Problem Statement

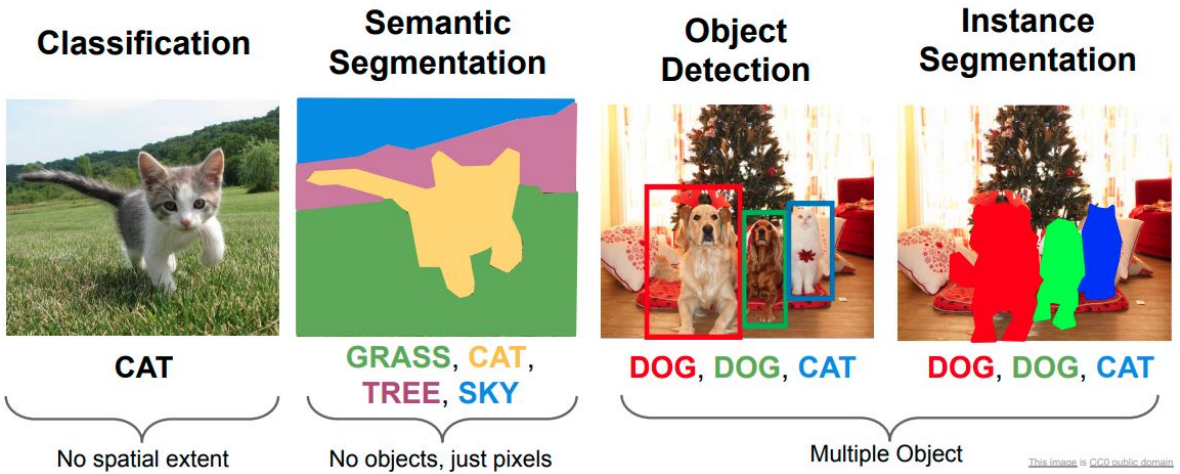
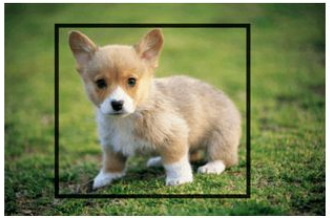


Image Source: http://cs231n.stanford.edu/

Object Localization

Object Classification is the task of identifying that picture is a dog



Object Localization involves the class label as well as a bounding box to show where the object is located.

Image Source:
https://www.commonlounge.com/discussion/c9975025c9ff473c8f9ed2c4b1c3ea6a#image-localization-detection-segmentation

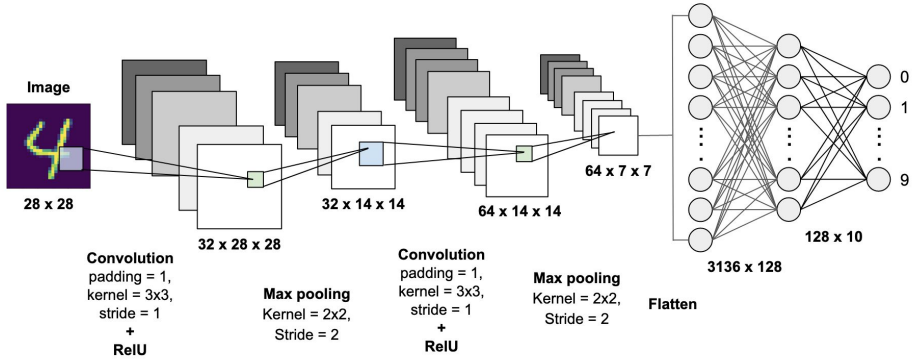


Image Source: MNIST Handwritten Digits Classification using a Convolutional Neural Network (CNN)

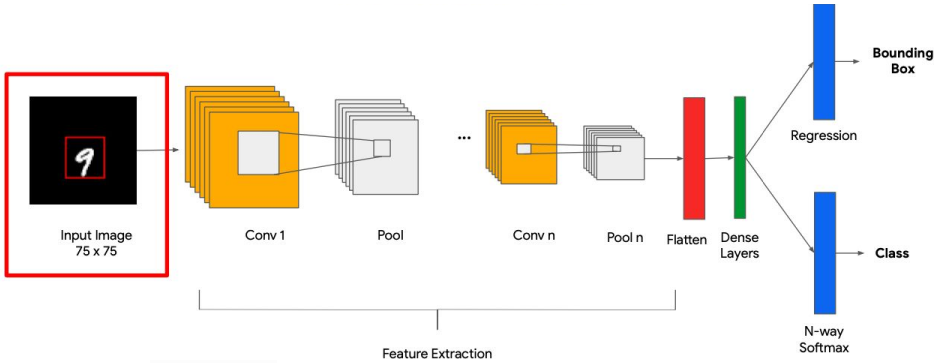


Image Source: deeplearning.ai

Idea: Sliding Window

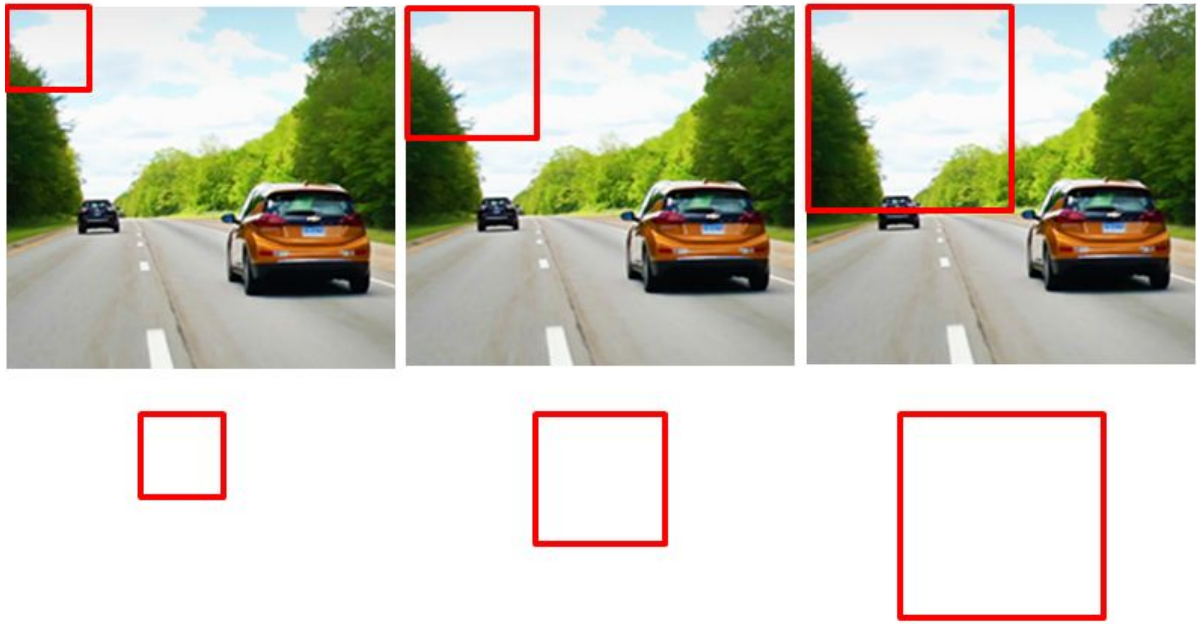


Image Source: https://datahacker.rs/deep-learning-object-detection/

Idea: Region Proposal

Felzenszwalb's Algorithm [2004] :
Efficient Graph-Based Image Segmentation

- Turn the image into an undirected graph **G = (V,E)**
  - Vertex $\mathbf{v_i} \in \mathbf{V}$ is a pixel
  - Edge $\mathbf{e = (v_i , v_j) \in E}$ connects two vertices
  - Weight $\mathbf{w(v_i , v_j)}$ measure dissimilarity between $\boldsymbol{v_i}$ and $\mathbf{v_j}$
- A segmentation solution **S** is a partition of **V** into connected components **{C}**

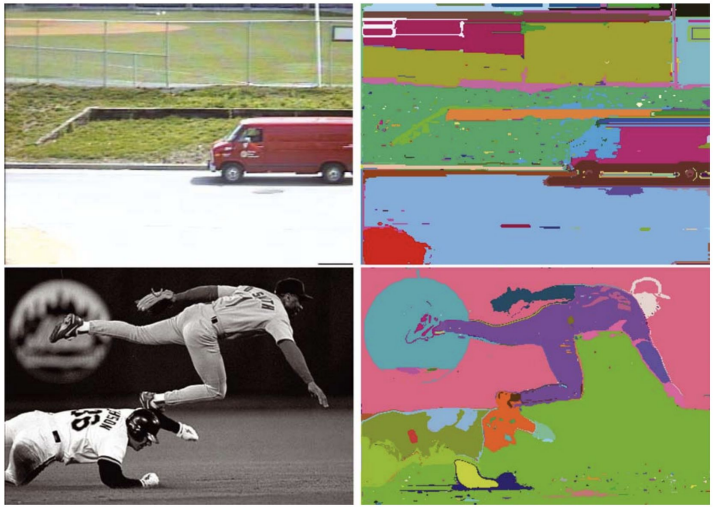


Image Source: Felzenszwalb, P.F., Huttenlocher, D.P. Efficient Graph-Based Image Segmentation. *International Journal of Computer Vision* 59, 167–181 (2004).

Idea: Region Proposal

Selective Search :

"Class Agnostic Object Detector"

- Start from Felzenszwalb's Segmentations
- Recursively combine similar regions into larger ones
- Convert regions to boxes

Input Image

Image Source: http://vision.stanford.edu/teaching/cs231b_spring1415

Overview: R-CNNs

R-CNN

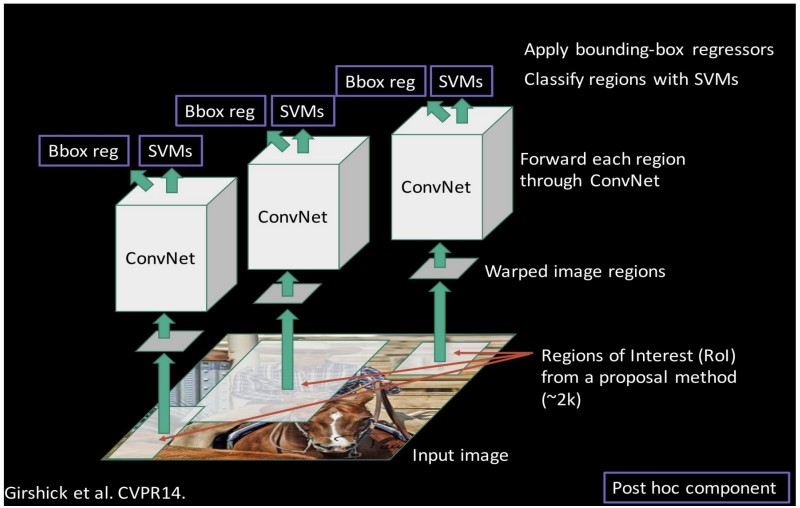


Image: Girschick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014

Fast R-CNN

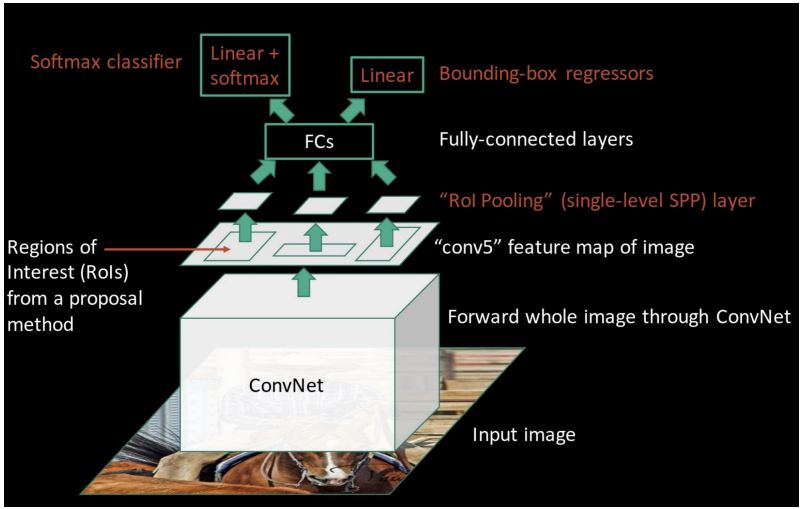


Image: Girschick, “Fast R-CNN”, ICCV 2015

Overview: R-CNNs

Faster R-CNN

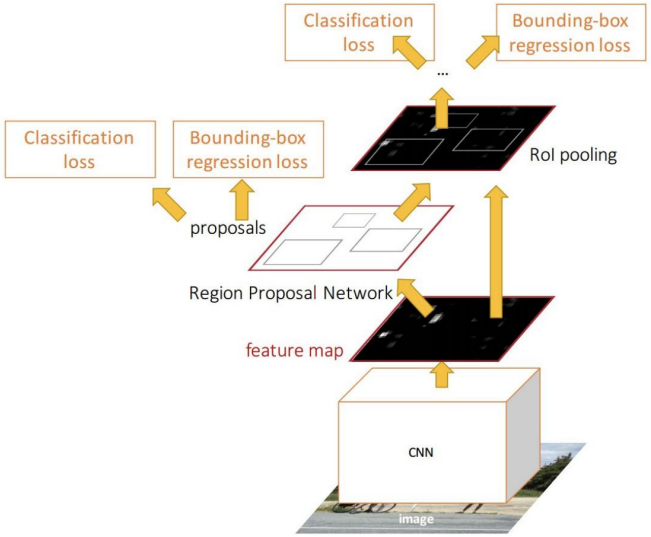


Image: Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Mask R-CNN

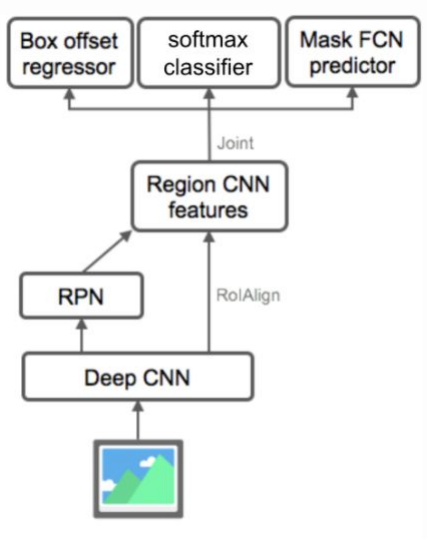


Image Source: Object Detection for Dummies Part 3: R-CNN Family

Model: Mask R-CNN

Transfer Learning:

- Start with a pretrained model
- Replace classifier and mask predictor
- Fine tune

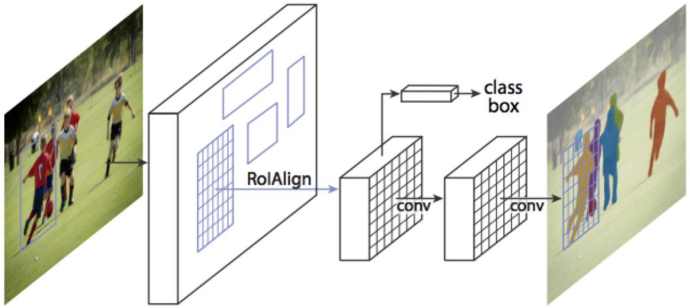


Image Source: Object Detection for Dummies Part 3: R-CNN Family

Loss Function: $\mathcal{L} = \mathcal{L}_{\text{cls}} + \mathcal{L}_{\text{box}} + \mathcal{L}_{\text{mask}}$

where;

$$\mathcal{L}(\{p_i\}, \{t_i\}) = \frac{1}{N_{\text{cls}}} \sum_i \mathcal{L}_{\text{cls}}(p_i, p_i^*) + \frac{\lambda}{N_{\text{box}}} \sum_i p_i^* \cdot L_1^{\text{smooth}}(t_i - t_i^*)$$

$$\mathcal{L}_{\text{cls}}(p_i, p_i^*) = -p_i^* \log p_i - (1 - p_i^*) \log(1 - p_i)$$

$$\mathcal{L}_{\text{mask}} = -\frac{1}{m^2} \sum_{1 \le i,j \le m} \left[y_{ij} \log \hat{y}_{ij}^k + (1 - y_{ij}) \log(1 - \hat{y}_{ij}^k) \right]$$

Model: Mask R-CNN

Transfer Learning:

- Start with a pretrained model
- Replace classifier and mask predictor
- Fine tune

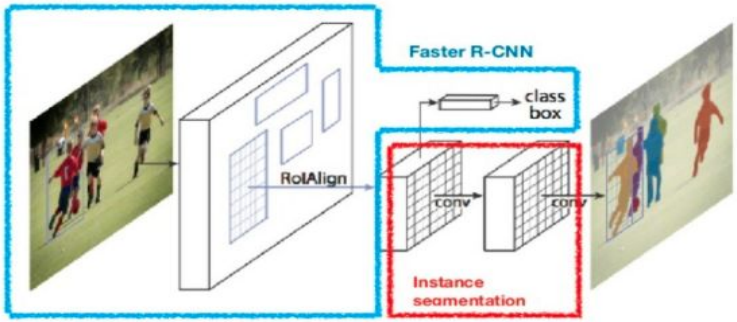


Image Source: Object Detection for Dummies Part 3: R-CNN Family

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Tutorials:

PyTorch:

- TORCHVISION OBJECT DETECTION FINETUNING TUTORIAL
  https://pytorch.org/tutorials/intermediate/torchvision_tutorial.html#torchvision-object-detection-finetuning-tutorial

Tensorflow:

- Object Detection API with Tensorflow 2
  https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/tf2.md

Keras:

- Object Detection with RetinaNet
  https://keras.io/examples/vision/retinanet/

Results: Metrics

- **Precision** = TP / (TP + FP)
- **Recall** = TP / (TP + FN)

- **Average Precision (AP):**
  Area under Precision/Recall curve

- **Mean AP (mAP):**
  Average AP over all classes

mAP@0.5 → TP if IoU > 0.5