

Lecture 14:

Structured Prediction

Detection and Segmentation

Administrative: Assignment 4

Due 5/25 11:59pm

- PyTorch,
- RNNs,
- LSTMs

Administrative: Fridays

This Friday

Exam Review

Administrative: Exam

In-class on Tuesday (May 20th)

Allowed one 8.5"x11" **handwritten** (no printing out) note-sheet

Lectures 2-12, A1-A3, sections 1-6 are fair game for exam

Refer to the [exam archive](#) for practice materials

Make a private post on Ed **by tonight** if you require a make-up exam

Image Classification: A core task in Computer Vision



[This image](#) by [Nikita](#) is
licensed under [CC-BY 2.0](#)

(assume given a set of possible labels)
{dog, cat, truck, plane, ...}



cat

Structured prediction tasks in vision

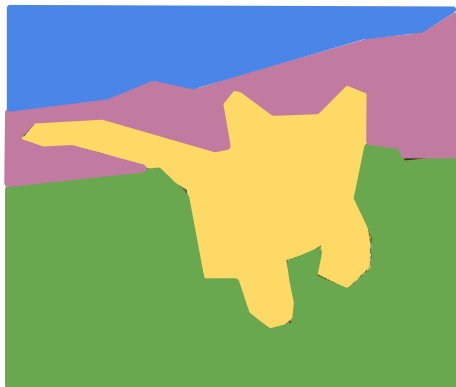
Classification



CAT

No spatial extent

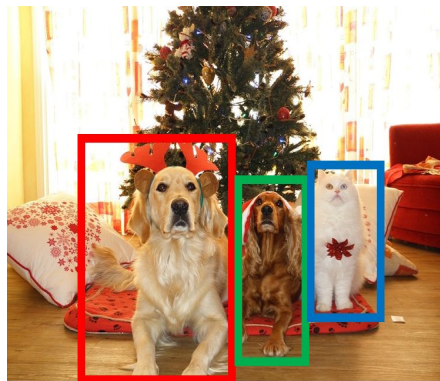
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

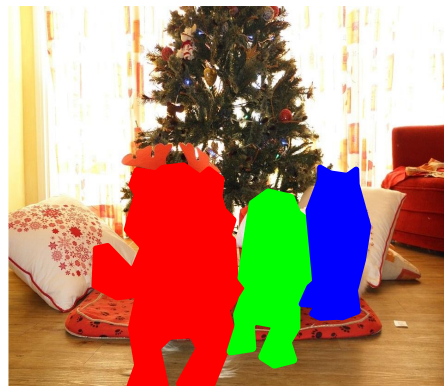
Object Detection



DOG, DOG, CAT

Multiple Object

Instance Segmentation



DOG, DOG, CAT

[This image is CC0 public domain](#)

Semantic Segmentation

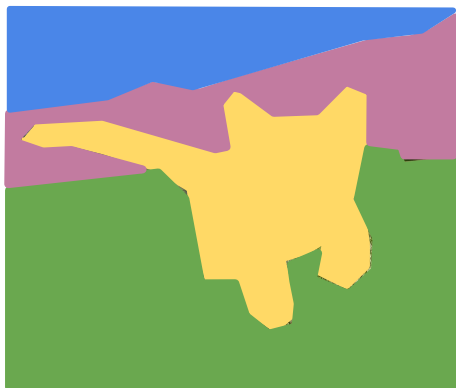
Classification



CAT

No spatial extent

Semantic
Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Object
Detection



DOG, DOG, CAT

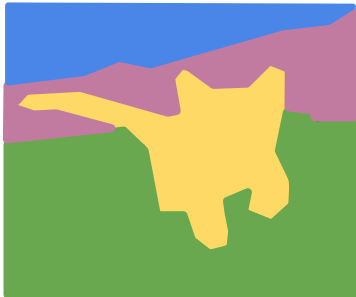
Multiple Object

Instance
Segmentation



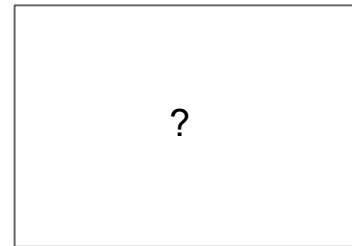
DOG, DOG, CAT

Semantic Segmentation: The Problem



GRASS, CAT,
TREE, SKY, ...

Paired training data: for each training image,
each pixel is labeled with a semantic category.



At test time, classify each pixel of a new image.

Semantic Segmentation Idea: Sliding Window

Full image



Semantic Segmentation Idea: Sliding Window

Full image

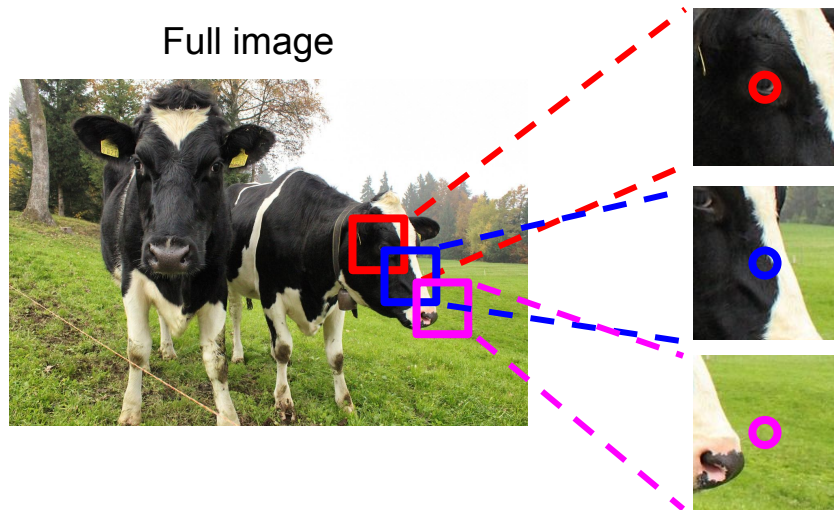


?

Impossible to classify without context

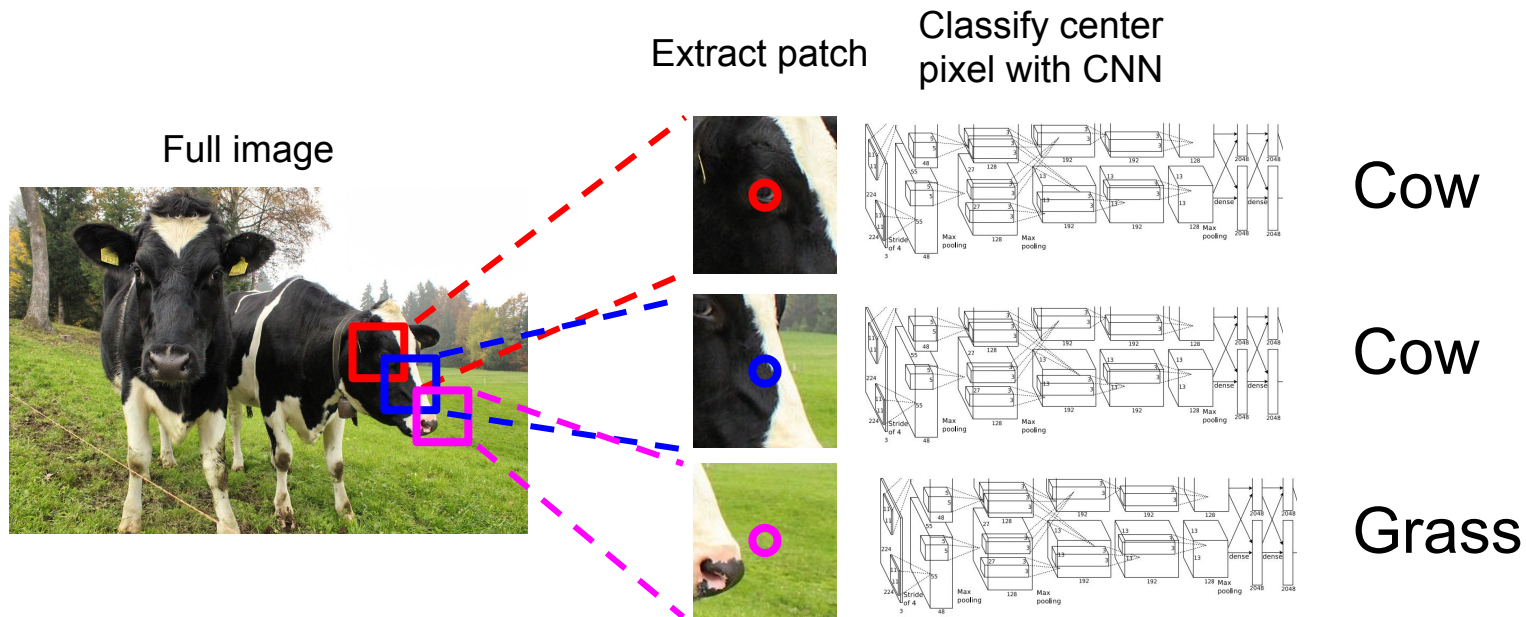
Q: how do we include context?

Semantic Segmentation Idea: Sliding Window



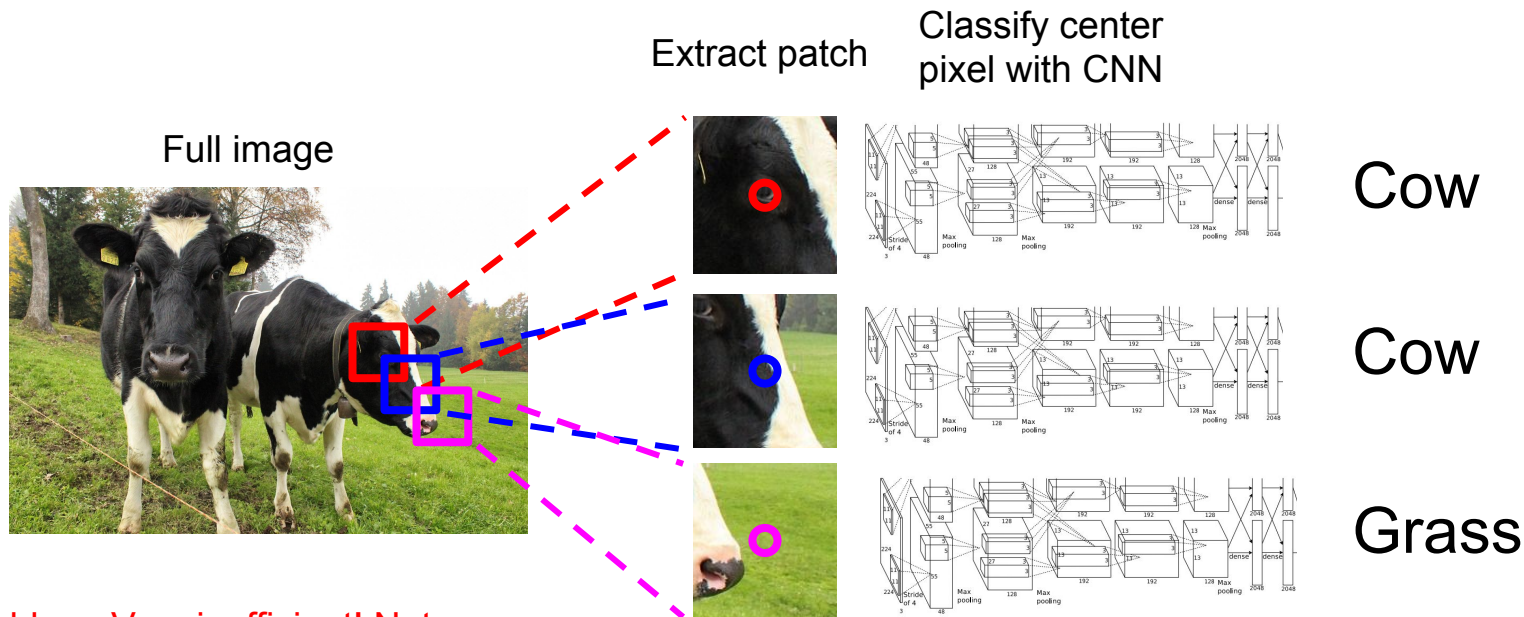
Q: how do we model this?

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

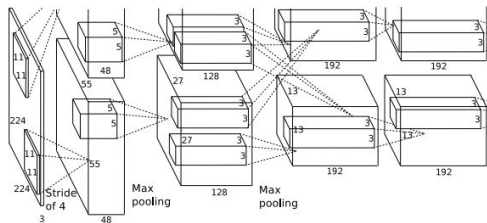


Problem: Very inefficient! Not reusing shared features between overlapping patches

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: Convolution

Full image

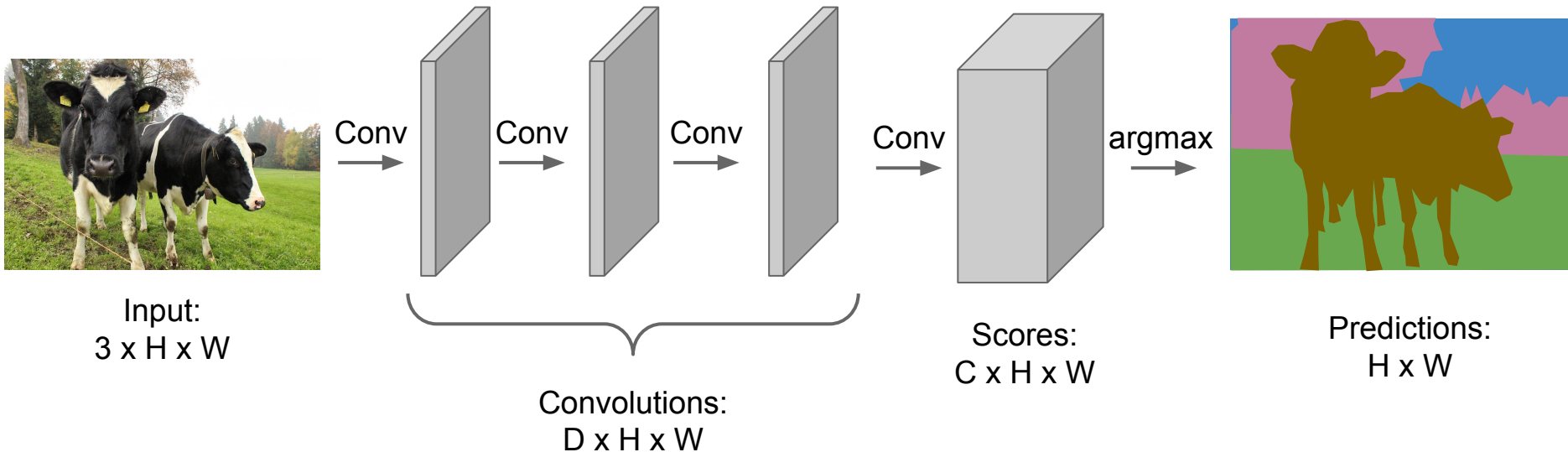


An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

Problem: classification architectures often reduce feature spatial sizes to go deeper, but semantic segmentation requires the output size to be the same as input size.

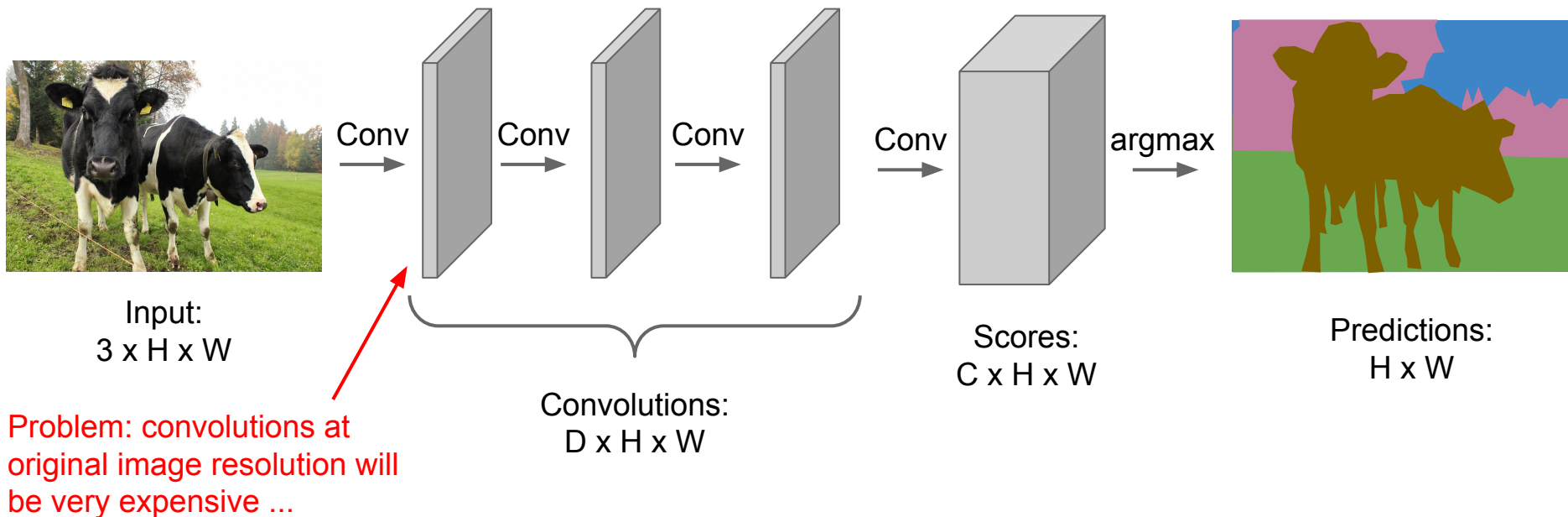
Semantic Segmentation Idea: Fully Convolutional

Design a network with only convolutional layers without downsampling operators to make predictions for pixels all at once!



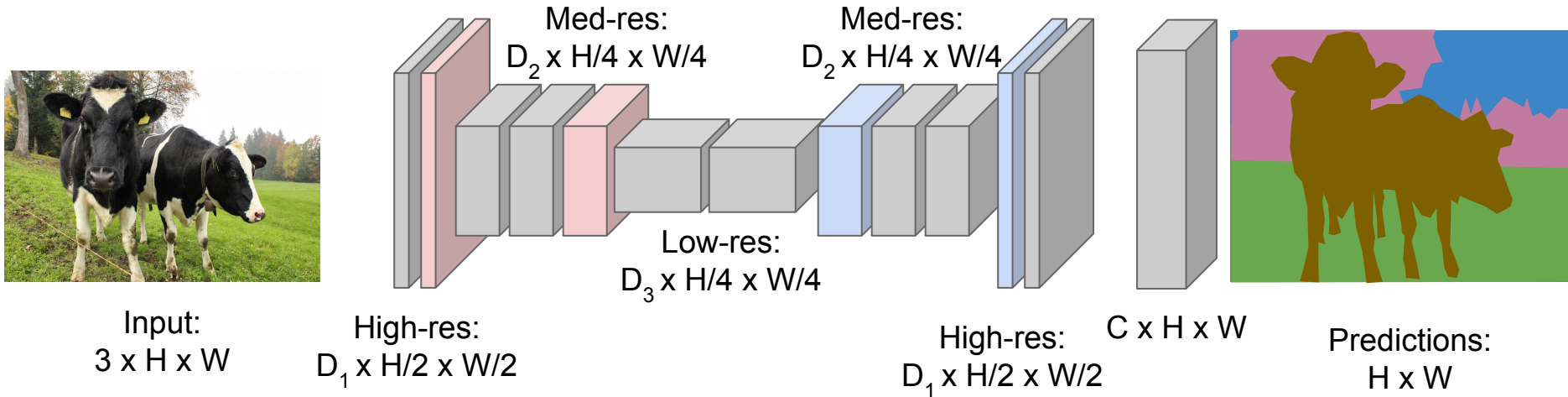
Semantic Segmentation Idea: Fully Convolutional

Design a network with only convolutional layers without downsampling operators 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!



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

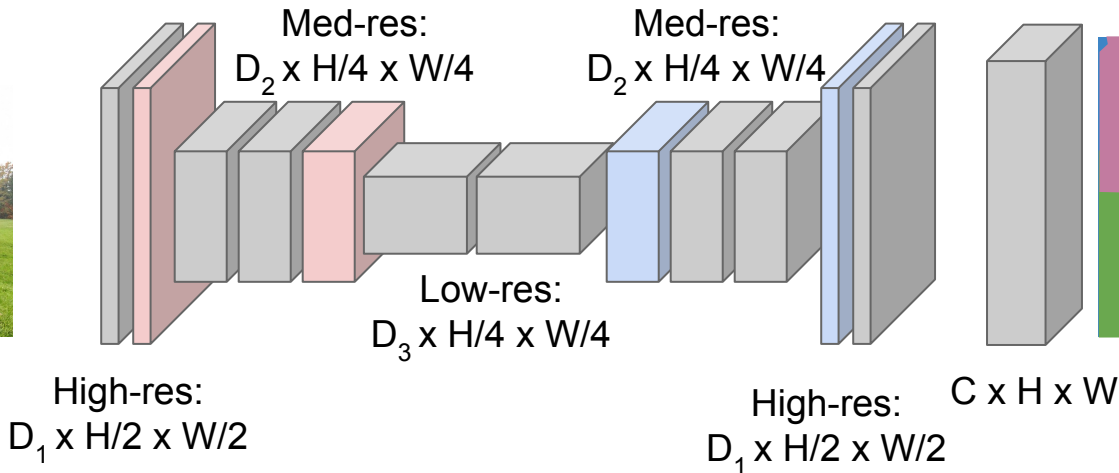
Downsampling:
Pooling, strided
convolution

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

Upsampling:
???



Input:
 $3 \times H \times W$



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

Input: 2 x 2



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

Output: 4 x 4

“Bed of Nails”

1	2
3	4

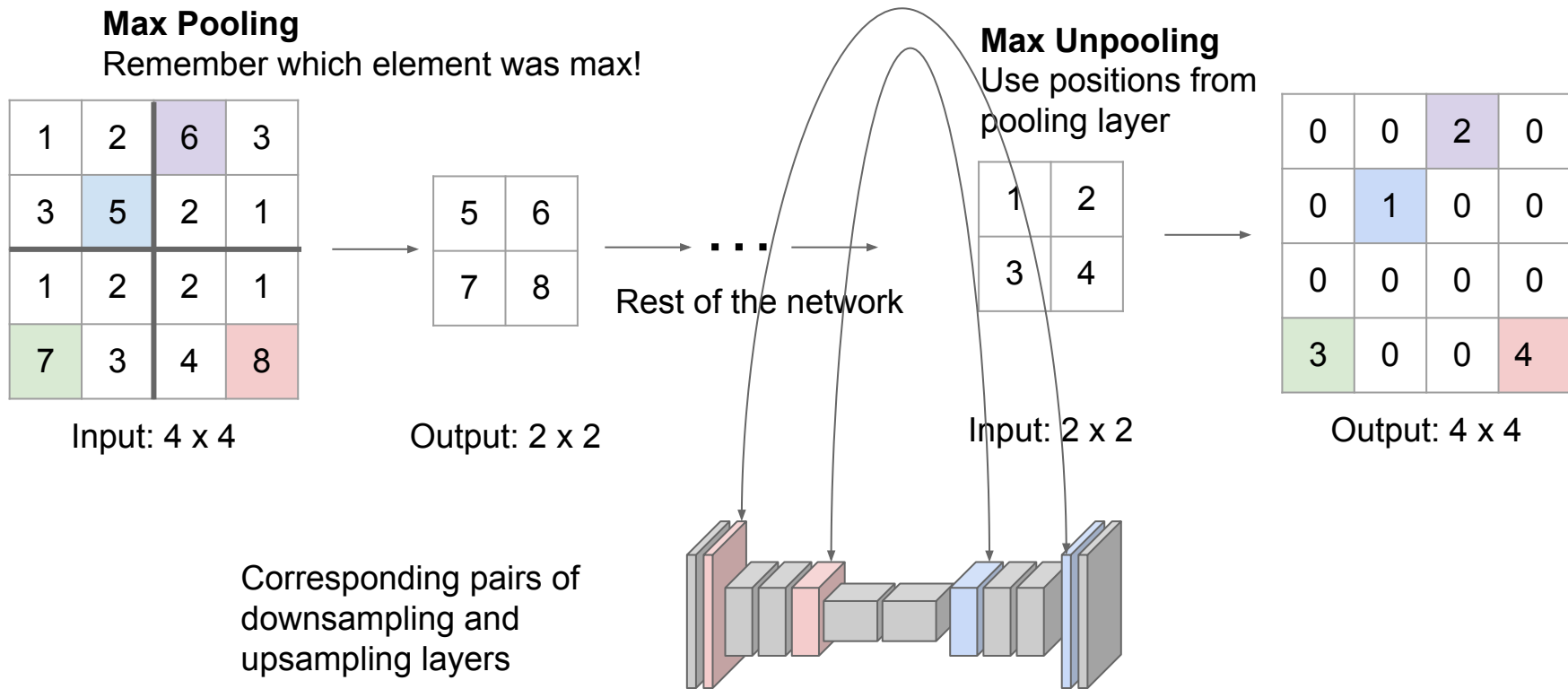
Input: 2 x 2



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

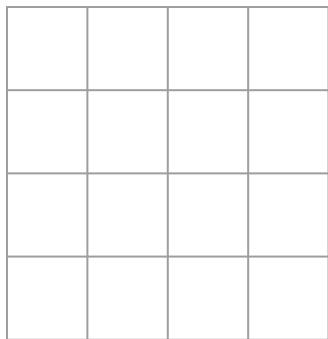
Output: 4 x 4

In-Network upsampling: “Max Unpooling”

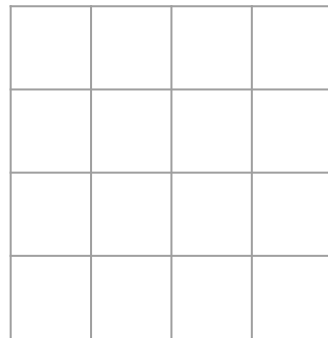


Learnable Upsampling

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



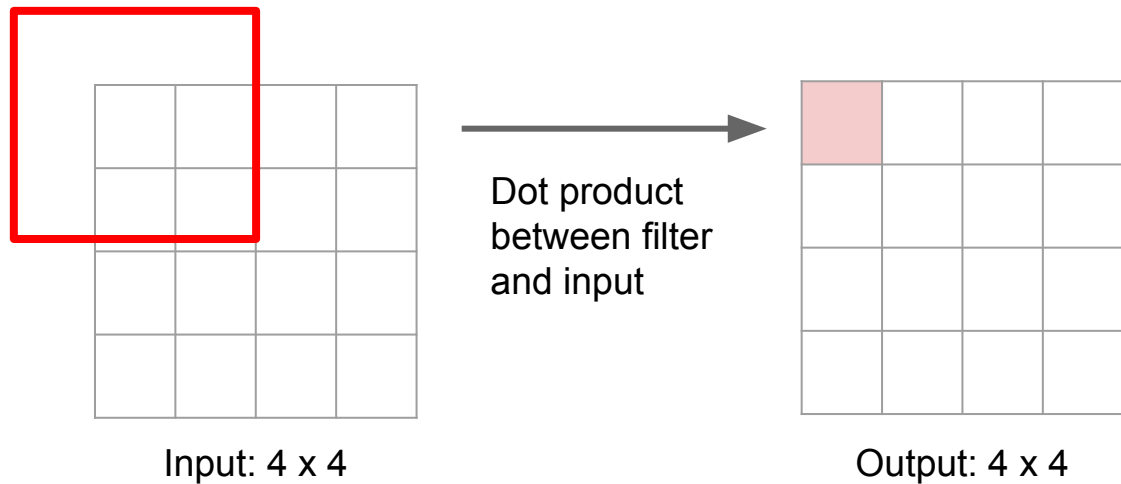
Input: 4 x 4



Output: 4 x 4

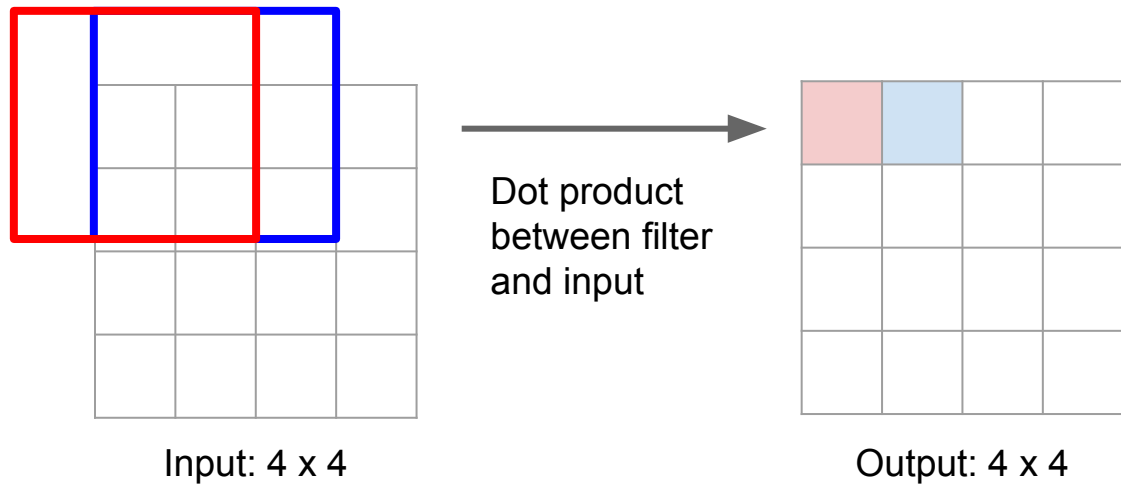
Learnable Upsampling

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



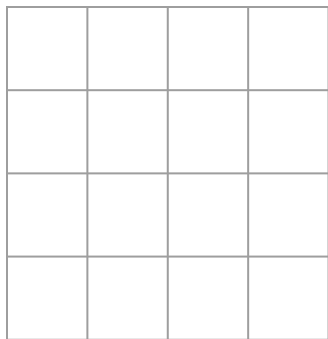
Learnable Upsampling

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

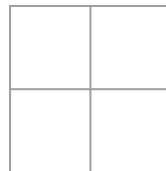


Learnable Upsampling

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



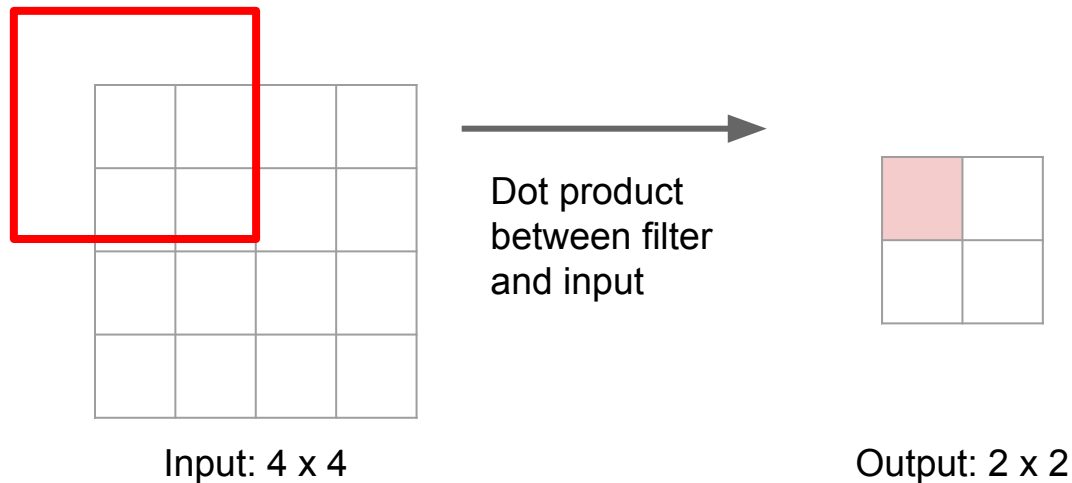
Input: 4 x 4



Output: 2 x 2

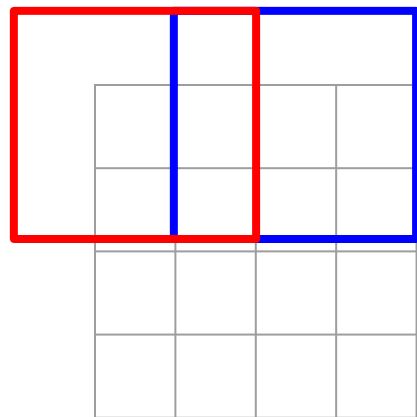
Learnable Upsampling

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



Learnable Upsampling

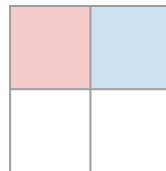
Recall: Normal 3 x 3 convolution, stride 2 pad 1



Input: 4 x 4



Dot product
between filter
and input



Output: 2 x 2

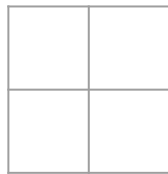
Filter moves 2 pixels in the input for every one pixel in the output

Stride gives ratio between movement in input and output

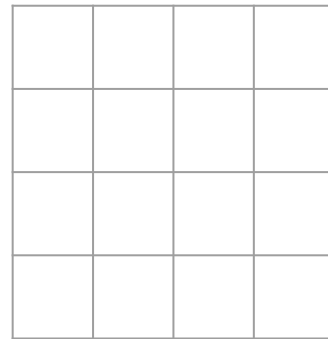
We can interpret strided convolution as “learnable downsampling”.

Learnable Upsampling: Transposed Convolution

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



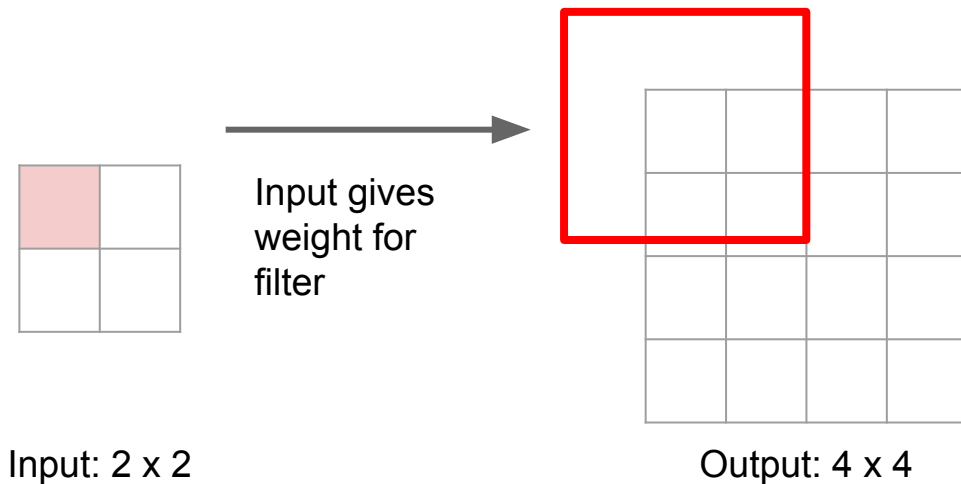
Input: 2 x 2



Output: 4 x 4

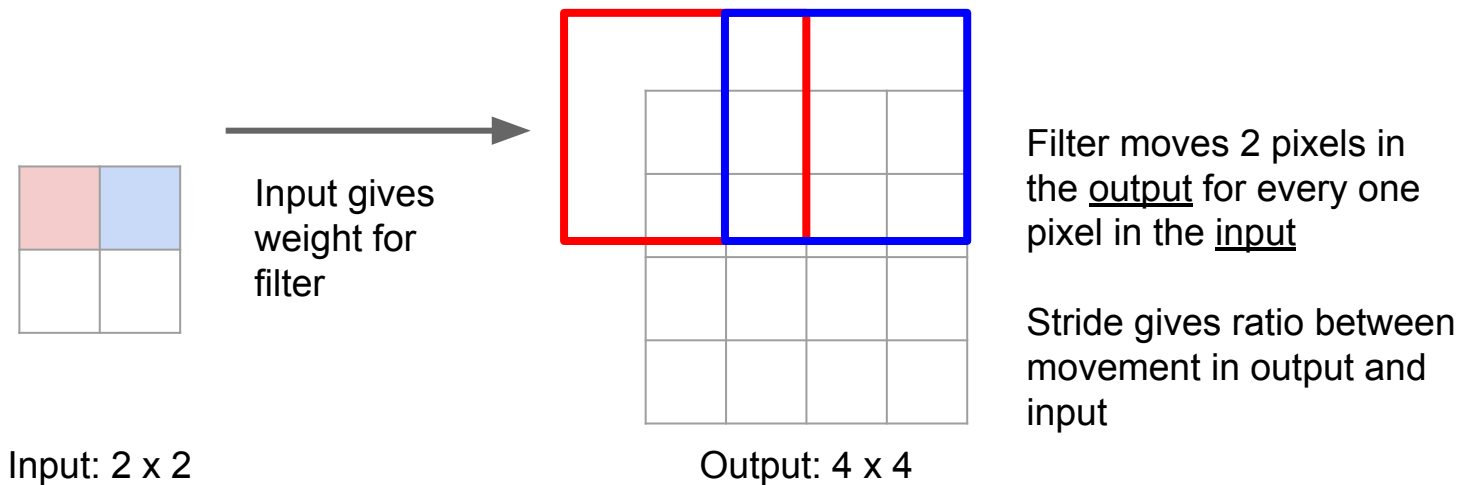
Learnable Upsampling: Transposed Convolution

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

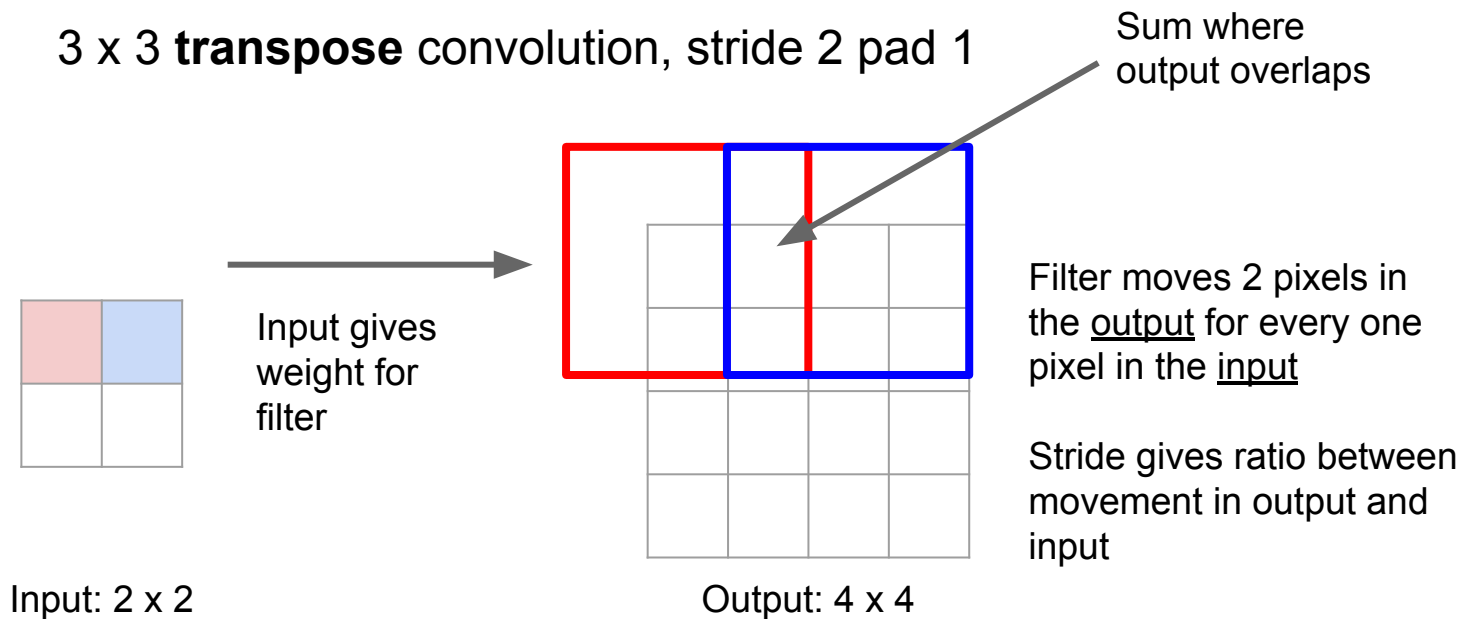


Learnable Upsampling: Transposed Convolution

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

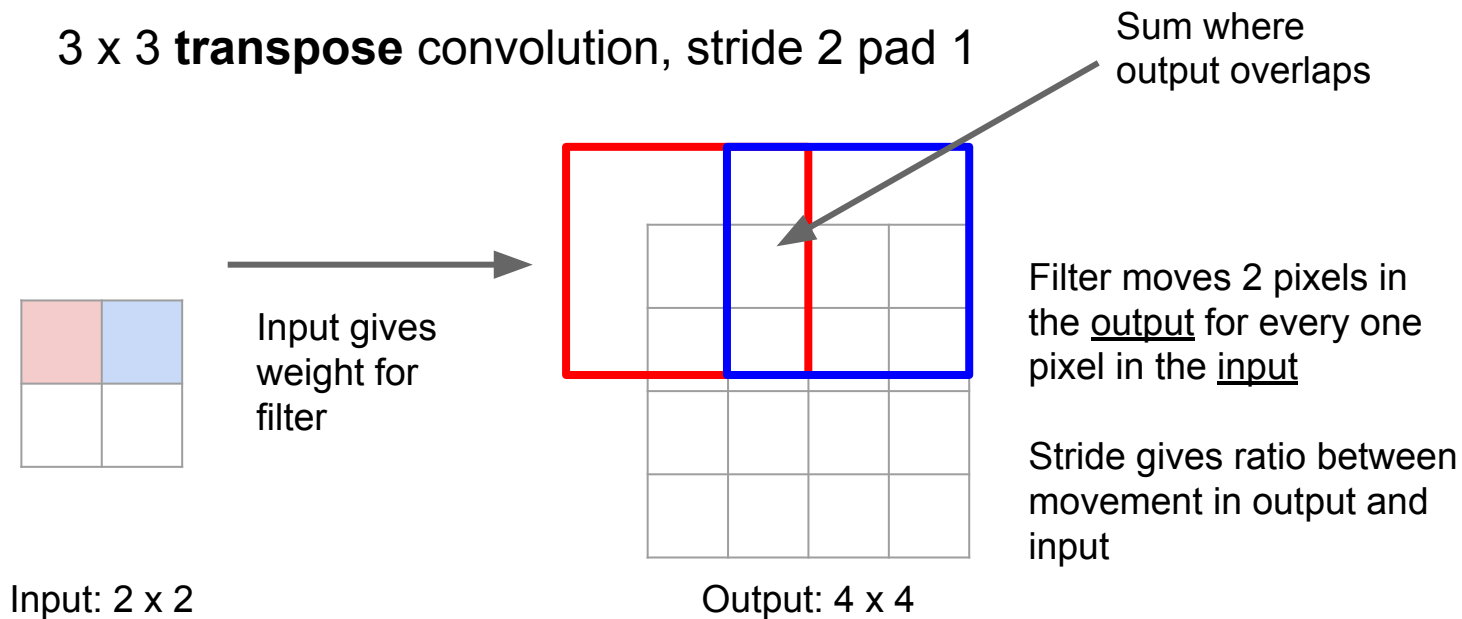


Learnable Upsampling: Transposed Convolution

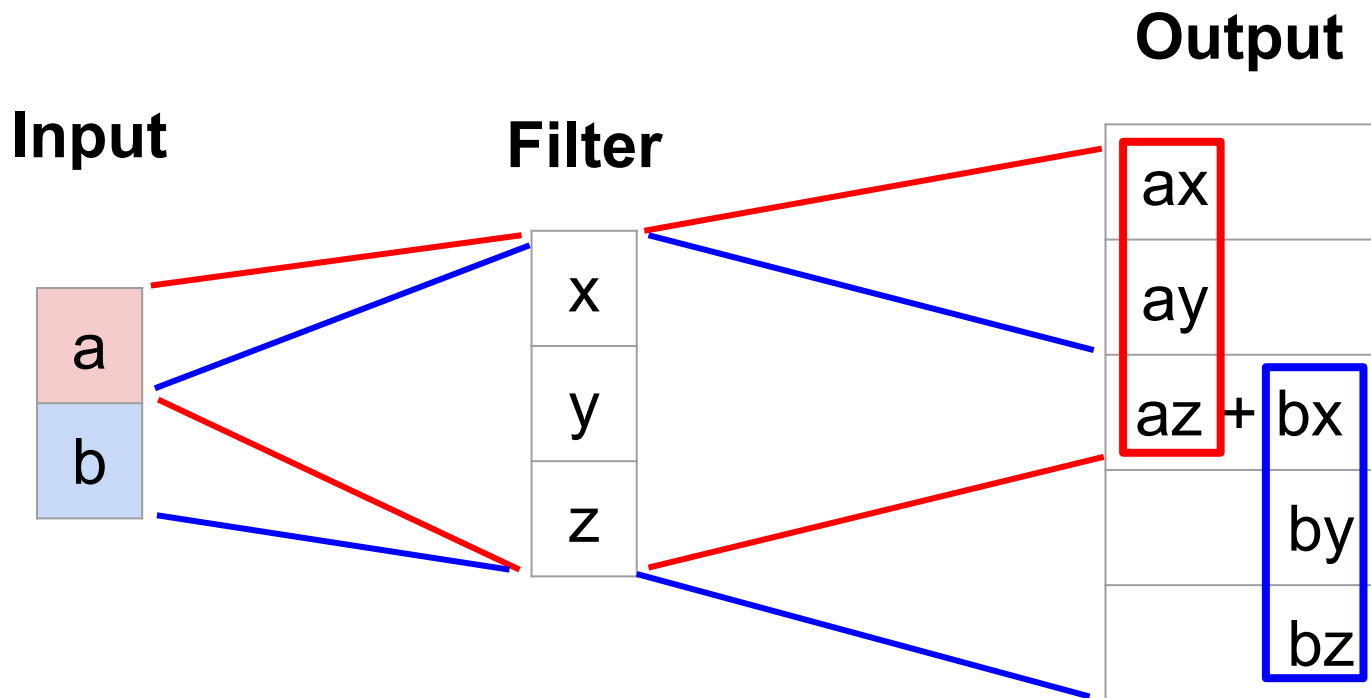


Learnable Upsampling: Transposed Convolution

Q: Why is it called transpose convolution?



Learnable Upsampling: 1D Example



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

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

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

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

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

Convolution transpose multiplies by the transpose of the same matrix:

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

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

Example: 1D transpose conv, kernel size=3, stride=2, padding=0

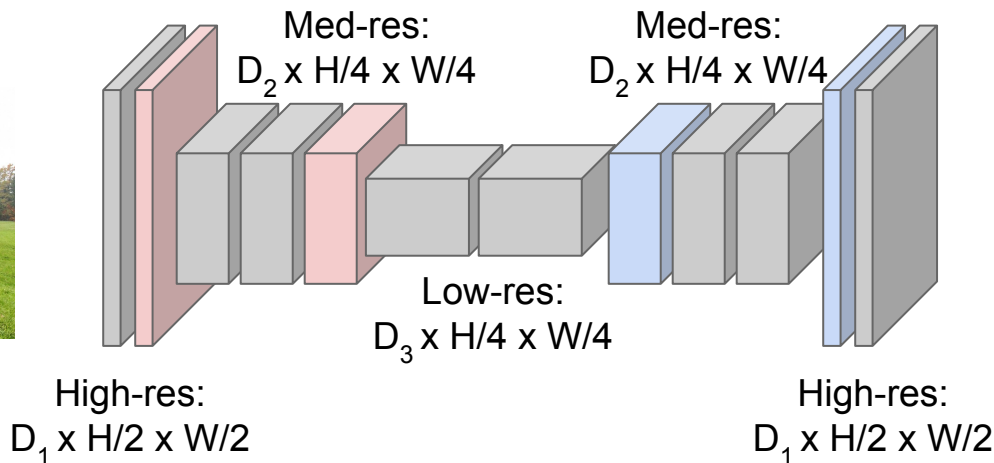
Semantic Segmentation Idea: Fully Convolutional

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!



Upsampling:
Unpooling or strided
transpose convolution



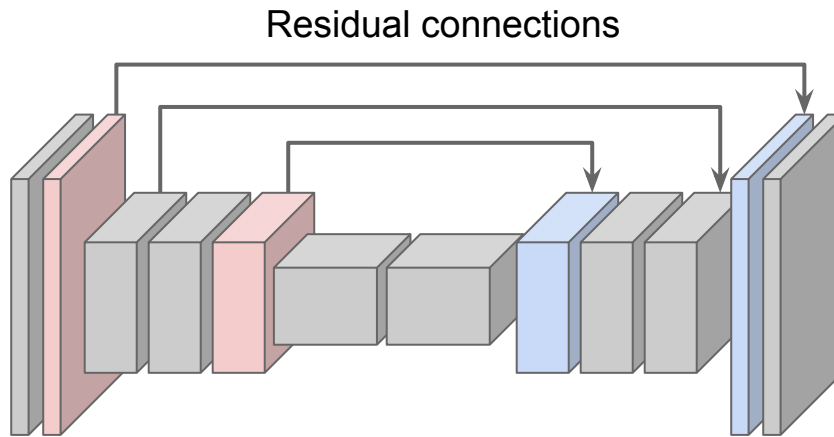
Predictions:
 $H \times W$

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

Today: UNet with residual connections



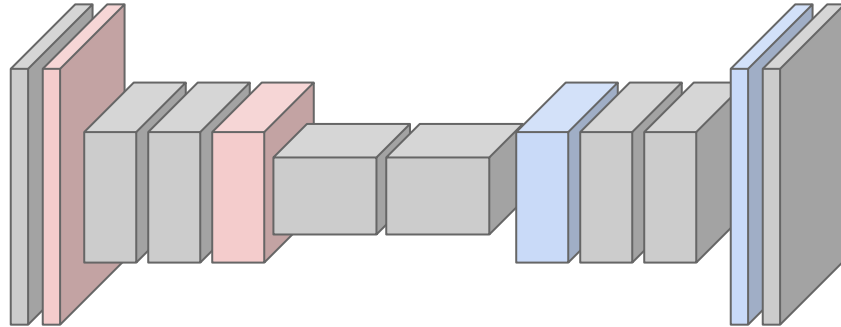
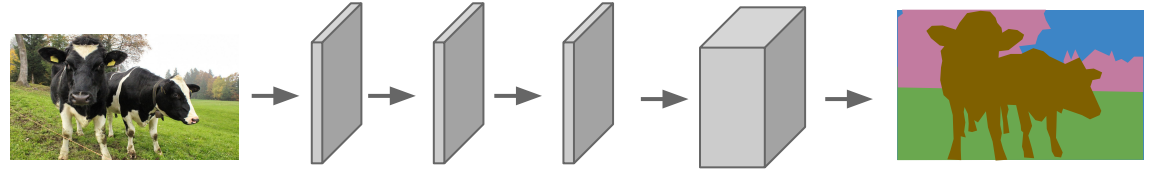
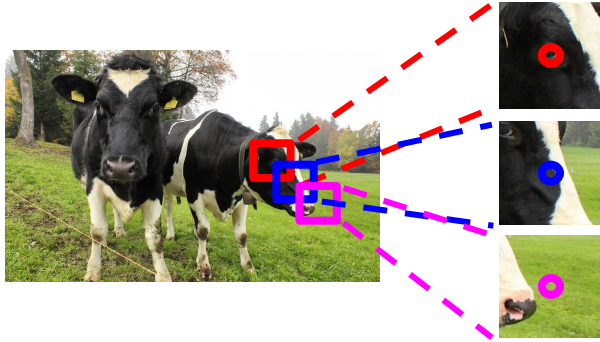
Input:
 $3 \times H \times W$



Predictions:
 $H \times W$

Newell et al. Stacked Hourglass Networks for Human Pose Estimation. ECCV 2016

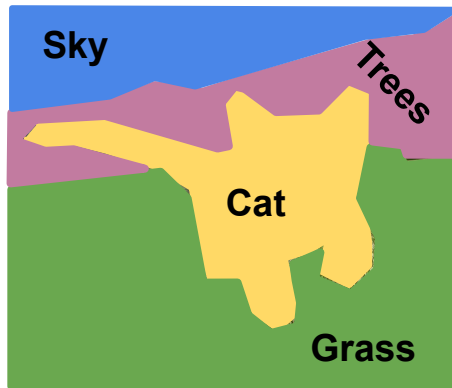
Semantic Segmentation: Summary



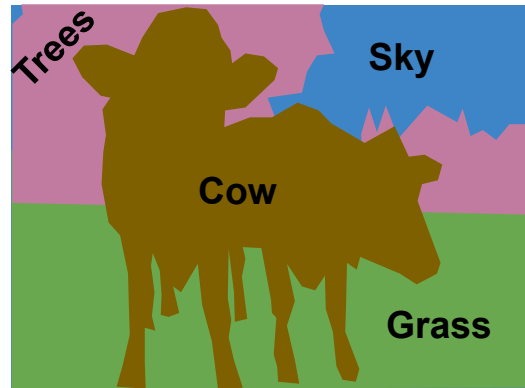
Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels



[This image](#) is [CC0 public domain](#)



Object Detection

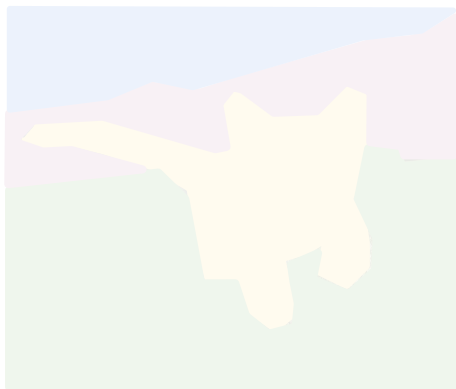
Classification



CAT

No spatial extent

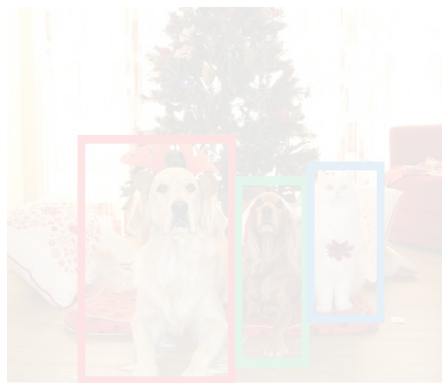
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

Multiple Object

Instance Segmentation



DOG, DOG, CAT

Object Detection

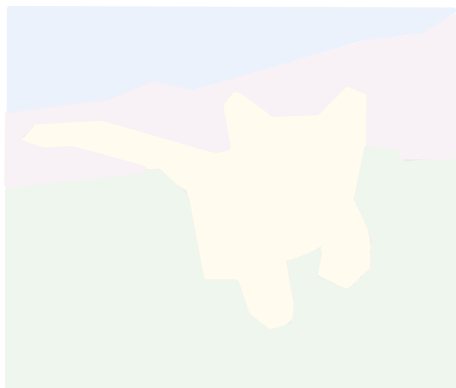
Classification



CAT

No spatial extent

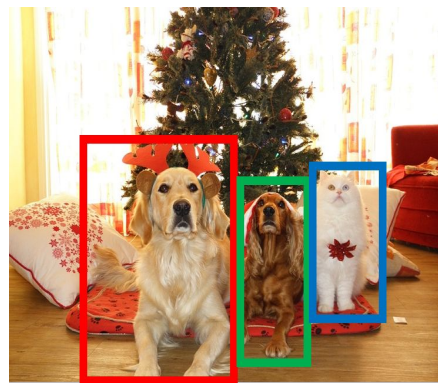
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

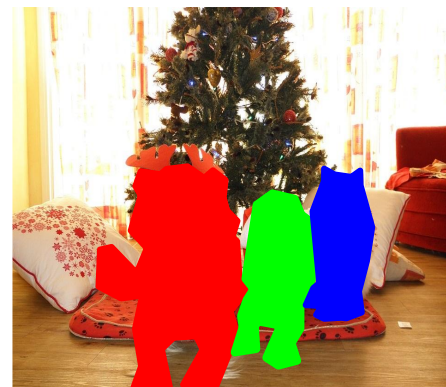
Object Detection



DOG, DOG, CAT

Multiple Object

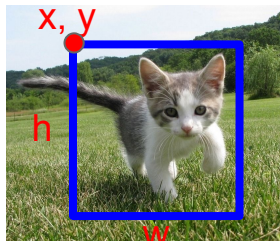
Instance Segmentation



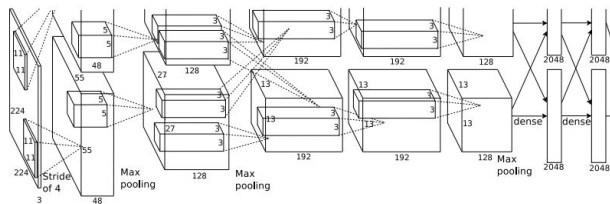
DOG, DOG, CAT

Object Detection: Single Object

(Classification + Localization)



[This image](#) is [CC0 public domain](#)



**Fully
Connected:**
4096 to 1000

Class Scores

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

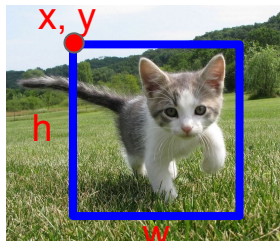
Vector:
4096

**Fully
Connected:**
4096 to 4

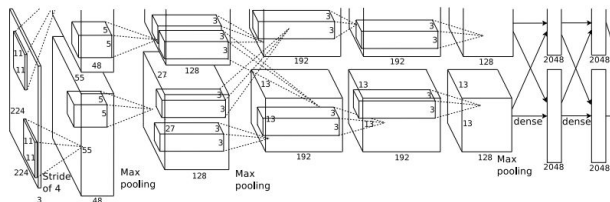
**Box
Coordinates**
(x, y, w, h)

Object Detection: Single Object

(Classification + Localization)



[This image is CC0 public domain](#)



Fully
Connected:
4096 to 1000

Class Scores

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

Correct label:
Cat

Softmax
Loss

Vector:
4096

Fully
Connected:
4096 to 4

Box
Coordinates
(x, y, w, h)

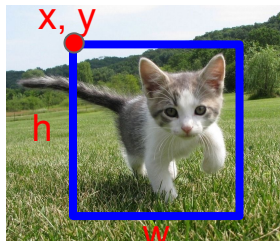
L2 Loss

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

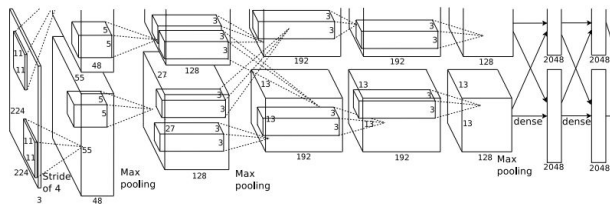
Treat localization as a
regression problem!

Object Detection: Single Object

(Classification + Localization)



[This image](#) is [CC0 public domain](#)



Fully
Connected:
4096 to 1000

Class Scores

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

Correct label:
Cat

Softmax
Loss

Multitask Loss

Vector:
4096

Fully
Connected:
4096 to 4

Box
Coordinates
(x, y, w, h)

L2 Loss

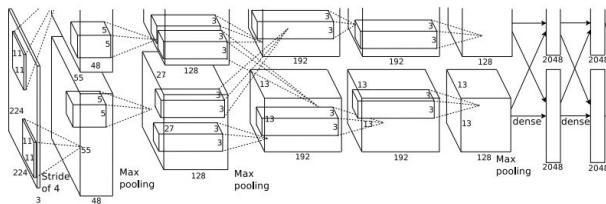
Correct box:
(x', y', w', h')

Treat localization as a
regression problem!

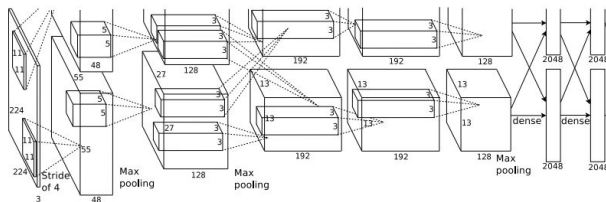
+

Loss

Object Detection: Multiple Objects



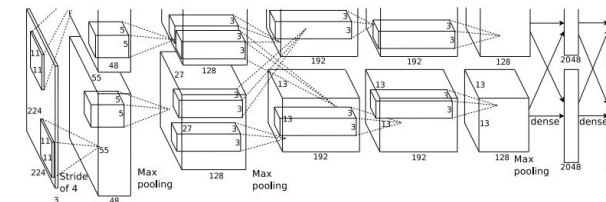
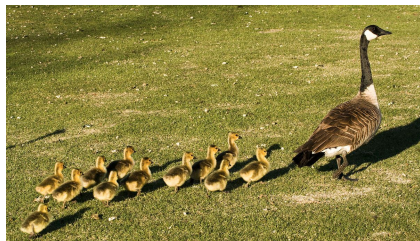
CAT: (x, y, w, h)



DOG: (x, y, w, h)

DOG: (x, y, w, h)

CAT: (x, y, w, h)



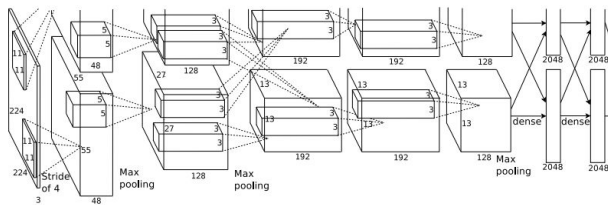
DUCK: (x, y, w, h)

DUCK: (x, y, w, h)

....

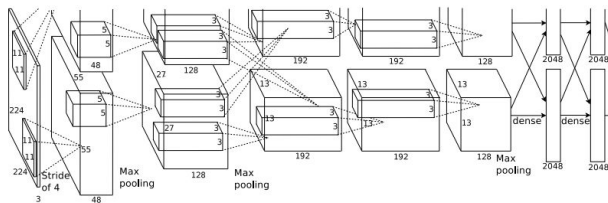
Object Detection: Multiple Objects

Each image needs a
different number of outputs!



CAT: (x, y, w, h)

4 numbers

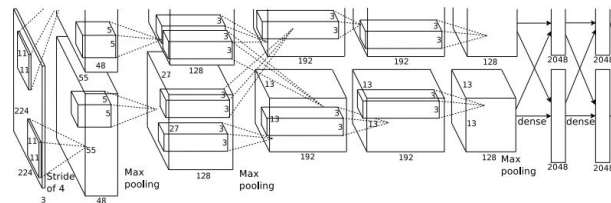
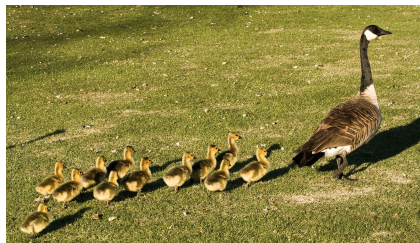


DOG: (x, y, w, h)

DOG: (x, y, w, h)

12 numbers

CAT: (x, y, w, h)



DUCK: (x, y, w, h)

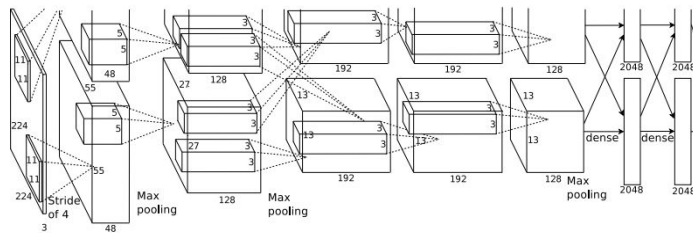
DUCK: (x, y, w, h)

Many
numbers!

....

Object Detection: Multiple Objects

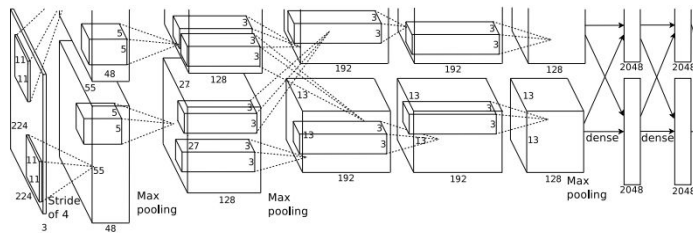
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection: Multiple Objects

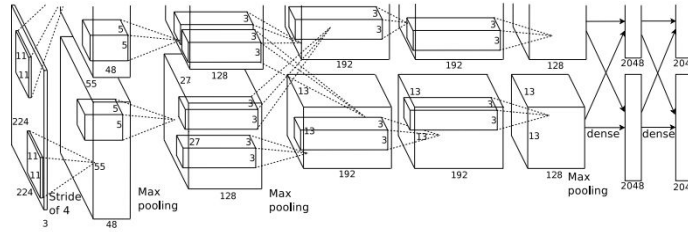
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

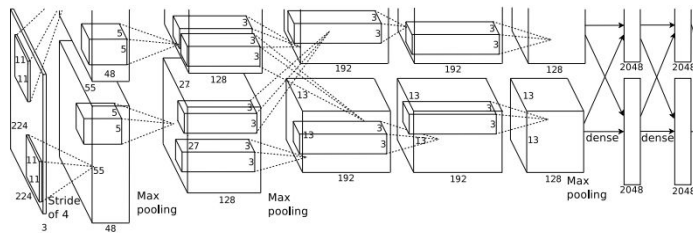
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



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

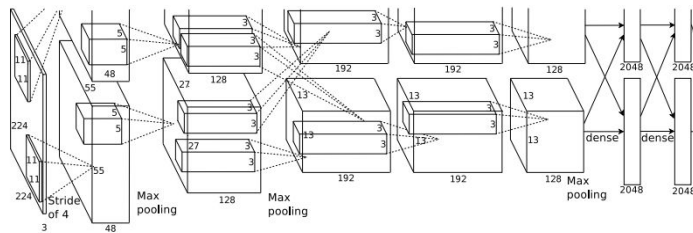
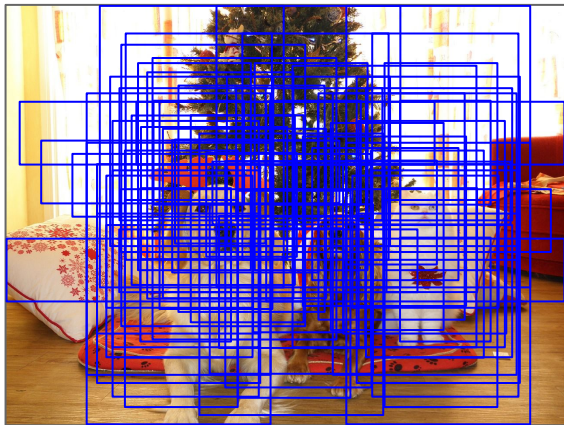


Dog? NO
Cat? YES
Background? NO

Q: What's the problem with this approach?

Object Detection: Multiple Objects

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

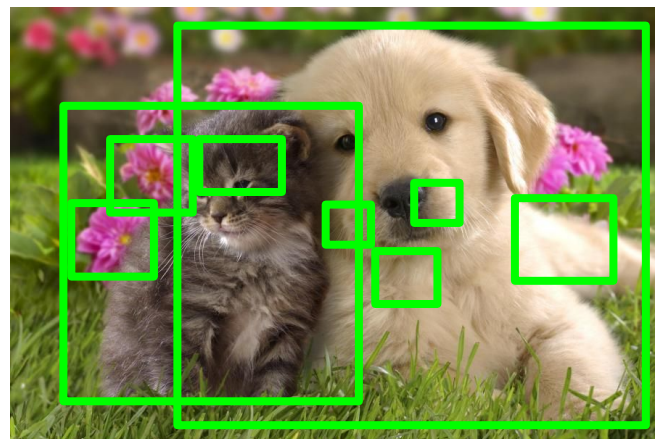


Dog? NO
Cat? YES
Background? NO

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

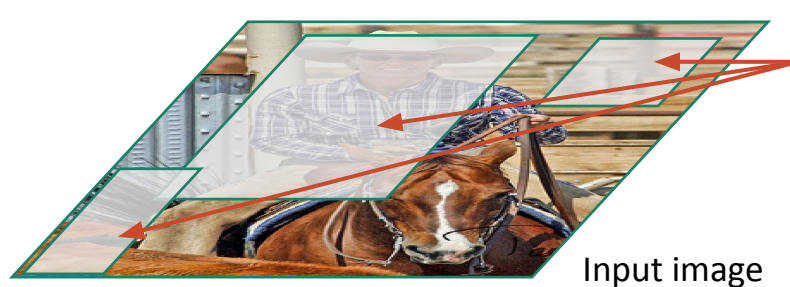
R-CNN



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.

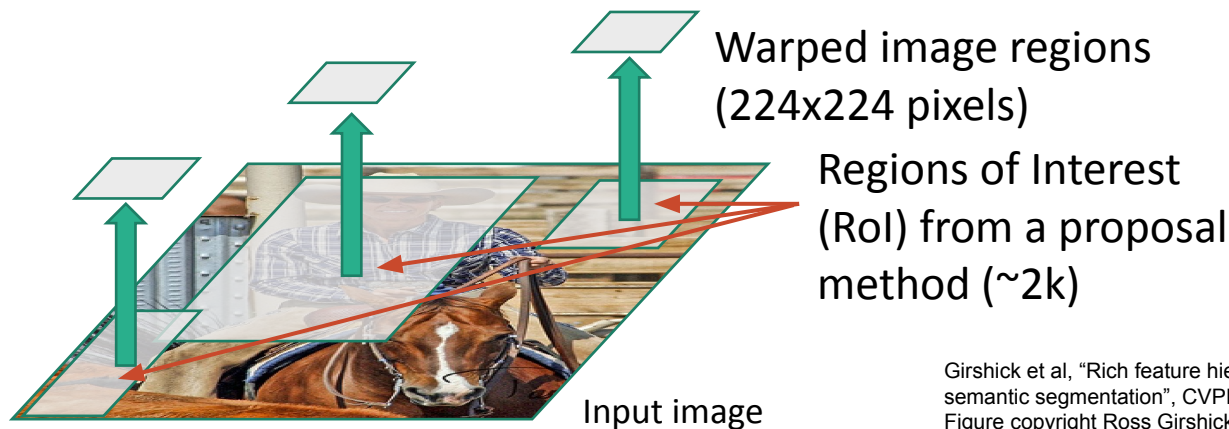
R-CNN



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

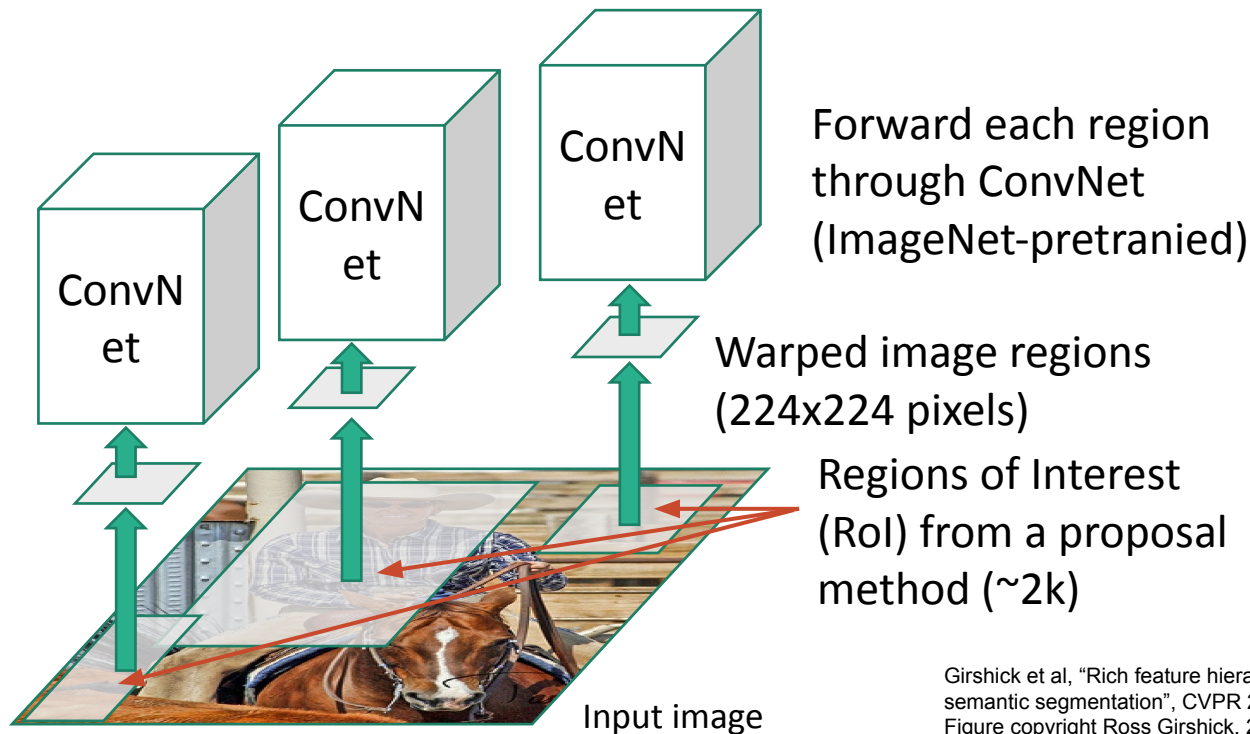
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN



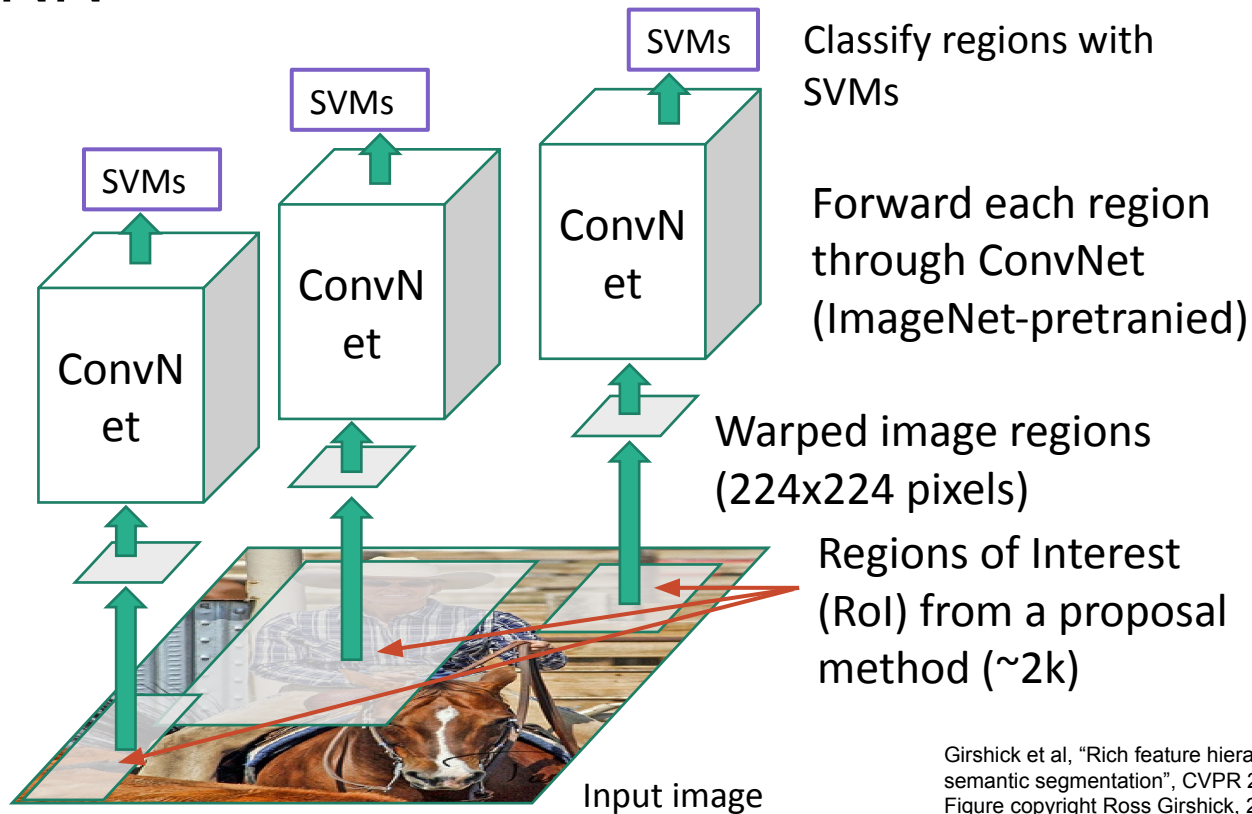
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

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.

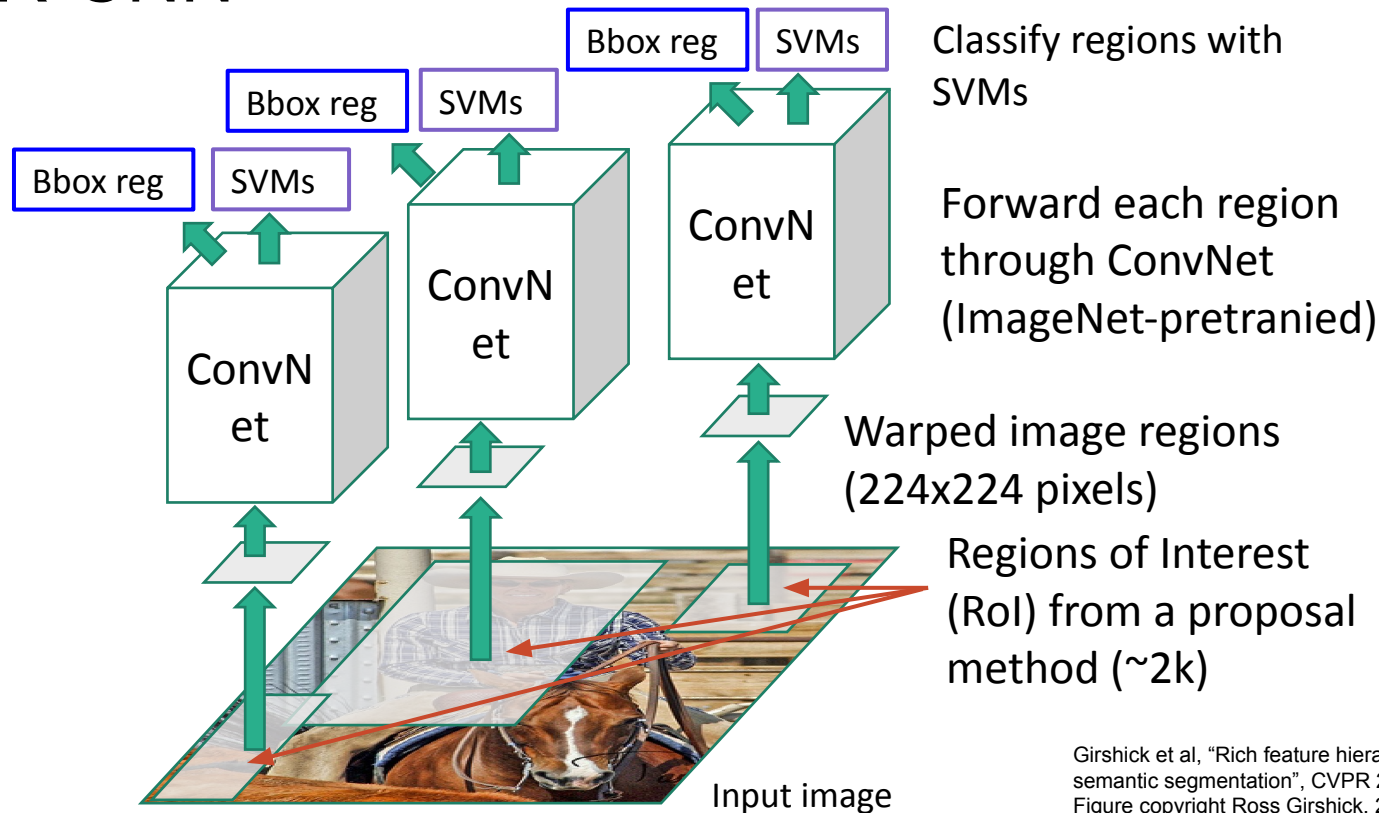
R-CNN



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

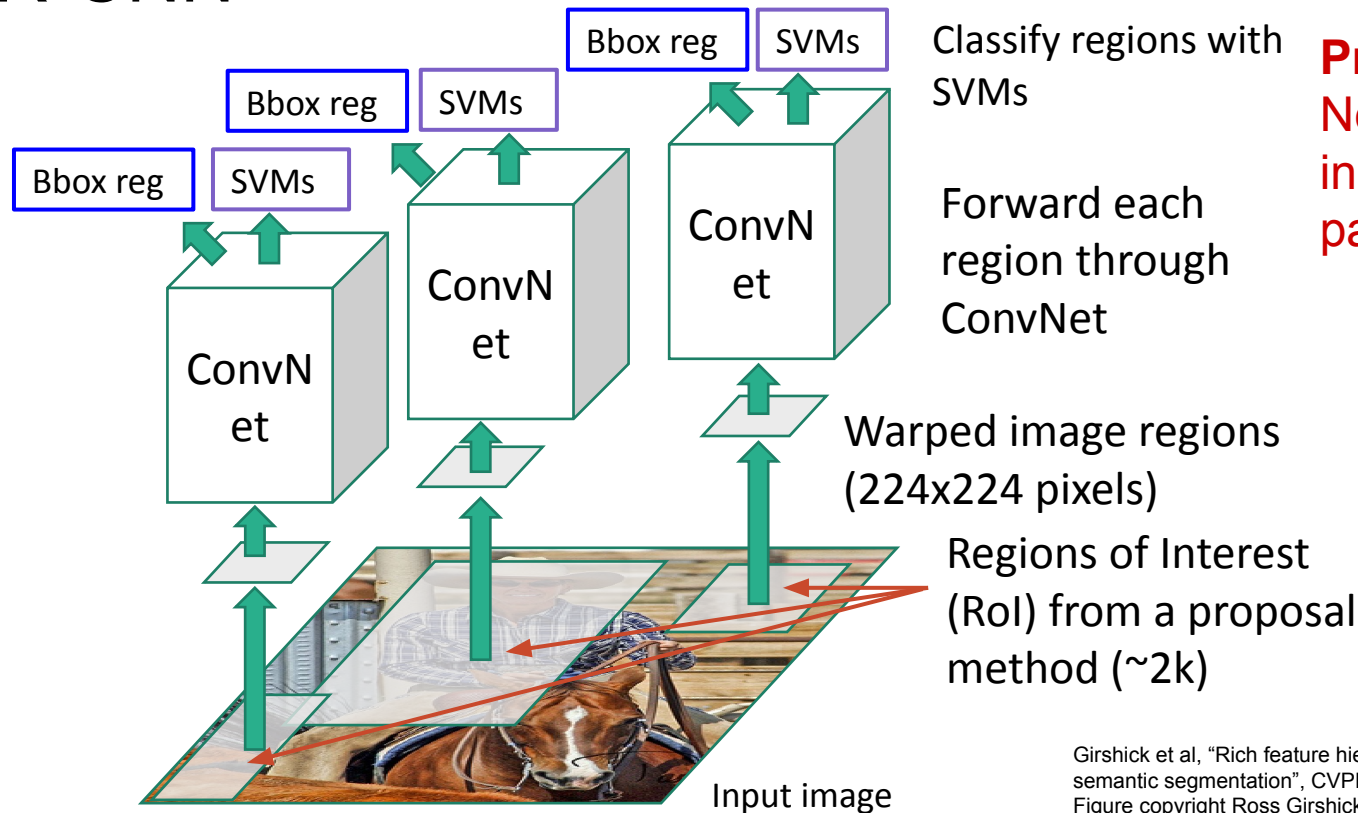
Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)



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)

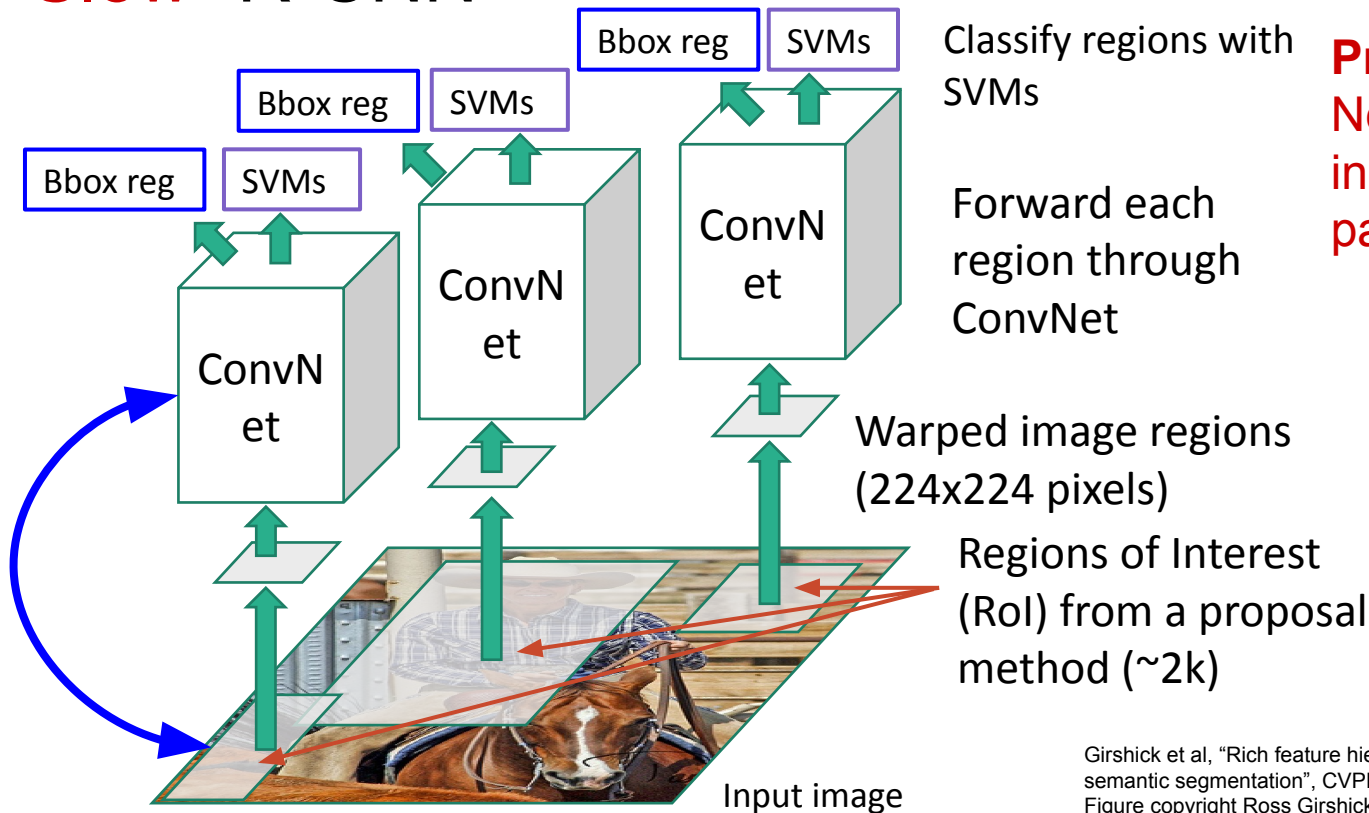


Problem: Very slow!
Need to do ~2k
independent forward
passes for each image!

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

“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: Pass the
image through
convnet before
cropping! Crop the
conv feature instead!

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

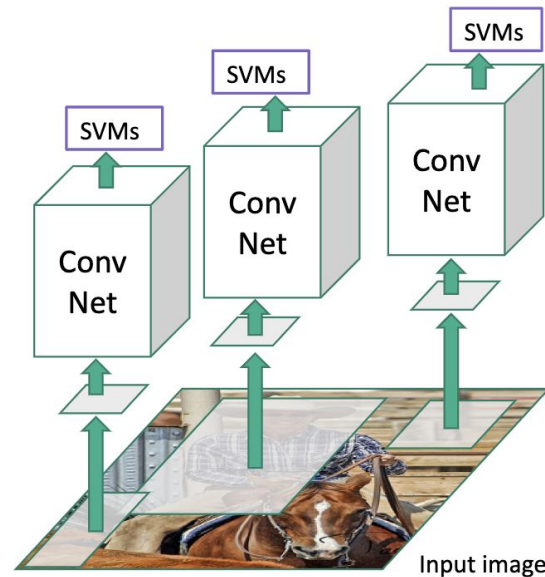
Fast R-CNN



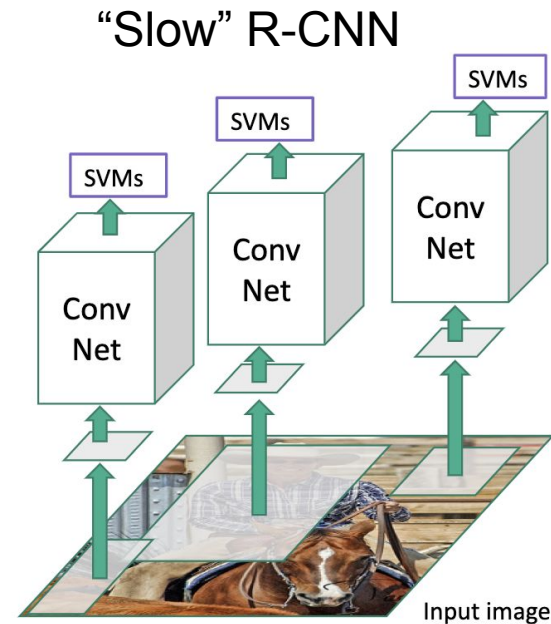
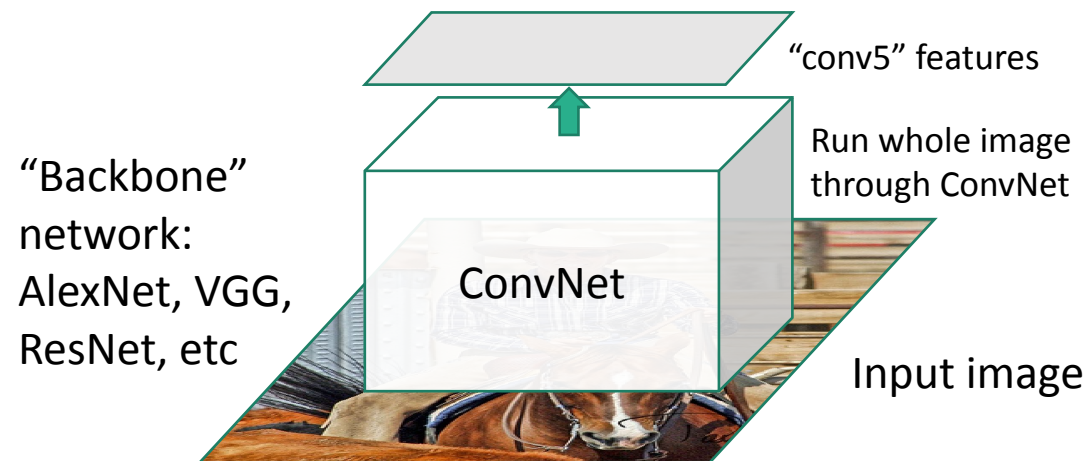
Input image

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

"Slow" R-CNN

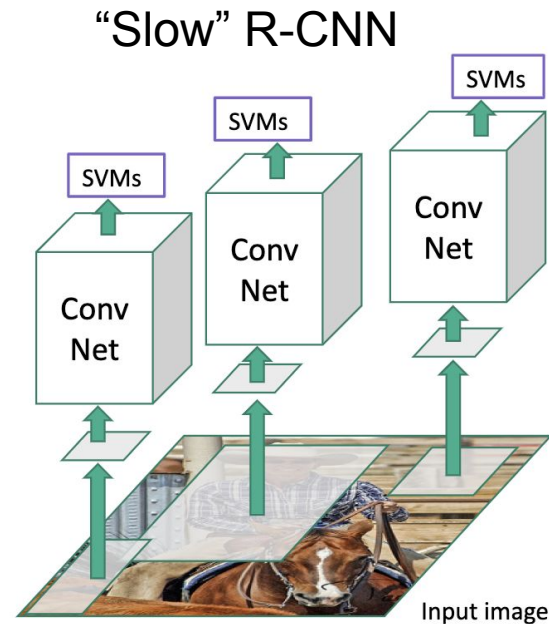
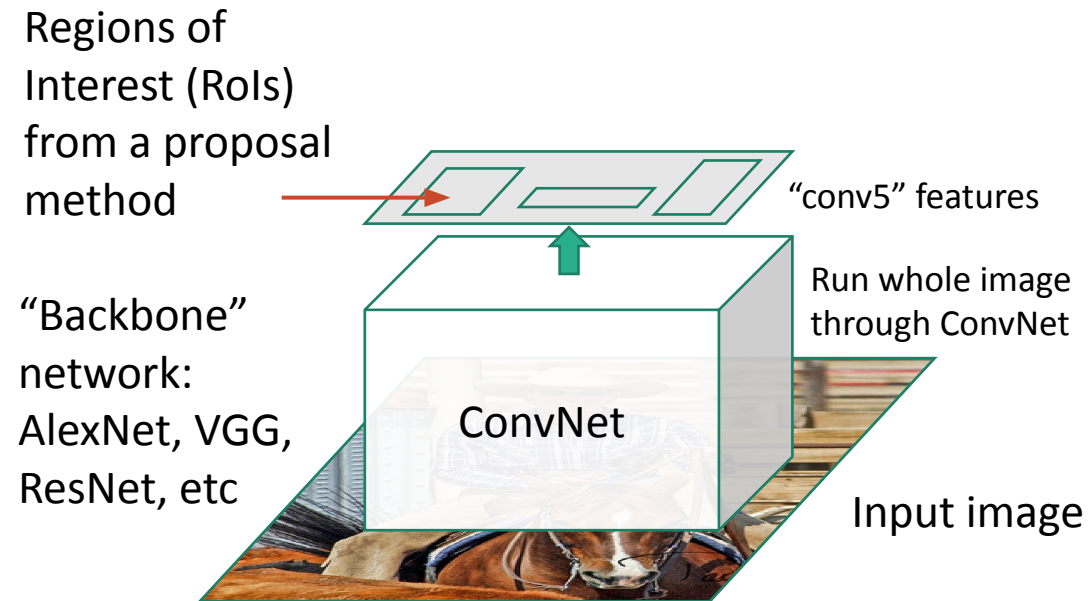


Fast R-CNN



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

Fast R-CNN

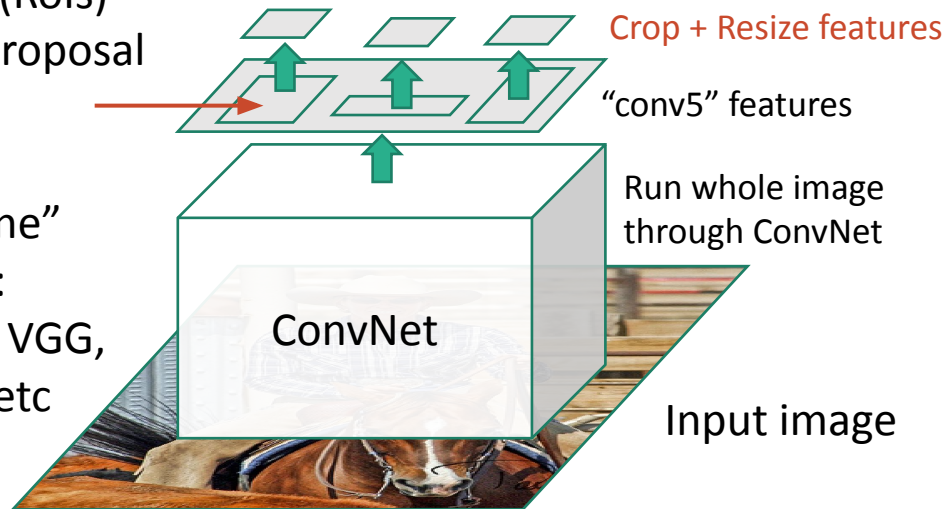


Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN

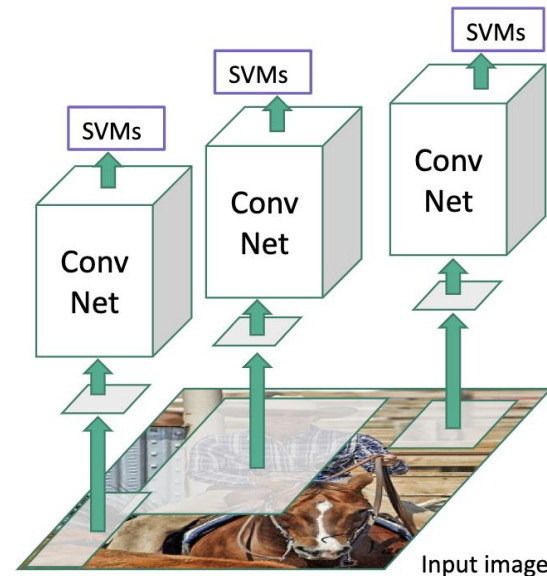
Regions of Interest (RoIs) from a proposal method

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

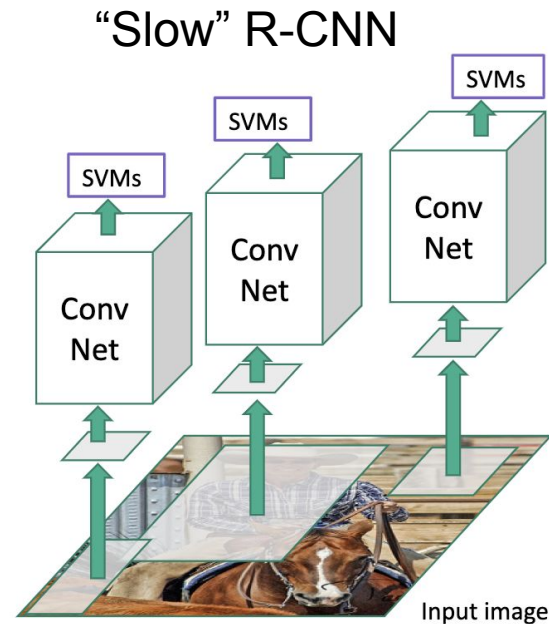
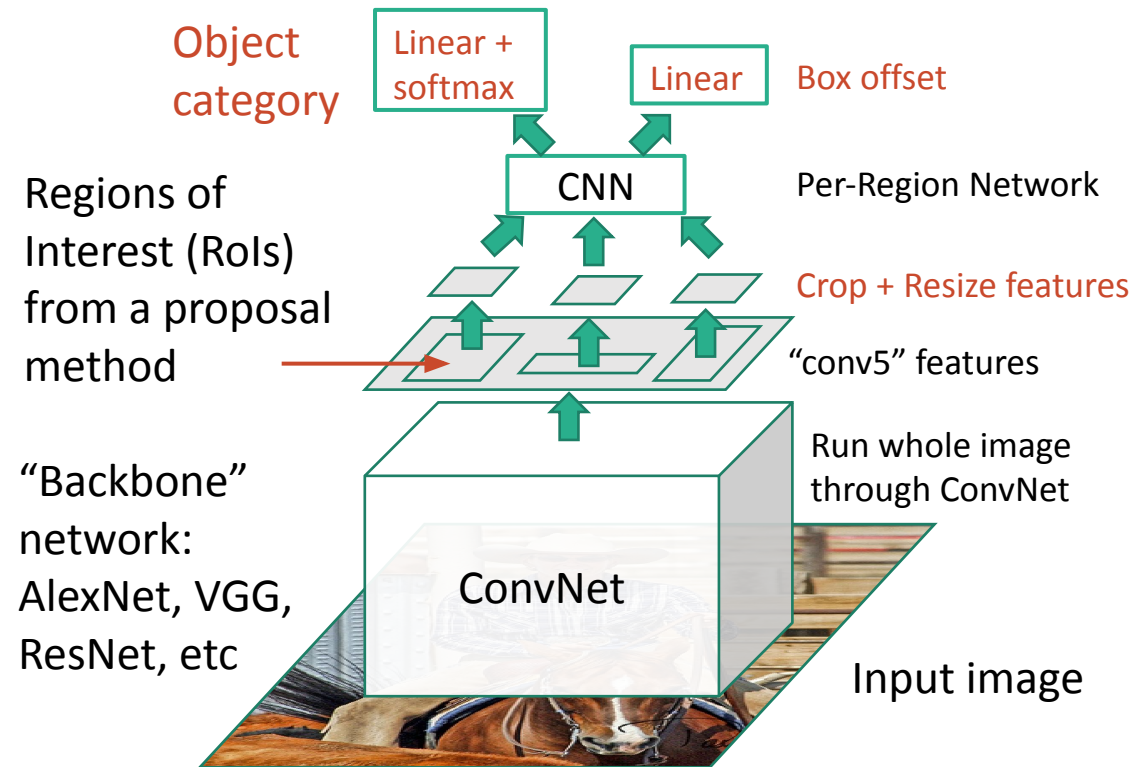


Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

“Slow” R-CNN

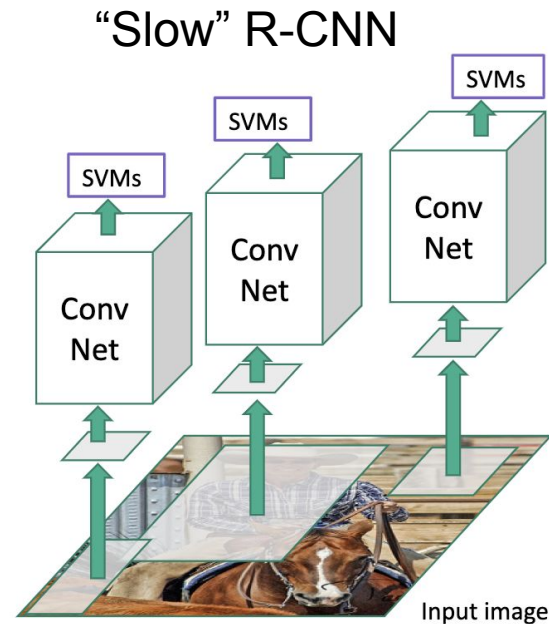
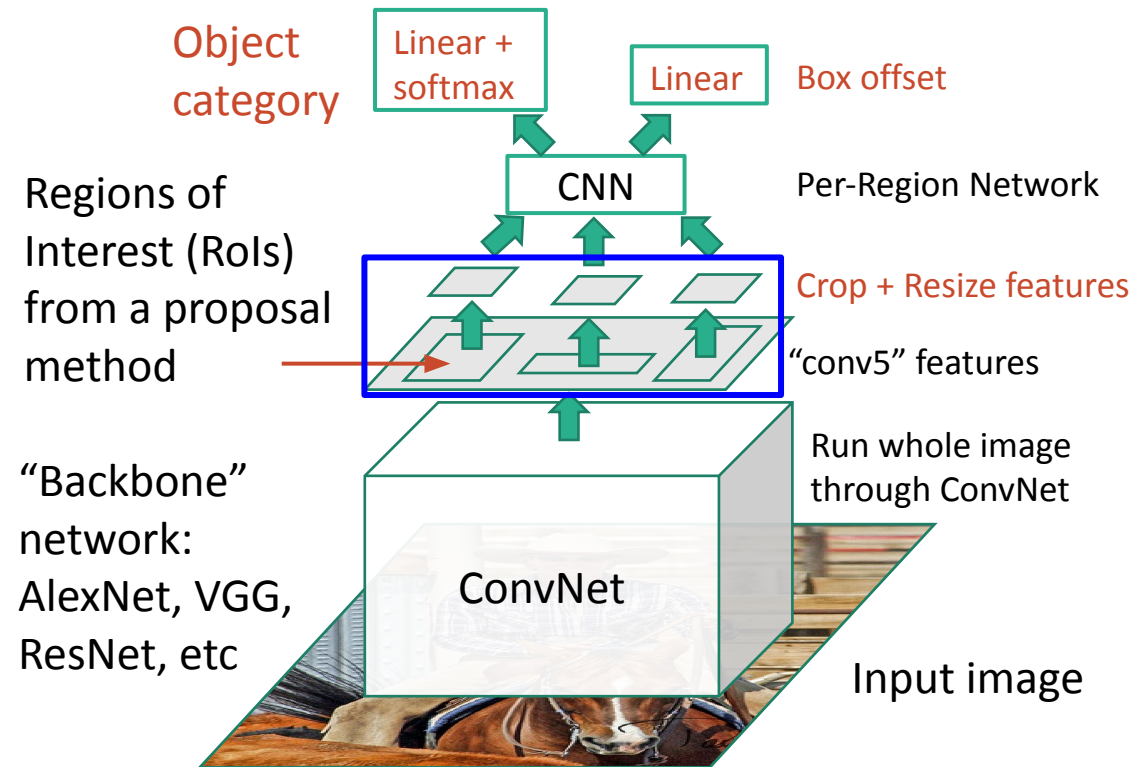


Fast R-CNN



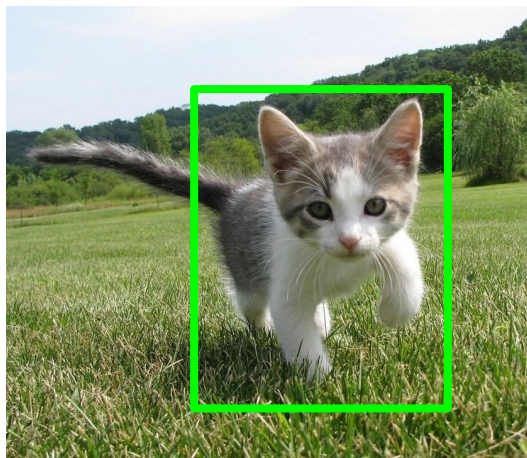
Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



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

Cropping Features: RoI Pool



Input Image
(e.g. 3 x 640 x 480)

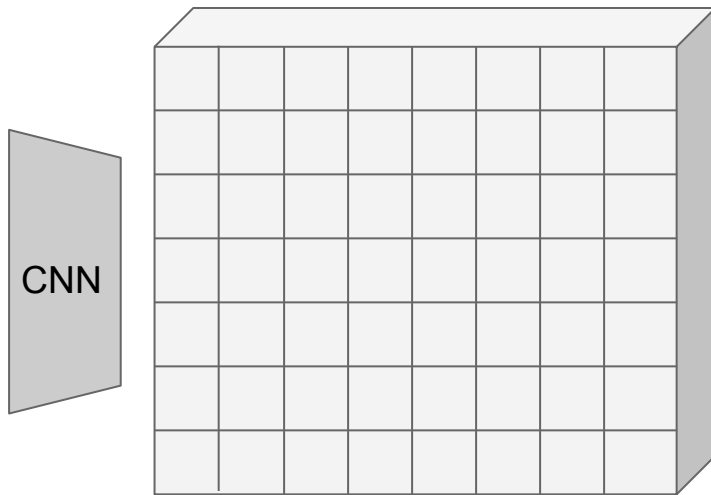
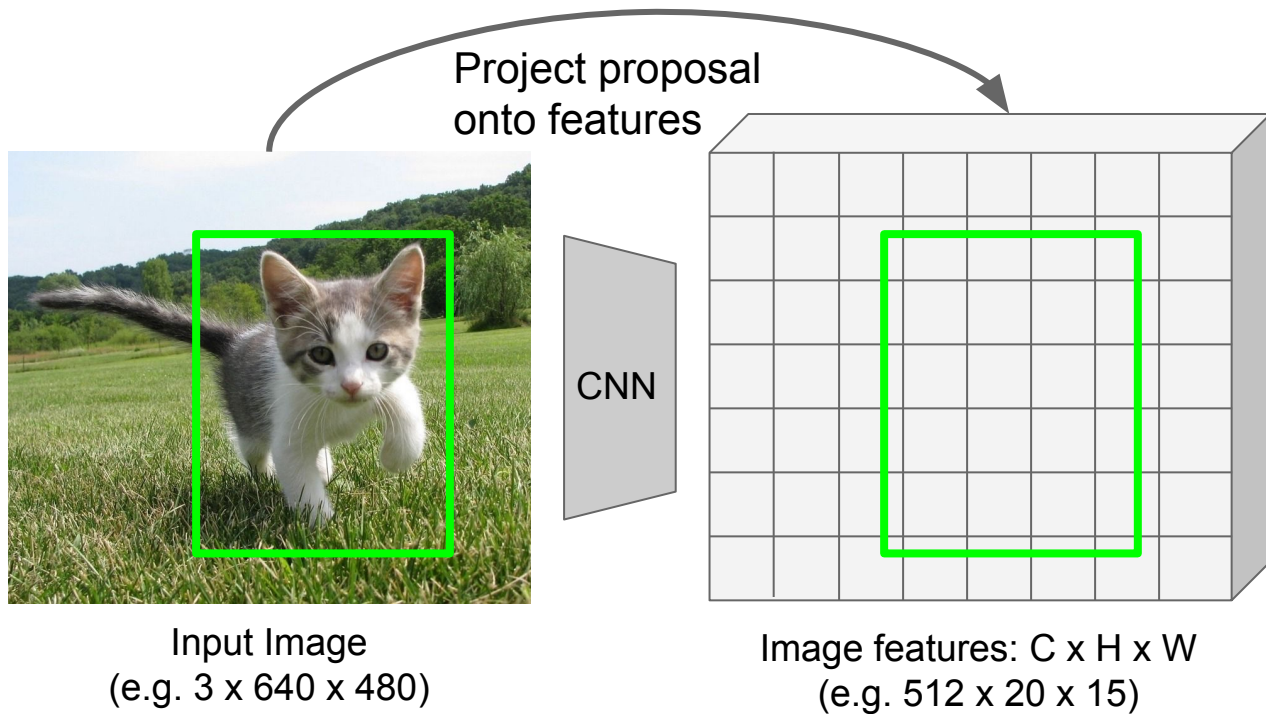


Image features: C x H x W
(e.g. 512 x 20 x 15)

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

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

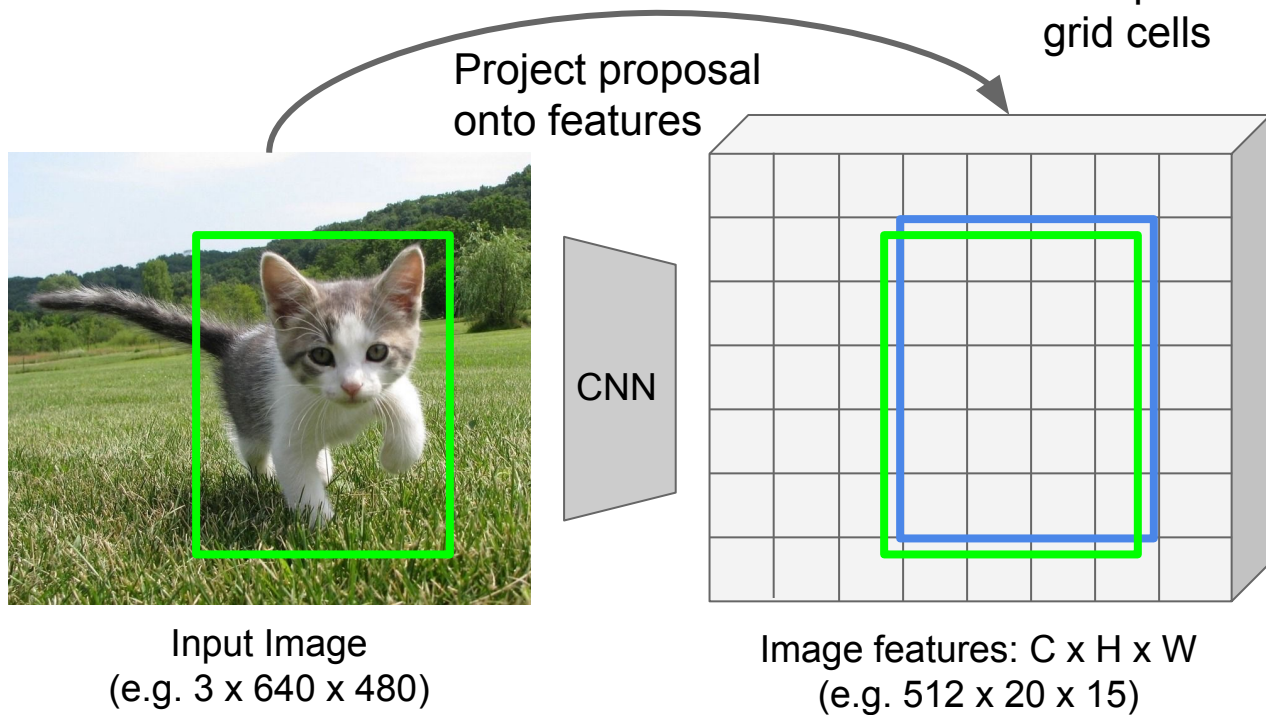
Cropping Features: RoI Pool



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

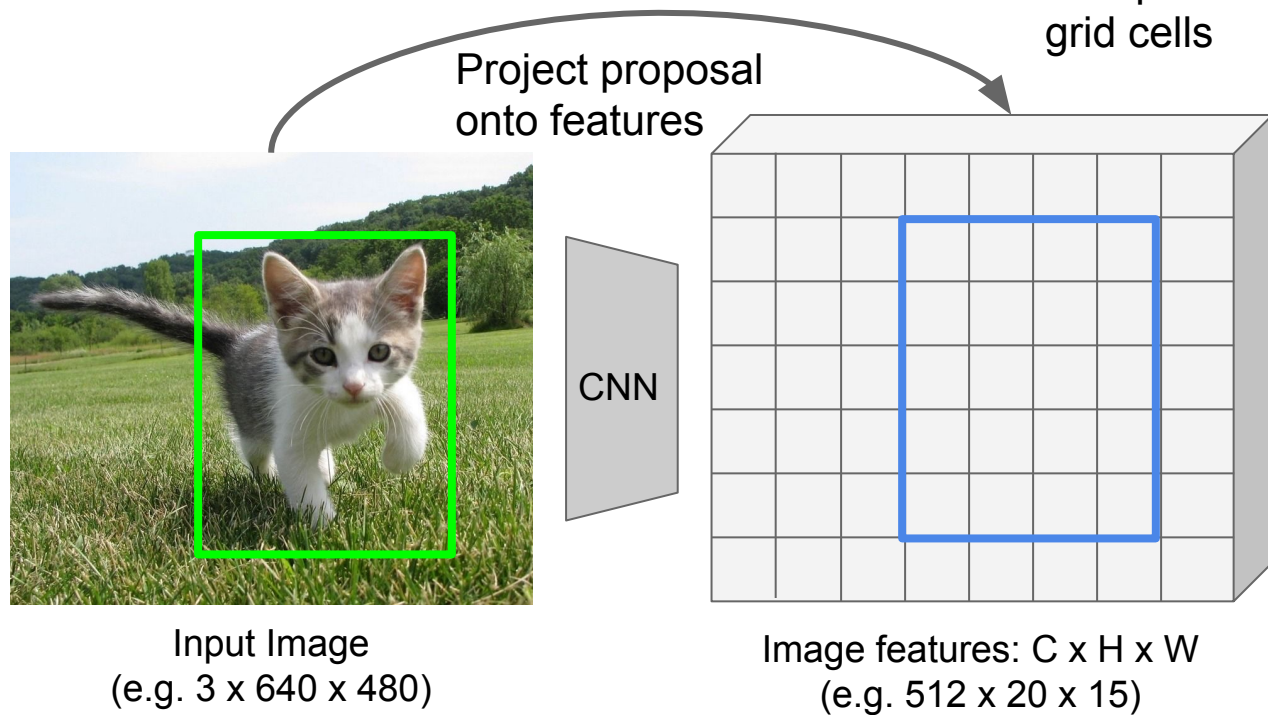
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool



Girshick, “Fast R-CNN”, ICCV 2015.

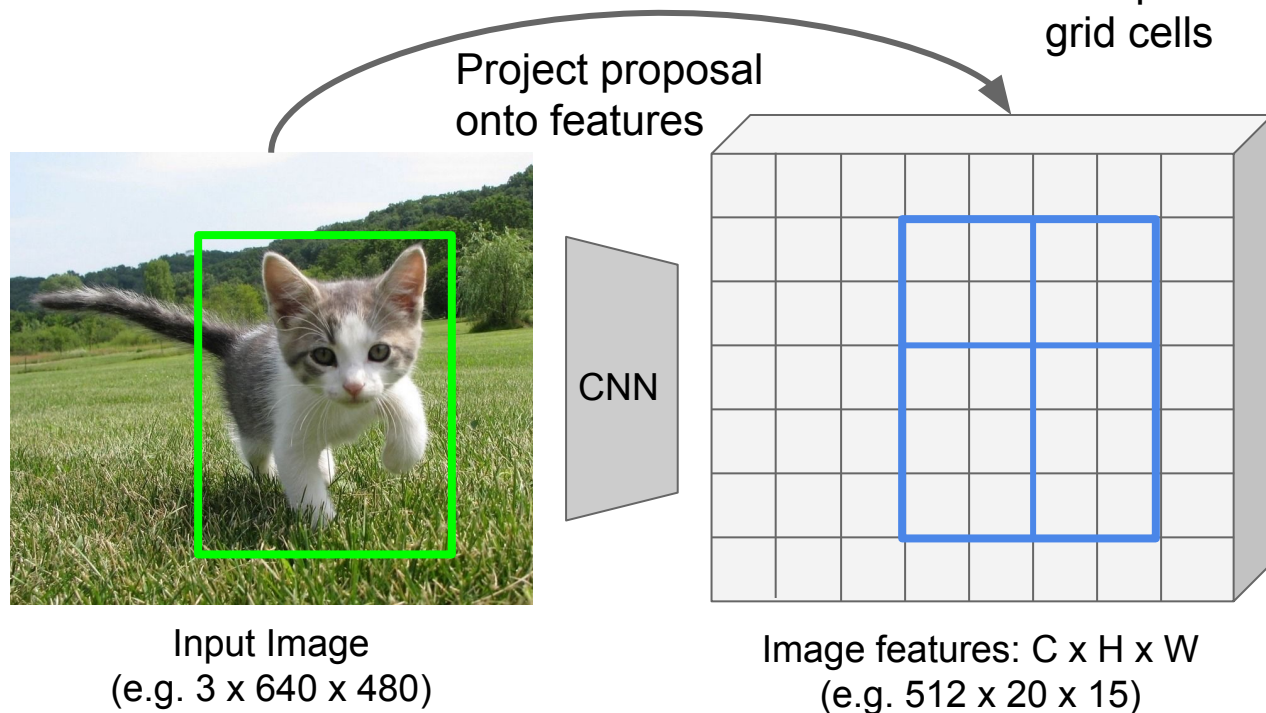
Cropping Features: RoI Pool



Q: how do we resize the 512 x 20 x 15 region to, e.g., a 512 x 2 x 2 tensor?.

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

Cropping Features: RoI Pool

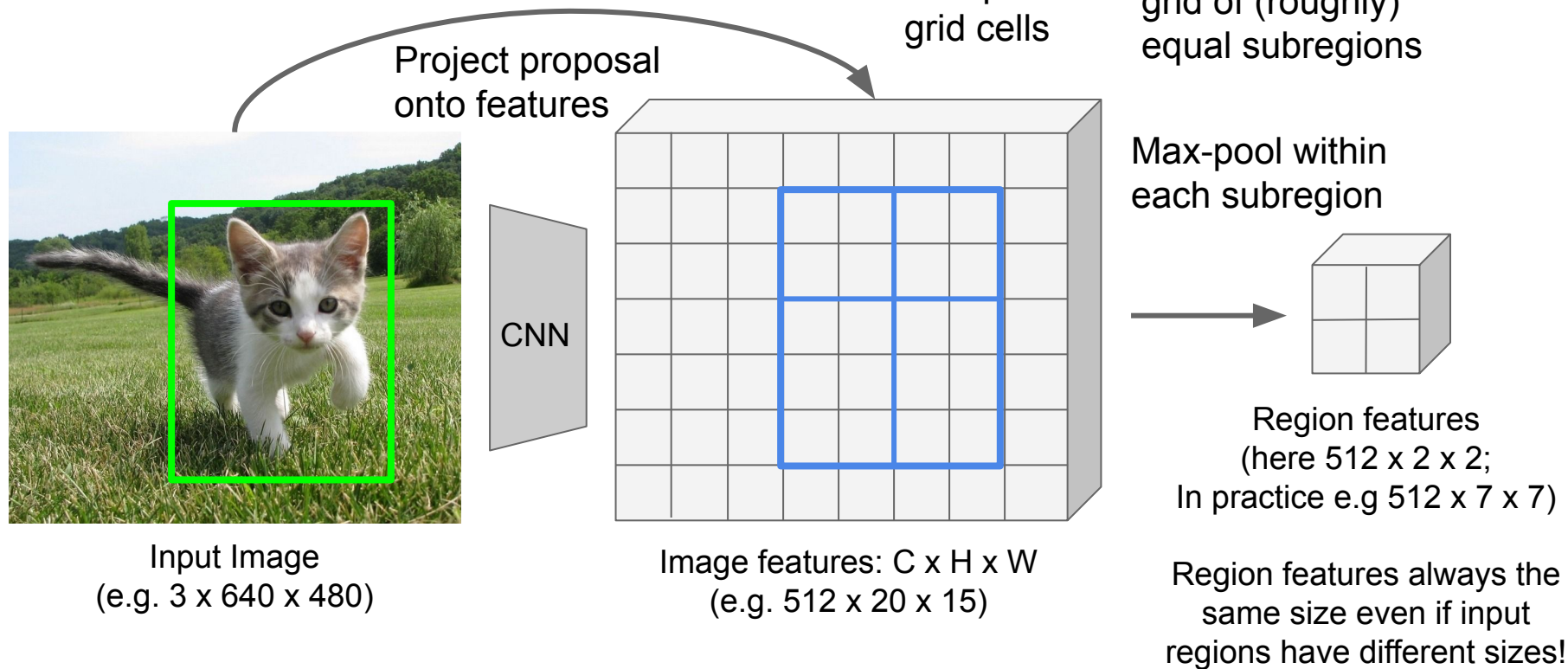


Divide into 2x2
grid of (roughly)
equal subregions

Q: how do we resize the 512
x 20 x 15 region to, e.g., a
512 x 2 x 2 tensor?.

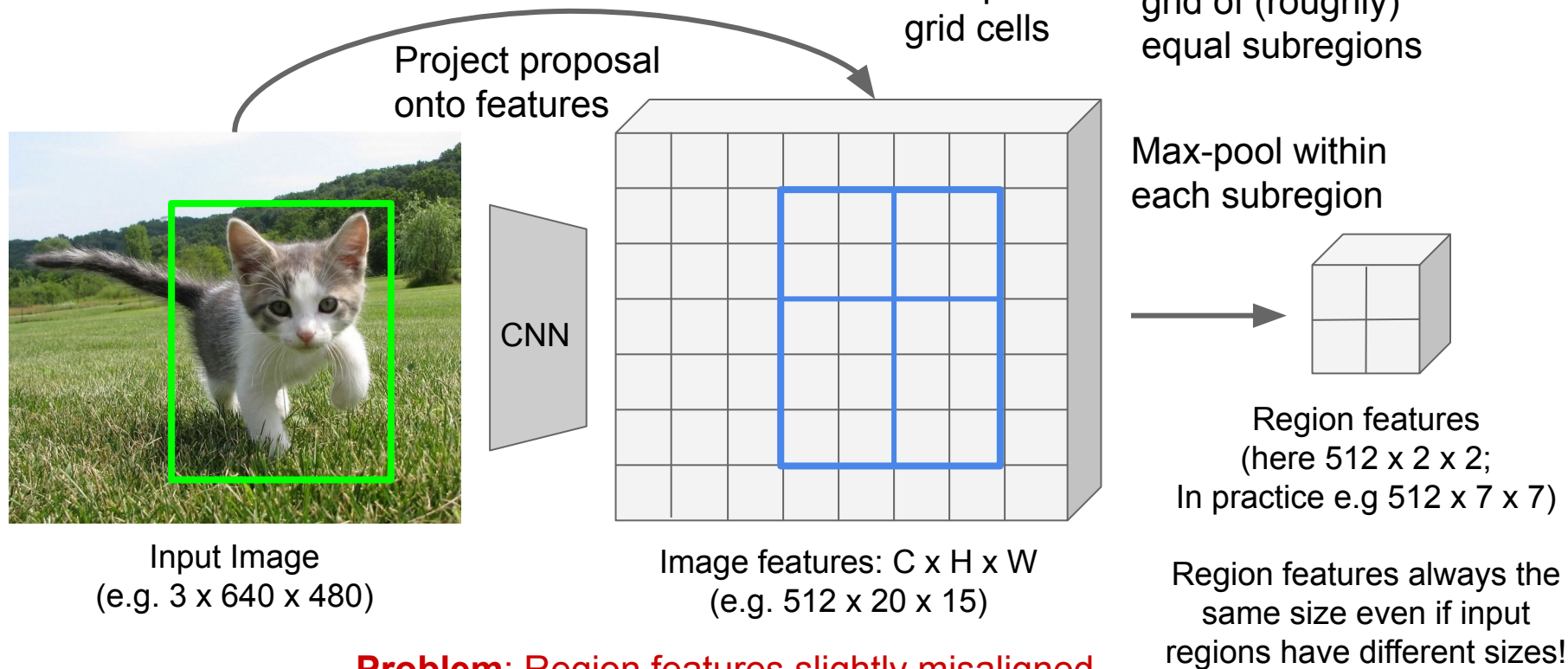
Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

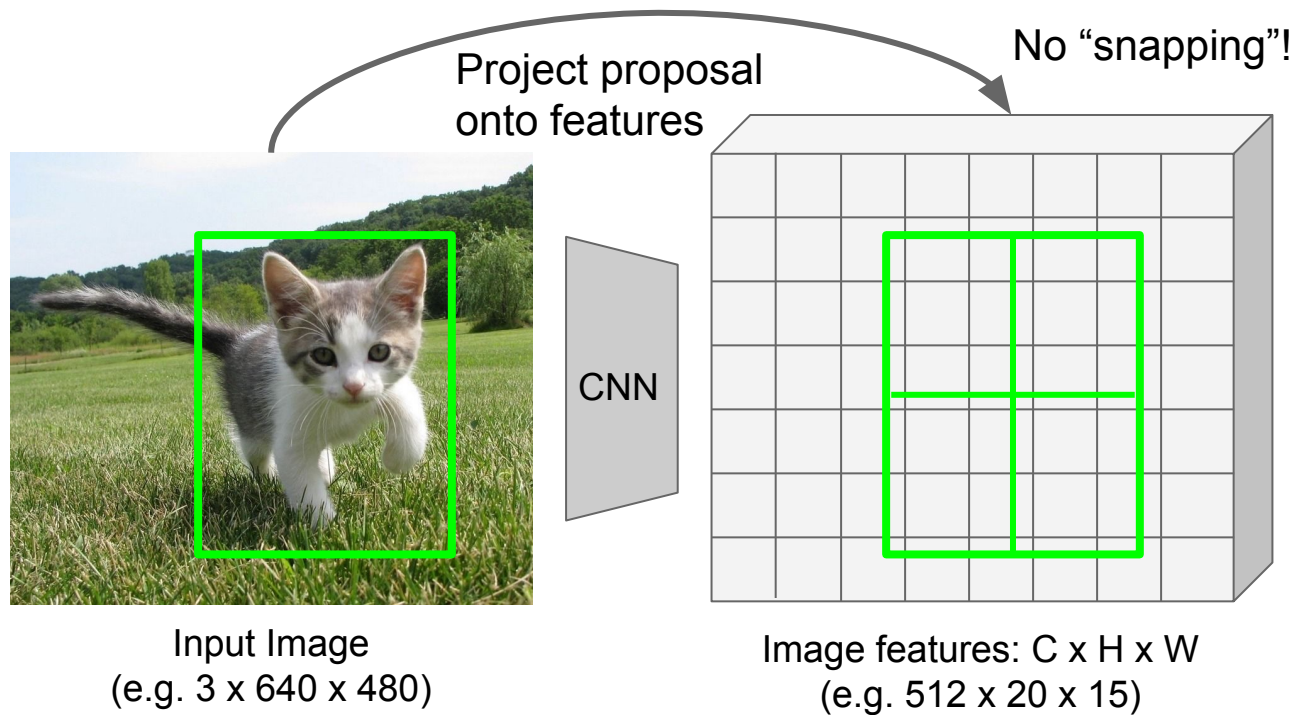
Cropping Features: RoI Pool



Problem: Region features slightly misaligned

Girshick, “Fast R-CNN”, ICCV 2015.

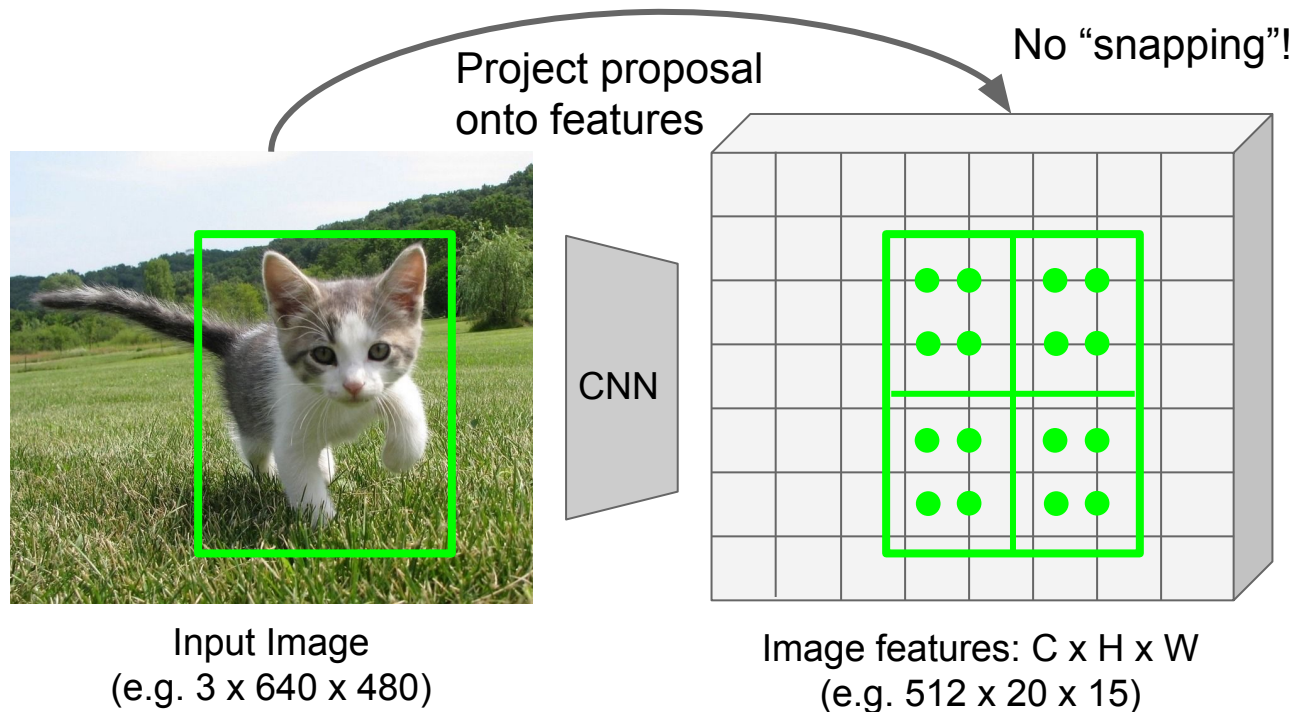
Cropping Features: RoI Align



He et al, “Mask R-CNN”, ICCV 2017

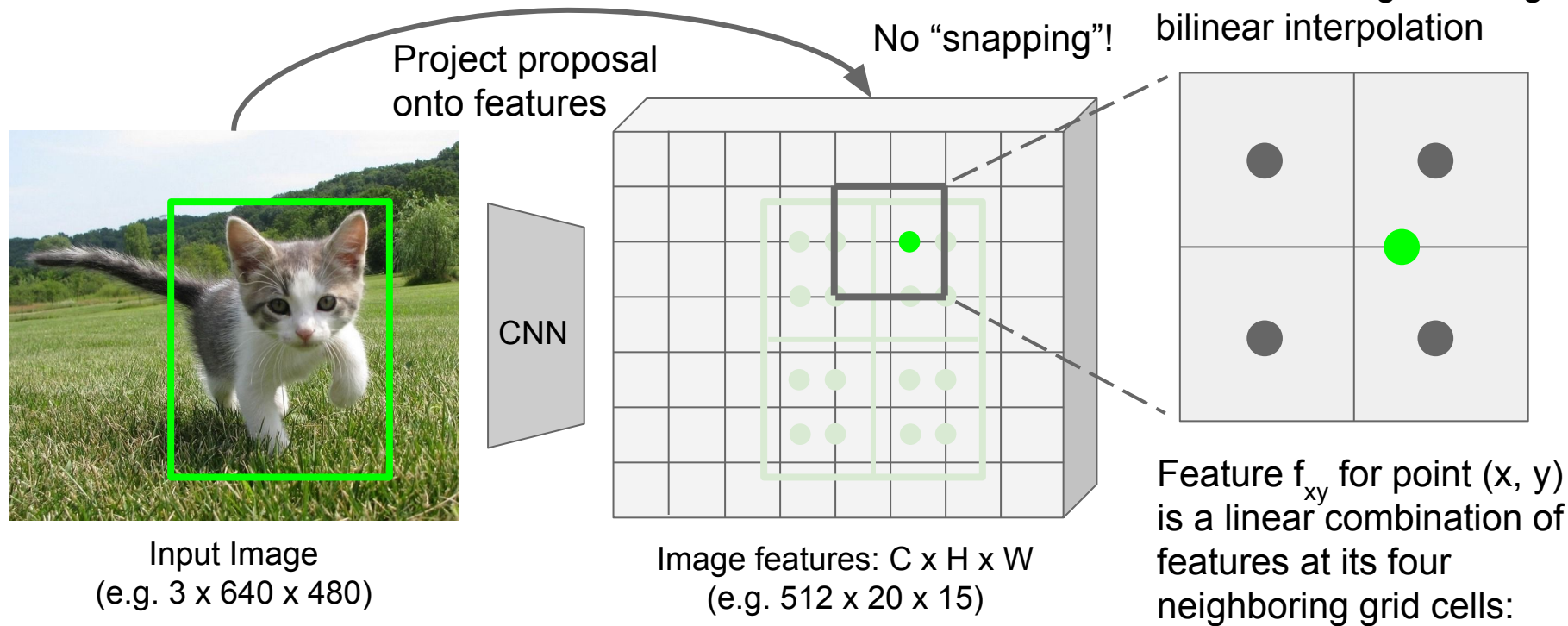
Cropping Features: RoI Align

Sample at regular points
in each subregion using
bilinear interpolation



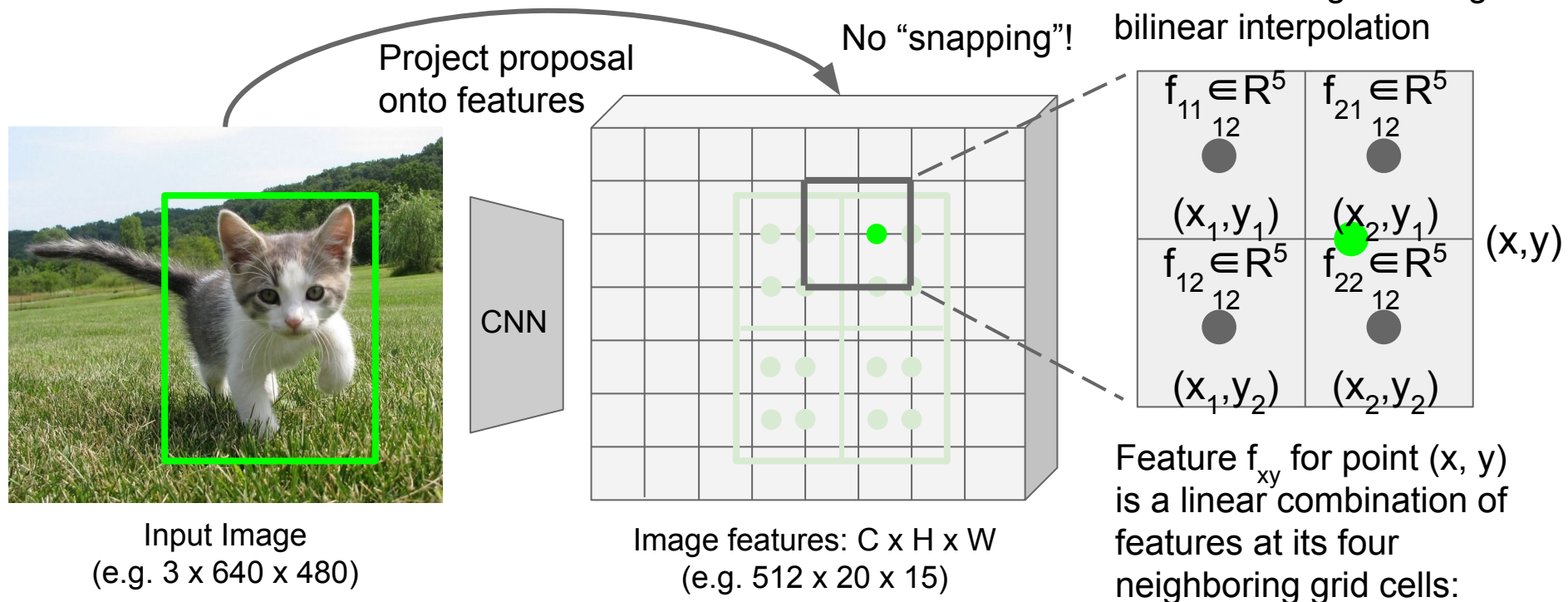
He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align



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

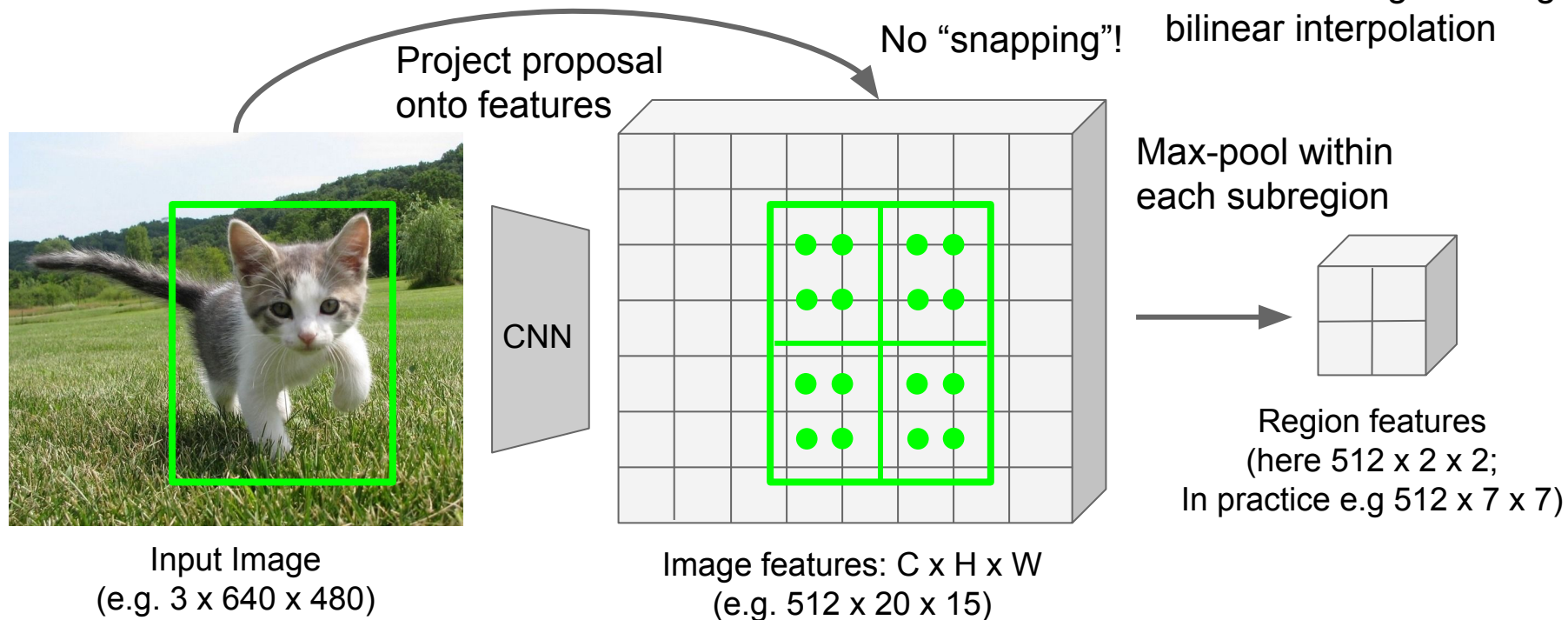
Cropping Features: RoI Align



$$f_{xy} = \sum_{i,j=1}^2 f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

He et al, “Mask R-CNN”, ICCV 2017

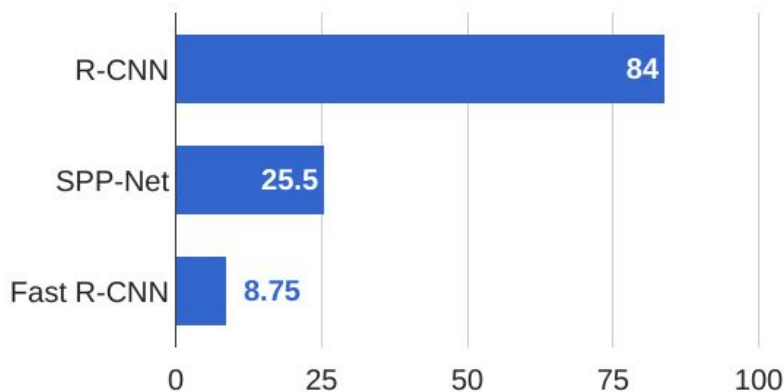
Cropping Features: RoI Align



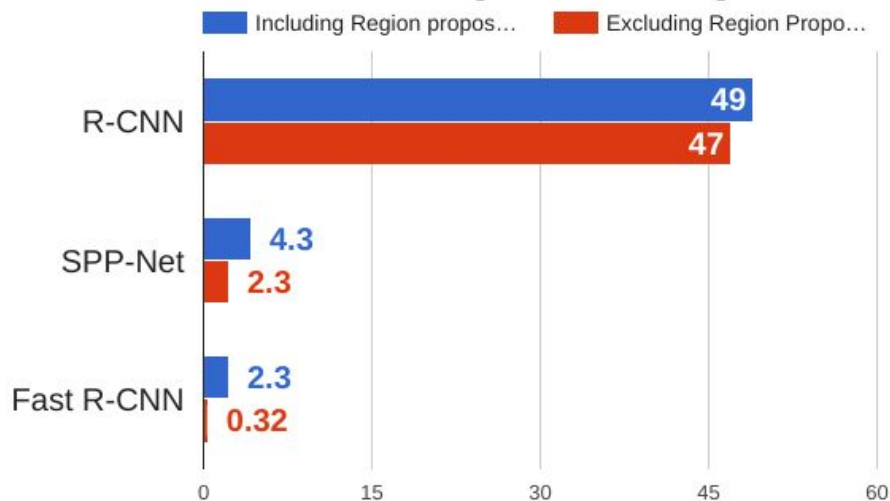
He et al, "Mask R-CNN", ICCV 2017

R-CNN vs Fast R-CNN

Training time (Hours)



Test time (seconds)



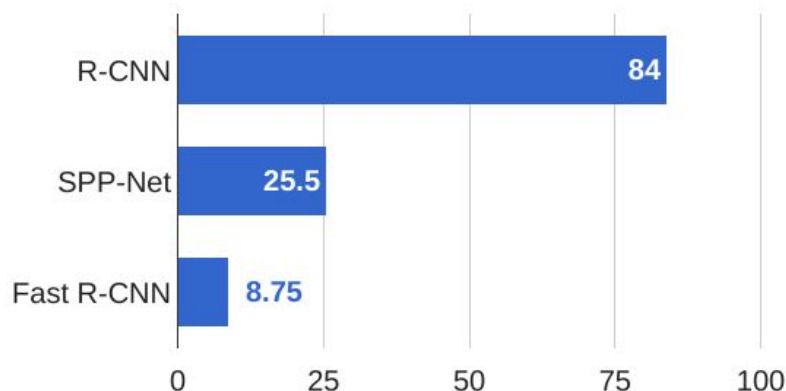
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

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

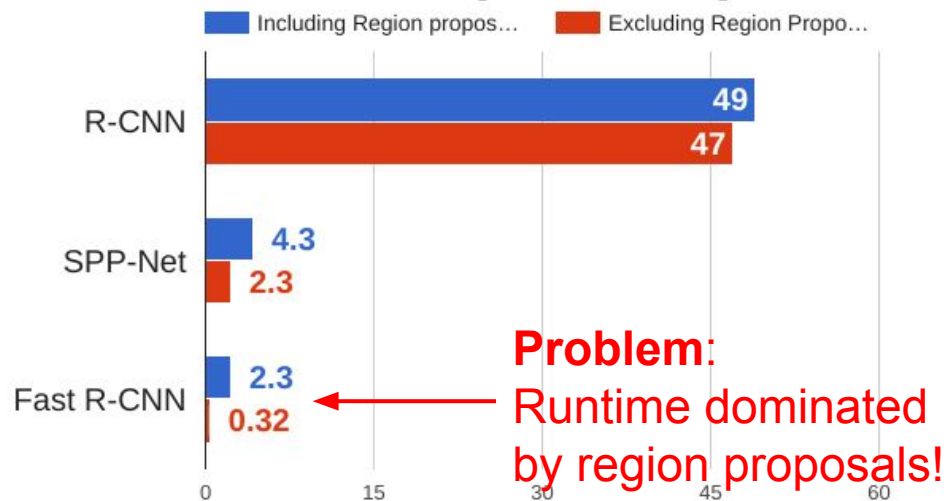
Girshick, "Fast R-CNN", ICCV 2015

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.

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

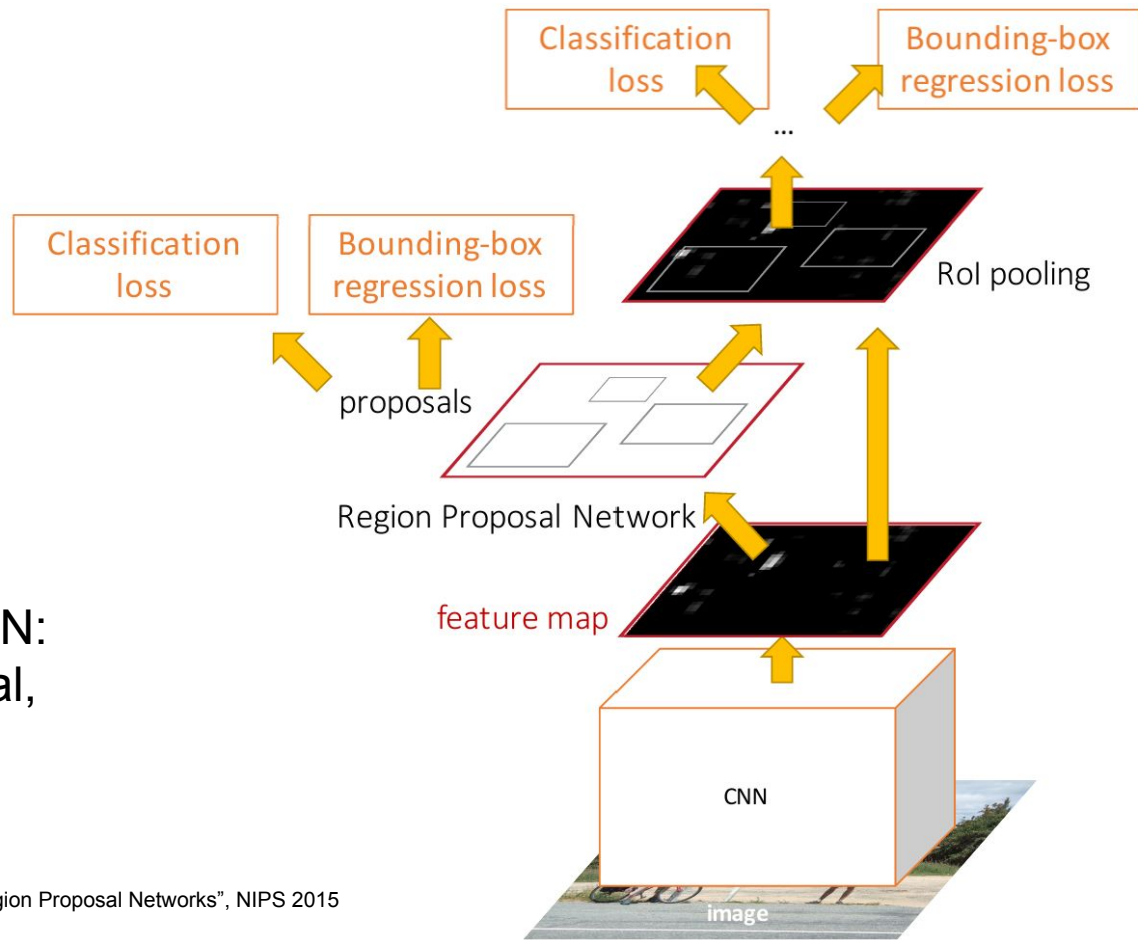
Girshick, "Fast R-CNN", ICCV 2015

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 x 640 x 480)

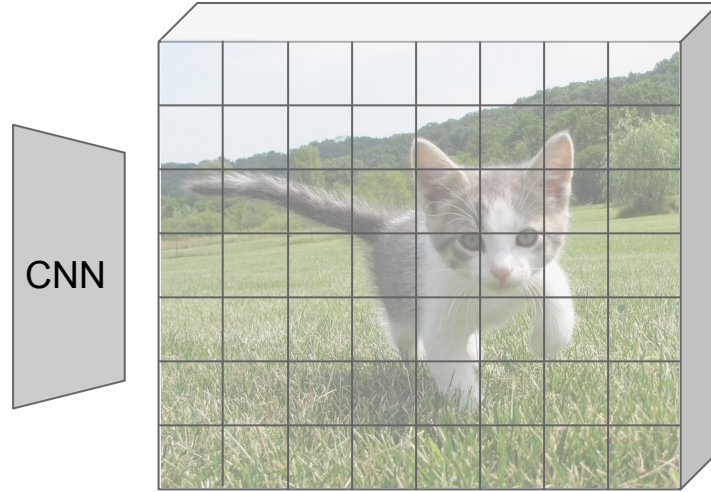


Image features
(e.g. 512 x 20 x 15)

Region Proposal Network

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



Input Image
(e.g. 3 x 640 x 480)

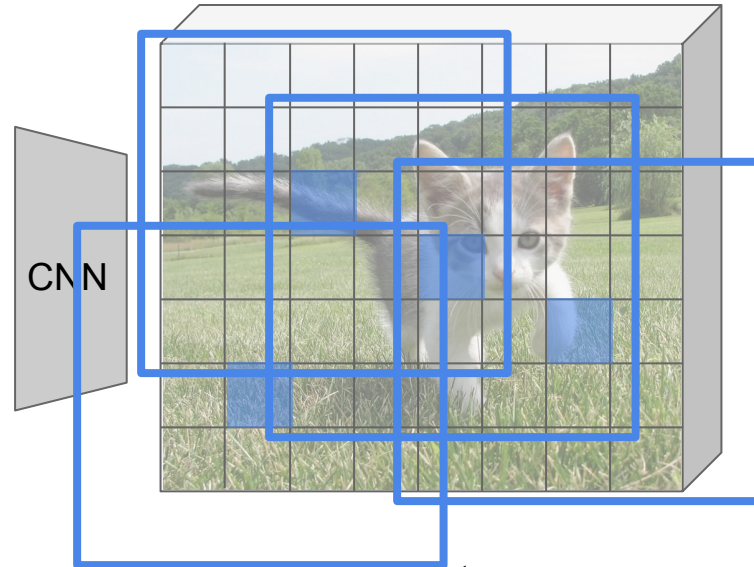


Image features
(e.g. 512 x 20 x 15)

Region Proposal Network



Input Image
(e.g. 3 x 640 x 480)

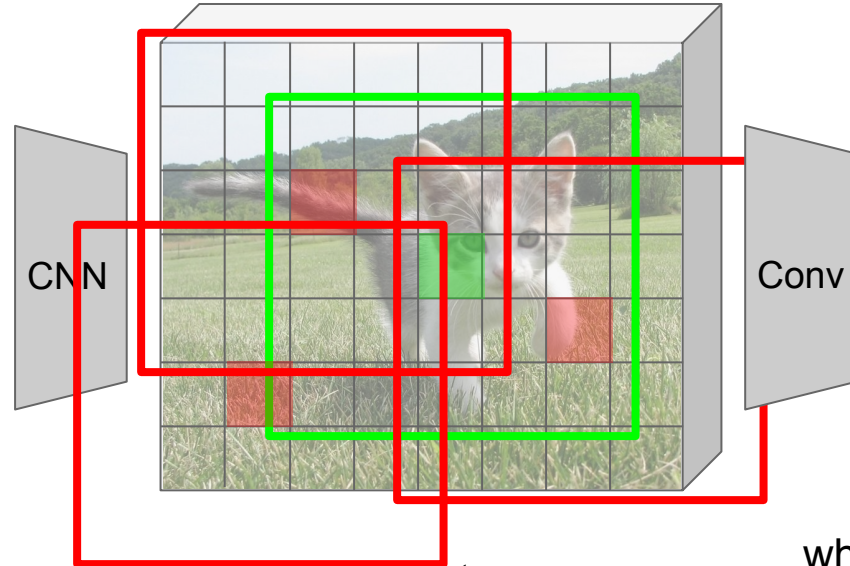


Image features
(e.g. 512 x 20 x 15)

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

Anchor is an object?
1 x 20 x 15

At each point, predict
whether the corresponding
anchor contains an object
(binary classification)

Region Proposal Network



Input Image
(e.g. 3 x 640 x 480)

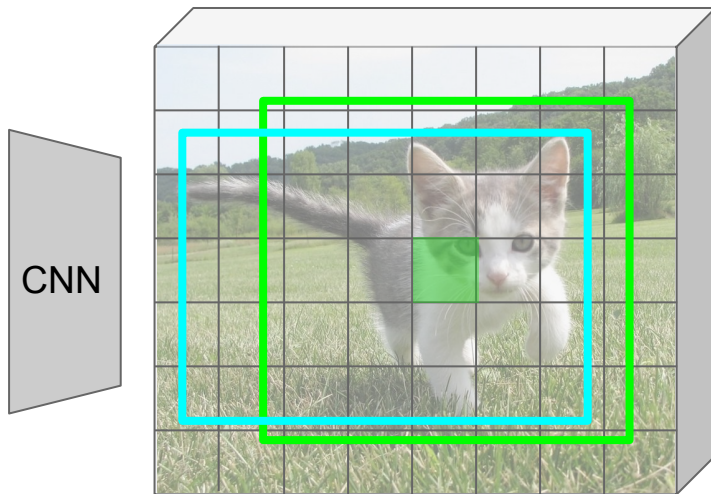


Image features
(e.g. 512 x 20 x 15)

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

Anchor is an object?
1 x 20 x 15

Box corrections
4 x 20 x 15

For positive boxes, also predict
a corrections from the anchor to
the ground-truth box (regress 4
numbers per pixel)

Region Proposal Network

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



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

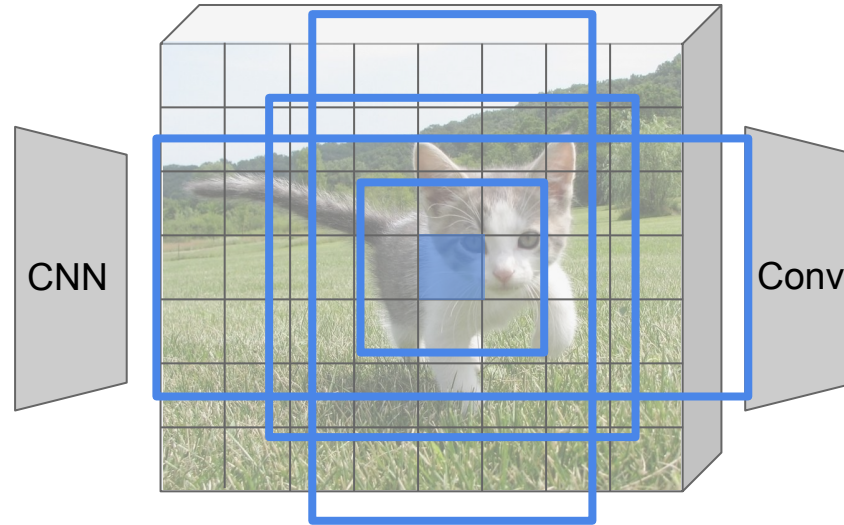


Image features
(e.g. $512 \times 20 \times 15$)

Anchor is an object?
 $K \times 20 \times 15$

Box transforms
 $4K \times 20 \times 15$

Region Proposal Network

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



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

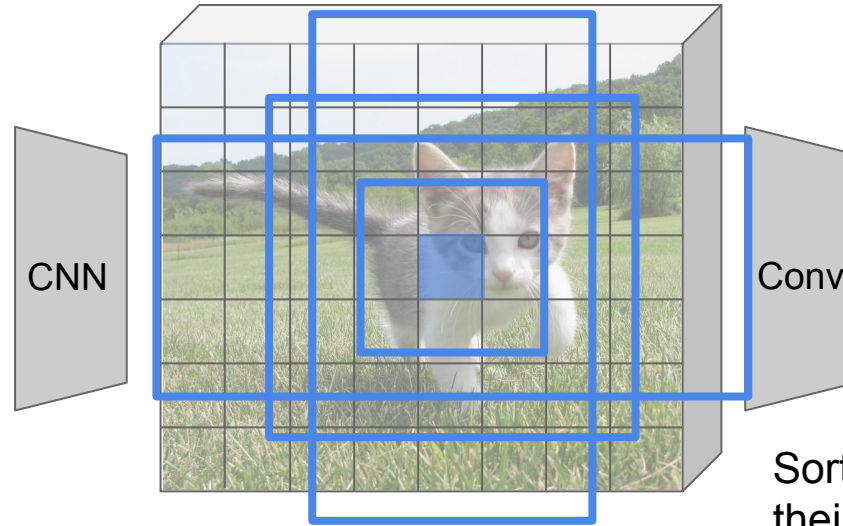


Image features
(e.g. $512 \times 20 \times 15$)

Anchor is an object?
 $K \times 20 \times 15$

Box transforms
 $4K \times 20 \times 15$

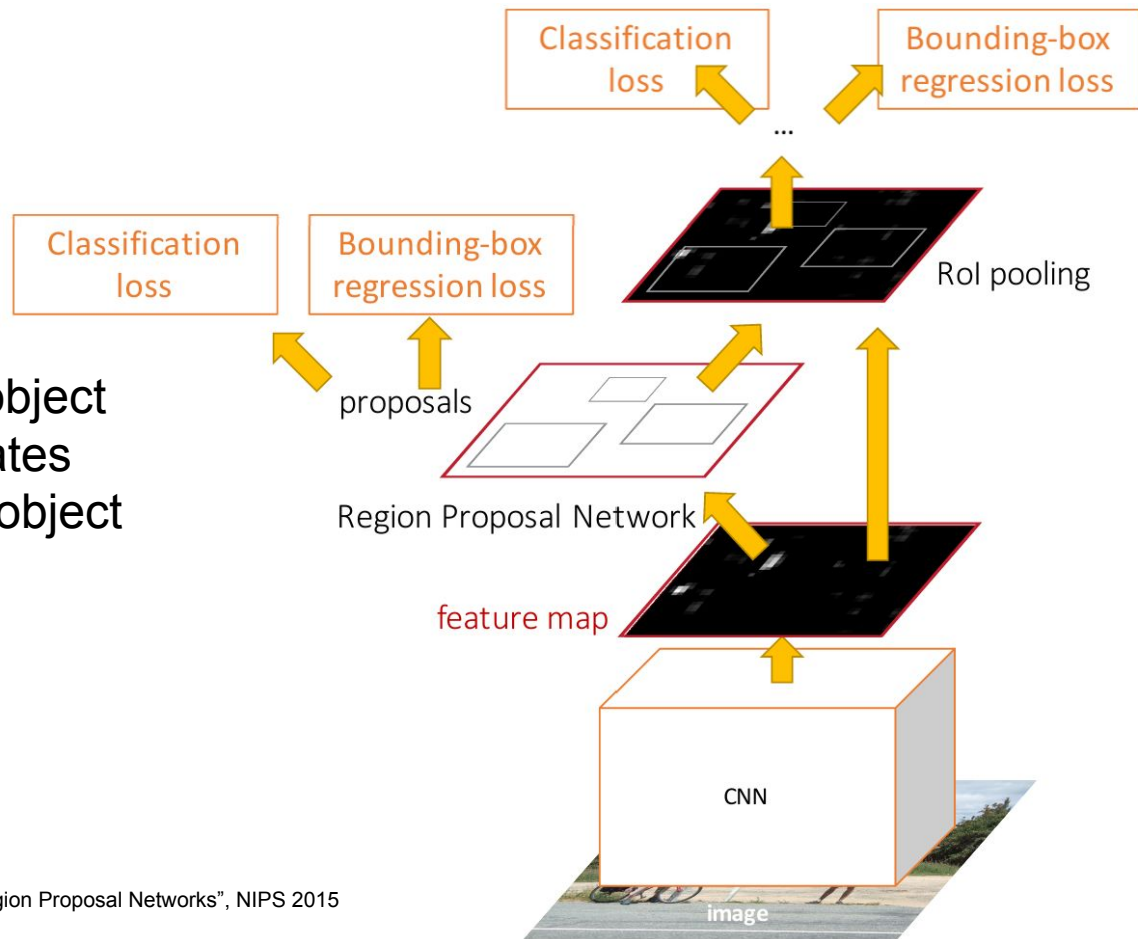
Sort the $K \times 20 \times 15$ boxes by their “objectness” score, take top ~ 300 as our proposals

Faster R-CNN:

Make CNN do proposals!

Jointly train with 4 losses:

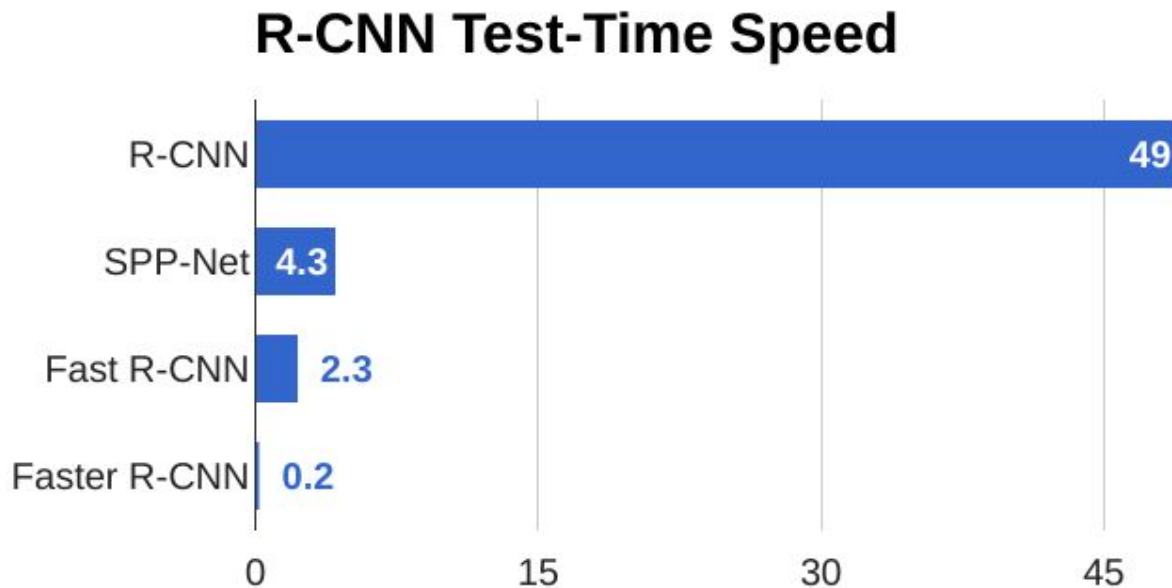
1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates



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!

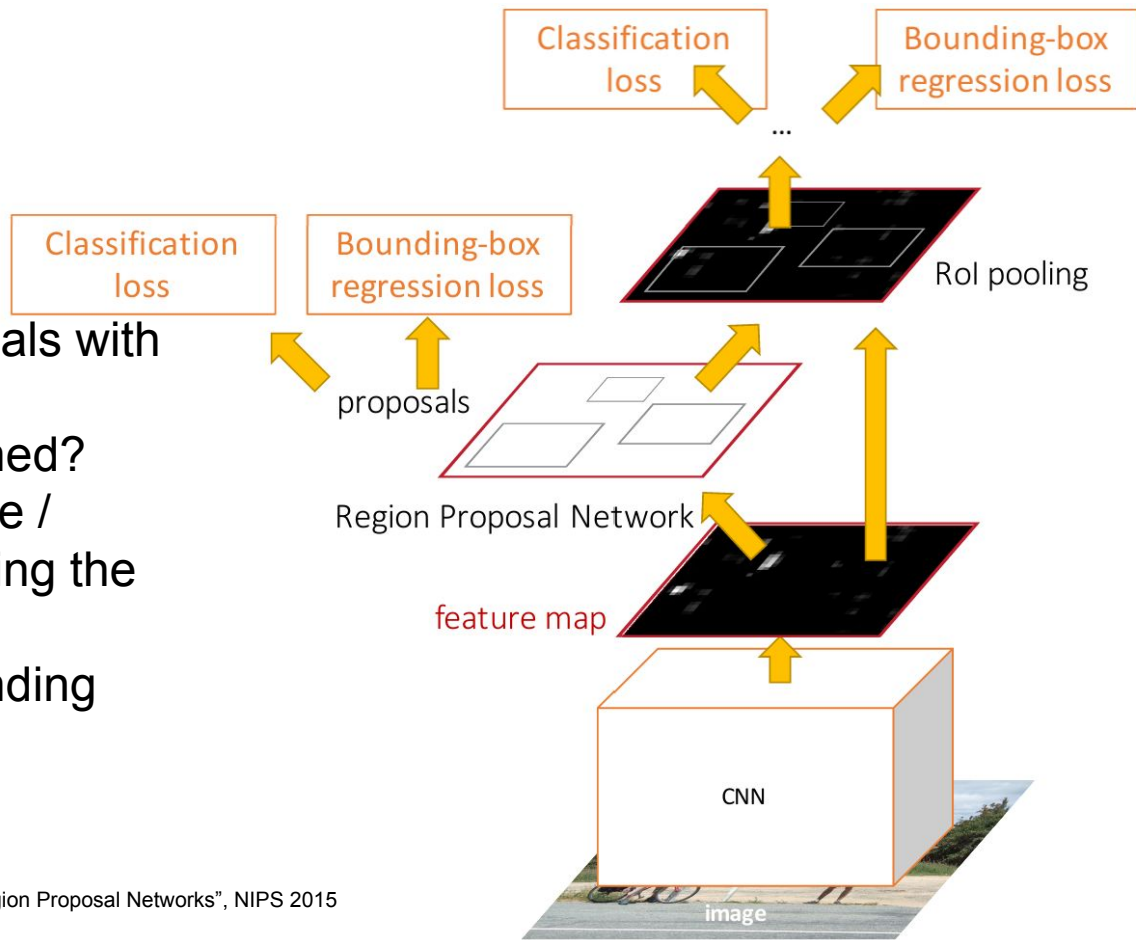


Faster R-CNN:

Make CNN do proposals!

Glossing over many details:

- Ignore overlapping proposals with **non-max suppression**
- How are anchors determined?
- How do we sample positive / negative samples for training the RPN?
- 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!

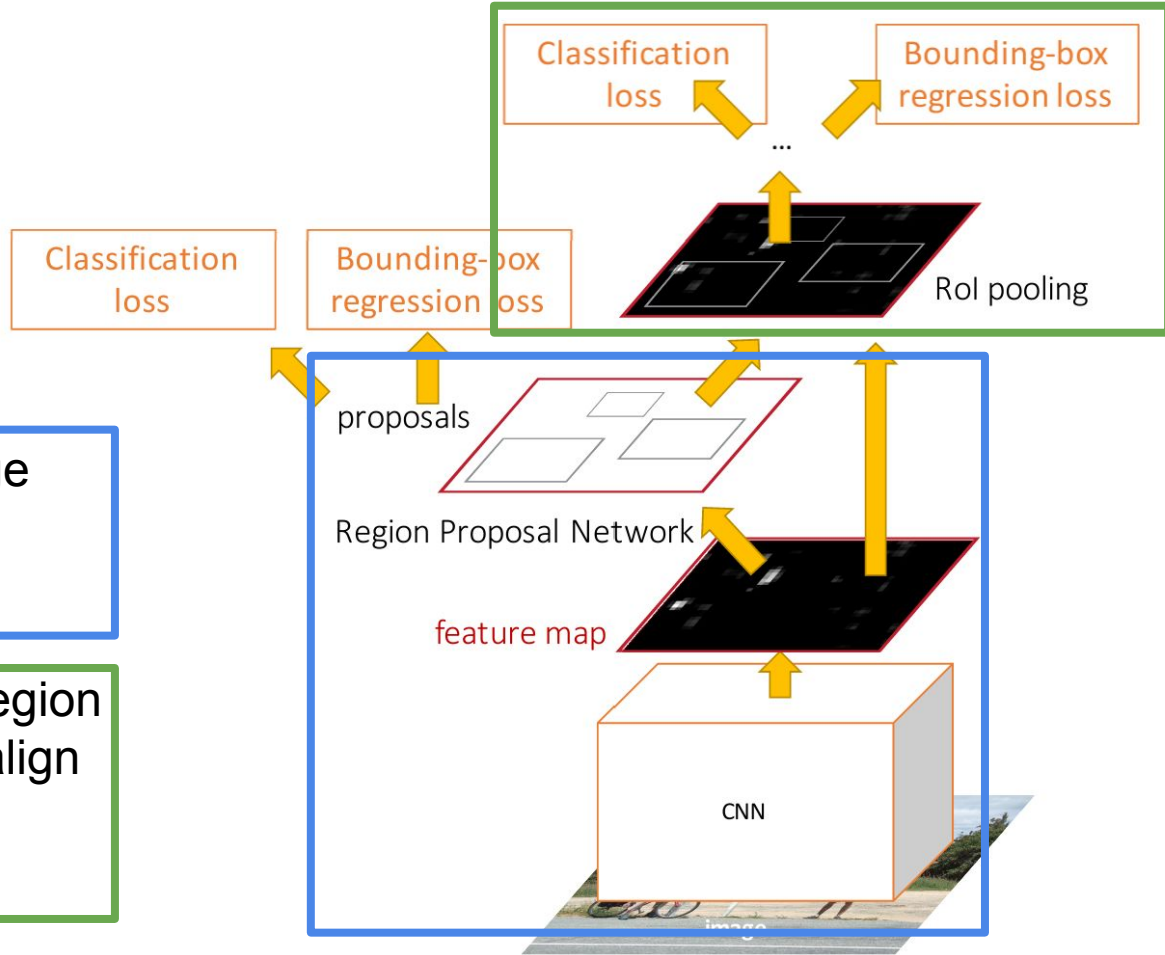
Faster R-CNN is a
Two-stage object detector

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

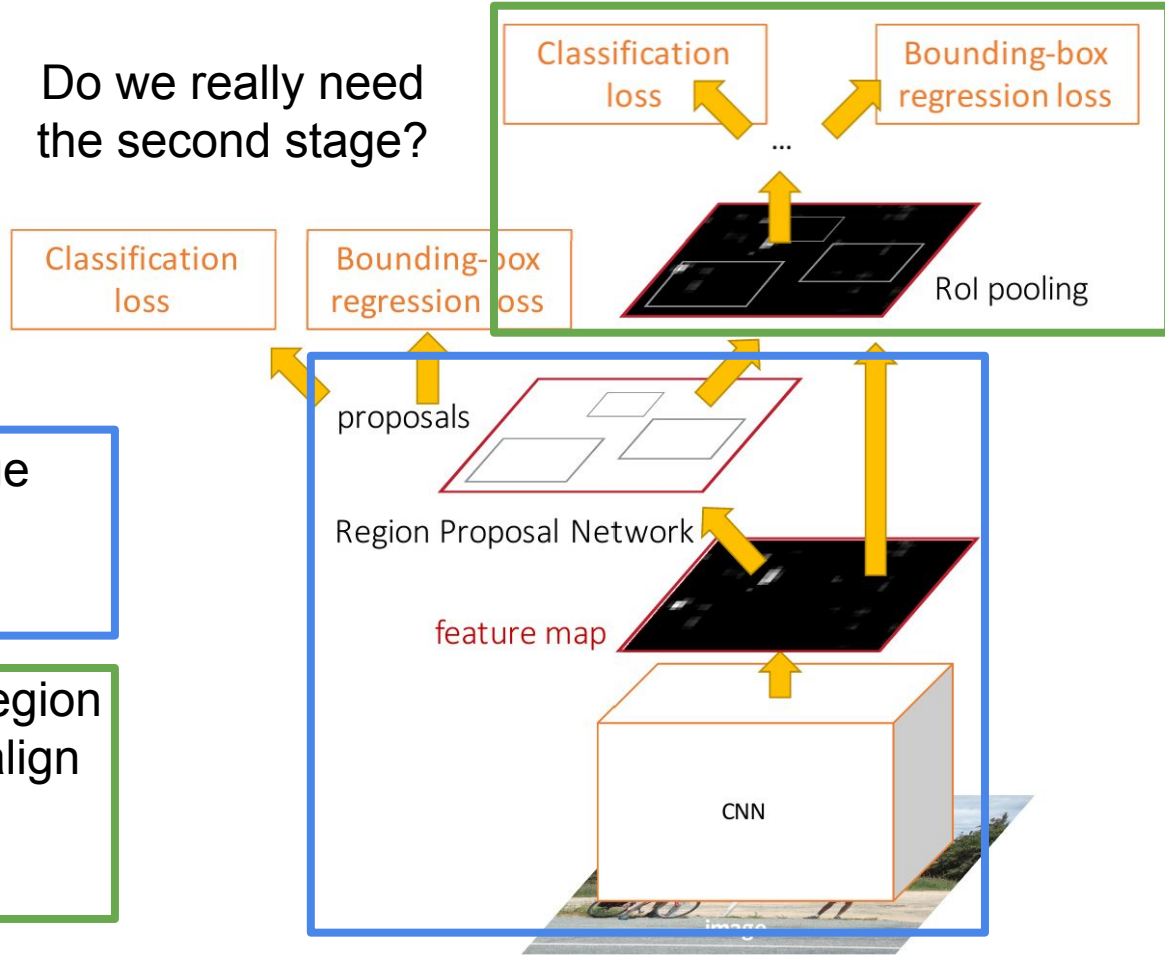
First stage: Run once per image

- Backbone network
- Region proposal network

Second stage: Run once per region

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

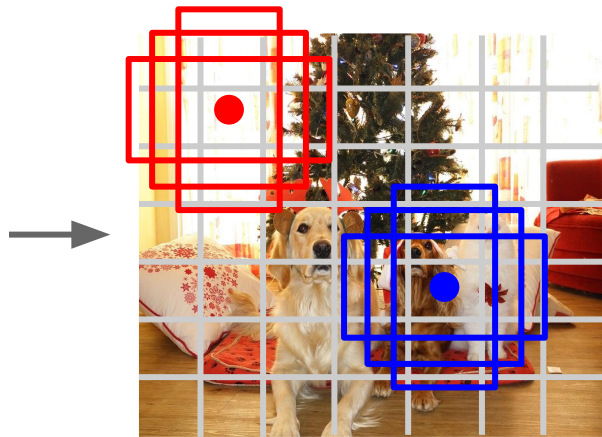
Do we really need
the second stage?



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 ...

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

Zou et al, “Object Detection in 20 Years: A Survey”, [arXiv 2019](#)

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

Instance Segmentation

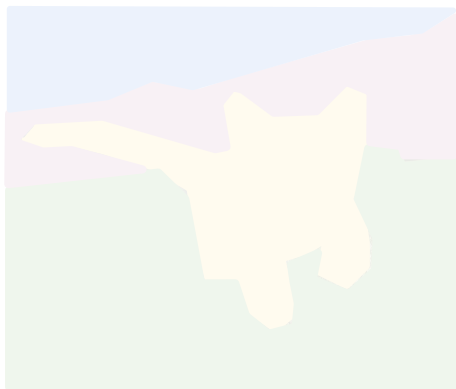
Classification



CAT

No spatial extent

Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

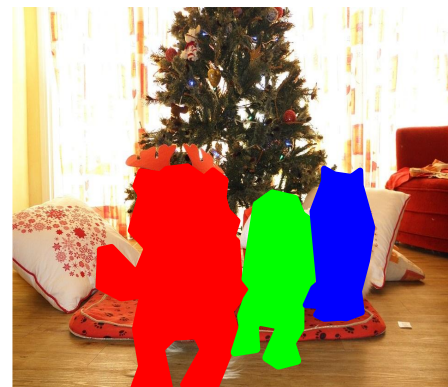
Object Detection



DOG, DOG, CAT

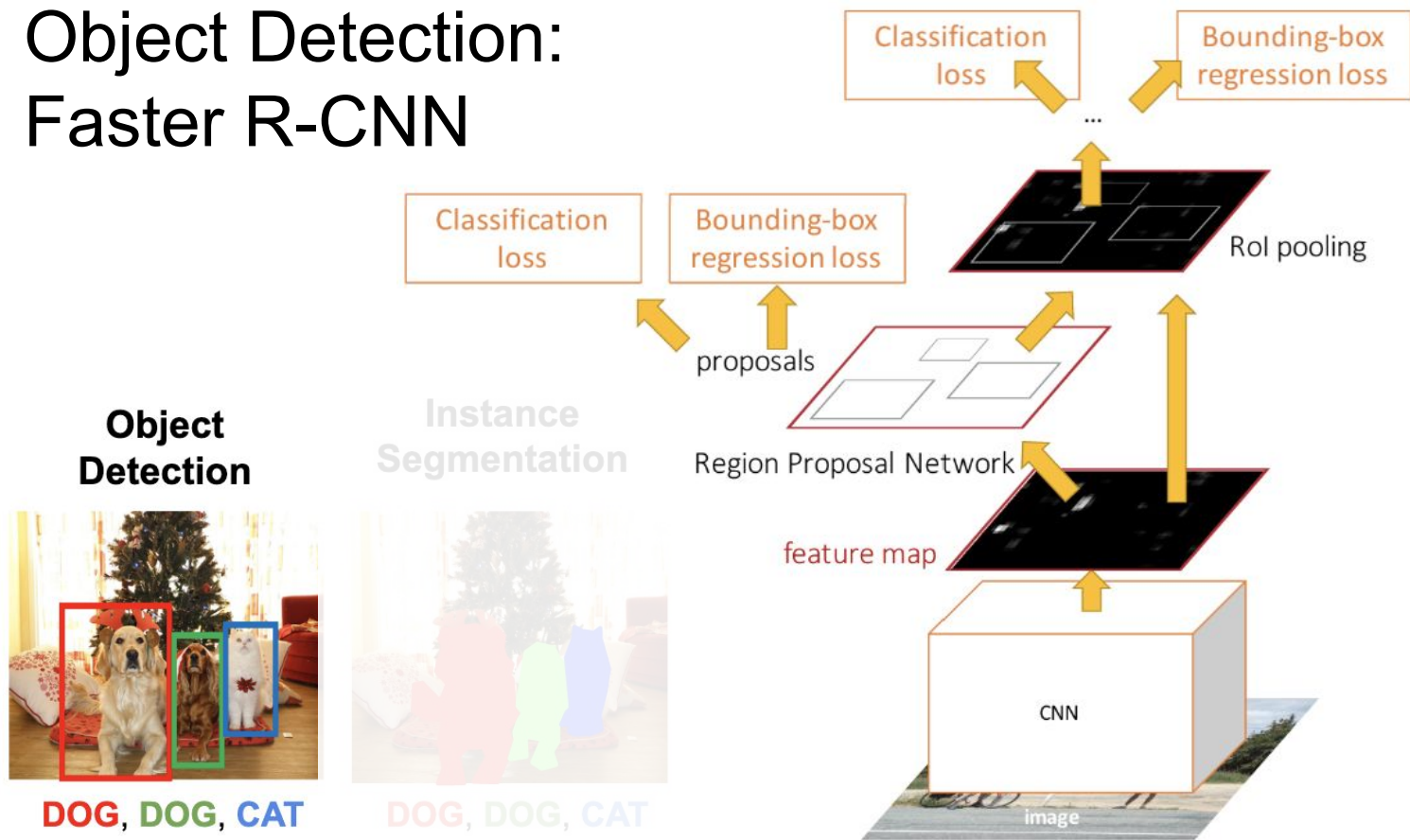
Multiple Object

Instance Segmentation

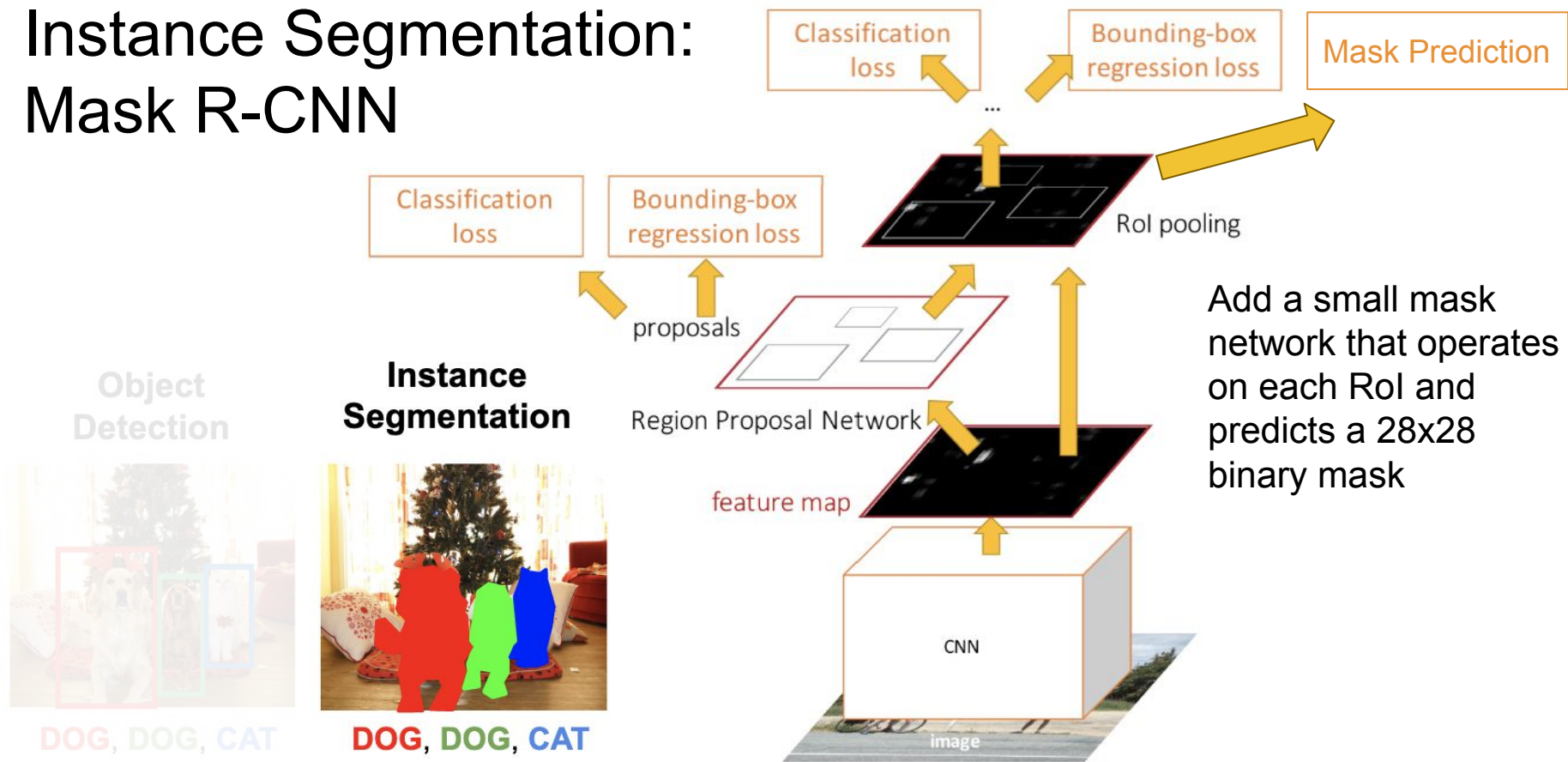


DOG, DOG, CAT

Object Detection: Faster R-CNN

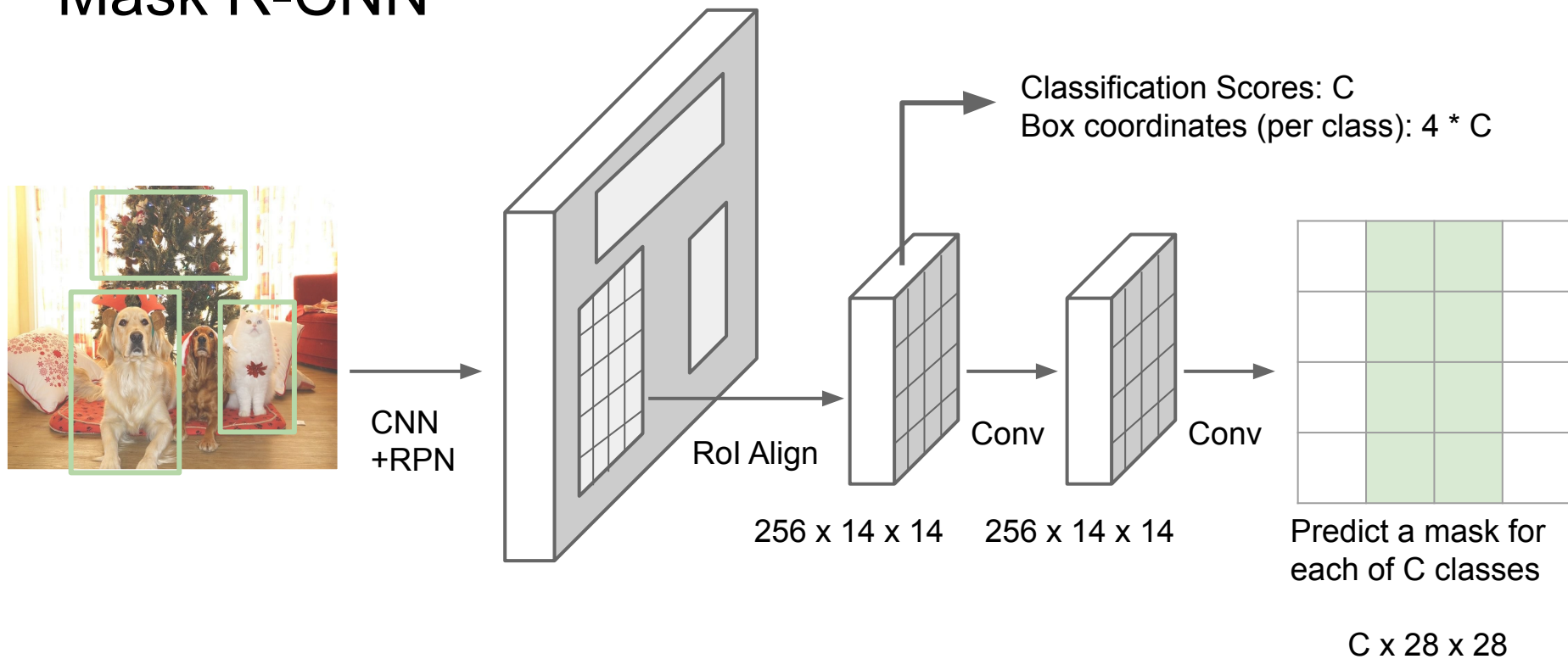


Instance Segmentation: Mask R-CNN



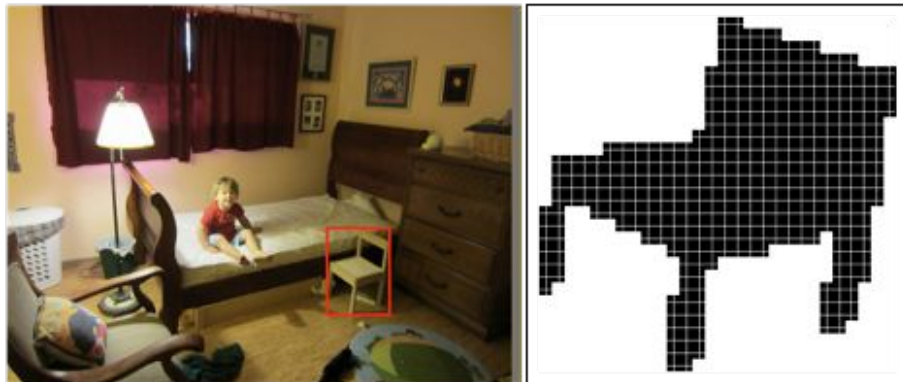
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN

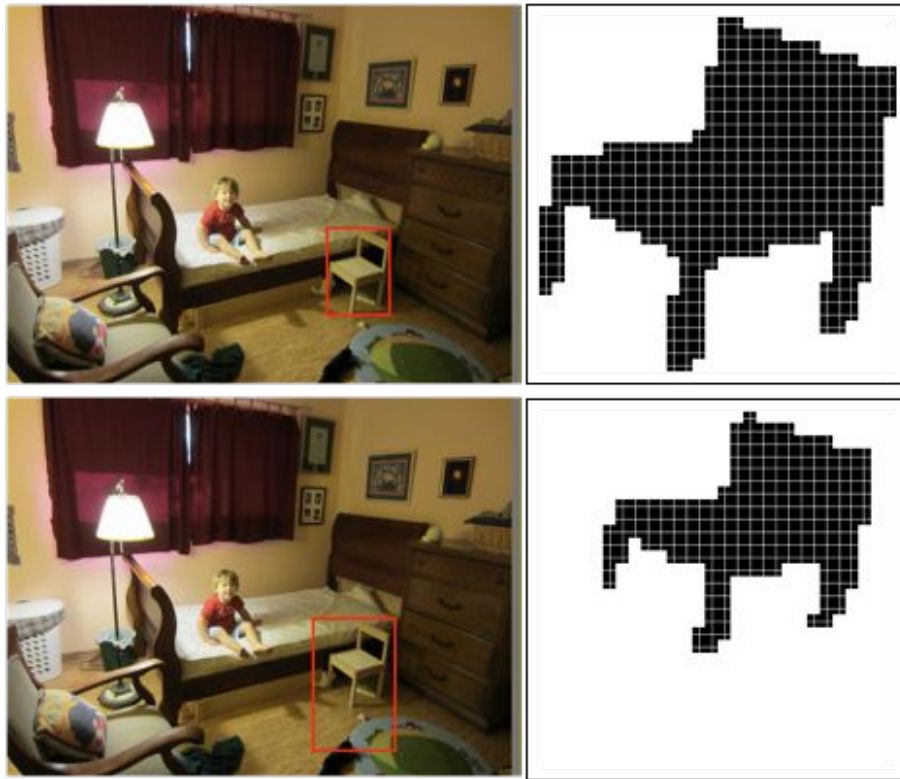


He et al, "Mask R-CNN", arXiv 2017

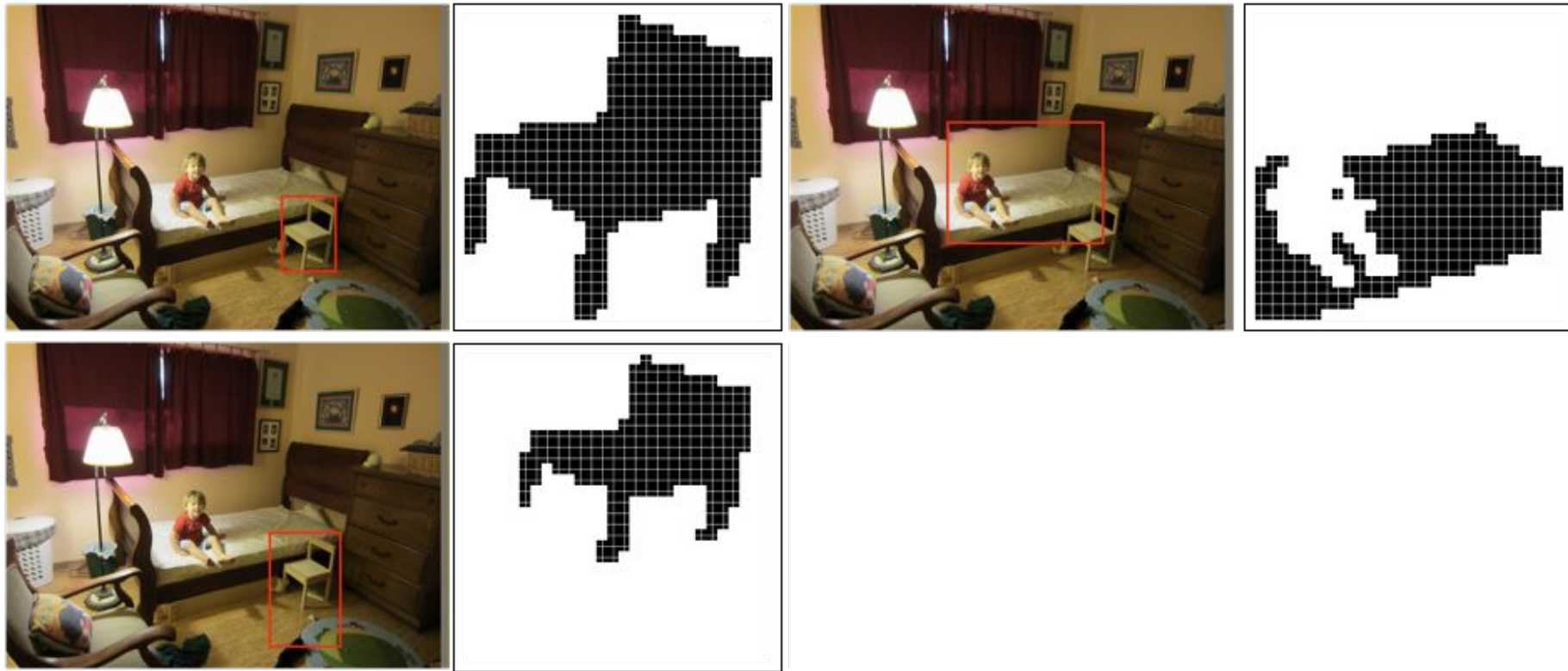
Mask R-CNN: Example Mask Training Targets



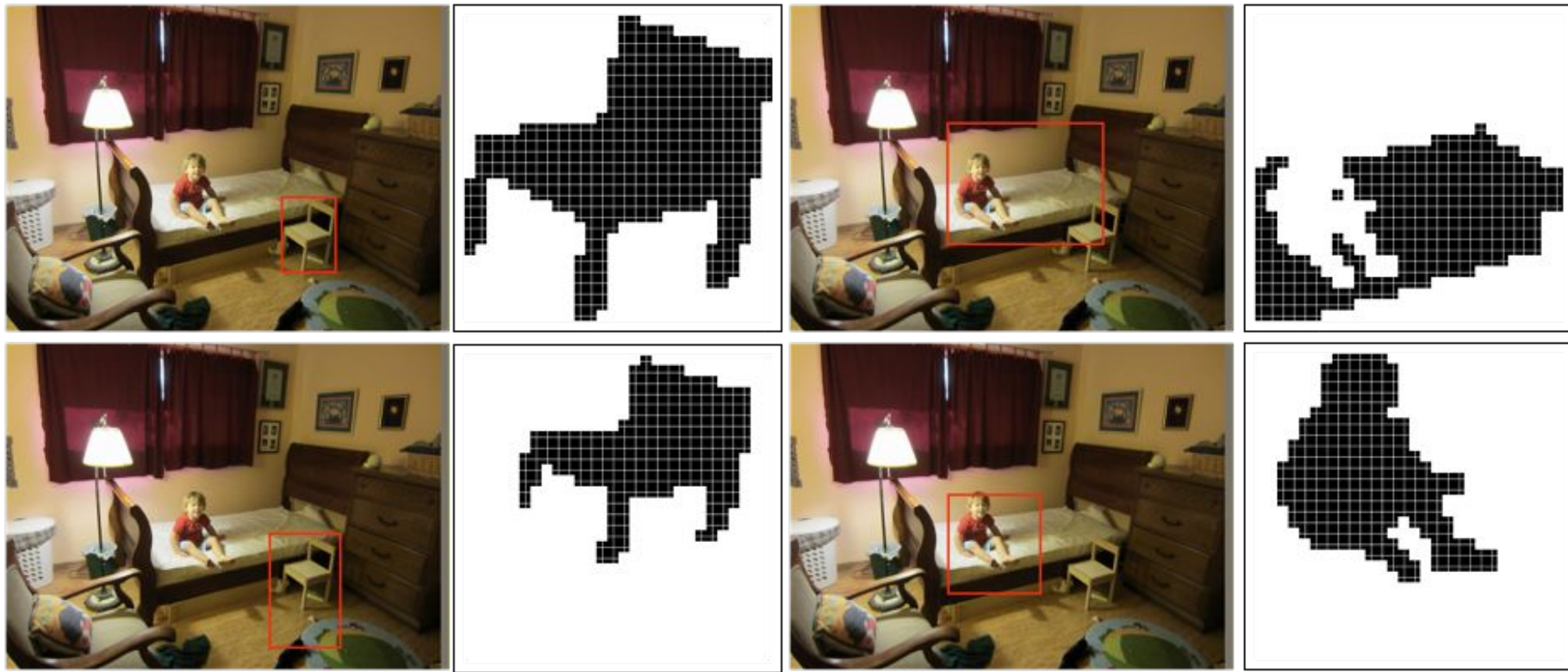
Mask R-CNN: Example Mask Training Targets



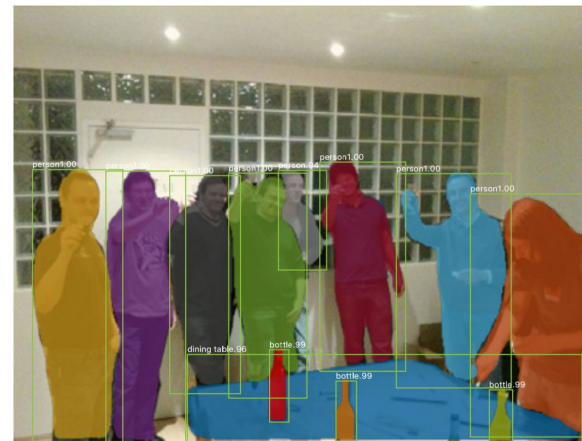
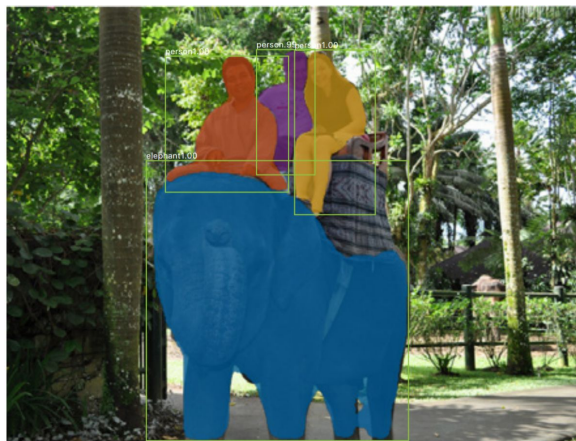
Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Example Mask Training Targets



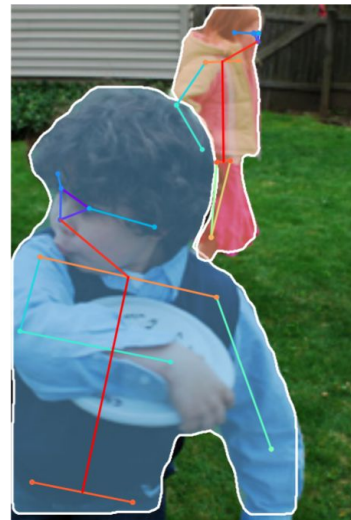
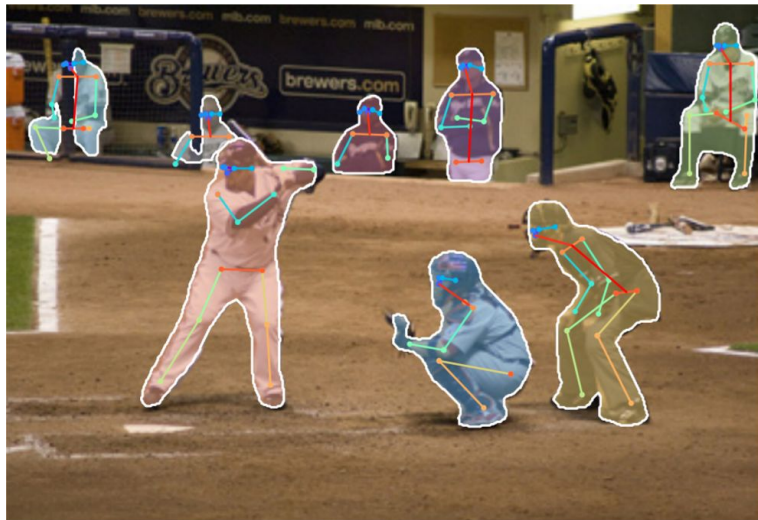
Mask R-CNN: Very Good Results!



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, ...

Detectron2 (PyTorch)

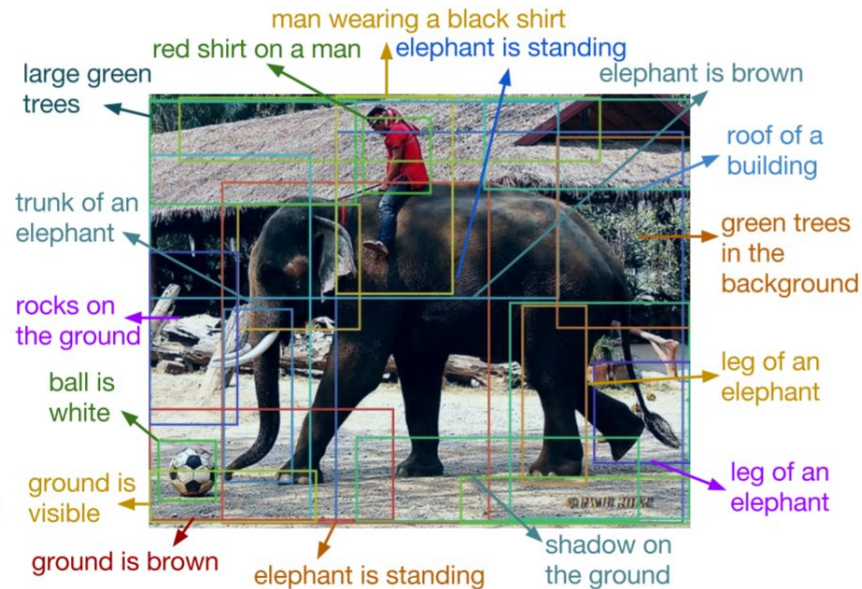
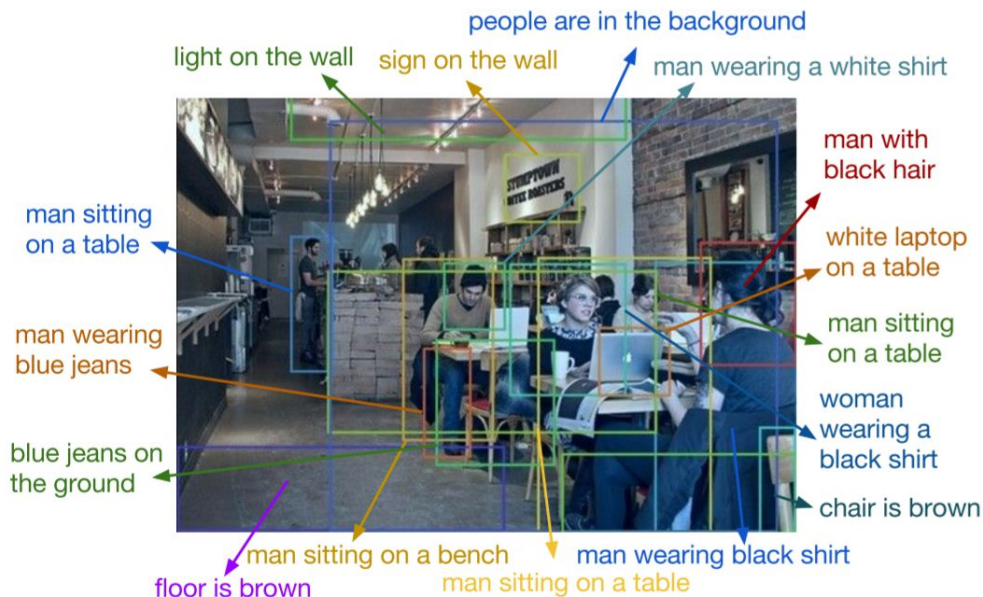
<https://github.com/facebookresearch/detectron2>

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

Finetune on your own dataset with pre-trained models

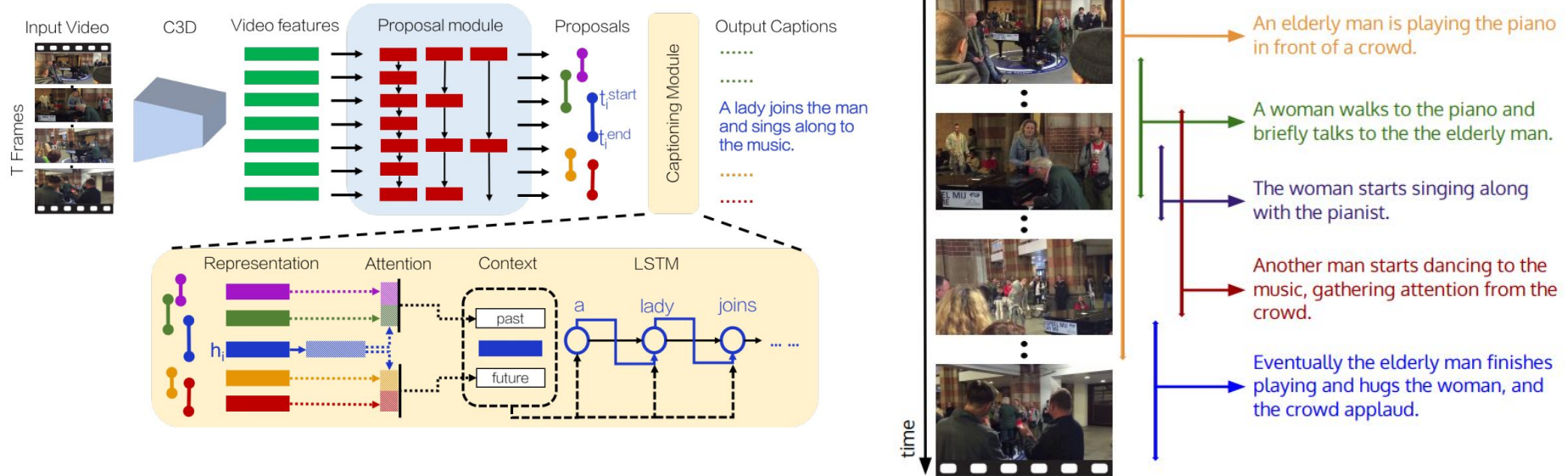
Beyond 2D Object Detection...

Object Detection + Captioning = Dense Captioning



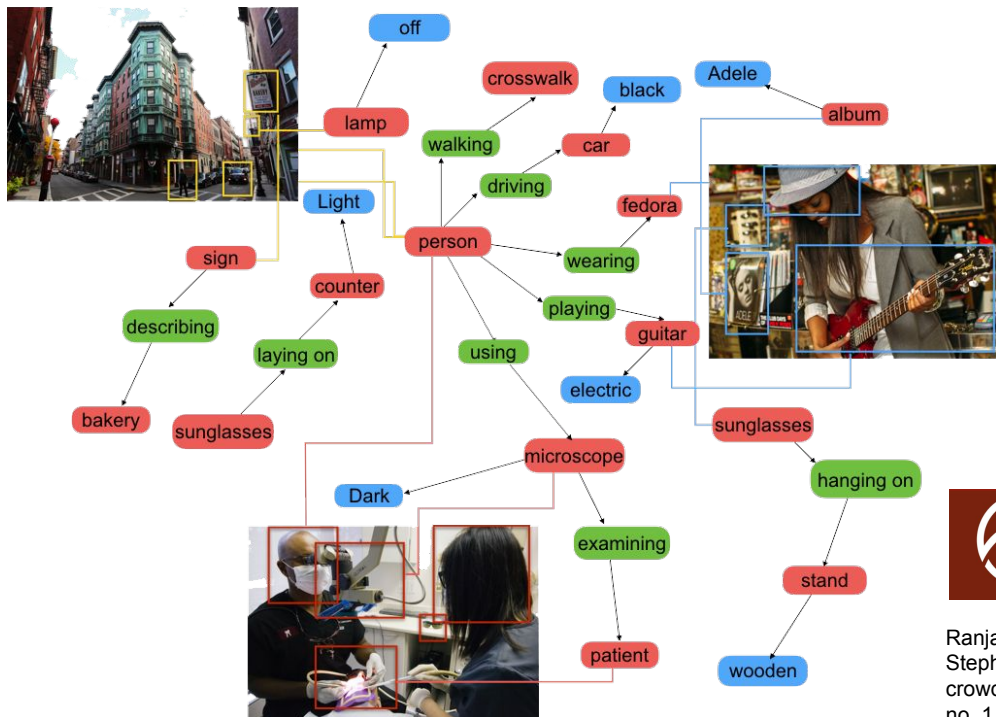
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016
Figure copyright IEEE, 2016. Reproduced for educational purposes.

Dense Video Captioning



Ranjay Krishna et al., "Dense-Captioning Events in Videos", ICCV 2017
Figure copyright IEEE, 2017. Reproduced with permission.

Objects + Relationships = Scene Graphs



108,077 Images

5.4 Million Region Descriptions

1.7 Million Visual Question Answers

3.8 Million Object Instances

2.8 Million Attributes

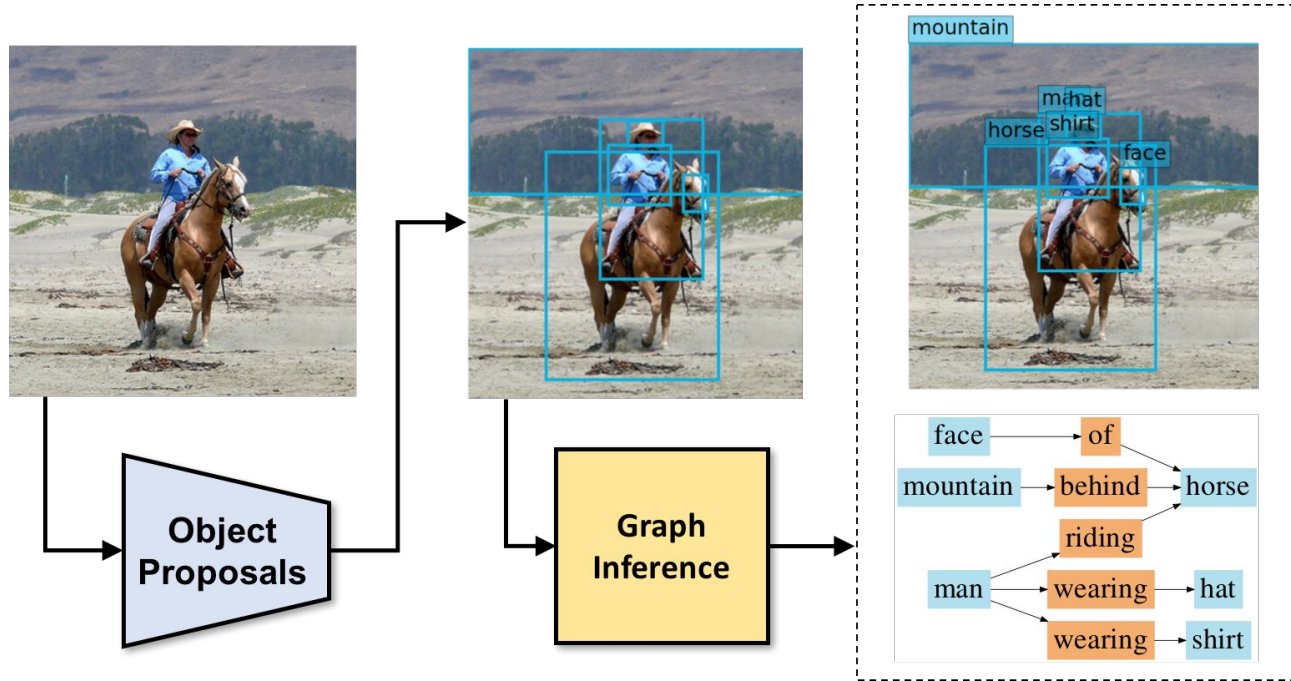
2.3 Million Relationships

Everything Mapped to Wordnet Synsets



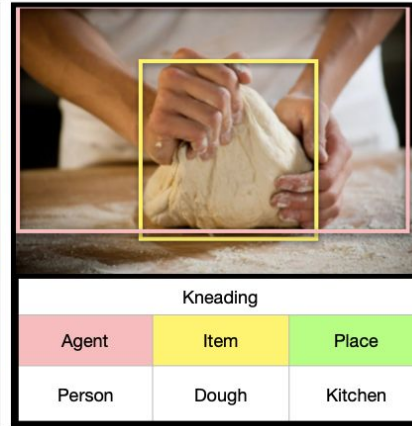
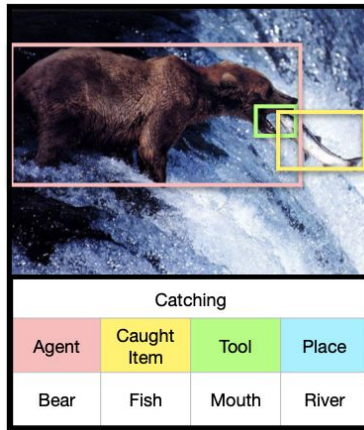
Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "Visual genome: Connecting language and vision using crowdsourced dense image annotations." International Journal of Computer Vision 123, no. 1 (2017): 32-73.

Scene Graph Prediction



Krishna, Lu, Bernstein, and Fei-Fei, "Scene Graph Generation by Iterative Message Passing", ECCV 2016
Figure copyright IEEE, 2018. Reproduced for educational purposes.

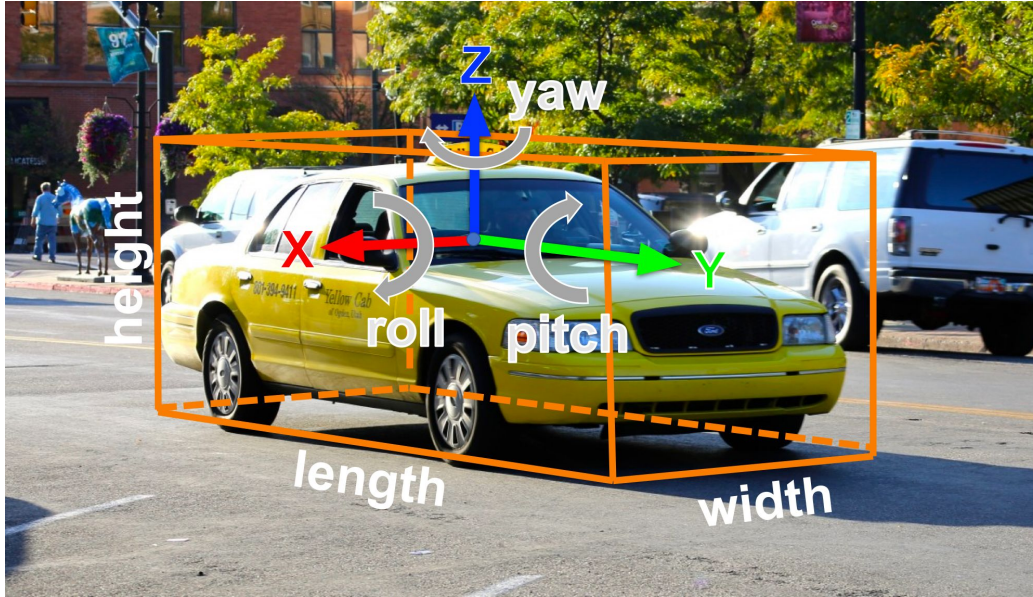
Grounded Situation Recognition



Capture semantic and physical relationships of objects

Tag each image with an action and ground each entity involved in that action

3D Object Detection



2D Object Detection:

2D bounding box

(x, y, w, h)

3D Object Detection:

3D oriented bounding box

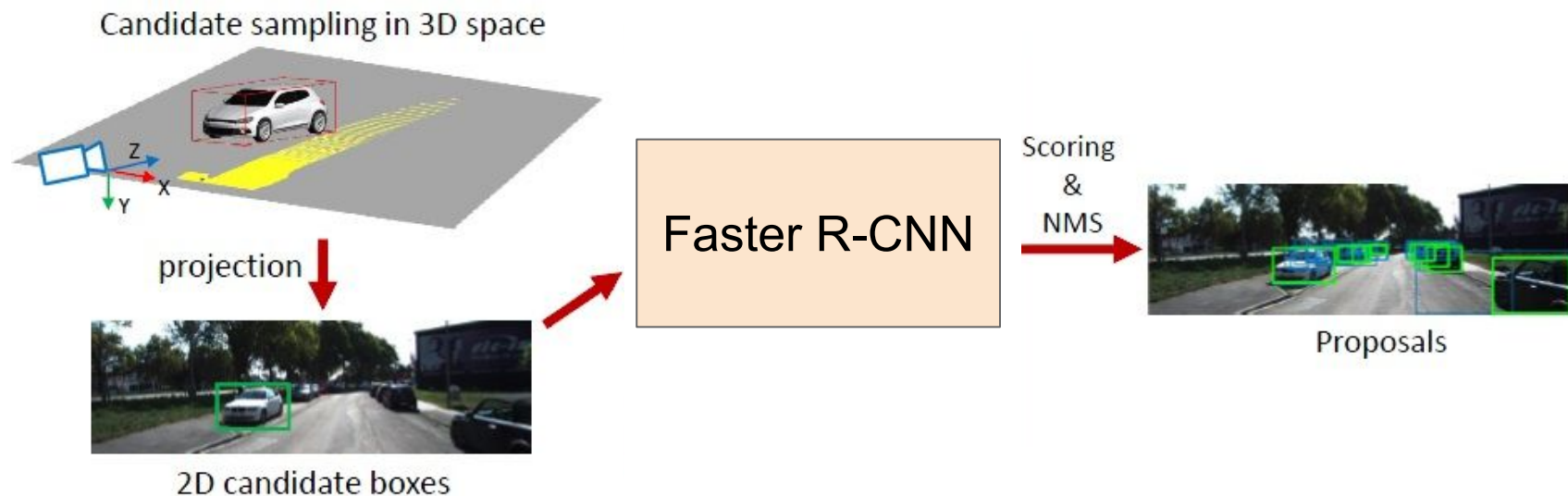
$(x, y, z, w, h, l, r, p, \gamma)$

Simplified bbox: no roll & pitch

Much harder problem than 2D
object detection!

[This image](#) is [CC0 public domain](#)

3D Object Detection: Monocular Camera



- Same idea as Faster RCNN, but proposals are in 3D
- 3D bounding box proposal, regress 3D box parameters + class score

Chen, Xiaozi, Kaustav Kundu, Ziyu Zhang, Huimin Ma, Sanja Fidler, and Raquel Urtasun. "Monocular 3d object detection for autonomous driving." CVPR 2016.

Recap: Lots of computer vision tasks!

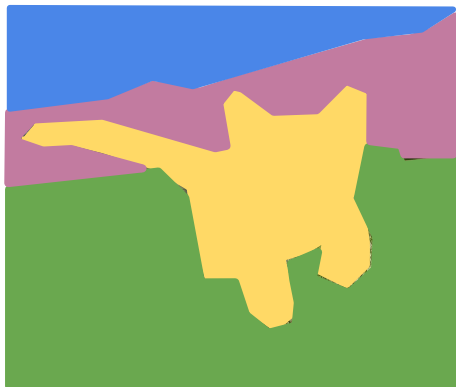
Classification



CAT

No spatial extent

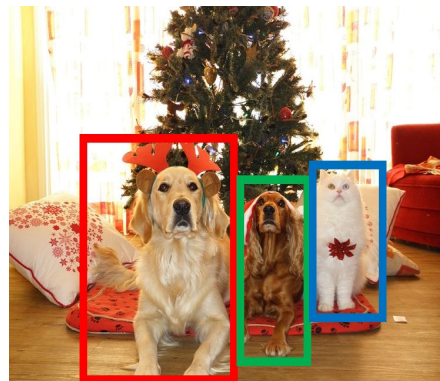
Semantic Segmentation



GRASS, **CAT**,
TREE, **SKY**

No objects, just pixels

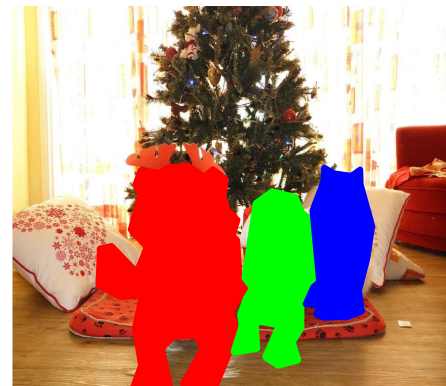
Object Detection



DOG, **DOG**, **CAT**

Multiple Object

Instance Segmentation

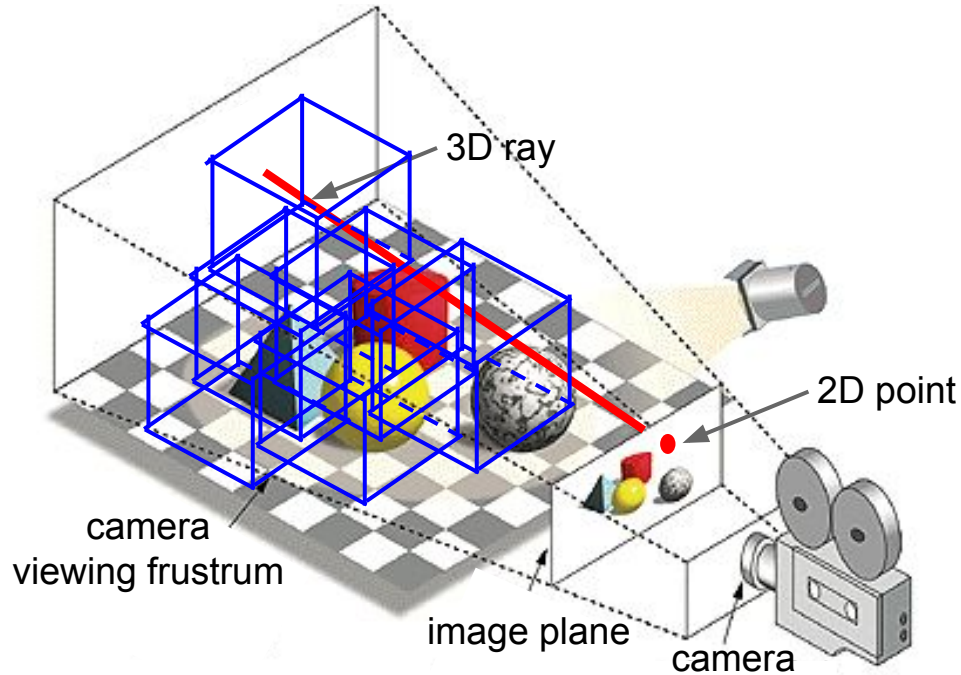


DOG, **DOG**, **CAT**

[This image is CC0 public domain](#)

Next time:
Self-Supervised

3D Object Detection: Simple Camera Model



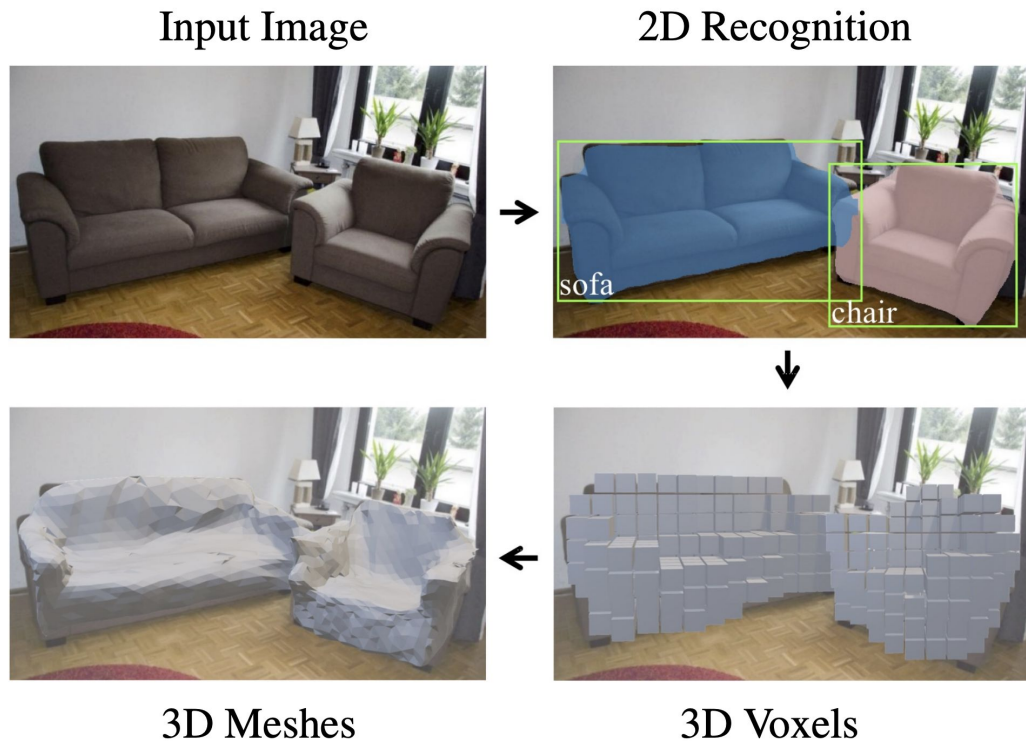
A point on the image plane corresponds to a **ray** in the 3D space

A 2D bounding box on an image is a **frustrum** in the 3D space

Localize an object in 3D:
The object can be anywhere in the **camera viewing frustrum**!

Image source: https://www.pcmag.com/encyclopedia_images/_FRUSTUM.GIF

3D Shape Prediction: Mesh R-CNN



Gkioxari et al., Mesh RCNN, ICCV 2019