Deep Learning for Image Analysis - Deep Learning for object detection

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Overview

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Classification, segmentation and detection

- Image Classification: assign a label to each image.
- Image Segmentation: partition the image, i.e. assign a label to each pixel.
- Image understanding requires the estimation of concepts and locations of objects contained in an image.
- Problem definition: Object detection is ac omputer vision task that aims to detect instances of semantic objects of certain classes in images [Ren et al., 2017, Zhao et al., 2019].
- Object detection has thus two components:
  - *Object localization:* to determine where objects are located in a given image
  - *Object classification:* which category each object belongs to

Object detection: example

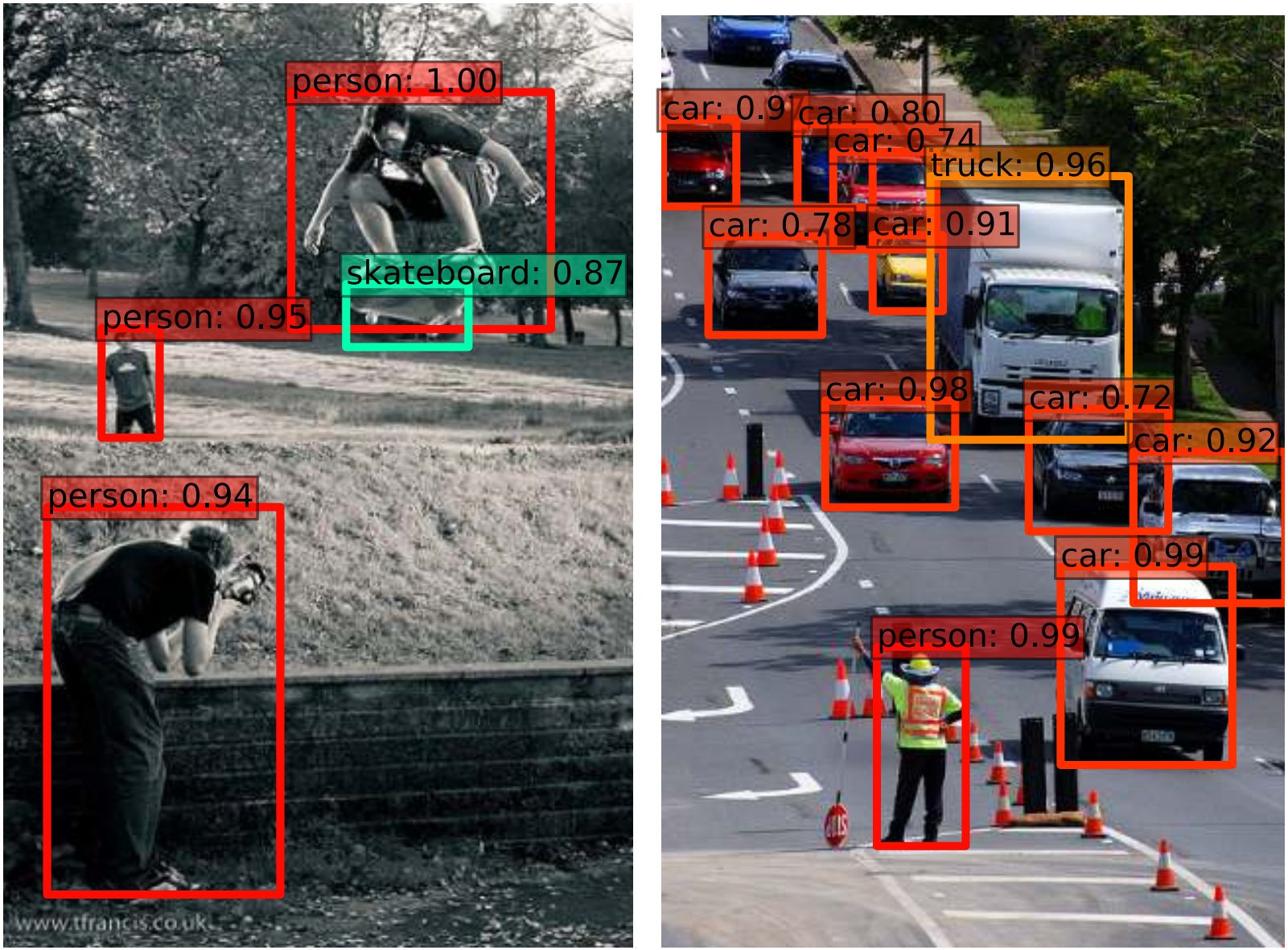
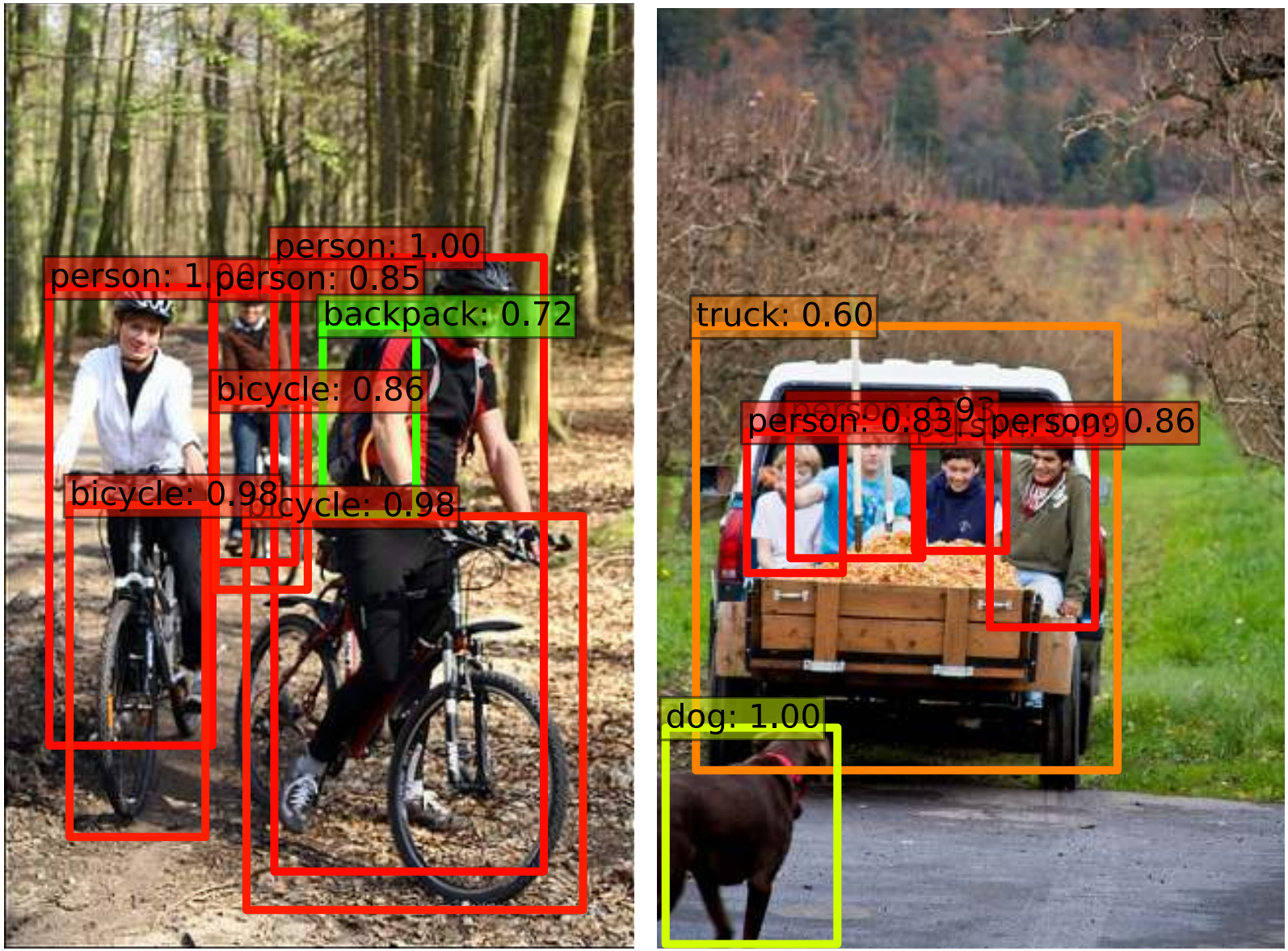


Figure: Object detection in action. Image taken from [Liu et al., 2016]

Object detection: example



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Object detection: example

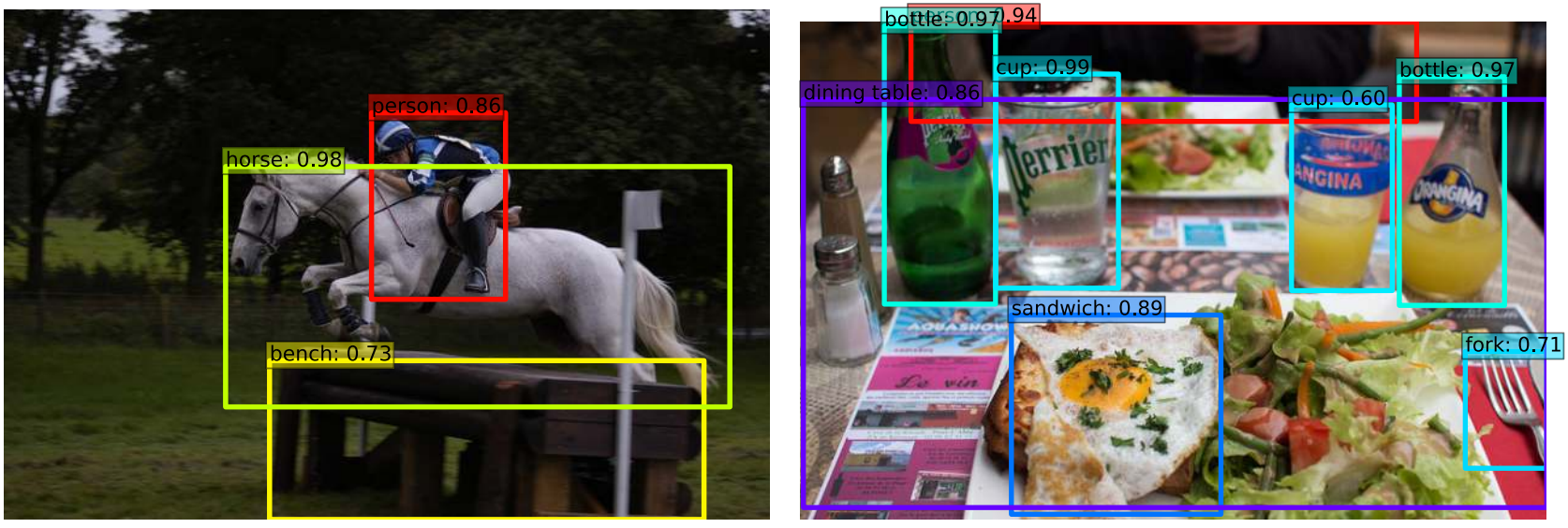

Figure: Object detection in action. Image taken from [Liu et al., 2016]

Early approaches: the sliding window approach

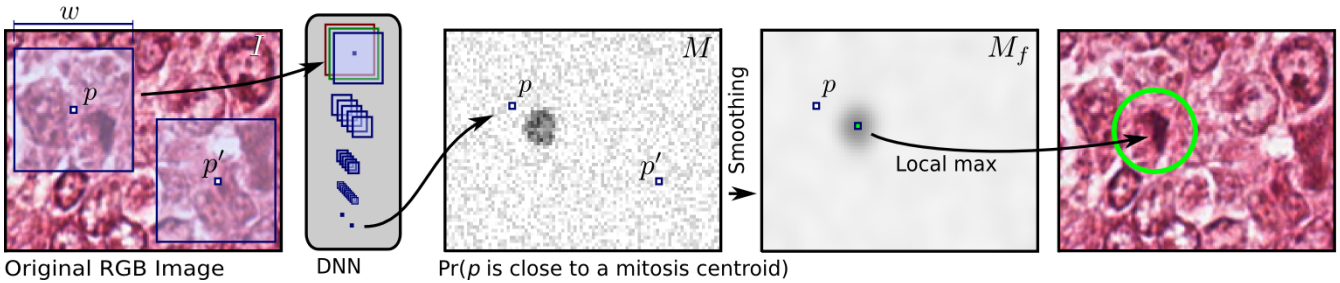

Figure: Mitosis detection in stained tissue sections [Cireșan et al., 2013].

- Approach was the winner of a mitosis detection challenge [Cireșan et al., 2013].
- Fixed size sliding window approach: each crop is presented to a CNN.
- The posterior probability is stored as an image value.
- Local maxima of this probability map indicate the presence of an object.
- Special case of object detection: the size of the objects was known before.

A milestone in object detection: R-CNN

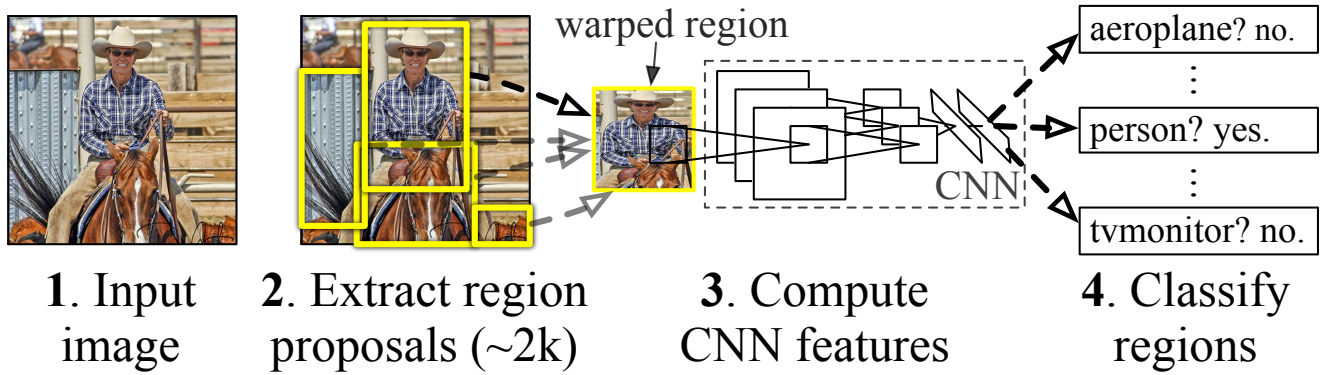

Figure: R-CNN strategy [Girshick et al., 2014]

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- Starting from region proposals (by any method): $\sim$ 2000 regions).
- Warping / Cropping of the selected regions into fixed resolution and extraction of a 4096-dimensional feature vector with a pretrained CNN.
- Classification with SVM (object types and background).
- Adjustment by bounding box regression
- Filtering with greedy non-maximum suppression (NMS): removal of regions with low overlap with a single object.

Drawbacks of R-CNN

- Fixed input size for the CNN: distortion and rescaling of images is necessary.
- Multi-stage pipeline.
- Training is expensive (time and space).
- Computational expensive, sub-optimal region proposal step.

Fast R-CNN

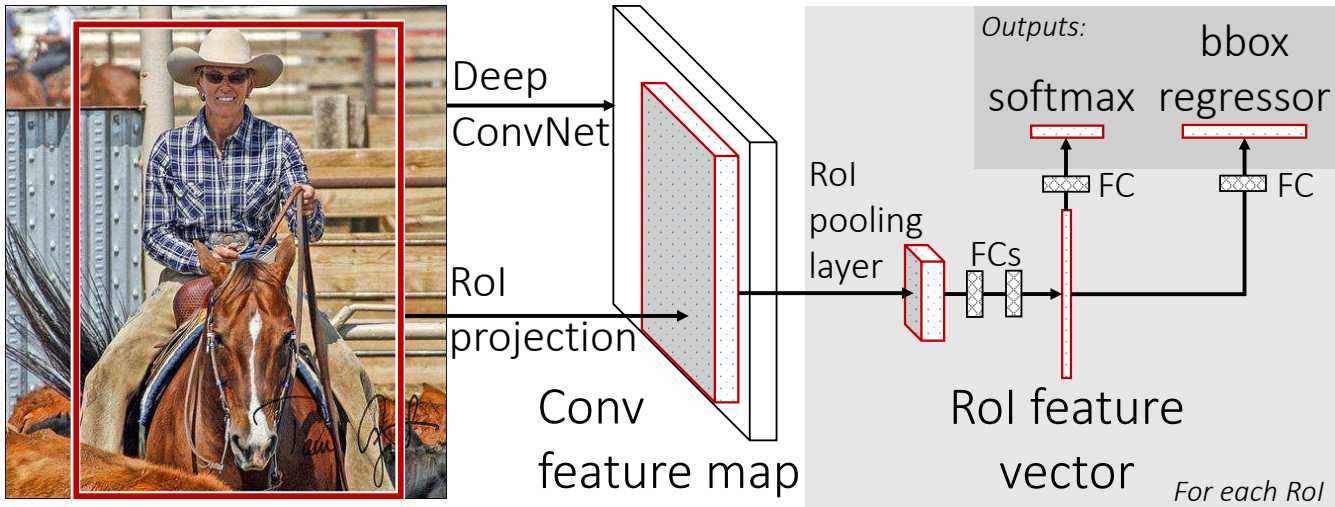

Figure: Fast R-CNN [Girshick, 2015]

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- The entire image is processed by a neural network: generation of feature maps.
- Region are proposed by some algorithm (as before).
- To each region, a ROI pooling layer is applied.

Fast R-CNN: ROI pooling layer

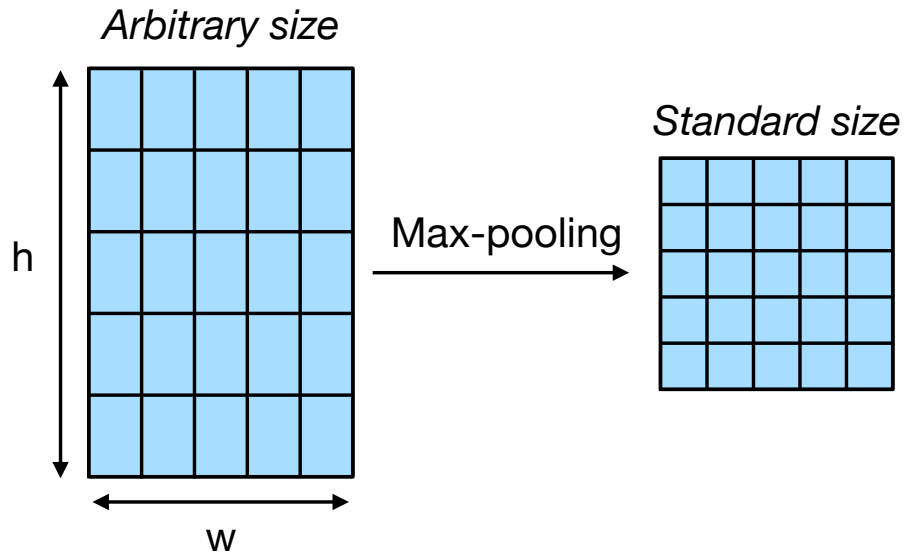

Figure: ROI pooling layer in Fast R-CNN

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- Each region of arbitrary size $w \times h$ is divided into $W \times H$ tiles. W and H are fixed, where as w and h are arbitrary.
- For each tile, the maximum is calculated (max-pooling operation) in the feature map.
- The output (fixed size) can then be processed by dense layers.

Fast R-CNN: Output layer

- Two outputs:
  - Classification output (with a standard softmax layer)
  - Bounding box regression: prediction of position and extension offsets with respect to the original region proposal.
- The loss has thus two components: L_{class} which is the standard cross-entropy loss and L_{loc}, the localization loss (L_1 loss of the offsets with respect to the proposed regions).
- Trick: during training, the batch is constructed from many objects drawn from very few images.
- For the prediction, each class gets its own region proposal, that is processed individually with non-maxima suppression.

Faster R-CNN: motivation

- Fast R-CNN solves nearly all problem of R-CNN, and is end-to-end given a set of region proposals.
- The problem is that we still need to make region proposals to start with (time-consuming and two-stage algorithm).
- Faster R-CNN [Ren et al., 2017] trains a network called Region Proposal Network (RPN) to overcome this issue.

Faster R-CNN: Idea

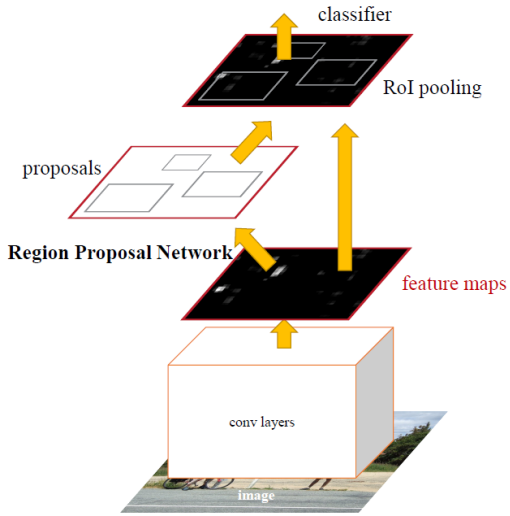

Figure: Faster R-CNN [Ren et al., 2017]

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The idea is to share convolutional feature maps at test-time, i.e. to use the CNN feature maps calculated for the entire image for both region proposal and object classification [Ren et al., 2017].

Faster R-CNN: shared layers

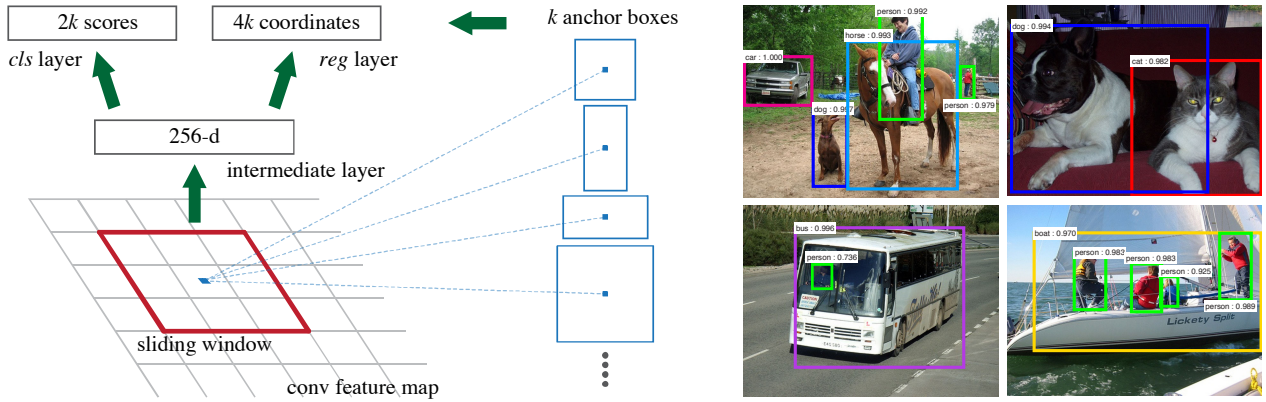

Figure: Faster R-CNN [Ren et al., 2017]

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- First, we run the image through convolutional layers of a CNN and obtain feature maps that will serve both the region proposal and the object classification.
- We now slide a small network over the common feature map, that outputs both scores (object yes/no) and regression offsets defining the bounding box.
- The size can be relatively small (in [Ren et al., 2017], it is 3×3); the receptive field is much larger.

Faster R-CNN: Region proposal network (RPN)

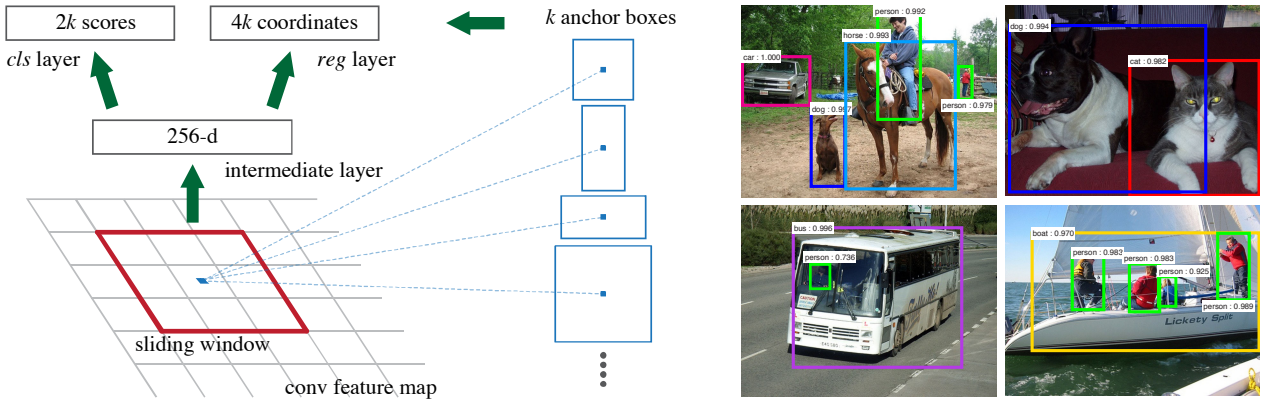

Figure: Faster R-CNN [Ren et al., 2017]

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- A Region Proposal Network (RPN) takes an image as input and outputs a set of rectangular object proposals, each with an objectness score.
- We define k anchor regions (defined by scale and aspect ratio).
- At each sliding-window location, we simultaneously predict k region proposals from the k anchor regions, for each we predict a score (object yes/no) and the box offsets.

Faster R-CNN: Region proposal network (RPN)

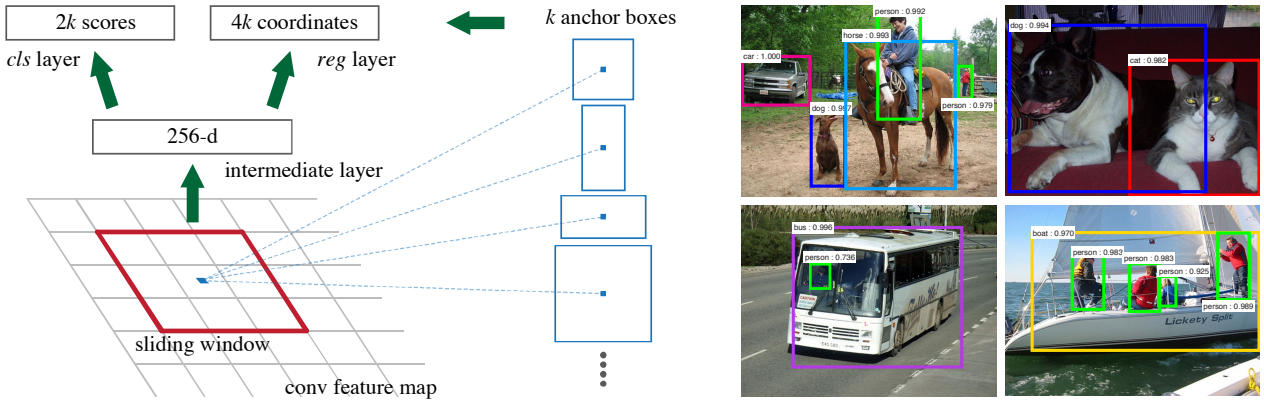

Figure: Faster R-CNN [Ren et al., 2017]

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- We define a combined loss (as for Fast R-CNN), as sum of the classification loss and bounding box regression loss.
- Classification loss: cross entropy for a binary classifier, indicating whether the region contains an object or not.
- Regression loss compares for each region proposal its offsets to the anchors with the offsets of the ground truth box.

Faster R-CNN: Training

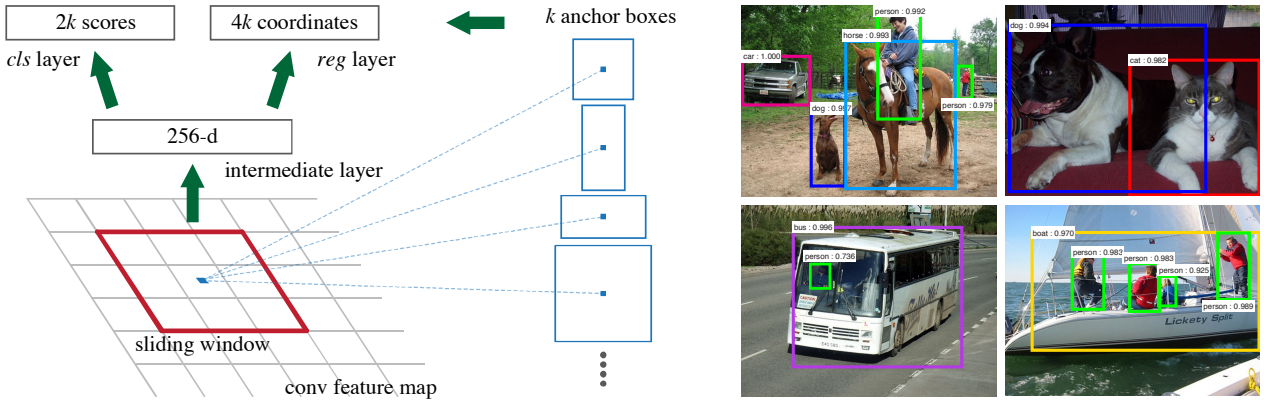

Figure: Faster R-CNN [Ren et al., 2017]

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- We now simply apply a Fast R-CNN to the region proposals provided by the RPN.
- The shared layers are trained in an alternating scheme.
- After this initial training, the shared layers are frozen and the separate layers are trained end-to-end.

Conclusion

- Object detection is a major challenge in Computer Vision with applications in biomedical image analysis, autonomous driving, industrial applications, etc.
- CNNs outperform most traditional methods by a large margin.
- Today, object detection is among the most stunning applications of Computer Vision.
- There are hundreds of methods, but the most important advances were achieved by R-CNN, Fast R-CNN and Faster R-CNN.
- They can be combined with segmentation (Mask R-CNN).

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