

# (Towards) Real-Time Object Detection with DeepNets

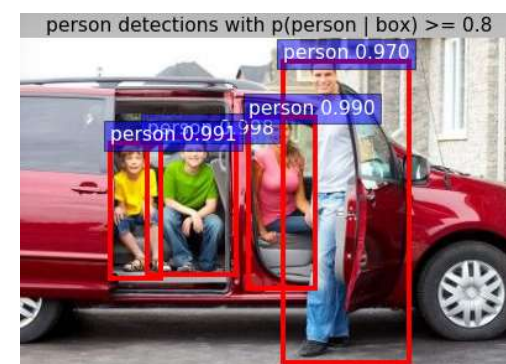
Implementer's Perspective of R-CNN, Fast R-CNN, and **Faster R-CNN**



McGill Deep Learning Reading Group

Anqi Xu

Nov. 30<sup>th</sup>, 2016

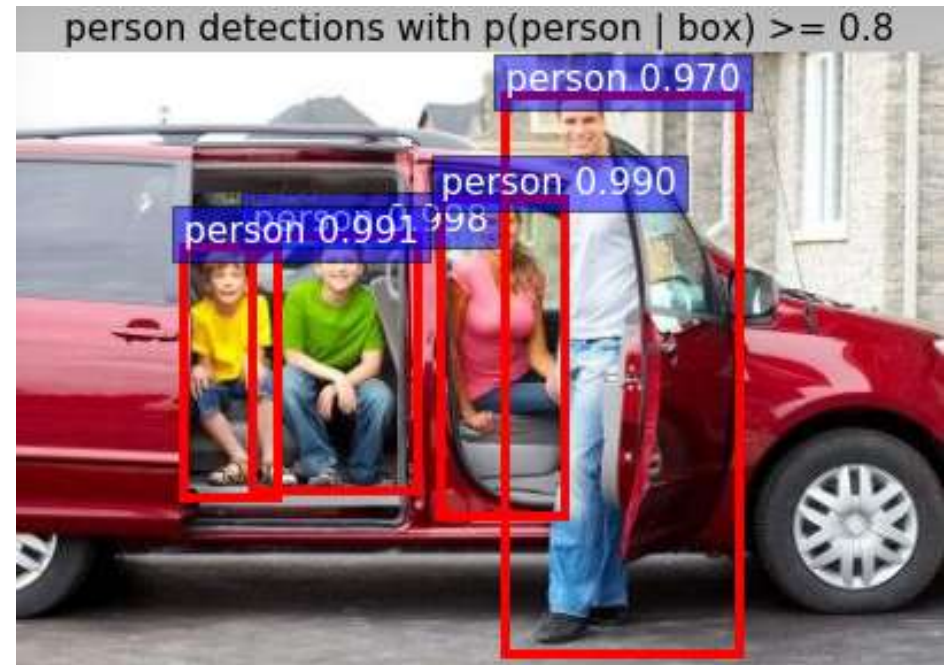


# Object Detection Problem

- What: *Locate* and *detect* **object (classes)** in images

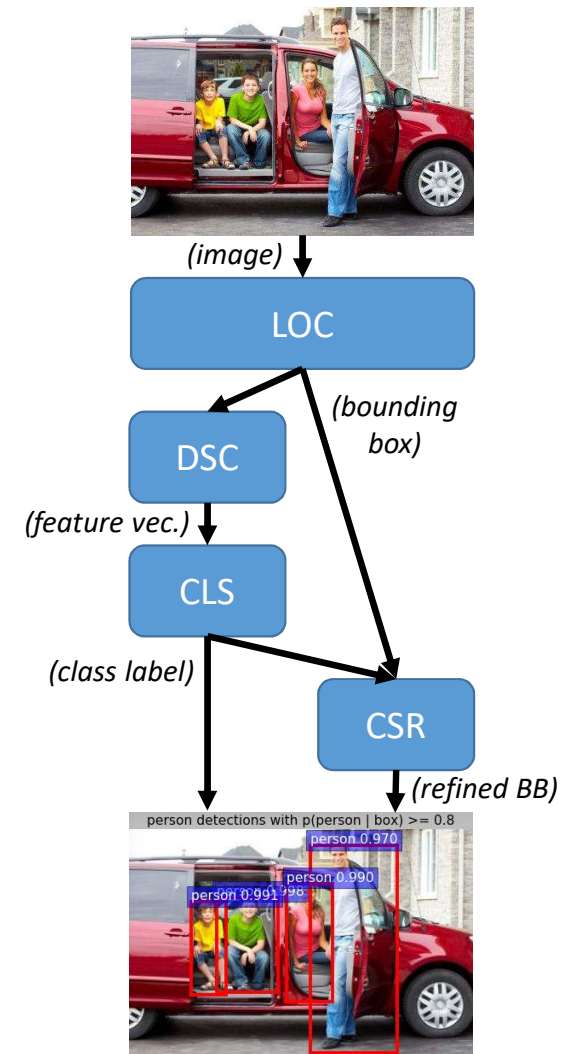
- Why?

- Automated Scene Understanding
- Vision-based Robotics Control
- Visual Human-Automation Interaction
- CV is cool!
- Etc.



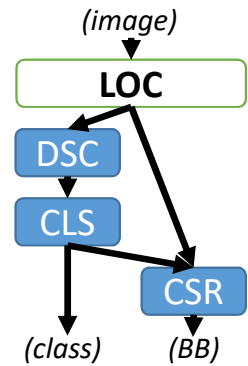
# Object Detection Problem: How

- Object Localization (LOC)
- Object Classification (via Features)
  - Feature Descriptor (DSC)
  - Feature-Based Classifier (CLS)
- Class-Specific Localization Refinement (CSR)



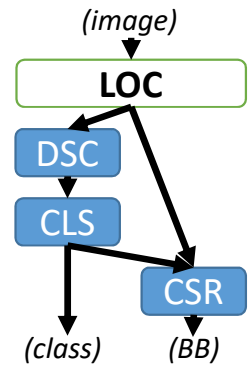
# LOC - Object Localization Overview

- Region Proposal: region (e.g. BB) *possibly* containing object
- Approaches
  - Greedy Search (a.k.a. exhaustive convolution of window-based object detection)
  - Objectness: object likelihood of image windows
  - Selective Search
  - Region Proposal Network



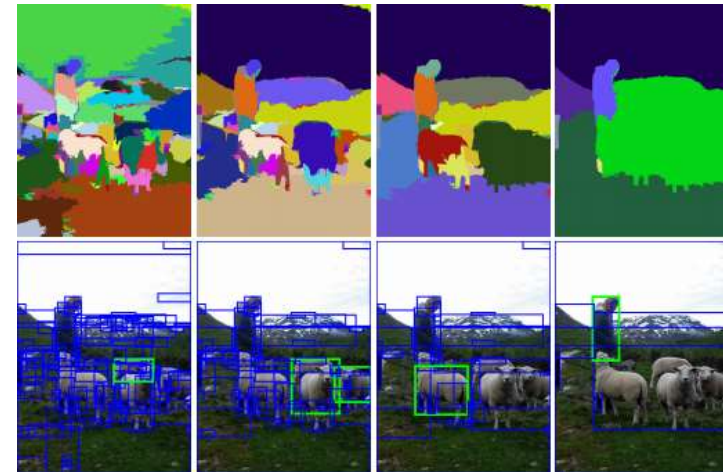
# LOC: Selective Search

- Uijlings *et al.*; Selective Search for Object Recognition; IJCV '12.



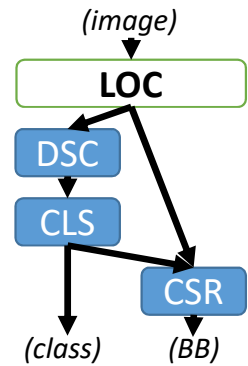
- Algorithm: Hierarchical Grouping

- Graph-based super-pixel segmentation into regions  $R = \{r_i\}$
- Initialize similarity set with pairwise similarity  $S = \{s(r_i, r_j)\}$
- While  $S \neq \emptyset$ :
  - Get  $s^{max}(r_i, r_j)$
  - Merge  $r_t = r_i \cup r_j$
  - Remove  $(r_i, r_*)$ ,  $(r_*, r_j)$  and add  $(r_t, r_*)$  to  $S$
  - Update  $r_t \rightarrow R$
- Return BB of each region in  $R$

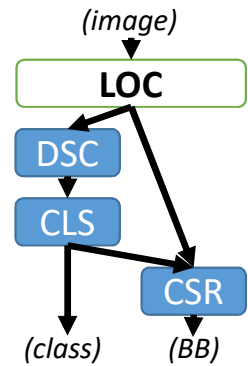


## LOC: Selective Search (cont.)

- Diversification Strategy A: multiple colour spaces
  - RGB, intensity, Lab, normalized rg, HSV, normalized rgb, C, Hue
- Diversification Strategy B: multiple region similarity metrics
  - Color: histogram similarity
  - Texture: HOG histogram
  - Size: pixel count
  - Fill: joint BB size - pixel count i – pixel count j



# LOC: Selective Search (cont.)



- Full Algorithm

- Compute groupings using combinations of colour spaces x similarity metrics
- Rank all object hypotheses based on grouping order \* rand[0,1]
- “Filter out lower ranked duplicates” (NMS based on IoU overlap?)

- Selective Search “Fast Mode”

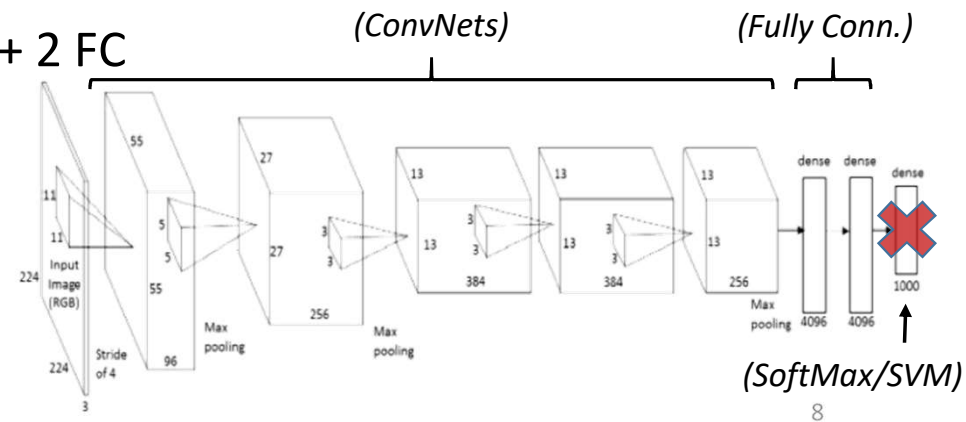
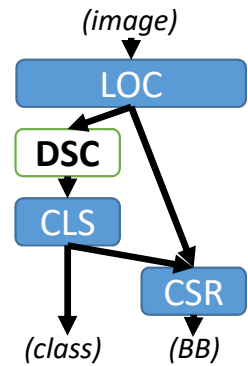
- {HSV, Lab, C+T+S+F, T+S+F} x {k=50,100}
- 8 strategies, ~2k windows, 0.799 MABO, 3.79s





# DSC: Feature Descriptor

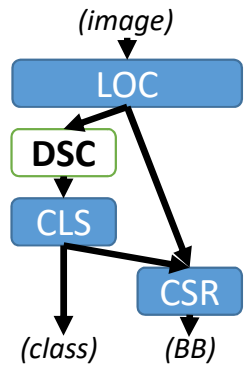
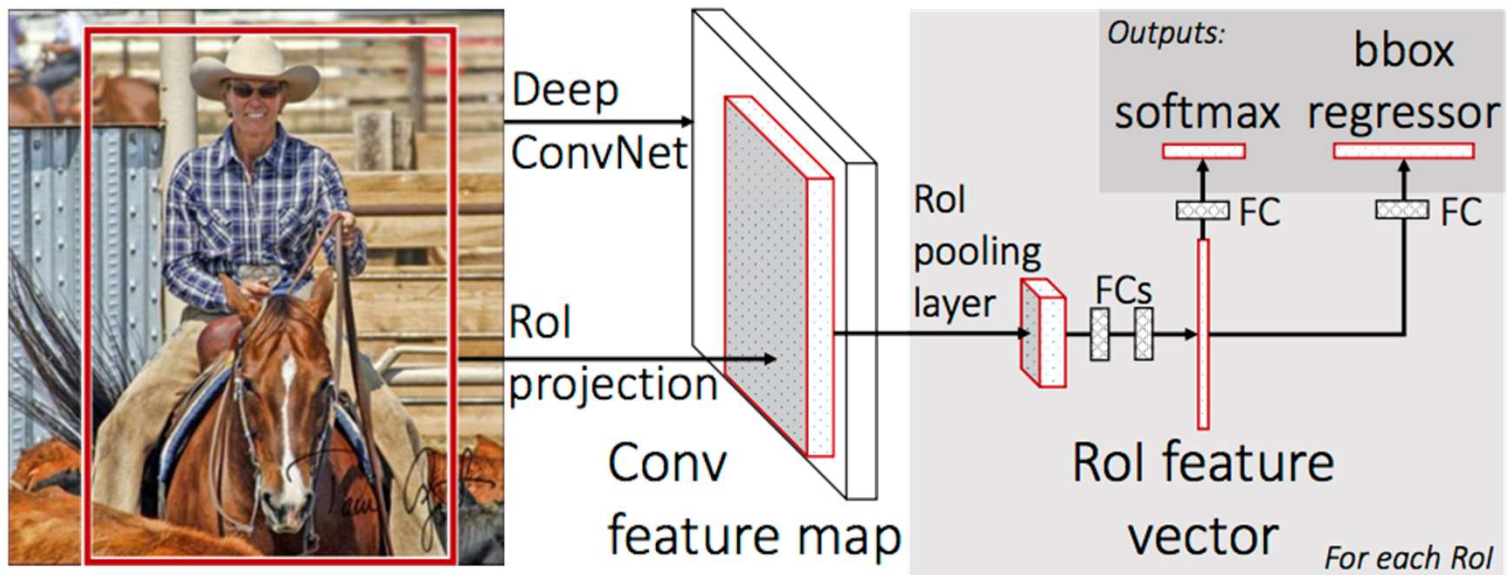
- (Semantic) vectorized data compression of pixel data
  - Engineered edge-based descriptors (e.g. HOG, wavelet, etc.)
  - Truncate classifier Deep Nets: Conv Layers + FC Layers
  - Fixed-size RoI descriptor via RoI Pooling
- Deep Nets, yo!
  - AlexNet/T-Net/CaffeNet (Hinton): 5 CN + 2 FC
  - Zeiler+Fergus: 5 CN + ? FC
  - VGG16 (Zisserman): 16 CN + 3(?) FC





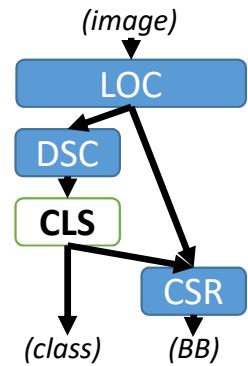
# DSC: RoI Pooling (Fast R-CNN)

- Downsize (h,w) RoI BB into fixed H x W (e.g. 7 x 7) descriptor
  - Per-channel max-pooling



# CLS: Feature-Based Classifier

- R-CNN Approach:
  - (Source image) -> warped RoI image -> Conv Layers -> (feature)  
-> **FC Layers** -> **class-specific SVMs**
- Fast(er) R-CNN Approach:
  - (Source image) -> RoI from region proposal step  
-> RoI Pooling Layer-> (feature)  
-> **FC Layers** -> **N+1 softmax Layer**



# CSR: Class-Specific BB Refinement

- R-CNN Approach: Bounding Box ridge regression

$$t_x = (G_x - P_x)/P_w$$

$$t_y = (G_y - P_y)/P_h$$

$$t_w = \log(G_w/P_w)$$

$$t_h = \log(G_h/P_h).$$

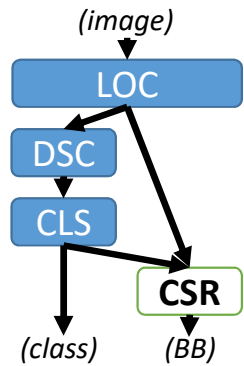
- Fast(er) R-CNN Approach: FC(s) + bounding box regressor (layer?)

$$t_x = (x - x_a)/w_a, \quad t_y = (y - y_a)/h_a,$$

$$t_w = \log(w/w_a), \quad t_h = \log(h/h_a),$$

$$t_x^* = (x^* - x_a)/w_a, \quad t_y^* = (y^* - y_a)/h_a,$$

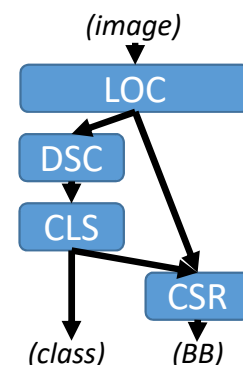
$$t_w^* = \log(w^*/w_a), \quad t_h^* = \log(h^*/h_a),$$



# Big Picture: R-CNN (2012)

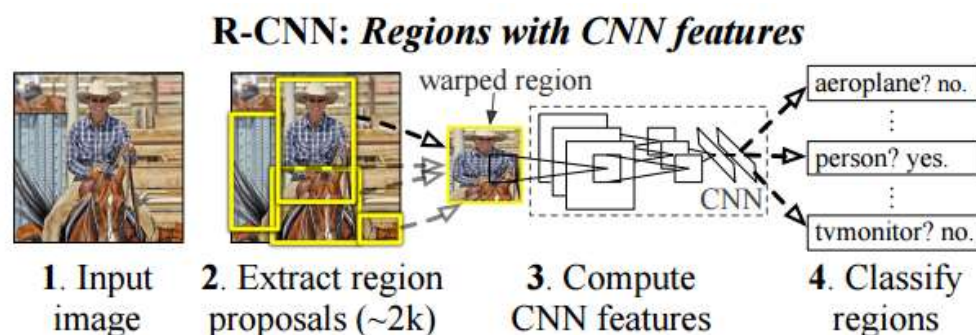
- Components

- LOC: Selective Search “fast mode”
- DSC: ConvNet (AlexNet/VGG16) + FCs
- CLS: class-specific SVMs
- CSR: class-specific BB ridge regression



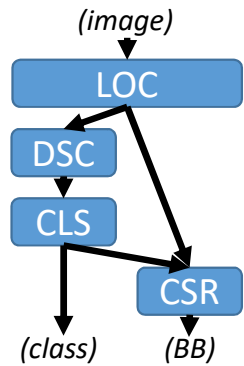
- Other Contributions

- Supervised Pre-Training: ILSVRC12 classification (image-level annotations only, w/o BB labels)
- Domain-specific fine-tuning: SGD on warped proposal windows (N=20 for VOC, N=200 for ILSVRC13)
- Empirical analysis: warped RoI better than “tightest square with context” & “tightest square without context” (a.k.a. *who needs aspect ratio?*)



## Big Picture: R-CNN (2012) (cont.)

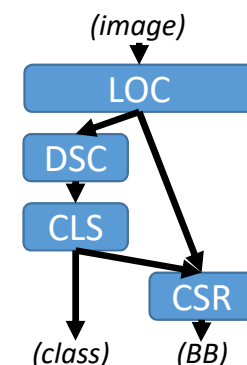
- Training Time: a few days on GTX560
- Run Time: ~10 secs on 2012-era GPU
- VOC07 test mAP: 58.5% (R-CNN BB) vs 34.3% (DPM HSC)
- ILSVRC13 mAP: 31.4% (R-CNN BB) vs 24.3% (Overfeat posthoc)



# Big Picture: Fast R-CNN (2014)

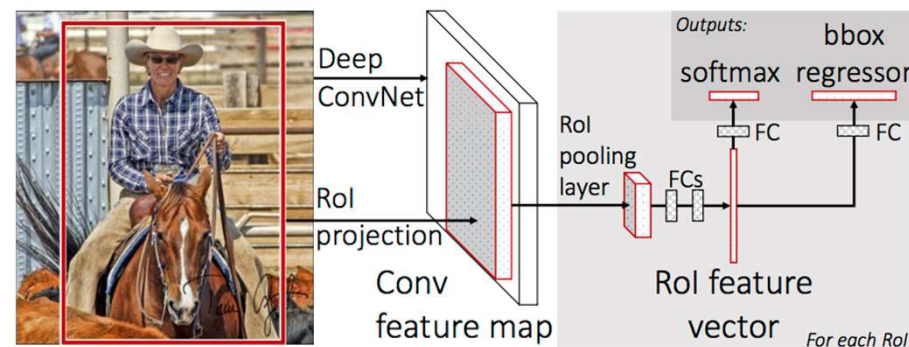
- Updated Components

- LOC: *Selective Search “fast mode” (unchanged)*
- DSC: ConvNet (CaffeNet/VGG\_CNN\_M\_1024/VGG16) **on whole image** + RoI pooling layer + FCs
- CLS: FC + softmax layer
- CSR: FC + regressor layer



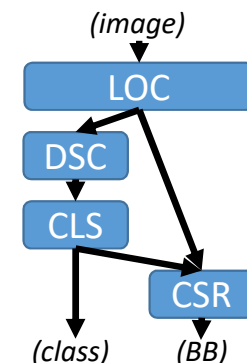
- Other Contributions

- Efficient backprop via Mini-Batch SGD:  $N=2$  images,  $R=128$  total regions
- Multi-task loss: log class likelihood + L-1 (x,y,w,h) BB regression
- Approximate scale normalization by matching image pyramid w/ RoI size
- Truncated SVD approximation of FC layers



## Big Picture: Fast R-CNN (2014) (cont.)

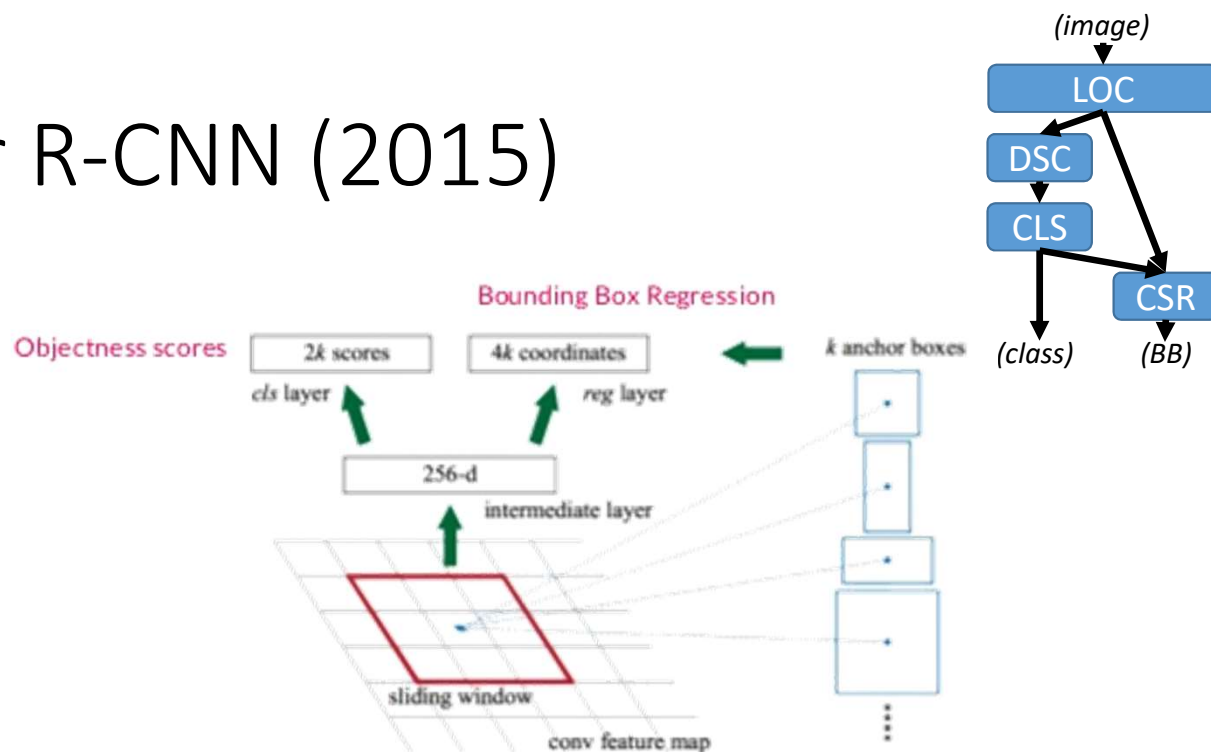
- Training Time: 1.2-9.5h (8-18x speedup)
  - On GTX 770?
- Run Time: 0.10-0.32s w/o SVD, 0.06-0.22s w/ SVD
- VOC07: 70.0% (Fast R-CNN) vs 66.0% (R-CNN BB) vs 63.1% (SPPNet BB)
- VOC12: 68.4% (Fast R-CNN) vs 62.4% (R-CNN BB) vs 63.2% (BabyLearning)





# Big Picture: Faster R-CNN (2015)

- Region Proposal Network



- Updated Components

- LOC: RPN (into k anchor boxes)
- DSC: ConvNet (ZG/VGG16) on whole image + RoI pooling layer + FCs
- CLS / CSR: *FC + softmax layer / FC + regressor layer (unchanged)*

In practice,  $k = 9$  (3 different scales and 3 aspect ratios)

# Faster R-CNN: Results, Demo, Discussion

- Results: see paper
- Live demo
- Discussion Seed Points
  - Failure cases
  - Improvements to individual steps (“SqueezeNet, anyone?”)
  - YOLO!