Detection and Segmentation

CS60010: Deep Learning

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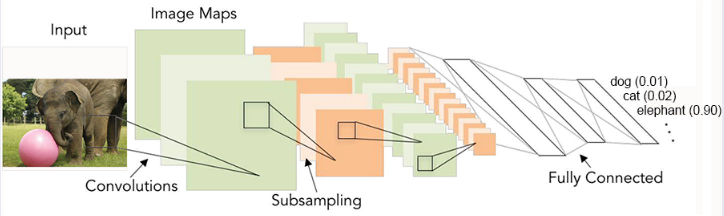
Feb 18, 19, Mar 02, 03, 04, 2022

Agenda

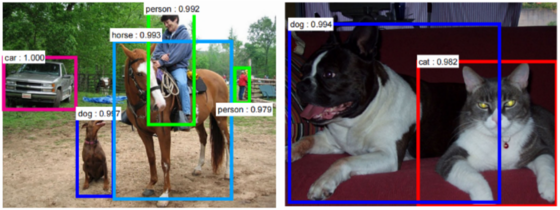
To get introduced to two important tasks of computer vision - detection and segmentation along with deep neural network's application in these areas in recent years.

From Classification to Detection

Classification

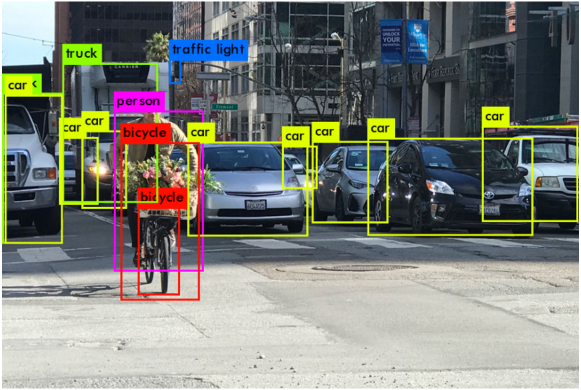


Detection

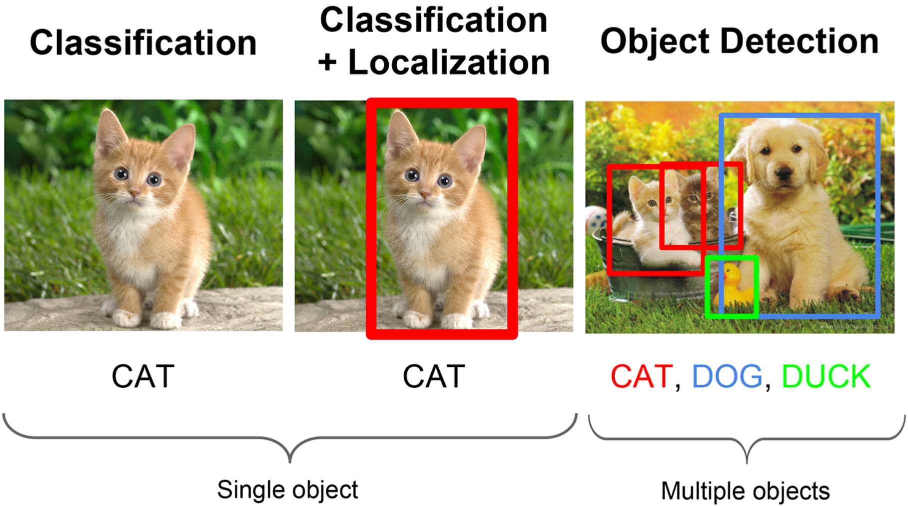


Challenges of Object Detection

- Simultaneous recognition and localization
- Images may contain objects from more than one class and multiple instances of the same class
- Evaluation

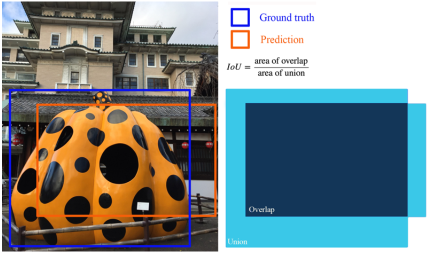


Localization and Detection



Evaluation

- At test time 3 things are predicted:- Bounding box coordinates, Bounding box class label, Confidence score
- Performance is measured in terms of IoU (Intersection over Union)

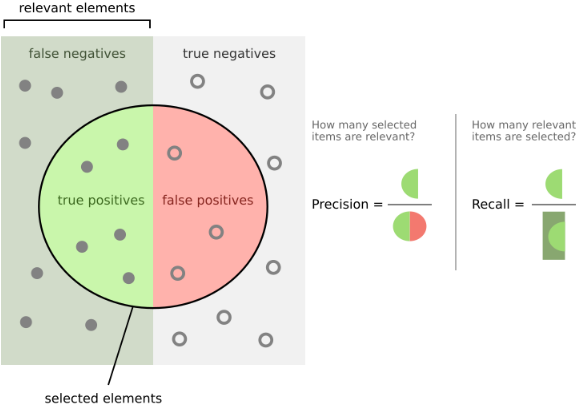


- According to PASCAL criterion,
  - a detection is correct if IoU > 0.5
  - For multiple detections only one is considered **true positive**

by the (decreasing) confidence output. Multiple detections of the same object in an image were considered false detections e.g. 5 detections of a single object counted as 1 correct detection and 4 false detections—it was the responsibility of the participant's system to filter multiple detections from its output.

Image Source

Evaluation: Precision-Recall



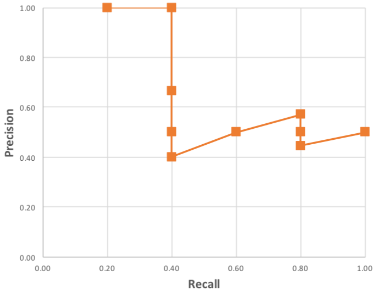
- precision $= \frac{tp}{tp+fp}$
- recall $= \frac{tp}{tp+fn}$

Image Source

Evaluation: Average Precision

Lets consider an image with 5 apples where our detector provides 10 detections.

Rank	Correct	Precision	Recall
1	True Positive	1.00	0.20
2	True Positive	1.00	0.40
3	False Positive	0.67	0.40
4	False Positive	0.50	0.40
5	False Positive	0.40	0.40
6	True Positive	0.50	0.60
7	True Positive	0.57	0.80
8	False Positive	0.50	0.80
9	False Positive	0.44	0.80
10	True Positive	0.50	1.00

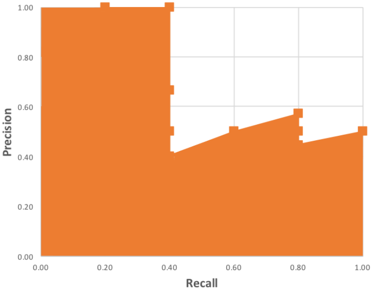


Source: This medium post

Evaluation: Average Precision

Area under curve is a measure of performance. This gives the average precision of the detector.

Rank	Correct	Precision	Recall
1	True Positive	1.00	0.20
2	True Positive	1.00	0.40
3	False Positive	0.67	0.40
4	False Positive	0.50	0.40
5	False Positive	0.40	0.40
6	True Positive	0.50	0.60
7	True Positive	0.57	0.80
8	False Positive	0.50	0.80
9	False Positive	0.44	0.80
10	True Positive	0.50	1.00

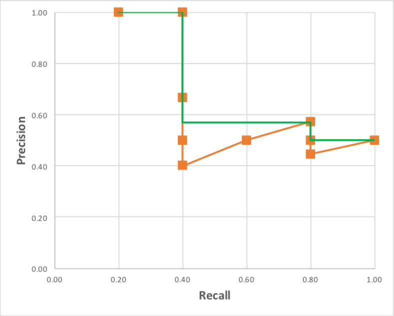


Source: This medium post

Evaluation: mean Average Precision

A little more detail:

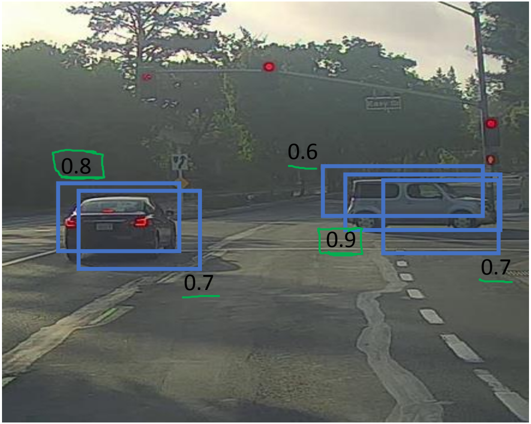
- The curve is made smooth from the zigzag pattern by finding the highest precision value at or to the right side of the recall values.
- Then the average is taken for 11 recall values (0, 0.1, 0.2, ... 1.0) - Average Precison (AP)
- The mean average precision (mAP) is the mean of the average precisions (AP) for all classes of objects.



Source: This medium post

Non-max Suppression

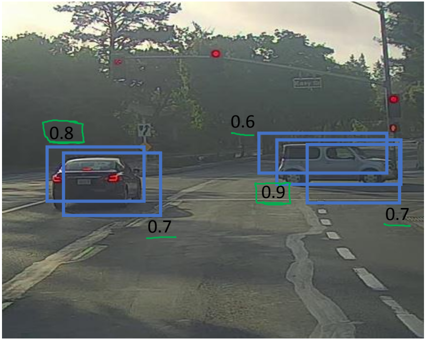
What to do if there are multiple detections of the same object? Can you think its effect on precision-recall?



Source: deeplearning.ai

Non-max Suppression

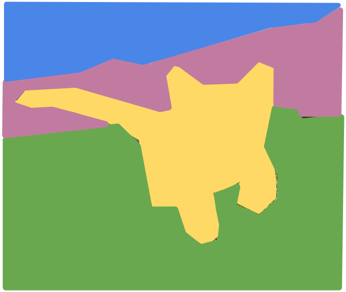
- Sort the predictions by the confidence scores
- Starting with the top score prediction, ignore any other prediction of the same class and high overlap (*e.g.*, IoU > 0.5) with the top ranked prediction
- Repeat the above step until all predictions are checked



Source: deeplearning.ai

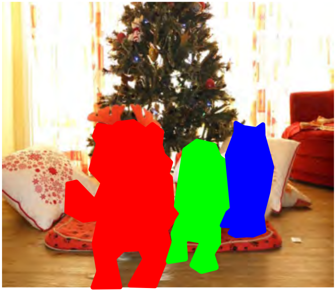
Segmentation

Semantic Segmentation



GRASS, CAT, TREE, SKY

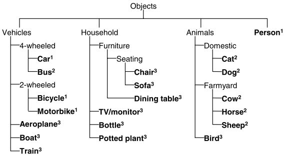
Instance Segmentation

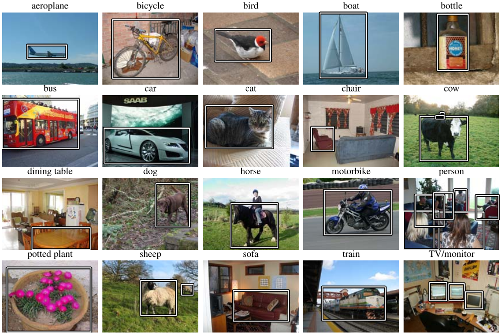


DOG, DOG, CAT

Source: cs231n course, Stanford University

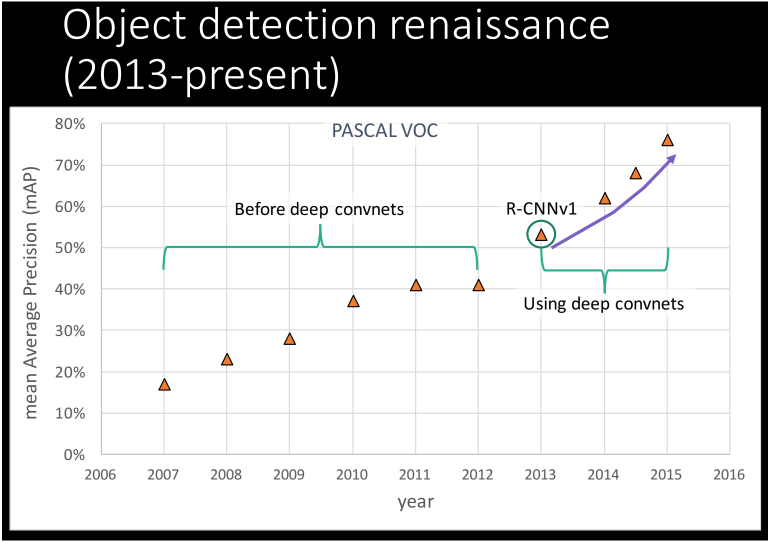
PASCAL VOC





- Dataset size (by 2012): 11.5K training/val images, 27K bounding boxes, 7K segmentations

PASCAL VOC



Source: ICCV '15, Fast R-CNN

COCO Dataset

COCO
Common Objects in Context

What is COCO?

COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

- Object segmentation
- Recognition in context
- Superpixel stuff segmentation
- 330K images (>200K labeled)
- 1.5 million object instances
- 80 object categories
- 91 stuff categories
- 5 captions per image
- 250,000 people with keypoints

Source: http://cocodataset.org

COCO Tasks

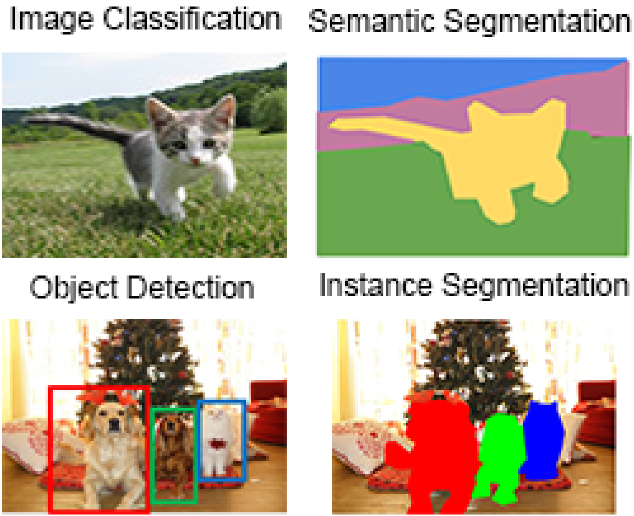


Image Classification
Semantic Segmentation
Object Detection
Instance Segmentation

Classification + Localization

Classification + Localization: Task

Classification: C classes
Input: Image
Output: Class label
Evaluation metric: Accuracy

Localization:
Input: Image
Output: Box in the image (x, y, w, h)
Evaluation metric: Intersection over Union

Classification + Localization: Do both

Source: cs231n course, Stanford University

Classification + Localization

Idea #1: Localization as Regression

Input: image

Neural Net →

Output:
Box coordinates
(4 numbers)

Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

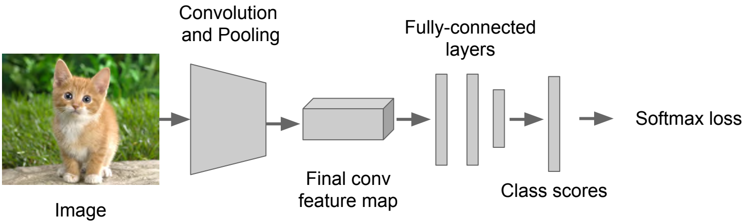
Only one object,
simpler than detection

Source: cs231n course, Stanford University

Classification + Localization

Simple Recipe for Classification + Localization

Step 1: Train (or download) a classification model (AlexNet, VGG, GoogLeNet)

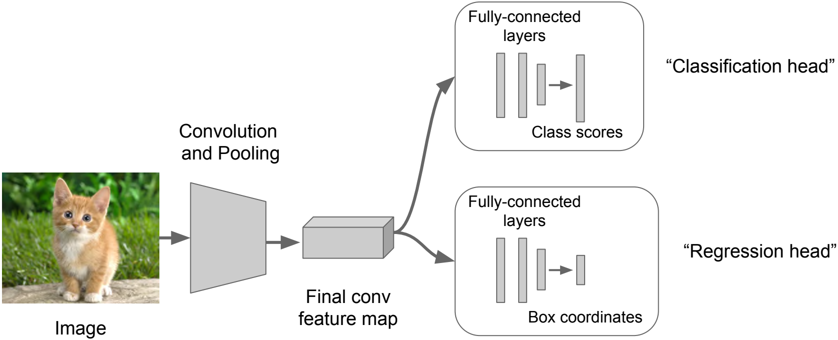


Source: cs231n course, Stanford University

Classification + Localization

Simple Recipe for Classification + Localization

Step 2: Attach new fully-connected "regression head" to the network

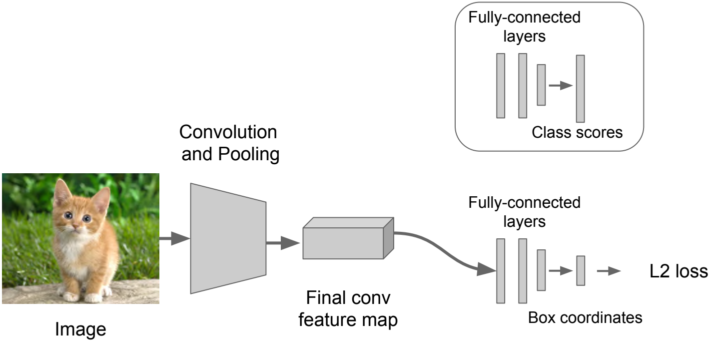


Source: cs231n course, Stanford University

Classification + Localization

Simple Recipe for Classification + Localization

Step 3: Train the regression head only with SGD and L2 loss

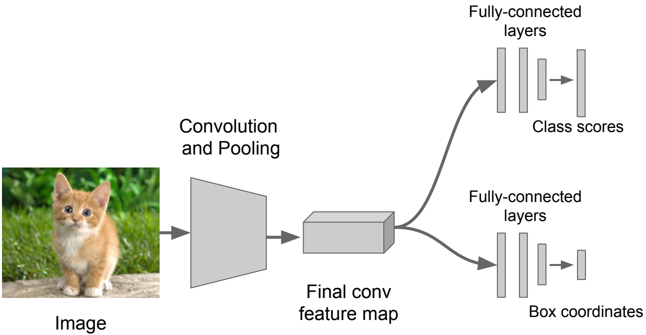


Source: cs231n course, Stanford University

Classification + Localization

Simple Recipe for Classification + Localization

Step 4: At test time use both heads



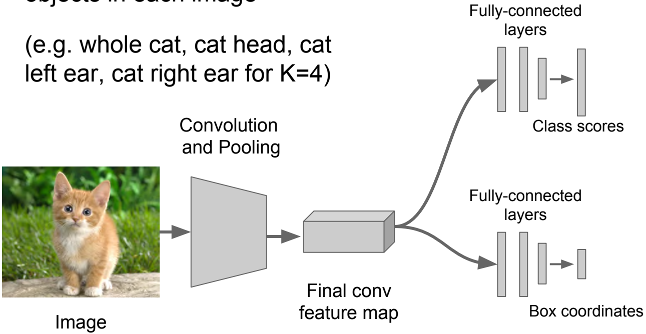
Source: cs231n course, Stanford University

Classification + Localization

Aside: Localizing multiple objects

Want to localize **exactly** K objects in each image

(e.g. whole cat, cat head, cat left ear, cat right ear for K=4)



K x 4 numbers (one box per object)

Source: cs231n course, Stanford University

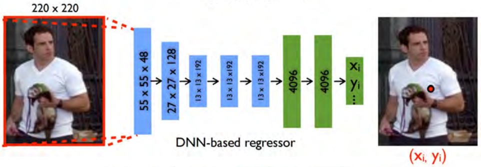
Classification + Localization

Aside: Human Pose Estimation

Represent a person by K joints

Regress (x, y) for each joint from last fully-connected layer of AlexNet

(Details: Normalized coordinates, iterative refinement)



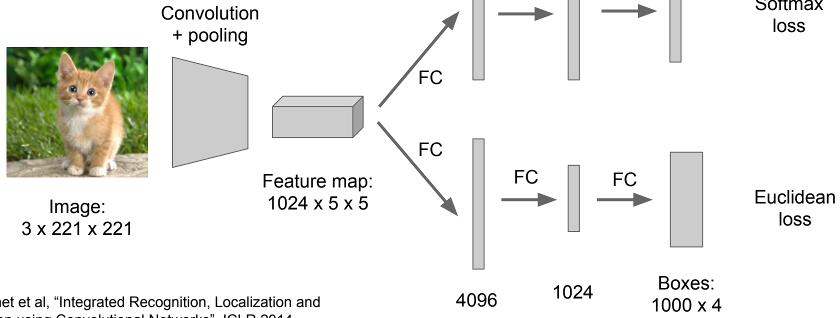
Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014

Source: cs231n course, Stanford University

Classification + Localization

Sliding Window: Overfeat

Winner of ILSVRC 2013 localization challenge

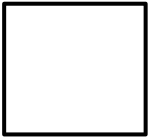


Sermanet et al, "Integrated Recognition, Localization and Detection using Convolutional Networks", ICLR 2014

Source: cs231n course, Stanford University

Classification + Localization

Sliding Window: Overfeat



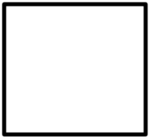
Network input:
3 x 221 x 221

Larger image:
3 x 257 x 257

Source: cs231n course, Stanford University

Classification + Localization

Sliding Window: Overfeat



Network input:
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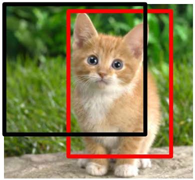


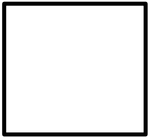
Larger image:
3 x 257 x 257

Classification scores:
P(cat)

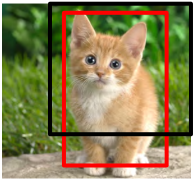
Source: cs231n course, Stanford University

Classification + Localization

Sliding Window: Overfeat



Network input:
3 x 221 x 221



Larger image:
3 x 257 x 257

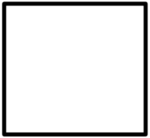
0.5	0.75

Classification scores:
P(cat)

Source: cs231n course, Stanford University

Classification + Localization

Sliding Window: Overfeat



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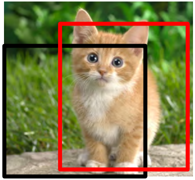
3 x 221 x 221



Larger image:
3 x 257 x 257

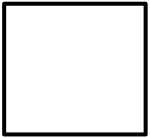
0.5	0.75
0.6	

Classification scores:
P(cat)

Source: cs231n course, Stanford University

Classification + Localization

Sliding Window: Overfeat



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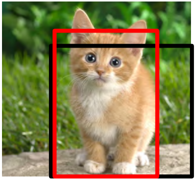


Larger image:
3 x 257 x 257

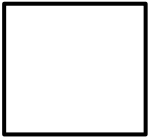
0.5	0.75
0.6	0.8

Classification scores:
P(cat)

Source: cs231n course, Stanford University

Classification + Localization

Sliding Window: Overfeat



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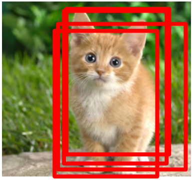


Larger image:
3 x 257 x 257

0.5	0.75
0.6	0.8

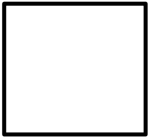
Classification scores:
P(cat)

Source: cs231n course, Stanford University

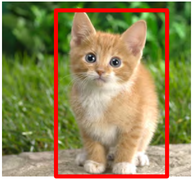
Classification + Localization

Sliding Window: Overfeat

Greedily merge boxes and scores (details in paper)



Network input:
3 x 221 x 221



Larger image:
3 x 257 x 257

0.8

Classification score: P (cat)

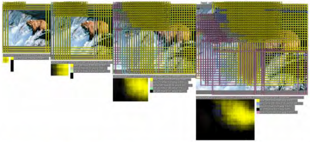
Source: cs231n course, Stanford University

Classification + Localization

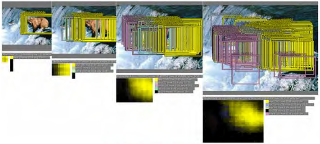
Sliding Window: Overfeat

In practice use many sliding window locations and multiple scales

Window positions + score maps



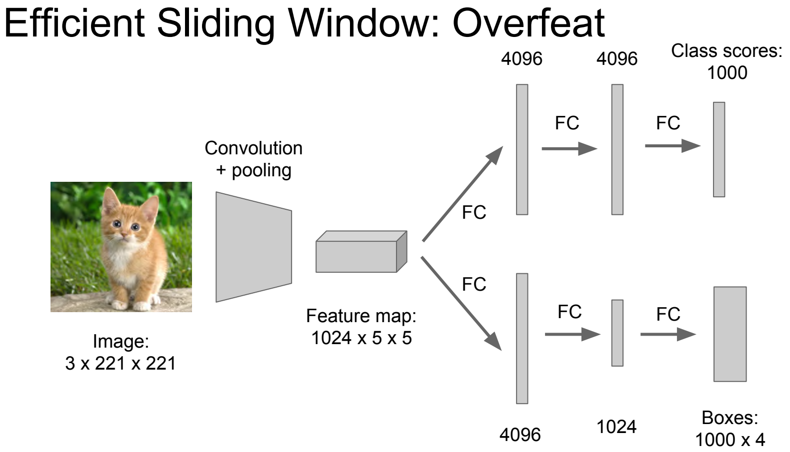
Box regression outputs



Final Predictions

Source: cs231n course, Stanford University

Classification + Localization

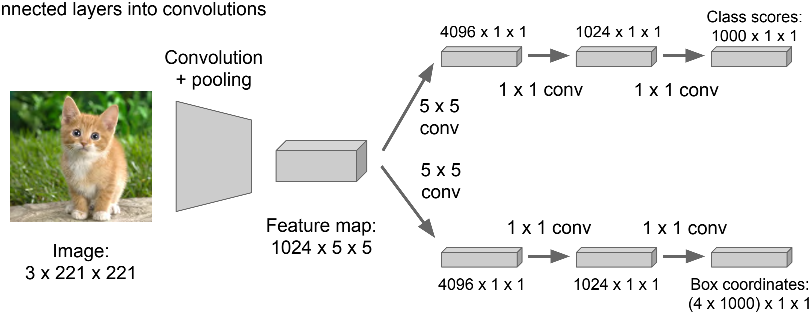


Source: cs231n course, Stanford University

Classification + Localization

Efficient Sliding Window: Overfeat

Efficient sliding window by converting fully-connected layers into convolutions



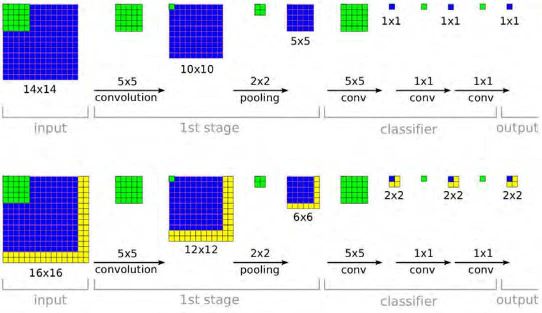
Source: cs231n course, Stanford University

Classification + Localization

Efficient Sliding Window: Overfeat

Training time: Small image, 1 x 1 classifier output

Test time: Larger image, 2 x 2 classifier output, only extra compute at yellow regions

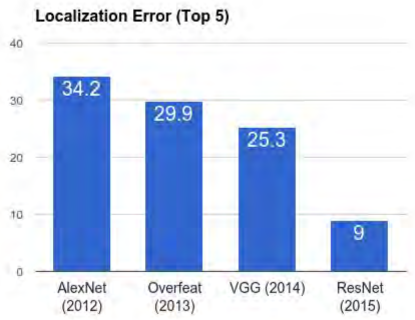


Sermanet et al, "Integrated Recognition, Localization and Detection using Convolutional Networks", ICLR 2014

Source: cs231n course, Stanford University

Classification + Localization

ImageNet Classification + Localization



AlexNet: Localization method not published

Overfeat: Multiscale convolutional regression with box merging

VGG: Same as Overfeat, but fewer scales and locations; simpler method, gains all due to deeper features

ResNet: Different localization method (RPN) and much deeper features

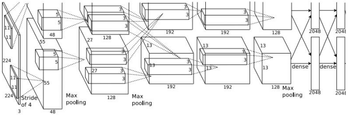
Source: cs231n course, Stanford University

Detection as Regression

- In detection you don't know the number of objects present
- So, it is problematic to address detection as regression
- How many output neurons to put?

Detection as Classification

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

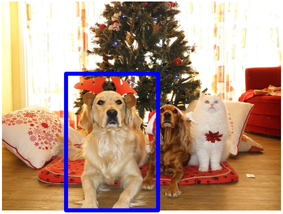


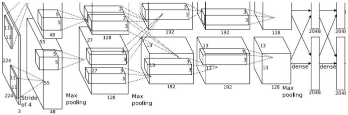
Dog? NO
Cat? NO
Background? YES

CS231n course, Stanford University

Detection as Classification

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



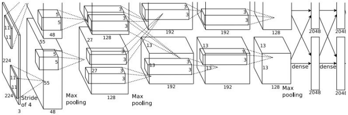


Dog? YES
Cat? NO
Background? NO

CS231n course, Stanford University

Detection as Classification

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

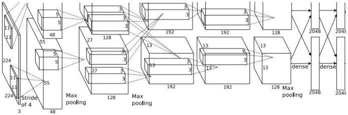


Dog? YES
Cat? NO
Background? NO

CS231n course, Stanford University

Detection as Classification

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

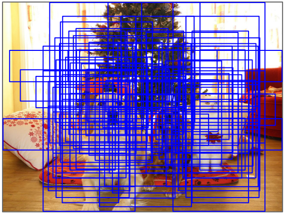


Dog? NO
Cat? YES
Background? NO

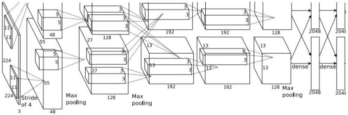
CS231n course, Stanford University

Detection as Classification

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Problem: Need to apply CNN to huge number of locations, scales, and aspect ratios, very computationally expensive!



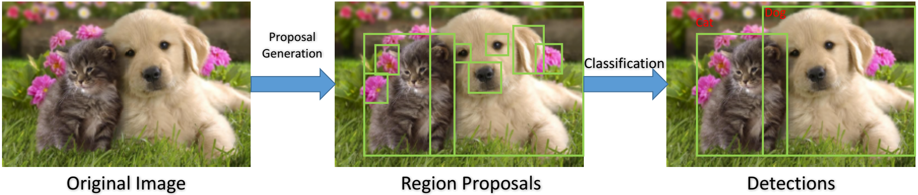
Dog? NO
Cat? YES
Background? NO

CS231n course, Stanford University

Detection as Classification

- Need to apply CNN to huge number of locations, scales and aspect ratios
- If the classifier is fast enough, this is done. Pre Deep Learning approach.
- Deep learning classifiers, first get a tiny subset of possible positions. Only these are passed through the deep classifiers.
- The possible positions are called 'candidate proposals' or 'region proposals'.

Detection with Region Proposals



- Generate and evaluate a few (much less than exhaustive search) region proposals
- Proposal mechanism can take advantage of low-level cues (*e.g.*, edges or connected components)
- Classifier can be slower but more powerful

Selective Search

J Uijlings, K van de Sande, T Gevers, and A Smeulders, 'Selective Search for Object Recognition', IJCV 2013

Selective Search

Algorithm 1: Hierarchical Grouping Algorithm

Input: (colour) image
Output: Set of object location hypotheses L

Obtain initial regions $R = \{r_1, \cdots, r_n\}$ using [13]
Initialise similarity set $S = \emptyset$
foreach *Neighbouring region pair* (r_i, r_j) **do**
  Calculate similarity $s(r_i, r_j)$
  $S = S \cup s(r_i, r_j)$

while $S \neq \emptyset$ **do**
  Get highest similarity $s(r_i, r_j) = \max(S)$
  Merge corresponding regions $r_t = r_i \cup r_j$
  Remove similarities regarding $r_i : S = S \setminus s(r_i, r_*)$
  Remove similarities regarding $r_j : S = S \setminus s(r_*, r_j)$
  Calculate similarity set S_t between r_t and its neighbours
  $S = S \cup S_t$
  $R = R \cup r_t$

Extract object location boxes L from all regions in R

J Uijlings, K van de Sande, T Gevers, and A Smeulders, 'Selective Search for Object Recognition', IJCV 2013

EdgeBoxes

- Edgeboxes depend on a fast scoring/evaluating method for bounding boxes.
- First edges are extracted for the whole image and they are grouped according to their similarity
- The main idea of scoring boxes builds on the fact that edges tend to correspond to object boundaries and bounding boxes that tightly enclose a set of edges are likely to contain an object.
- Gets 75% recall with 800 boxes (vs 1400 for Selective Search) and is 40 times faster

C Zitnick and P Dollar, 'Edge Boxes: Locating Object Proposals from Edges', ECCV 2014

Many Region Proposal Methods

Method	Approach	Outputs Segments	Outputs Score	Control #proposals	Time (sec.)	Repea-tability	Recall Results	Detection Results
Bing [18]	Window scoring		✓	✓	0.2	★★★	★	·
CPMC [19]	Grouping	✓	✓	✓	250	-	★★	★
EdgeBoxes [20]	Window scoring		✓	✓	0.3	★★	★★★	★★★
Endres [21]	Grouping	✓	✓	✓	100	-	★★★	★★
Geodesic [22]	Grouping	✓		✓	1	★	★★★	★★
MCG [23]	Grouping	✓	✓	✓	30	★	★★★	★★★
Objectness [24]	Window scoring		✓	✓	3	·	★	·
Rahtu [25]	Window scoring		✓	✓	3	·	·	★
RandomizedPrim's [26]	Grouping	✓		✓	1	★	★	★★
Rantalankila [27]	Grouping	✓		✓	10	★★	·	★★
Rigor [28]	Grouping	✓		✓	10	★	★★	★★
SelectiveSearch [29]	Grouping	✓	✓	✓	10	★★	★★★	★★★
Gaussian				✓	0	·	·	★
SlidingWindow				✓	0	★★★	·	·
Superpixels		✓			1	★	·	·
Uniform				✓	0	·	·	·

J Hosang, R Benenson, P Dollar and B Schiele, 'What makes for effective detection proposals?', IEEE TPAMI 2016