Deep Learning for Computer Vision

CNNs for Object Detection

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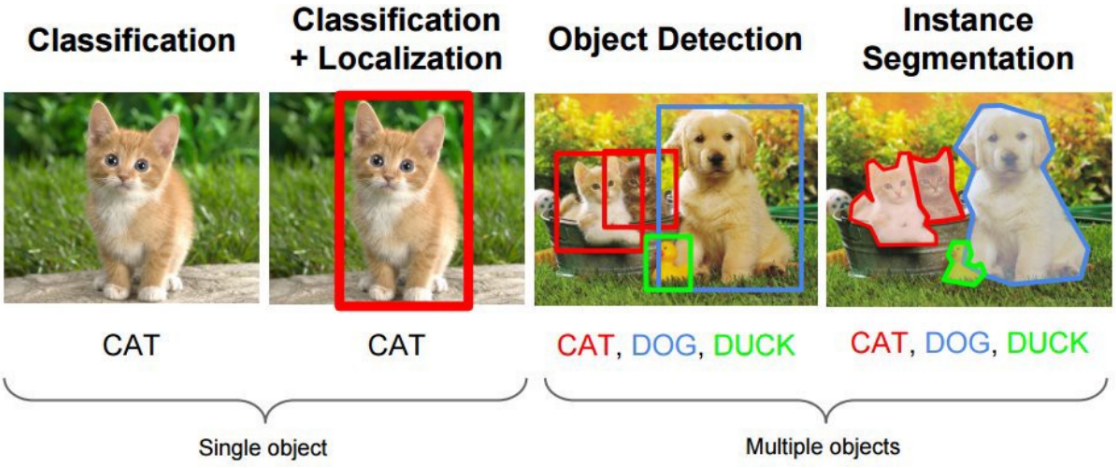
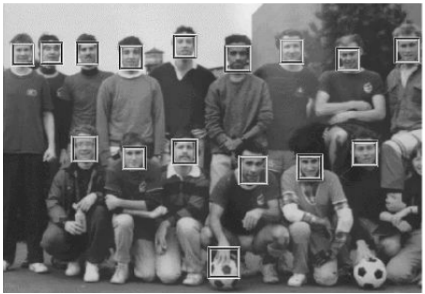
Classification vs Localization vs Detection



Credit: Mike Tamir, SIG & UC Berkeley

Detection in the Pre-Deep Learning Era: Viola-Jones Algorithm[1]

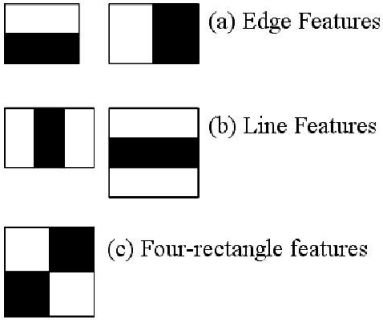
- A framework to perform object detection in real-time
- Used predominantly for detecting frontal upright faces.
- Consists of three main components:
  - Weak classification using **Haar-like features** and **Integral Images**
  - Adaboost to build strong classifier
  - Classifier cascades



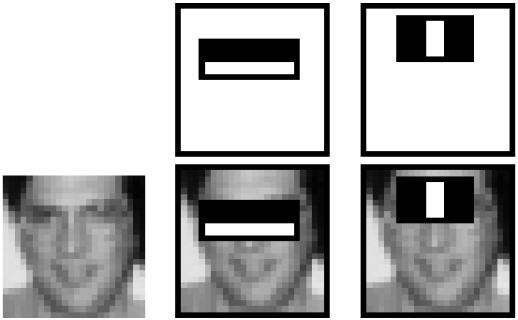
[1] Viola, Jones, Rapid Object Detection using a Boosted Cascade of Simple Features, CVPR 2001

Haar-like Features

- Rectangular features based on Haar wavelets
- Feature value given by sum of pixels in white rectangles subtracted from sum in black rectangles, i.e.
  $f = \Sigma(\textit{pixels inside black rectangle})$
  $-\Sigma(\textit{pixels inside white rectangle})$
- To normalize for images of all scales, features are scaled through height and width



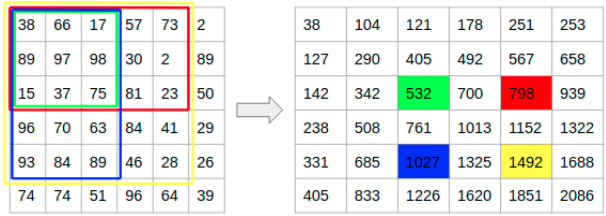
Haar Features: Intuition



Integral Image

- Reduces computational complexity caused while adding pixel intensities for any image operation
- For image i, Integral image ii is given by:

$$ii(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y')$$



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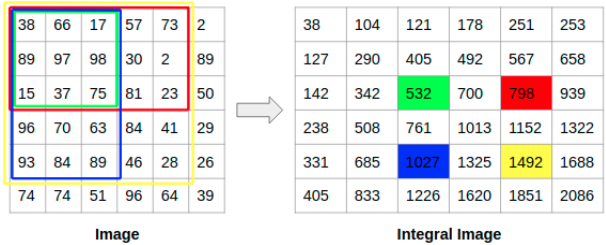


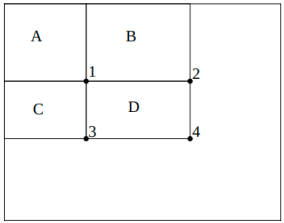
- Recurrent definition of $ii(x, y)$:

$$s(x, y) = s(x, y-1) + i(x, y)$$
$$ii(x, y) = ii(x-1, y) + s(x, y)$$

where $s(x, y)$ is cumulative row sum

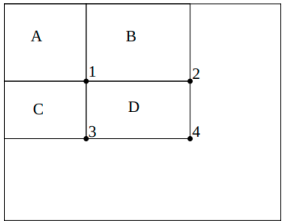
$$s(x, -1) = 0, ii(-1, y) = 0$$

Integral Image



- Sum of pixels within rectangle 1234 = D+A-(B+C) (Why?)

Integral Image



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- More formally, sum of pixels in rectangle with upper-left pixel as (x_1, y_1) and bottom-right pixel as (x_2, y_2) is given by:

$$\text{Sum} = ii(x_2, y_2) + ii(x_1 - 1, y_1 - 1) - \big(ii(x_1 - 1, y_2) + ii(x_2, y_1 - 1)\big)$$

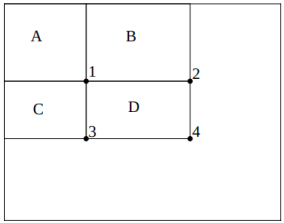
38	66	17	57	73	2
89	97	98	30	2	89
15	37	75	81	23	50
96	70	63	84	41	29
93	84	89	46	28	26
74	74	51	96	64	39

Sum of pixels = 199

38	104	121	178	251	253
127	290	405	492	567	658
142	342	532	700	798	939
238	508	761	1013	1152	1322
331	685	1027	1325	1492	1688
405	833	1226	1620	1851	2086

Sum of pixels = 1492 + 532 - 1027 -798 = 199

Integral Image



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2-rectangle features now require 6 look-ups. How many lookups do 3-rectangle and 4-rectangle features need? Homework!

Weak Classifiers

- Each feature is considered as a weak classifier
- Given feature f_j, a threshold θ_j and a parity p_j indicating the direction of the inequality sign, classifier can be defined as:

$$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$$

- Each classifier weak on its own, but combination gives strong classifiers

Do you see any problem here?

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Do you see any problem here?

For a sliding window base detector of size 24×24, there exist over 160k features. How to identify the best ones?

Classifier Training using AdaBoost

Recall: AdaBoost learns a strong classifier as a linear combination of weak classifiers

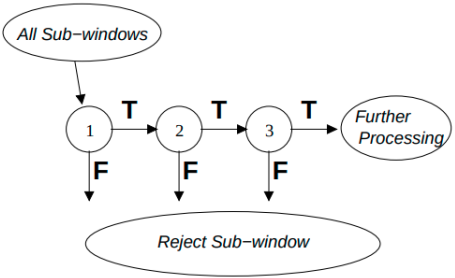
- Given example images $(x_1, y_1), \ldots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \ldots, T$:
  1. Normalize the weights,
  $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
  so that w_t is a probability distribution.
  2. For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i \left| h_j(x_i) - y_i \right|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
  $$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$
  where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is:
$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
where $\alpha_t = \log \frac{1}{\beta_t}$

Viola, Jones, Rapid Object Detection using a Boosted Cascade of Simple Features, CVPR 2001

Classifier Cascade

Intuition:

- Very less number of sub-windows actually have objects (False positive rate very high)
- But computation is equal across all sub-windows
- Eliminate negative windows earlier thereby, reducing computation time spent on them



Classifier Cascade: Why does it matter?

- A 1 MP has $\sim 10^6$ pixels and a comparable number of candidate face locations $\implies$ our ideal false positive (FP) rate has to be less than 10^{-6}

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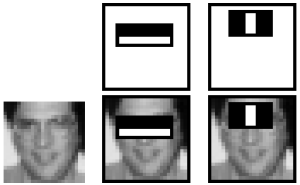

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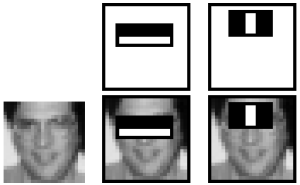

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- A 200-feature classifier can yield 95% detection rate and FP rate of 1 in 14084. Not enough!

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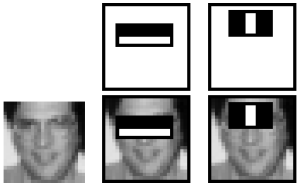

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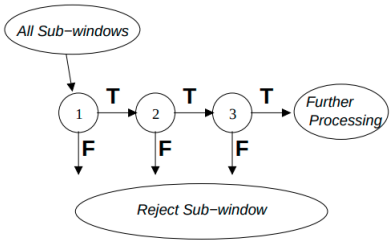
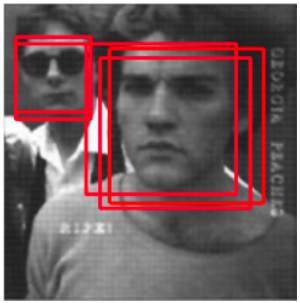


- Detection rate and FP rate of cascade are found by multiplying respective rates of individual stages
- Detection rate of 0.9 and FP rate on the order of 10^{-6} can be achieved by a 10-stage cascade if each stage has detection rate of 0.99 ($0.99^{10} \approx 0.9$) and FP rate of about 0.30 ($0.3^{10} \approx 6 \times 10^{-6}$)

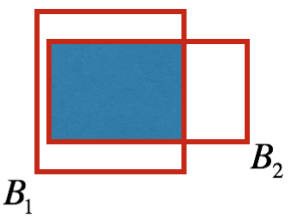
Non-Maximum Suppression (NMS)

- Usually, more than one bounding box is detected for same object
- Use bounding box similarity measures to identify duplicate bounding boxes which can be removed

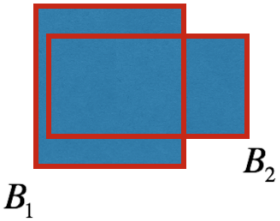


Intersection over Union (IoU)

Intersection

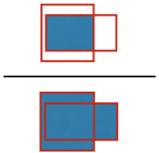


Union



Intersection over Union

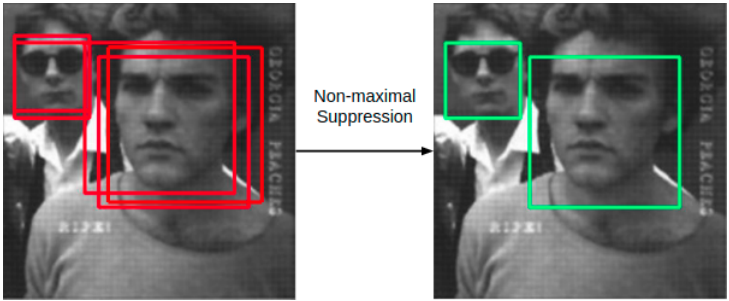
$$IoU = \frac{B_1 \cap B_2}{B_1 \cup B_2} =$$



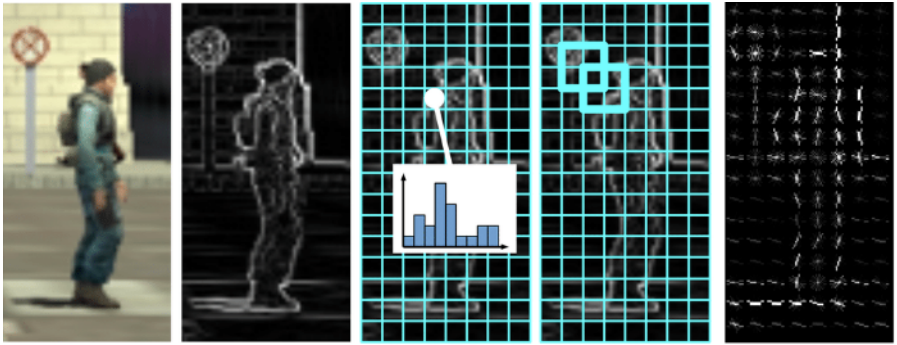
Credit: Hands-On Convolutional Neural Networks with TensorFlow, Iffat Zafar

Non-Maximum Suppression (NMS)

- Select a random box from a bounding box proposal list
- Compare it with rest of the boxes; if IoU > 0.5, remove box from list
- Repeat until boxes left are exclusive



Histograms of Oriented Gradients[2]



detection window slides over an image

at each location where the window is applied, gradients are computed

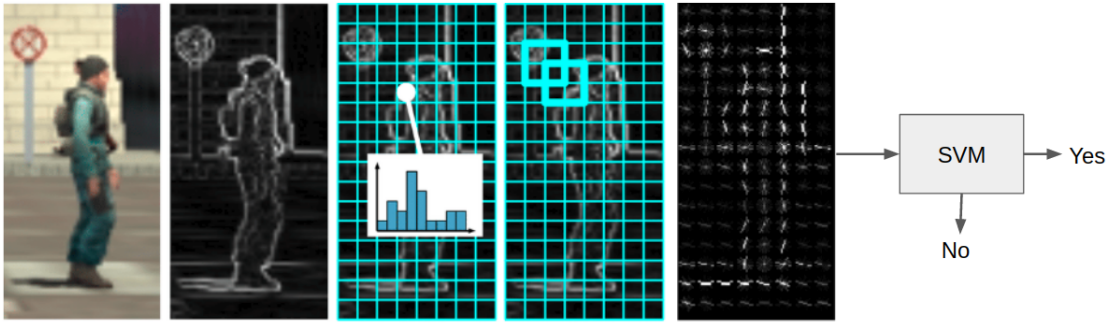
window is evently partitioned into cells and each pixel of the cell contirbutes to cell gradient orientation histogram

orientation histograms for overlapping 2x2 blocks of cells are normalized and collected to form the final descriptor
This is called Contrast Normalization

Final descriptor

[2]Dalal and Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Histograms of Oriented Gradients[2]



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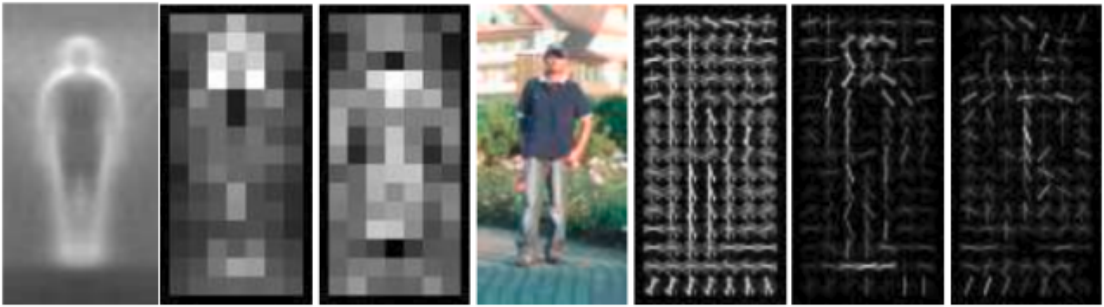
HOG: SVM Weights



Average gradient image over training examples

Maximum positive and negative SVM weights respectively centred on the block

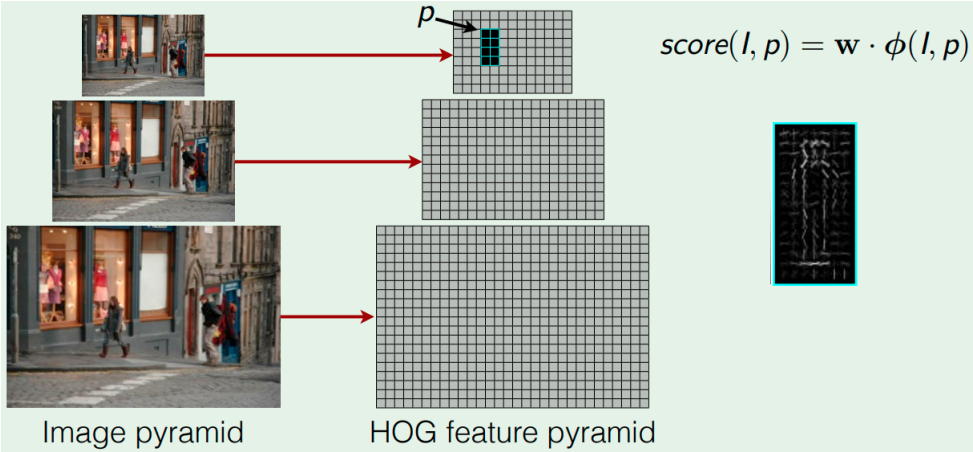
Test Image

HOG descriptor for test image

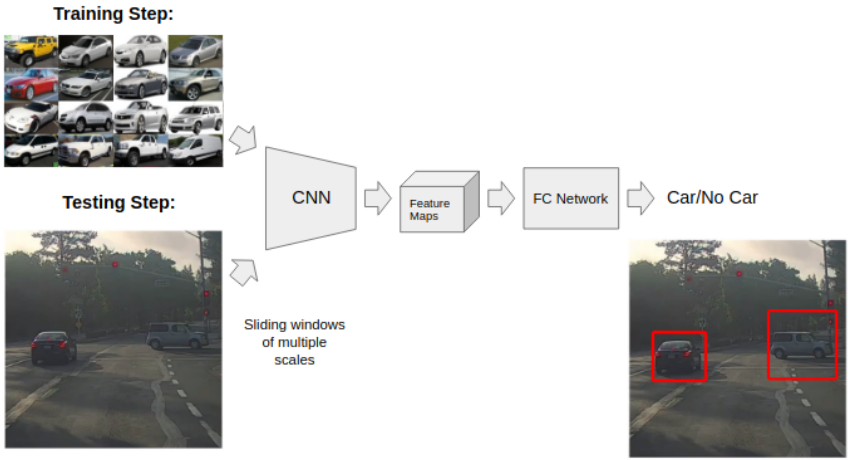
HOG descriptor weighted by positive and negative SVM weights respectively

Image Pyramid

To identify images of all sizes, repeat the process across multiple image scales

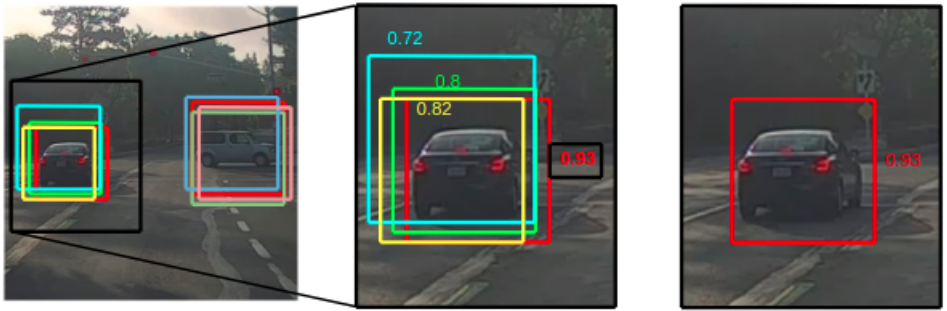


Object Detection using CNNs



Credit: Stanford Cars dataset, Jonathan Krause

Non-Maximum Suppression using Class Scores



List of all bounding boxes

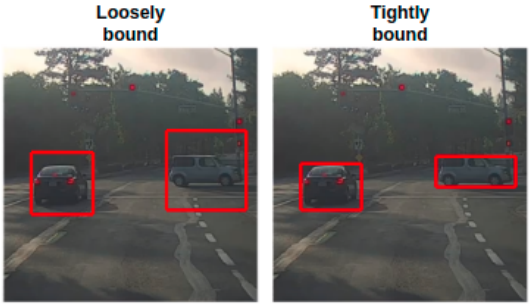
Identify box with highest class signal(0.93 red)

Eliminate the boxes with IOU>0.5 w.r.t red box

Object Detection using CNNs and Sliding Windows: Disadvantages

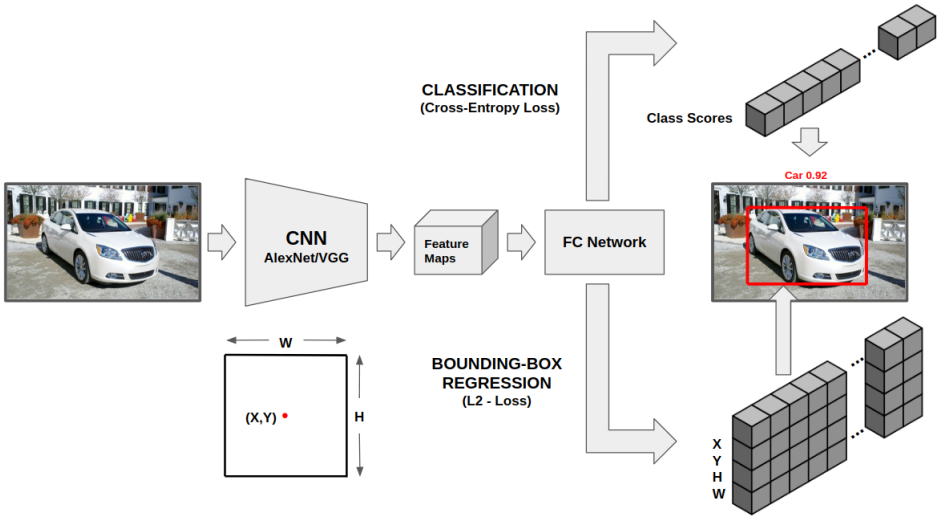
Object Detection using CNNs and Sliding Windows: Disadvantages

- Bounding boxes may not be tightly around the object



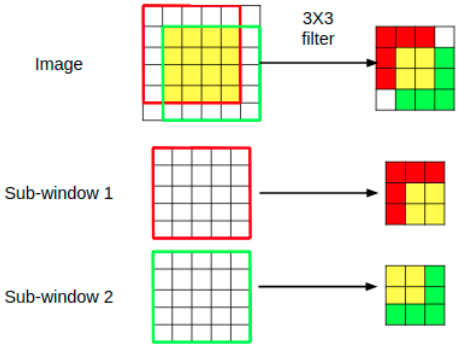
- Evaluating a CNN network on all sliding windows is computationally intensive and time consuming

Object Localization using Bounding Box Regression



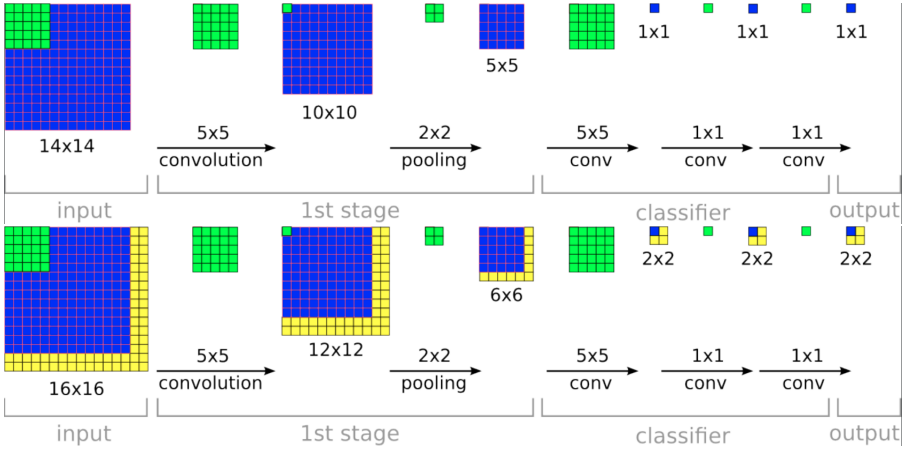
OverFeat: Integrated Recognition, Localization and Detection[3]

- Winner of ILSVRC 2013 Localization Challenge
- **Intuition**: Avoid computation time over sub-windows by applying filter directly to image



[3]Sermanet et al, OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks, ICLR 2014

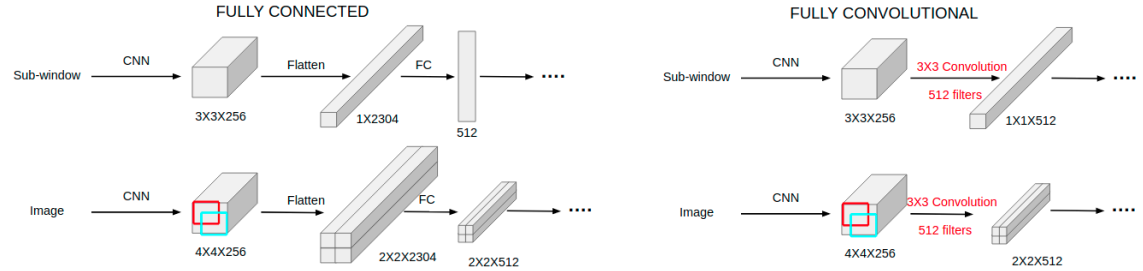
OverFeat: Integrated Recognition, Localization and Detection[4]



[4]Sermanet et al, OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks, ICLR 2014

OverFeat: Integrated Recognition, Localization and Detection[5]

The network used is fully convolutional, replacing fully connected layers with convolutional layers. Why?



[5]Sermanet et al, OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks, ICLR 2014

Contemporary Object Detection Methods

Region Proposal-based:

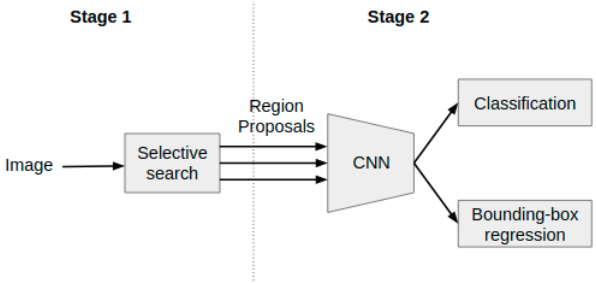
- Two-stage detection framework
- In the first stage, potential object regions are proposed (through methods such as Selective Search or Region Proposal Network, which we will see soon)
- In the second stage, a classifier processes the candidate regions
- More robust in performance but slower

Dense Sampling-based:

- One-stage detection framework
- Integrates region proposals and detection by acting on a dense sampling of possible locations
- Simple and fast but performance not as good as Region Proposal-based methods

R-CNN (Region-based Convolutional Neural Networks)[6]

- Region proposal-based object detection network
- Uses **Selective Search** as region proposal algorithm to identify potential objects
- Each region is then evaluated by a CNN that performs classification and bounding box regression



[6] Girshick et al, Rich feature hierarchies for accurate object detection and semantic segmentation, CVPR 2014

R-CNN: Selective Search

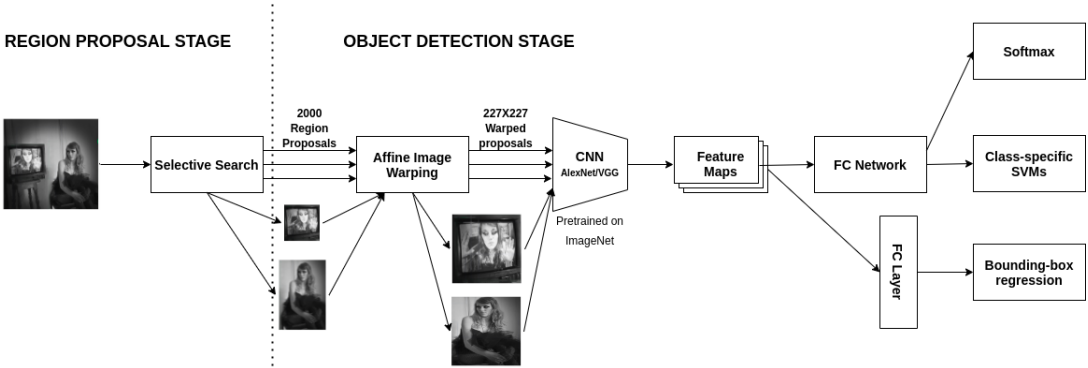
- Uses graph-based image segmentation or mean shift method for initial set of region hypotheses
- Hypotheses are hierarchically grouped/combined based on region similarity measures like color, texture, size and region-filling

R-CNN: Selective Search

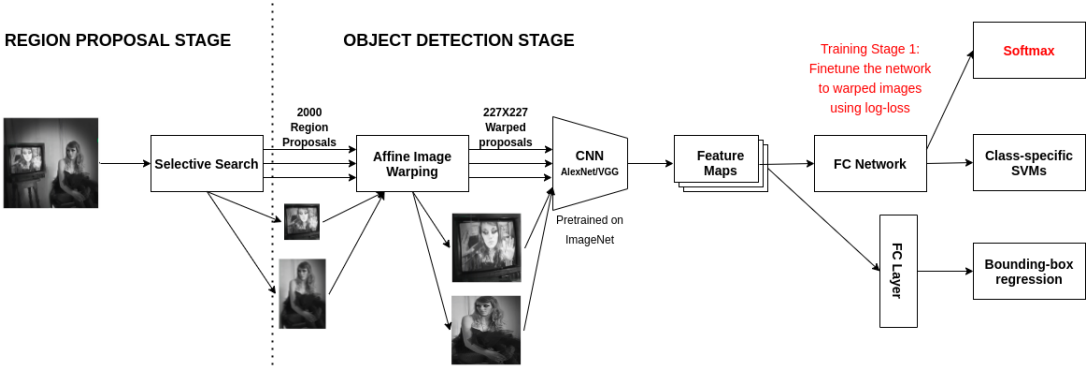
Initial proposals

Regions coalesce as we travel up the hierarchy

R-CNN


REGION PROPOSAL STAGE
OBJECT DETECTION STAGE
Selective Search
2000 Region Proposals
Affine Image Warping
227X227 Warped proposals
CNN
AlexNet/VGG
Pretrained on ImageNet
Feature Maps
FC Network
Softmax
Class-specific SVMs
FC Layer
Bounding-box regression

R-CNN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227X227 Warped proposals
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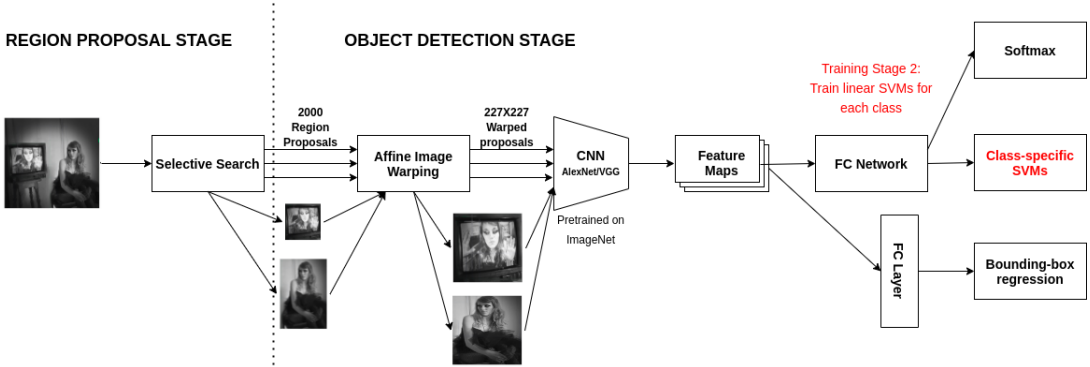
Feature Maps
FC Network
Training Stage 1: Finetune the network to warped images using log-loss
Softmax
Class-specific SVMs
FC Layer
Bounding-box regression

R-CNN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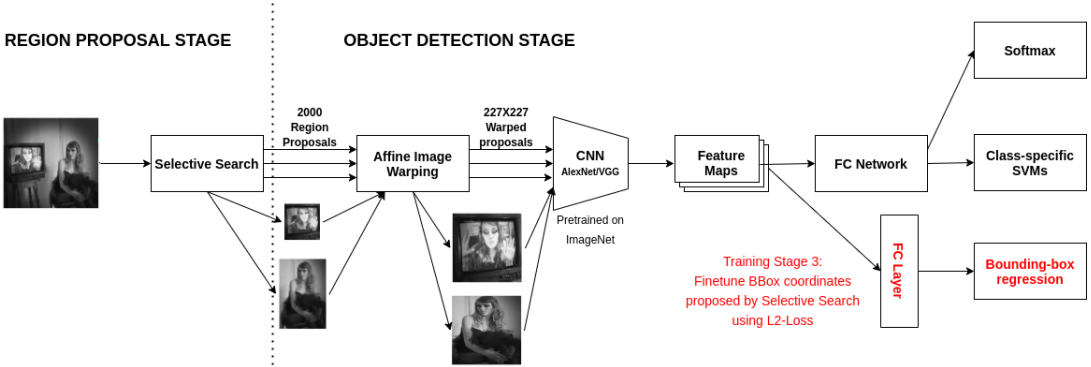
Selective Search
2000
Region
Proposals
Affine Image
Warping
227X227
Warped
proposals
CNN
AlexNet/VGG
Pretrained on
ImageNet
Feature
Maps
FC Network
Training Stage 2:
Train linear SVMs for
each class
Softmax
Class-specific
SVMs
FC Layer
Bounding-box
regression

R-CNN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Feature
Maps
FC Network
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SVMs
FC Layer
Bounding-box
regression
Training Stage 3:
Finetune BBox coordinates
proposed by Selective Search
using L2-Loss

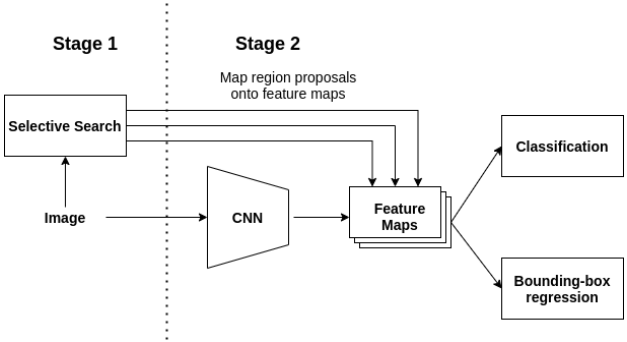
R-CNN: Limitations

R-CNN: Limitations

- Multi-stage pipeline of training
- Feature extraction of region proposals requires a lot of time and space; e.g. PASCAL VOC07 dataset with 5k images requires 2.5 GPU-days and several hundred GBs
- Object detection takes 47s/image at test time

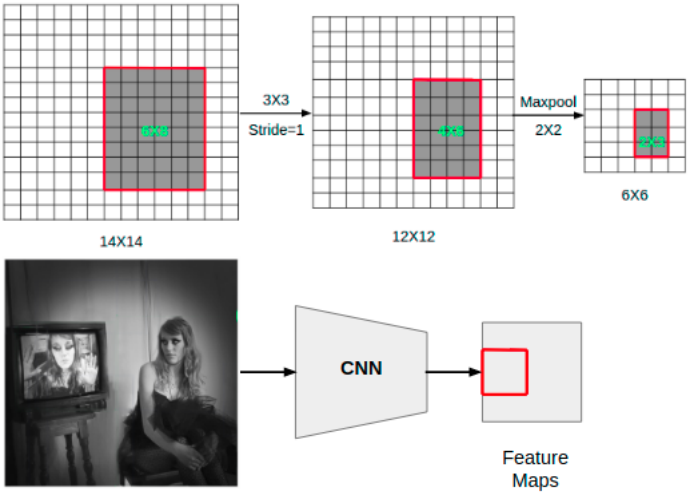
Fast R-CNN[7]

- Instead of passing each region proposal through CNN, extract their features directly from feature maps
- Use multi-task loss to integrate classification and bounding box regression training stages (no SVMs)



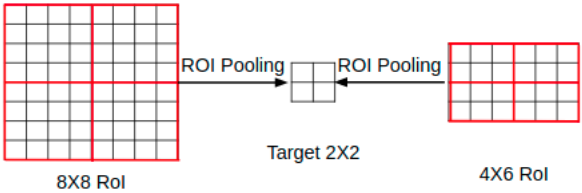
[7] Girshick, Fast R-CNN, ICCV 2015

Fast R-CNN: RoI Projection



Fast R-CNN: RoI Pooling

- RoIs can be of different scales
- We need a scale-invariant way of pooling
- Given an RoI of size $h \times w$, **RoI Pooling** converts this region into $H \times W$ grid of subwindows with each subwindow of size approximately equal to h/H, w/W



Fast R-CNN: Multi-Task Loss

- Let u be true class, and $\mathbf{v}$ be ground truth bounding box regression targets
- Let p be predicted class probability, and $\mathbf{t}^u = (t^u_x, t^u_y, t^u_w, t^u_h)$ be bounding box regression offsets for true class
- Loss for each ROI is then given by:

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

where:

$$L_{cls}(p, u) = -\log p_u$$

and Iverson bracket indicator function $[u \geq 1] = \begin{cases} 1 & \text{if } u \geq 1 \\ 0 & \text{otherwise} \end{cases}$

Fast R-CNN: Multi-task Loss

- Localization loss L_{loc} given by:

$$L_{loc}(\mathbf{t}^u, \mathbf{v}) = \sum_{i \in \{x,y,w,h\}} smooth_{L1}(\mathbf{t}_i^u - \mathbf{v}_i)$$

$$\text{where } smooth_{L1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases}$$

- Smooth L1 loss is less sensitive to outliers than L2 loss. Why?

Fast R-CNN: Multi-task Loss

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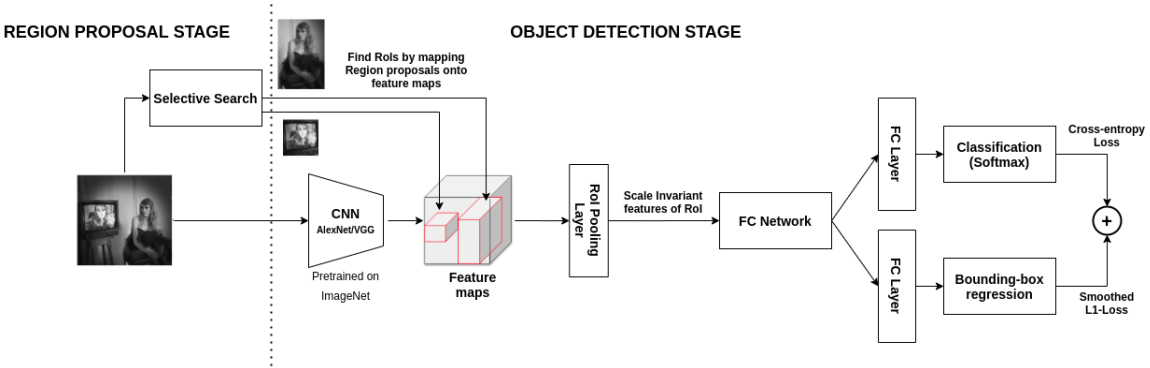
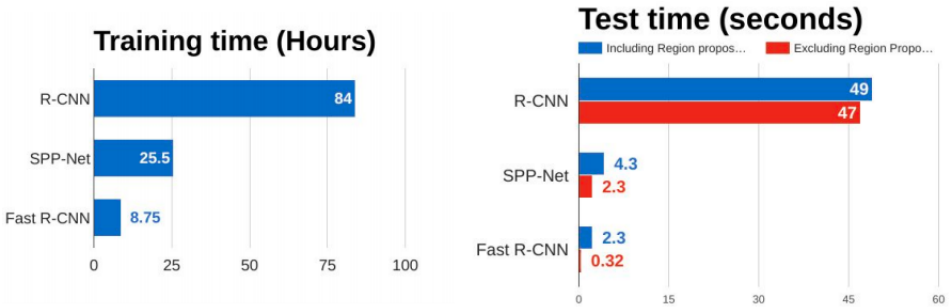
- Smooth L1 loss is less sensitive to outliers than L2 loss. Why? Homework!

Fast R-CNN: Summary



R-CNN vs Fast R-CNN: Time Comparison



Region proposals are slowing down Fast R-CNN

Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, cs231n, Stanford Univ

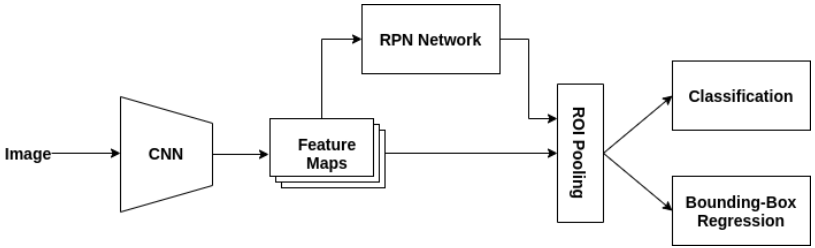
Faster R-CNN[8]

- Replaces Selective Search with a **Region Proposal Network** (RPN) to reduce time to compute regions

[8] Ren at al, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NeurIPS 2015

Faster R-CNN[8]

- Replaces Selective Search with a **Region Proposal Network** (RPN) to reduce time to compute regions
- Uses **anchor boxes** of different scales and aspect ratios to identify multiple objects present in the same window



[8]Ren at al, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NeurIPS 2015

Faster R-CNN: Anchor Boxes

Input Image
(e.g. 3 x 640 x 480)

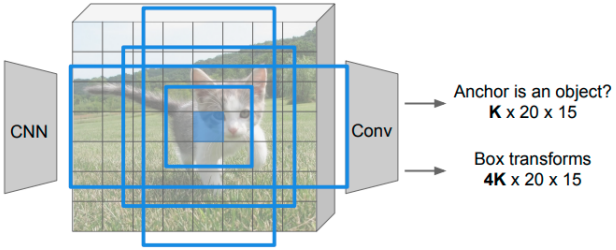
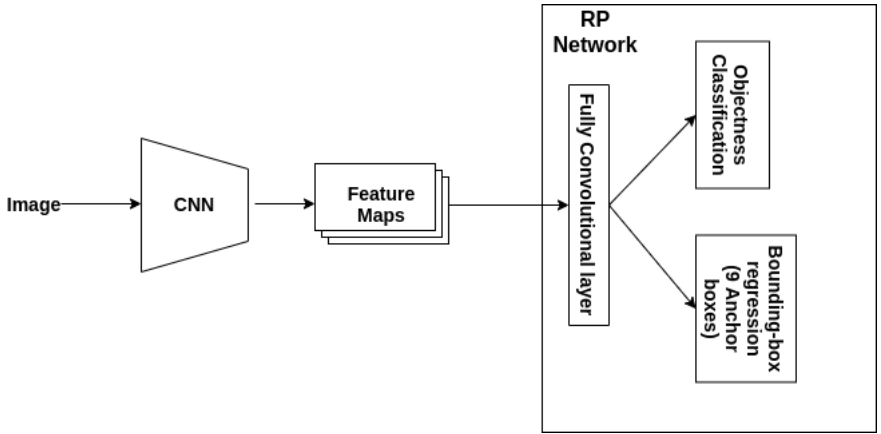


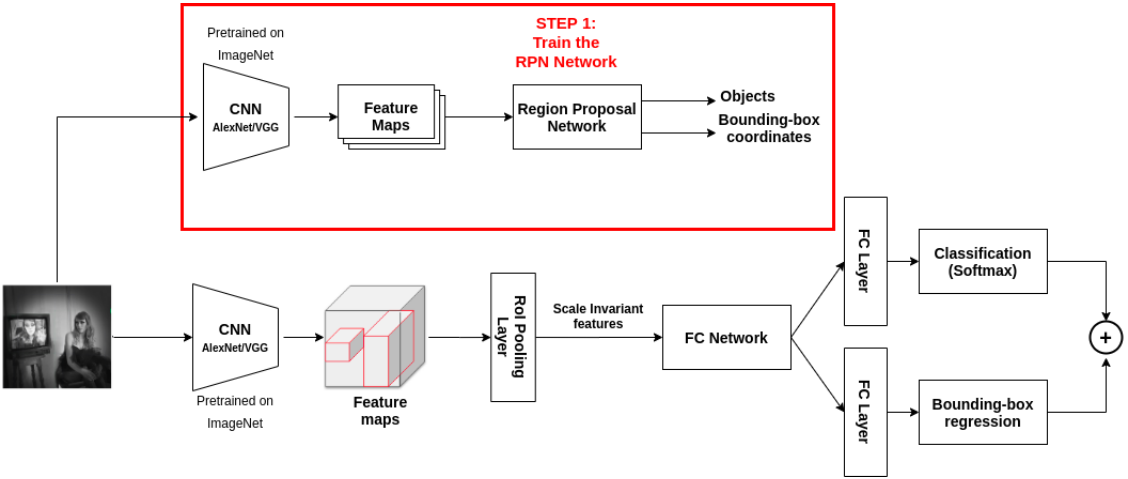
Image features
(e.g. 512 x 20 x 15)

Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, cs231n, Stanford Univ

Faster R-CNN: Region Proposal Network



Faster R-CNN: 4-step Training



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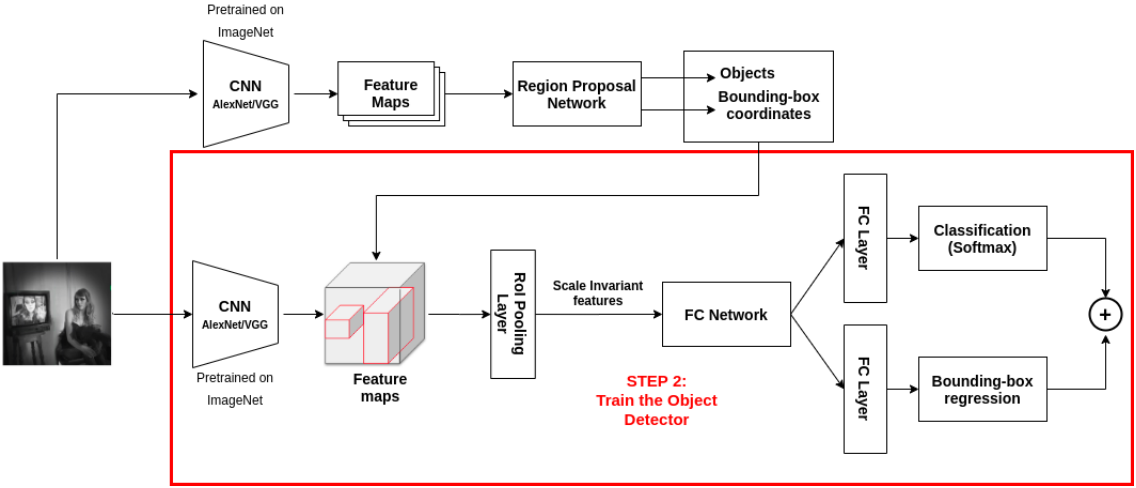

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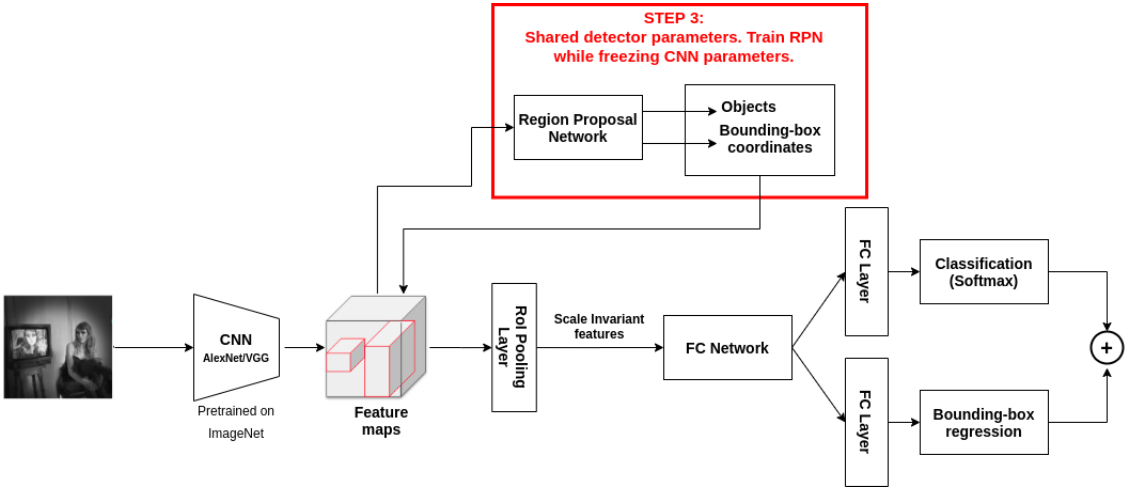

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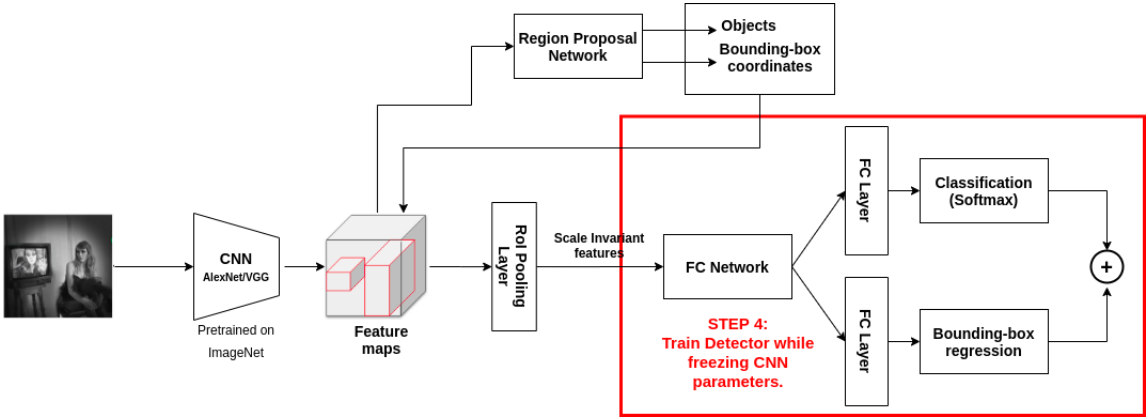
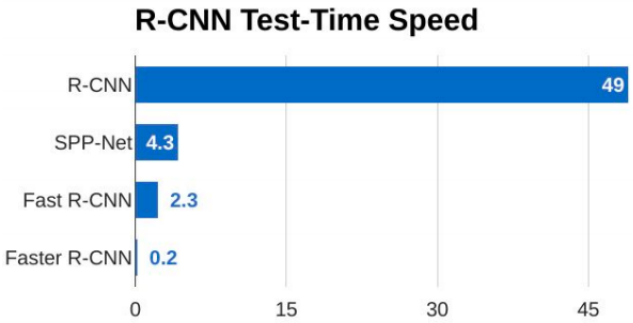


Faster R-CNN Performance



Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, cs231n, Stanford Univ

Homework

Readings

- Viola-Jones Object Detection Framework
- Object Detection for Dummies (Parts 1-3)
- Understanding Overfeat

Video Series

- Evolution of Object Detection Models (Chapter 5-8)

Exercise

Smooth L1 loss is less sensitive to outliers than L2 loss. Why?

References

Paul Viola and Michael Jones. "Rapid object detection using a boosted cascade of simple features". In: *Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001*. Vol. 1. IEEE. 2001, pp. I–I.

Navneet Dalal and Bill Triggs. "Histograms of oriented gradients for human detection". In: *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*. Vol. 1. IEEE. 2005, pp. 886–893.

Ross Girshick et al. "Rich feature hierarchies for accurate object detection and semantic segmentation". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014, pp. 580–587.

Ross Girshick. "Fast r-cnn". In: *Proceedings of the IEEE international conference on computer vision*. 2015, pp. 1440–1448.

Shaoqing Ren et al. "Faster r-cnn: Towards real-time object detection with region proposal networks". In: *Advances in neural information processing systems*. 2015, pp. 91–99.