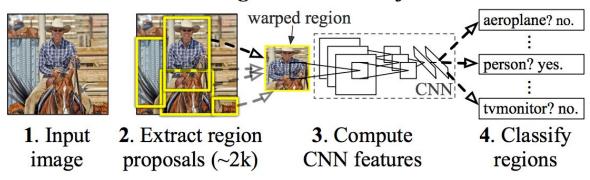
EVOLUTION OF RCNNs

1. R-CNN

- proposes a bunch of boxes in the image and sees if any of them correspond to an object
- Creates region proposal boxes using "Selective Search"
 - Selective search looks at the image through windows of different sizes
 - Tries to group adjacent pixels by texture, color, and intensity. Things with similar attributes are probably one object

R-CNN: Regions with CNN features



- When all proposals are created each region is warped to a square size and passed through a CNN to extract feature maps.
- Then, an SVM just classifies the feature map.
- Once an object is found, the box can be tightened even more to be more precise
 - o Runs a linear regression
 - Input: sub regions of the image that corresponds to each object
 - Output: new bounding box coordinates for each object

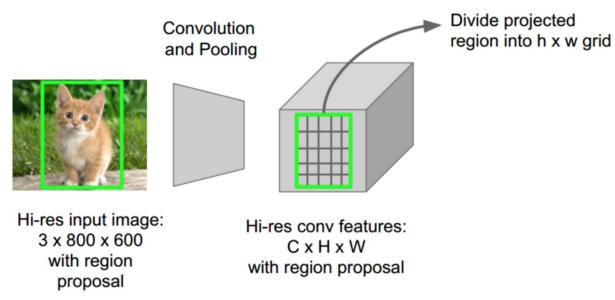
Why R-CNN sucks:

- Needs a forward pass through the CNN (step 3) for each region proposal... and there are usually a lot of region proposals so that an object isn't missed
 - A lot of region proposals also overlap, leading to useless computation
- It has to train 3 different models separately
 - CNN, the SVM classifier, regression model to tighten box

2. Fast R-CNN

BENEFIT 1: Run the image through the CNN just once per image...

Region of Interest Pooling (ROI pool):



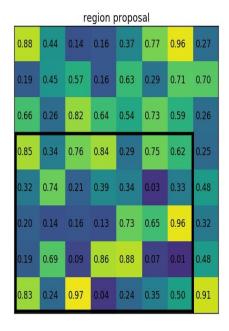
- ROI pool shares the forward pass for each sub region because it is all done at once
- features for each region in the original image is obtained by going to the corresponding area in the feature map
- Then all the features in a region are max pooled, so now the regions with a high value probably have an object in them.

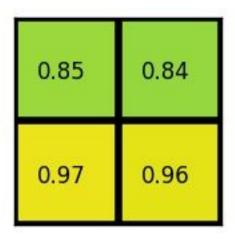
• IN DEPTH:

- ROI pooling layer inputs:
 - feature map from deep CNN
 - N x 5 matrix which has a list of ROI, where N in number of regions
 - Each row is a ROI
 - first column = image index

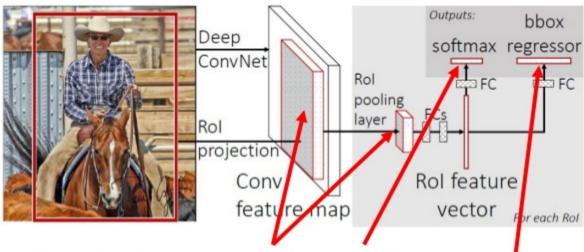
- last 4 cols = coordinates for corners of region
- For every inputted region of interest, it takes the corresponding section of the feature map and scales it to some predefined size (p x p)
 - Divide the ROI into 'p' number of equal sized sections
 - Max pool each section
- This is fast because you can use the same feature map for every region proposal, no useless recalculating.

pooling sections							
0.88	0.44	0.14	0.16	0.37	0.77	0.96	0.27
0.19	0.45	0.57	0.16	0.63	0.29	0.71	0.70
0.66	0.26	0.82	0.64	0.54	0.73	0.59	0.26
0.85	0.34	0.76	0.84	0.29	0.75	0.62	0.25
0.32	0.74	0.21	0.39	0.34	0.03	0.33	0.48
0.20	0.14	0.16	0.13	0.73	0.65	0.96	0.32
0.19	0.69	0.09	0.86	0.88	0.07	0.01	0.48
0.83	0.24	0.97	0.04	0.24	0.35	0.50	0.91





Fast R-CNN: Joint Training Framework

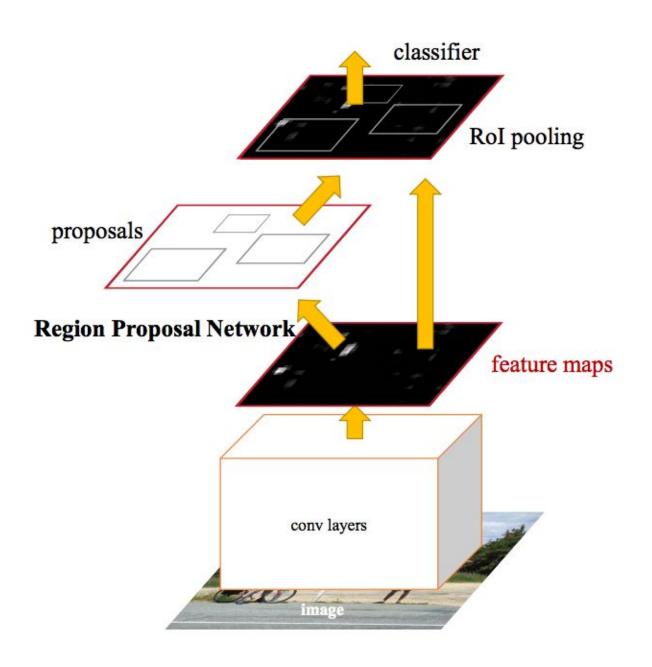


Joint the feature extractor, classifier, regressor together in a unified framework

- SVM classifier has been replaced with a softmax layer after the CNN.
- The regression layer is now parallel to the softmax layer.
- Inputs: Images with region proposals
- Outputs: classifications and tighter boxes

3. EVEN FASTER R-CNN

- Problems with Fast R-CNN
 - Region proposal process of selective search is still very slow
- Faster R-CNN uses the feature map extracted from the CNN both to do classification and do extract region proposals

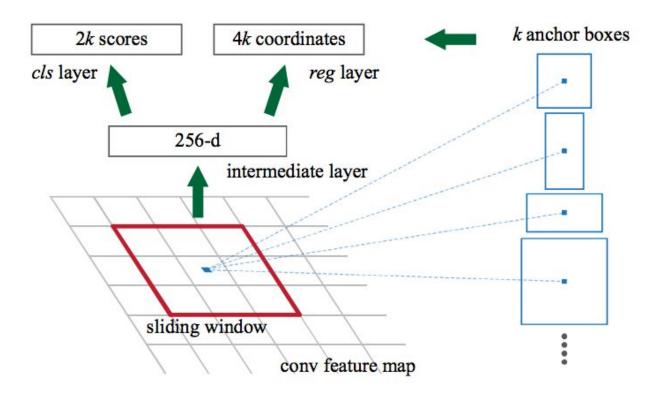


•	only	one	CNN	needs	to	be	traine	ed
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- Inputs:
 - just the raw image, no need to inputs region proposal boxes since we just generate those with the same feature map
- Outputs:
 - classifications and bounding boxes of objects

But how are the regions generated with just a feature map?!?!?!?!

- Region Proposal Network
 - Another CNN operating on the features extracted from the first CNN



- Passes a sliding window over the CNN feature map (kind of like a convolution but not rly...)
 - At each window location, the network outputs a score (for whether or not its an object) and the bounding box per anchor
- In the end, outputs 'k' number of potential bounding boxes and scores for each box.

Anchor boxes:

- Some common aspect rations for the thing we are looking for
- Example: we are looking for a ball
 - The aspect ratio of a ball will never be extremely thin so one anchor box could be 1:1
- For each anchor box like that you output one bounding box and score per position in the image.
 - This lets the network know where the object we are looking for is in the image

Inputs:

CNN feature map

Outputs:

 1 bounding box per anchor, and a score representing how likely the thing in there is an object