible.

Fast R-CNN

- Published 2015 in [Girshick, 2015]
- Extension/Modification of R-CNN
- Also applies Region Proposals
- Enables End-to-End training by Hierarchical Sampling and Multi-Task-Loss
- Benefits:
  - Higher detection quality (mAP) than RCNN and SPPnet
  - No disk-storage for feature caching
  - Single-stage training: Fast R-CNN uses a streamlined training process with one fine-tuning stage that jointly optimizes a softmax classifier and bounding-box regressors. This is enabled by:
    - Hierarchical Minibatch Sampling
    - Multi-task loss function
    - Back-propagation learning through RoI-pooling layers

Fast RCNN

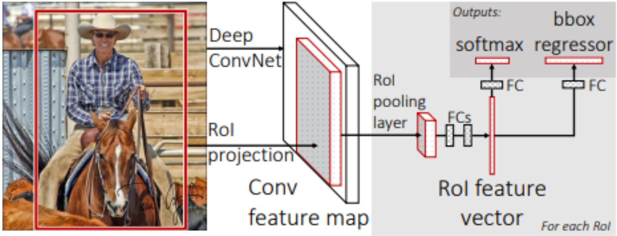


Figure 1. Fast R-CNN architecture. An input image and multiple regions of interest (RoIs) are input into a fully convolutional network. Each RoI is pooled into a fixed-size feature map and then mapped to a feature vector by fully connected layers (FCs). The network has two output vectors per RoI: softmax probabilities and per-class bounding-box regression offsets. The architecture is trained end-to-end with a multi-task loss.

Source: [Girshick, 2015]

Fast RCNN: Hierarchical Sampling

- In R-CNN and SPPnet: Minibatches of size $N = 128$ were constructed by sampling one RoI from 128 different images.
- Sampling multiple RoIs from a single image was supposed to be inadequate, because RoIs from the same image are correlated, causing slow training convergence.
- Since at the end of the Feature Extractor each RoI has a large receptive field (sometimes covering the entire image), fine-tuning of the Feature Extractor would be very expensive. Therefore, the Feature Extractor have not been fine-tuned in R-CNN and SPPnet.
- In Fast-RCNN minibatches are sampled hierarchically:
    - First sample N images ($N = 2$), than sampling R/N RoIs from each image ($R = 128$).
    - Samples from the same image share computation and memory in Forward- and Backwardpass
    - $64\times$ decrease in training time compared to sampling $R = 128$ different images.
    - The concern of slow convergence due to correlated samples within a minibatch has appeared to be not true in the research on Fast R-CNN.

Fast RCNN: Multi-Task Loss

- Two output-layers of Fast R-CNN:
  - Softmax-Output with $K+1$ for class-probabilities $p=(p_0,p_1,\ldots,p_K)$
  - Bounding-Box regressors $t^k=(t^k_x,t^k_y,t^k_w,t^k_h)$ for each of the K classes
- Each training RoI is labeled with a groundtruth class u and a groundtruth bounding-box regresssion target v.
- Multi-task loss L on each labeled RoI to jointly train for classification and bounding-box regression:

$$L(p,u,t^u,v)=L_{cls}+\lambda[u\geq 1]L_{loc}(t^u,v),$$

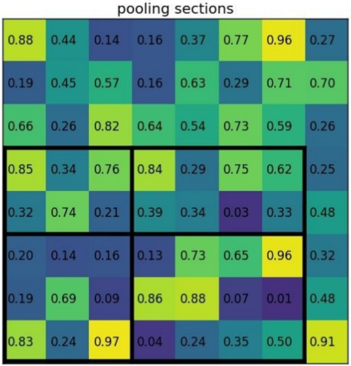
  where
  - the $[u\geq 1]$-operator evaluates to 1 for $u\geq 1$ and 0 otherwise (class-index $u=0$ indicates *no-known class*).
  - L_{cls} is the log-loss function for true class u and L_{loc} is a L_1 loss-function between the elements of the predicted- and the groundtruth bounding-box quadruple (see [Girshick, 2015]).

Fast RCNN: RoI Max-Pooling

- ROI of size $h \times w$ at the last convolutional layer is partitioned into a $H \times W$-grid, where each region is approximately of size $h/H \times w/W$. Typical values: $W = H = 7$.
- This is like level-1 partitioning in SPP.
- Features in each region are Max-pooled.
- Applied independently to each feature map

Fast RCNN: RoI Max-Pooling

RoI Partitioning



Source: https://deepsense.ai/region-of-interest-pooling-explained/

Result of Max Pooling

Yolo: You only look once

- Published 2015 in [Redmon et al., 2015]
- First real-time object detector with 45 fps on Titan X GPU. Faster version achieves 155 fps.
- https://pjreddie.com/darknet/yolo/
- Doesn't require other modules such as region proposals
- Instead: Single Regression Pipeline, which can be learned end-to-end
- YOLO sees the entire image during training and test time so it regards entire context (information, which is lost in sub-window approaches) $\Rightarrow$ YOLO makes less than half the number of background errors compared to Fast R-CNN.

Yolo Concept

- Partition entire image into a regular grid of $S \times S$ cells (typical: $S = 7$)
- The grid-cell which contains the center of an object is responsible to detect this object
- Each grid-cell predicts B bounding boxes (typical: $B = 2$) and confidence scores for these boxes.
- Confidence scores reflect
  - how confident the model is that the box contains an object: $P(object)$
  - how accurate the predicted box is: $IoU(pred, truth)$

$$Confidence = P(object) \cdot IoU(pred, truth)$$

- Each bounding box consists of 5 predictions: $x, y, w, h, Confidence$.
- Each grid-cell predicts C conditional class probabilities $P(C_j|object)$.
- At test time calculate class-specific confidence scores as follows

$$P(C_j|object) \cdot P(object) \cdot IoU(pred, truth) = P(C_j) \cdot IoU(pred, truth)$$

- This score encode probability of that class appearing in the box and how well the predicted box fits the object.

Yolo Concept

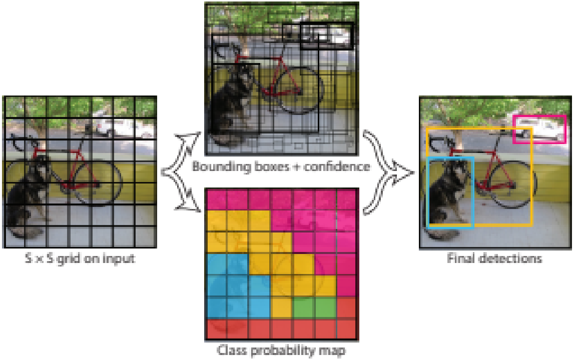


Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

Yolo Architecture

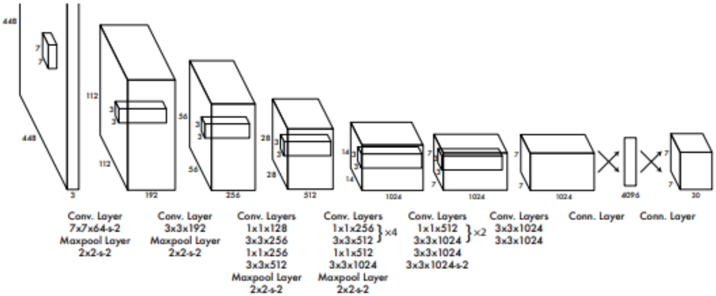


Figure 3: The Architecture. Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating 1×1 convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution (224×224 input image) and then double the resolution for detection.

Source: [Redmon et al., 2015]

Architecture

- Network output is a tensor of size $S \times S \times (5 \cdot B + C)$. With $C = 20$ classes and the parameters mentioned above, this tensor contains $49 \cdot 30$ elemenets.
- The faster Yolo version contains only 9 instead of 24 conv-layers and less feature maps.
- Conv-layers are pretrained with the ILSVRC classification benchmark.
- Loss-function: see [Redmon et al., 2015]

Performance compared to R-CNN

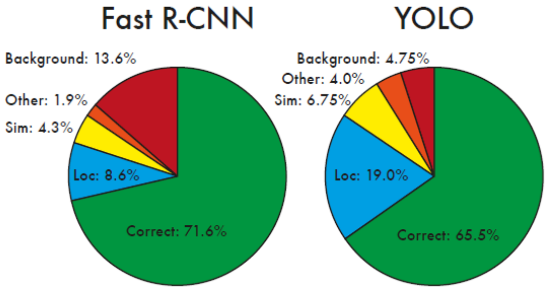


Figure 4: Error Analysis: Fast R-CNN vs. YOLO These charts show the percentage of localization and background errors in the top N detections for various categories (N = # objects in that category).

Source: [Redmon et al., 2015]

Meanwhile Yolo has been improved significantly

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