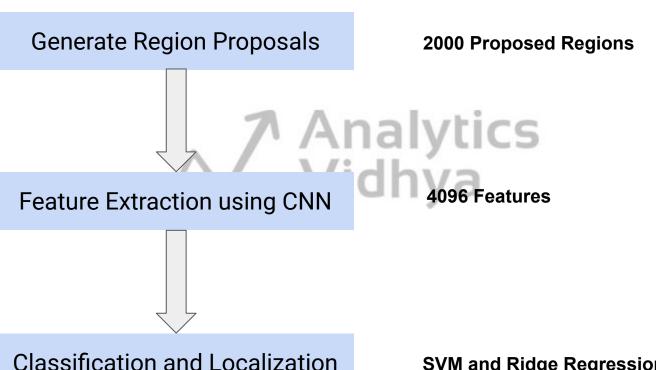




Drawbacks of R-CNN



SVM and Ridge Regression

Fast R-CNN

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Abstract

This paper proposes a Fast Region-based Convolutional Network method (Fast R-CNN) for object detection. Fast R-CNN builds on previous work to efficiently classify object proposals using deep convolutional networks. Compared to previous work, Fast R-CNN employs several innovations to improve training and testing speed while also increasing detection accuracy. Fast R-CNN trains the very deep VGG16 network 9× faster than R-CNN, is 213× faster at test-time, and achieves a higher mAP on PASCAL VOC 2012. Compared to SPPnet, Fast R-CNN trains VGG16 3× faster, tests 10× faster, and is more accurate. Fast R-CNN is implemented in Python and C++ (using Caffe) and is

while achieving top accuracy on PASCAL VOC 2012 [7] with a mAP of 66% (vs. 62% for R-CNN).

1.1. R-CNN and SPPnet

The Region-based Convolutional Network method (R-CNN) [9] achieves excellent object detection accuracy by using a deep ConvNet to classify object proposals. R-CNN, however, has notable drawbacks:

 Training is a multi-stage pipeline. R-CNN first finetunes a ConvNet on object proposals using log loss. Then, it fits SVMs to ConvNet features. These SVMs act as object detectors, replacing the softmax classifier learnt by fine-tuning. In the third training stage,



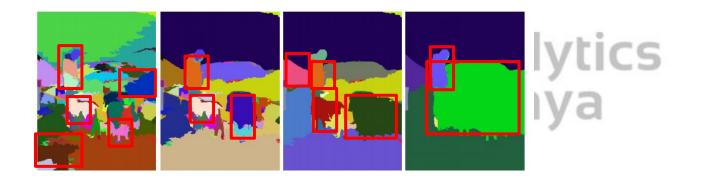
Fast R-CNN - Architectural Changes

Feature Extraction on the complete Image

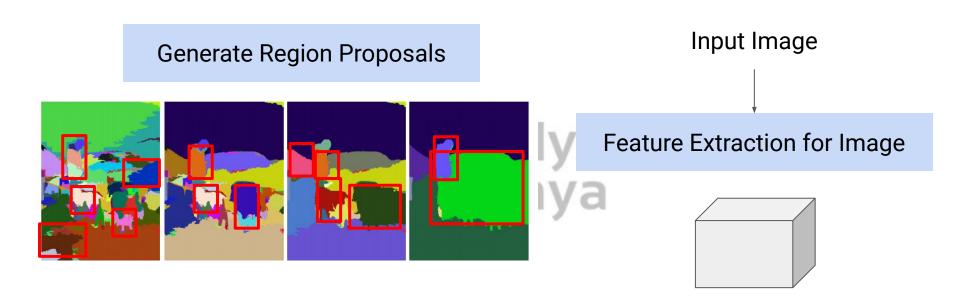




Generate Region Proposals



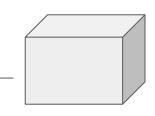




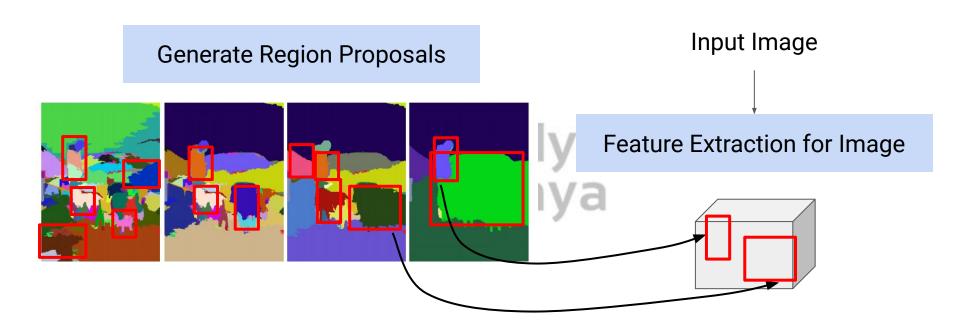


Feature Extraction in Fast R-CNN

Layer	# filters	Filter size	Stride	Padding	Size of feature map	Activation function
Input	~	-			224 X 224 X 3	
Conv 1	64	3X3	1	1	224 X 224 X 64	ReLU
Conv 2	64	3X3	3X3 1 1 224 X 224 X 64		ReLU	
Max Pooling 1	-	2X2	2		112 X 112 X 64	
Conv 3	128	3X3	1	1	112 X 112 X 128	ReLU
Conv 4	128	3X3	1	1	112 X 112 X 128	ReLU
Max Pooling 2	~	2X2	2		56 X 56 X 128	
Conv 5	256	3X3	1	1	56 X 56 X 256	ReLU
Conv 6	256	3X3	1	1	56 X 56 X 256	ReLU
Conv 7	256	3X3	1	1	56 X 56 X 256	ReLU
Max Pooling 3	~	2X2	2		28 X 28 X 256	
Conv 8	512	3X3	1	1	28 X 28 X 512	ReLU
Conv 9	512	3X3	1	1	28 X 28 X 512	ReLU
Conv 10	512	3X3	1	1	28 X 28 X 512	ReLU
Max Pooling 4	~	2X2	2		14 X 14 X 512	
Conv 11	512	3X3	1	1	14 X 14 X 512	ReLU
Conv 12	512	3X3	1	1	14 X 14 X 512	ReLU
Conv 13	512	3X3	1	1	14 X 14 X 512	ReLU
Max Pooling 5	~	2X2	2		7 X 7 X 512	
Fully Connected 1					4096	ReLU
Fully Connected 2					4094	ReLU









Layer	# filters	Filter size	Stride	Padding	Size of feature map	Activation function
Input	224 X 224 X 3					
Conv 1	64	3X3	1	1 1 224 X 224 X 64		ReLU
Conv 2	64	3X3	1	1	224 X 224 X 64	ReLU
Max Pooling 1	-	2X2	2		112 X 112 X 64	
Conv 3	128	3X3	1	1	112 X 112 X 128	ReLU
Conv 4	128	3X3	1	1	112 X 112 X 128	ReLU
Max Pooling 2	2	2X2	2		56 X 56 X 128	
Conv 5	256	3X3	1	1	56 X 56 X 256	ReLU
Conv 6	256	3X3	1	1	56 X 56 X 256	ReLU
Conv 7	256	3X3	1	1	56 X 56 X 256	ReLU
Max Pooling 3	2	2X2	2		28 X 28 X 256	
Conv 8	512	3X3	1	1	28 X 28 X 512	ReLU
Conv 9	512	3X3	1	1	28 X 28 X 512	ReLU
Conv 10	512	3X3	1	1	28 X 28 X 512	ReLU
Max Pooling 4	-	2X2	2		14 X 14 X 512	
Conv 11	512	3X3	1	1	14 X 14 X 512	ReLU
Conv 12	512	3X3	1	1	14 X 14 X 512	ReLU
Conv 13	512	3X3	1	1	14 X 14 X 512	ReLU
Max Pooling 5	¥	2X2	2		7 X 7 X 512	
Fully Connected 1					4096	ReLU
Fully Connected 2					4094	ReLU

ROI pooling



Fast R-CNN - Architectural Changes

- Feature Extraction on the complete Image
- Use Rol (Region of Interest) Pooling

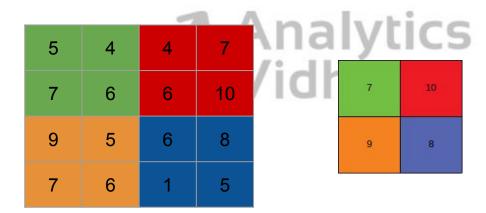


Max Pooling Operation

5	4	4	7	Analytic
7	6	6	10	/idhya
9	5	6	8	
7	6	1	5	



Max Pooling Operation





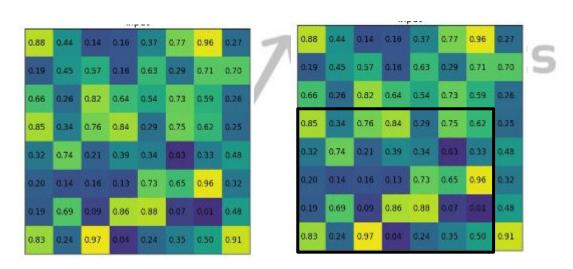
Region of Interest (RoI) Pooling



Feature Map



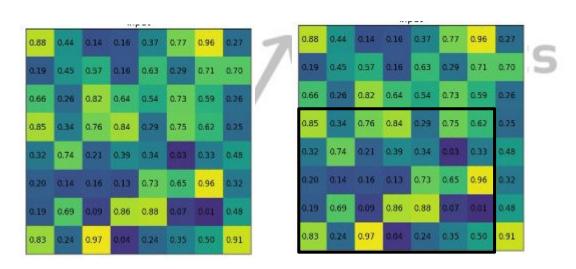
Region of Interest (RoI) Pooling



Feature Map



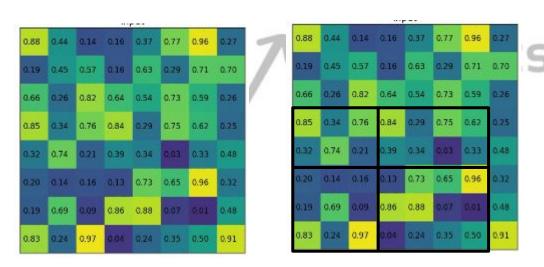
Region of Interest (RoI) Pooling



Feature Map

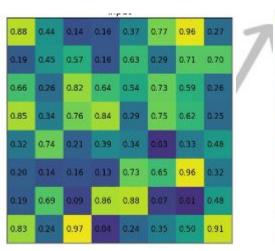


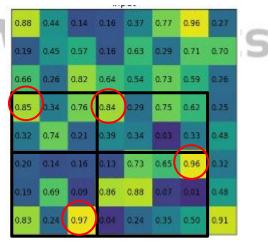
Region of Interest (RoI) Pooling



Feature Map



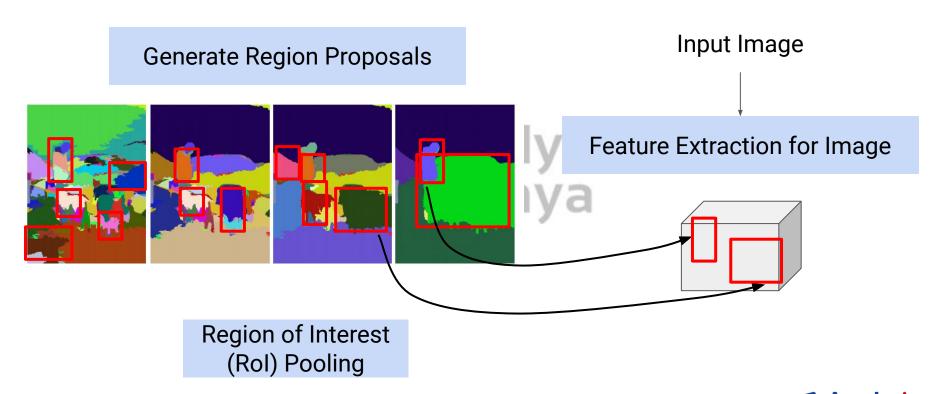




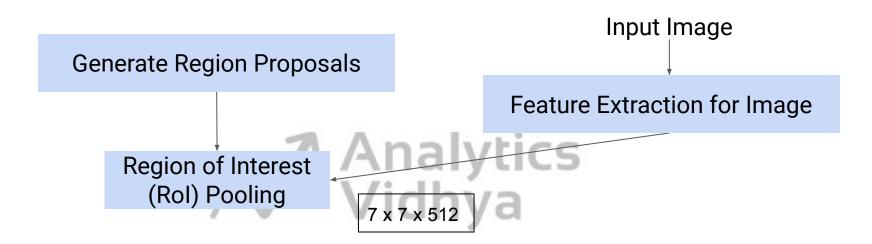
0.85	0.84
0.97	0.96

Feature Map







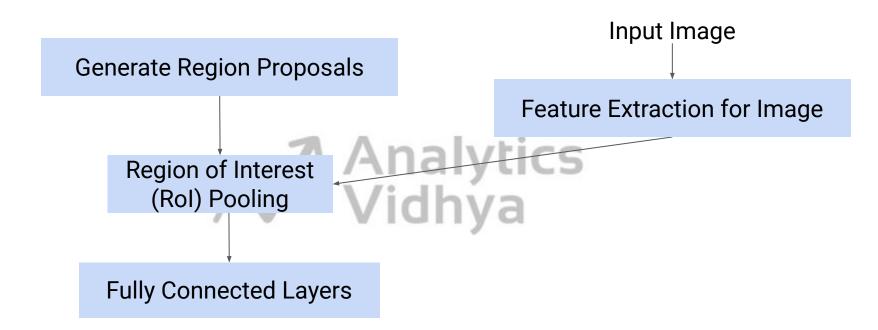




Fast R-CNN - Architecture

Layer	# filters	Filter size	Stride	Padding	Size of feature map	Activation function	
Input	-	-			224 X 224 X 3		
Conv 1	64	3X3	1	1	224 X 224 X 64	ReLU	
Conv 2	64	3X3	1	1	224 X 224 X 64	ReLU	
Max Pooling 1	-	2X2	2		112 X 112 X 64		
Conv 3	128	3X3	1	1	112 X 112 X 128	ReLU	
Conv 4	128	3X3	1	1	112 X 112 X 128	ReLU	
Max Pooling 2	-	2X2	2		56 X 56 X 128		rico
Conv 5	256	3X3	1	1	56 X 56 X 256	ReLU	
Conv 6	256	3X3	1	1	56 X 56 X 256	ReLU	
Conv 7	256	3X3	1	1	56 X 56 X 256	ReLU	a
Max Pooling 3	-	2X2	2		28 X 28 X 256		10 m
Conv 8	512	3X3	1	1	28 X 28 X 512	ReLU	
Conv 9	512	3X3	1	1	28 X 28 X 512	ReLU	
Conv 10	512	3X3	1	1	28 X 28 X 512	ReLU	
Max Pooling 4	-	2X2	2		14 X 14 X 512		
Conv 11	512	3X3	1	1	14 X 14 X 512	ReLU	
Conv 12	512	3X3	1	1	14 X 14 X 512	ReLU	
Conv 13	512	3X3	1	1	14 X 14 X 512	ReLU	
Max Pooling 5	-	2X2	2		7 X 7 X 512		
Fully Connected 1					4096	ReLU	
Fully Connected 2	1				4094	ReLU	



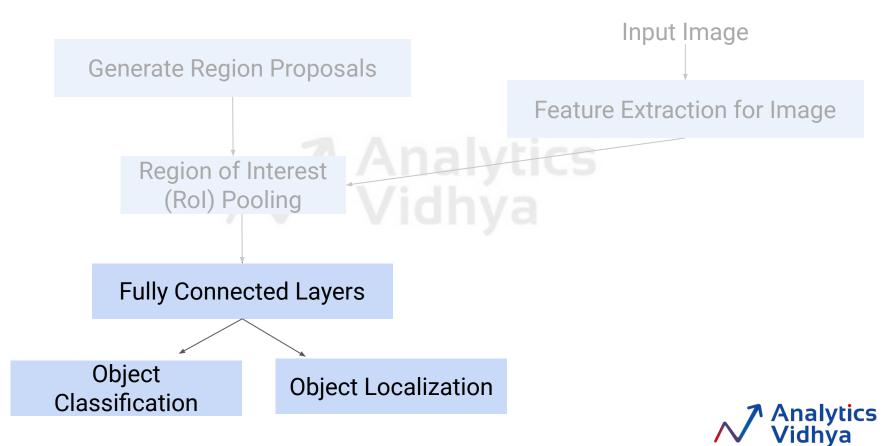


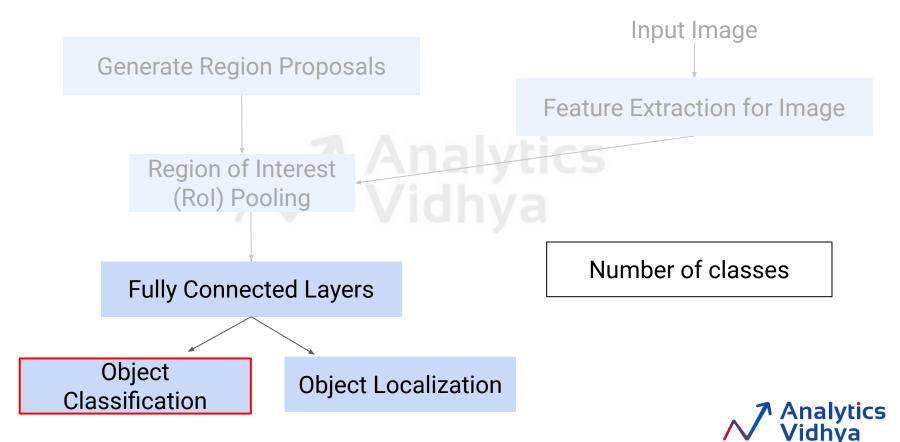


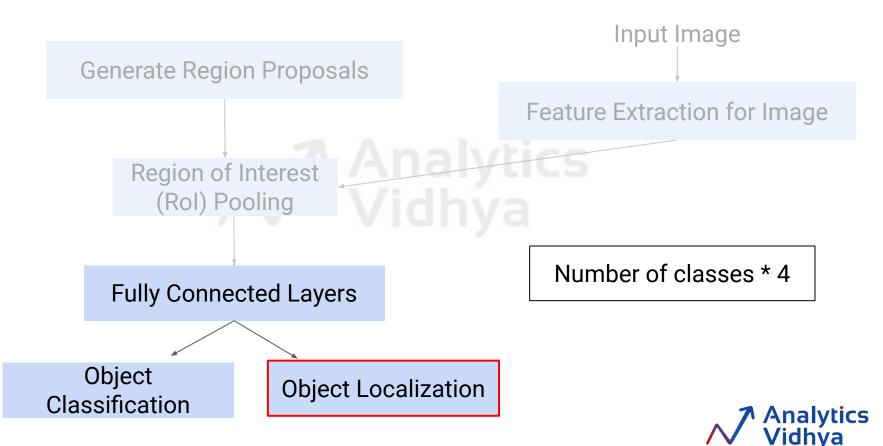
Fast R-CNN - Architectural Changes

- Feature Extraction on the complete Image
- Use Rol (Region of Interest) Pooling
- Use Dense Layers instead of SVM and Ridge Regression









Advantages of Fast R-CNN (over R-CNN)

Significantly faster than RCNN





Advantages of Fast R-CNN (over R-CNN)

Significantly faster than RCNN



Feature Extraction process for complete image



Can we Make fast R-CNN faster?

- Extracting 2000 Regions per image is time consuming
- Alternative to selective search?





