

Lecture 12: Detection and Segmentation

Computer Vision Tasks

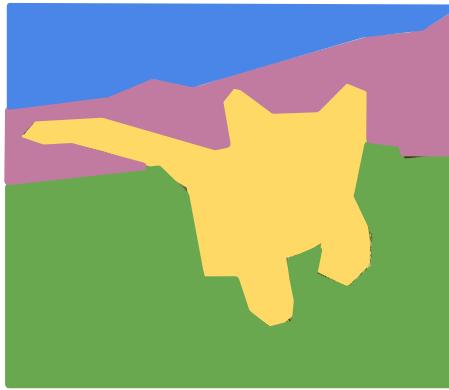
Classification



CAT

No spatial extent

Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

Multiple Object

Instance Segmentation



DOG, DOG, CAT

This image is CC0 public domain

Semantic Segmentation

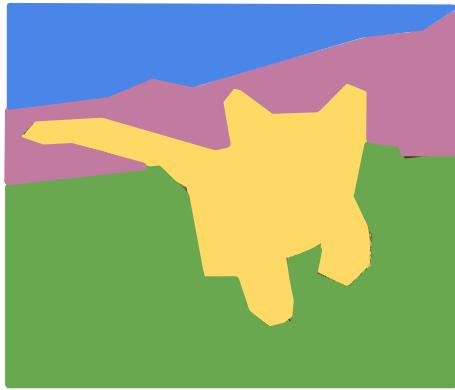
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CAT

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Semantic Segmentation



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TREE, SKY

No objects, just pixels

Object
Detection



Instance
Segmentation



DOG, DOG, CAT

Multiple Object

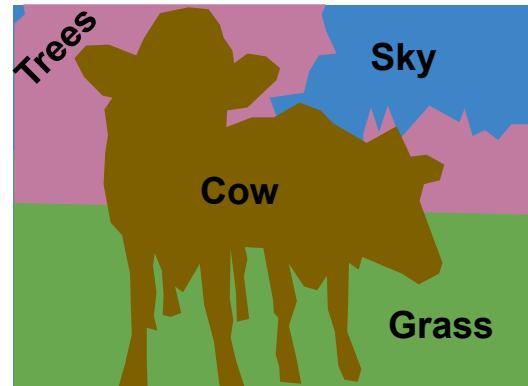
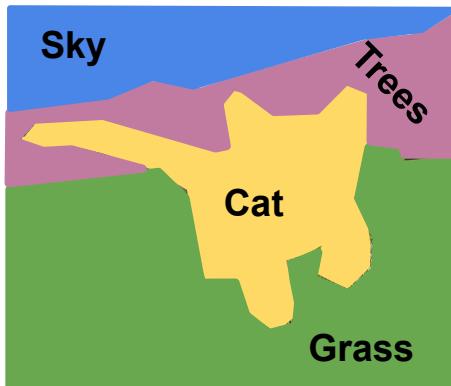
Semantic Segmentation

Label each pixel in the image with a category label

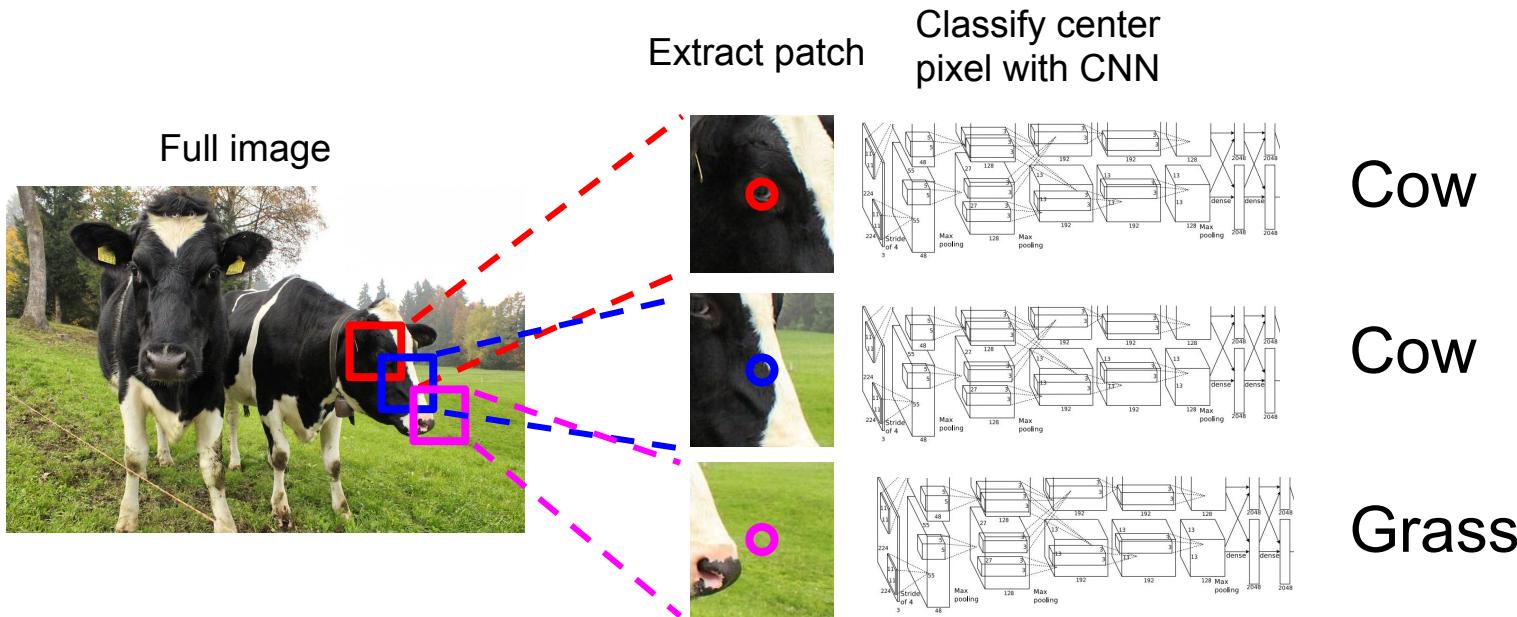
Don't differentiate instances, only care about pixels



[This image is CC0 public domain](#)

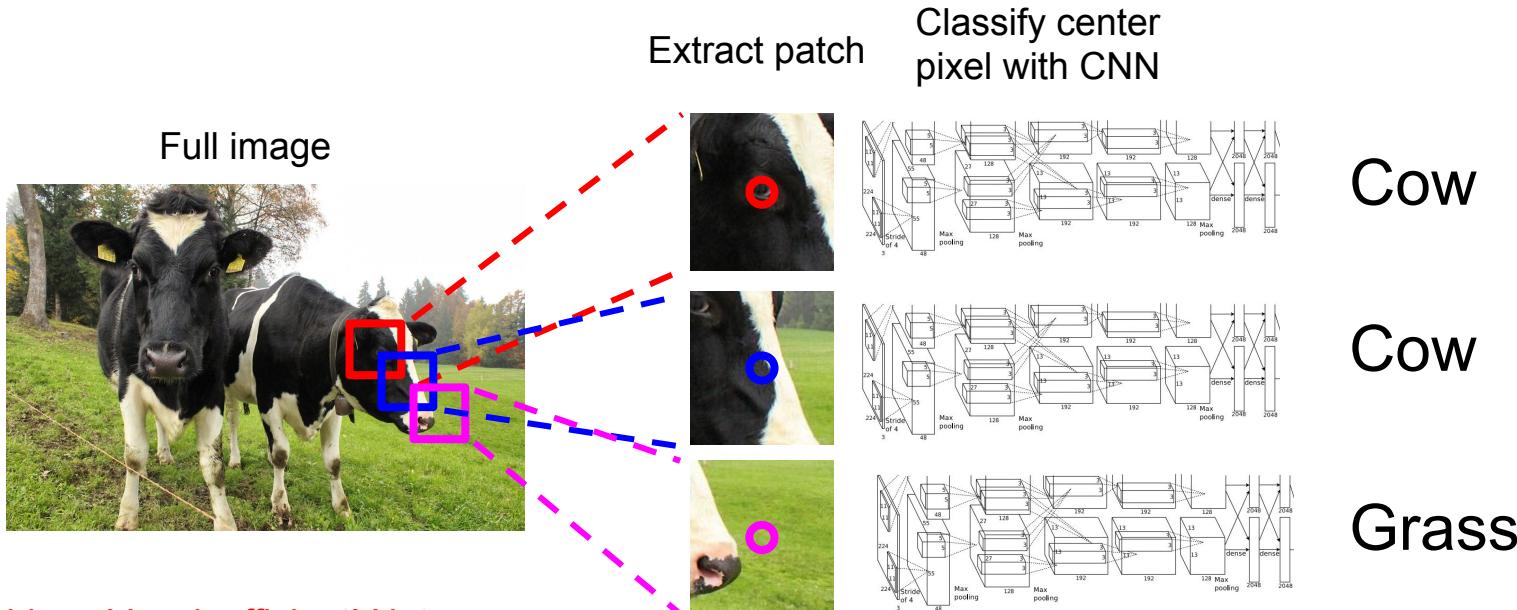


Semantic Segmentation Idea: Sliding Window



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

Semantic Segmentation Idea: Sliding Window

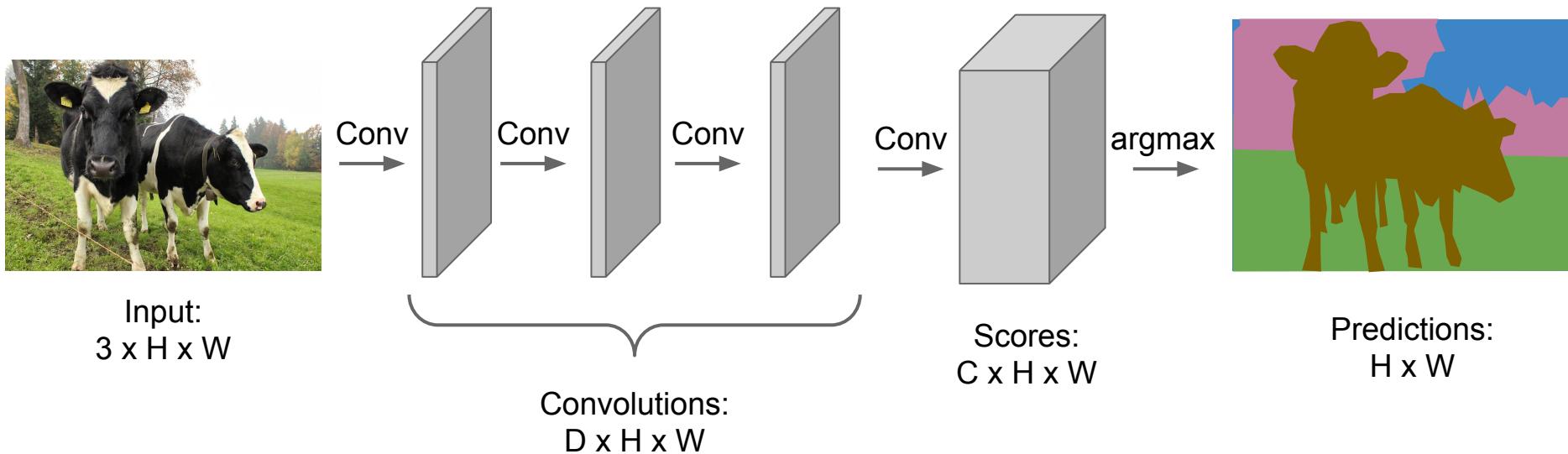


Problem: Very inefficient! Not reusing shared features between overlapping patches

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

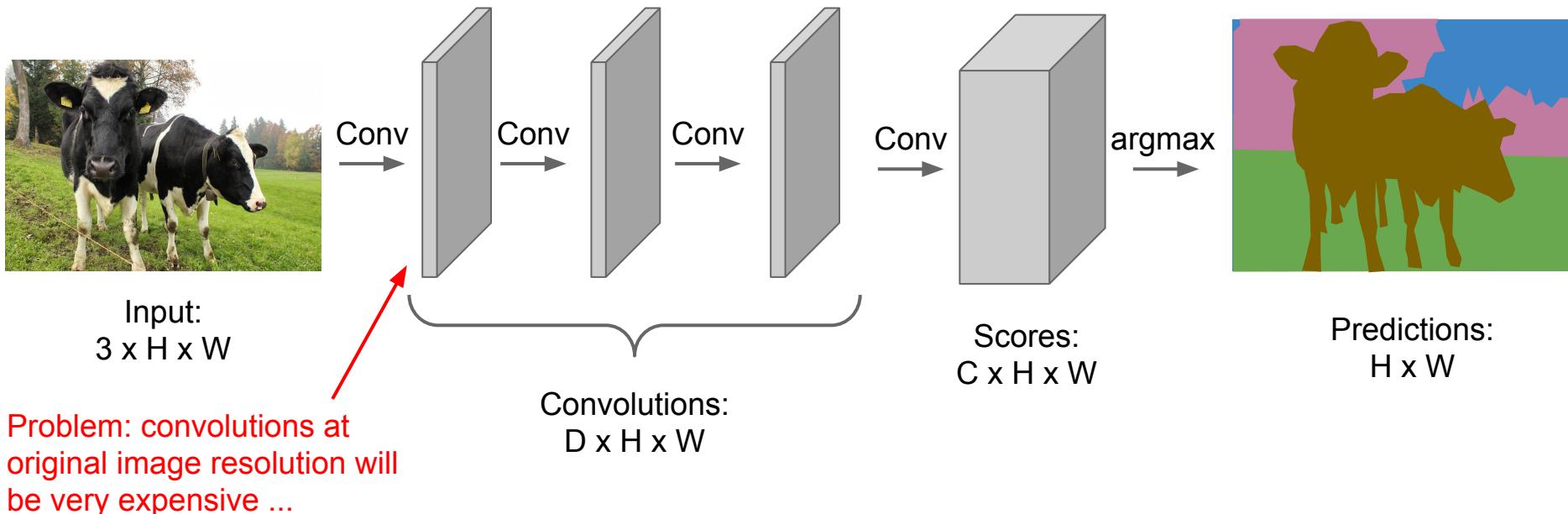
Semantic Segmentation Idea: Fully Convolutional

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



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

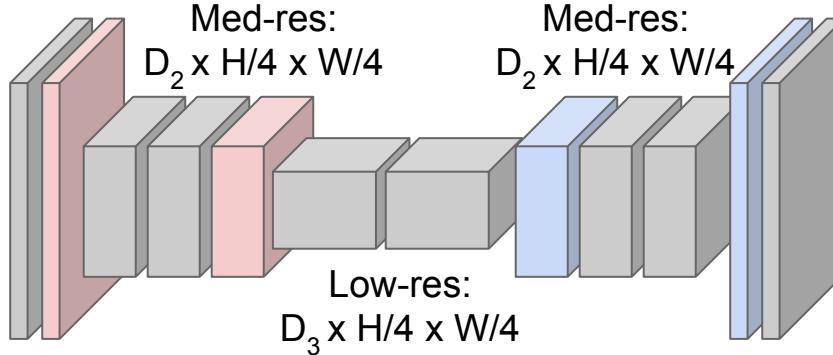


Semantic Segmentation Idea: Fully Convolutional

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



Input:
 $3 \times H \times W$



High-res:
 $D_1 \times H/2 \times W/2$

High-res:
 $D_1 \times H/2 \times W/2$



Predictions:
 $H \times W$

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

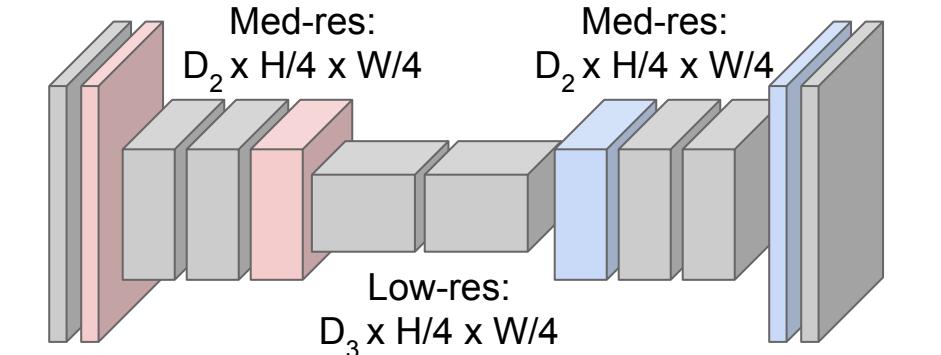
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided
convolution



Input:
 $3 \times H \times W$

High-res:
 $D_1 \times H/2 \times W/2$



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

Upsampling:
???



Predictions:
 $H \times W$

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

In-Network upsampling: “Unpooling”

Nearest Neighbor

1	2
3	4



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

Input: 2 x 2

Output: 4 x 4

“Bed of Nails”

1	2
3	4



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

Output: 4 x 4

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

Max Unpooling

Use positions from pooling layer

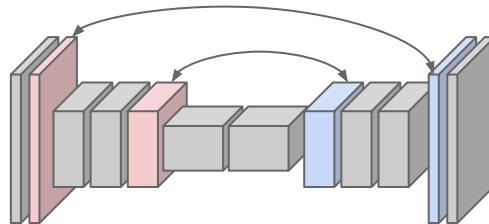
1	2
3	4

Rest of the network

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

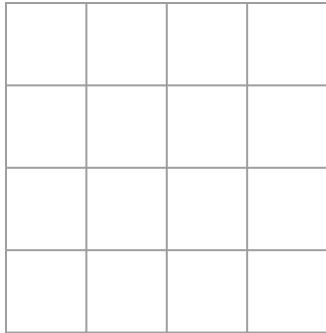
Output: 4 x 4

Corresponding pairs of
downsampling and
upsampling layers

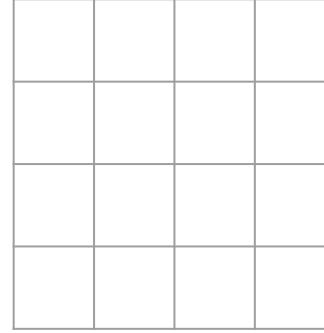


Learnable Upsampling: Transpose Convolution

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



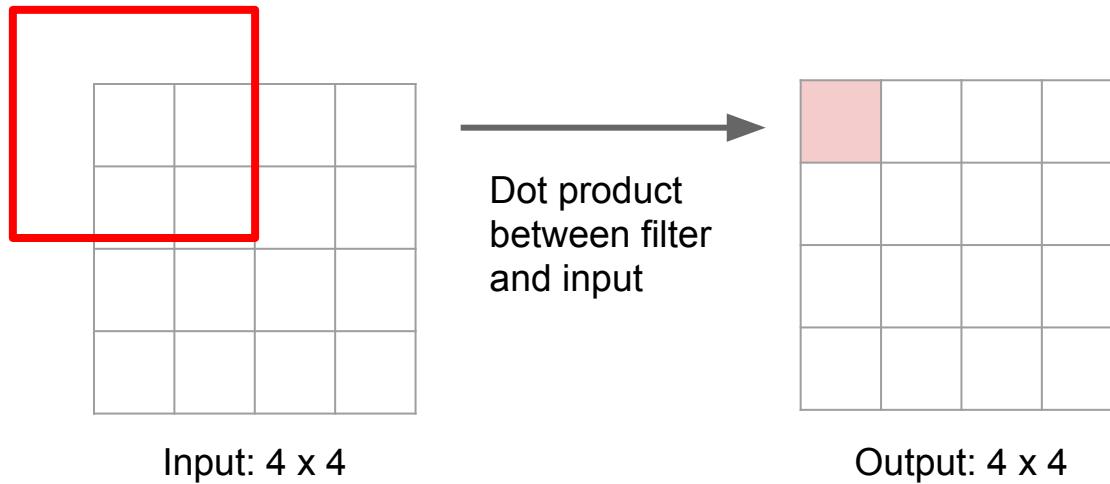
Input: 4×4



Output: 4×4

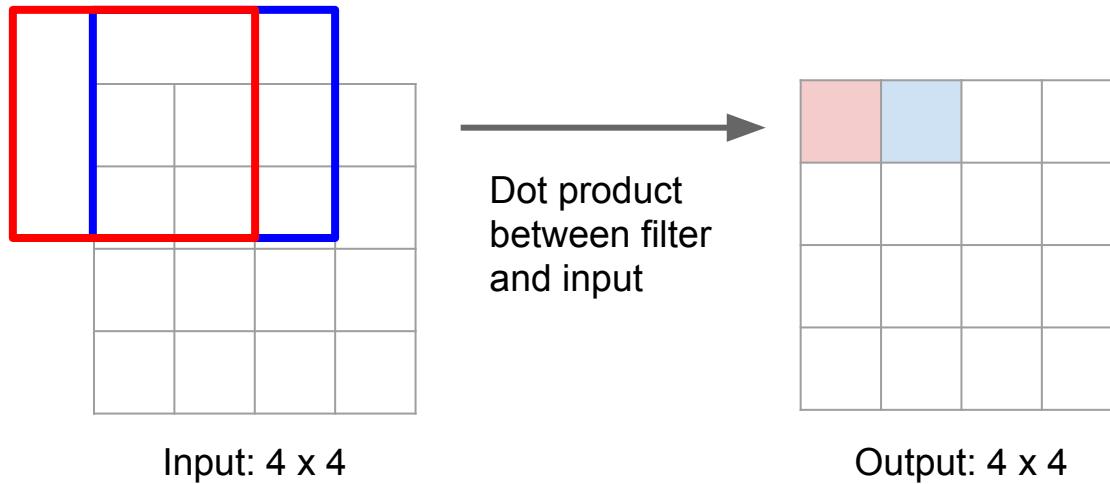
Learnable Upsampling: Transpose Convolution

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



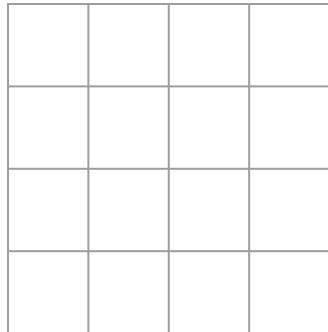
Learnable Upsampling: Transpose Convolution

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

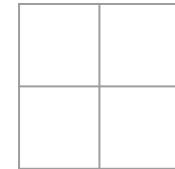


Learnable Upsampling: Transpose Convolution

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



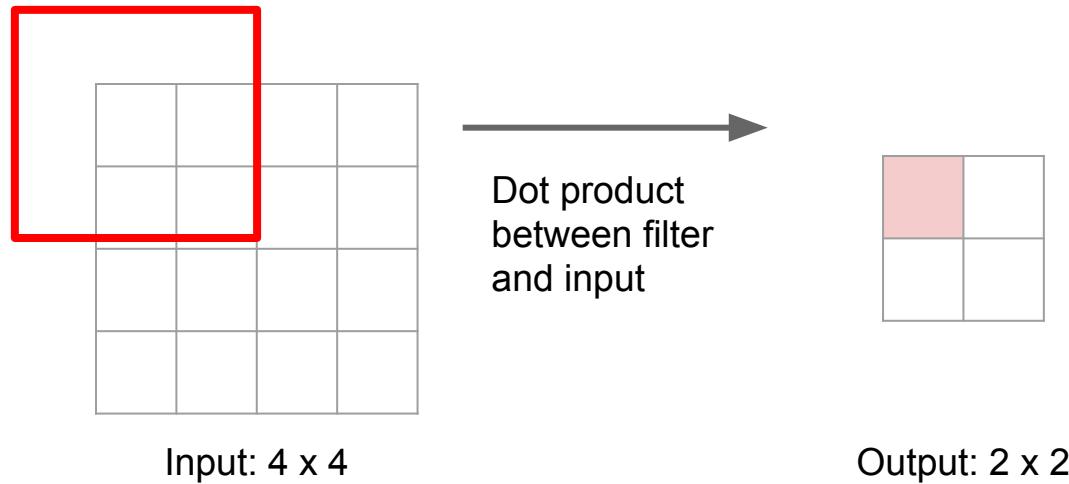
Input: 4×4



Output: 2×2

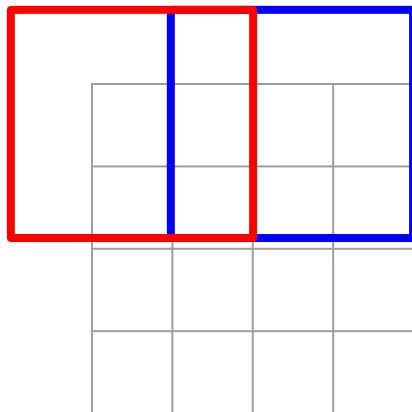
Learnable Upsampling: Transpose Convolution

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



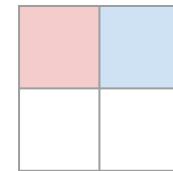
Learnable Upsampling: Transpose Convolution

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



Input: 4×4

Dot product
between filter
and input



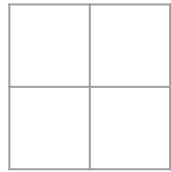
Output: 2×2

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

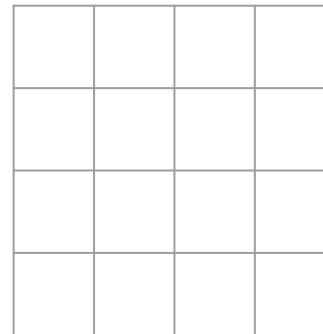
Stride gives ratio between
movement in input and
output

Learnable Upsampling: Transpose Convolution

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



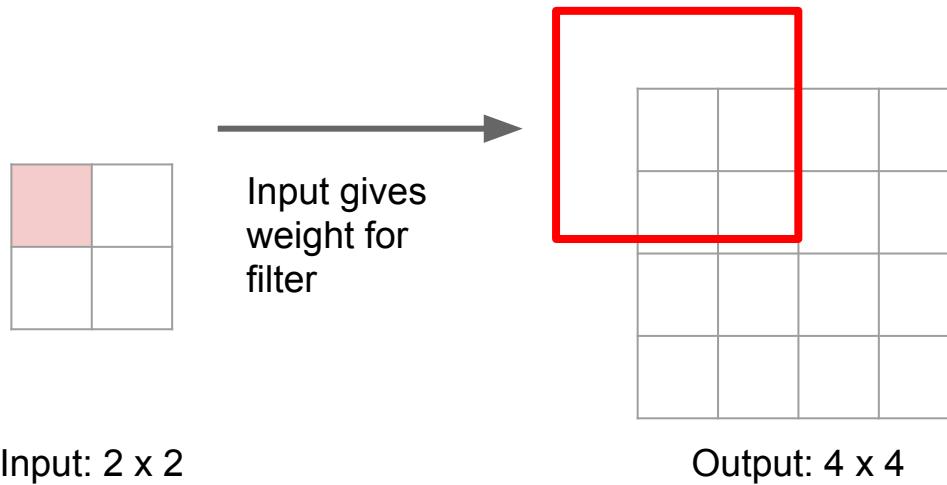
Input: 2×2



Output: 4×4

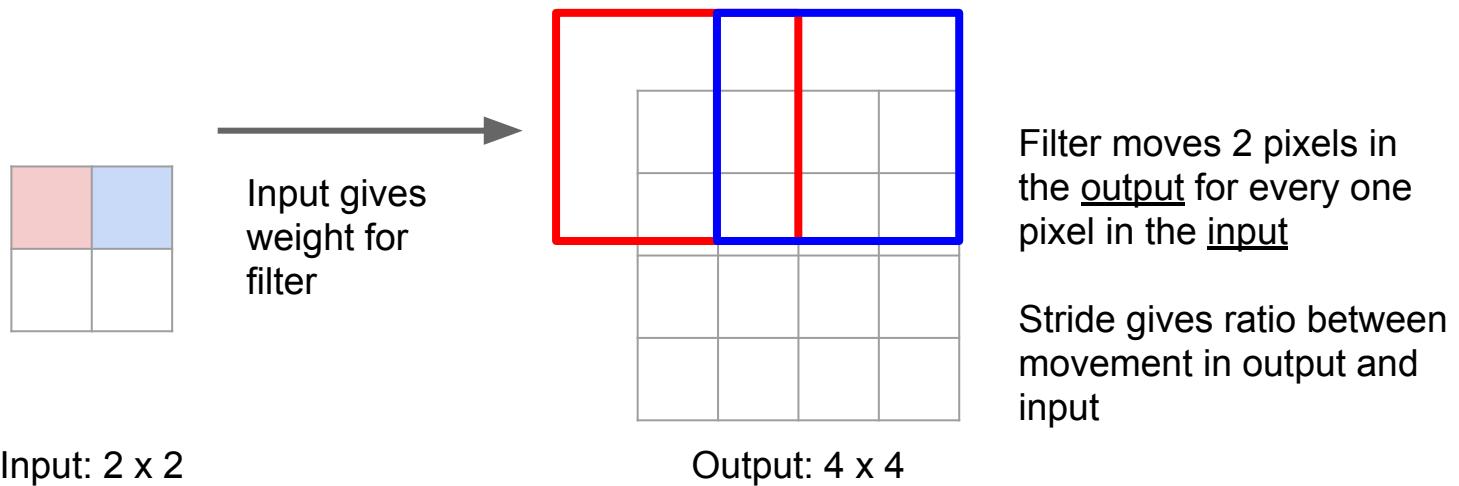
Learnable Upsampling: Transpose Convolution

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

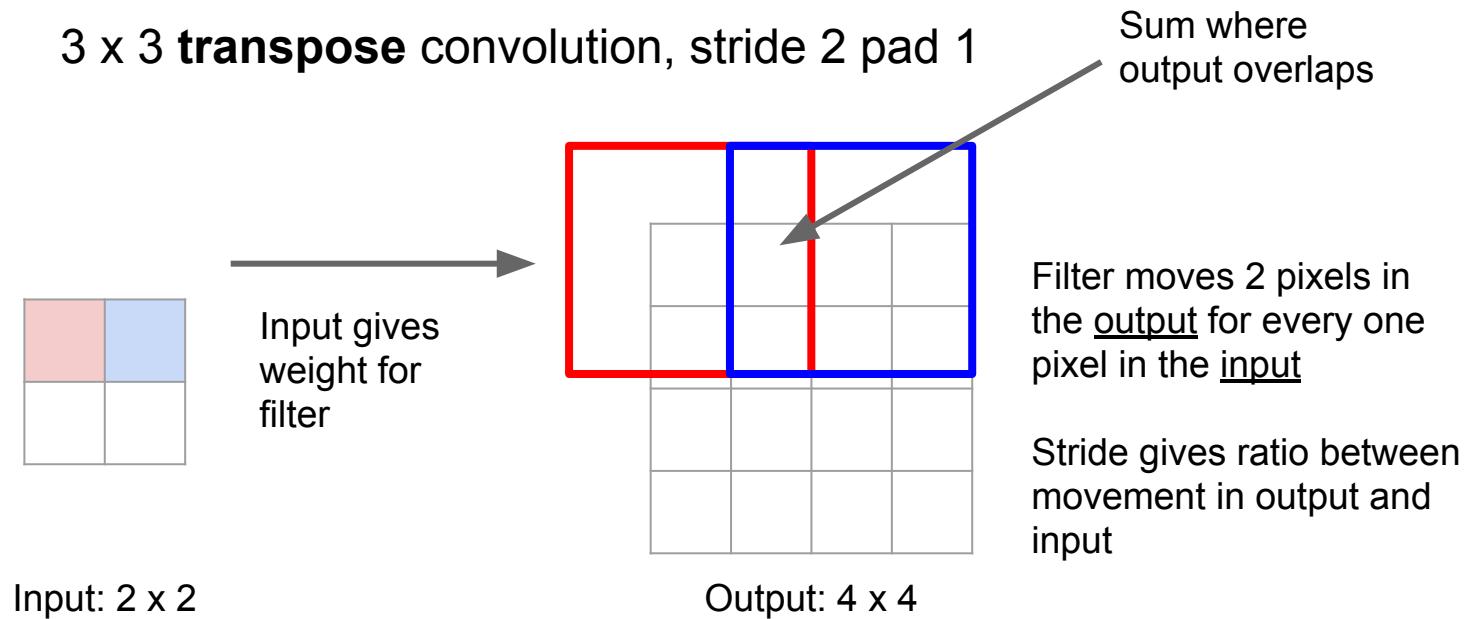


Learnable Upsampling: Transpose Convolution

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



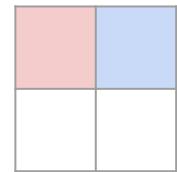
Learnable Upsampling: Transpose Convolution



Learnable Upsampling: Transpose Convolution

Other names:

- Deconvolution (bad)
- Upconvolution
- Fractionally strided convolution
- Backward strided convolution

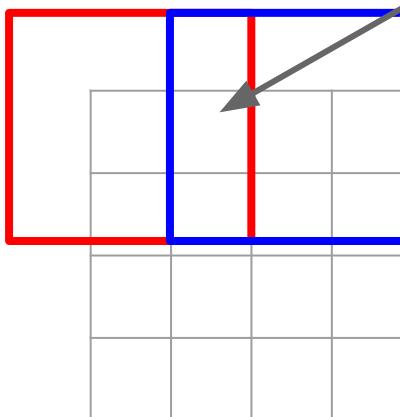


Input: 2 x 2

3 x 3 transpose convolution, stride 2 pad 1



Input gives weight for filter



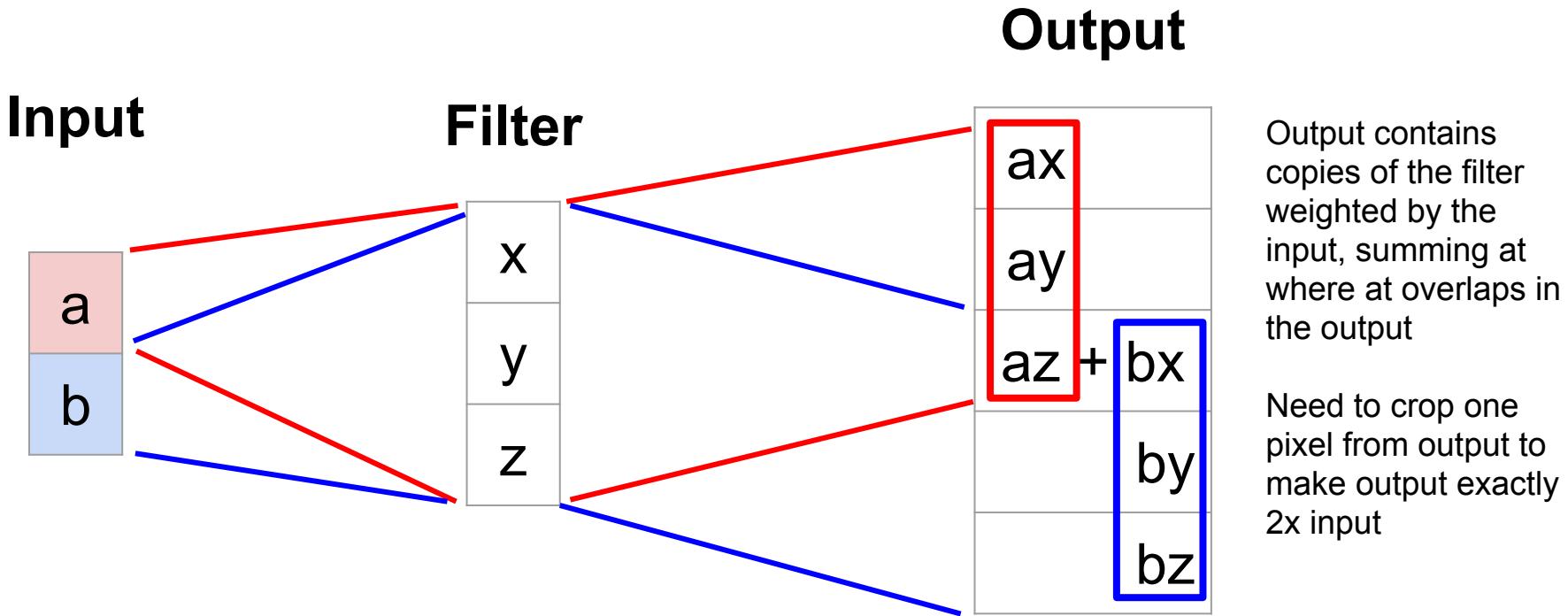
Output: 4 x 4

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

Stride gives ratio between movement in output and input

Sum where output overlaps

Learnable Upsampling: 1D Example



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 as Matrix Multiplication (1D Example)

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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)

Convolution as Matrix Multiplication (1D Example)

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Example: 1D conv, kernel size=3, stride=2, padding=1

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, stride=2, 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!

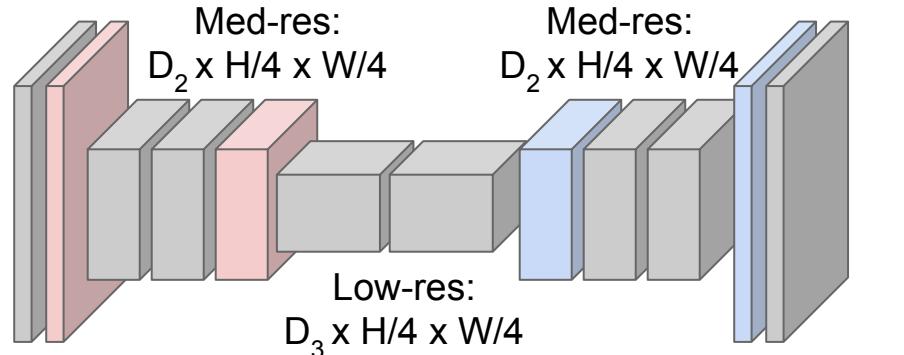
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution



Input:
 $3 \times H \times W$

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



High-res:
 $D_1 \times H/2 \times W/2$

Low-res:
 $D_3 \times H/4 \times W/4$

High-res:
 $D_1 \times H/2 \times W/2$

Upsampling:
Unpooling or strided transpose convolution



Predictions:
 $H \times W$

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

Object Detection

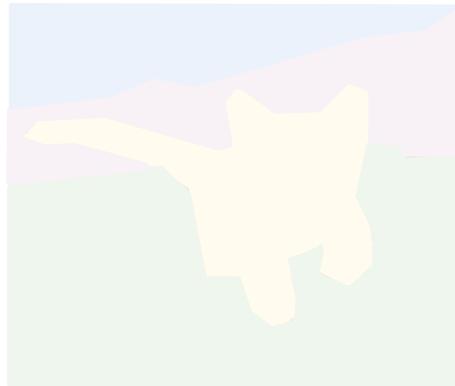
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Object
Detection



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Multiple Object

Instance
Segmentation



DOG, DOG, CAT

Object Detection: Impact of Deep Learning

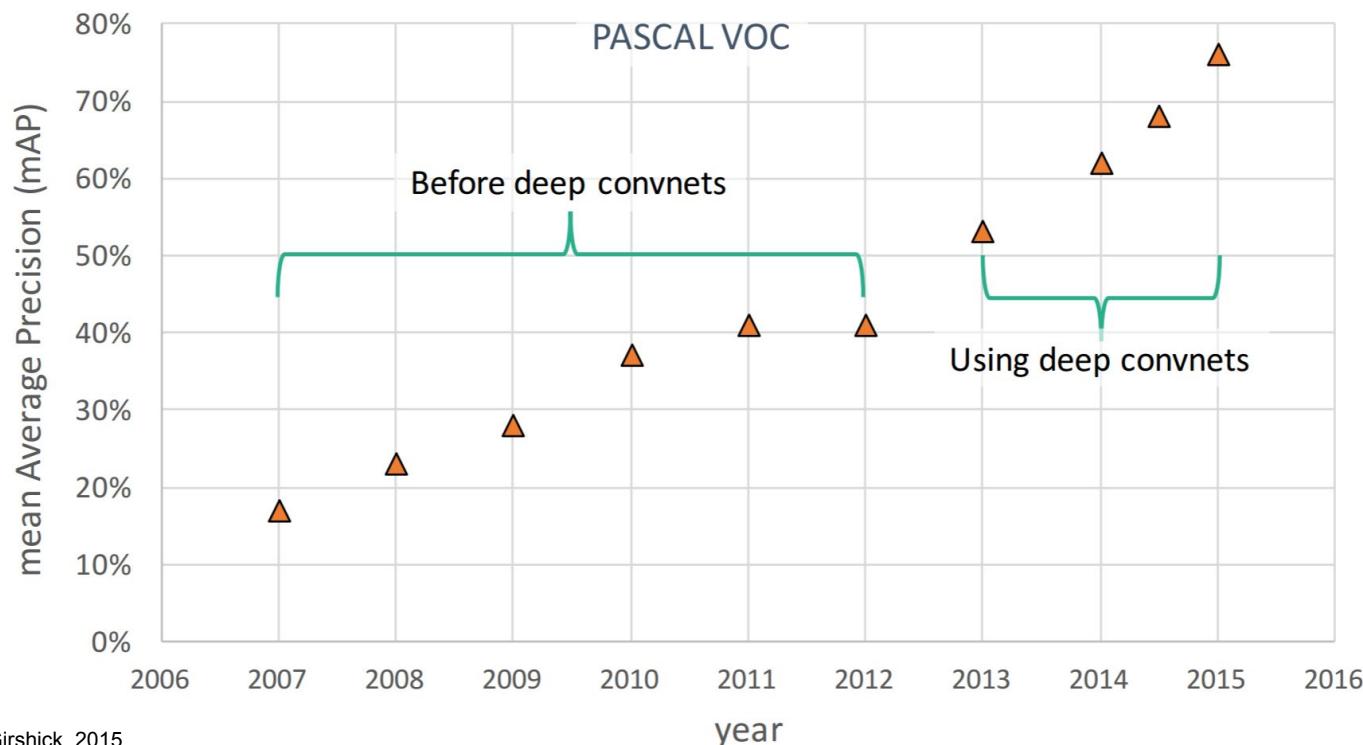


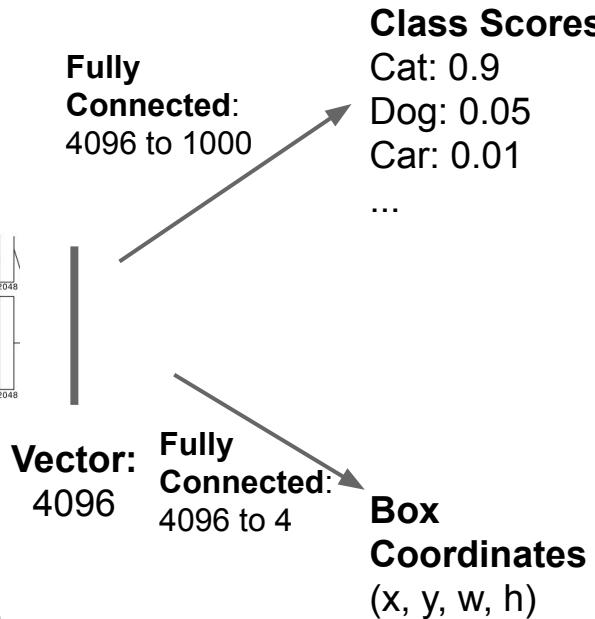
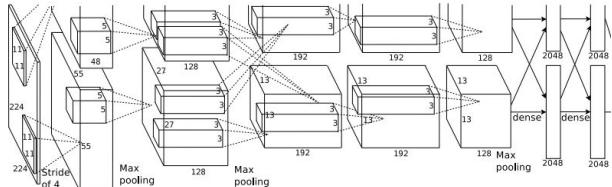
Figure copyright Ross Girshick, 2015.
Reproduced with permission.

Object Detection: Single Object

(Classification + Localization)



This image is CC0 public domain

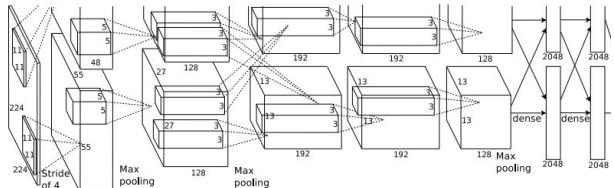


Treat localization as a
regression problem!

Object Detection: Single Object (Classification + Localization)



This image is CC0 public domain



Treat localization as a
regression problem!

Fully
Connected:
4096 to 1000

Vector:
Fully
Connected:
4096 to 4

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

Box
Coordinates → L2 Loss
(x, y, w, h)

Correct label:
Cat

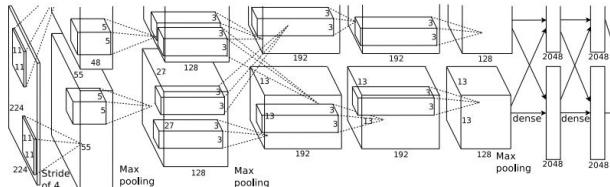
Softmax
Loss

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

Object Detection: Single Object (Classification + Localization)



This image is CC0 public domain



Treat localization as a
regression problem!

Vector:
Fully Connected:
4096 to 4

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

Multitask Loss

Box
Coordinates → L2 Loss
(x, y, w, h)

Correct label:
Cat

Softmax
Loss

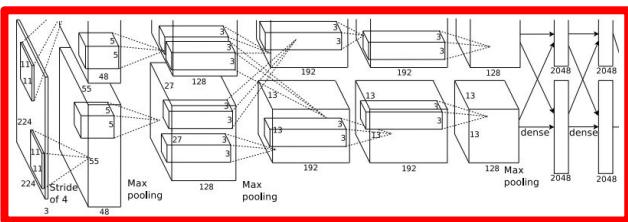
+

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

Object Detection: Single Object (Classification + Localization)



This image is CC0 public domain



Often pretrained on ImageNet
(Transfer learning)

Treat localization as a
regression problem!

Vector: 4096
Fully Connected: 4096 to 4

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

Box
Coordinates → L2 Loss
(x, y, w, h)

Correct label:
Cat

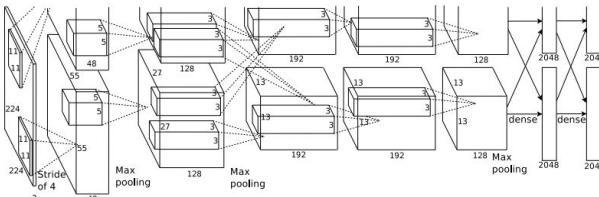
Softmax
Loss

+

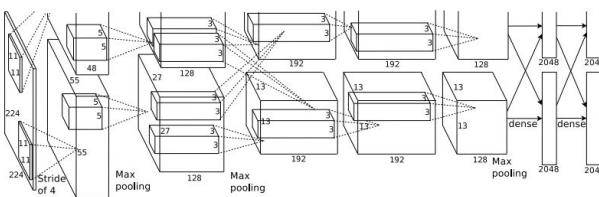
Loss

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

Object Detection: Multiple Objects



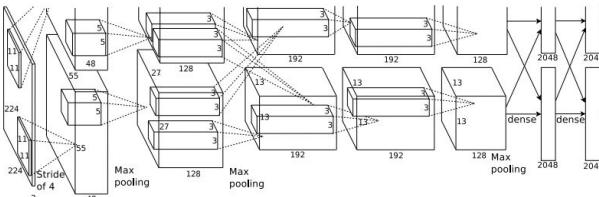
CAT: (x, y, w, h)



DOG: (x, y, w, h)

DOG: (x, y, w, h)

CAT: (x, y, w, h)



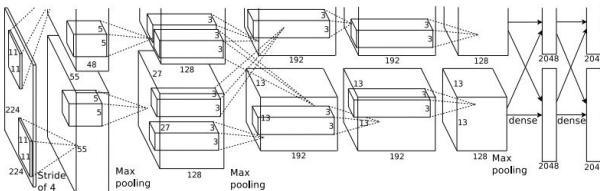
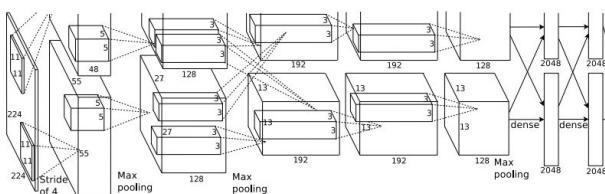
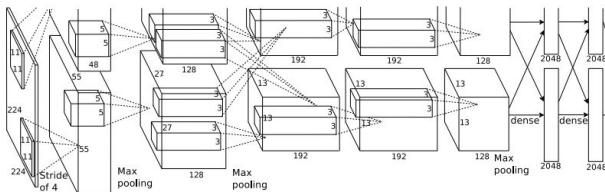
DUCK: (x, y, w, h)

DUCK: (x, y, w, h)

...

Object Detection: Multiple Objects

Each image needs a different number of outputs!



CAT: (x, y, w, h)

4 numbers

DOG: (x, y, w, h)

16 numbers

CAT: (x, y, w, h)

DUCK: (x, y, w, h)

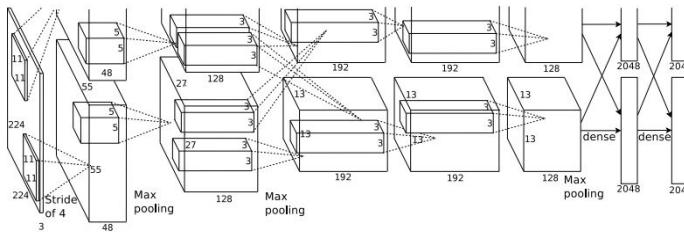
Many
numbers!

DUCK: (x, y, w, h)

...

Object Detection: Multiple Objects

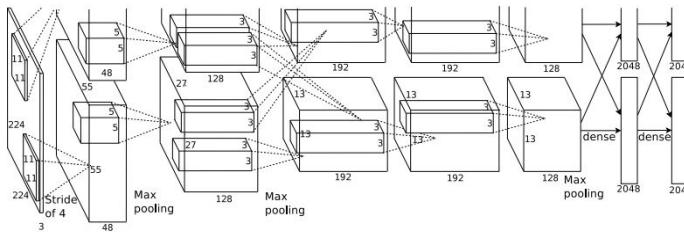
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection: Multiple Objects

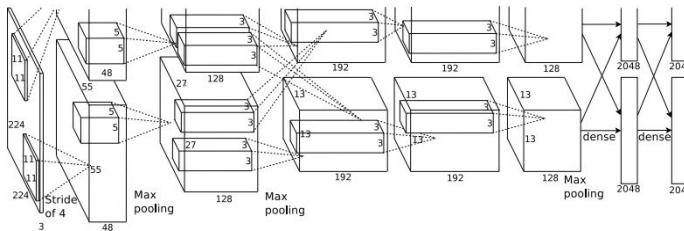
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

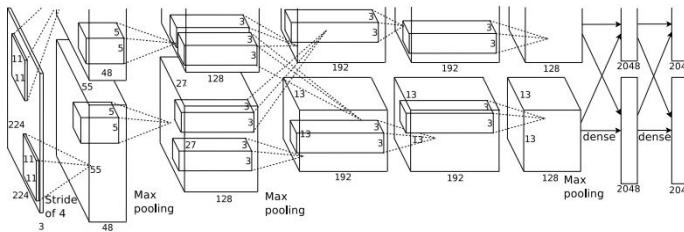
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

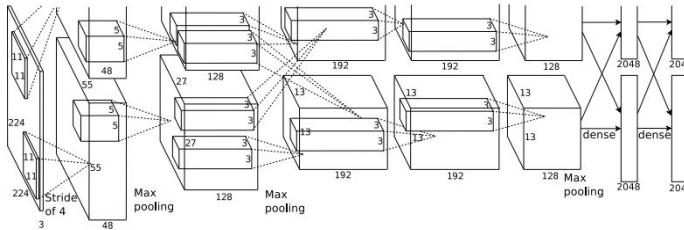
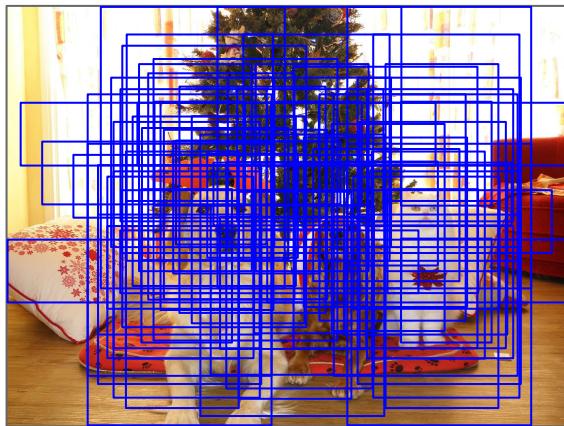
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? YES
Background? NO

Object Detection: Multiple Objects

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

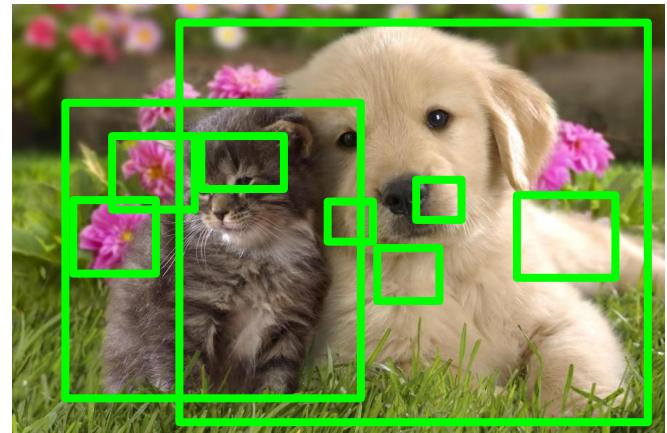


Dog? NO
Cat? YES
Background? NO

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

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

R-CNN



Input image

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

R-CNN

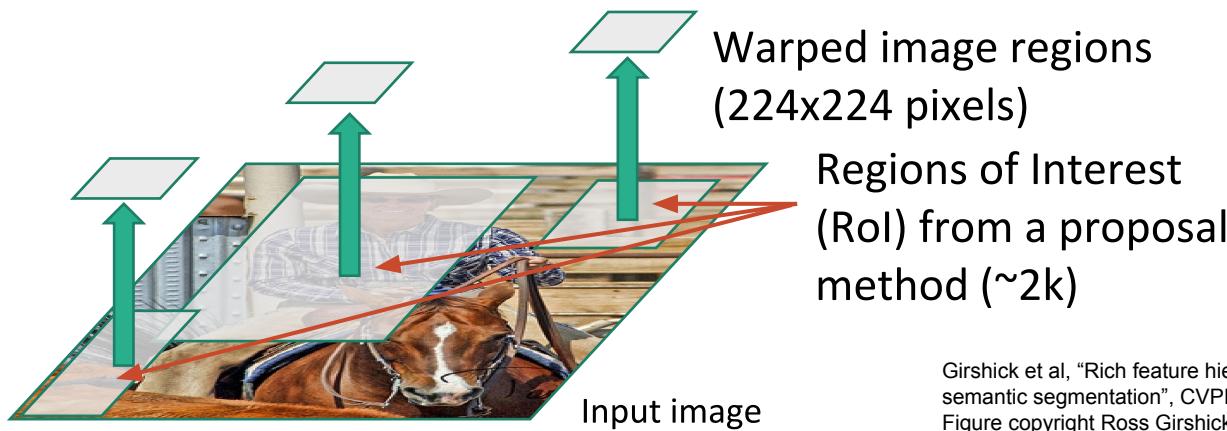


Input image

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

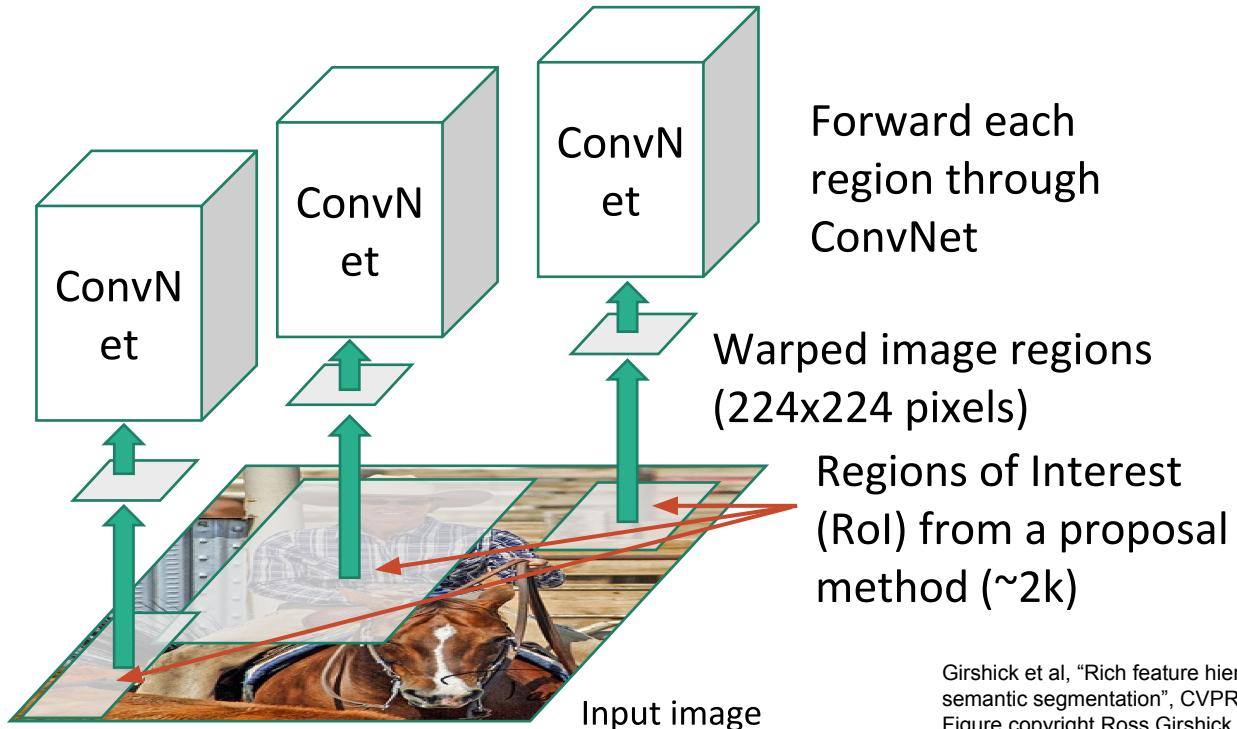
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN



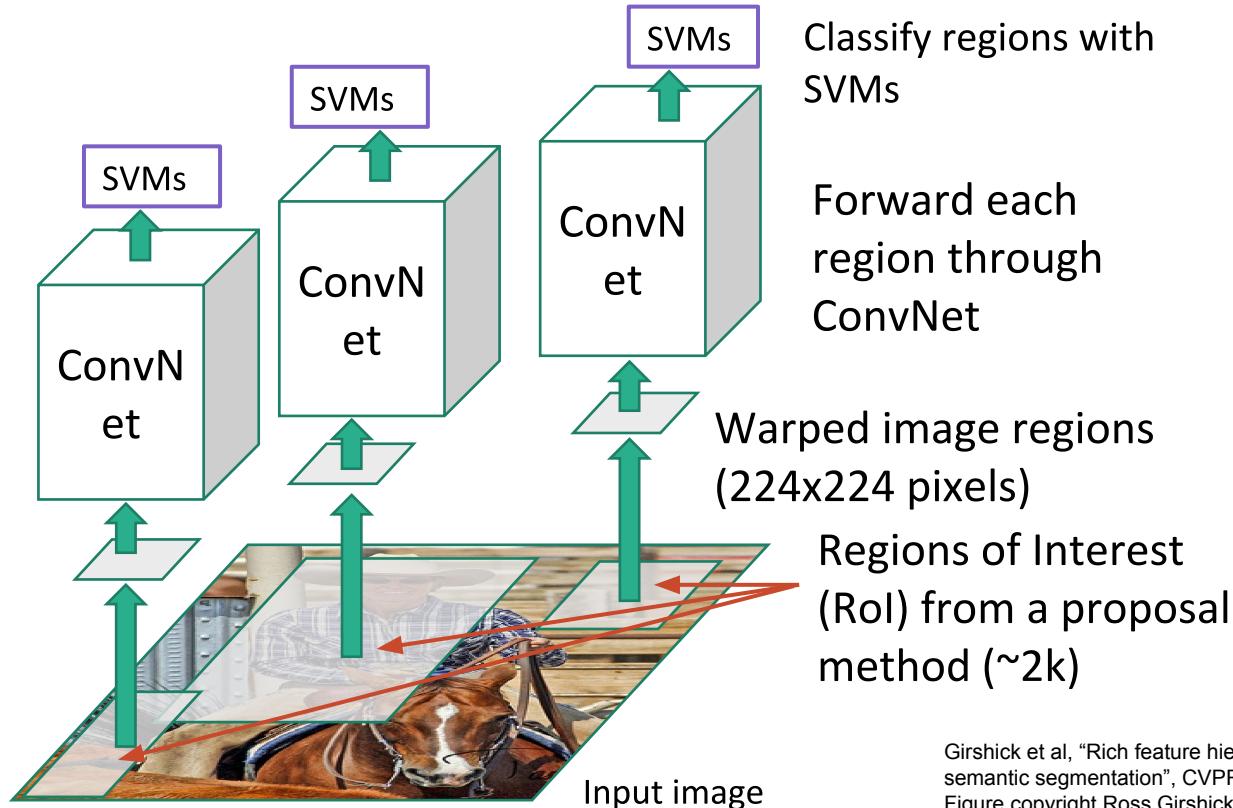
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

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.

R-CNN

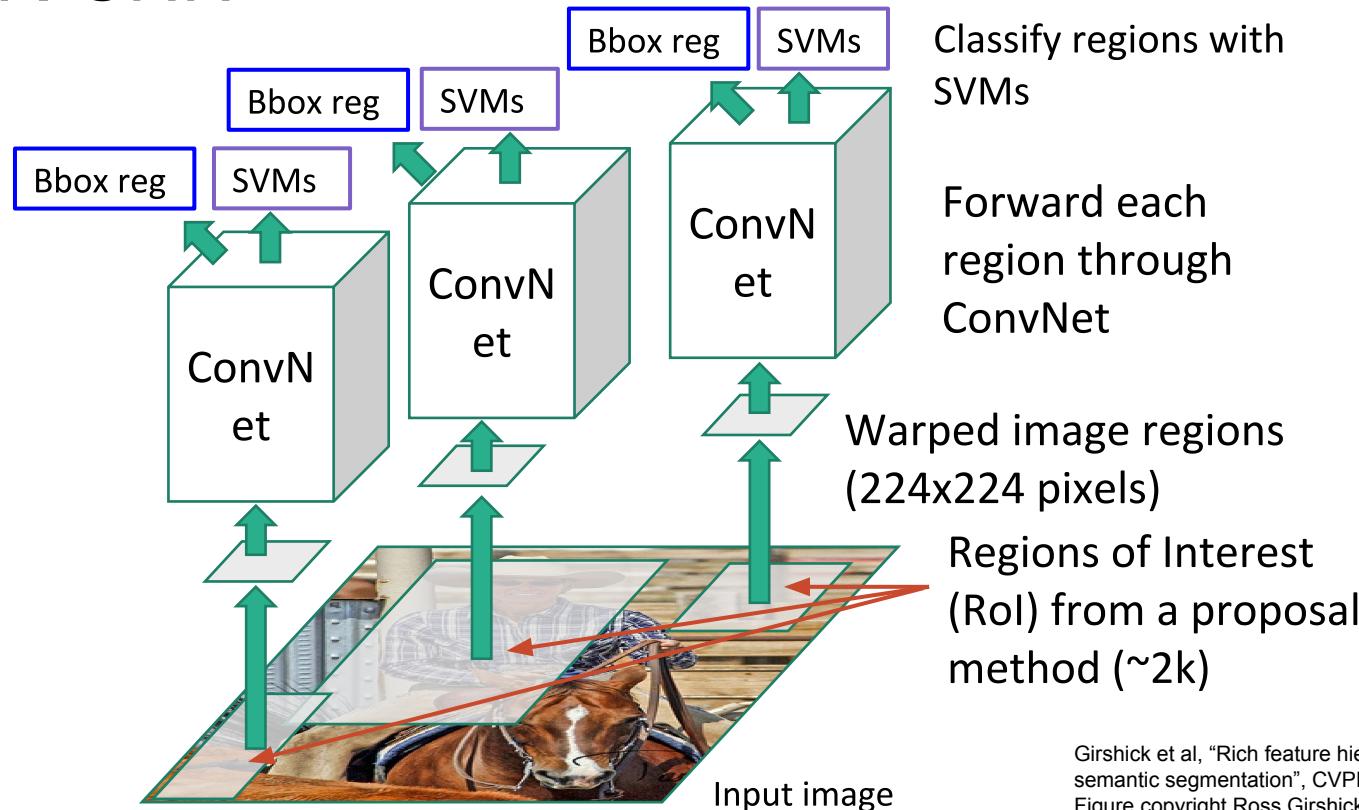


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)

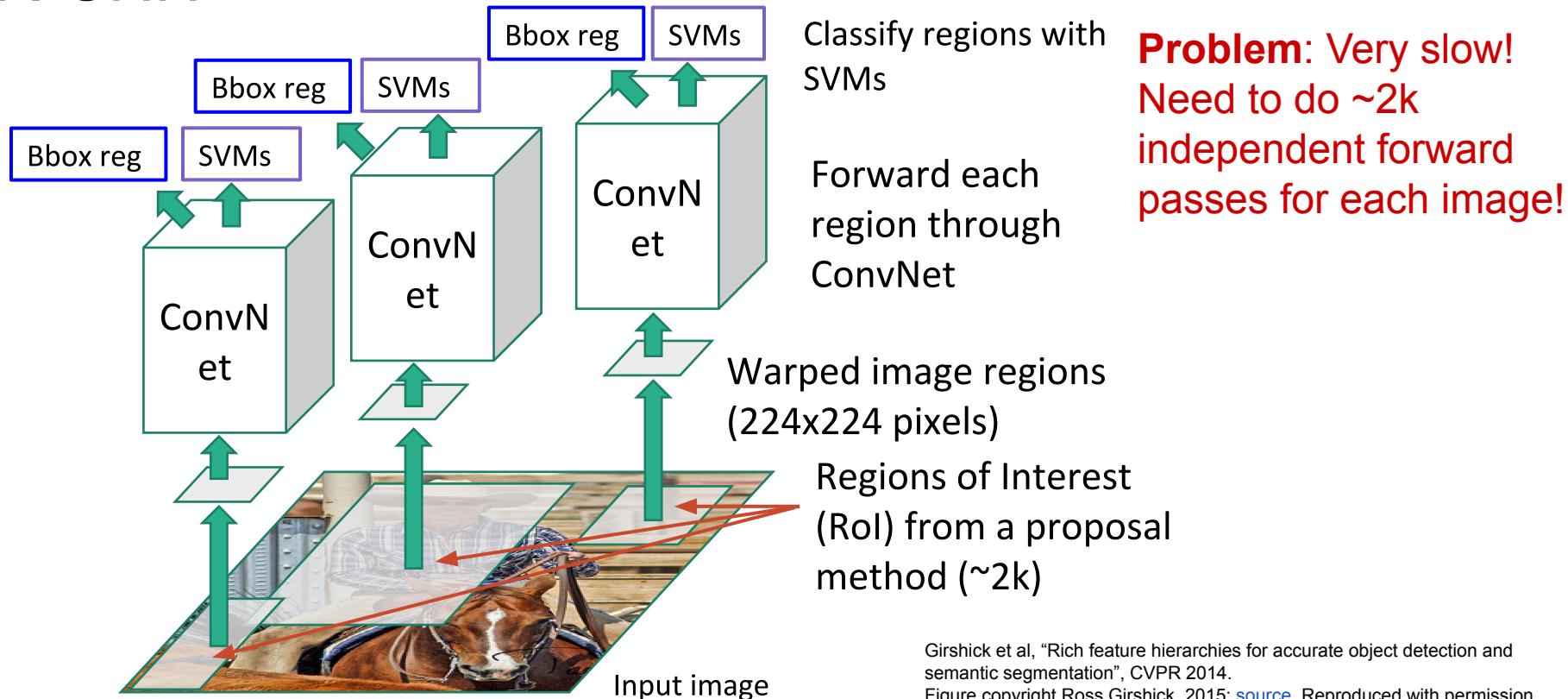


Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)

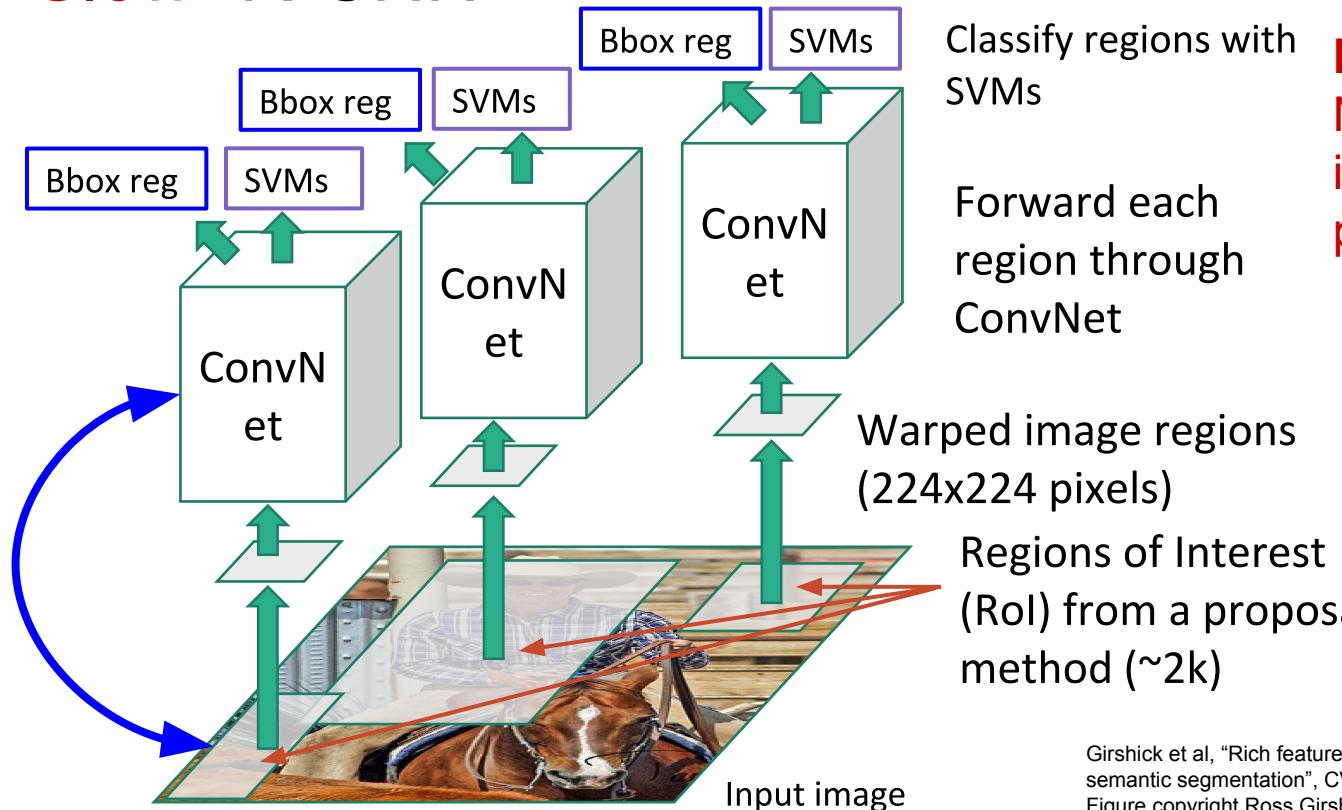


Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

“Slow” R-CNN

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)



Problem: Very slow!
Need to do ~2k independent forward passes for each image!

Idea: Process image before cropping!
Swap convolution and cropping!

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

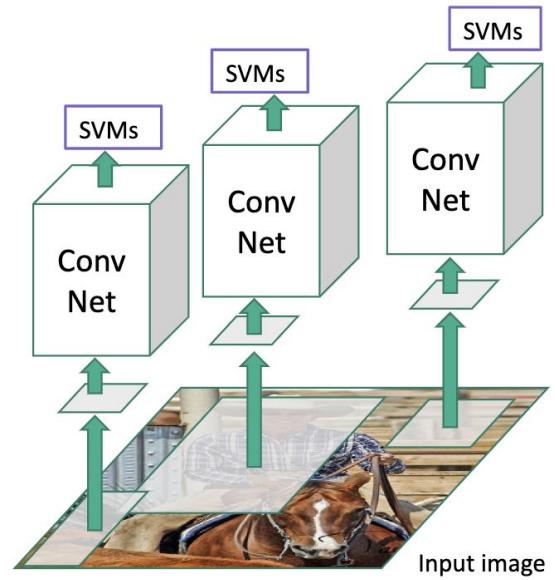
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



Input image

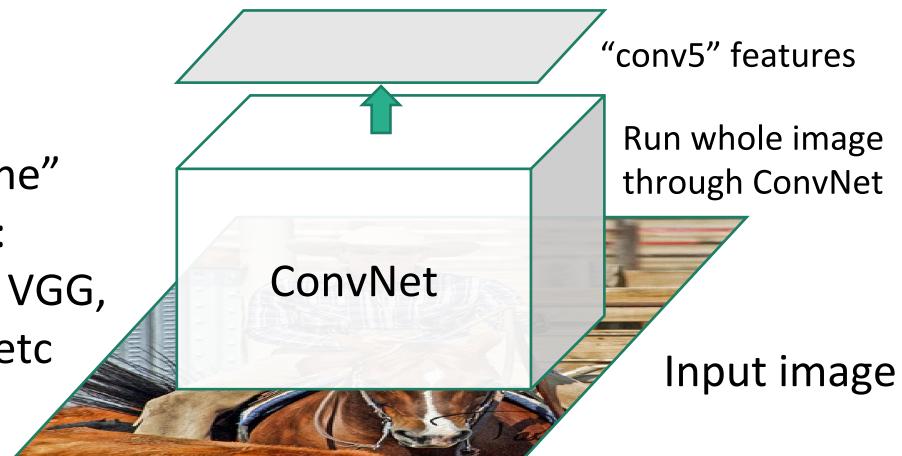
“Slow” R-CNN



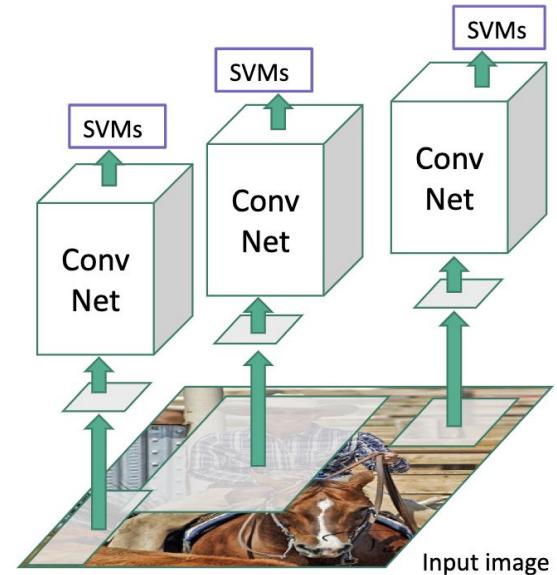
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN

“Backbone” network:
AlexNet, VGG,
ResNet, etc

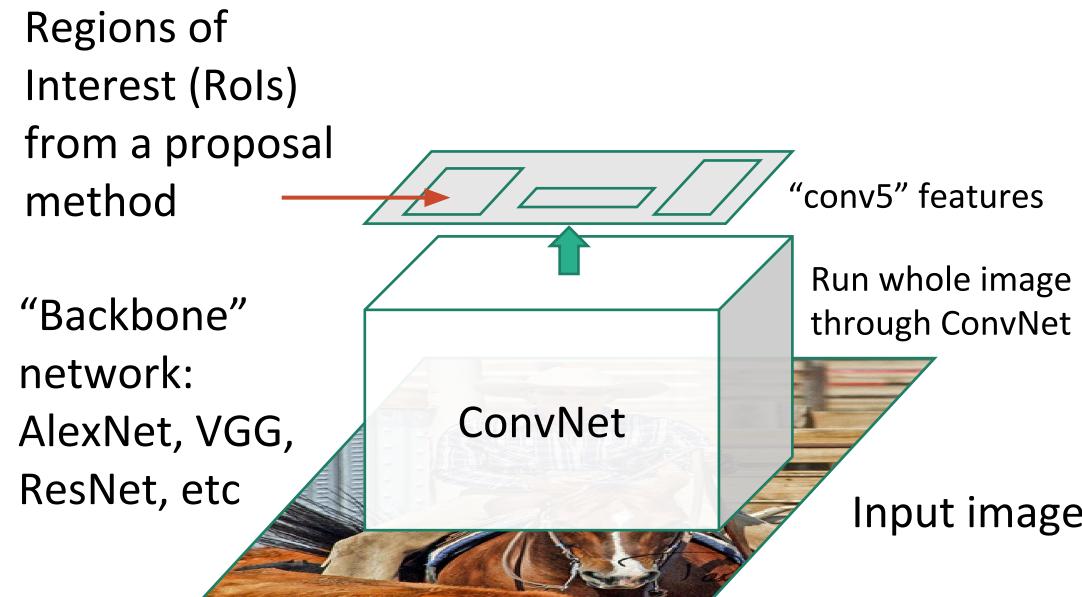


“Slow” R-CNN

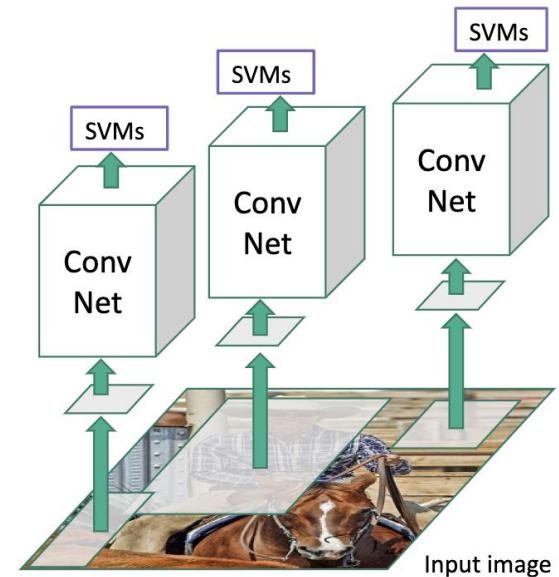


Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



“Slow” R-CNN

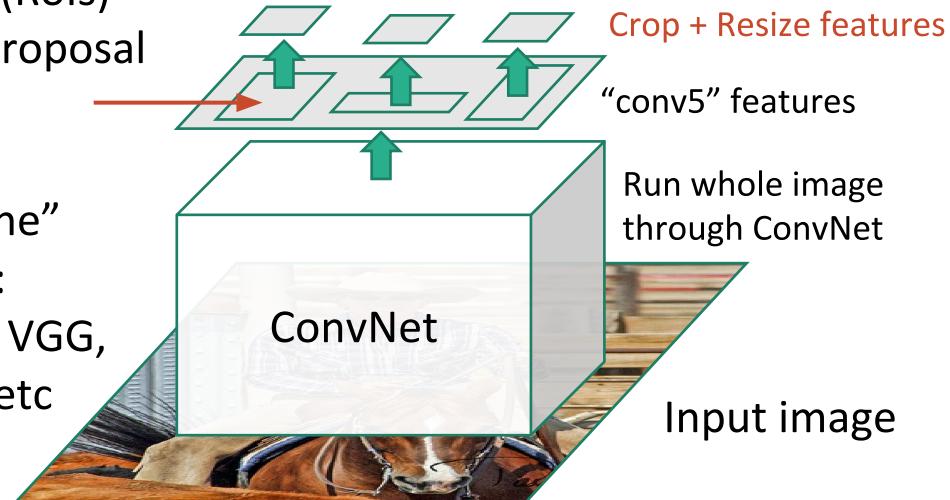


Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

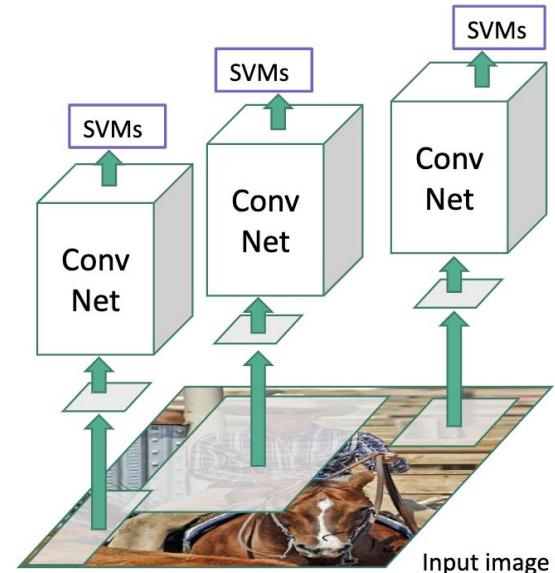
Fast R-CNN

Regions of Interest (RoIs)
from a proposal
method

“Backbone”
network:
AlexNet, VGG,
ResNet, etc

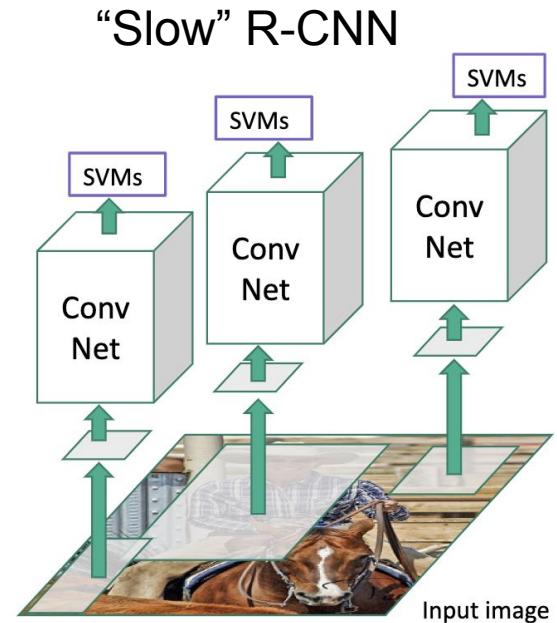
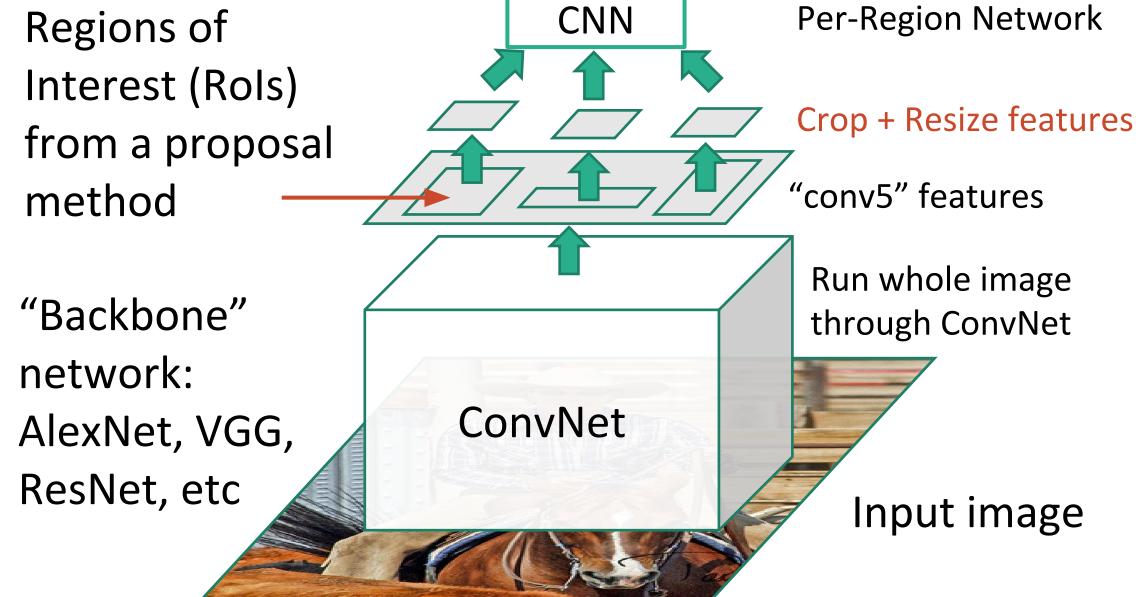


“Slow” R-CNN



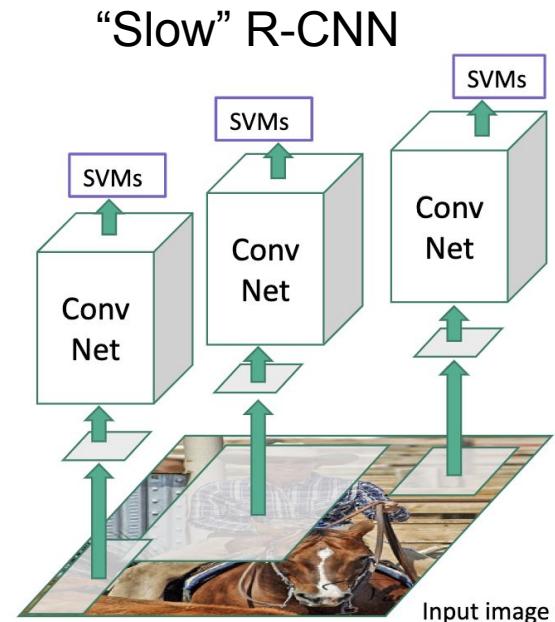
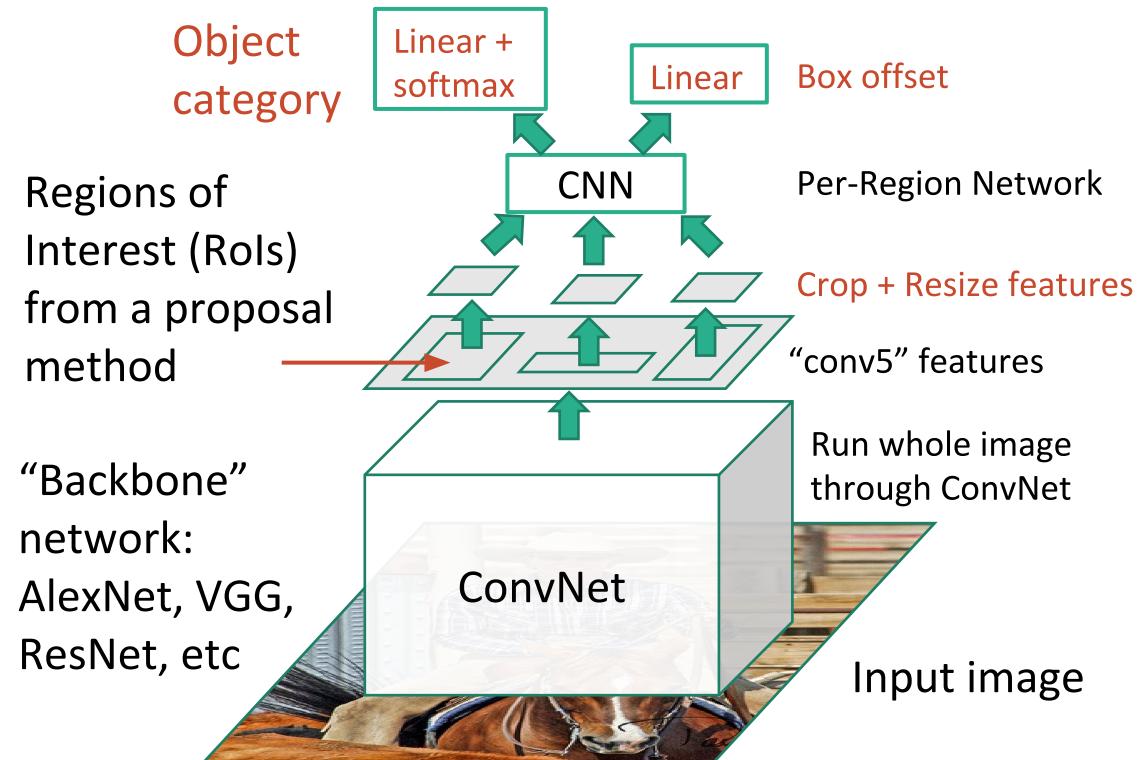
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



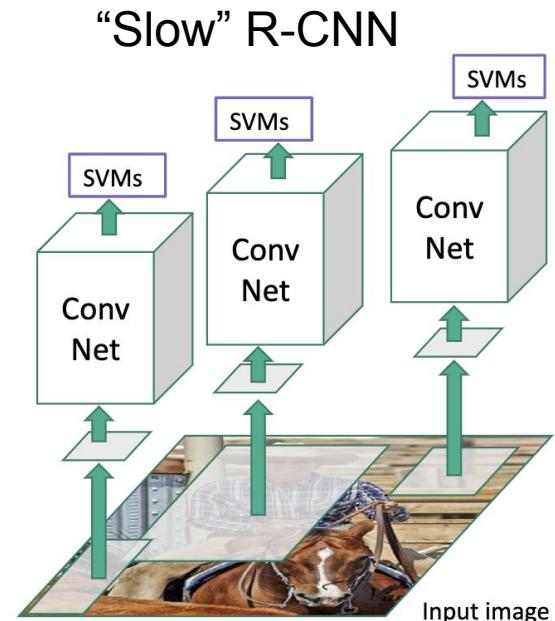
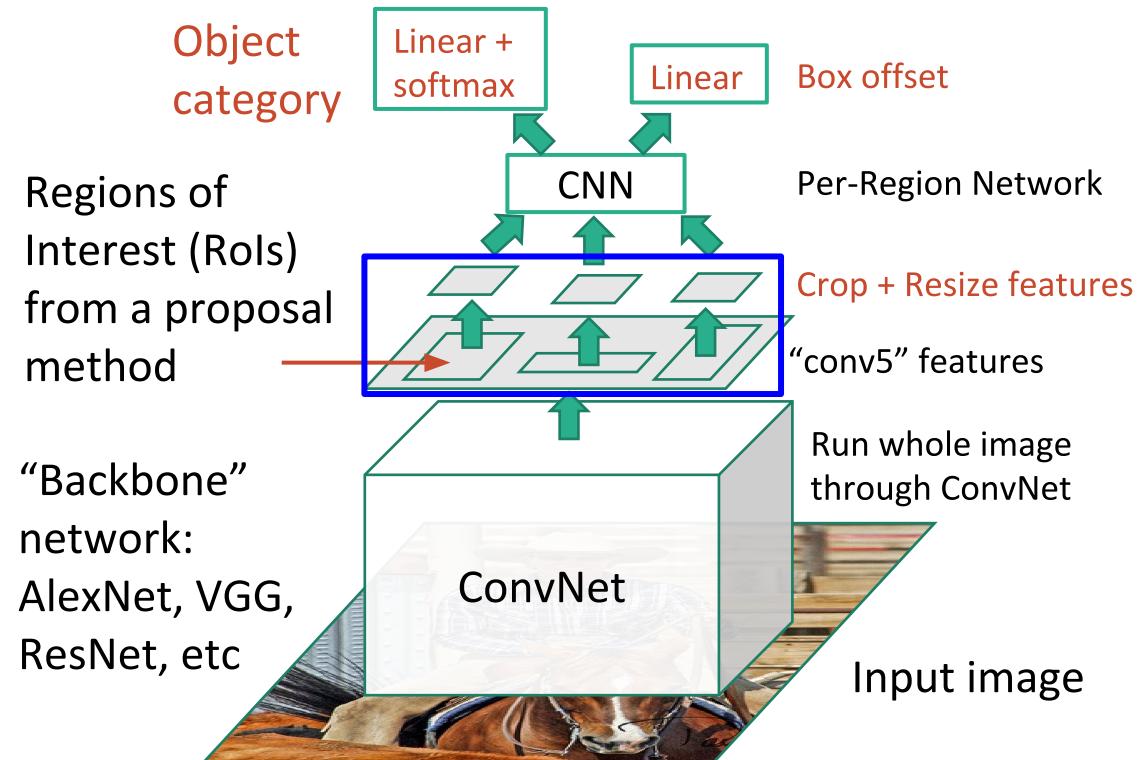
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



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

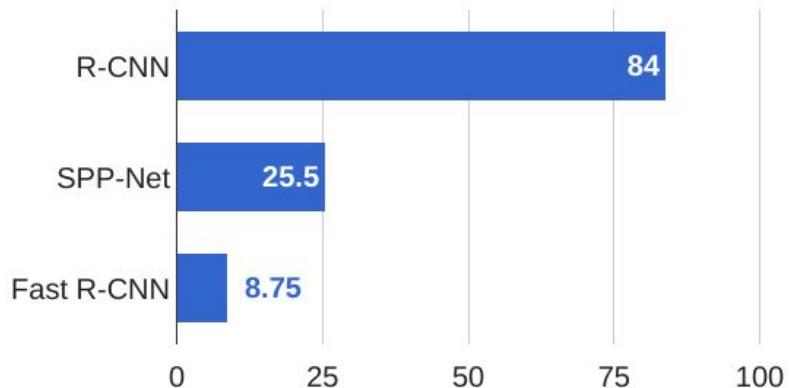
Fast R-CNN



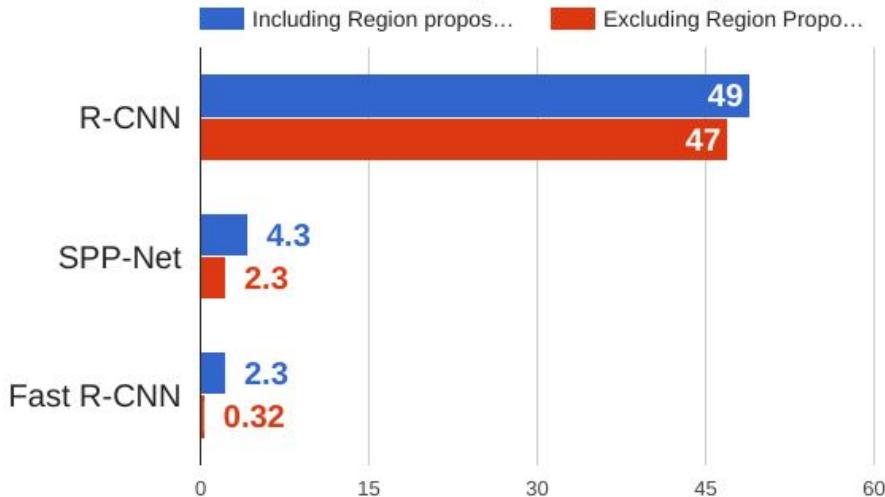
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN vs Fast R-CNN

Training time (Hours)



Test time (seconds)



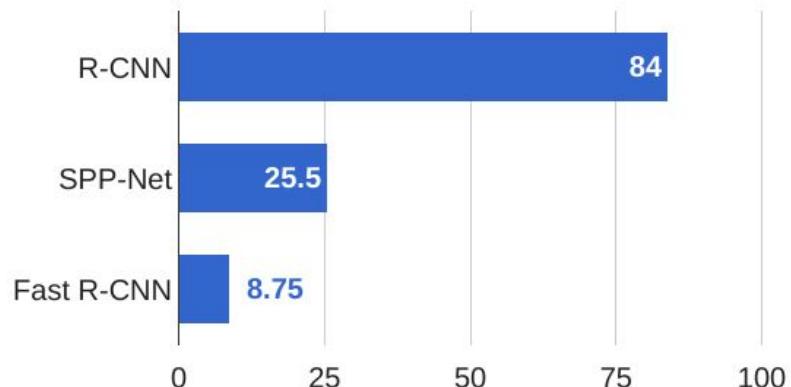
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014

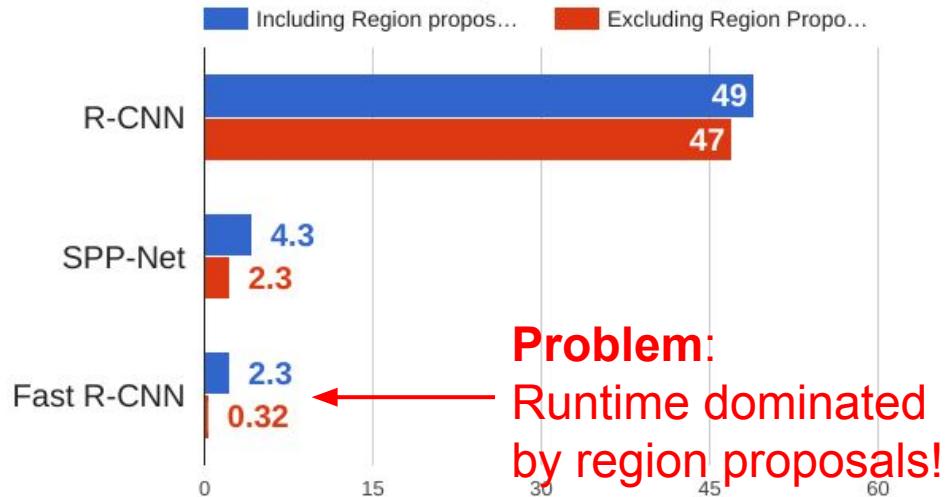
Girshick, "Fast R-CNN", ICCV 2015

R-CNN vs Fast R-CNN

Training time (Hours)



Test time (seconds)



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

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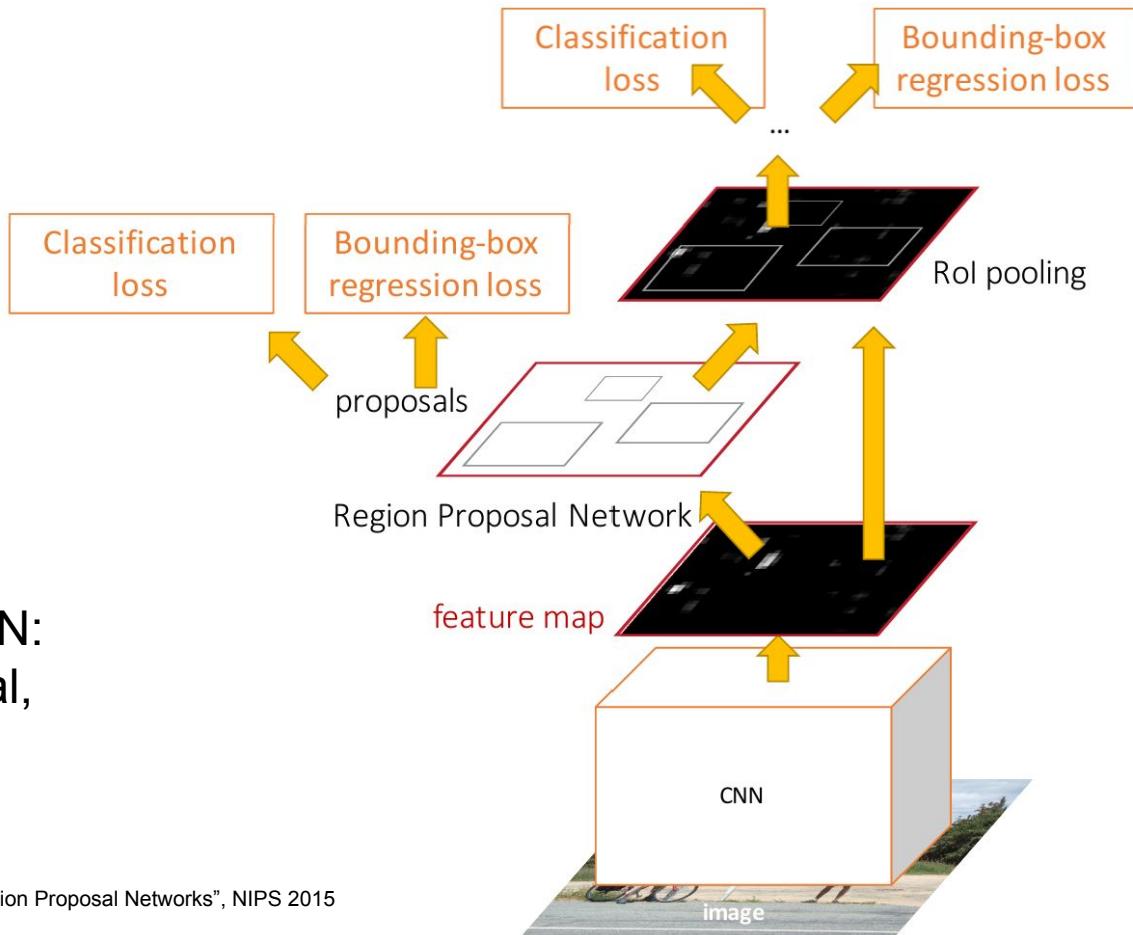
Girshick, "Fast R-CNN", ICCV 2015

Faster R-CNN:

Make CNN do proposals!

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

Otherwise same as Fast R-CNN:
Crop features for each proposal,
classify each one



Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

Region Proposal Network



Input Image
(e.g. $3 \times 640 \times 480$)

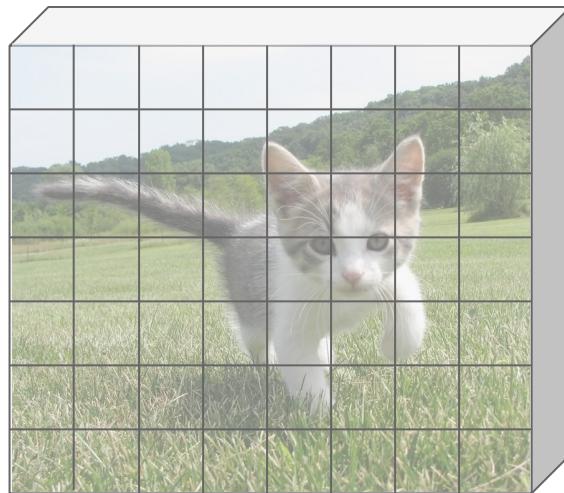
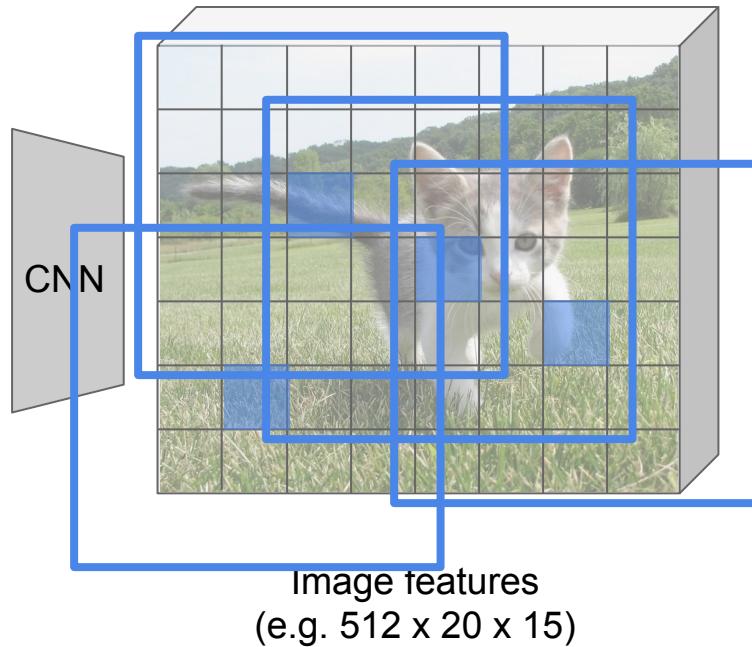


Image features
(e.g. $512 \times 20 \times 15$)

Region Proposal Network



Input Image
(e.g. $3 \times 640 \times 480$)

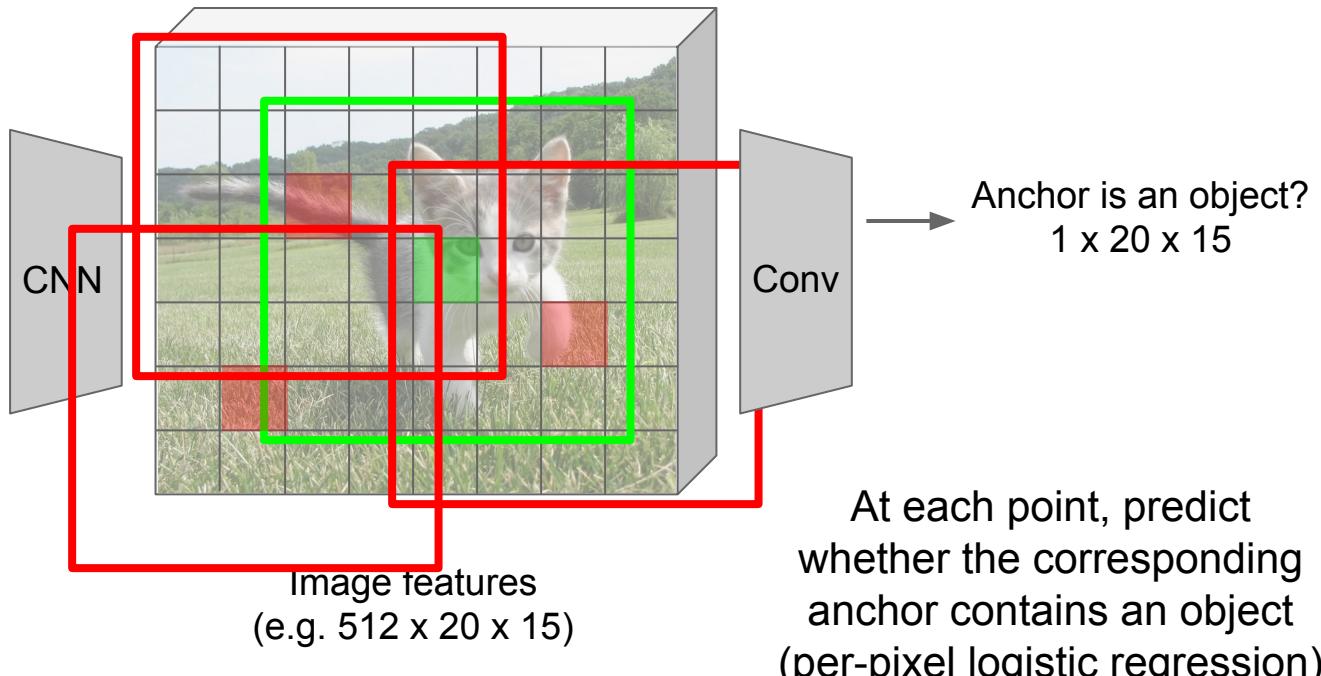


Imagine an **anchor box** of fixed size at each point in the feature map

Region Proposal Network



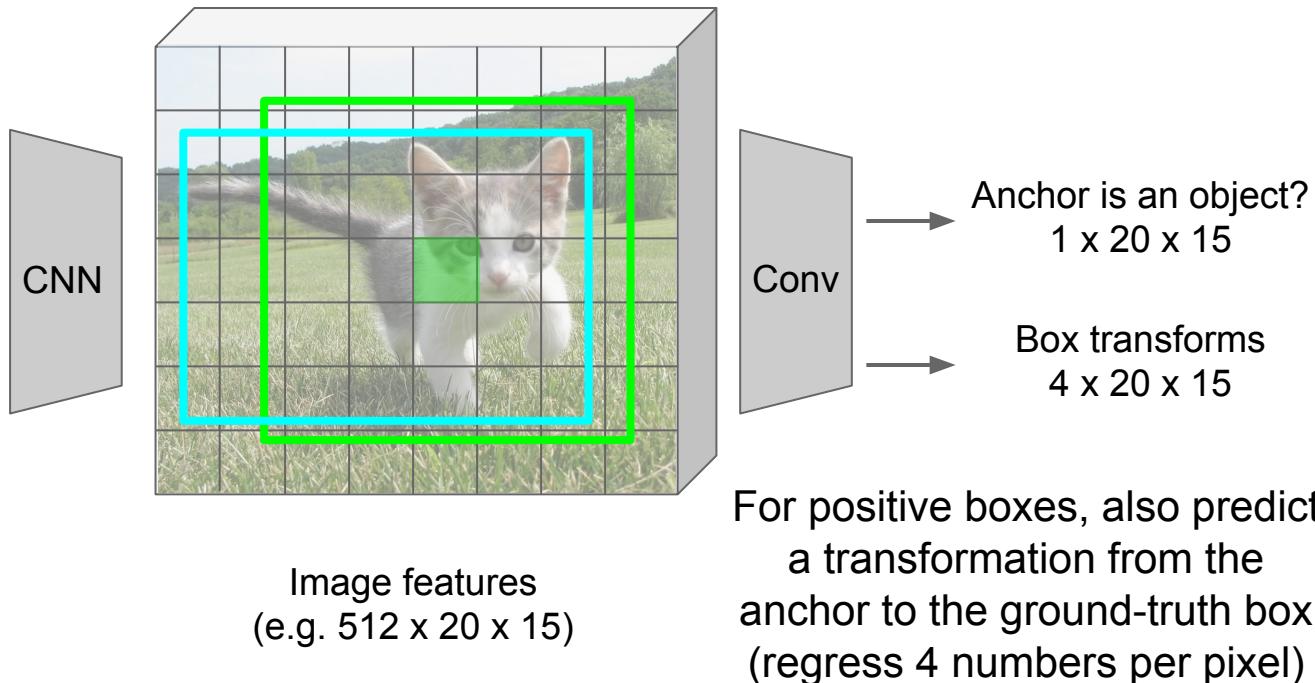
Input Image
(e.g. $3 \times 640 \times 480$)



Region Proposal Network



Input Image
(e.g. $3 \times 640 \times 480$)



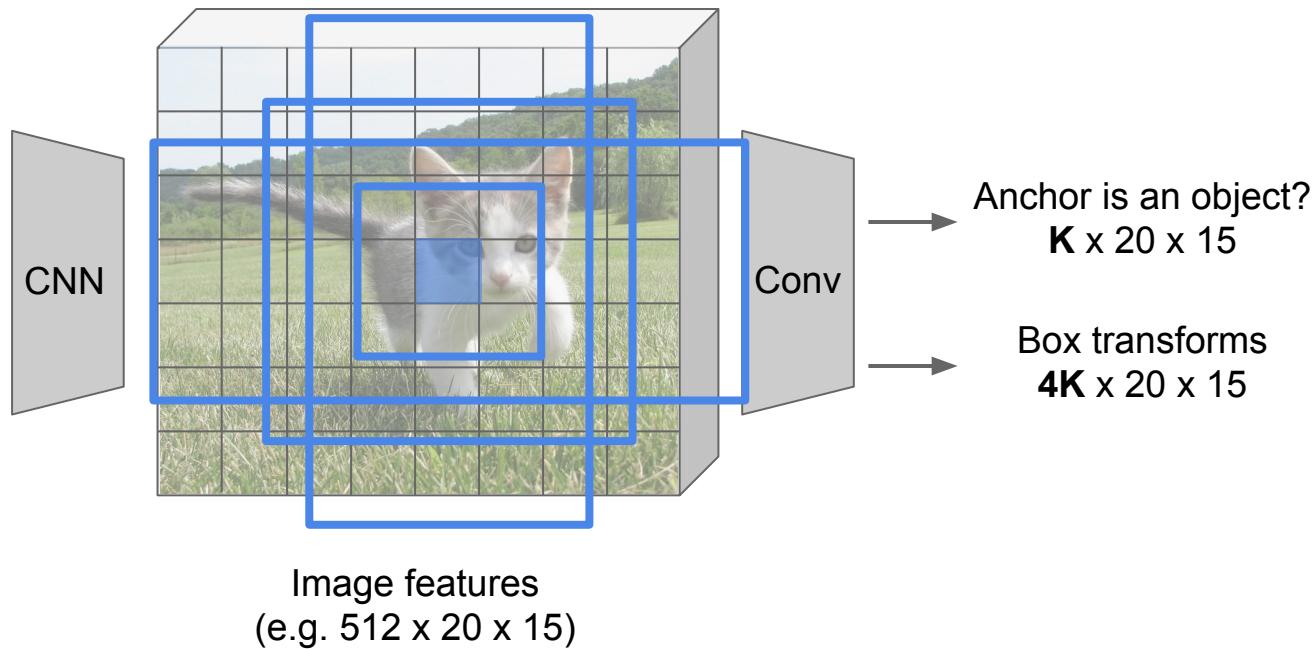
Imagine an **anchor box** of fixed size at each point in the feature map

Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point



Input Image
(e.g. $3 \times 640 \times 480$)

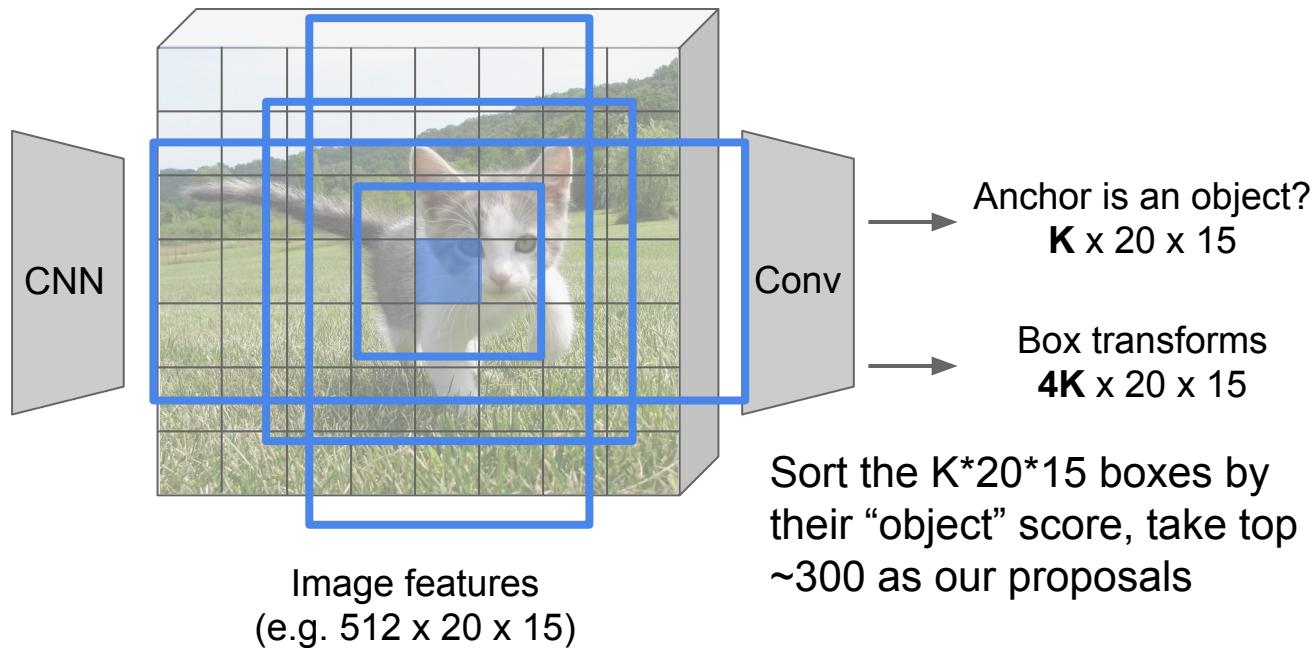


Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point



Input Image
(e.g. $3 \times 640 \times 480$)

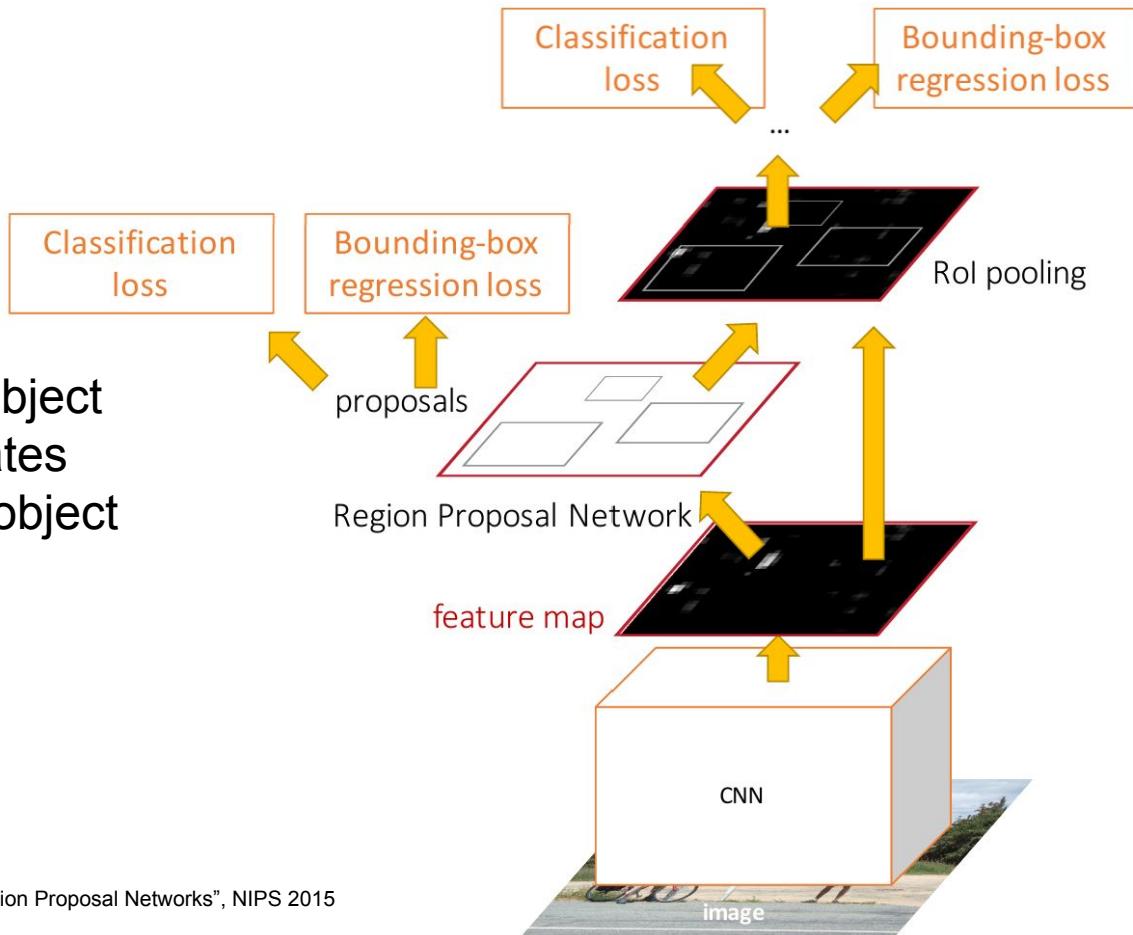


Faster R-CNN:

Make CNN do proposals!

Jointly train with 4 losses:

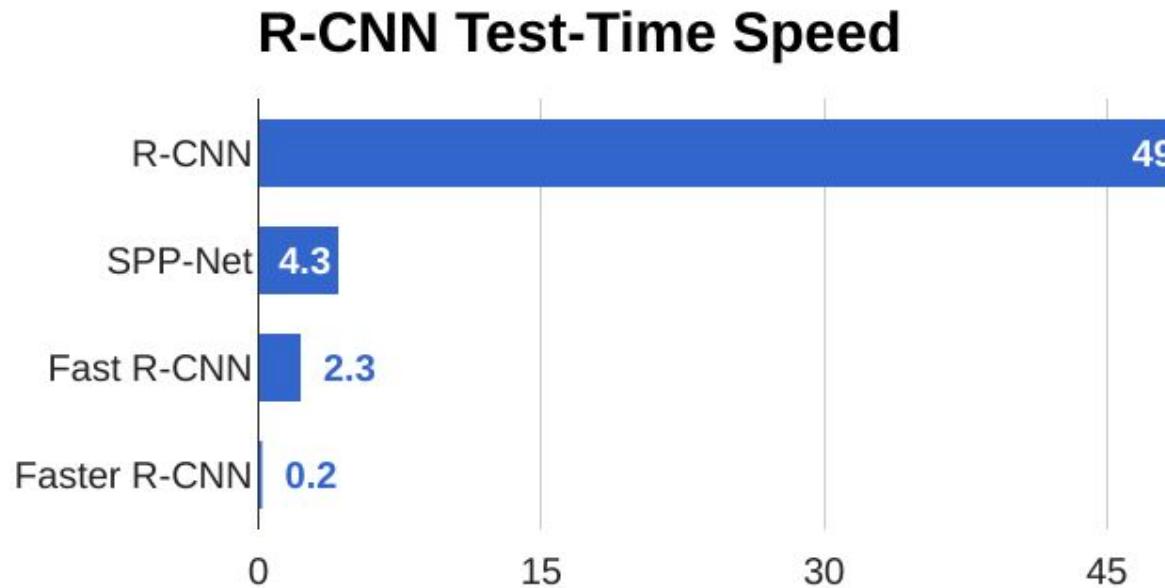
1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates



Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

Faster R-CNN:

Make CNN do proposals!

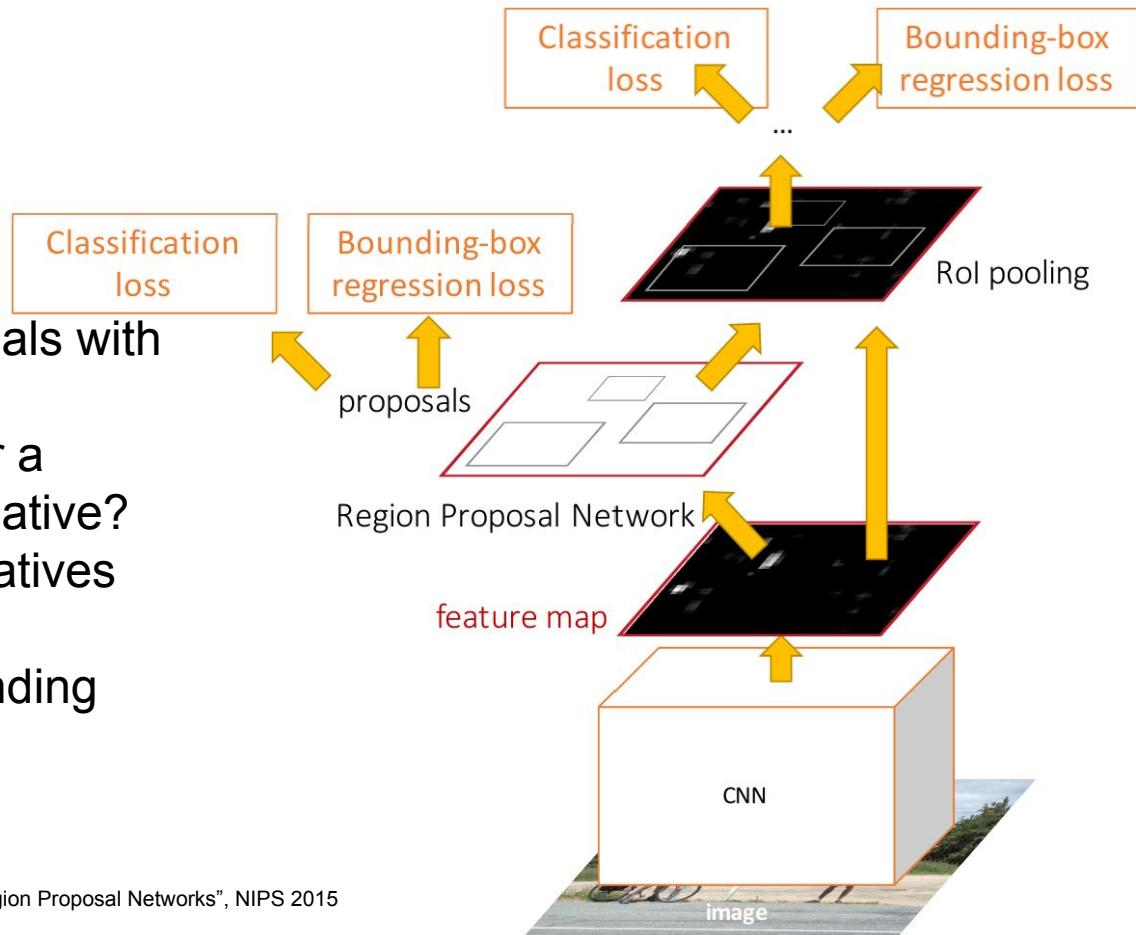


Faster R-CNN:

Make CNN do proposals!

Glossing over many details:

- Ignore overlapping proposals with **non-max suppression**
- How to determine whether a proposal is positive or negative?
- How many positives / negatives to send to second stage?
- How to parameterize bounding box regression?



Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

Faster R-CNN: Make CNN do proposals!

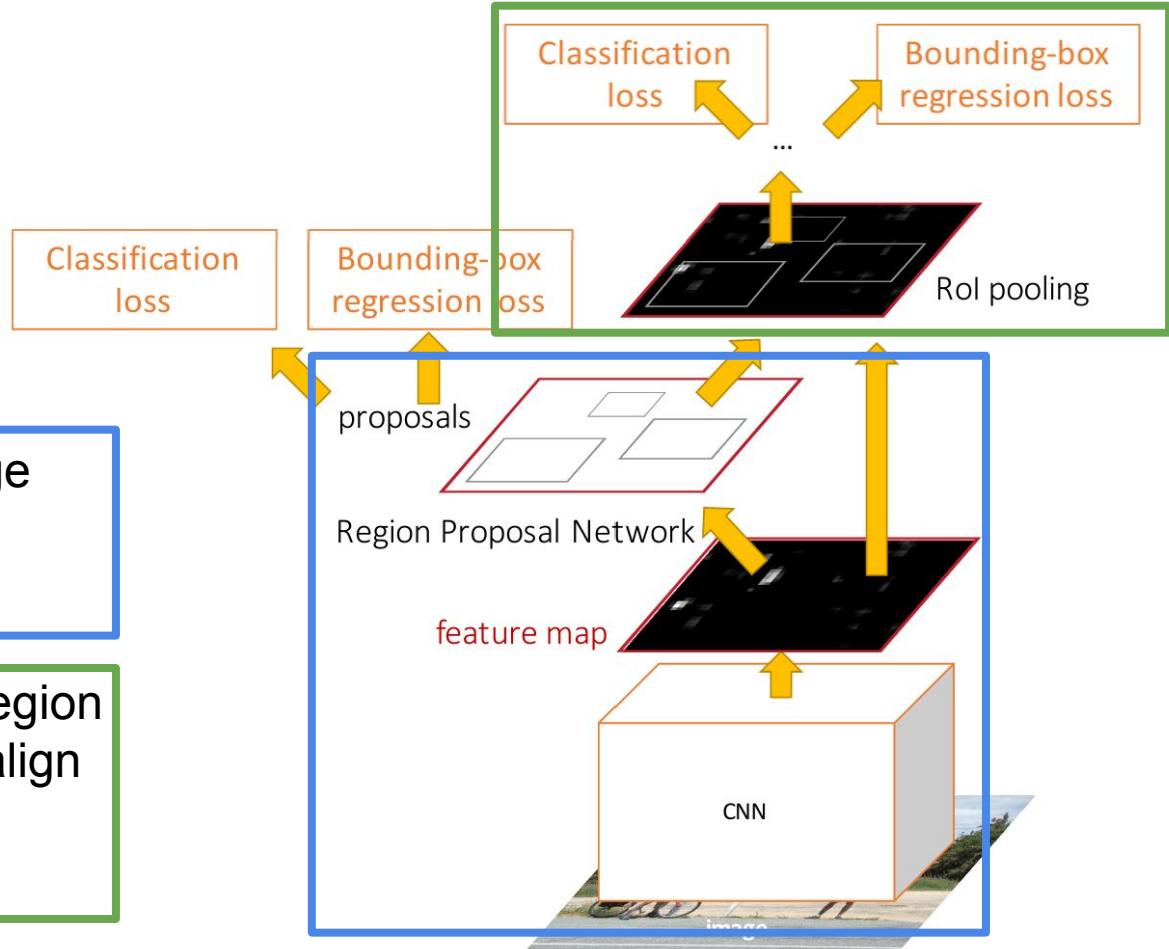
Faster R-CNN is a
Two-stage object detector

First stage: Run once per image

- Backbone network
- Region proposal network

Second stage: Run once per region

- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



Faster R-CNN: Make CNN do proposals!

Faster R-CNN is a
Two-stage object detector

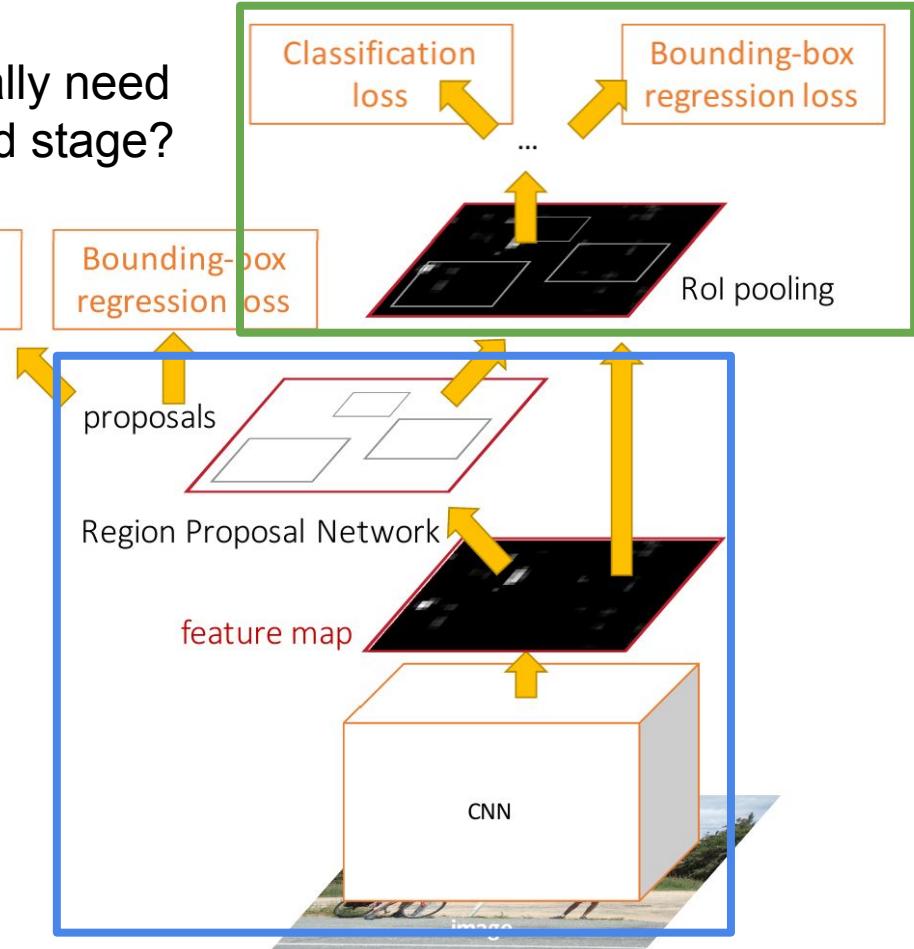
First stage: Run once per image

- Backbone network
- Region proposal network

Second stage: Run once per region

- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset

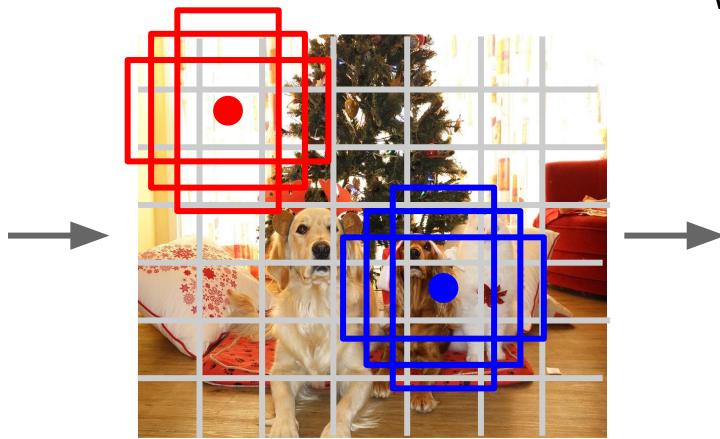
Do we really need
the second stage?



Single-Stage Object Detectors: YOLO / SSD / RetinaNet



Input image
 $3 \times H \times W$



Divide image into grid
 7×7

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)
- Looks a lot like RPN, but category-specific!

Output:

$7 \times 7 \times (5 * B + C)$

Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016
Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Object Detection: Lots of variables ...

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

“Meta-Architecture”
Two-stage: Faster R-CNN
Single-stage: YOLO / SSD
Hybrid: R-FCN

Image Size
Region Proposals
...

Takeaways
Faster R-CNN is slower but more accurate

SSD is much faster but not as accurate

Bigger / Deeper backbones work better

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

Object Detection: Lots of variables ...

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ResNet-101
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Inception V3
Inception
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MobileNet

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Region Proposals
...

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Huang et al, “Speed/accuracy trade-offs for modern convolutional object detectors”, CVPR 2017
Zou et al, “Object Detection in 20 Years: A Survey”, arXiv 2019 (today!)

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

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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

Instance Segmentation

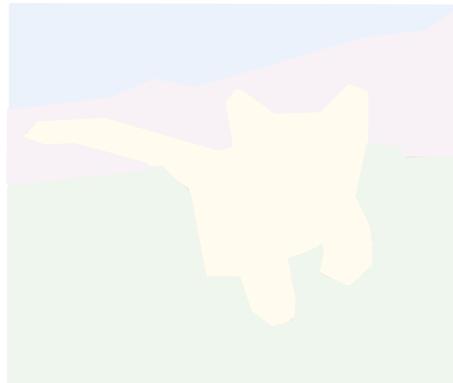
Classification



CAT

No spatial extent

Semantic
Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Object
Detection



DOG, DOG, CAT

Multiple Object

Instance
Segmentation



DOG, DOG, CAT

Object Detection: Faster R-CNN

Object Detection

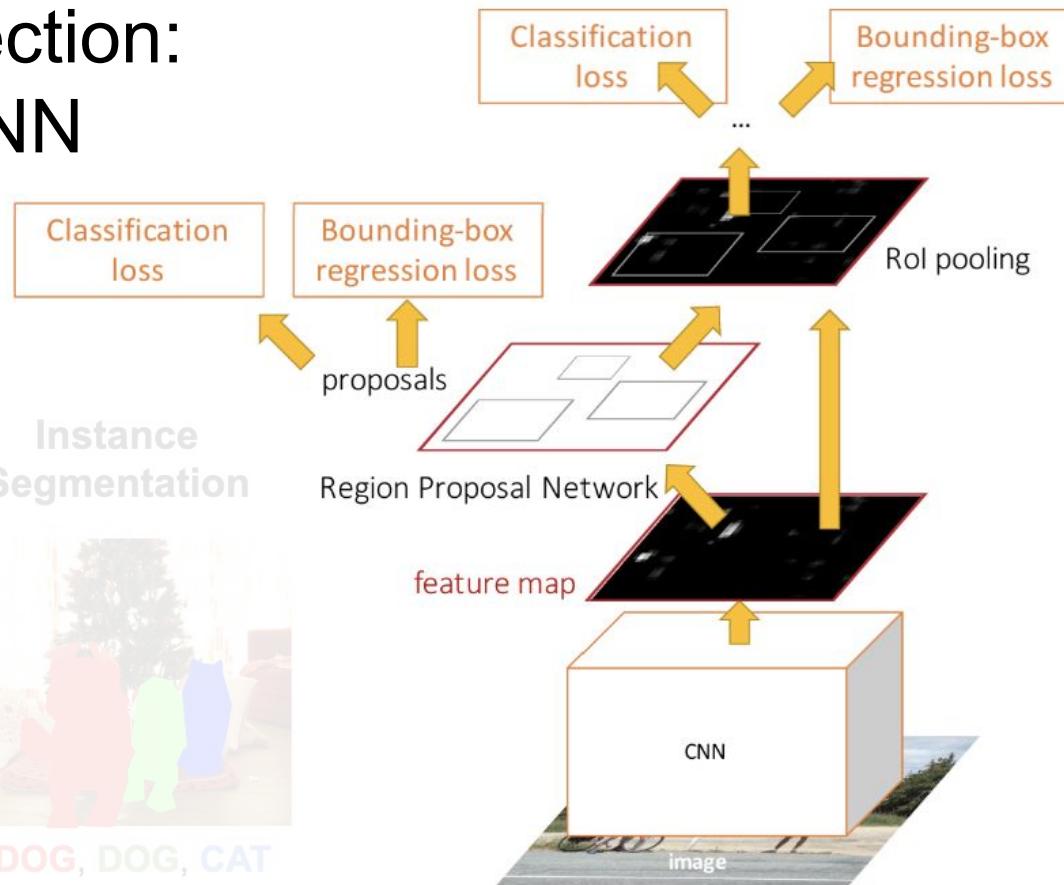


DOG, DOG, CAT

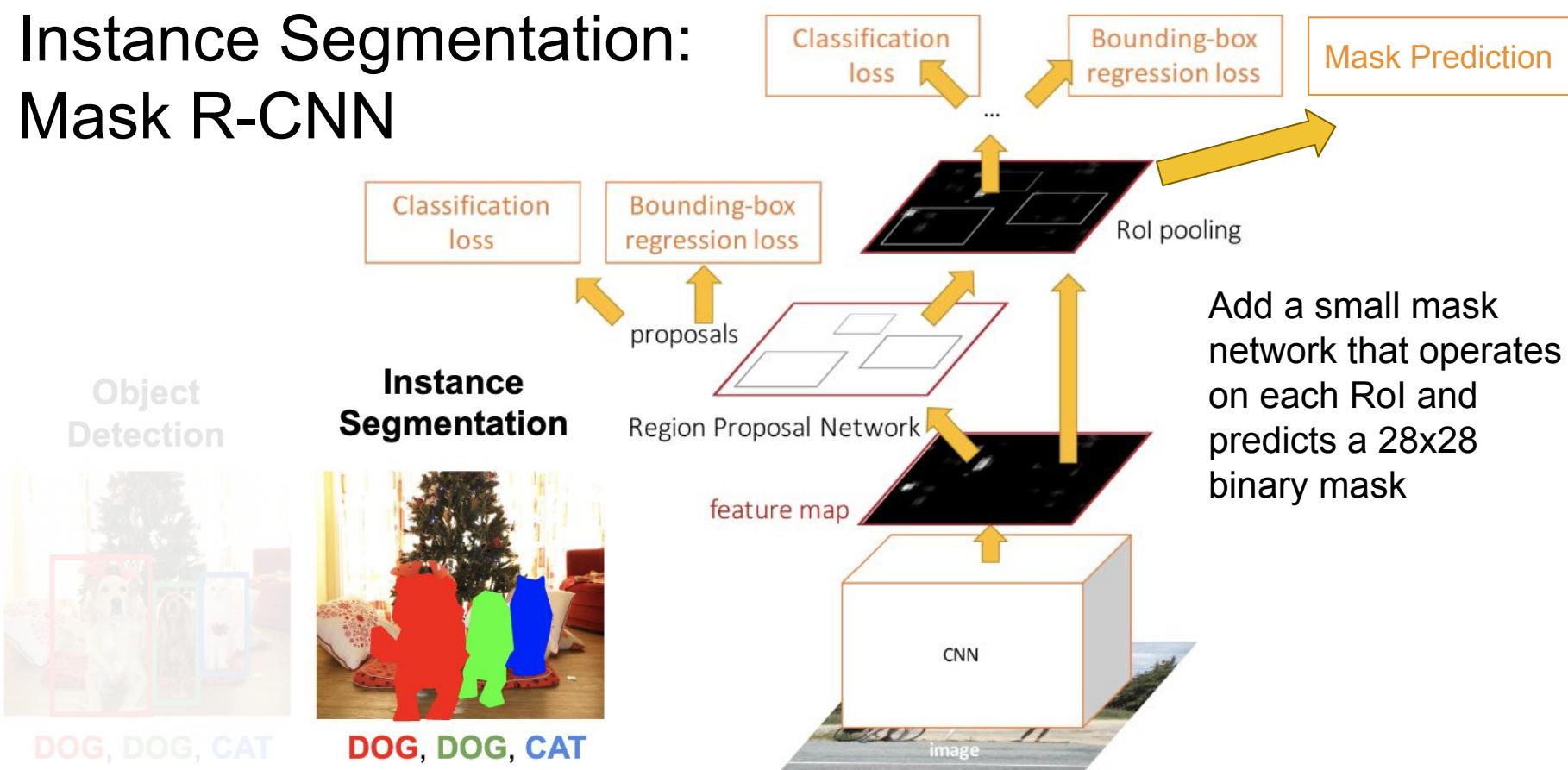
Instance Segmentation



DOG, DOG, CAT

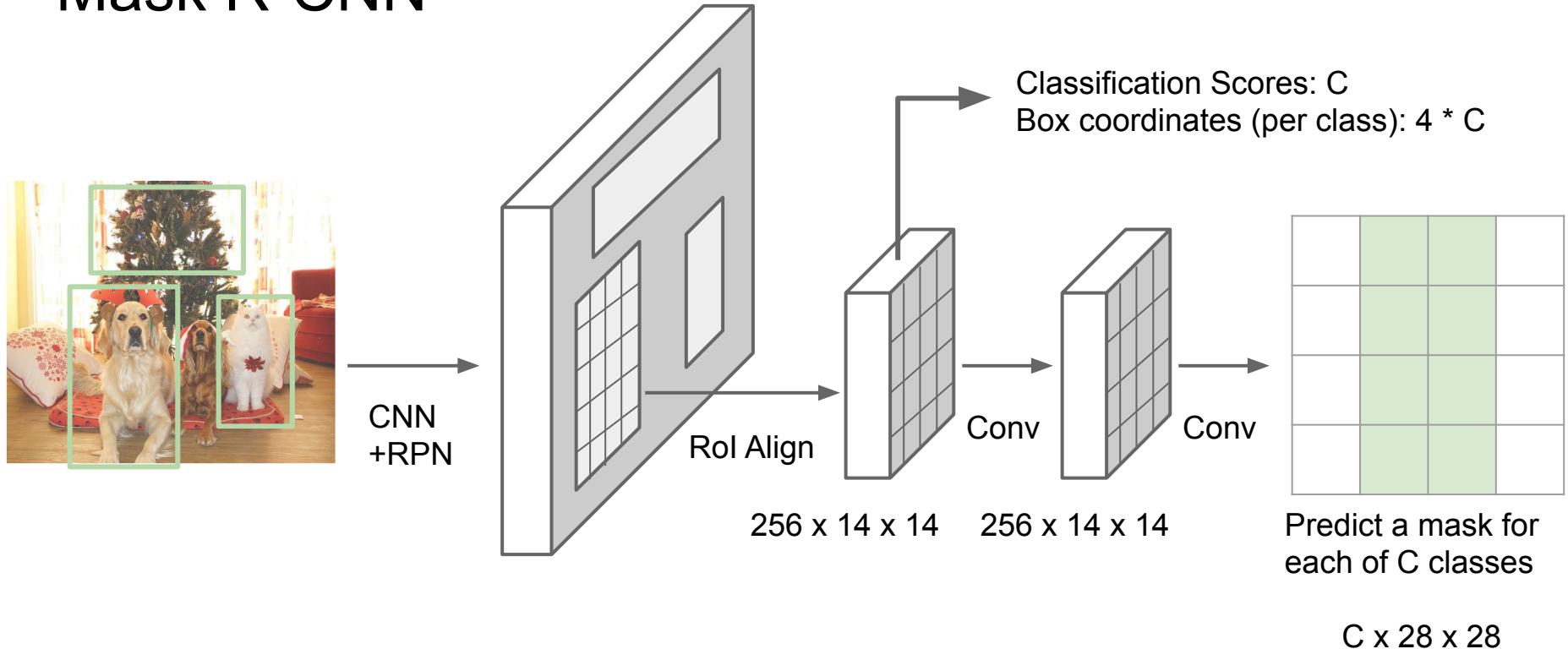


Instance Segmentation: Mask R-CNN



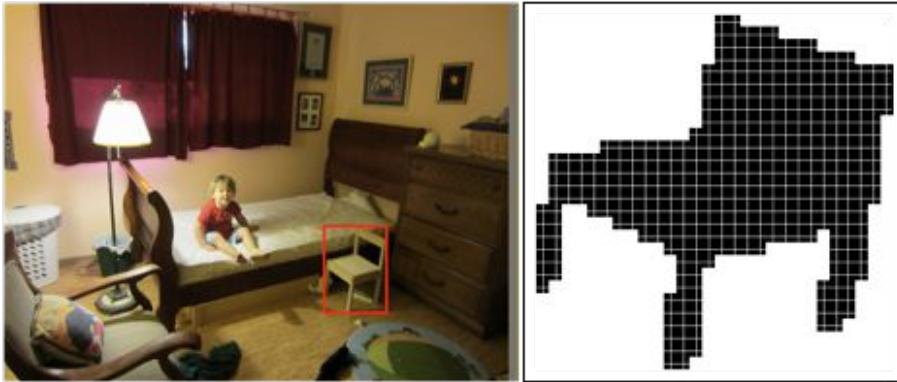
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN

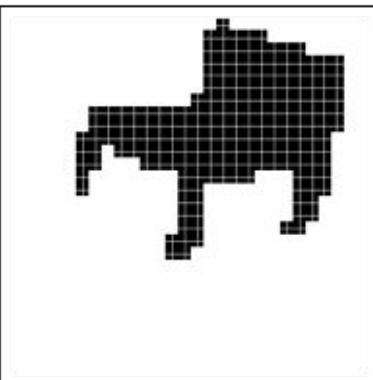


He et al, "Mask R-CNN", arXiv 2017

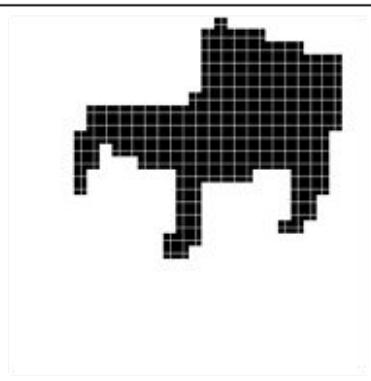
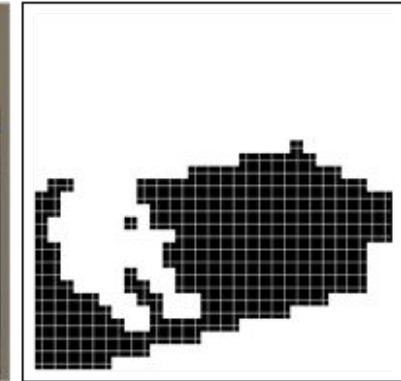
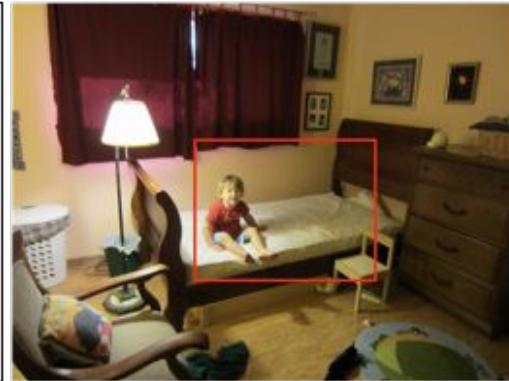
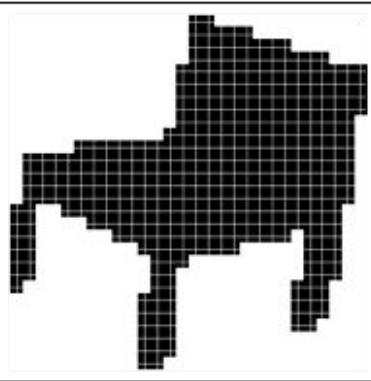
Mask R-CNN: Example Mask Training Targets



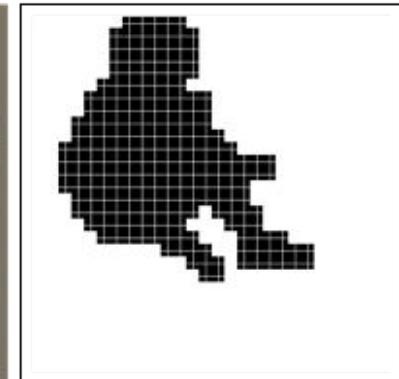
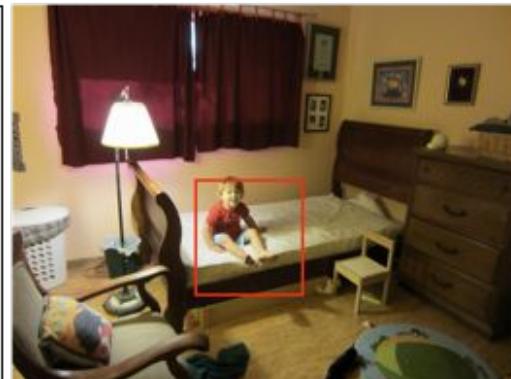
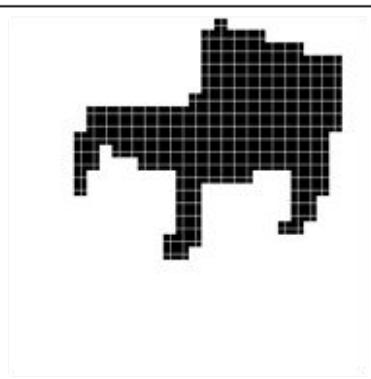
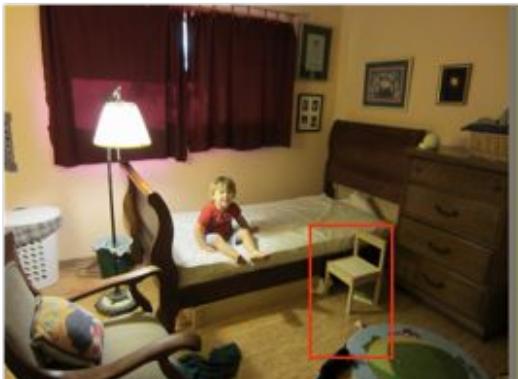
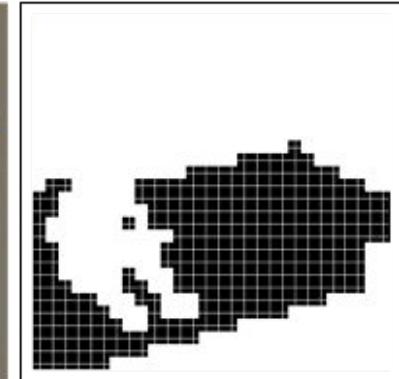
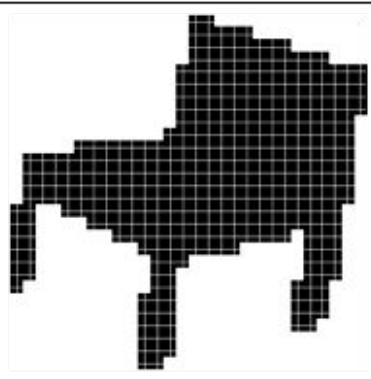
Mask R-CNN: Example Mask Training Targets



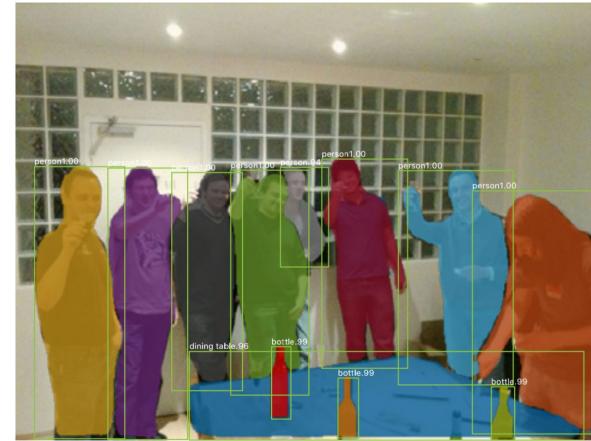
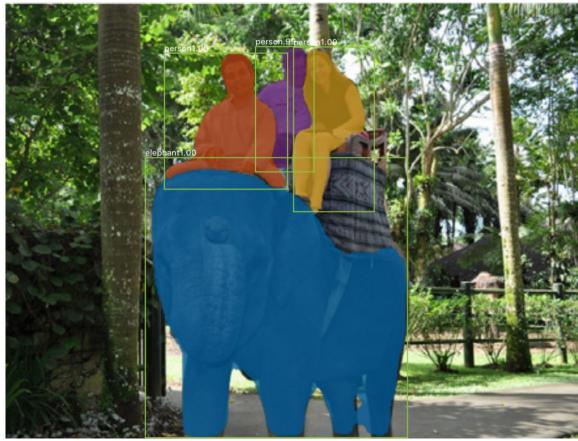
Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Very Good Results!



He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN

Also does pose



He et al, "Mask R-CNN", ICCV 2017

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