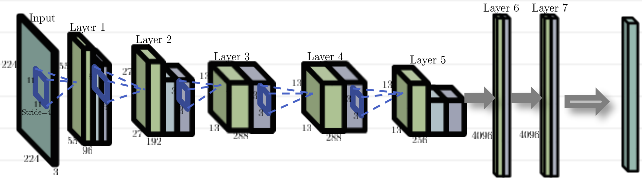
Lecture 6: Convolutional Networks in Computer Vision

Haven't it all been about computer vision?

(in fact, No)

What is this? Ostrich



What is this? Cat

The art of asking right questions

What *is this?*

It is a car (and a road and a building)

A lot of applications need to answer ***Where?***

The art of asking right questions

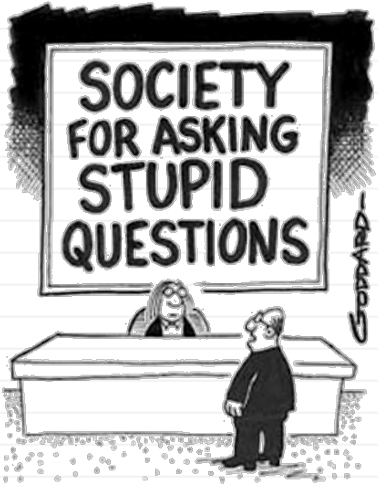
What is this?

It is a human!

A lot of applications need to answer ***Who? / Is it the same person as X?***

Questions answered by computer vision

- ***What*** is this?
- ***Where*** are the things?
  - ..in the image
  - ..in the 3D world
- ***Who*** is this?
- ***How far*** is this thing?
- ***What is*** he/she/they ***doing***?
- *What is the shape*?
- ….



"Excuse me, is this the Society for Asking Stupid Questions?"

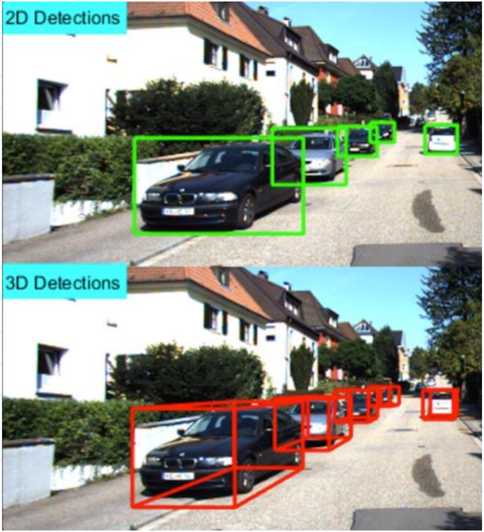
Answering the where question

Format 1: semantic segmentation

Answering the where question

Format 2: object detection

Today



Answering the where question

Format 3: instance segmentation

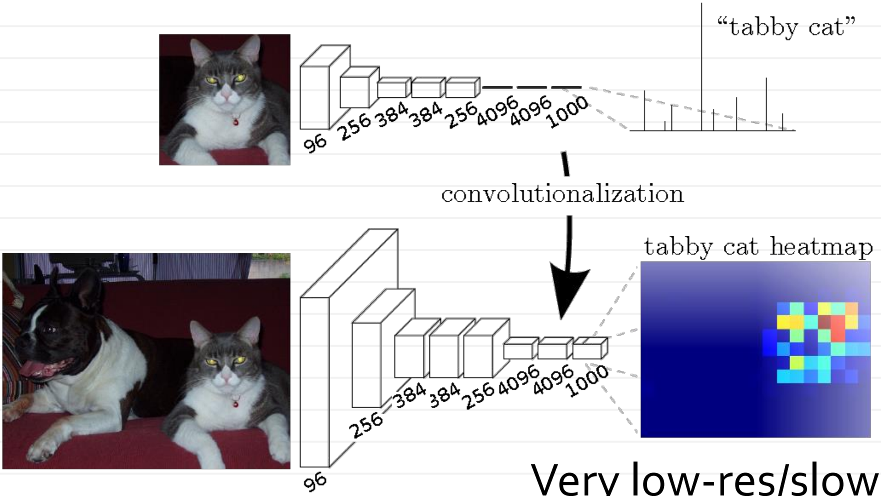
Images from Chaosmail Blog

Answering the where question

- Semantic segmentaion:
  - Relatively fast/easy
  - Allows “complete” explanation
  - Merges instances
- Object detection
  - Relatively fast/easy
  - Distinguishes instances
  - Inaccurate for some classes
  - Incomplete
- Instance segmentation
  - Complete
  - Distinguish instances
  - Accurate
  - Slow/hard

Today

From classification to Segmentation

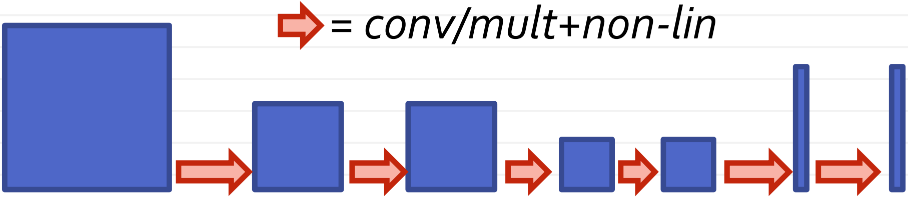


Very low-res/slow!

[Long et al. 2015]

From classification to segmentation

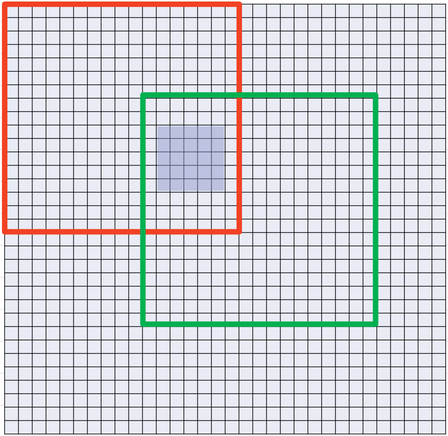
Consider a classification net *without* max-poolings:



Can we make an equivalent network that computes the result of this network for all window locations?

Answer: yes

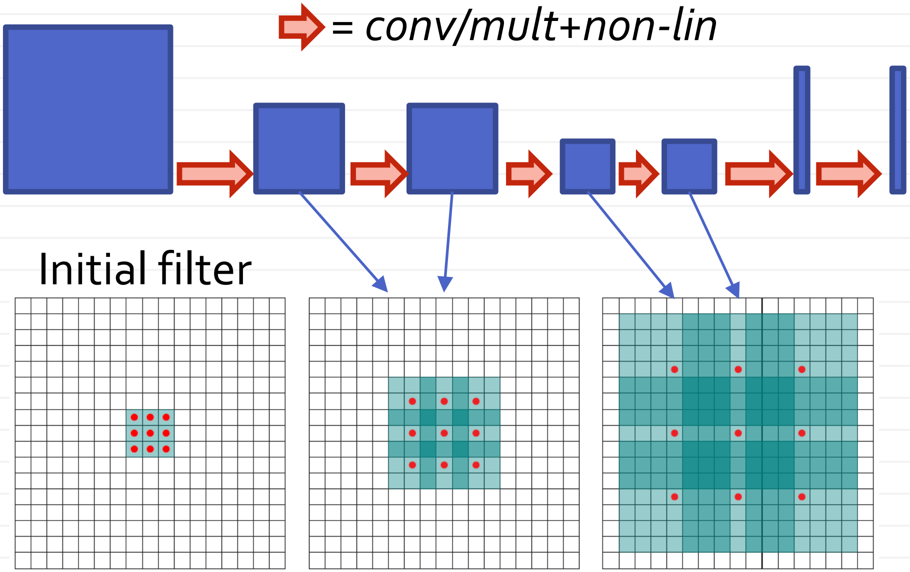
"Convolutionization"



- Classifying overlapping patches incur shared convolutions
- We can convolve the entire map with a kernel straight away ("fully-convolutional")
- Slight difference (non-zero padding)

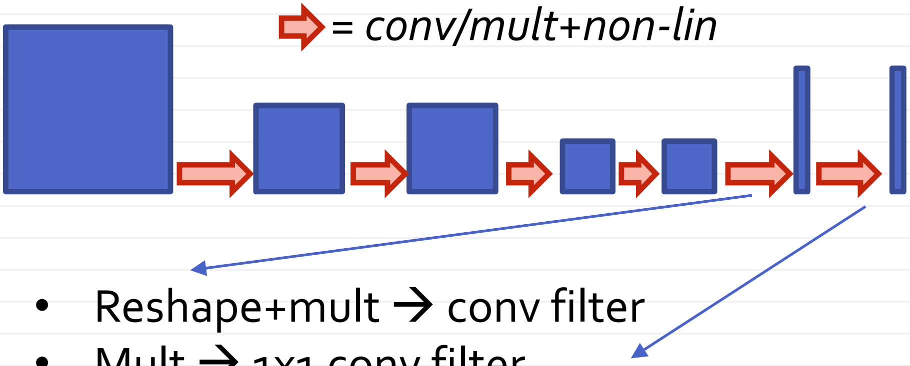
Things get more complicated with strides > 1 and maxpoolings

Dilated convolutions



[Yu & Koltun ICLR16]

Dilated convolutions

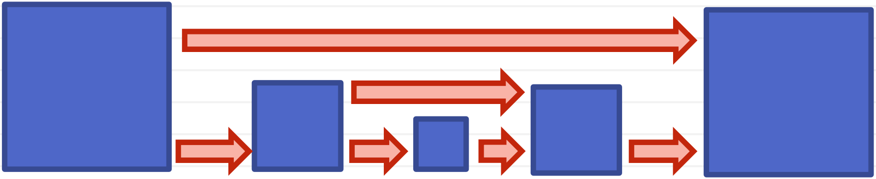


- Reshape+mult → conv filter
- Mult → 1x1 conv filter

Max-pooling in classification can be approximated with max-filtering + dilation increase in the segmentation network

Downsampling-upsampling architectures

These architectures look approximately like:

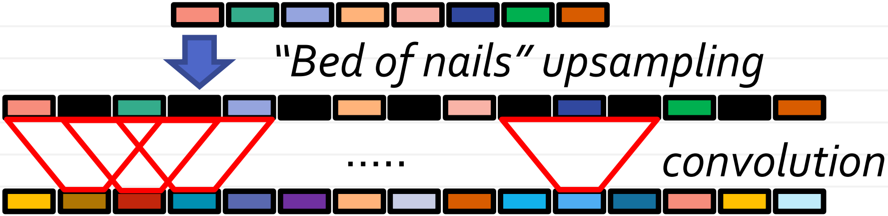


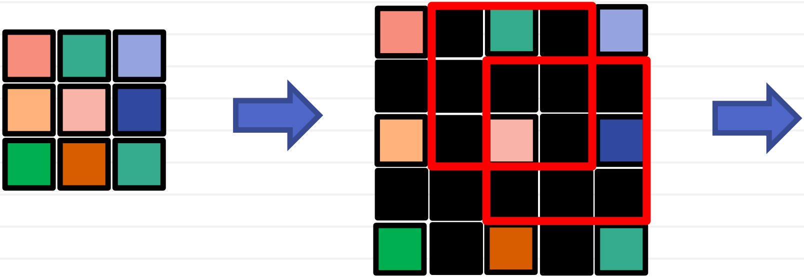
RGB image

Pixel-wise probabilities

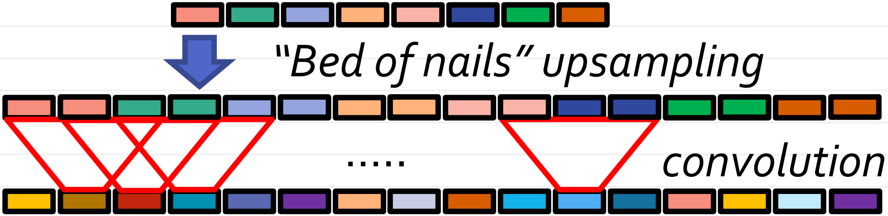
- Are not equivalent to classification
- Need to define upsampling/upconvolution

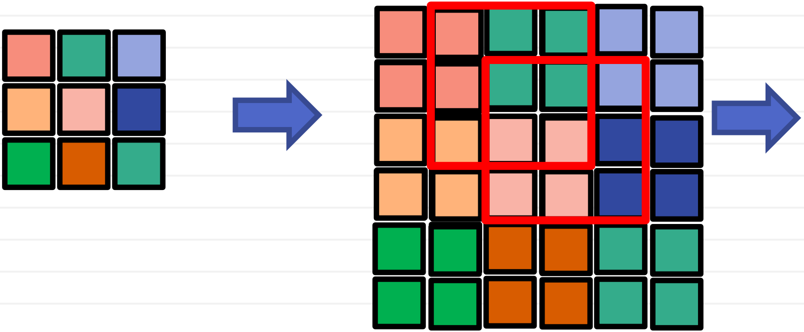
Bed-of-nails upsampling operation





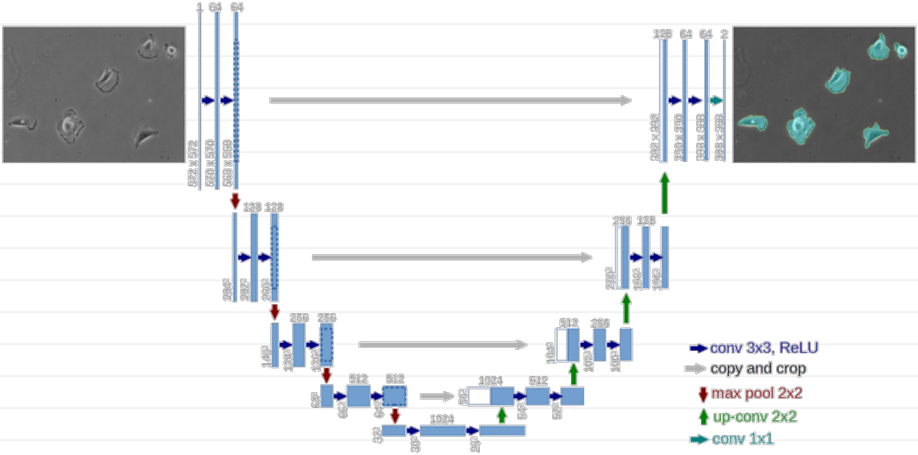
Nearest upsampling operation





U-Net

An example of non-equivalent formulation

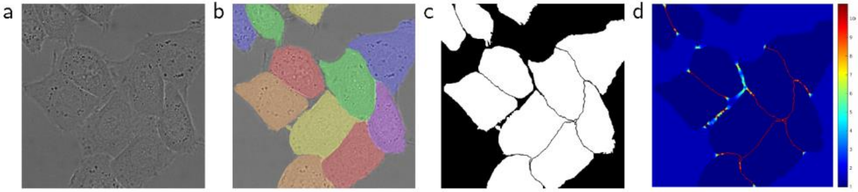


[Ronnerberger et al. MICCAI15]

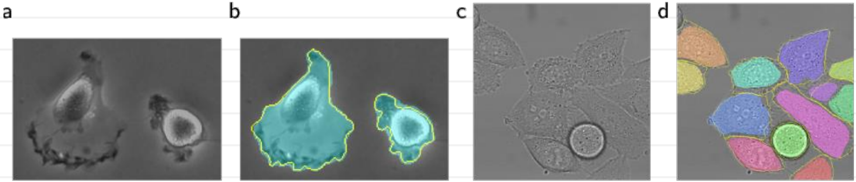
U-Net

[Ronnerberger et al. MICCAI15]

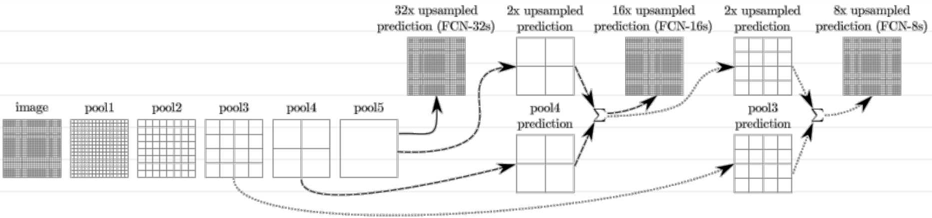
Upweighting thin borders:

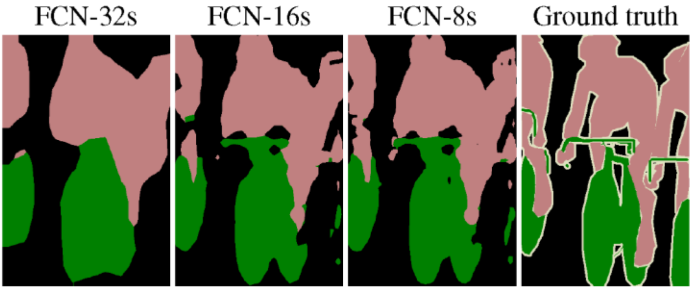


Result:



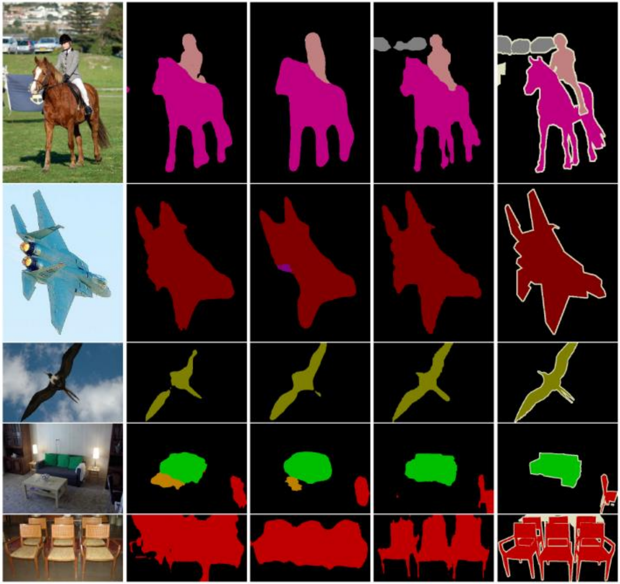
"Fully-convolutional networks"





[Long et al. 2015]

Dilated convolutions



FCN Dilated [Yu & Koltun ICLR16]

Recap: ideas in semantic segmentation

- Dilated convolutions
- Upsampling layers/upconvolution layers (aka *transposed convolution/deconvolution*)
- Skip connections (to retain fine-details)
- We can mix and match all of the above

Detection vs classification

Detection is harder than classification:

- Localization errors
- Huge class disbalance
- Variation in scale and aspect ratio's
- Tricky occlusions, including “intra”-occlusions

Intersection-over-Union measure

Common criterion for correct boxes:

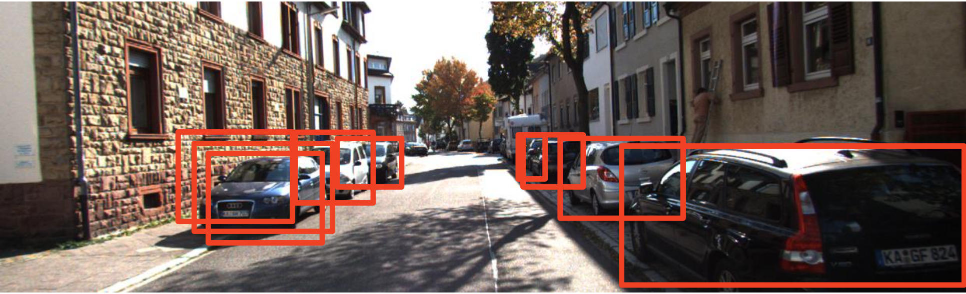
Intersection / Union > threshold (e.g. 0.5)

Double detection

Double detection of the same object is penalized as false positive

Non-maximum suppression

Almost invariably used in detection algorithms:

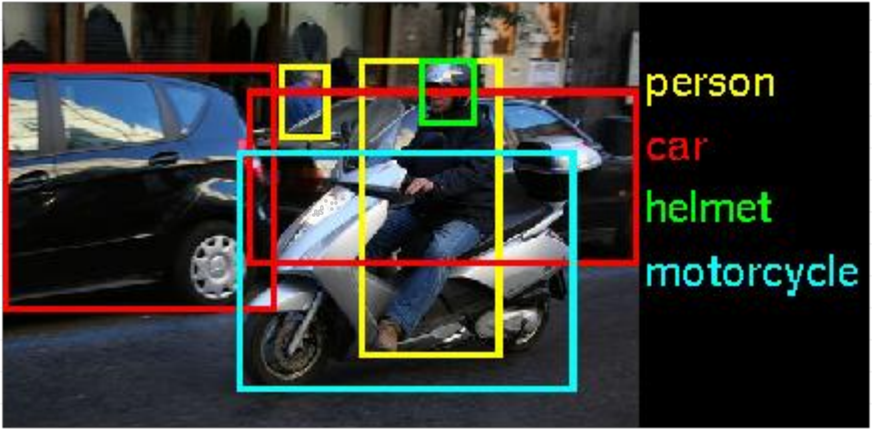


Input: set of detections ($\{B_i, s_i\}$)

- *Sort in the descending order of s_i*
- *For i = 1 to N*
- *Pick the bounding box i*
- *Suppress all subsequent boxes with IoU > 50%*

Multi-class detection

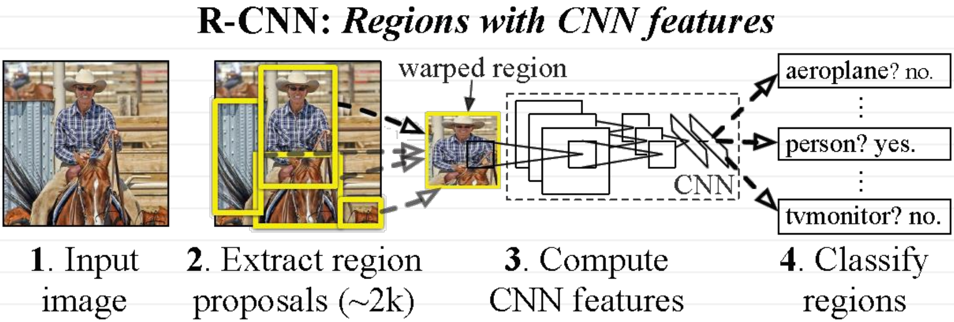
- Lots of research is going towards object detection for a large number of classes:



General ideas for object detection

- **Sliding-window:** use binary classification to classify every possible subwindow (infeasible with DL)
- **Region proposal:** pick a subset of prospective regions and score them with a binary classifier
- **Bounding box regression:** predict the coordinates of the boxes as real-valued variables

R-CNN framework

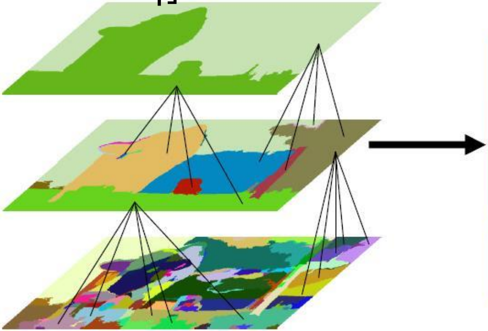


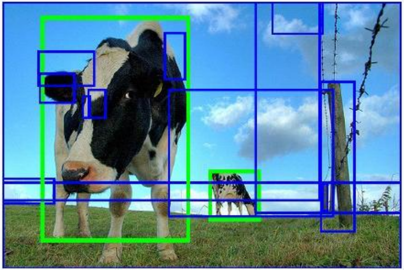
- Use an external box proposal method
- Fine-tune a CNN to score proposal

[Girshik et al. CVPR14]

Example source of external proposals

Graph-based hierarchical segmentation based on maximum-spanning trees [Felsenszwalb & Huttenlocher IJCV2004] :

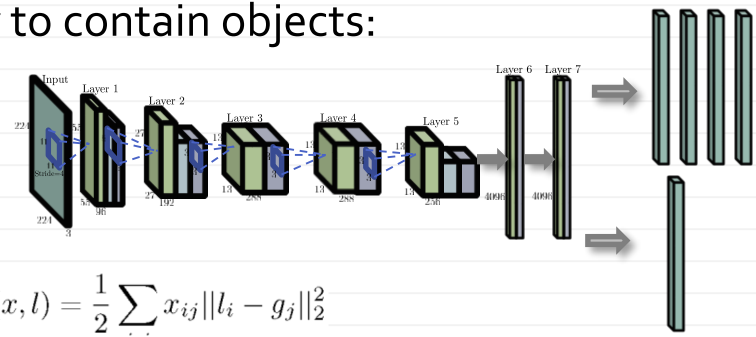




[Uijlings et al. ICCV11]

Bounding box regression

Goal: predicting 100 boxes that are likely to contain objects:



$$F_{\text{match}}(x,l) = \frac{1}{2}\sum_{i,j} x_{ij}\|l_i - g_j\|_2^2$$

$$F_{\text{conf}}(x,c) = -\sum_{i,j} x_{ij}\log(c_i) - \sum_i \Big(1 - \sum_j x_{ij}\Big)\log(1-c_i)$$

$$F(x,l,c) = \alpha F_{\text{match}}(x,l) + F_{\text{conf}}(x,c)$$

[Szegedy et al. 2013]

Optimization for bounding box regression

[Szegedy et al. 2014]

$$F_{\text{match}}(x, l) = \frac{1}{2} \sum_{i,j} x_{ij} ||l_i - g_j||_2^2$$

$$F_{\text{conf}}(x, c) = -\sum_{i,j} x_{ij} \log(c_i) - \sum_i (1 - \sum_j x_{ij}) \log(1 - c_i)$$

$$F(x, l, c) = \alpha F_{\text{match}}(x, l) + F_{\text{conf}}(x, c)$$

Alternate:

- Optimize x (optimal matching)

$$x^* = \arg\min_x F(x, l, c)$$

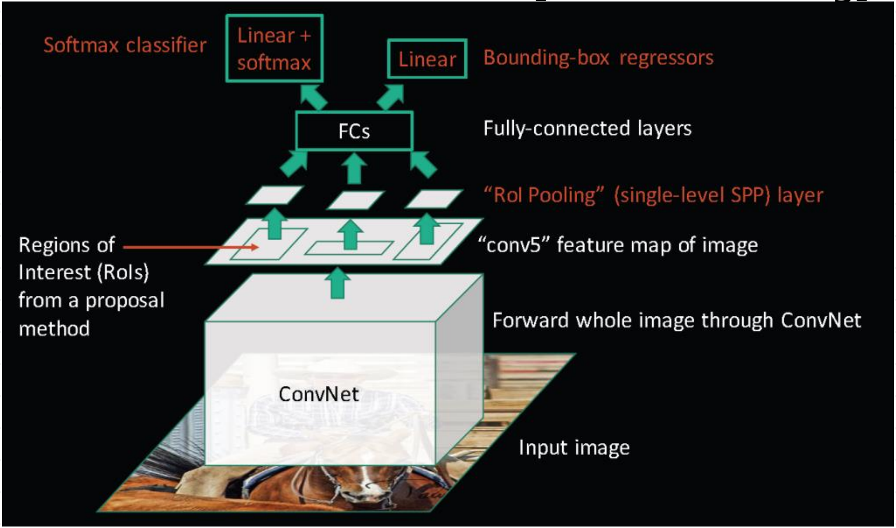
$$\text{subject to} \quad x_{ij} \in \{0, 1\}, \sum_i x_{ij} = 1$$

- Optimize network params (backprop)

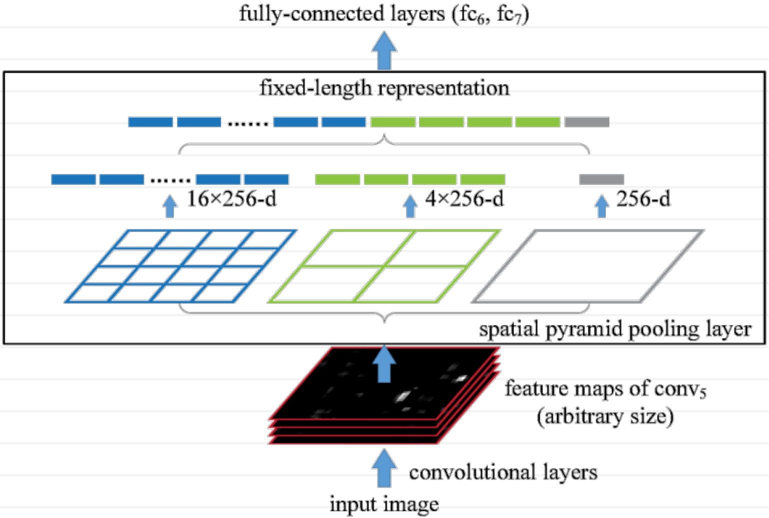
Fast R-CNN

- Processing lots of overlapping boxes is inefficient
- Alternative:

[Girshick ICCV15]



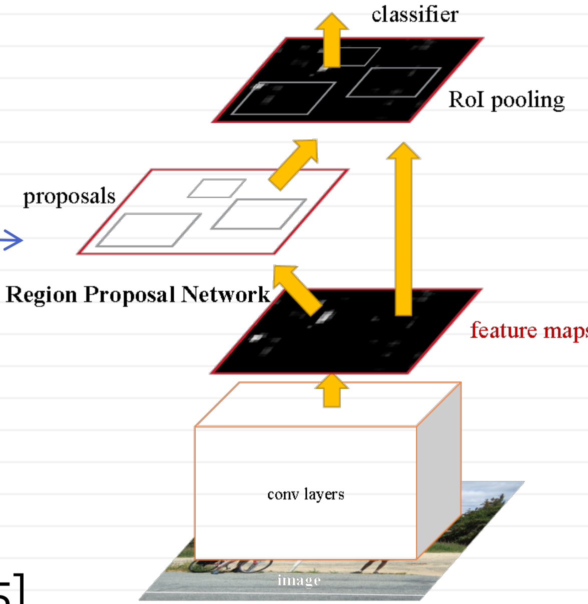
Spatial pyramid pooling



[He et al. ECCV14]

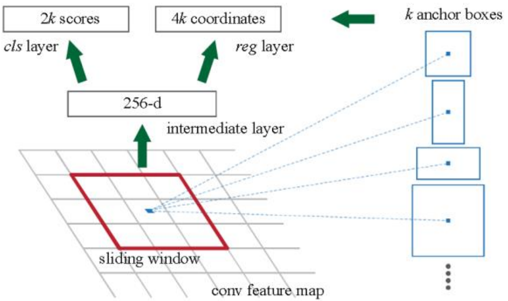
Faster CNN

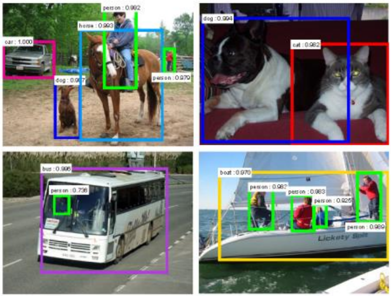
Key novelty: the proposals come from "sparse sliding window search"

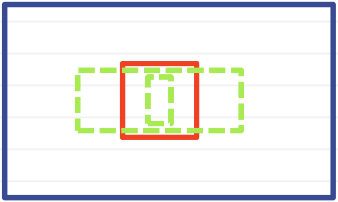


[Ren et al. NIPS15]

Faster CNN: Region-proposal network





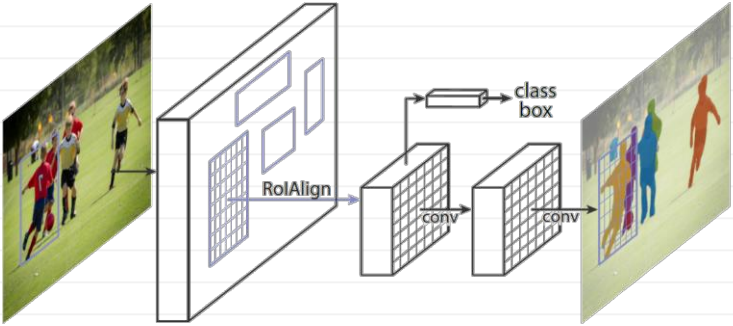


[Ren et al. NIPS15]

- Sparse set of positions
- At each positions, 9 centered "anchor" windows
- Each anchor is adjusted and scored for each class

Extension for Instance Segmentation

Mask R-CNN: adding mask prediction



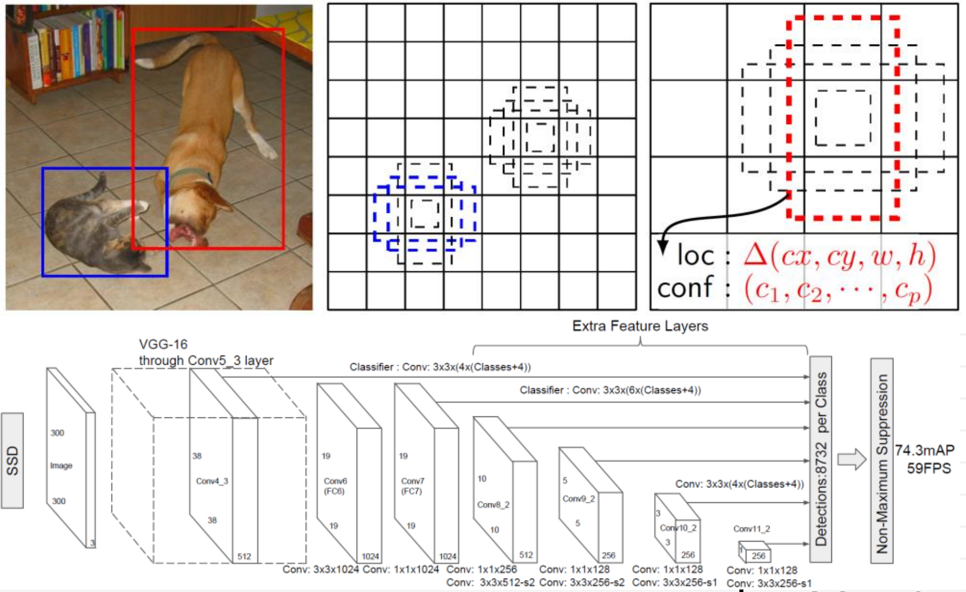
Masks for different classes are predicted and scored independently (decoupling classification and segmentation)

[He et al. 2017]

Mask R-CNN results

[He et al. 2017]

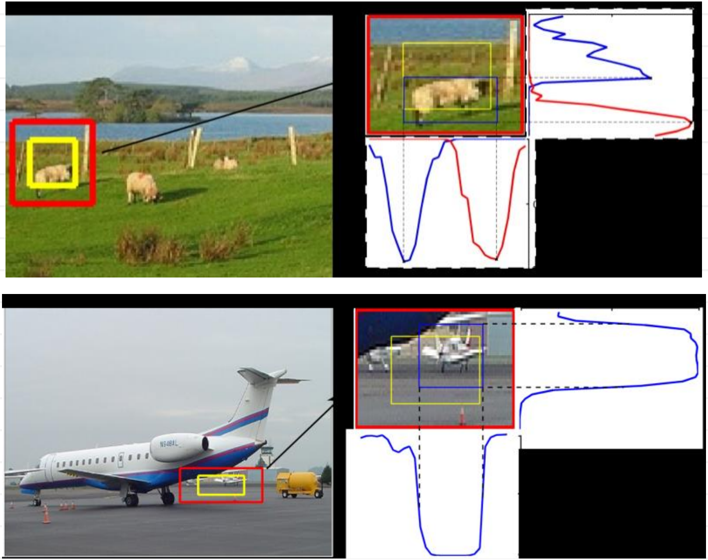
Latest king of the hill: SSD detector



[Liu et al. ECCV16]

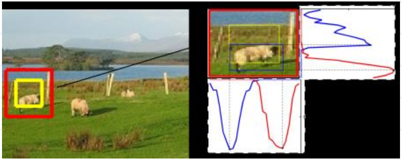
Examples: SSD detection

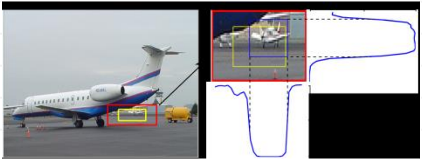
Localization Network

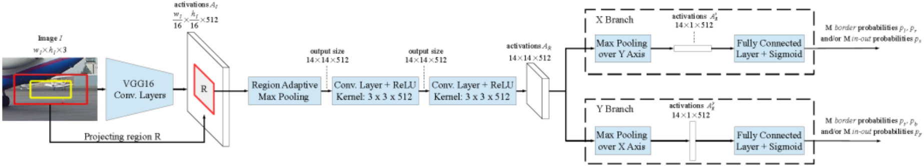


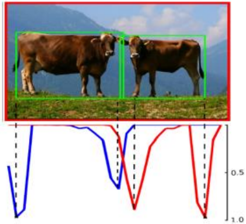
[Gidaris & Komodakis 2015]

Localization Network









[Gidaris & Komodakis 2015]

Recap: ideas for detection

- **ROI-pooling:** sharing convolutional features
- **Anchor+Regression:** “fast sliding window”
- **External proposals:** can be better if there is a good external source

Verification problems in vision

Key question: do two photos show the same object/subject? (*verification)*

Face recognition datasets (e.g. *MSRA-CF*):

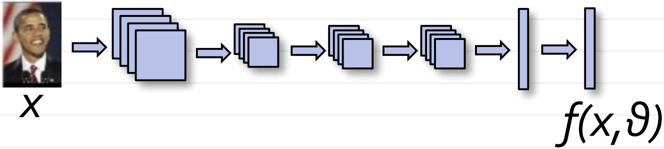
Re-identification datasets (e.g. *ViPER*):

Verification vs Classification

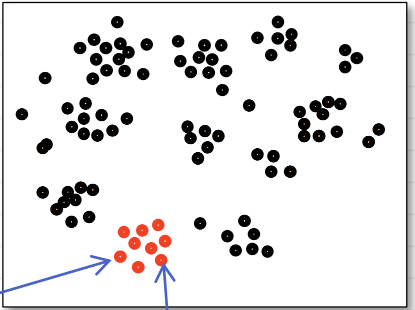
Key question: do two photos show the same object/subject? (*verification*)

- System must be able to handle unseen "classes"
- During training classes can be numerous, small-sized, imbalanced, etc.
- Example from last lecture: retrieval

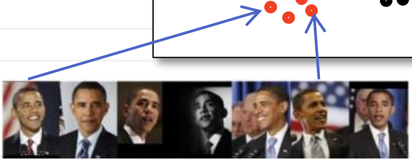
Verification as embedding learning



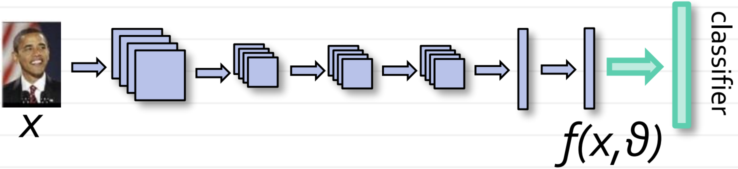
Semantic space:



NB: always normalize your descriptors!



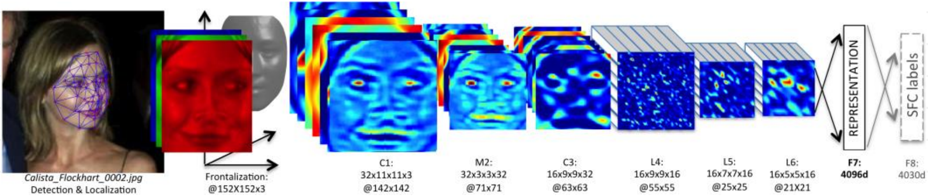
Approach 1: classification-based



- Same idea as "Train on ImageNet, use for retrieval"
- The bigger the classification dataset, the better is the performance
- Training-time classes can be seen as prototypes for test-time classes

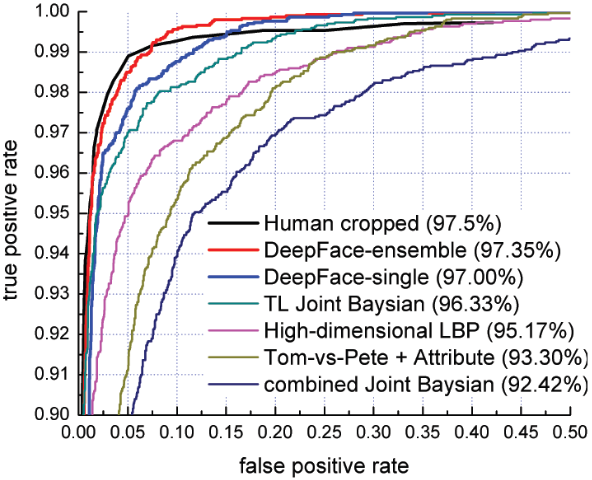
Face verification: “Deep face”

[Taigman et al. 2014]



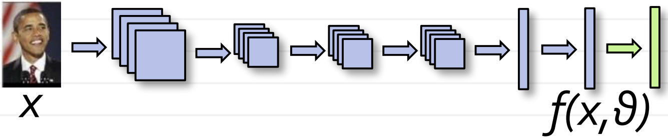
- *Classification* network trained on 4030 people x ~1000 images.
- Target problem: *verification* (same vs different)

Face verification: "Deep face"



Different CNNs combined using SVM-learned weights on validation set

Pair-based learning (*aka Siamese*)



Example distances:

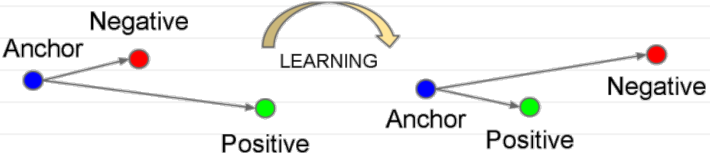
- 1 – cos
- L2 (equivalent if normalization is added)
- Separate network (verification network)

NB: all embedding-based systems work better with normalized descriptors

[Chopra et al. CVPR05]

Google "FaceNet"

[Schroff et al. CVPR15]



Simple **triplet loss**: $$\sum_{i}^{N} \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]_+$$

- Use large mini-batches (1800, 40 images for several classes + lots of random)
- Take all positives from the batch
- Mine "*semi-hard*" negatives

$$\|f(x_i^a) - f(x_i^p)\|_2^2 < \|f(x_i^a) - f(x_i^n)\|_2^2$$

Google "FaceNet" results

[Schroff et al. CVPR15]

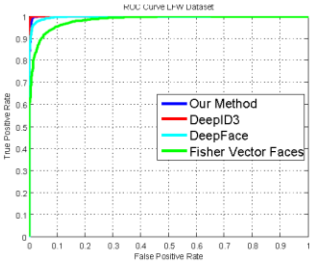
- Upto 99.63% on LFW (human is ~97%)

Performance vs training data:

#images	VAL
2.6M	76.3%
26M	85.1%
52M	85.1%
260M	86.2%

Oxford Face Recognition

No.	Method	Images	Networks	Acc.
1	Fisher Vector Faces [21]	-	-	93.10
2	DeepFace [29]	4M	3	97.35
3	Fusion [30]	500M	5	98.37
4	DeepID-2,3		200	99.47
5	FaceNet [17]	200M	1	98.87
6	FaceNet [17] + Alignment	200M	1	99.63
7	Ours	2.6M	1	98.95

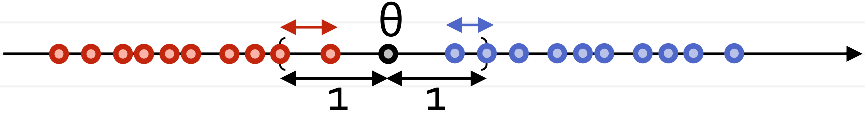


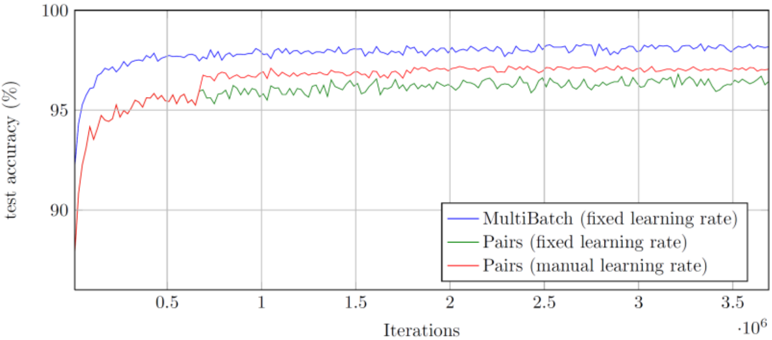
- Start with classification
- Fine-tune **last layers only** with moderately hard triplets
- Dataset publicly available
- Models are available in Caffe zoo and MatConvNet zoo

[Parkhi et al. BMVC15]

Quadruplet losses: multi-batch loss

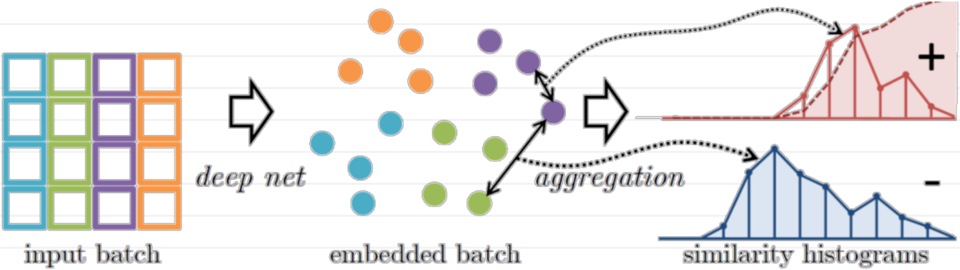
$$l(w,\theta;\ x_i,x_j,y_{ij}) = \left(1 - y_{ij}\left(\theta - \|f_w(x_i) - f_w(x_j)\|^2\right)\right)_+$$





[Tadmor et al, NIPS16]

Quadruplet losses: histogram loss

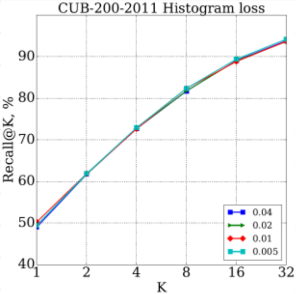


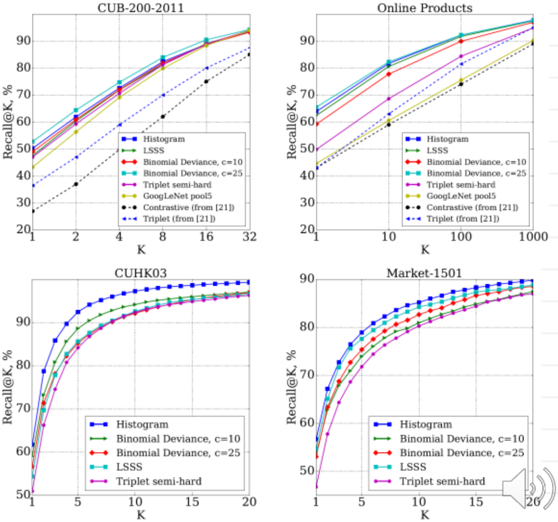
$$p_{\text{reverse}} = \int_{-1}^{1} p^{-}(x) \left[\int_{-1}^{x} p^{+}(y)\, dy \right] dx = \int_{-1}^{1} p^{-}(x)\, \Phi^{+}(x)\, dx$$

[Ustinova & Lempitsky NIPS16]

Quadruplet losses: histogram loss

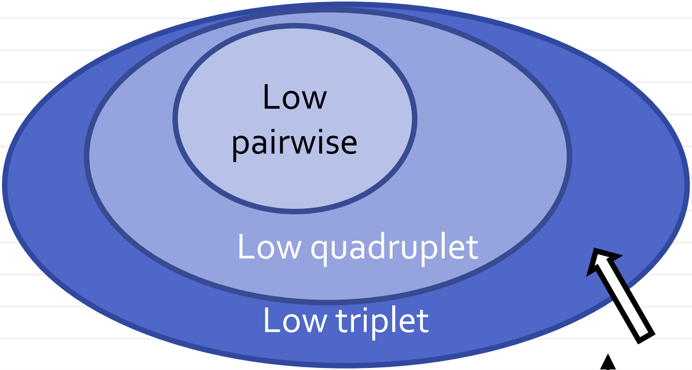
Sensitivity to the bin size:



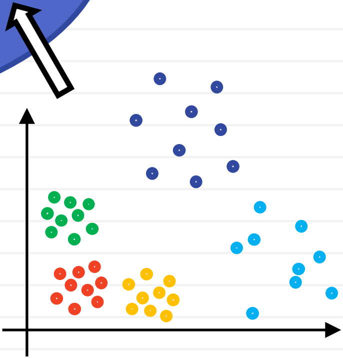


[Ustinova & Lempitsky NIPS16]

Embedding learning: recap



Recommendation: use quadruplet, or soft pairwise (binomial loss)



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