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FAST R-CNN
(REGION-BASED CONVOLUTIONAL NETWORK)

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SHORT SUMMARY

- The problem that is being addressed:
  - Training is a multi-stage pipeline
  - Training is expensive in space and time
  - Object detection is slow.
- Its significance:
  - 9x faster than R-CNN (0.3s to process images at runtime)
  - Higher mAP of 66% (vs. 62% for R-CNN)
- Approach used to solve the problems:
  - The RoI pooling layer
  - Initializing from pre-trained networks
  - Fine-tuning
- Setup:
  - CaffeNet with Python and C++
  - VOC07, 2010, and 2012 vs SPPNet, R-CNN, SegDeepM, and BabyLearning

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WHAT IS CNN?

- Convolutional Neural Network
- Input -> Convolutional layer (transformed) -> output
- Features
  - Objects, textures, edges, shapes, etc.
- Layers = Filters
- Simple layers(edge 3x3) -> intermediate layers(corners, shapes) -> complicated layers(dog, cat)

WHAT IS RELU(RECTIFIED LINEAR UNIT) ACTIVATION FUNCTION AND BACKPROPAGATION?

- First, neural network consists of nodes and connections between the nodes that provides the weights and biases.
- Back propagation fills the empty parameters -> slope and intercept
- Bent activation node, zero until a point, rest is linear.

- Chain rule and gradient descent to provide the weights and biases for backpropagation.
- First determine the last parameter bias by gradient descent and with optimal past parameters.
- Then use derivative of SSR over the last parameter bias.

WHAT IS MAX POOLING & SOFTMAX

- Follows the convolutional layer output.
- Decreases the image pixel width and height.
- Defined by filter size (like 2x2) and stride(how many pixel to slide).

- SoftMax = higher dimension sigmoid.
- Goal is to transform the unbounded probability into a probability vector.
- It uses euler's exponent.

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WHAT IS R-CNN?

- Input image -> selective search -> initial segmentation -> after many iteration -> bounding box -> into the CNN
- Extract region proposal from bounding box -> crop -> CNN -> classification
- Problem addressed:

  Region loses detail when cropped to fit into the fixed-sized CNN.

  There could be too much bounding box to pass to the CNN and they have to pass one by one
- Significance of the problems:
  - Computationally expensive.

FAST R-CNN

- Approach used to solve the problems:
  - Still does selective search region proposals.
  - Passes the entire image into the deep ConvNet other than each RoI -> the bounding box is projected onto the RoI feature map -> RoI pooling layer makes the projection into a fixed size -> Fully connected network classification CNN
- Because CNN is just layers of filters and max pooling, it can estimate at the end of the image output.
- There may exist yet undiscovered techniques that allow dense boxes to perform as well as sparse proposals (wink wink)

FAST R-CNN

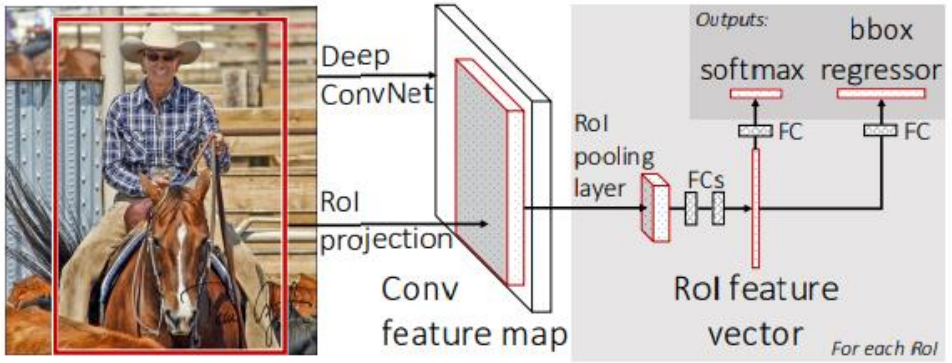
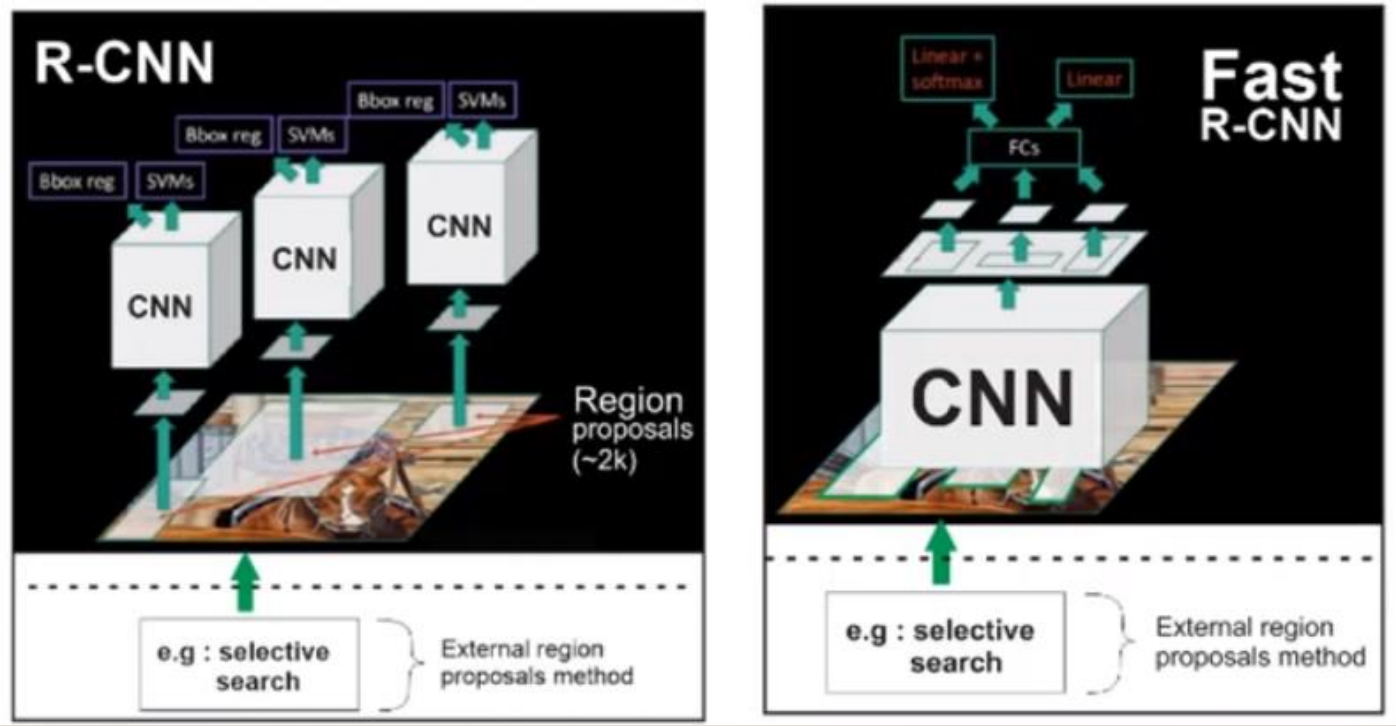


Figure 1. Fast R-CNN architecture. An input image and multiple regions of interest (RoIs) are input into a fully convolutional network. Each RoI is pooled into a fixed-size feature map and then mapped to a feature vector by fully connected layers (FCs). The network has two output vectors per RoI: softmax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

R-CNN VS FAST R-CNN



FINE TUNING

- Uses Stochastic gradient descent (just like regular gradient descent but random and better to update) for mini-batch sampling (25% of the RoIs).
- 2 output layers:
  - Discrete probability distribution per RoI over K+1 categories.
  - Bounding-box regression offset for each of the K object classes.
- Back propagation routes derivatives through the RoI pooling layer.
- SGD hyper-parameter: softmax & bounding-box initialized from zero-mean Gaussian distribution with standard deviations 0.01 and 0.001.
- Using both brute force(single scale) and image pyramid for scale invariance

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ASSESSMENT OF STRENGTHS

- Higher detection quality (mAP) than R-CNN, SPPNet
- Training is single-stage, using a multi-task loss
- Training can update all network layers
- No disk storage is required for feature caching
- softmax slightly outperforming SVM

TRAINING AND TESTING TIME

- For VGG16, Fast R-CNN processes images 146× faster than R-CNN without truncated SVD and 213× faster with it.
- Training time is reduced by 9×, from 84 hours to 9.5.
- Compared to SPPnet, Fast RCNN trains VGG16 2.7× faster (in 9.5 vs. 25.5 hours) and tests 7× faster without truncated SVD or 10× faster with it.
- Fast R-CNN also eliminates hundreds of gigabytes of disk storage, because it does not cache features.

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ASSESSMENT OF WEAKNESSES

- Assumptions that are used:
  - Brute force(single-scale)
  - Multi-task training
  - Training data size
- When the algorithm might fail:
  - Scale invariance - Larger networks with a single-scale offer the best speed / accuracy tradeoff.
  - The multi-scale approach offers only a small increase in mAP at a large cost in compute time.
  - Across all three networks we observe that multi-task training improves pure classification accuracy relative to training for classification alone.
  - Enlarging the training set improves mAP.
  - + Problems mentioned before

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FASTER R-CNN (THE NEXT GEN)

- The entire image is fed through the convolutional layers for feature extraction just like the Fast R-CNN.
- The difference: the projection on the feature maps is not from the selective cells -> Uses RPN(Region Proposal Network) after the CNN output.
- Uses anchor and its intersection of union ratio 7:3 to determine the object bounding box
- No selective cells -> the feature map -> passed into the RPN CNN -> gets object classification, bounding box, and whether an object is present -> RoI pooling and classifier

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QUESTIONS REGARDING THE WORK

- Later works that replaced Fast R-CNN:
  - Faster R-CNN -> Mask R-CNN Detectron(Facebook)
  - YOLO (You only look once)
  - Single Shot Detectors(SSD)