High Level Computer Vision

Object Detection & Segmentation

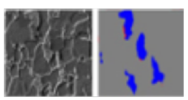
Bernt Schiele - schiele@mpi-inf.mpg.de
Mario Fritz - fritz@cispa.saarland

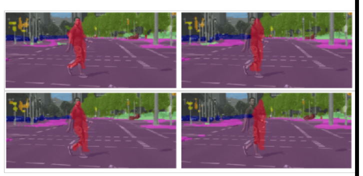
https://www.mpi-inf.mpg.de/hlcv

Research

Computer Vision

- Scene Understanding
- Segmentation
- QA and Captioning





Ours: a skier is headed down a steep slope

What sport is this man enjoying?

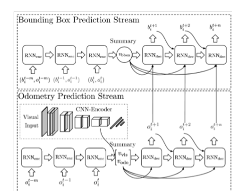
snowboarding

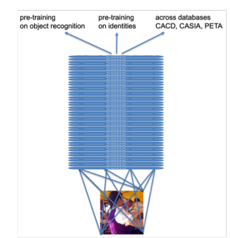
Security & Privacy

- Understanding & Controlling Privacy of Data & Models
- Adversarial Machine Learning
- Uncertainty
- Interpretability

Machine Learning

- Deep Learning
- Domain Adaptation
- Generative Adversarial Networks, Variational Autoencoders





So far: Image Classification

This image is CC0 public domain

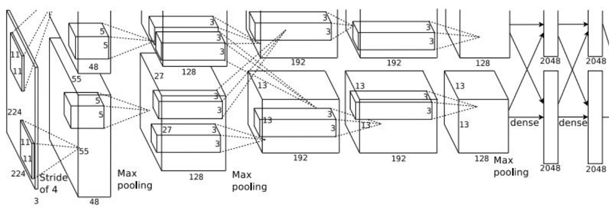


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Vector:
4096

Fully-Connected:
4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

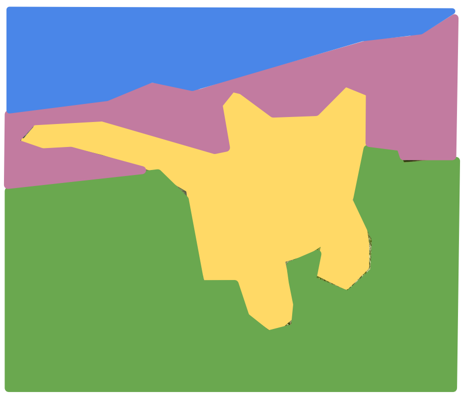
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Today: Detection, Segmentation

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Other Computer Vision Tasks

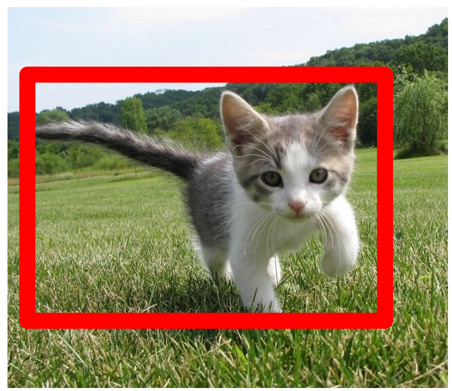
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

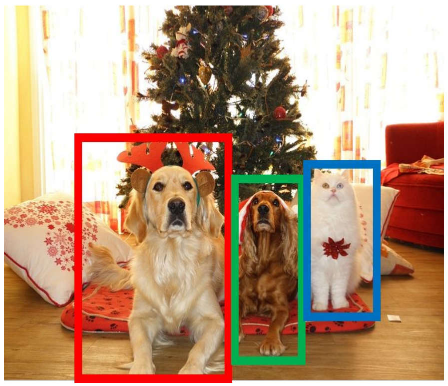
Classification + Localization



CAT

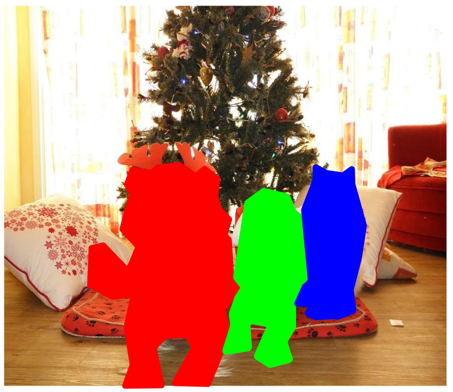
Single Object

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

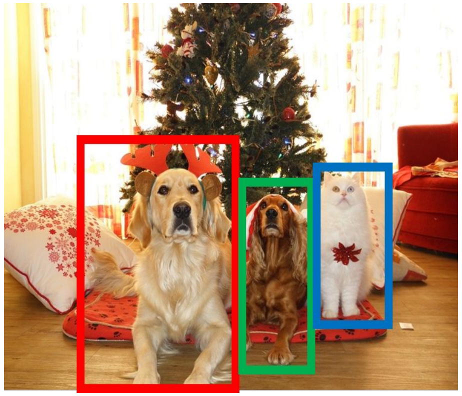
Other Computer Vision Tasks

Semantic Segmentation

GRASS, CAT, TREE, SKY

No objects, just pixels

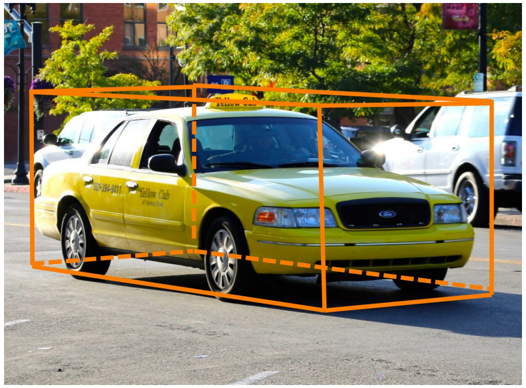
2D Object Detection



DOG, DOG, CAT

Object categories + 2D bounding boxes

3D Object Detection



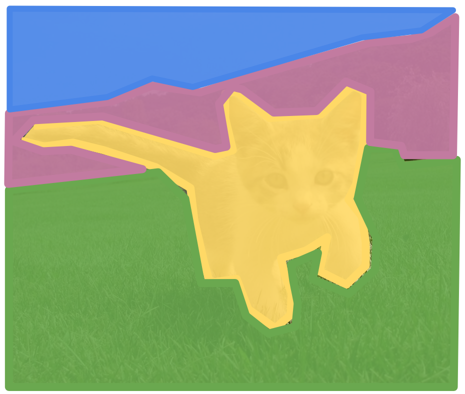
Car

Object categories + 3D bounding boxes

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Semantic Segmentation

Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

2D Object Detection

DOG, DOG, CAT

Object categories + 2D bounding boxes

3D Object Detection

Car

Object categories + 3D bounding boxes

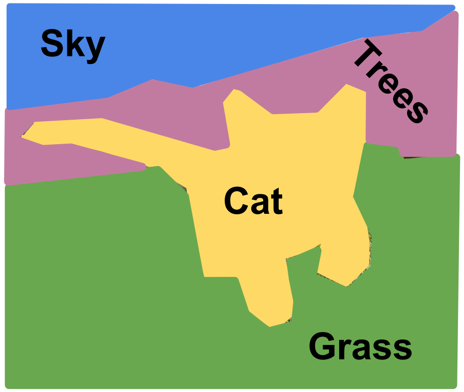
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

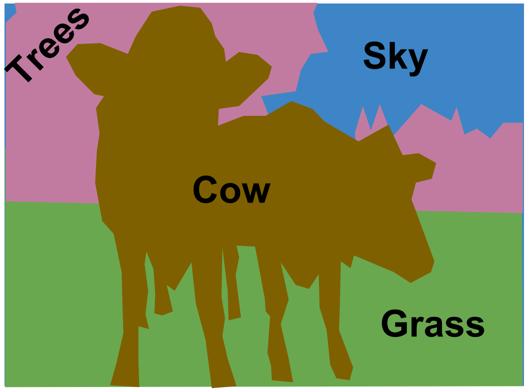
Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

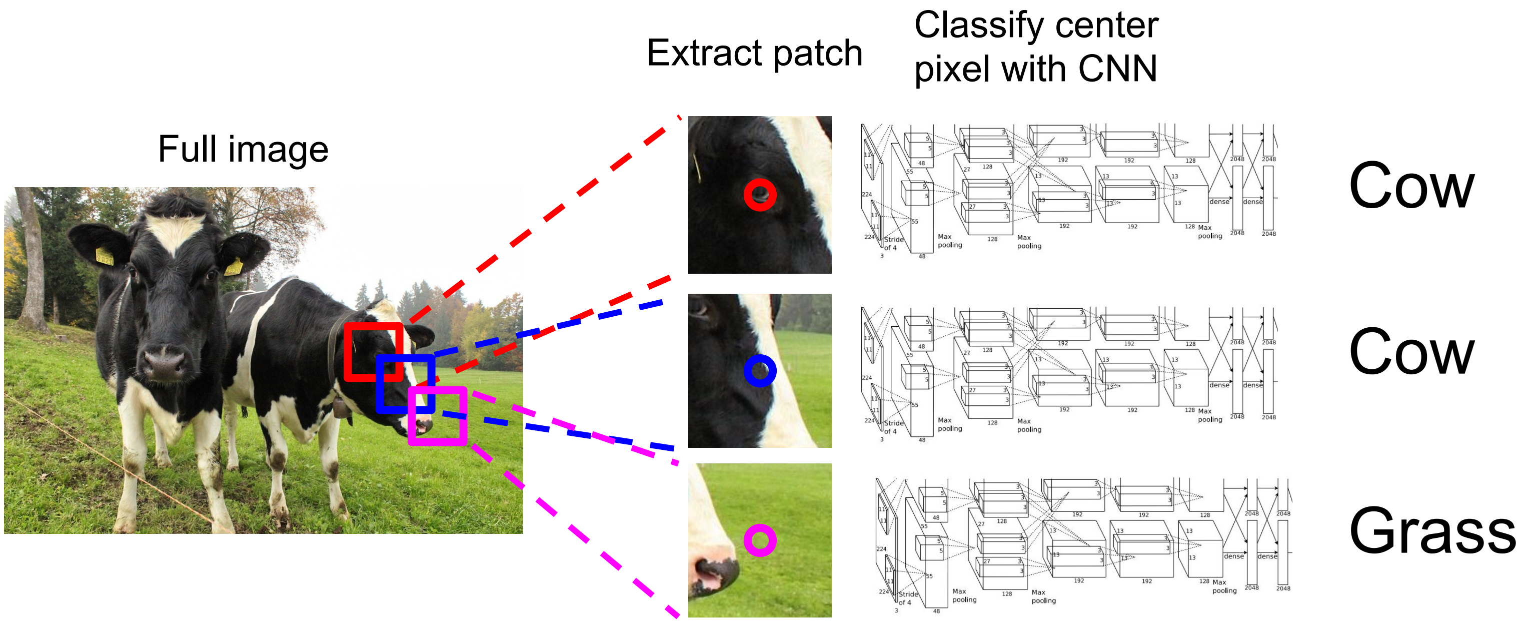
This image is CC0 public domain





slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Semantic Segmentation Idea: Sliding Window



Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

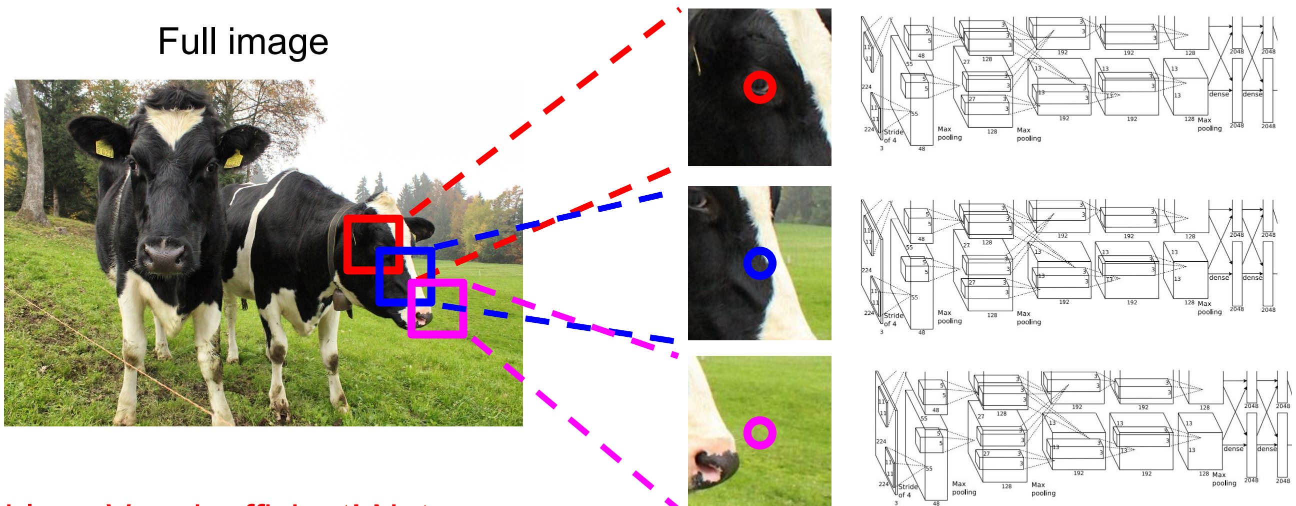
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Semantic Segmentation Idea: Sliding Window

Full image

Extract patch

Classify center pixel with CNN



Cow

Cow

Grass

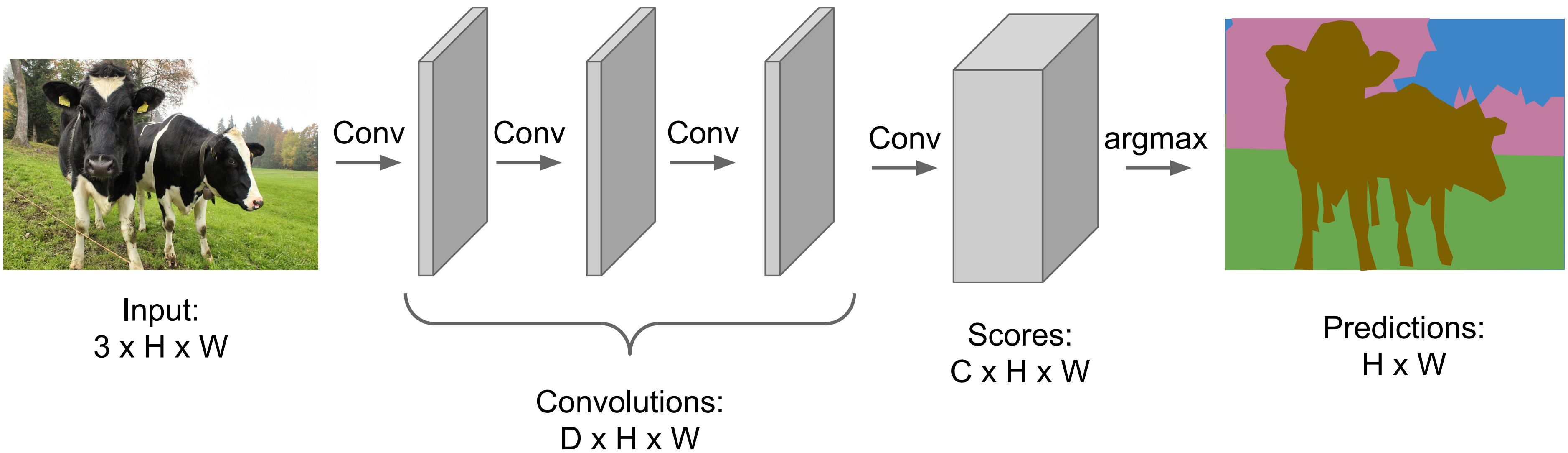
Problem: Very inefficient! Not reusing shared features between overlapping patches

Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Semantic Segmentation Idea: Fully Convolutional

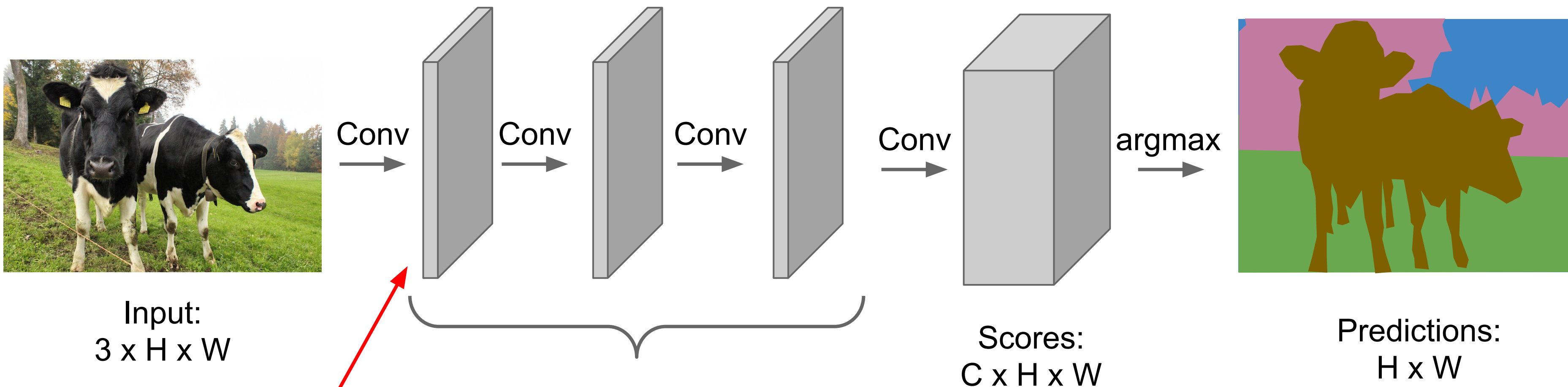
Design a network as a bunch of convolutional layers
to make predictions for pixels all at once!



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Semantic Segmentation Idea: Fully Convolutional

Design a network as a bunch of convolutional layers
to make predictions for pixels all at once!



Convolutions:
D x H x W

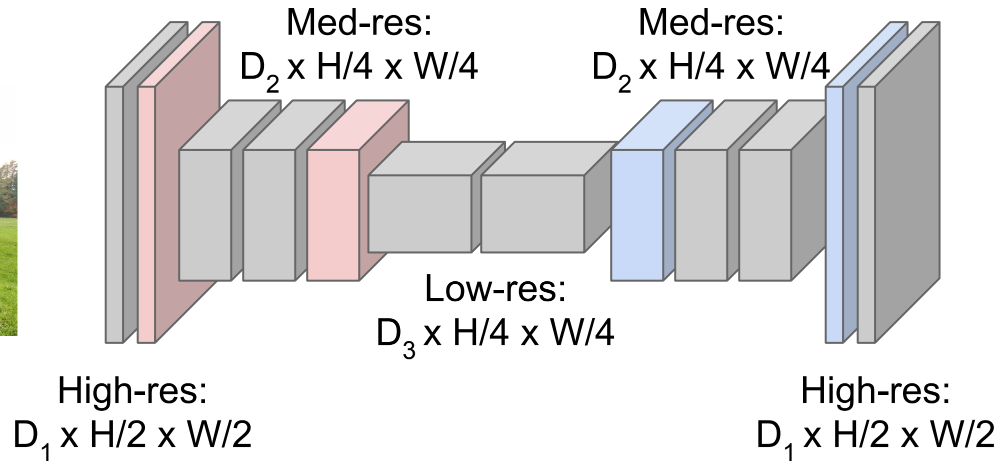
Problem: convolutions at original image resolution will be very expensive ...

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Semantic Segmentation Idea: Fully Convolutional

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Input:
3 x H x W



Predictions:
H x W

Long, Shelhamer, and Darrell, “Fully Convolutional Networks for Semantic Segmentation”, CVPR 2015
Noh et al, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

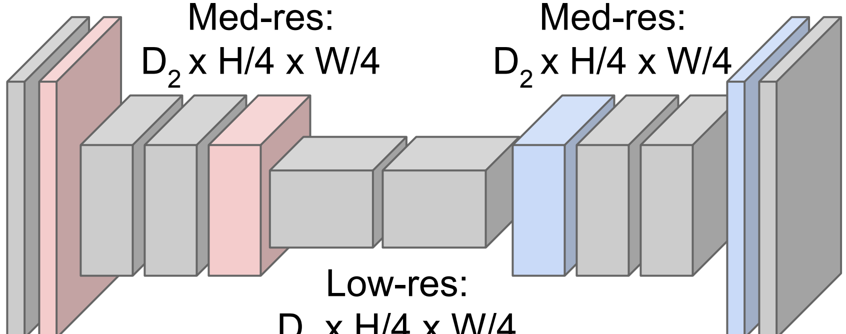
Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling: ???

Input:
3 x H x W



Predictions:
H x W

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

In-Network upsampling: “Unpooling”

Nearest Neighbor

Input: 2 x 2

1	2
3	4

Output: 4 x 4

1	1	2	2
1	1	2	2
3	3	4	4
3	3	4	4

“Bed of Nails”

Input: 2 x 2

1	2
3	4

Output: 4 x 4

1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

In-Network upsampling: “Max Unpooling”

Max Pooling
Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

…

Rest of the network

Max Unpooling
Use positions from pooling layer

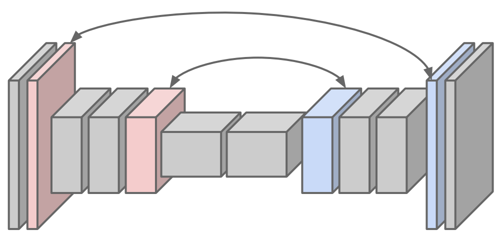
1	2
3	4

Input: 2 x 2

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

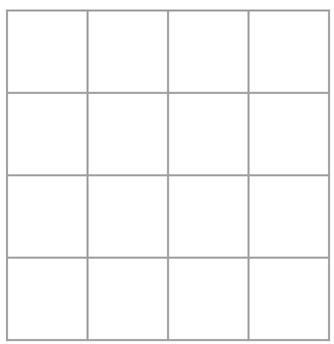
Corresponding pairs of downsampling and upsampling layers



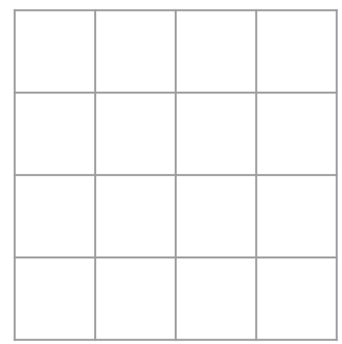
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

Recall: Typical 3 x 3 convolution, stride 1 pad 1



Input: 4 x 4

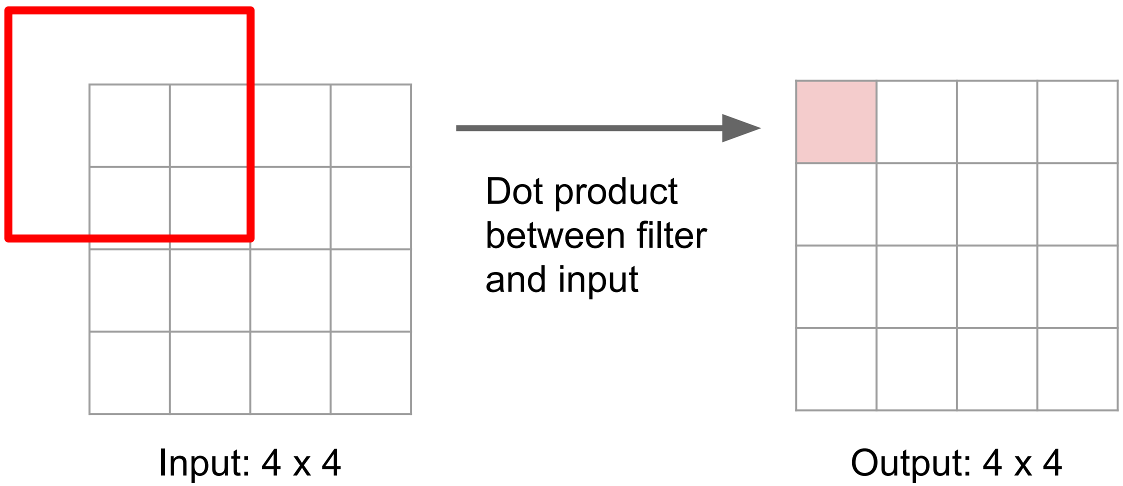


Output: 4 x 4

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

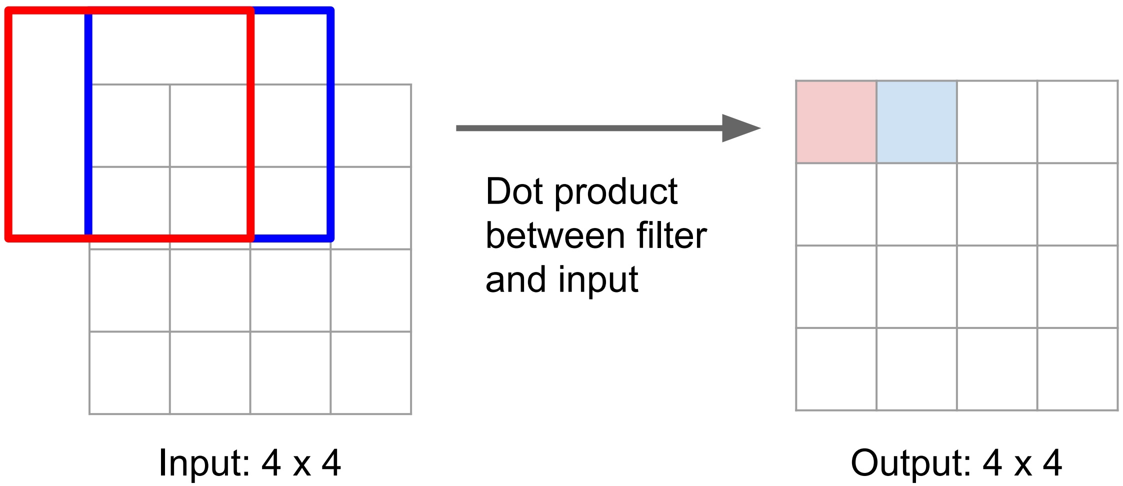
Recall: Normal 3 x 3 convolution, stride 1 pad 1



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

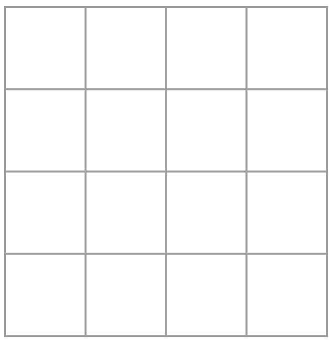
Recall: Normal 3 x 3 convolution, stride 1 pad 1



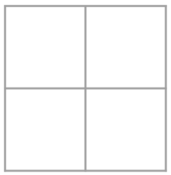
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



Input: 4 x 4

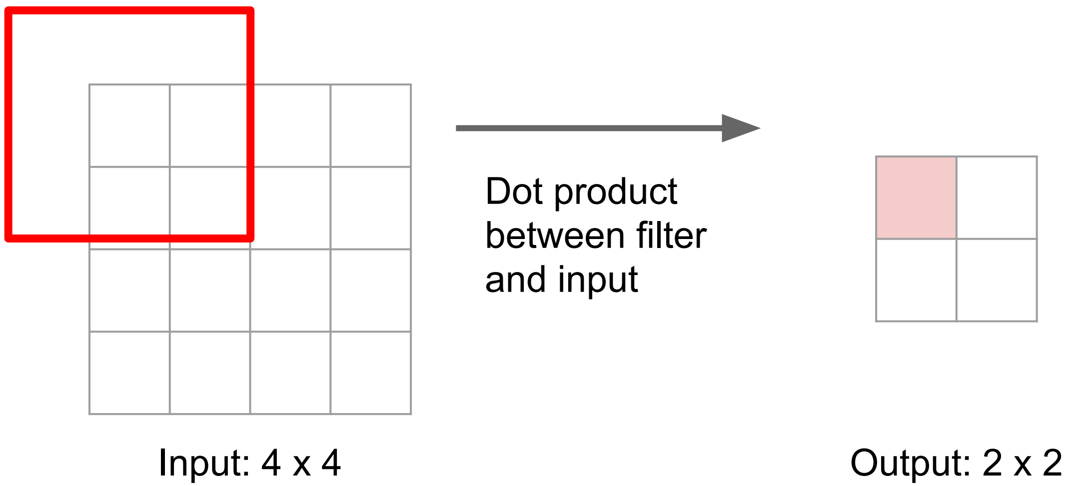


Output: 2 x 2

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

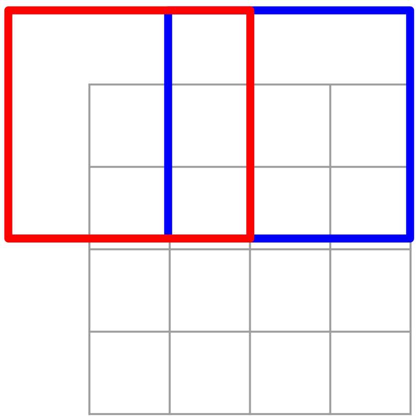
Recall: Normal 3 x 3 convolution, stride 2 pad 1



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

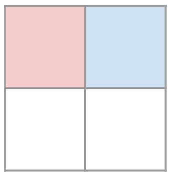
Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



Input: 4 x 4

Dot product between filter and input



Output: 2 x 2

Filter moves 2 pixels in the input for every one pixel in the output

Stride gives ratio between movement in input and output

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

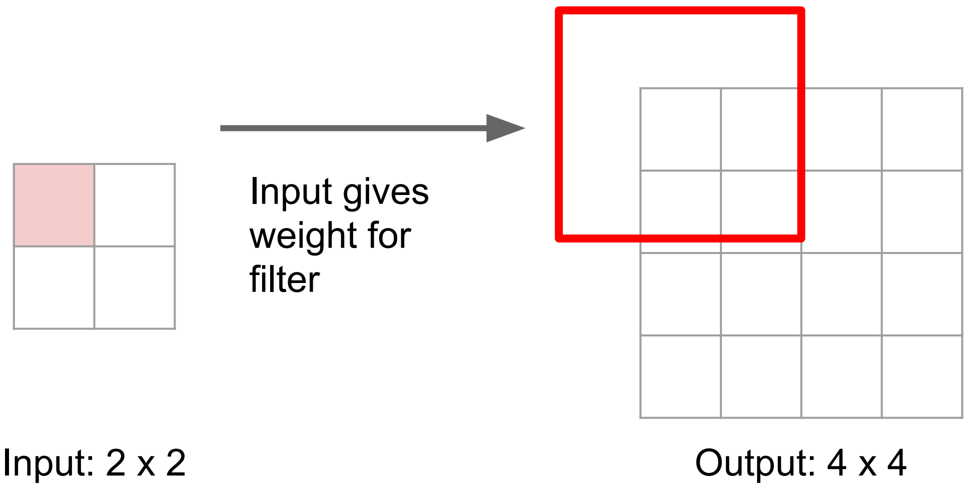
Input: 2 x 2

Output: 4 x 4

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

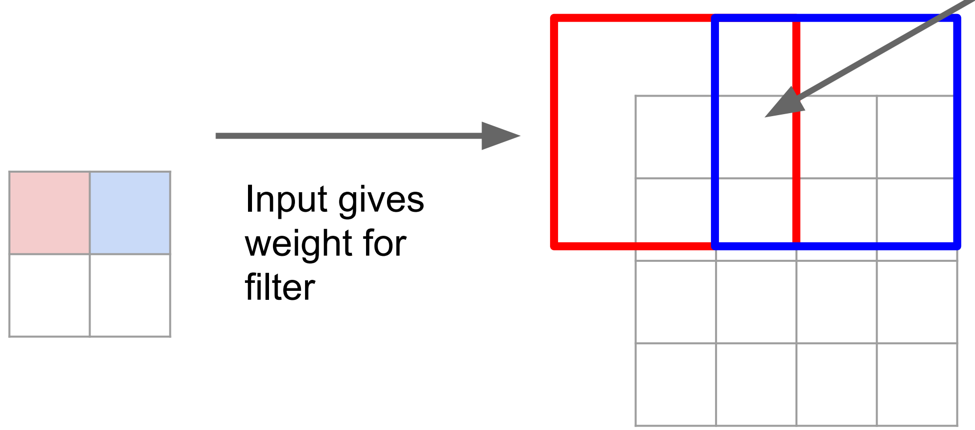


slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

Sum where output overlaps



Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

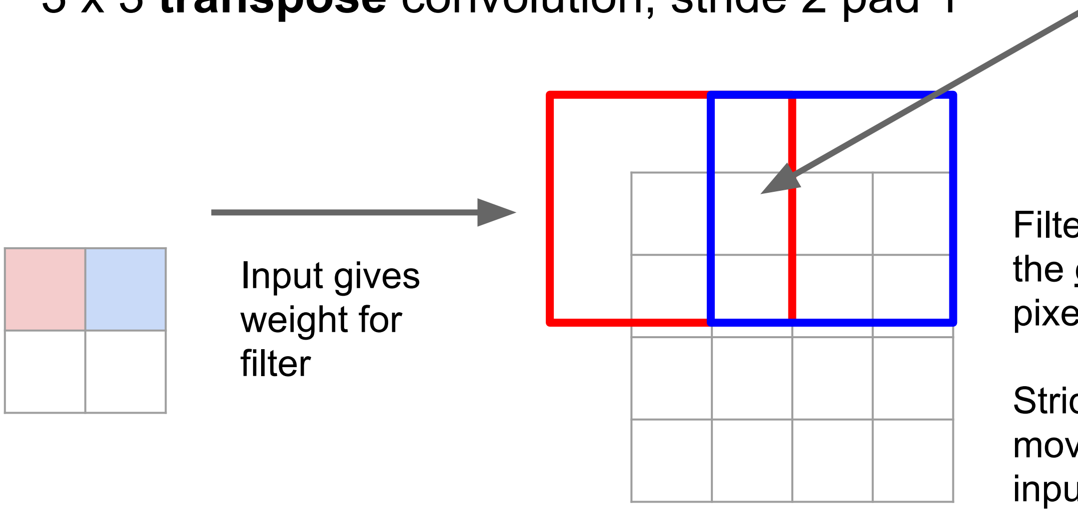
Input: 2 x 2

Output: 4 x 4

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1



Sum where output overlaps

Input gives weight for filter

Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Input: 2 x 2

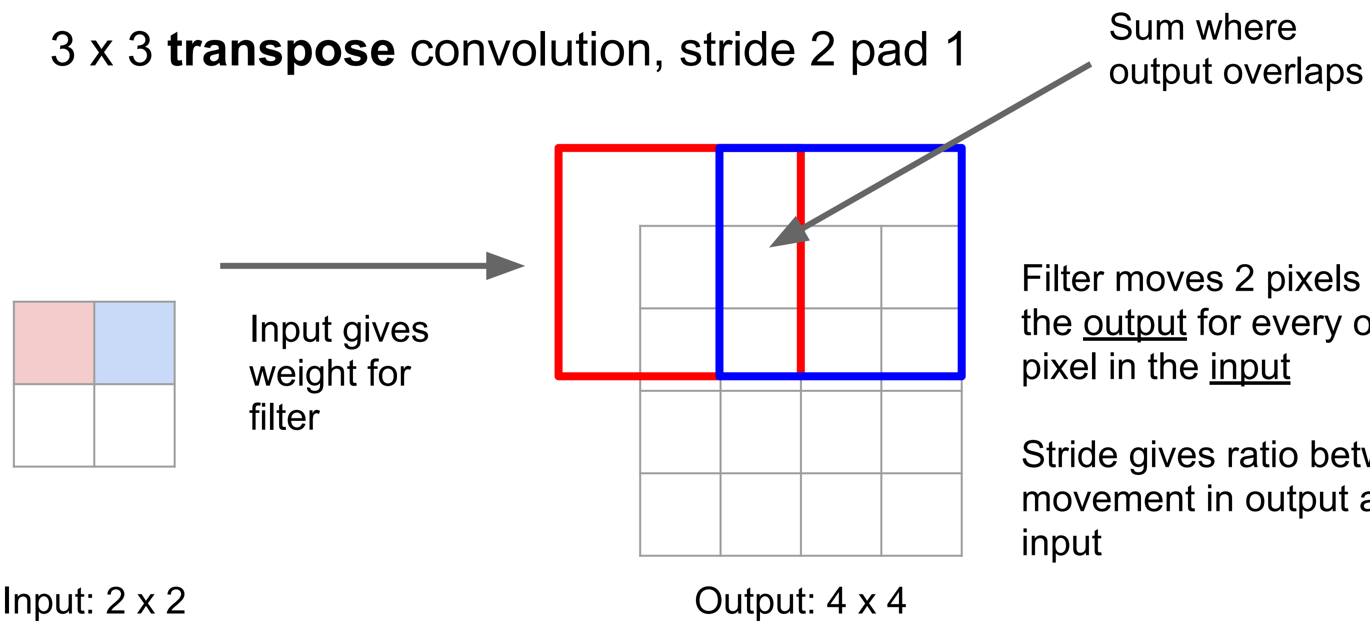
Output: 4 x 4

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: Transpose Convolution

Other names:
-Deconvolution (bad)
-Upconvolution
-Fractionally strided convolution
-Backward strided convolution

3 x 3 **transpose** convolution, stride 2 pad 1

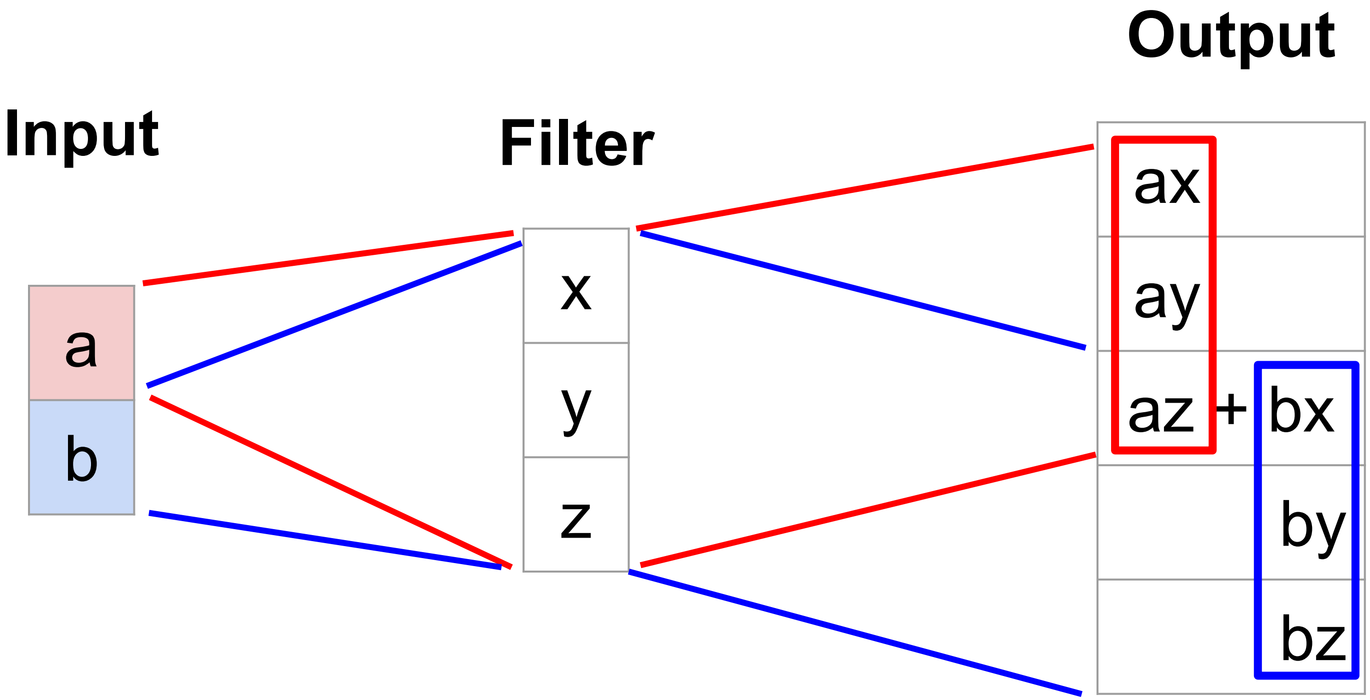


Filter moves 2 pixels in the <u>output</u> for every one pixel in the <u>input</u>

Stride gives ratio between movement in output and input

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Learnable Upsampling: 1D Example



Output contains copies of the filter weighted by the input, summing at where at overlaps in the output

Need to crop one pixel from output to make output exactly 2x input

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & x & 0 & 0 & 0 \\ 0 & x & y & x & 0 & 0 \\ 0 & 0 & x & y & x & 0 \\ 0 & 0 & 0 & x & y & x \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ ax + by + cz \\ bx + cy + dz \\ cx + dy \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=1, padding=1

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & x & 0 & 0 & 0 \\ 0 & x & y & x & 0 & 0 \\ 0 & 0 & x & y & x & 0 \\ 0 & 0 & 0 & x & y & x \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ ax + by + cz \\ bx + cy + dz \\ cx + dy \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=1, padding=1

Convolution transpose multiplies by the transpose of the same matrix:

$$\vec{x} *^T \vec{a} = X^T\vec{a}$$

$$\begin{bmatrix} x & 0 & 0 & 0 \\ y & x & 0 & 0 \\ z & y & x & 0 \\ 0 & z & y & x \\ 0 & 0 & z & y \\ 0 & 0 & 0 & z \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} ax \\ ay + bx \\ az + by + cx \\ bz + cy + dx \\ cz + dy \\ dz \end{bmatrix}$$

When stride=1, convolution transpose is just a regular convolution (with different padding rules)

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & x & 0 & 0 & 0 \\ 0 & 0 & x & y & x & 0 \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ bx + cy + dz \end{bmatrix}$$

Example: 1D conv, kernel size=3, <u>stride=2</u>, padding=1

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & 0 & x & y & z & 0 \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ bx + cy + dz \end{bmatrix}$$

Example: 1D conv, kernel size=3, <u>stride=2</u>, padding=1

Convolution transpose multiplies by the transpose of the same matrix:

$$\vec{x} *^T \vec{a} = X^T\vec{a}$$

$$\begin{bmatrix} x & 0 \\ y & 0 \\ z & x \\ 0 & y \\ 0 & z \\ 0 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} ax \\ ay \\ az + bx \\ by \\ bz \\ 0 \end{bmatrix}$$

When stride>1, convolution transpose is no longer a normal convolution!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

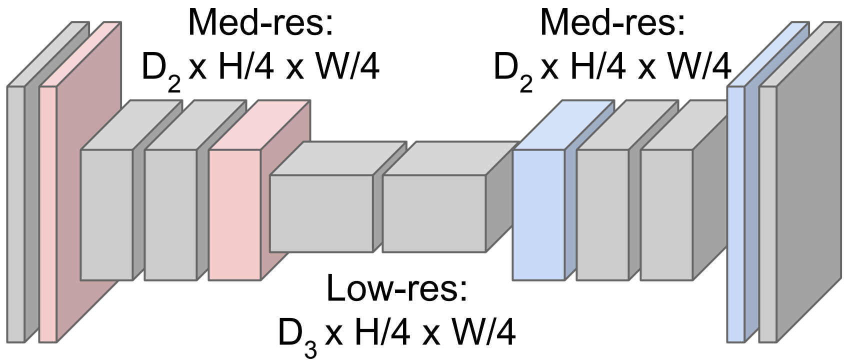
Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling: Unpooling or strided transpose convolution

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

High-res:
D_1 x H/2 x W/2

Predictions:
H x W

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

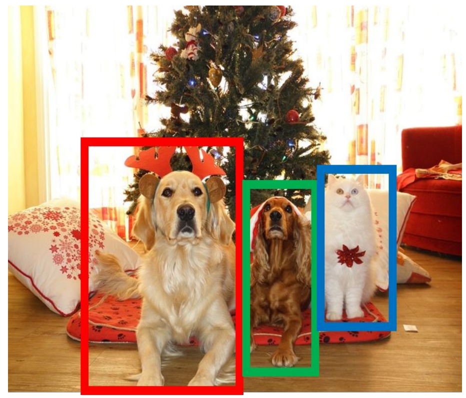
2D Object Detection

Semantic Segmentation

GRASS, CAT, TREE, SKY

No objects, just pixels

2D Object Detection



DOG, DOG, CAT

Object categories + 2D bounding boxes

3D Object Detection

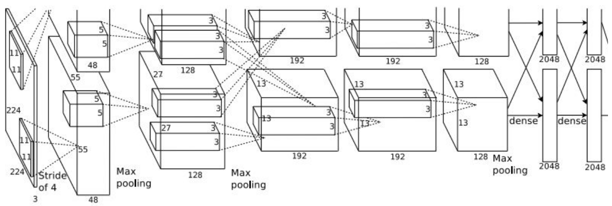
Car

Object categories + 3D bounding boxes

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Classification + Localization

This image is CC0 public domain



Fully Connected:
4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Vector:
4096

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

Treat localization as a regression problem!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Classification + Localization

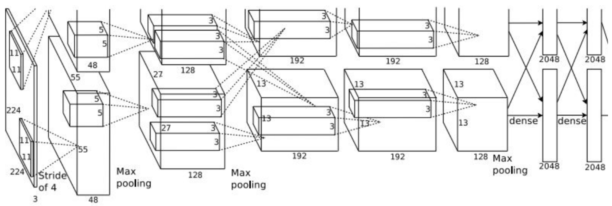
Correct label:
Cat

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax Loss

Fully Connected:
4096 to 1000

This image is CC0 public domain



Vector:
4096

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

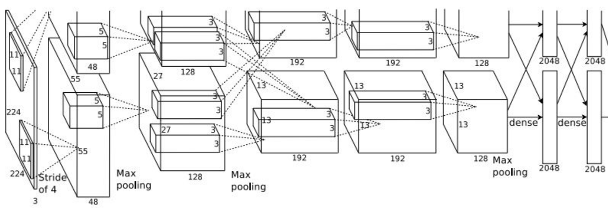
L2 Loss

Correct box:
(x', y', w', h')

Treat localization as a regression problem!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Classification + Localization



Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label: Cat

Softmax Loss

Fully Connected: 4096 to 4

Box Coordinates (x, y, w, h)

Correct box: (x', y', w', h')

L2 Loss

Multitask Loss

+ → **Loss**

Treat localization as a regression problem!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Classification + Localization

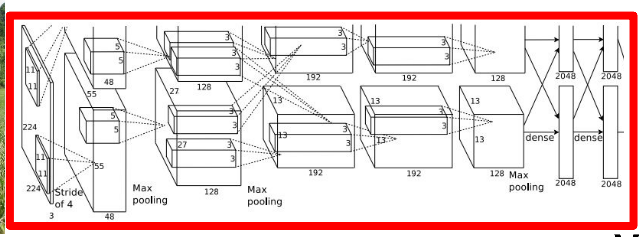
Correct label:
Cat

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax Loss

Fully Connected:
4096 to 1000

This image is CC0 public domain



Often pretrained on ImageNet
(Transfer learning)

Vector:
4096

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

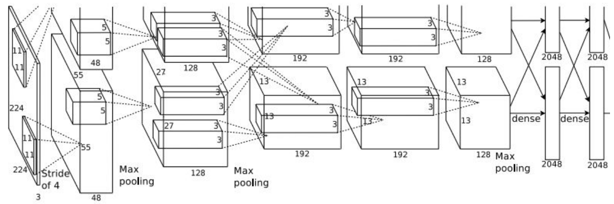
+ → Loss

Correct box:
(x', y', w', h')

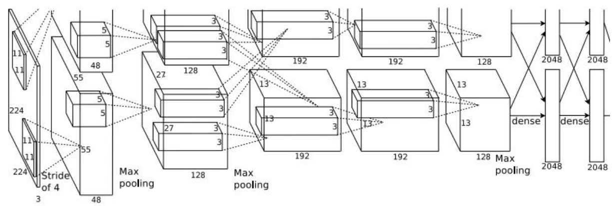
Treat localization as a regression problem!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

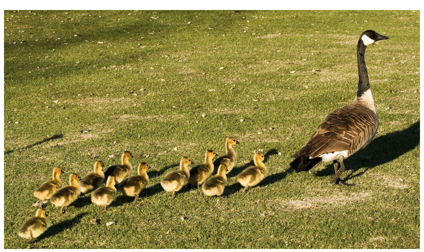
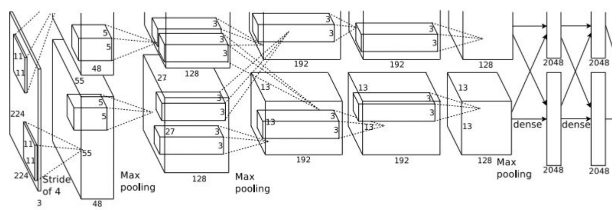
Object Detection as Regression?

CAT: (x, y, w, h)

DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)

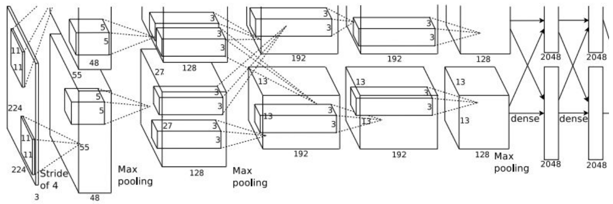



DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

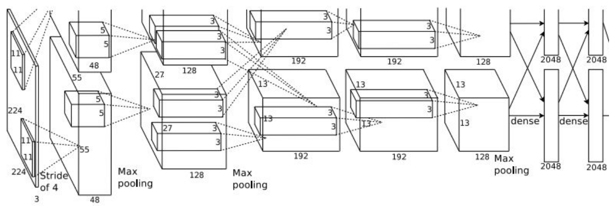
slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection as Regression?

Each image needs a different number of outputs!

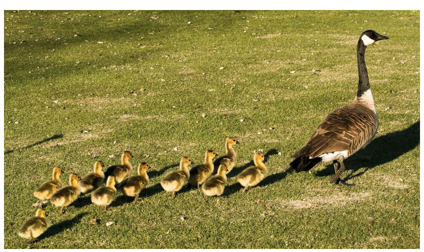


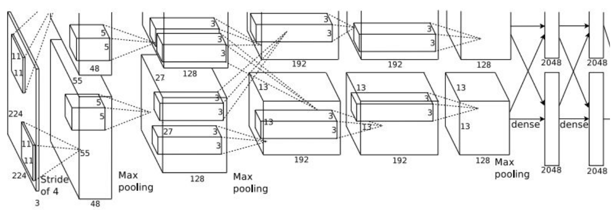
CAT: (x, y, w, h) 4 numbers



DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)

16 numbers





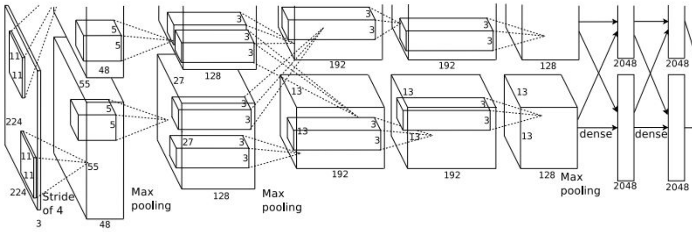
DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

Many numbers!

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection as Classification: Sliding Window

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

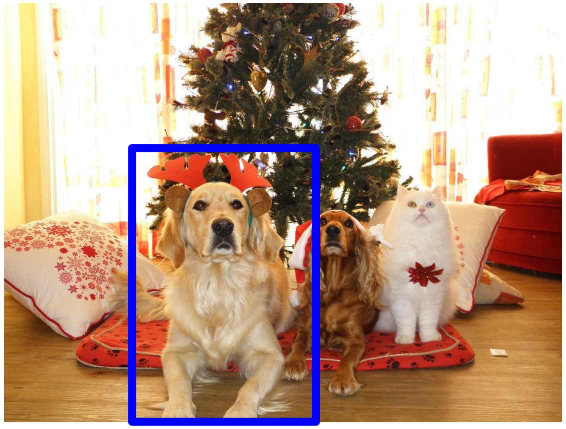


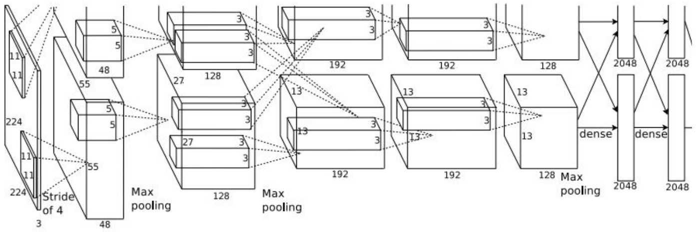
Dog? NO
Cat? NO
Background? YES

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection as Classification: Sliding Window

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



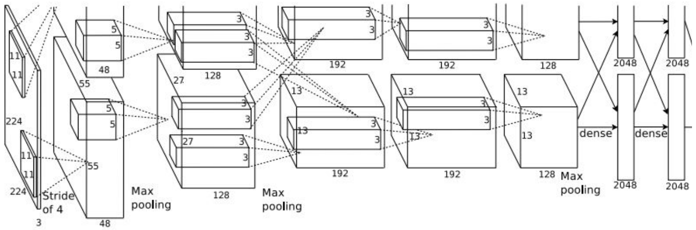


Dog? YES
Cat? NO
Background? NO

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection as Classification: Sliding Window

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

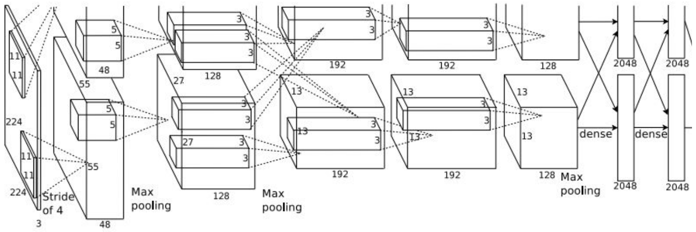


Dog? YES
Cat? NO
Background? NO

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection as Classification: Sliding Window

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

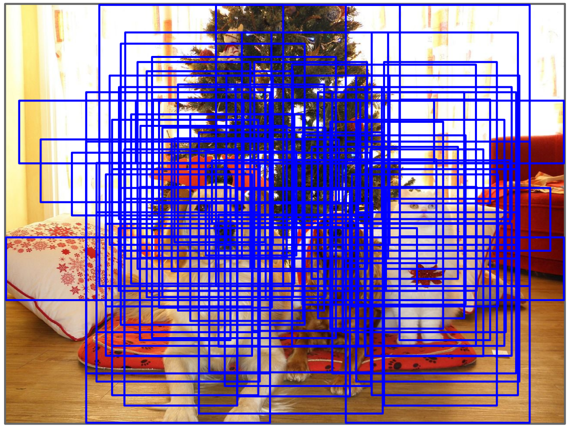


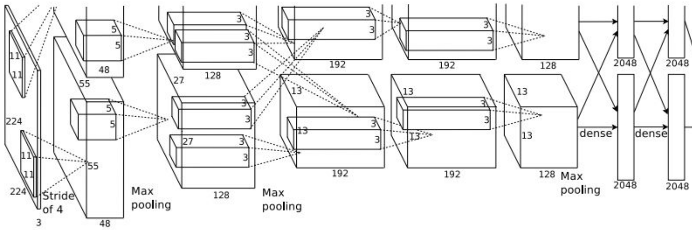
Dog? NO
Cat? YES
Background? NO

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection as Classification: Sliding Window

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





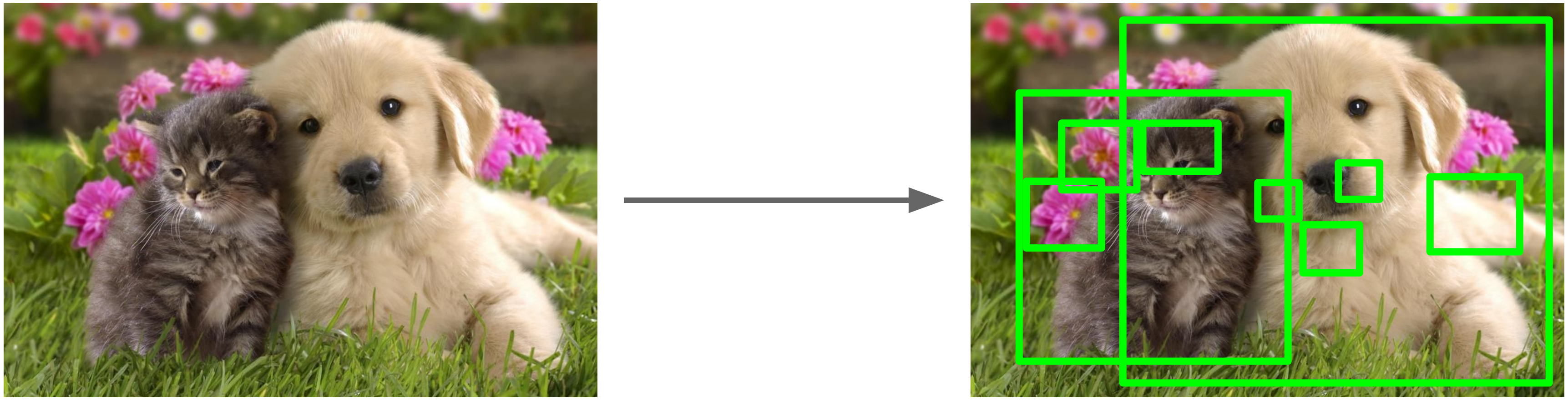
Dog? NO
Cat? YES
Background? NO

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

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Region Proposals / Selective Search

- Find “blobby” image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 2000 region proposals in a few seconds on CPU



Alexe et al, “Measuring the objectness of image windows”, TPAMI 2012
Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013
Cheng et al, “BING: Binarized normed gradients for objectness estimation at 300fps”, CVPR 2014
Zitnick and Dollar, “Edge boxes: Locating object proposals from edges”, ECCV 2014

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

R-CNN

Input image

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

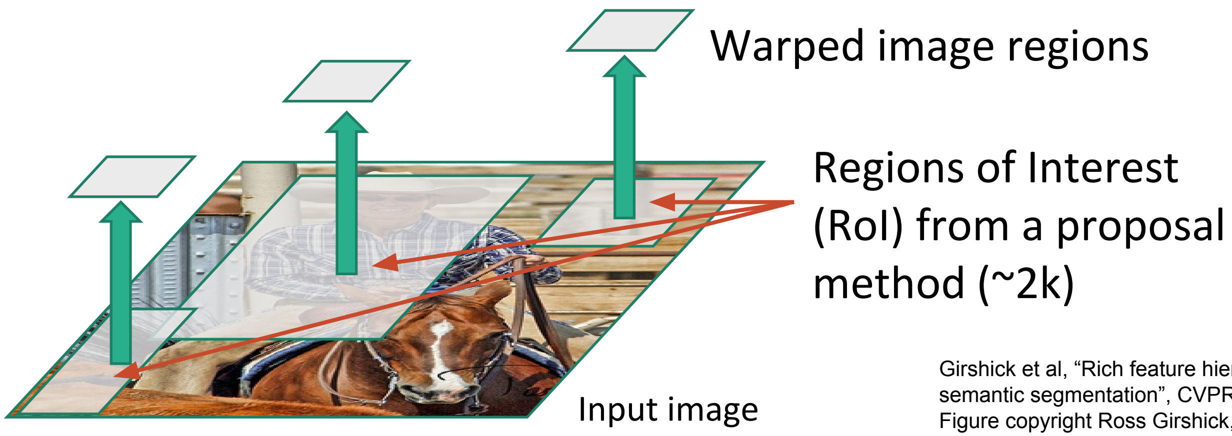
R-CNN

Regions of Interest (RoI) from a proposal method (~2k)

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

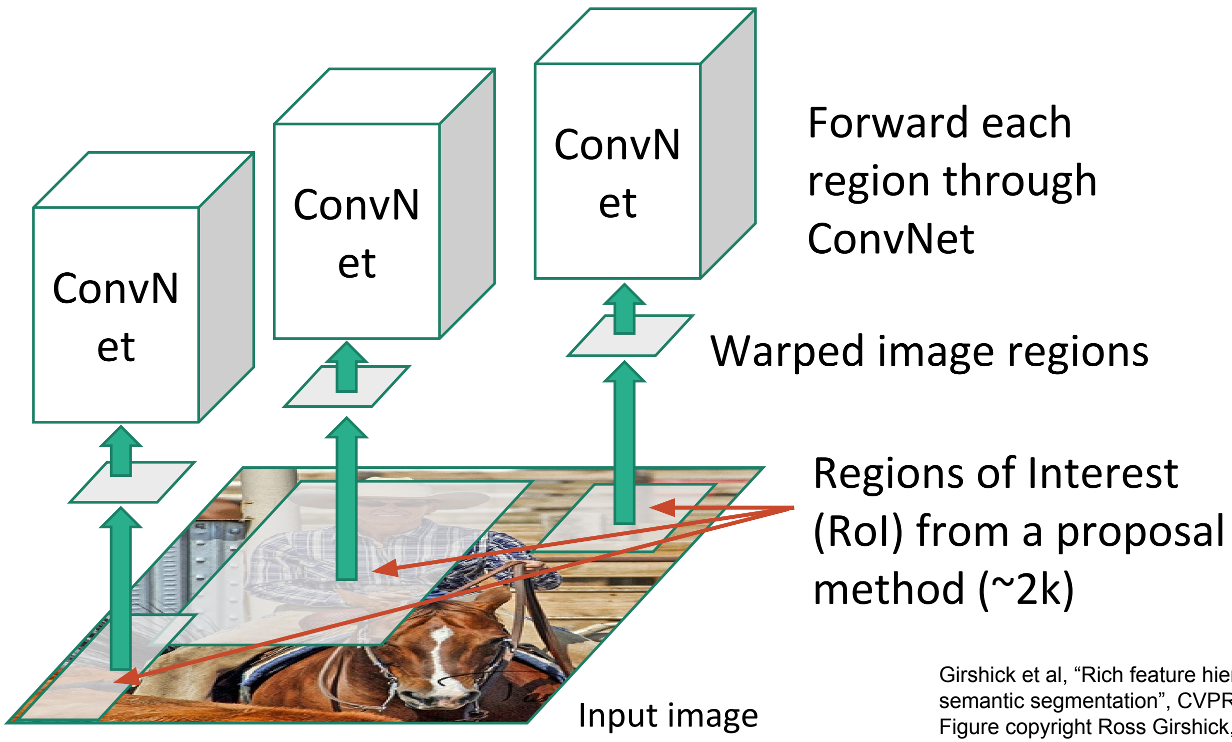
R-CNN



Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

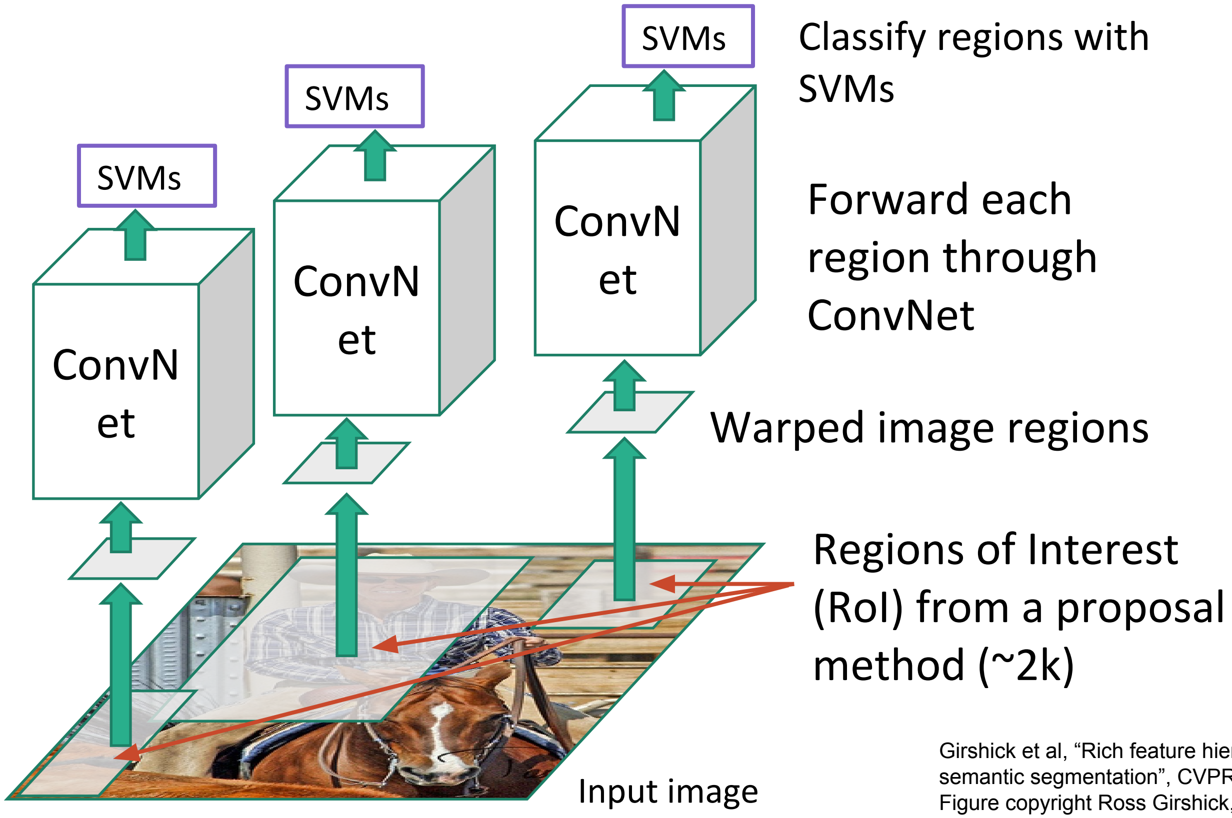
R-CNN



Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

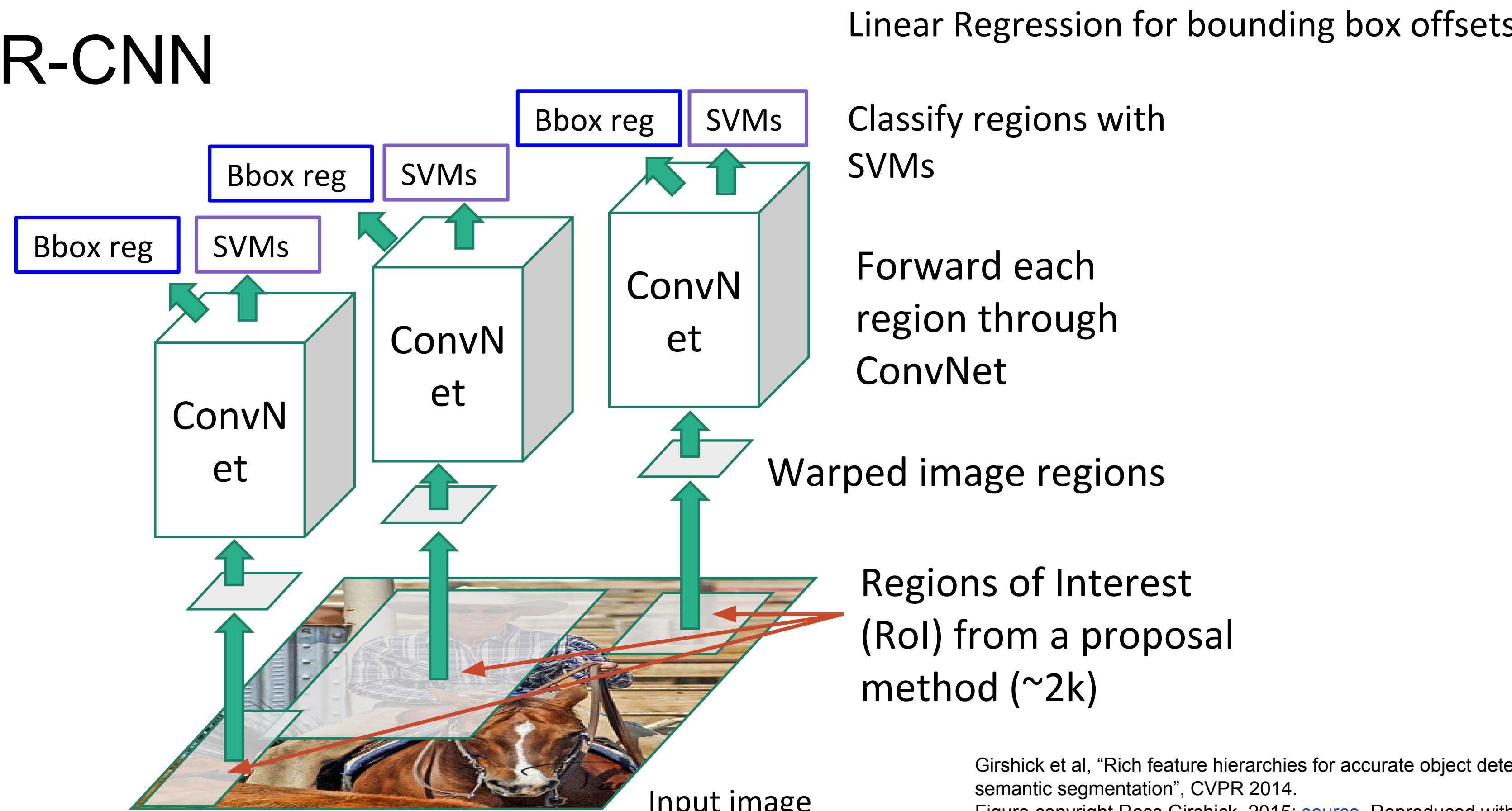
R-CNN



Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](). Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

R-CNN

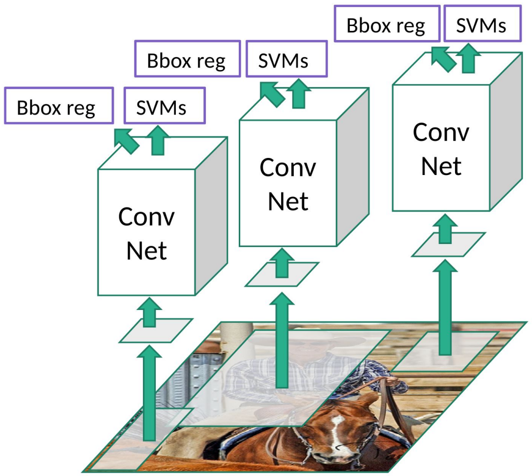


Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

R-CNN: Problems

- Ad hoc training objectives
  - Fine-tune network with softmax classifier (log loss)
  - Train post-hoc linear SVMs (hinge loss)
  - Train post-hoc bounding-box regressions (least squares)
- Training is slow (84h), takes a lot of disk space
- Inference (detection) is slow
  - 47s / image with VGG16 [Simonyan & Zisserman. ICLR15]
  - Fixed by SPP-net [He et al. ECCV14]



Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

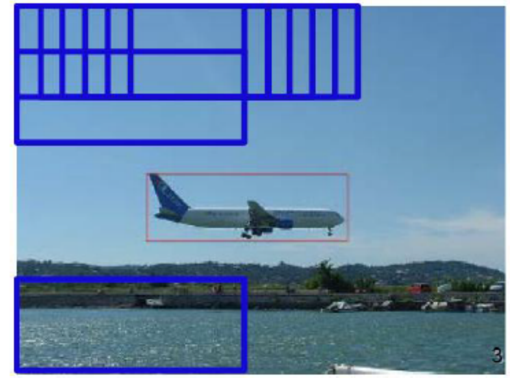
Segmentation as Selective Search for Object Recognition

K. van de Sande[1], J. Uijlings[2], T. Gevers[1], and A. Smeulders[1]
University of Amsterdam[1] and University of Trento[2]

Reading Group presentation by Esa Rahtu

(material taken from van de Sande's ICCV paper and PASCAL presentations)

Motivation



- Most current approaches use exhaustive search
  - Visit every location in an image
  - Imposes computational constraints on
    - Number of possible locations -> grid/fixed aspect ratio)
    - Evaluation cost per location -> simple features/classifiers
  - To go beyond this, we need something more sophisticated

Viola IJCV 2004
Dalal CVPR 2005
Felzenszwalb TPAMI 2010
Vedaldi ICCV 2009

Main design criteria

- **High recall**
  - We do not want to lose any objects, since they cannot be recovered later.
- Coarse locations are sufficient
  - Accurate delineation is not necessary for recognition
  - In contrary, nearby context might be useful
    -> use bounding boxes
- Fast to compute
  - Necessary when operating with large datasets
    -> <10s/image

How to obtain high recall?

- Images are intrinsically hierarchical

- Segmentation at single scale are not enough -> hypotheses based on hierarchical grouping

Proposed method

- Start by oversegmenting the input image

"Efficient graph-based image segmentation"
Felzenszwalb and Huttenlocher, IJCV 2004

Method

- compute similarity measure between all adjacent region pairs a and b (e.g.) as:

$$S(a,b) = \alpha S_{zize}(a,b) + \beta S_{color}(a,b)$$

  - with

$$S_{size}(a,b) = 1 - \frac{\mathrm{size}(a) + \mathrm{size}(b)}{\mathrm{size}(image)}$$

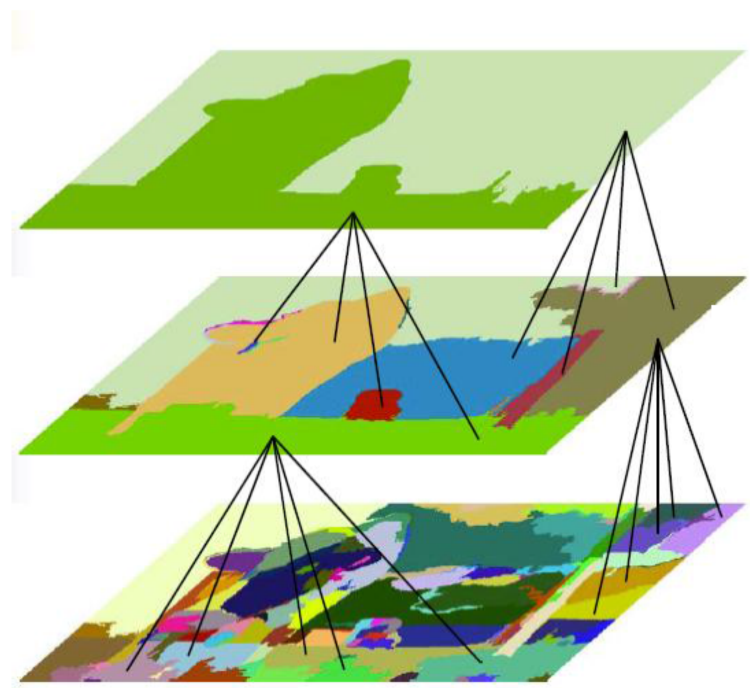
    encourages small regions to merge early
  - and

$$S_{color}(a,b) = \sum_{k=1}^{n} \min(a^k, b^k)$$

    a^k, b^k are color histograms, encouraging "similar" regions to merge
  - for slightly more elaborated similarities see their IJCV-paper

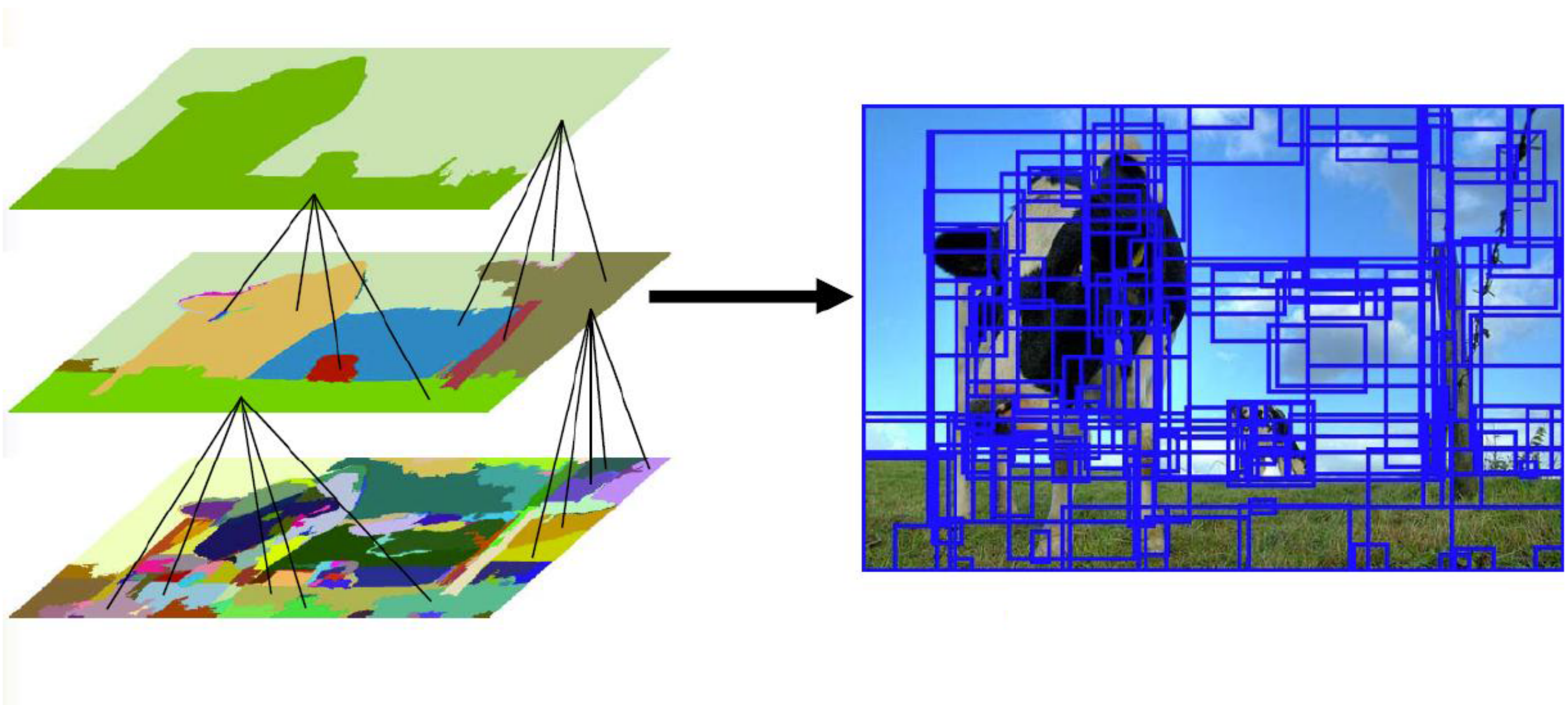
Proposed method

1. Merge two most similar regions based on *S.*
2. Update similarities between the new region and its neighbors.
3. Go back to step 1. until the whole image is a single region.

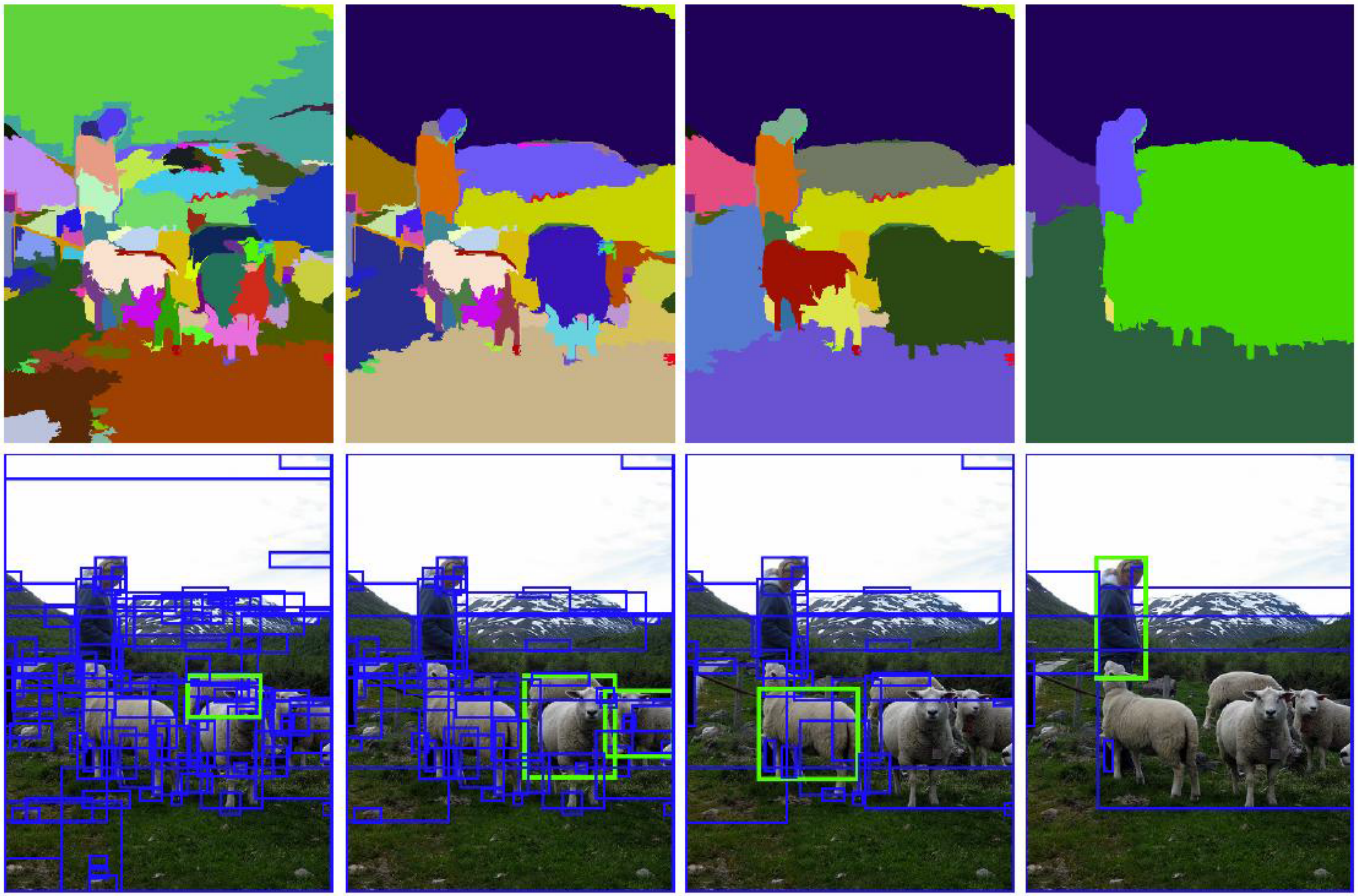


Proposed method

- Take bounding boxes of all generated regions and treat them as possible object locations.



Proposed method

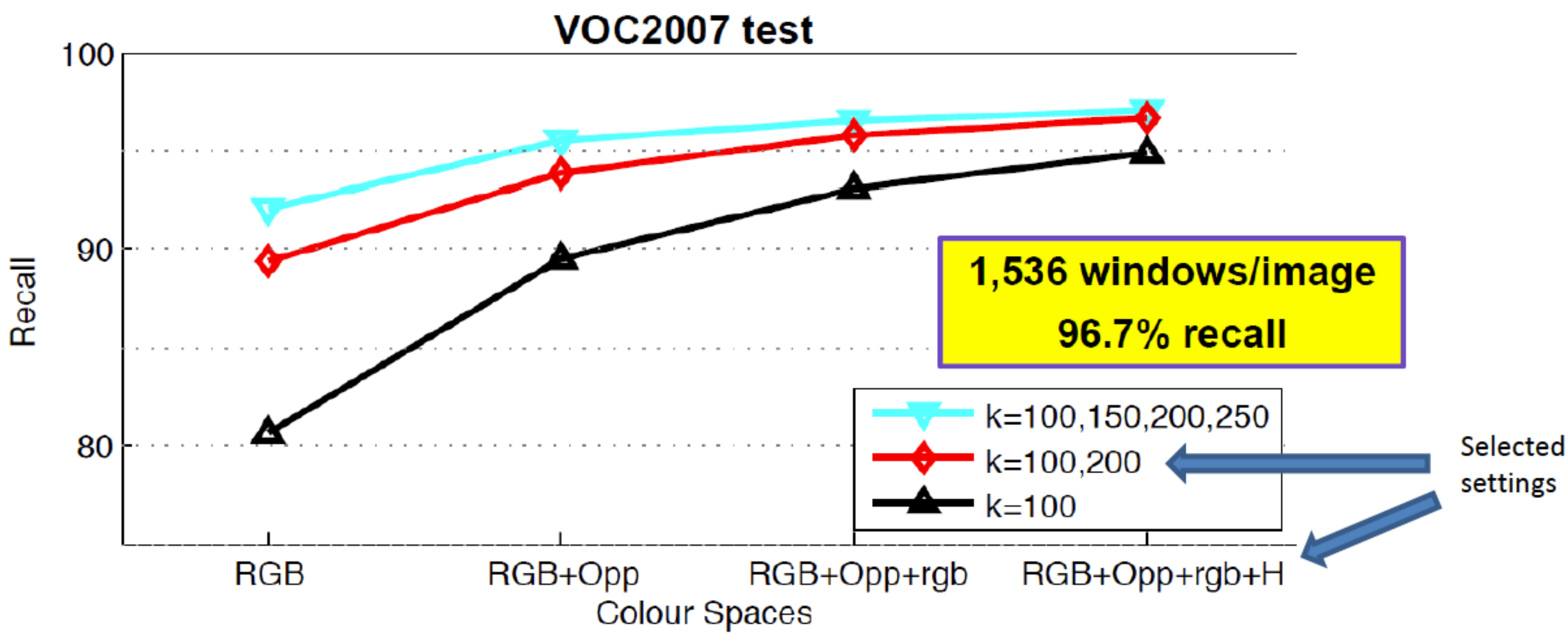


High recall revisited

- No single segmentation works for all cases
  -> diversify the set of segmentations
- Use different color spaces
  - RGB, Opponent color, normalized RGB, and hue
- Use different parameters in Felzenswalb method
  - k = [100, 150, 200, 250] (k = threshold parameter)

Evaluation of object hypotheses

- Recall is a proportion of objects that are covered by some box with >0.5 overlap



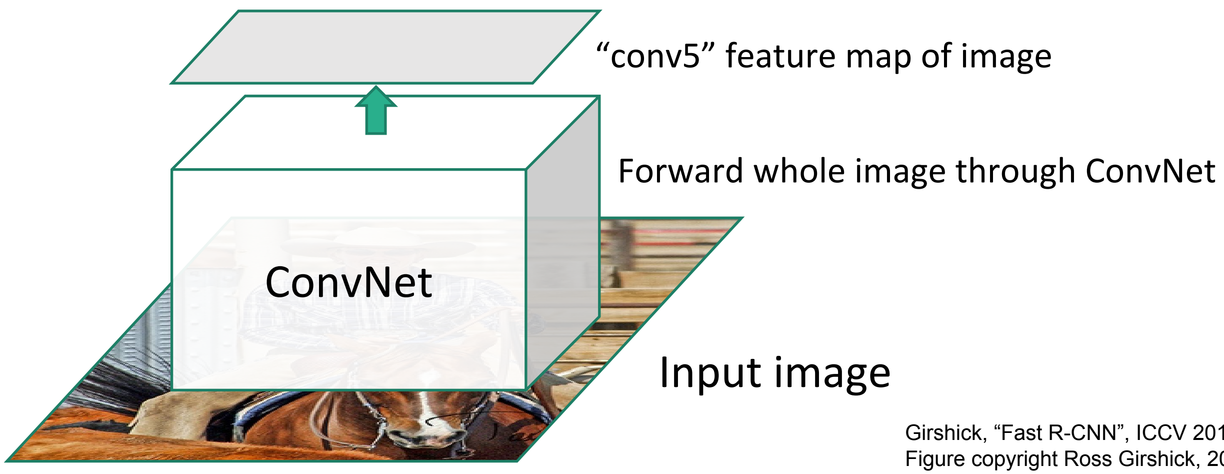
Fast R-CNN

Input image

Girshick, “Fast R-CNN”, ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](). Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

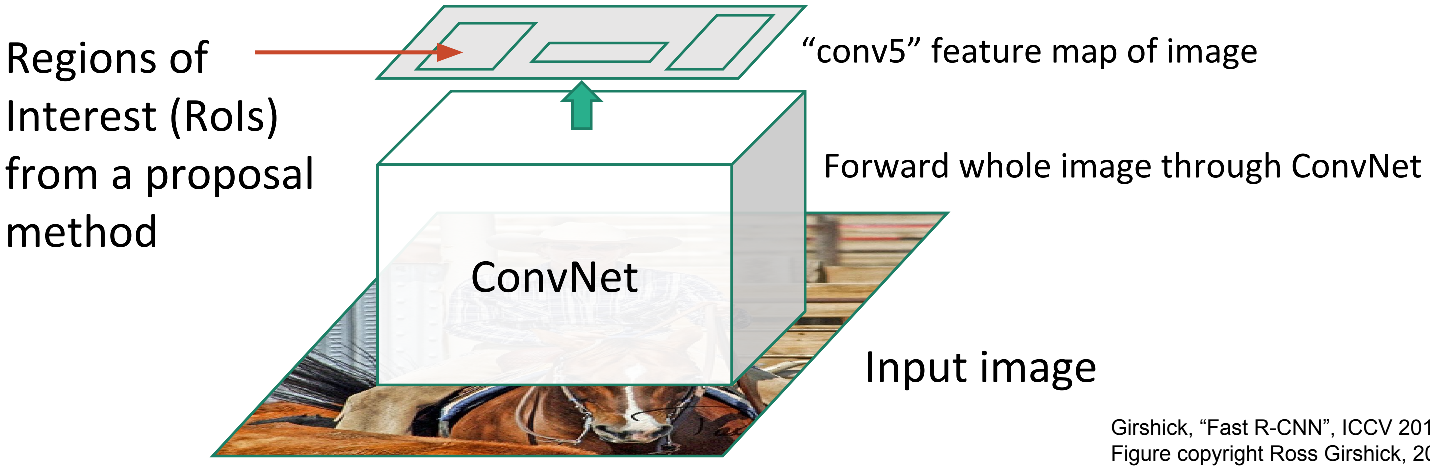
Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

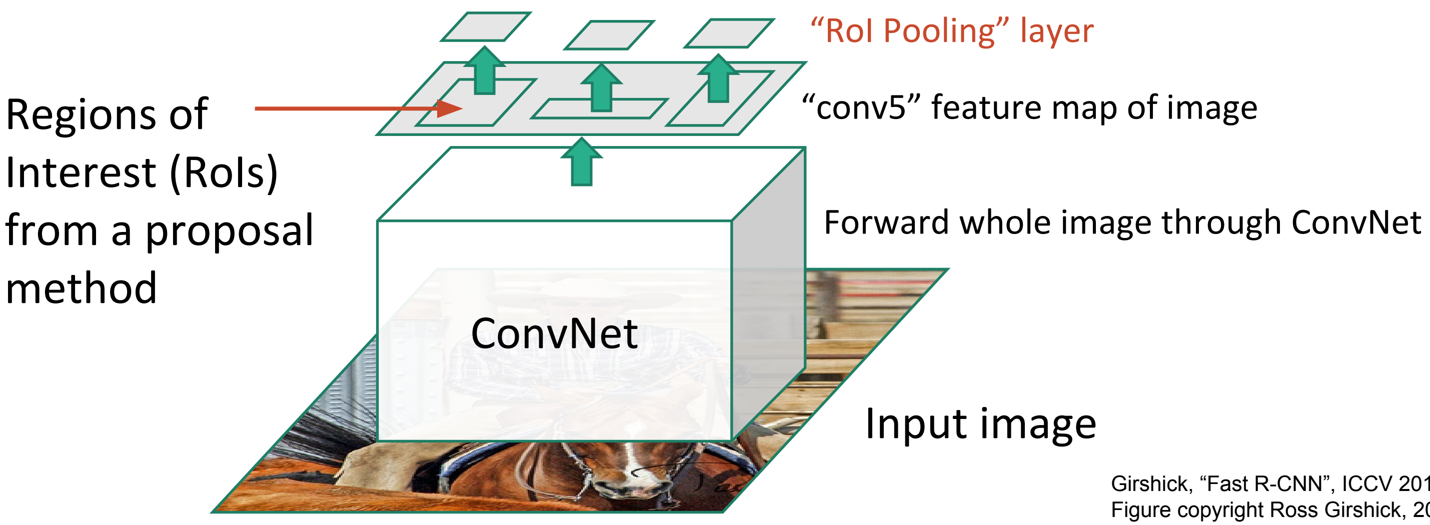
Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](). Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

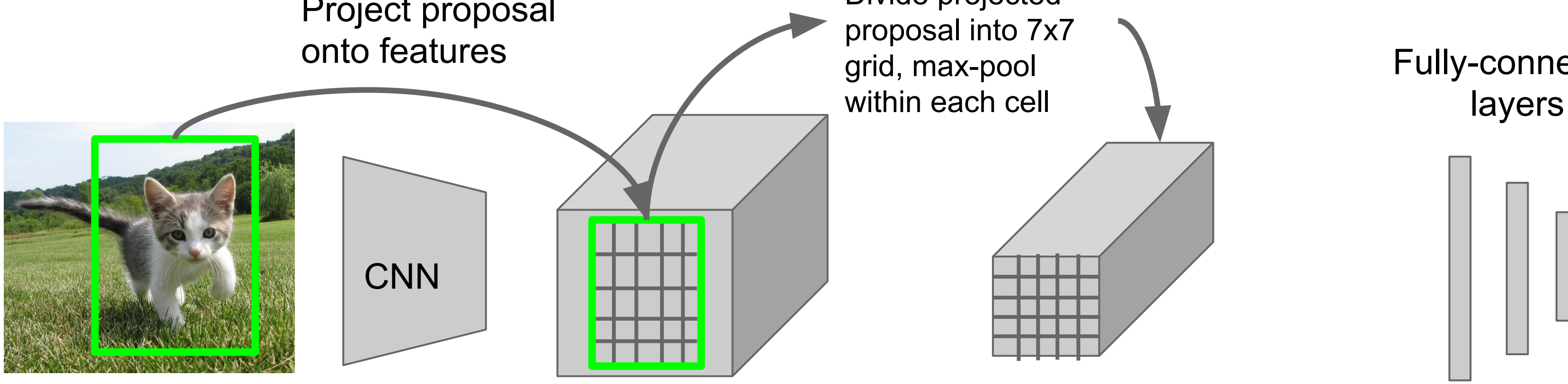
Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

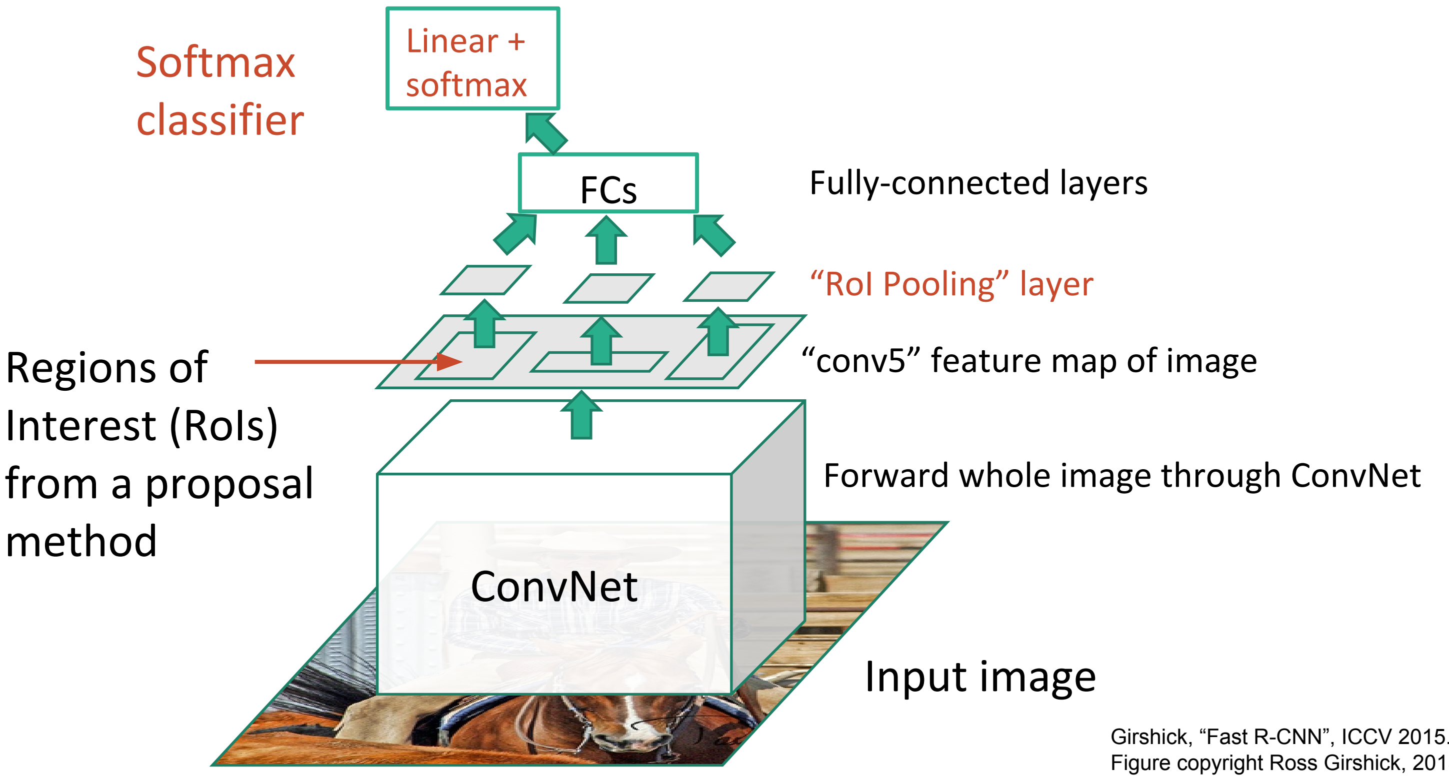
Fast R-CNN: RoI Pooling



Girshick, “Fast R-CNN”, ICCV 2015.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

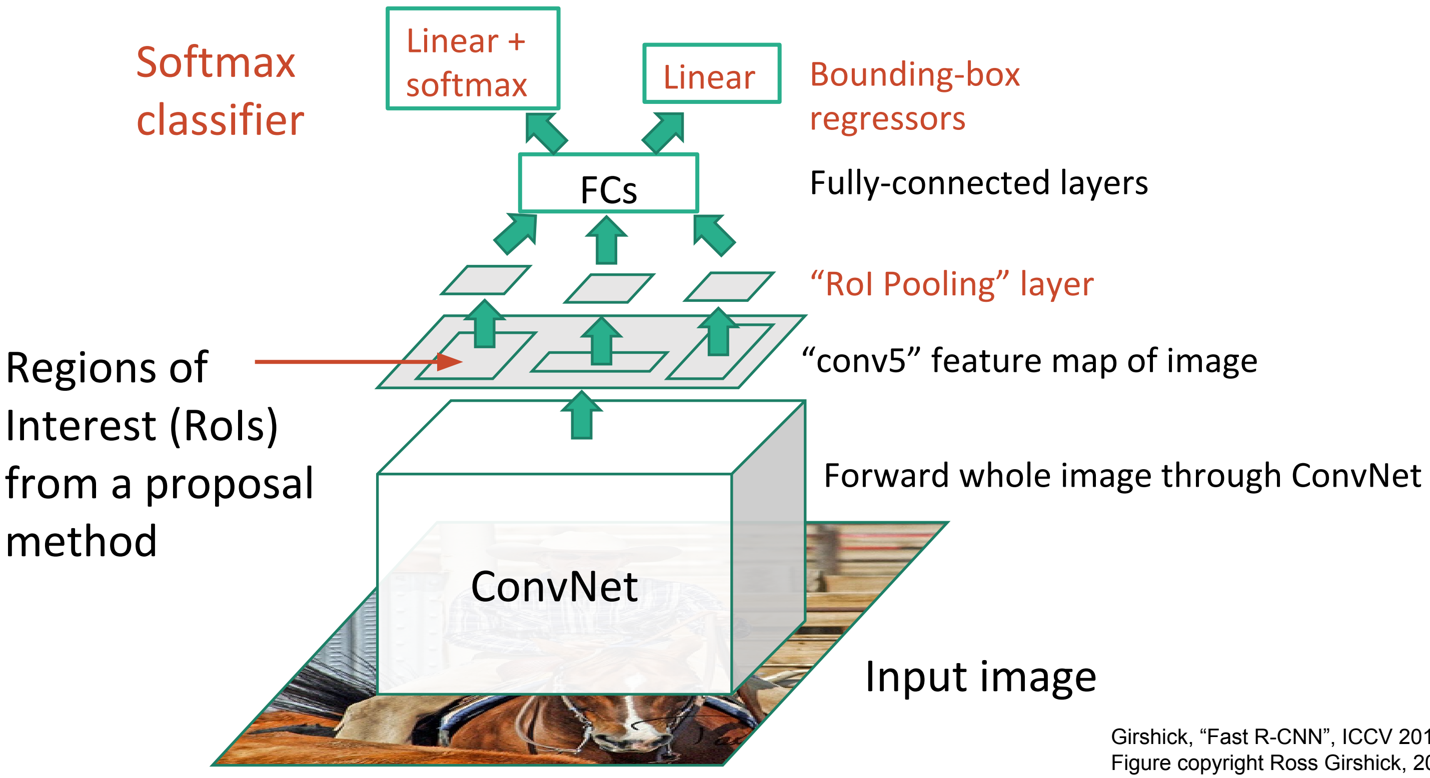
Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](). Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

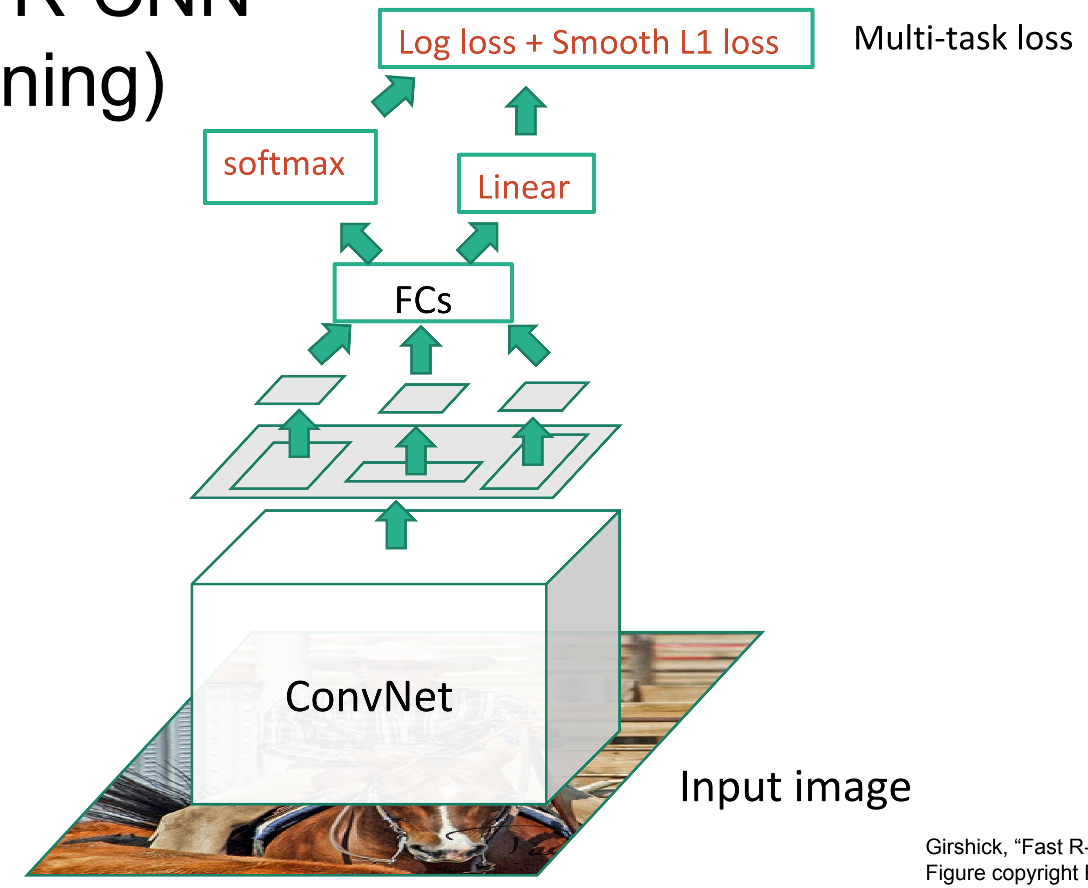
Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

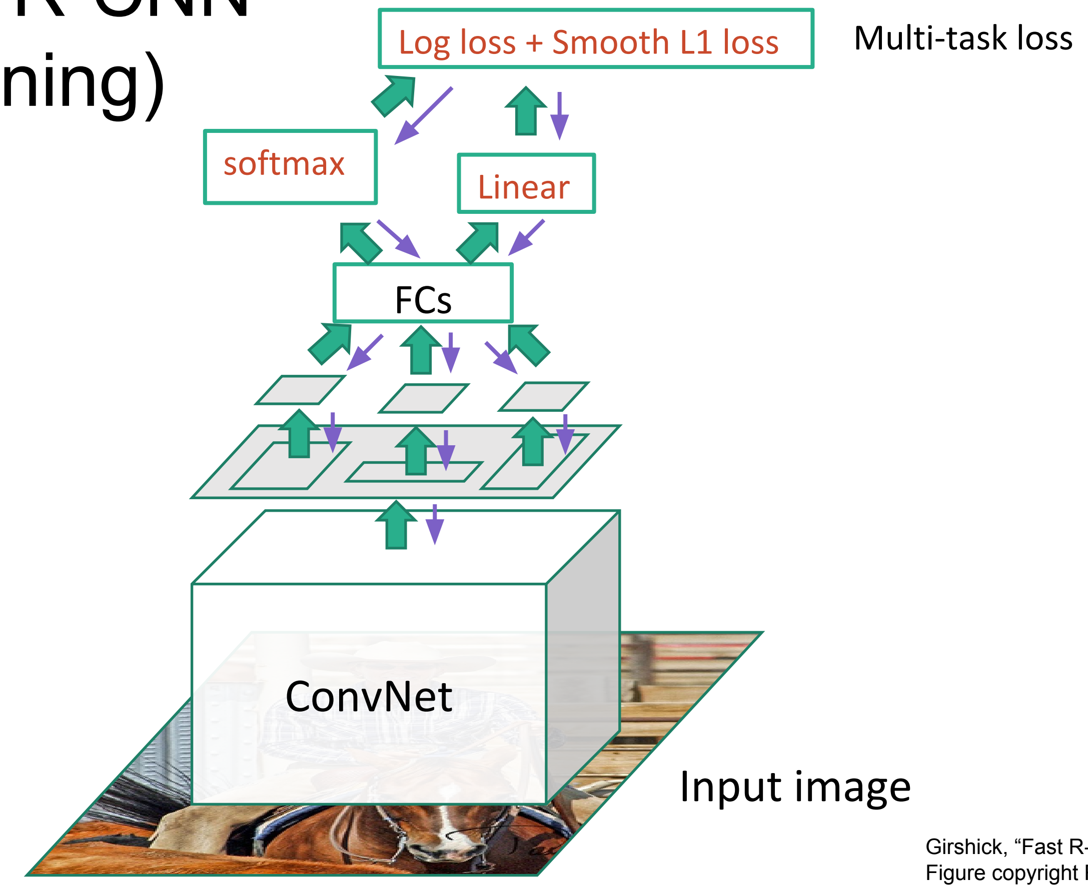
Fast R-CNN (Training)



Girshick, "Fast R-CNN", ICCV 2015.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

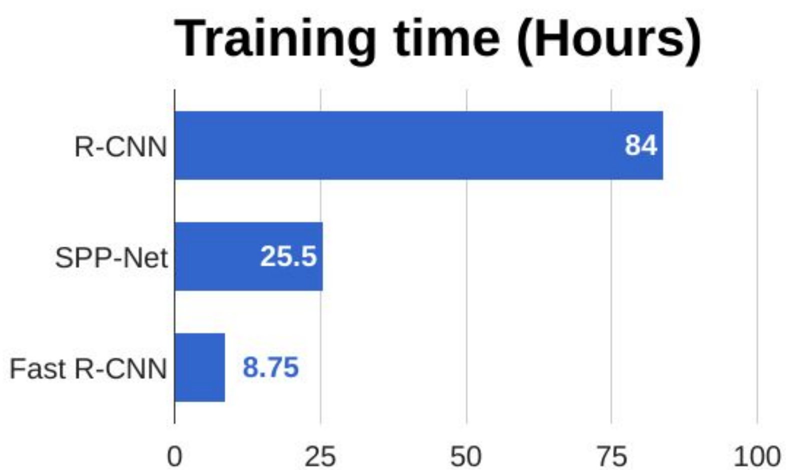
Fast R-CNN (Training)

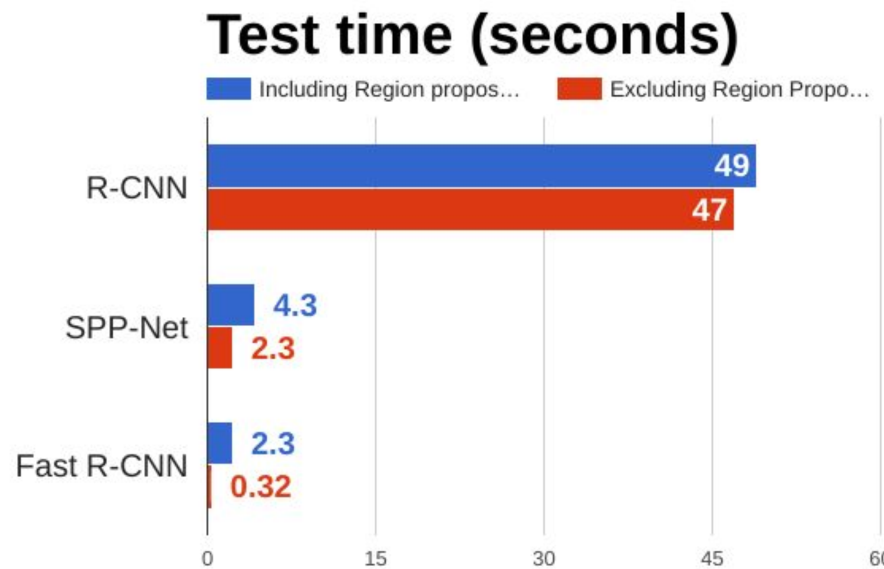


Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

R-CNN vs SPP vs Fast R-CNN

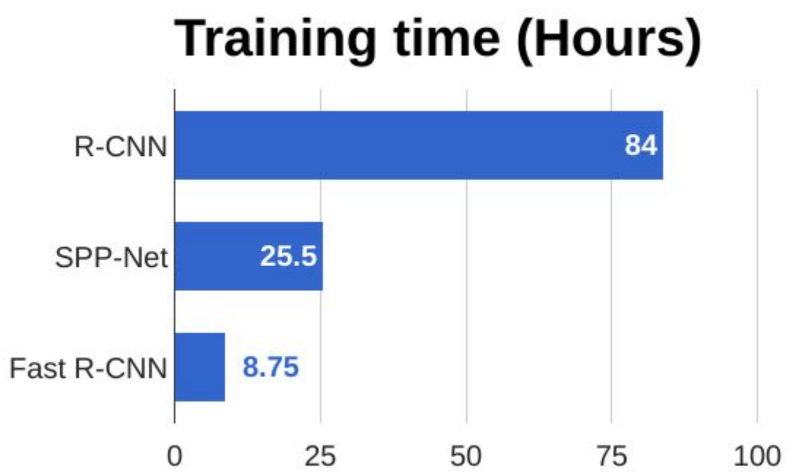


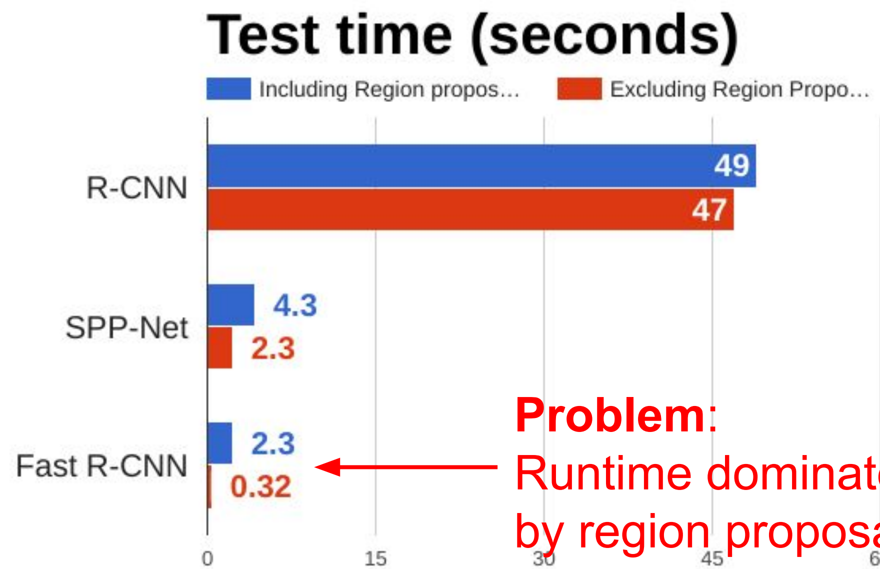


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

R-CNN vs SPP vs Fast R-CNN





Problem:
Runtime dominated by region proposals!

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

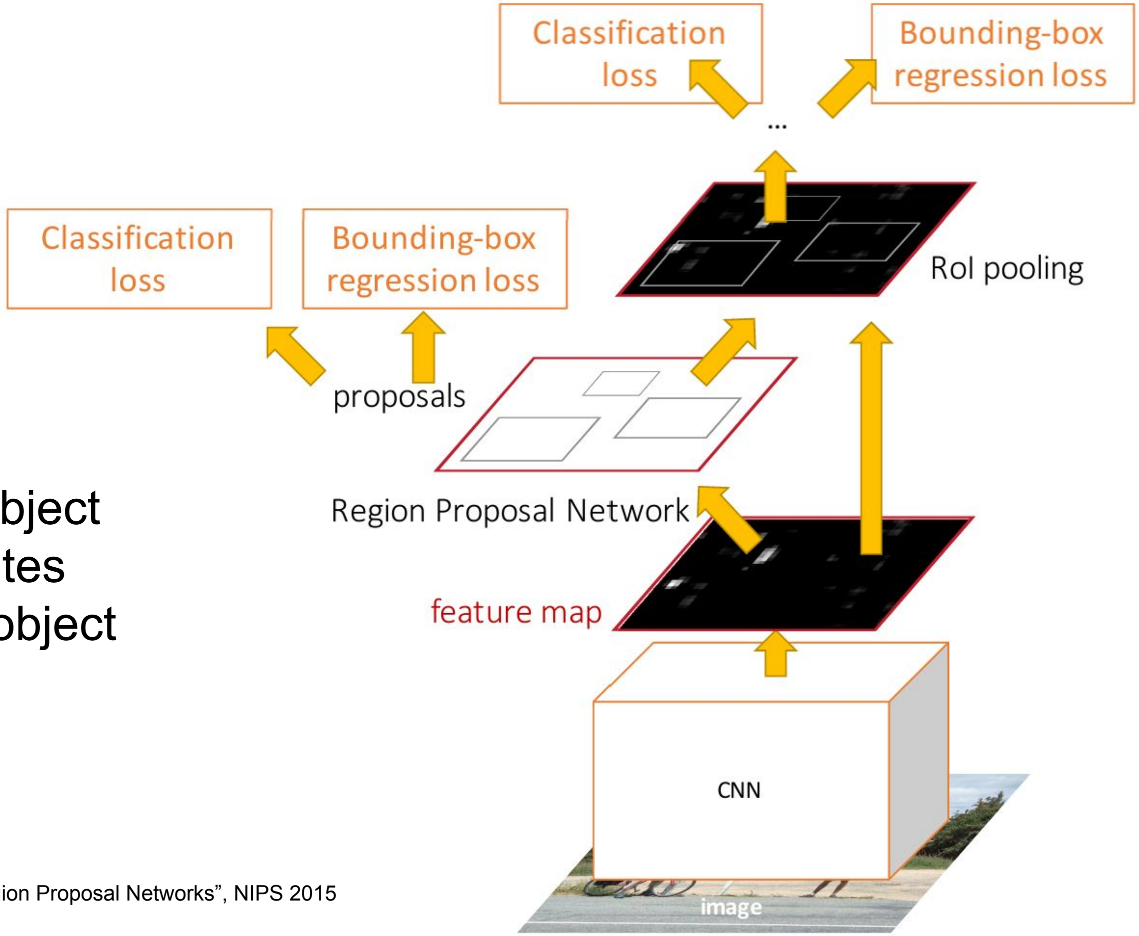
Faster R-CNN:

Make CNN do proposals!

Insert **Region Proposal Network (RPN)** to predict proposals from features

Jointly train with 4 losses:

1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates

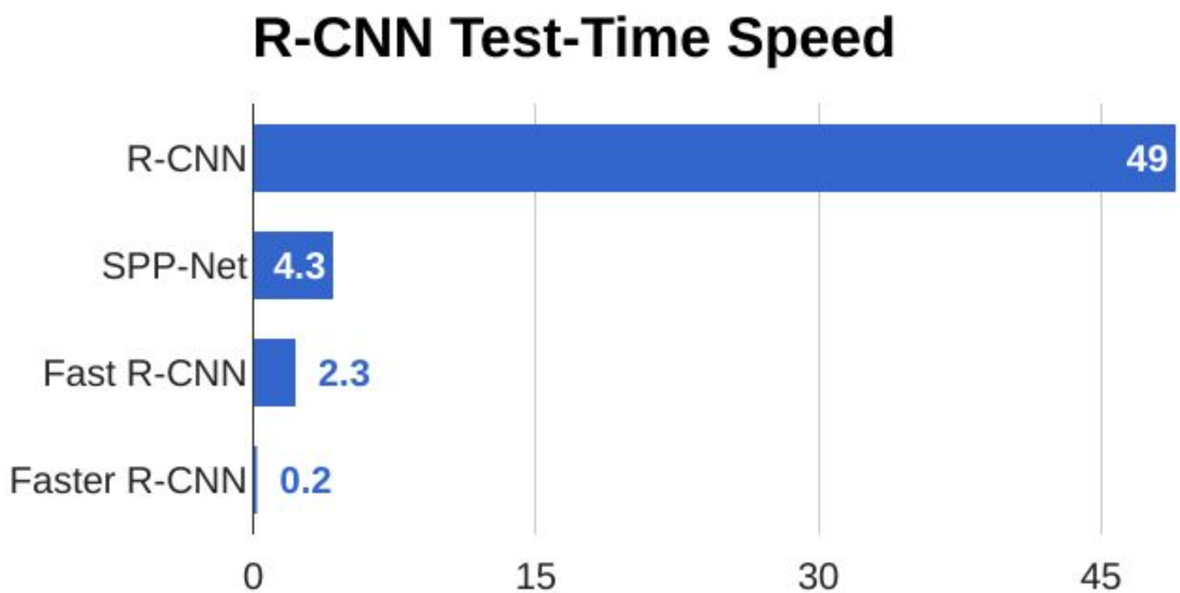


Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

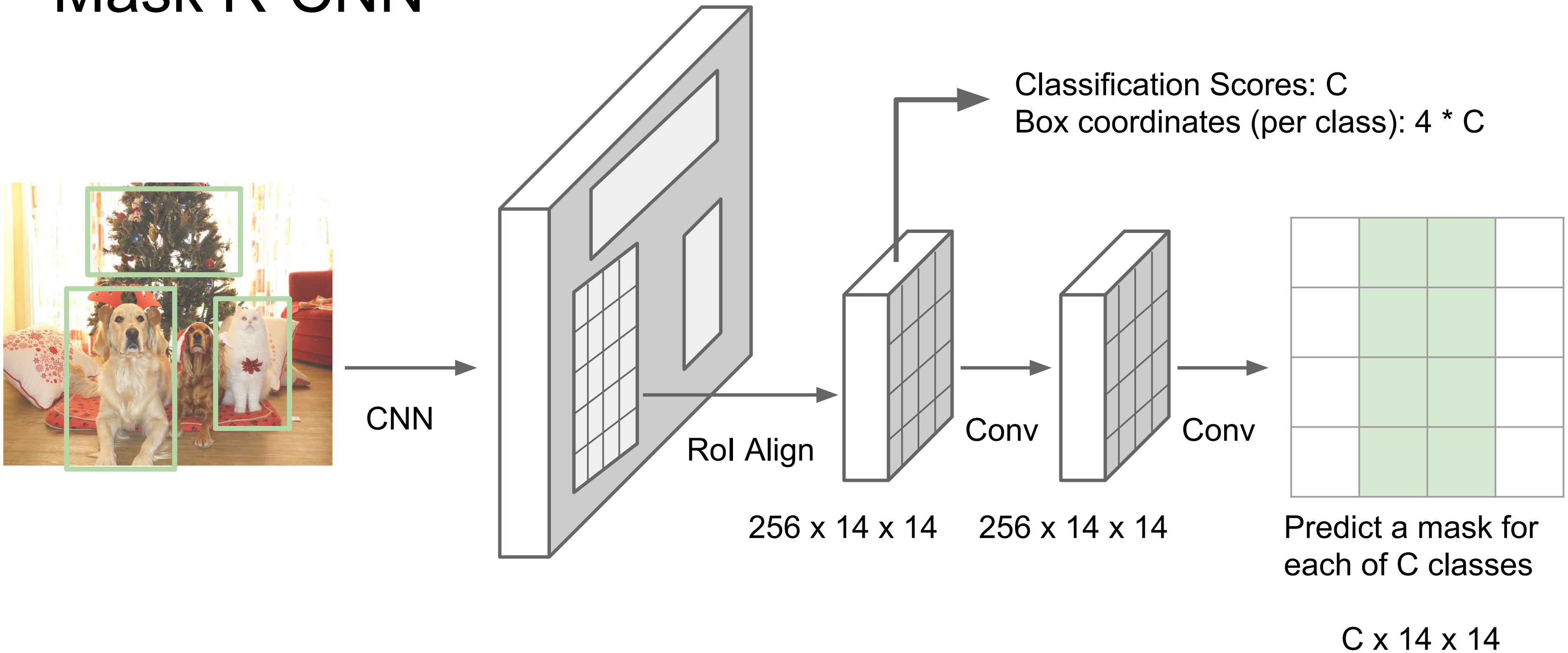
Faster R-CNN:

Make CNN do proposals!



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Mask R-CNN



He et al, “Mask R-CNN”, arXiv 2017

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

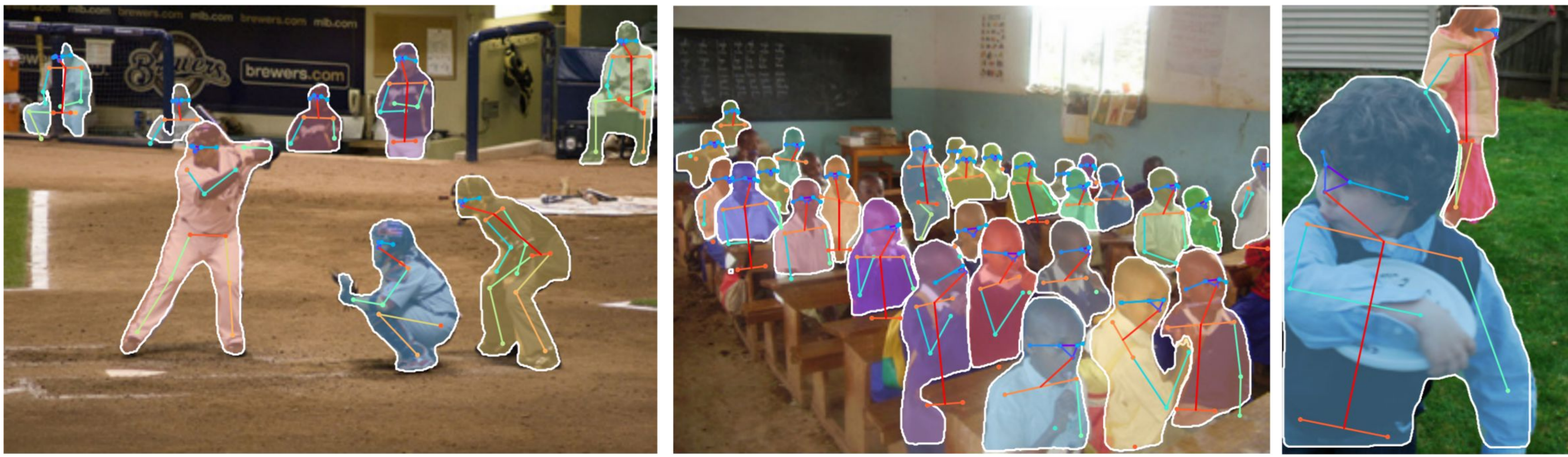
Mask R-CNN: Very Good Results!



He et al, “Mask R-CNN”, arXiv 2017
Figures copyright Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick, 2017.
Reproduced with permission.

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Mask R-CNN
Also does pose

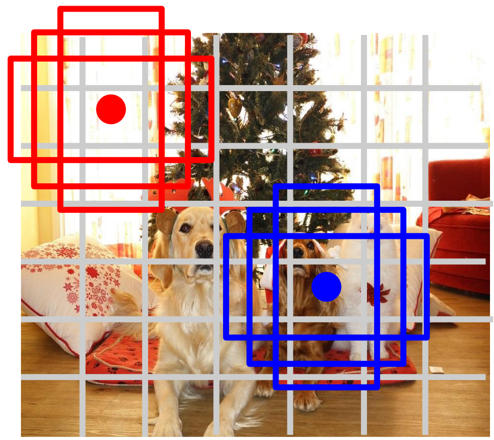


He et al, “Mask R-CNN”, arXiv 2017

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Detection without Proposals: YOLO / SSD

Input image
3 x H x W



Divide image into grid
7 x 7

Image a set of **base boxes** centered at each grid cell
Here B = 3

Within each grid cell:

- Regress from each of the B base boxes to a final box with 5 numbers:
  (dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)

Output:
7 x 7 x (5 * B + C)

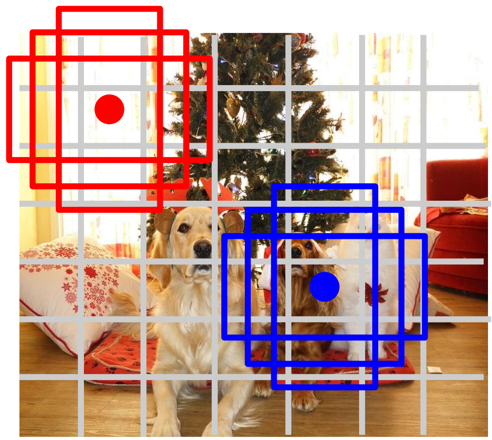
Redmon et al, “You Only Look Once: Unified, Real-Time Object Detection”, CVPR 2016
Liu et al, “SSD: Single-Shot MultiBox Detector”, ECCV 2016

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Detection without Proposals: YOLO / SSD

Go from input image to tensor of scores with one big convolutional network!

Input image
3 x H x W



Divide image into grid
7 x 7

Image a set of **base boxes** centered at each grid cell
Here B = 3

Within each grid cell:
- Regress from each of the B base boxes to a final box with 5 numbers:
  (dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)

Output:
7 x 7 x (5 * B + C)

Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection: Lots of variables ...

Base Network
VGG16
ResNet-101
Inception V2
Inception V3
Inception ResNet
MobileNet

Object Detection architecture
Faster R-CNN
R-FCN
SSD

Image Size
 # Region Proposals
…

Takeaways
Faster R-CNN is slower but more accurate

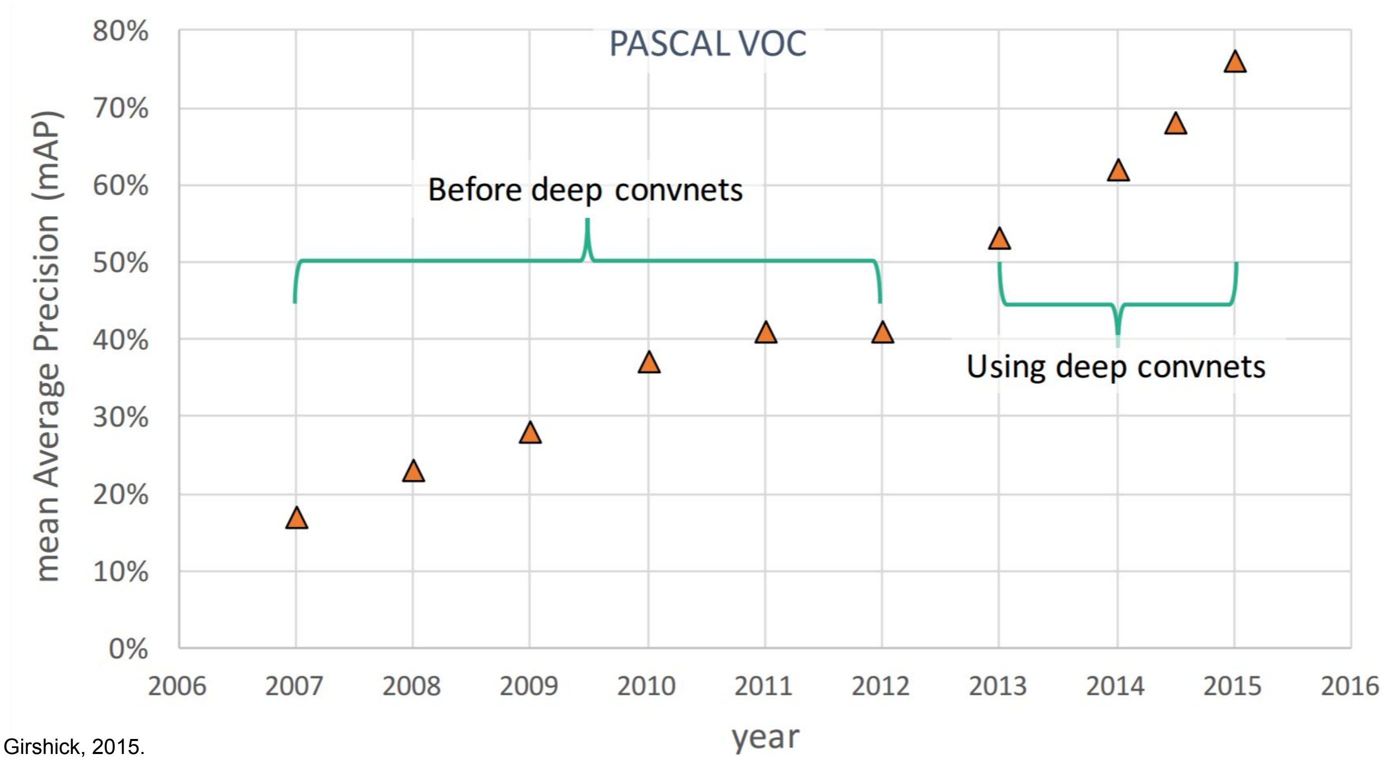
SSD is much faster but not as accurate

Huang et al, "Speed/accuracy trade-offs for modern convolutional object detectors", CVPR 2017

R-FCN: Dai et al, "R-FCN: Object Detection via Region-based Fully Convolutional Networks", NIPS 2016
Inception-V2: Ioffe and Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015
Inception V3: Szegedy et al, "Rethinking the Inception Architecture for Computer Vision", arXiv 2016
Inception ResNet: Szegedy et al, "Inception-V4, Inception-ResNet and the Impact of Residual Connections on Learning", arXiv 2016
MobileNet: Howard et al, "Efficient Convolutional Neural Networks for Mobile Vision Applications", arXiv 2017

slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Object Detection: Impact of Deep Learning



slide credit: Fei-Fei, Justin Johnson, Serena Yeung

Open Source Frameworks

Lots of good implementations on GitHub!

TensorFlow Detection API:

https://github.com/tensorflow/models/tree/master/research/object_detection

Faster RCNN, SSD, RFCN, Mask R-CNN

Caffe2 Detectron:

https://github.com/facebookresearch/Detectron

Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, R-FCN

Finetune on your own dataset with pre-trained models

slide credit: Fei-Fei, Justin Johnson, Serena Yeung