

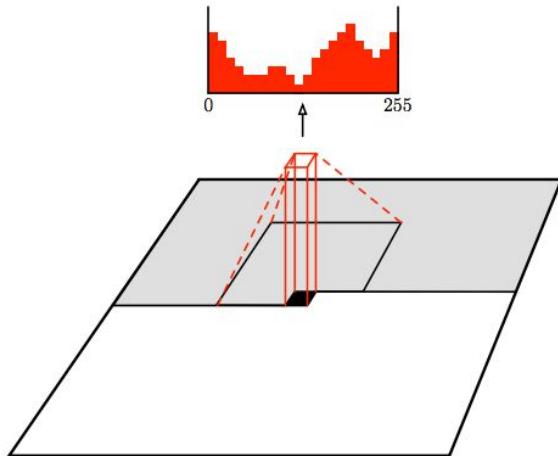
Lecture 12: Detection and Segmentation

Administrative

- Project Milestone due tomorrow 5/20
- Midterm grades will be out soon

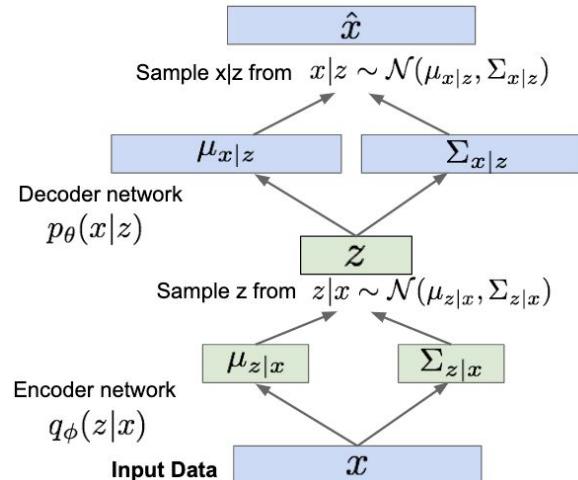
Last Time: Generative Models

Autoregressive models:
PixelRNN, PixelCNN



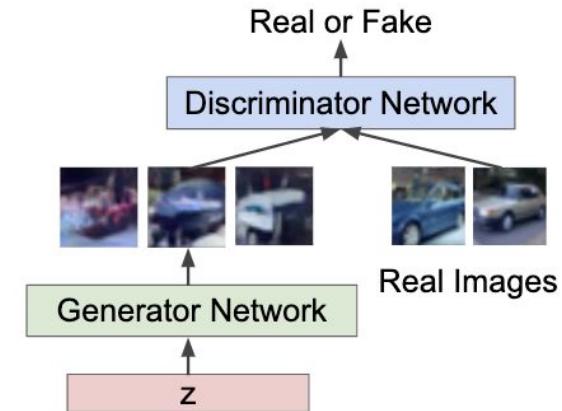
Van der Oord et al, "Conditional image generation with pixelCNN decoders", NIPS 2016

Variational Autoencoders



Kingma and Welling, "Auto-encoding variational bayes", ICLR 2013

Generative Adversarial Networks (GANs)



Goodfellow et al, "Generative Adversarial Nets", NIPS 2014

Today: Segmentation, Detection

Computer Vision Tasks

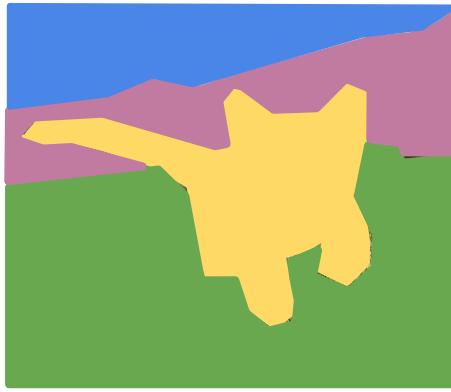
Classification



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

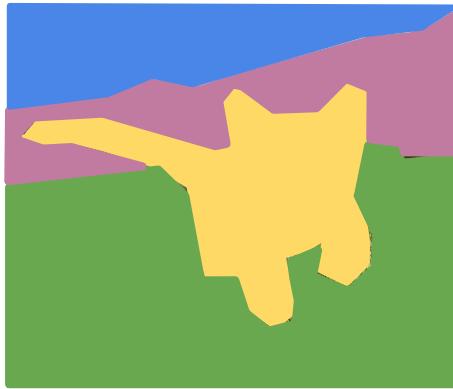
Classification



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Semantic Segmentation



GRASS, CAT,
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No objects, just pixels

Object
Detection



Instance
Segmentation



DOG, DOG, CAT

Multiple Object

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



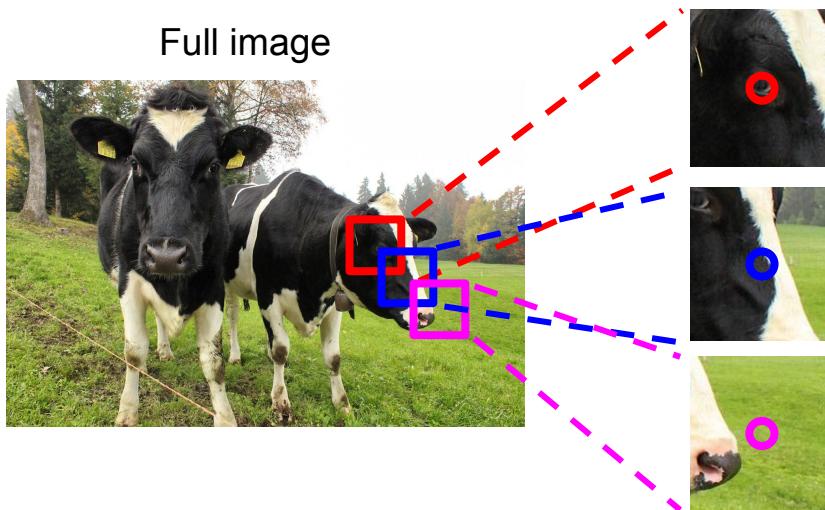
?



Impossible to classify without context

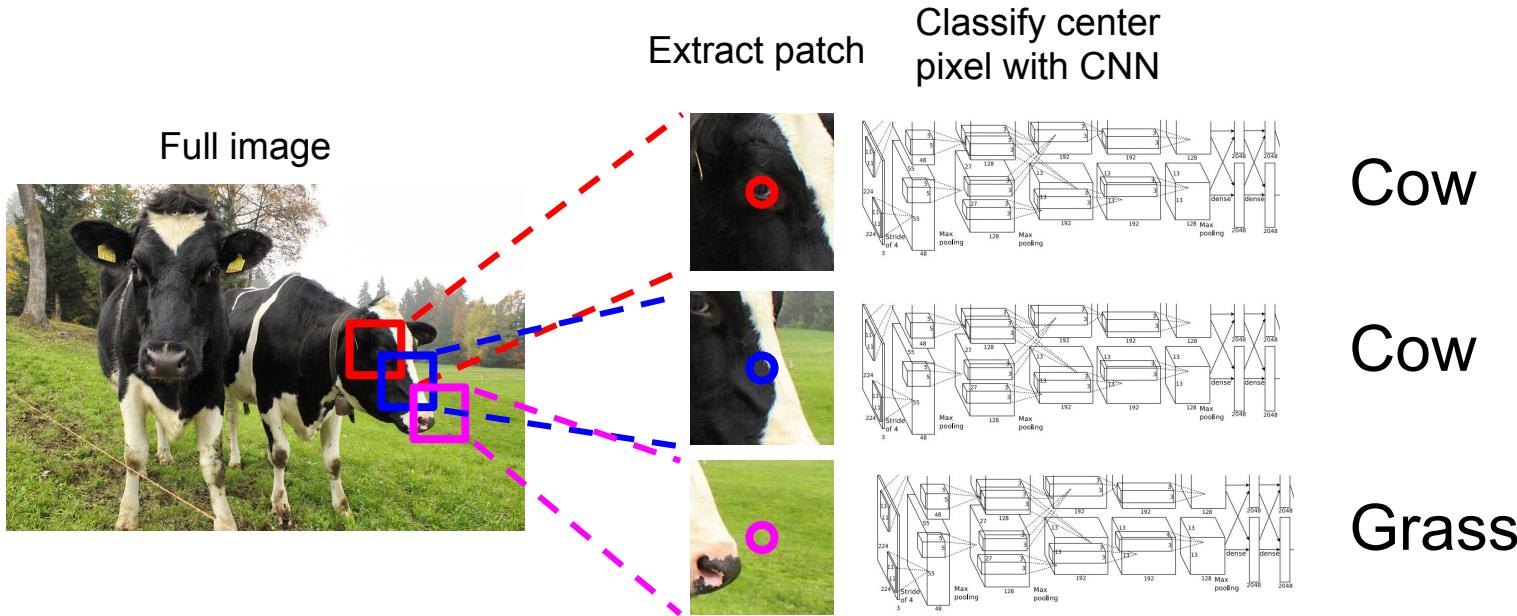
Q: how do we include context?

Semantic Segmentation Idea: Sliding Window



Q: how do we model this?

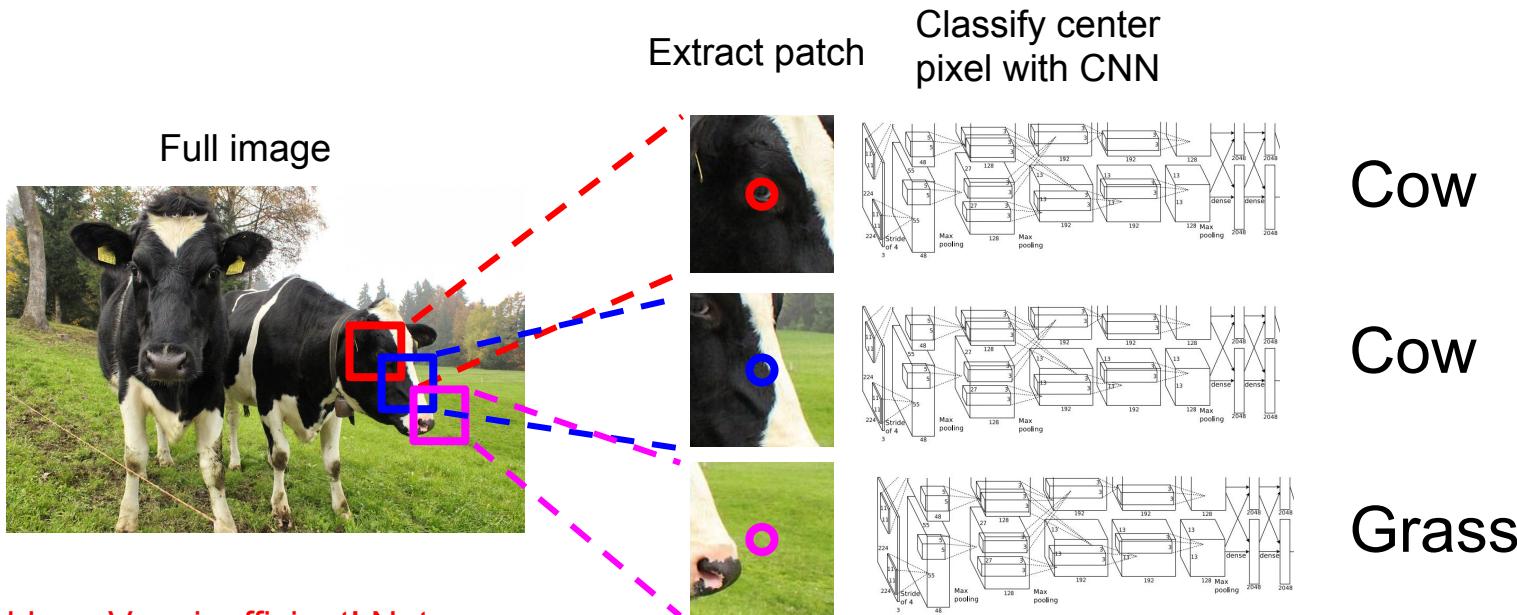
Semantic Segmentation Idea: Sliding Window



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

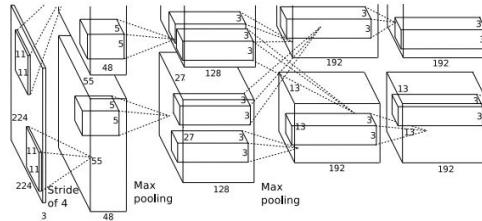


Problem: Very inefficient! Not reusing shared features between overlapping patches

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

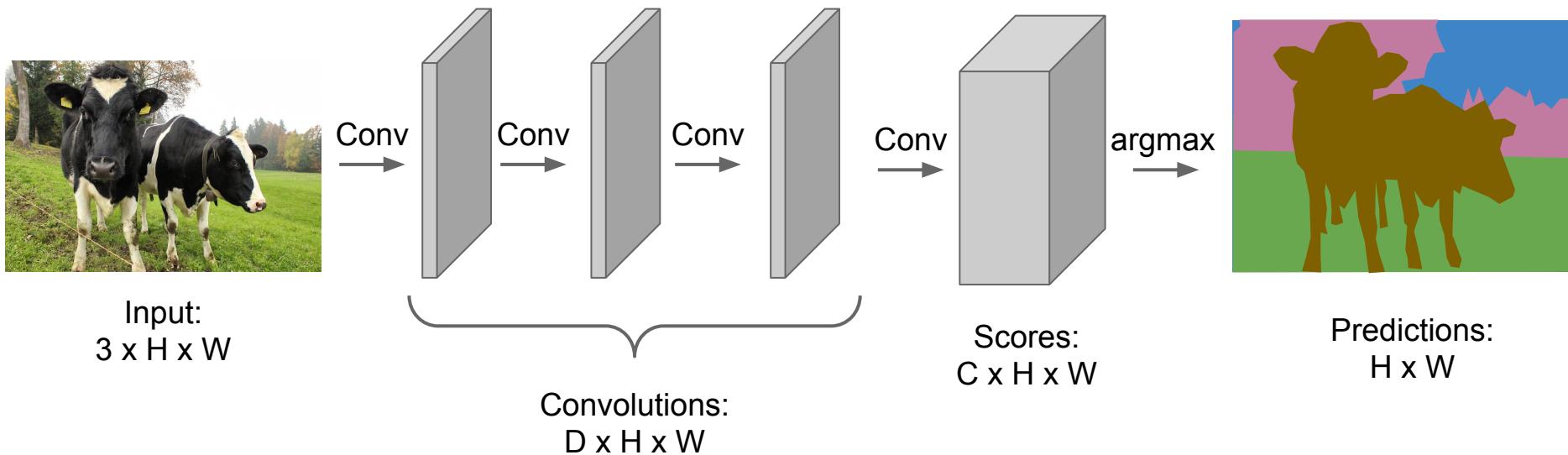


An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

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.

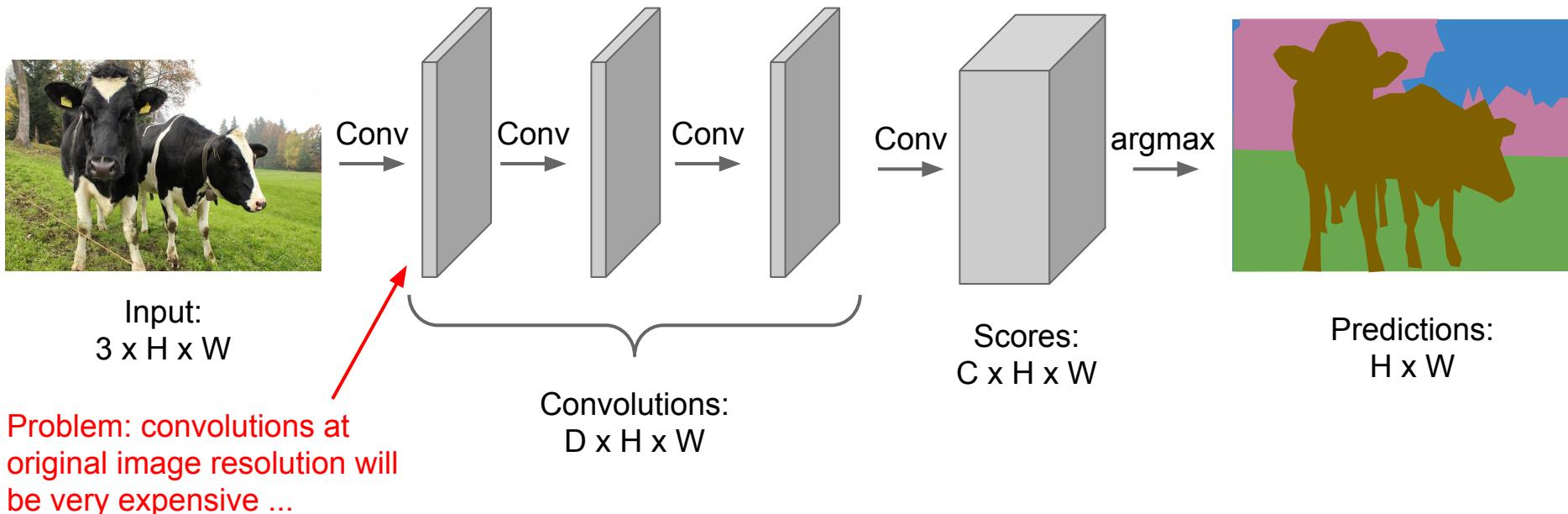
Semantic Segmentation Idea: Fully Convolutional

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!

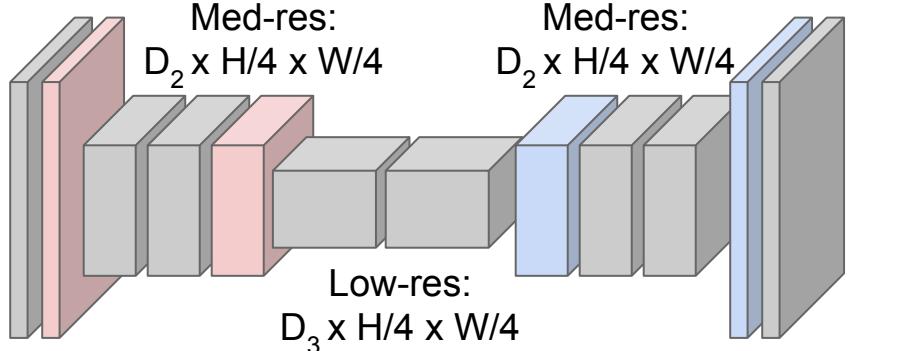


Semantic Segmentation Idea: Fully Convolutional

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



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

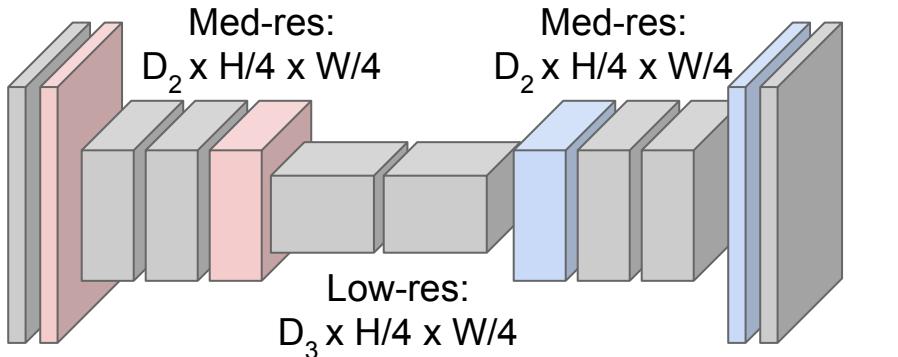
Downsampling:
Pooling, strided
convolution



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

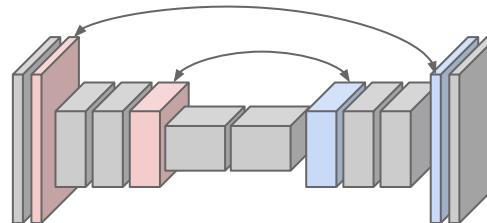
1	2
3	4

Rest of the network

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

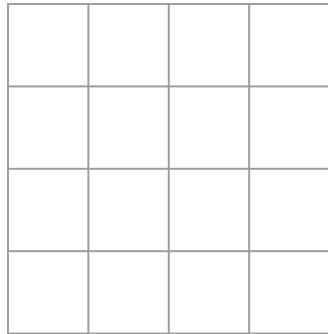
Output: 4 x 4

Corresponding pairs of
downsampling and
upsampling layers

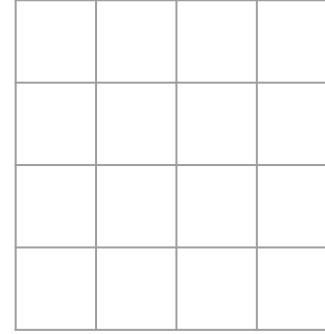


Learnable Upsampling: Transpose Convolution

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



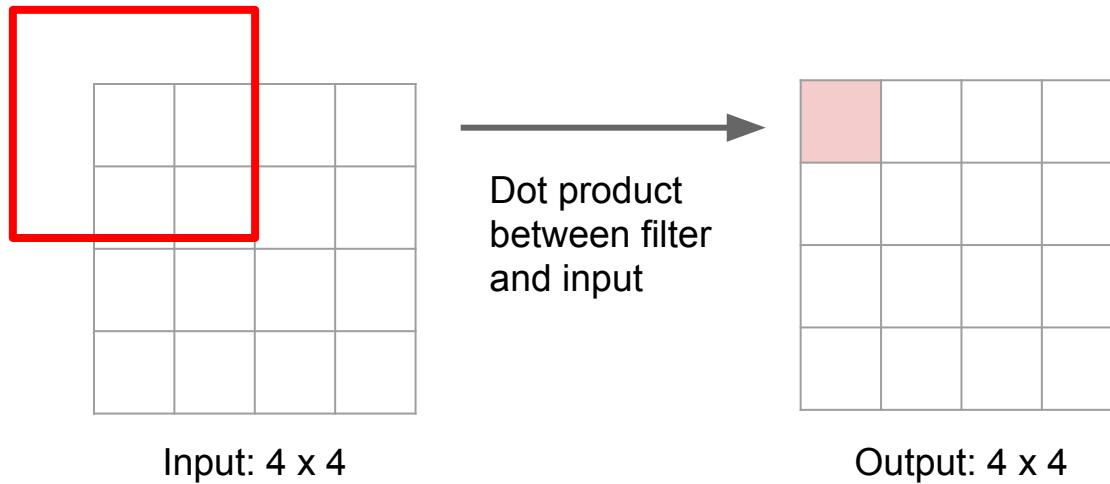
Input: 4×4



Output: 4×4

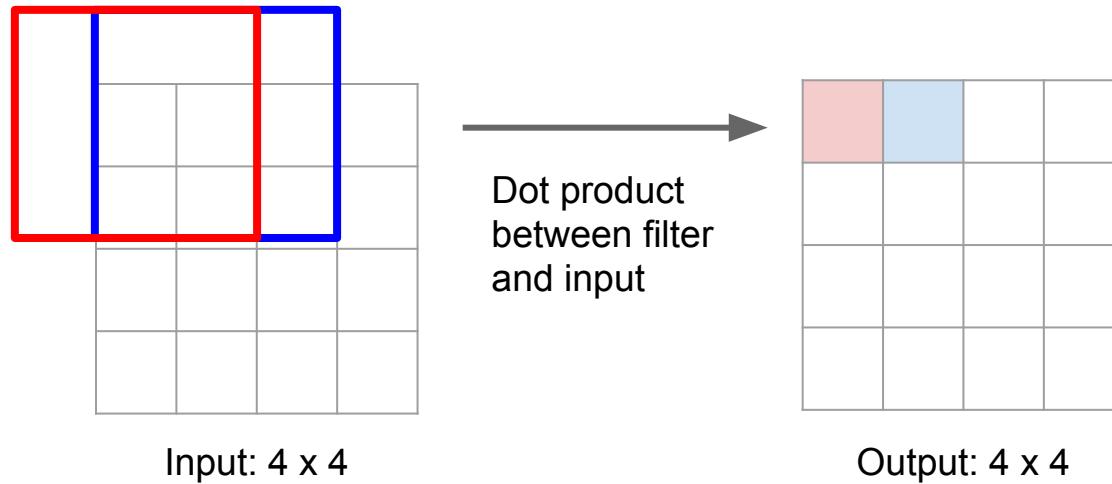
Learnable Upsampling: Transpose Convolution

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



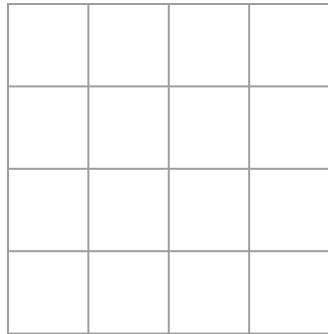
Learnable Upsampling: Transpose Convolution

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

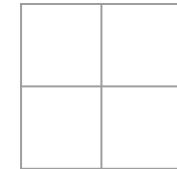


Learnable Upsampling: Transpose Convolution

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



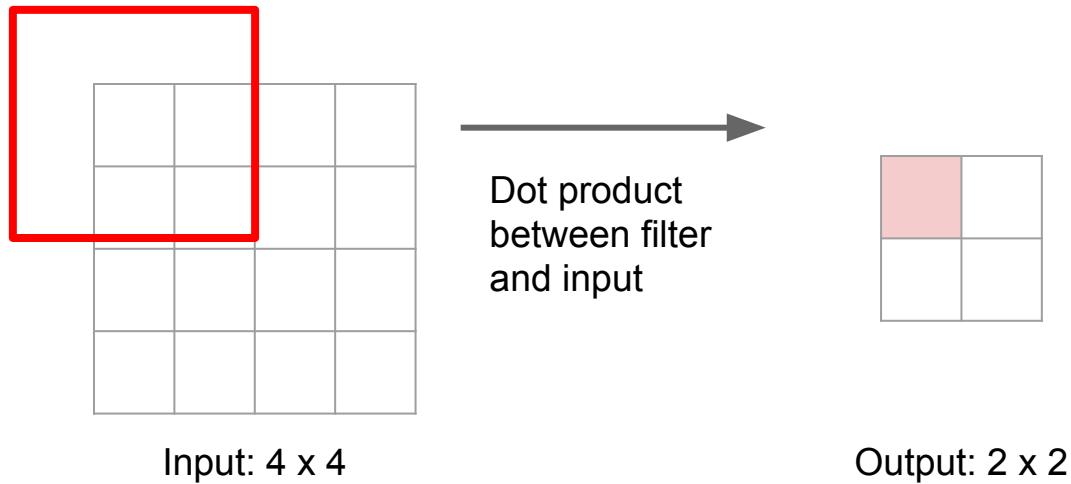
Input: 4×4



Output: 2×2

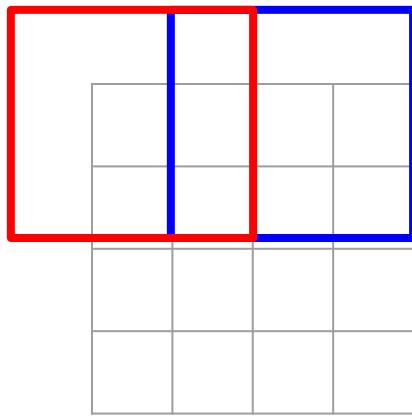
Learnable Upsampling: Transpose Convolution

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

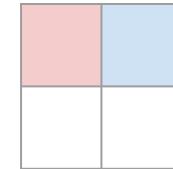


Learnable Upsampling: Transpose Convolution

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



Dot product
between filter
and input



Output: 2×2

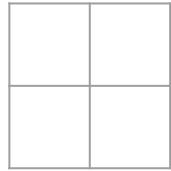
Filter moves 2 pixels in
the input for every one
pixel in the output

Stride gives ratio between
movement in input and
output

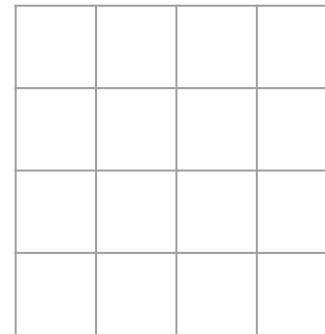
We can interpret strided
convolution as “learnable
downsampling”.

Learnable Upsampling: Transpose Convolution

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



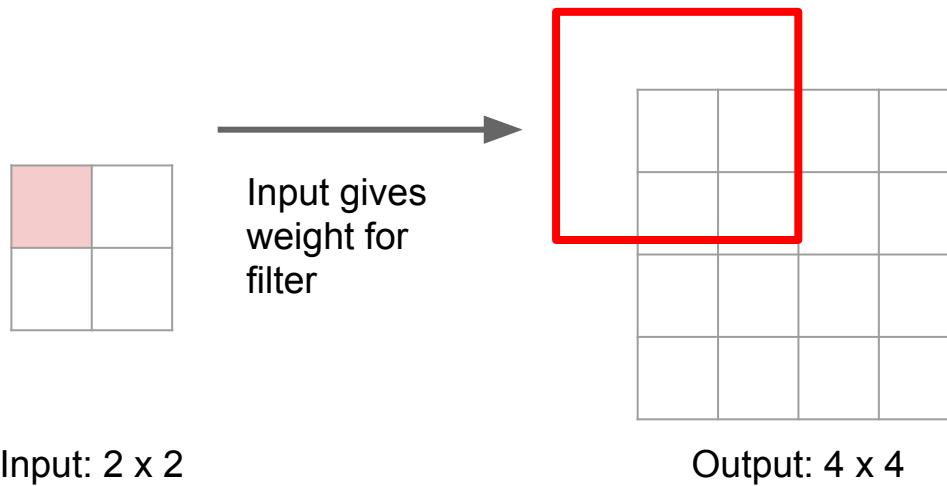
Input: 2×2



Output: 4×4

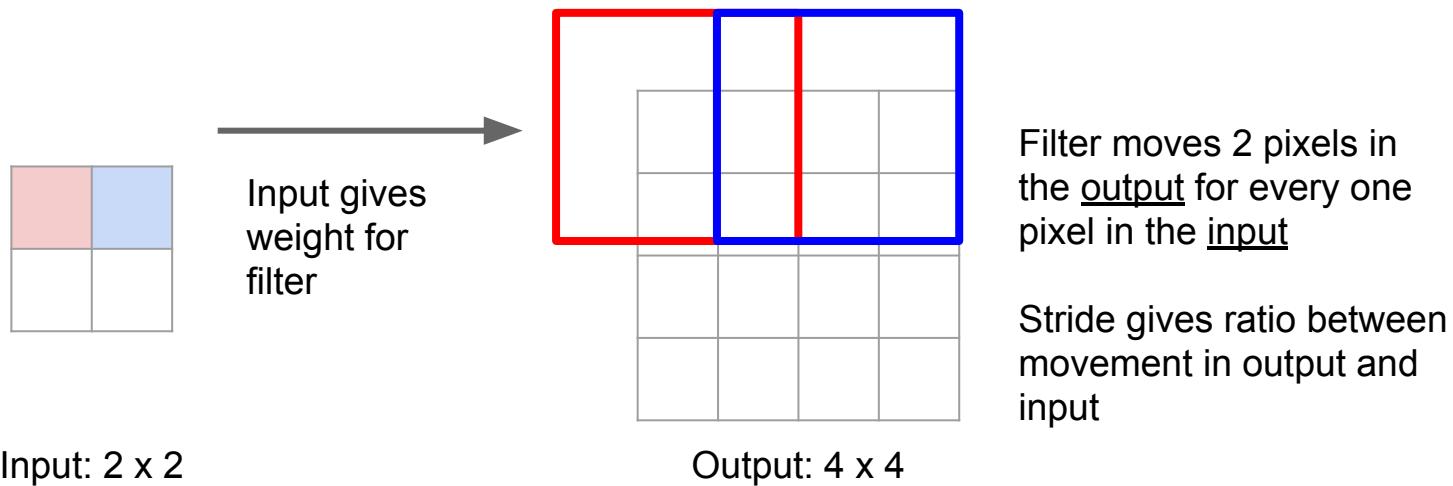
Learnable Upsampling: Transpose Convolution

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

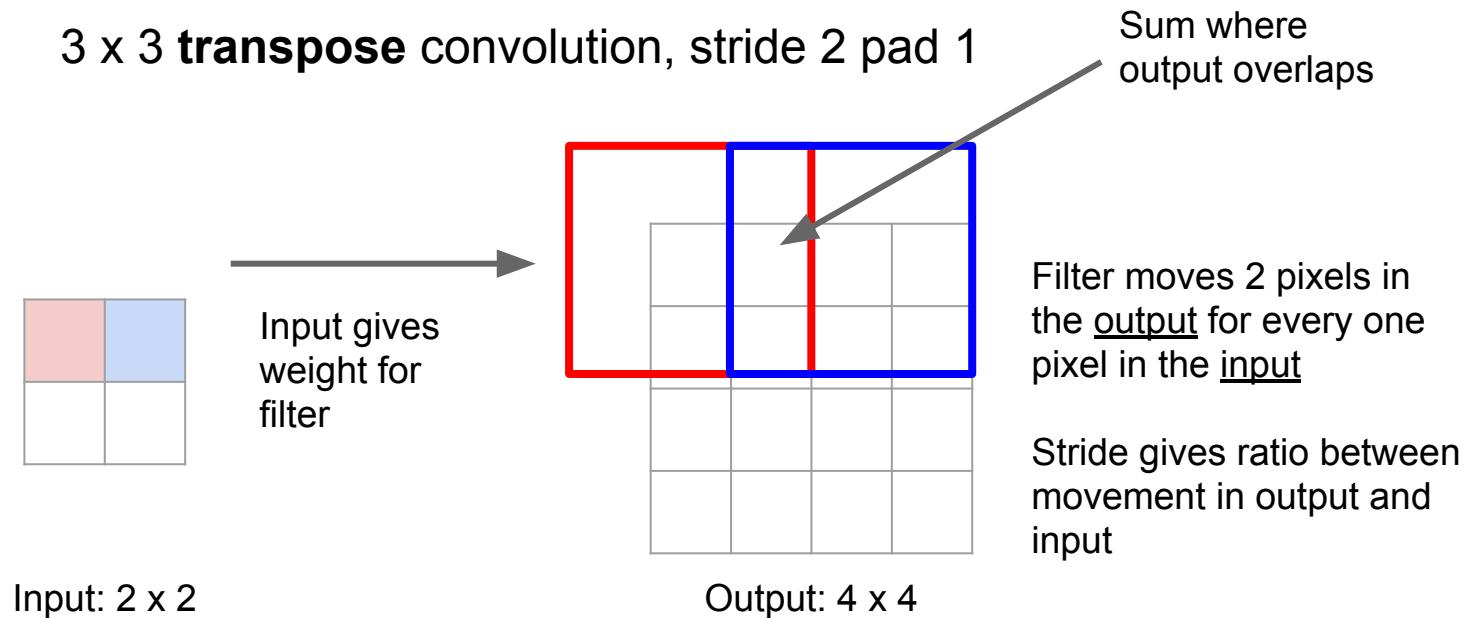


Learnable Upsampling: Transpose Convolution

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



Learnable Upsampling: Transpose Convolution

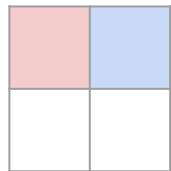


Learnable Upsampling: Transpose Convolution

Other names:

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

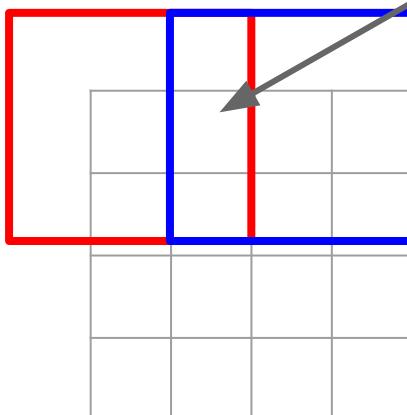
Q: Why is it called transpose convolution?



Input: 2 x 2

3 x 3 transpose convolution, stride 2 pad 1

Input gives weight for filter



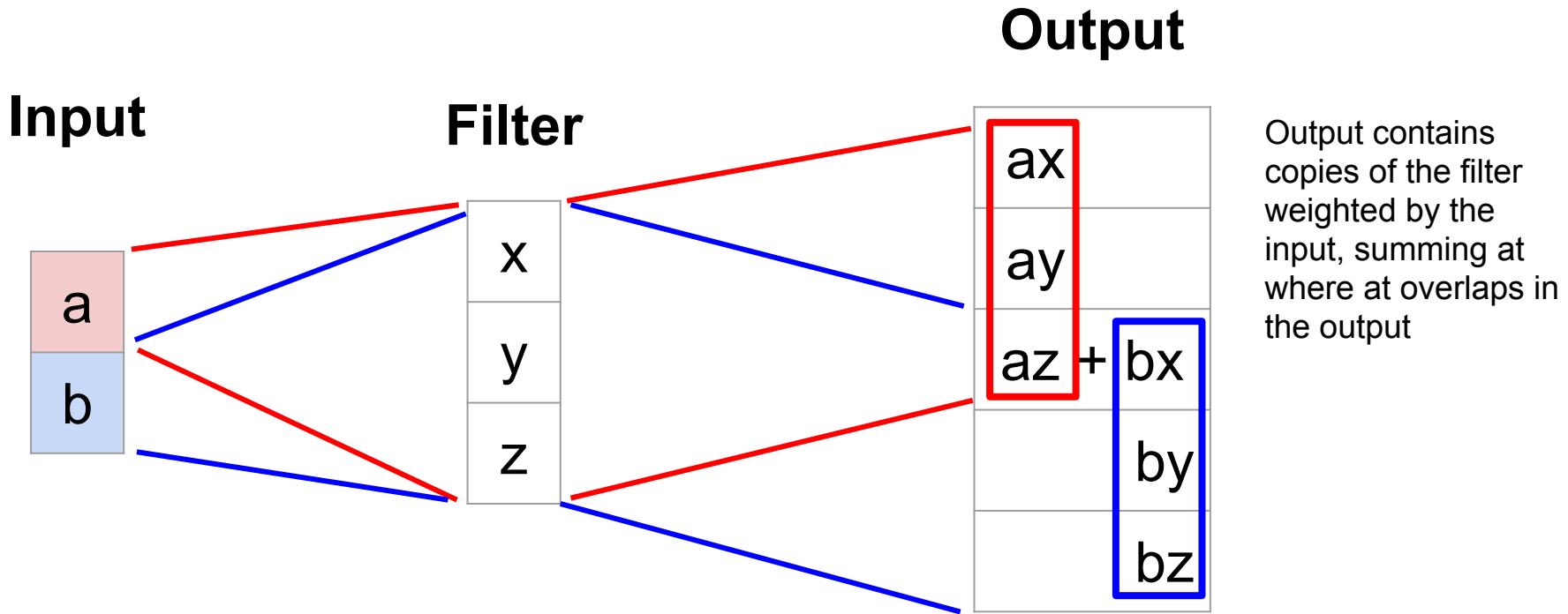
Output: 4 x 4

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

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

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

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

Convolution as Matrix Multiplication (1D Example)

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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

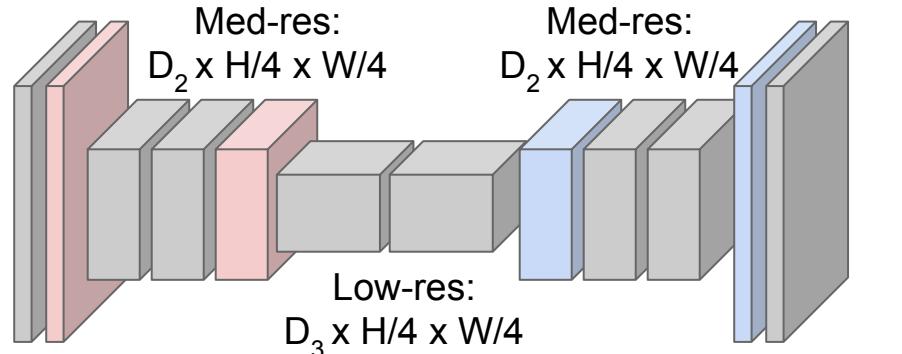
Semantic Segmentation Idea: Fully Convolutional

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!



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

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

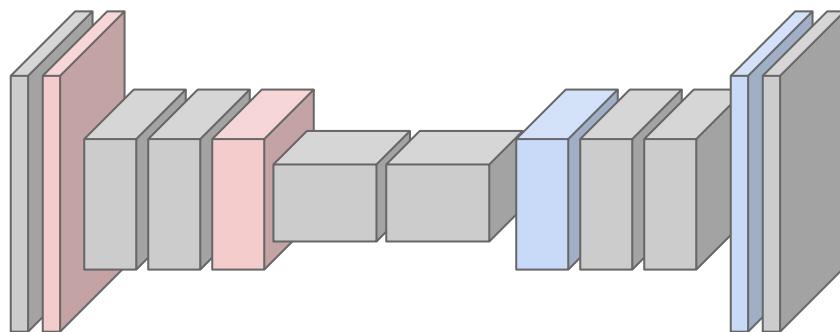
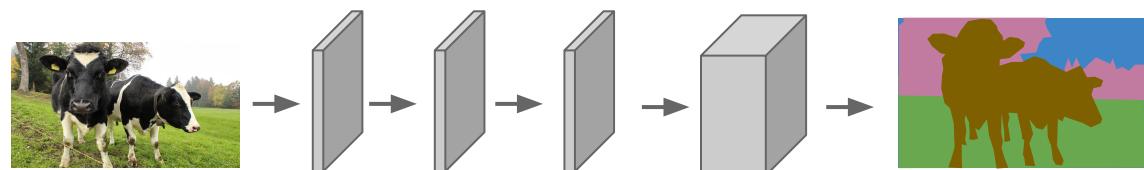
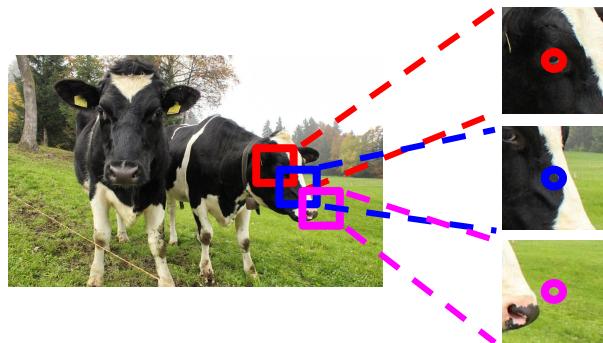
Upsampling:
Unpooling or strided transpose convolution



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

Semantic Segmentation: Summary



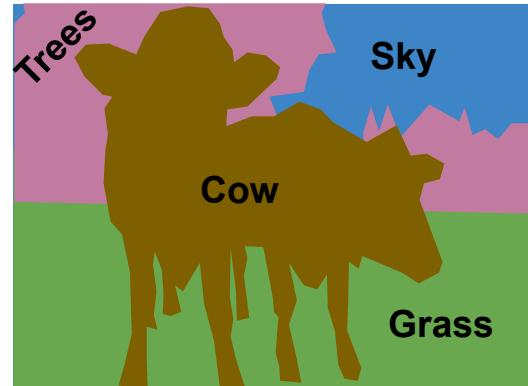
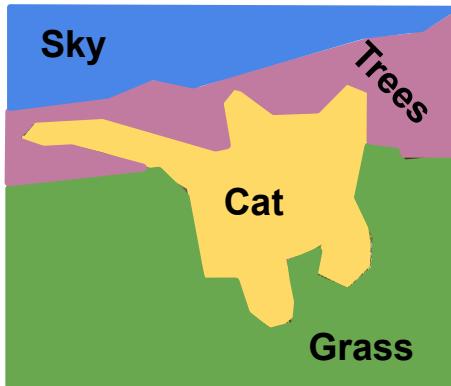
Semantic Segmentation

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

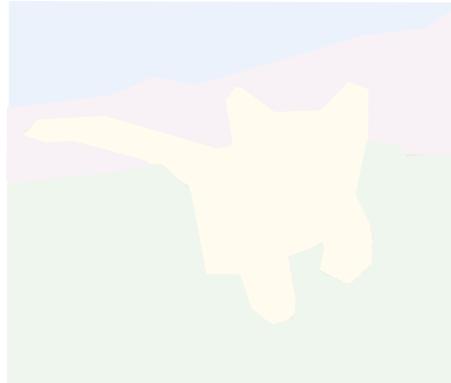
Classification



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

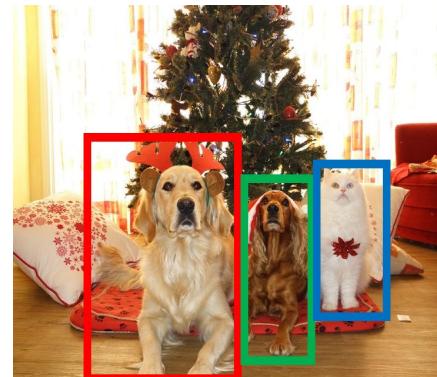
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Object
Detection



DOG, DOG, CAT

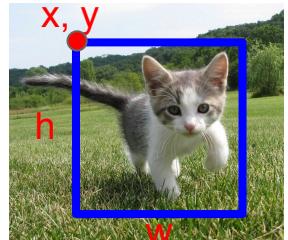
Multiple Object

Instance
Segmentation

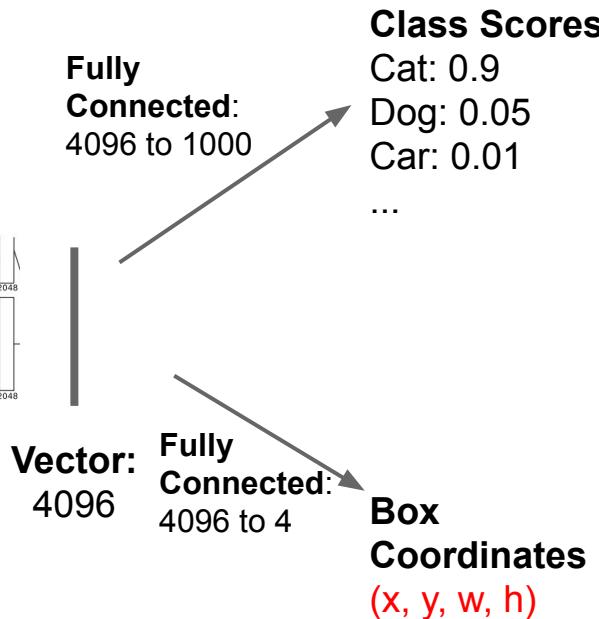
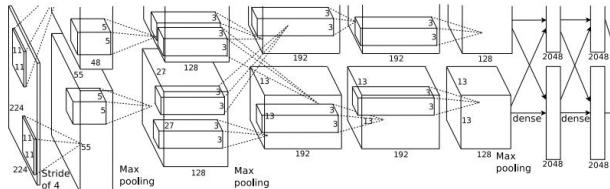


DOG, DOG, CAT

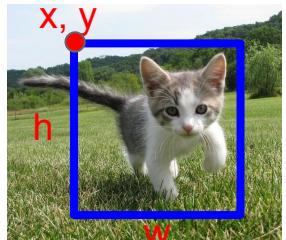
Object Detection: Single Object (Classification + Localization)



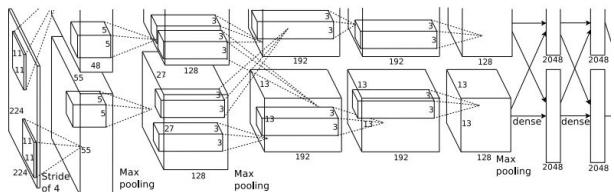
This image is CC0 public domain



Object Detection: Single Object (Classification + Localization)



This image is CC0 public domain



Fully
Connected:
4096 to 1000

Vector:
Fully
Connected:
4096 to 4

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

Correct label:
Cat

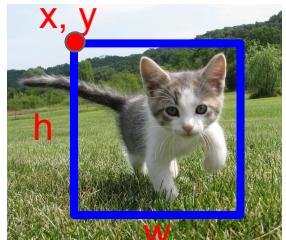
Softmax
Loss

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

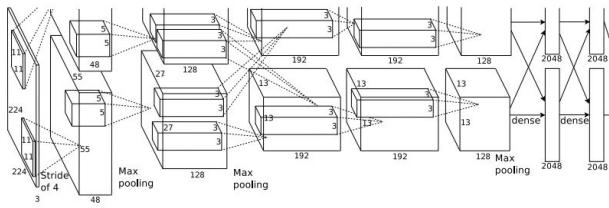
Correct box:
(x' , y' , w' , h')

Treat localization as a
regression problem!

Object Detection: Single Object (Classification + Localization)



This image is CC0 public domain



Fully
Connected:
4096 to 1000

Vector:
Fully
Connected:
4096 to 4

Treat localization as a
regression problem!

Multitask Loss

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

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

Correct label:
Cat

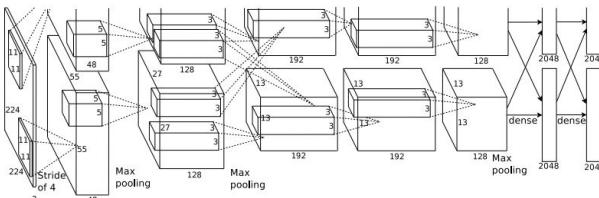
Softmax
Loss

+

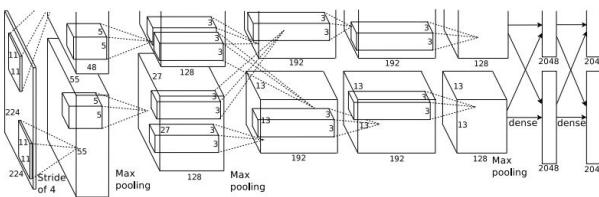
Loss

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

Object Detection: Multiple Objects



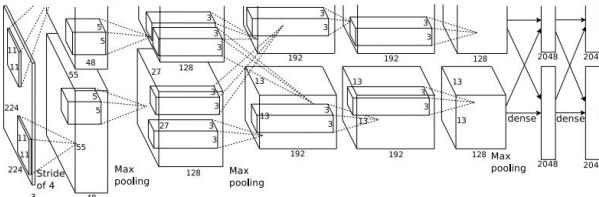
CAT: (x, y, w, h)



DOG: (x, y, w, h)

DOG: (x, y, w, h)

CAT: (x, y, w, h)



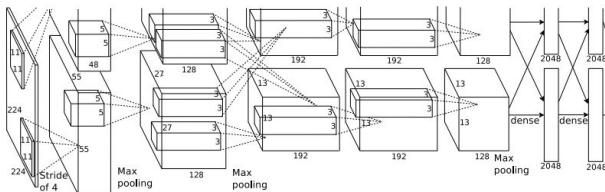
DUCK: (x, y, w, h)

DUCK: (x, y, w, h)

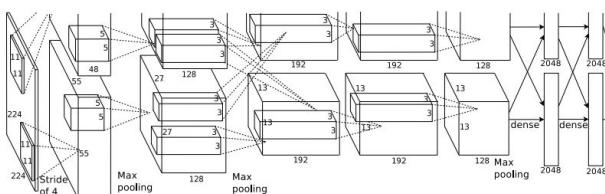
...

Object Detection: Multiple Objects

Each image needs a different number of outputs!

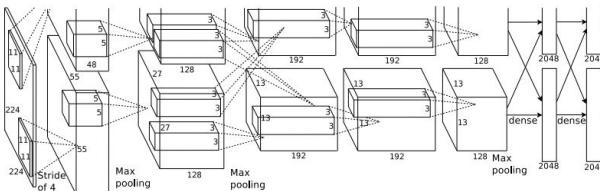


CAT: (x, y, w, h) 4 numbers



DOG: (x, y, w, h)
DOG: (x, y, w, h) 12 numbers

CAT: (x, y, w, h)

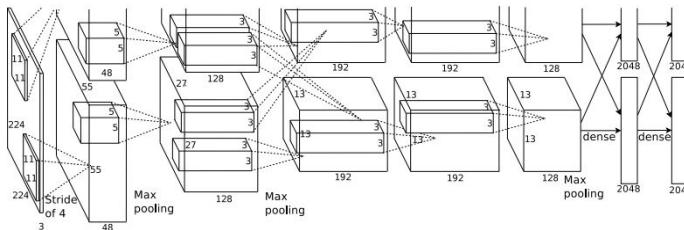


DUCK: (x, y, w, h) Many
DUCK: (x, y, w, h) numbers!

...

Object Detection: Multiple Objects

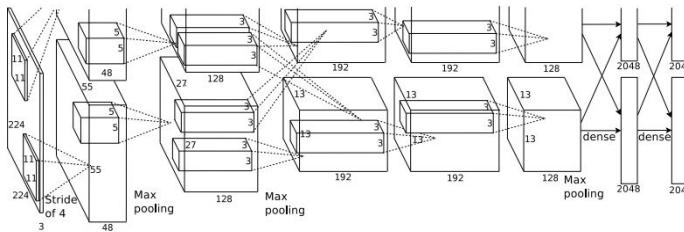
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection: Multiple Objects

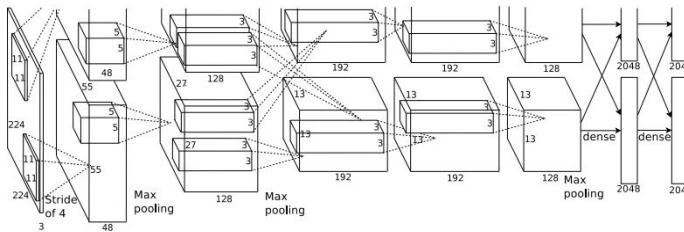
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Dog? YES
Cat? NO
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Object Detection: Multiple Objects

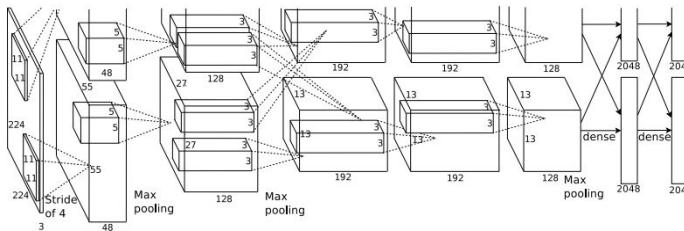
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



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

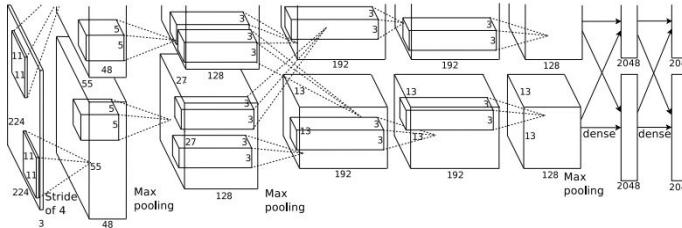
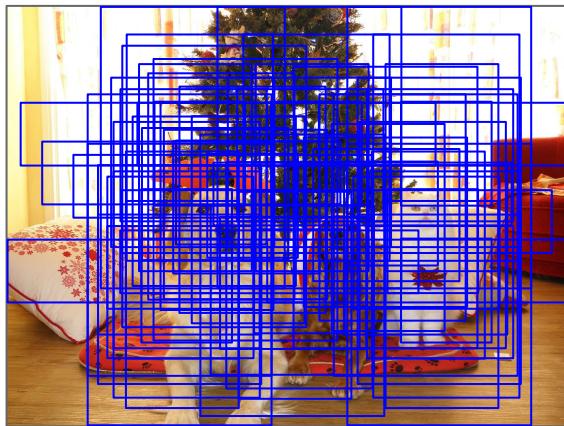


Dog? NO
Cat? YES
Background? NO

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

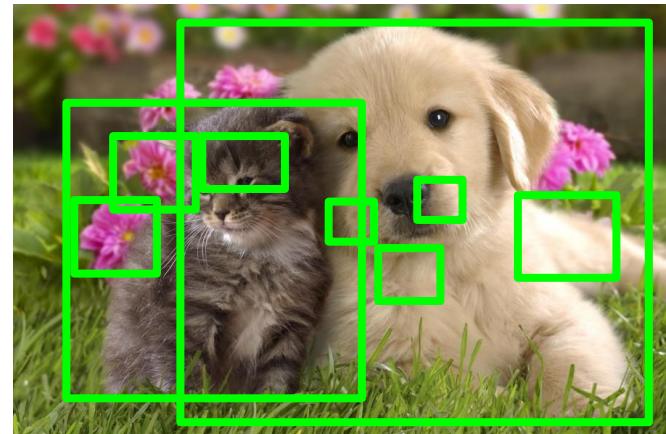


Dog? NO
Cat? YES
Background? NO

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



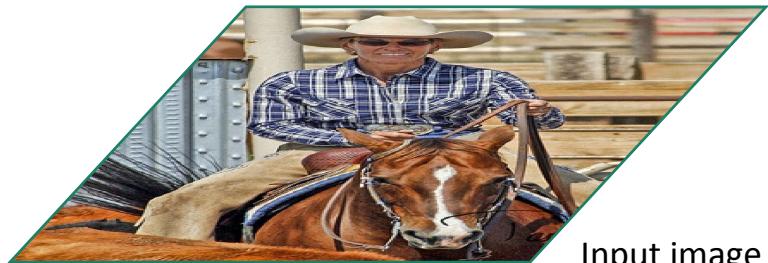
Alexe et al, "Measuring the objectness of image windows", TPAMI 2012

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.

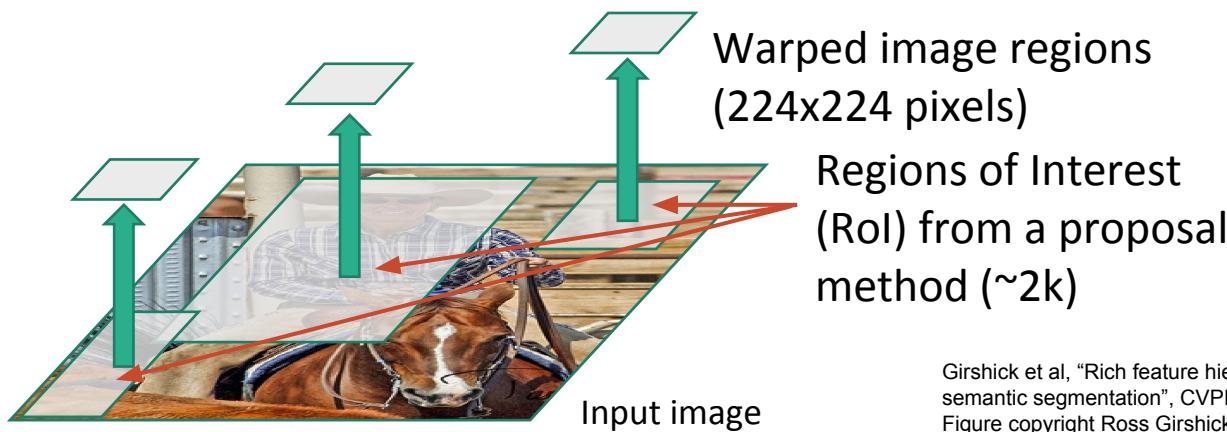
R-CNN



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.

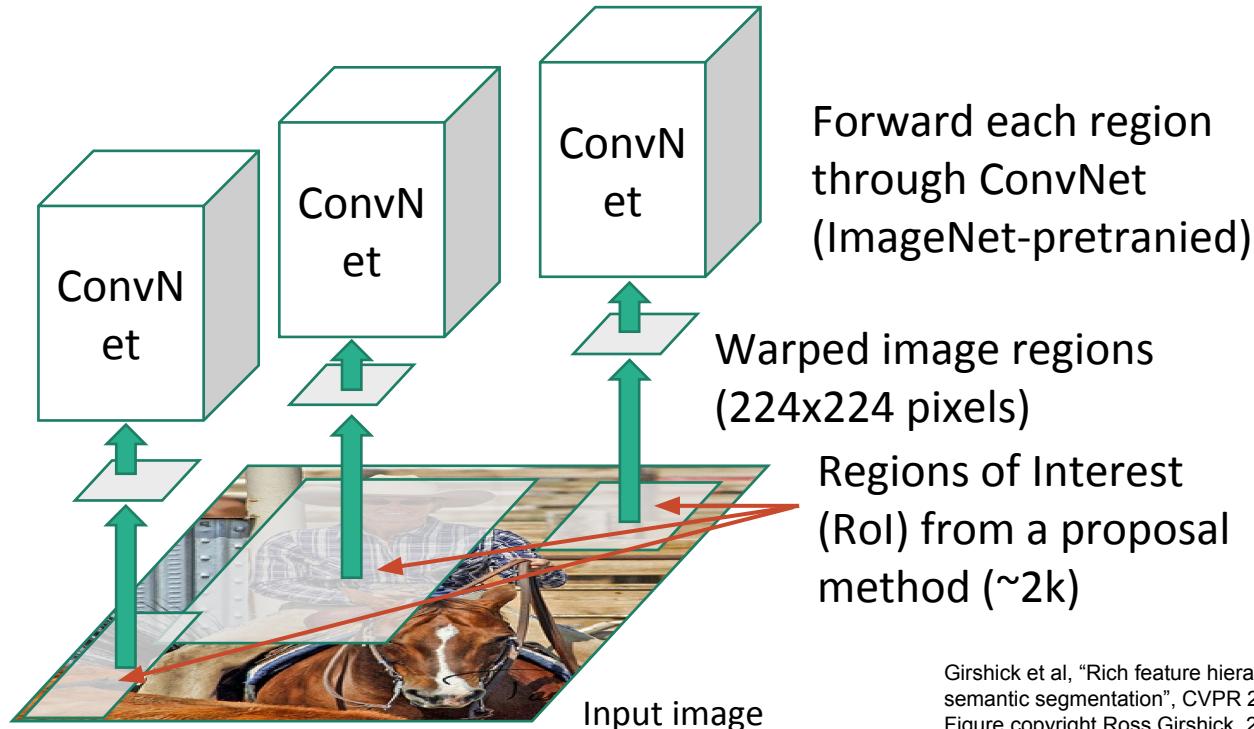
R-CNN



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

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

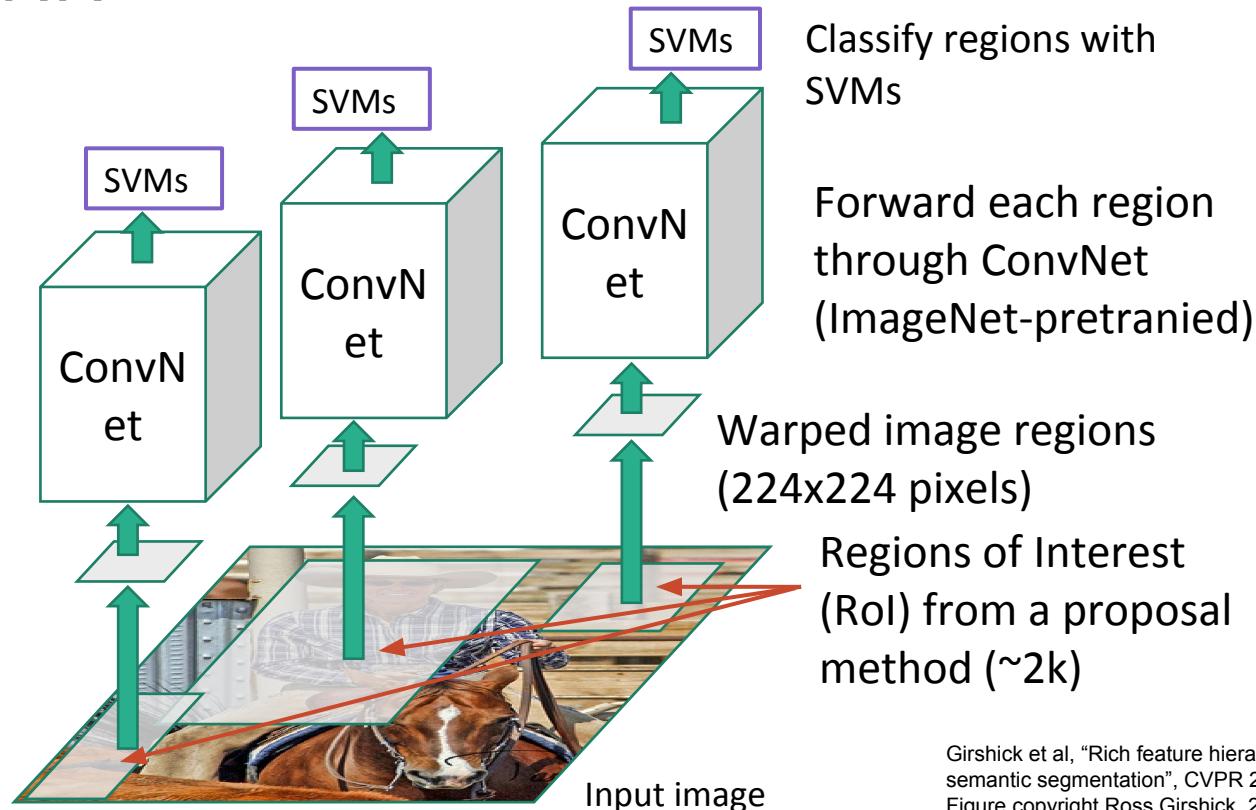
R-CNN



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

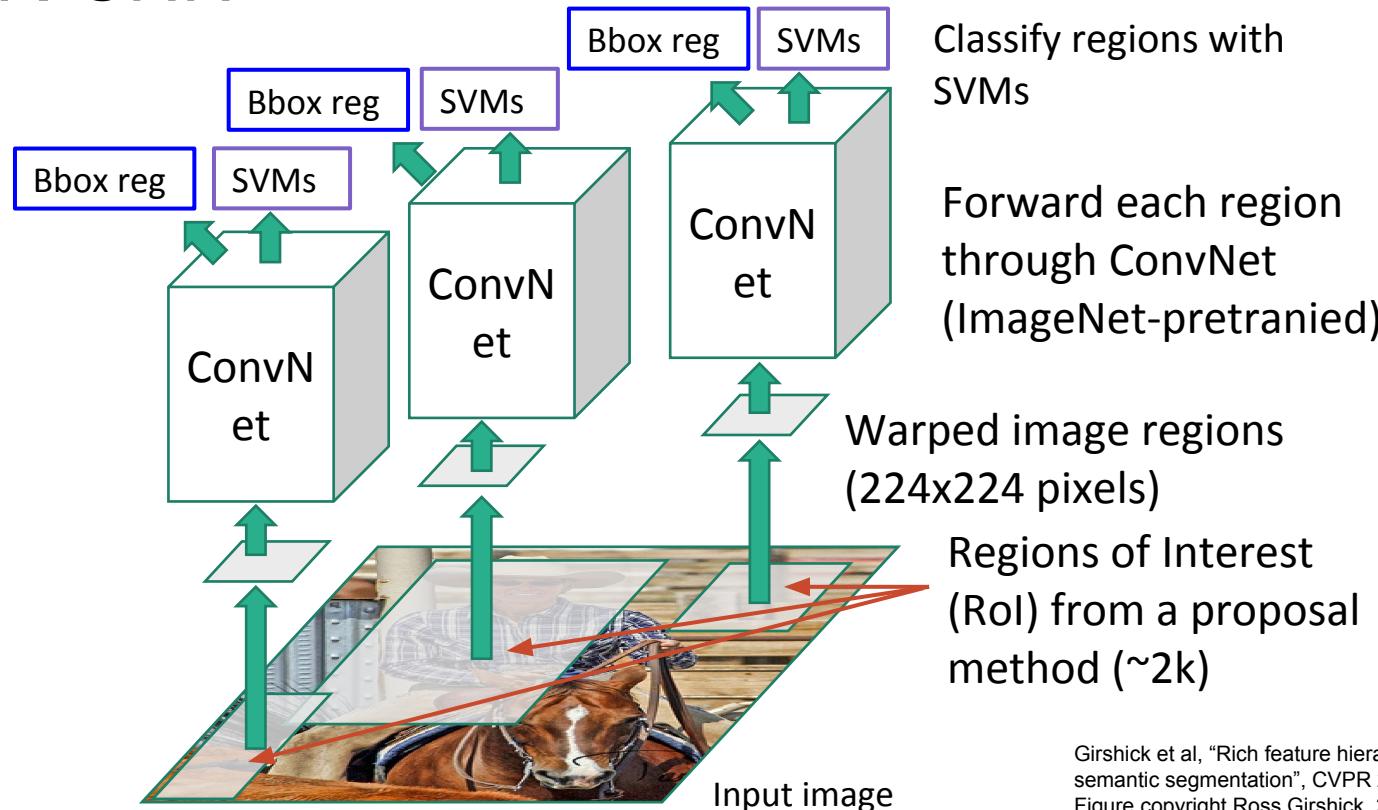


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

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

R-CNN

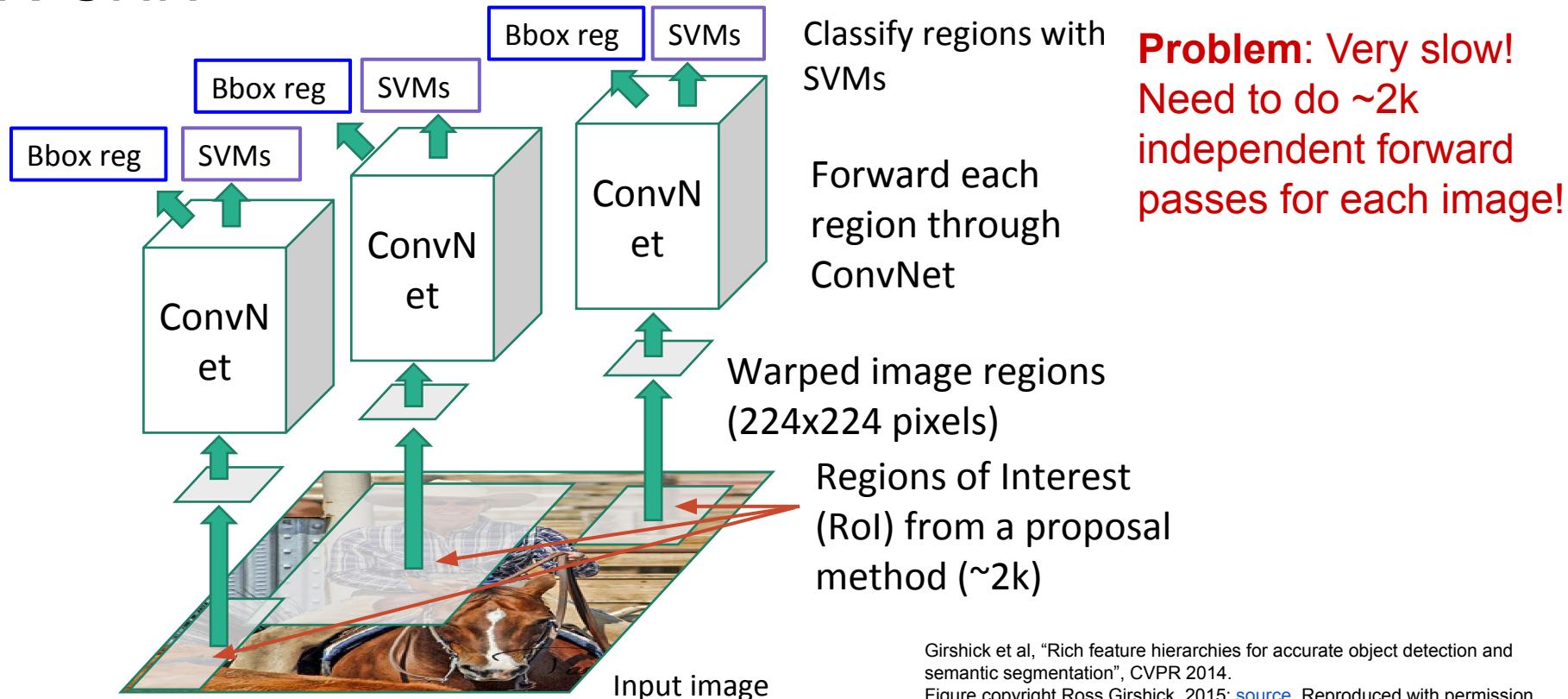
Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)



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)

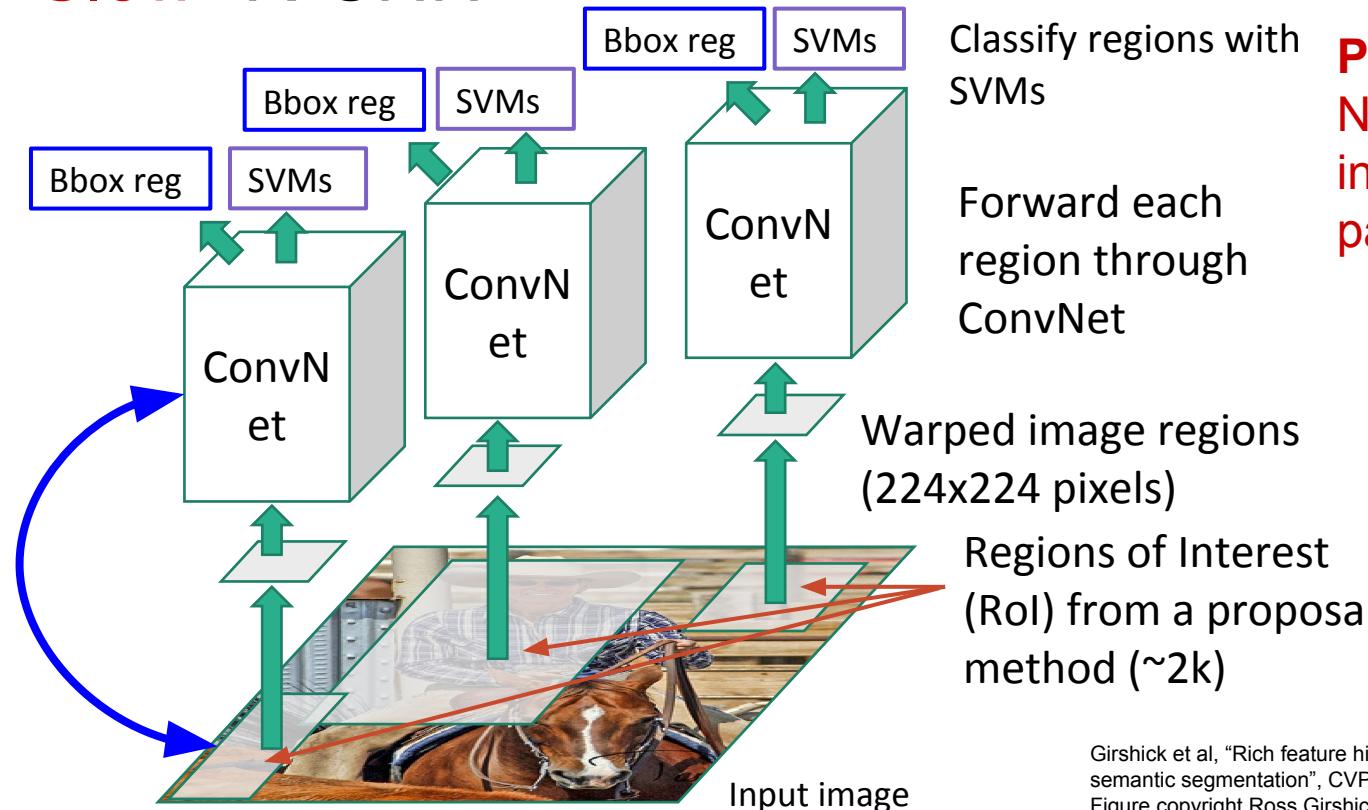


Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

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.

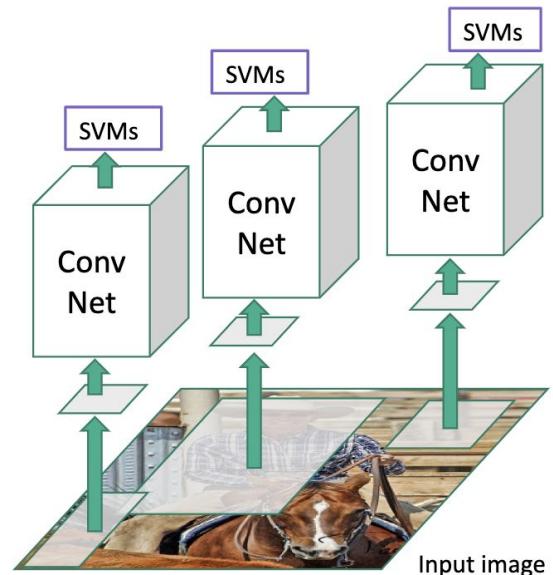
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



Input image

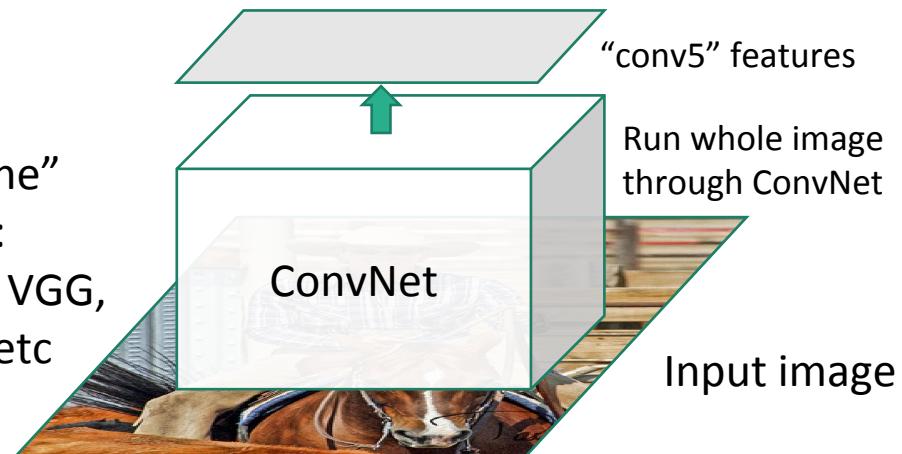
“Slow” R-CNN



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

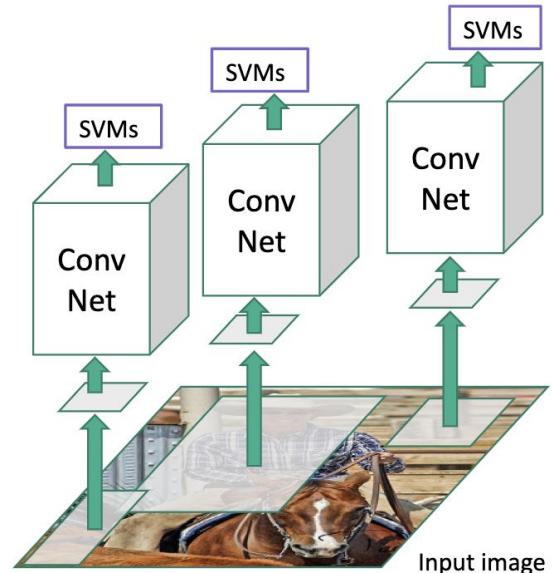
Fast R-CNN

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



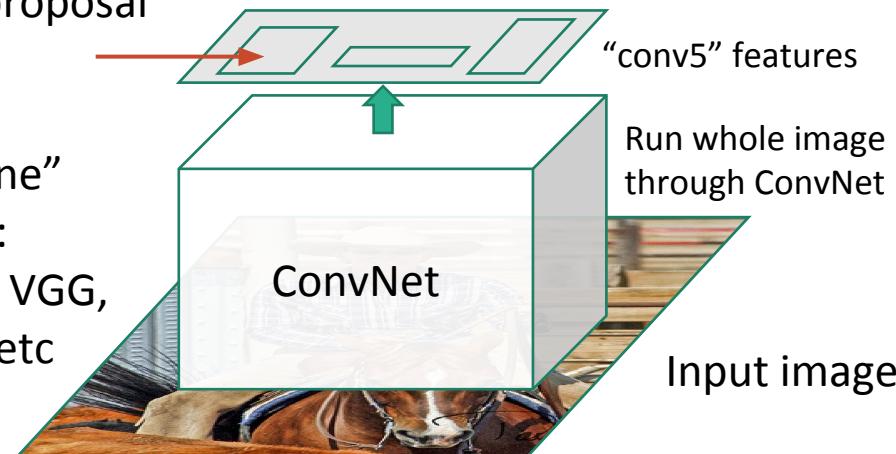
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

“Slow” R-CNN

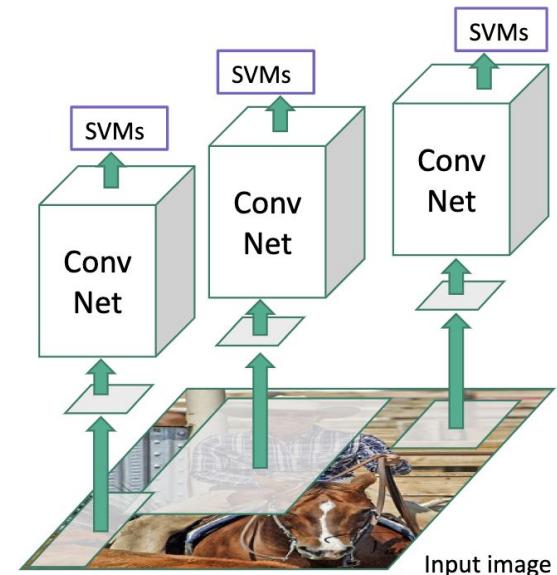


Fast R-CNN

Regions of Interest (RoIs)
from a proposal
method



“Slow” R-CNN

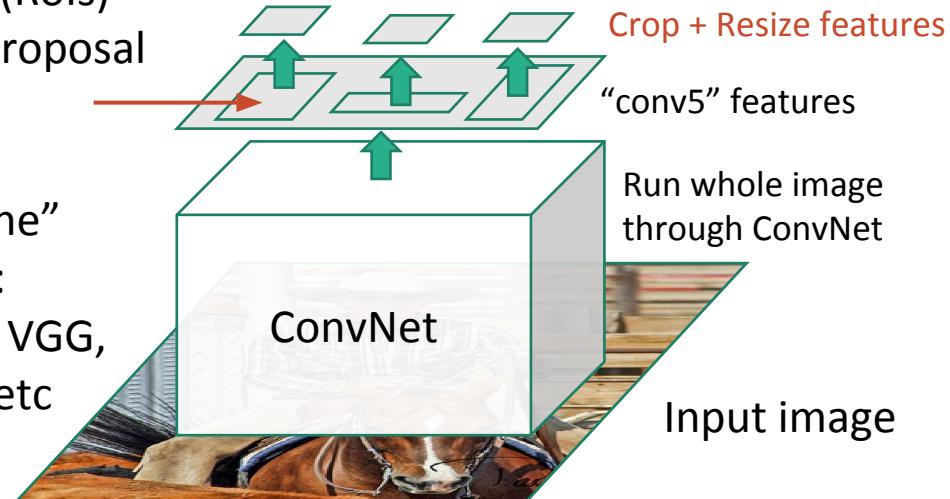


Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

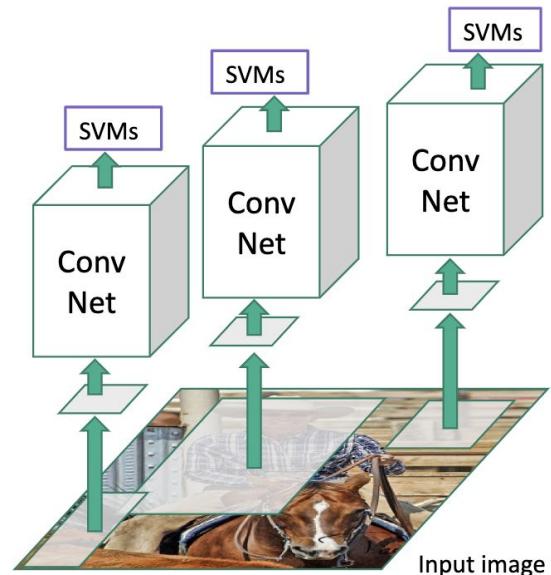
Fast R-CNN

Regions of Interest (RoIs)
from a proposal
method

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

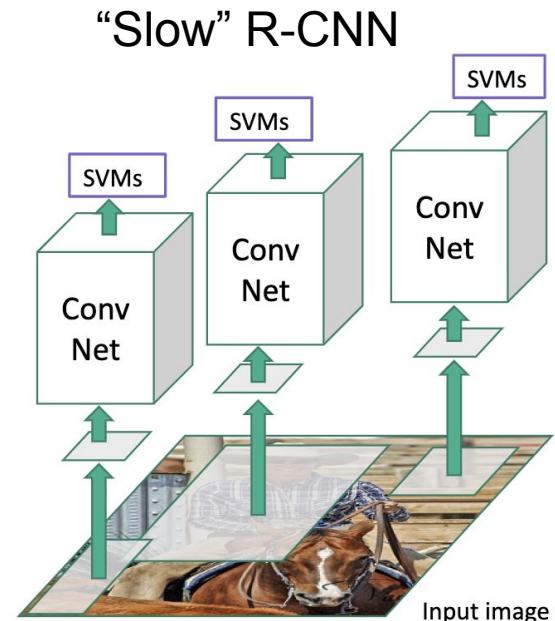
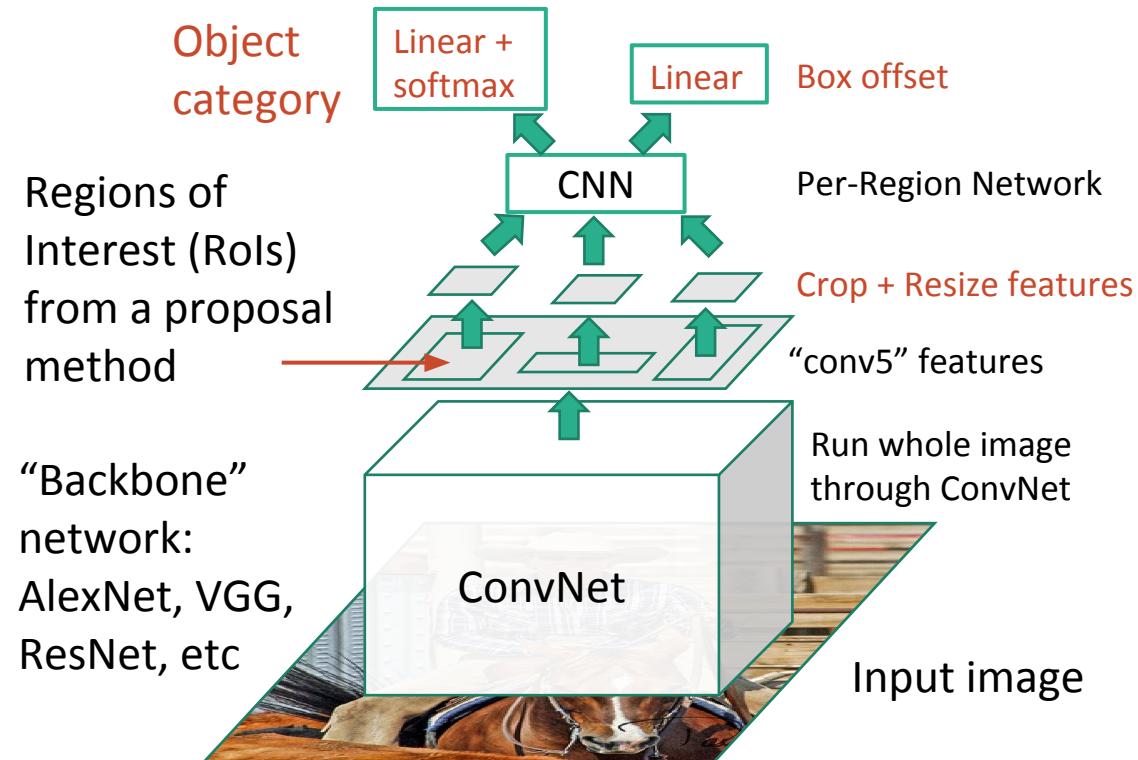


“Slow” R-CNN



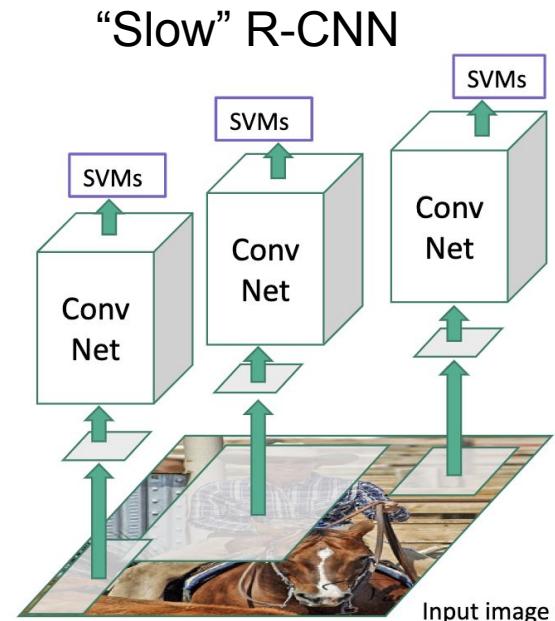
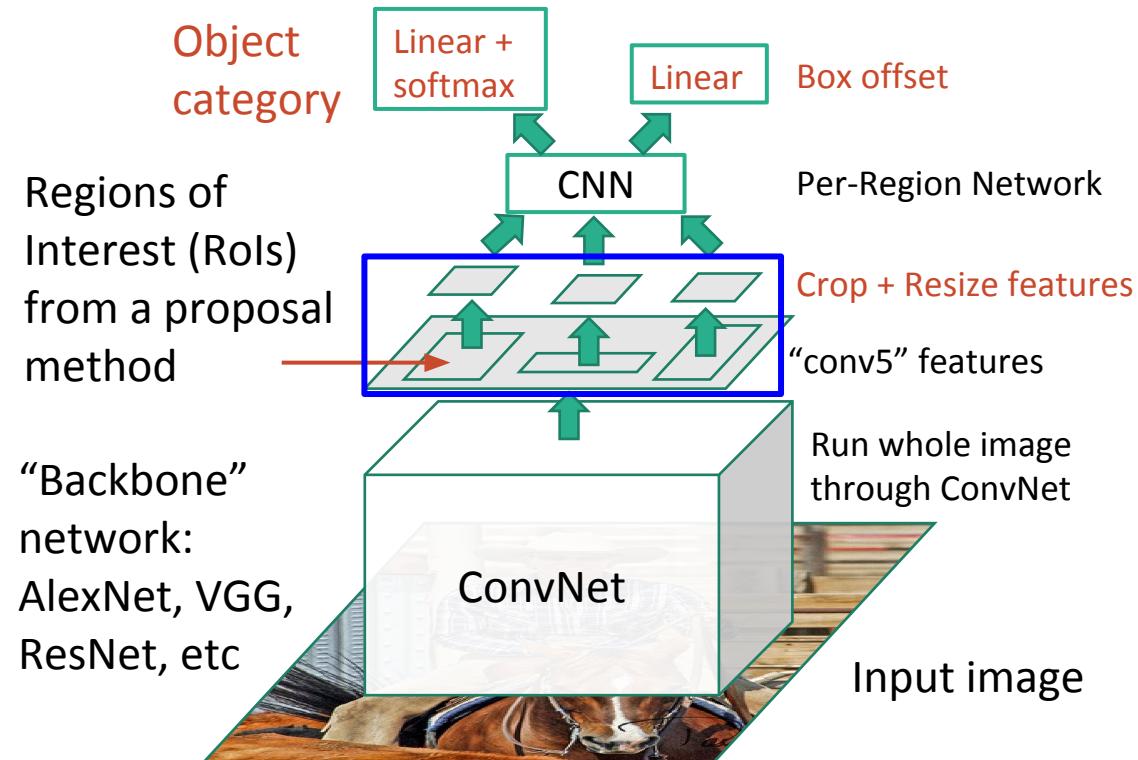
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



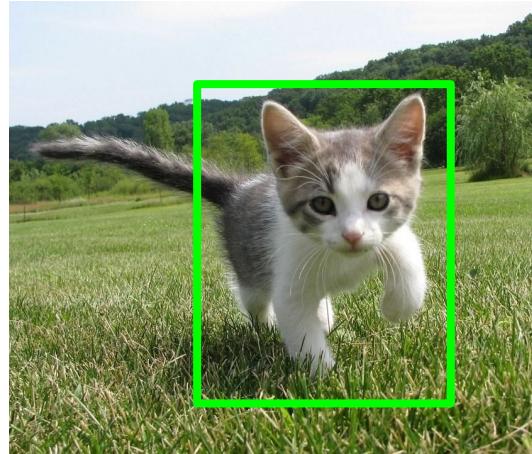
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



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

Cropping Features: RoI Pool



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

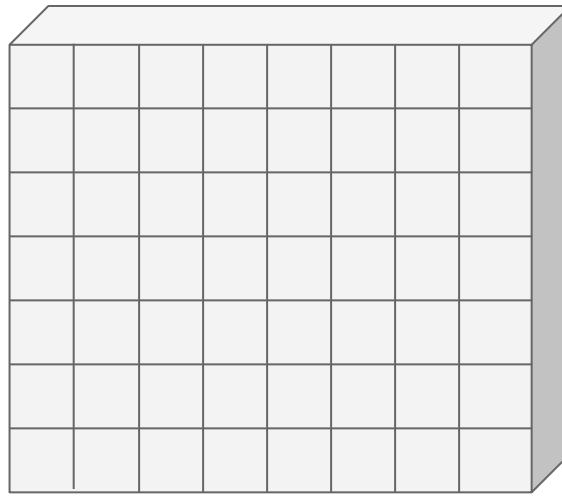
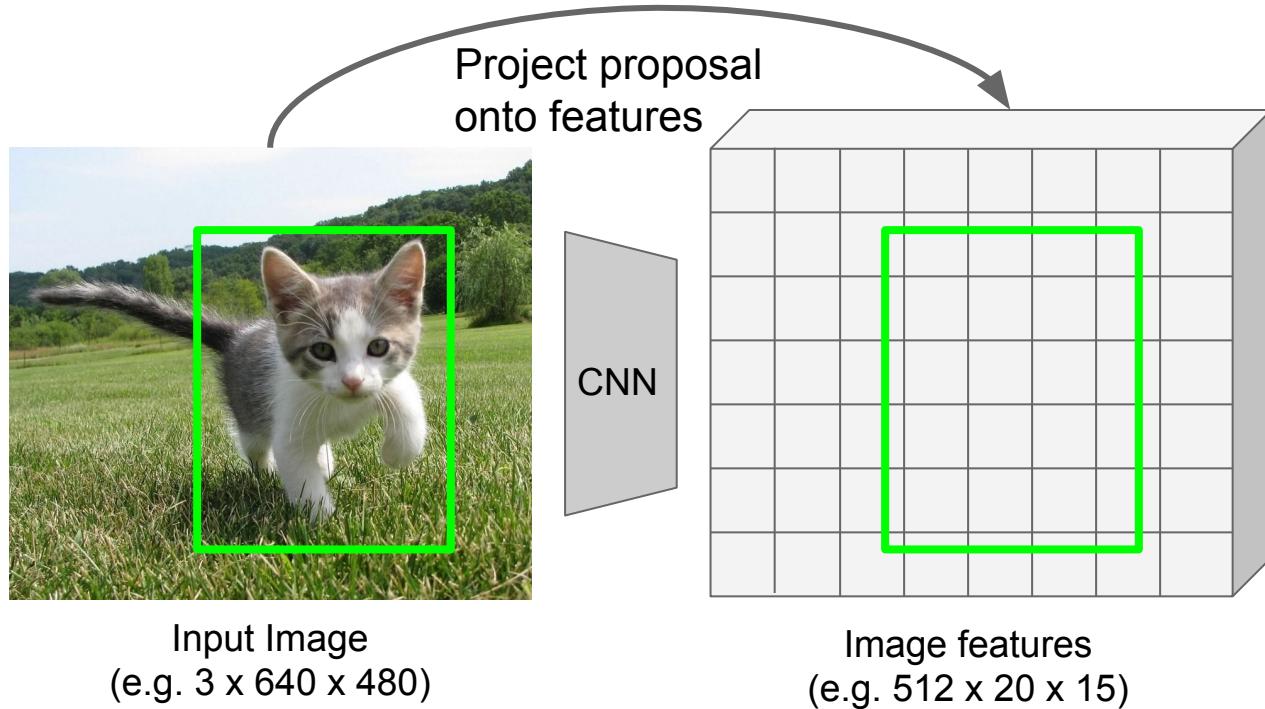


Image features
(e.g. $512 \times 20 \times 15$)

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

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

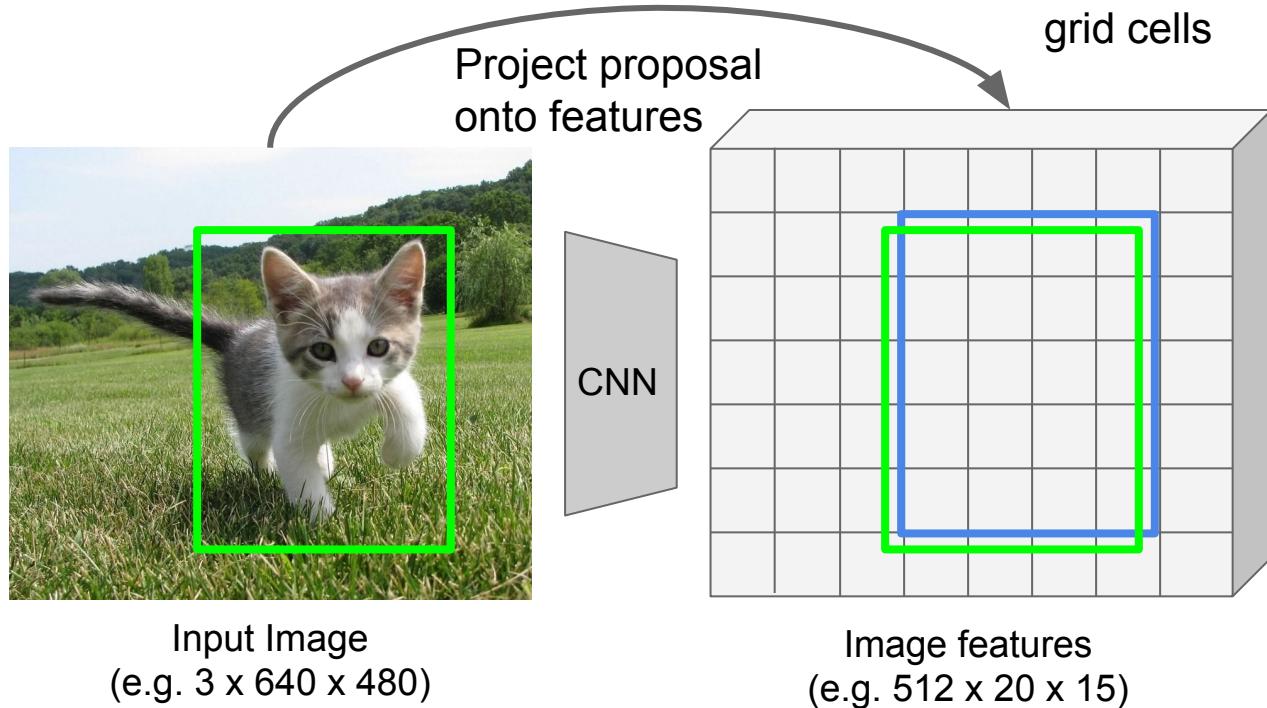
Cropping Features: RoI Pool



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

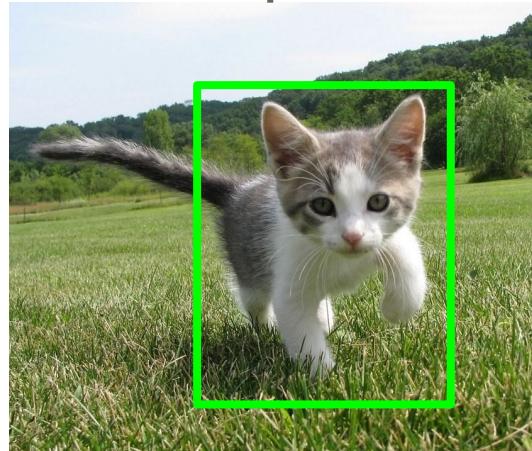
Girshick, "Fast R-CNN", ICCV 2015.

Cropping Features: RoI Pool



Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

Project proposal
onto features

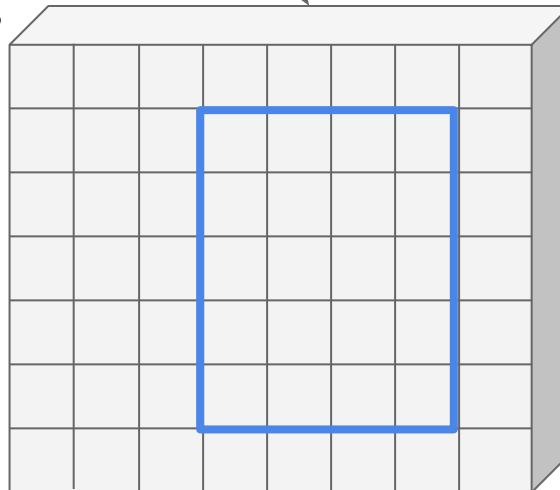


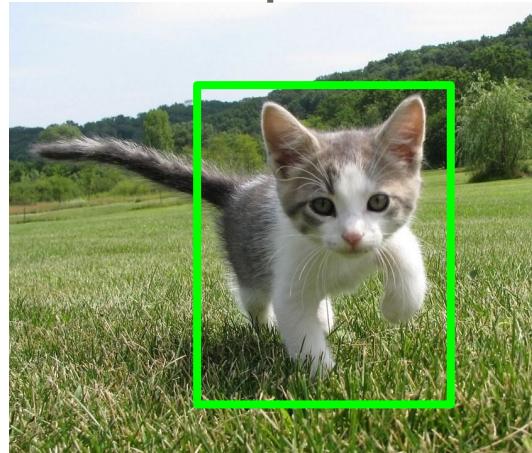
Image features
(e.g. $512 \times 20 \times 15$)

“Snap” to
grid cells

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

Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

Project proposal
onto features

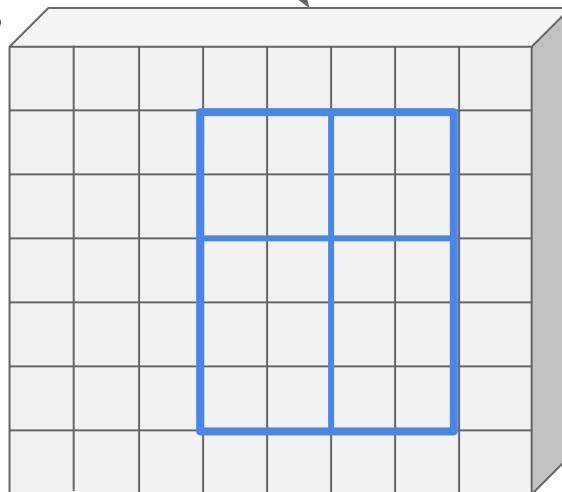


Image features
(e.g. $512 \times 20 \times 15$)

“Snap” to
grid cells

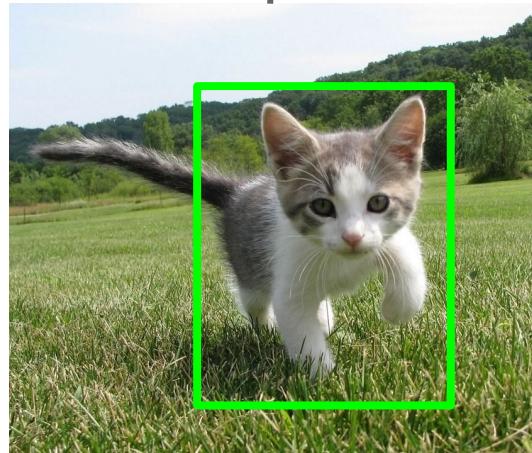
Divide into 2×2
grid of (roughly)
equal subregions

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



Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

Project proposal
onto features

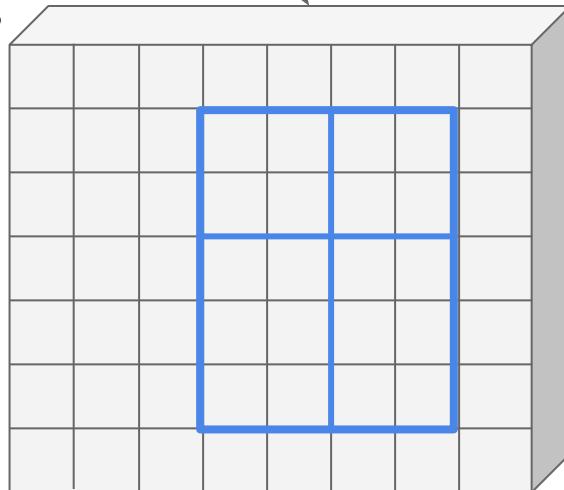
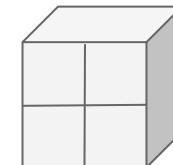


Image features
(e.g. $512 \times 20 \times 15$)

“Snap” to
grid cells

Divide into 2×2
grid of (roughly)
equal subregions

Max-pool within
each subregion

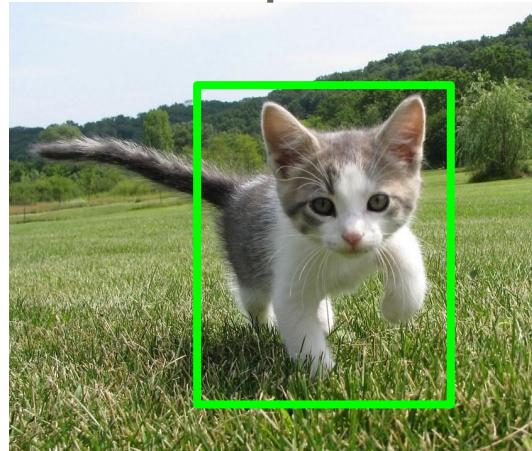


Region features
(here $512 \times 2 \times 2$;
In practice e.g. $512 \times 7 \times 7$)

Region features always the
same size even if input
regions have different sizes!

Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Pool



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

Project proposal
onto features

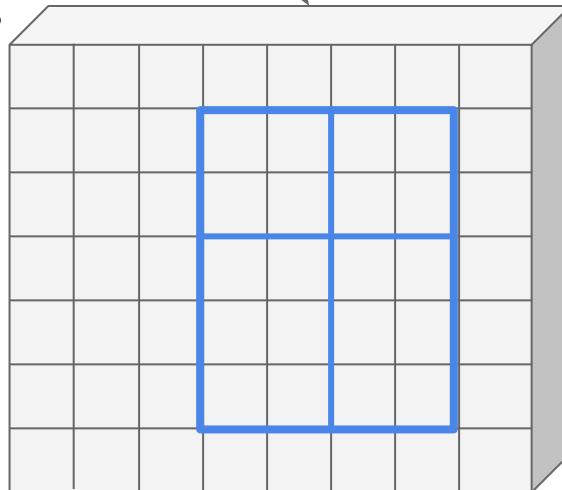
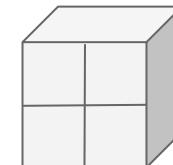


Image features
(e.g. $512 \times 20 \times 15$)

“Snap” to
grid cells

Divide into 2×2
grid of (roughly)
equal subregions

Max-pool within
each subregion



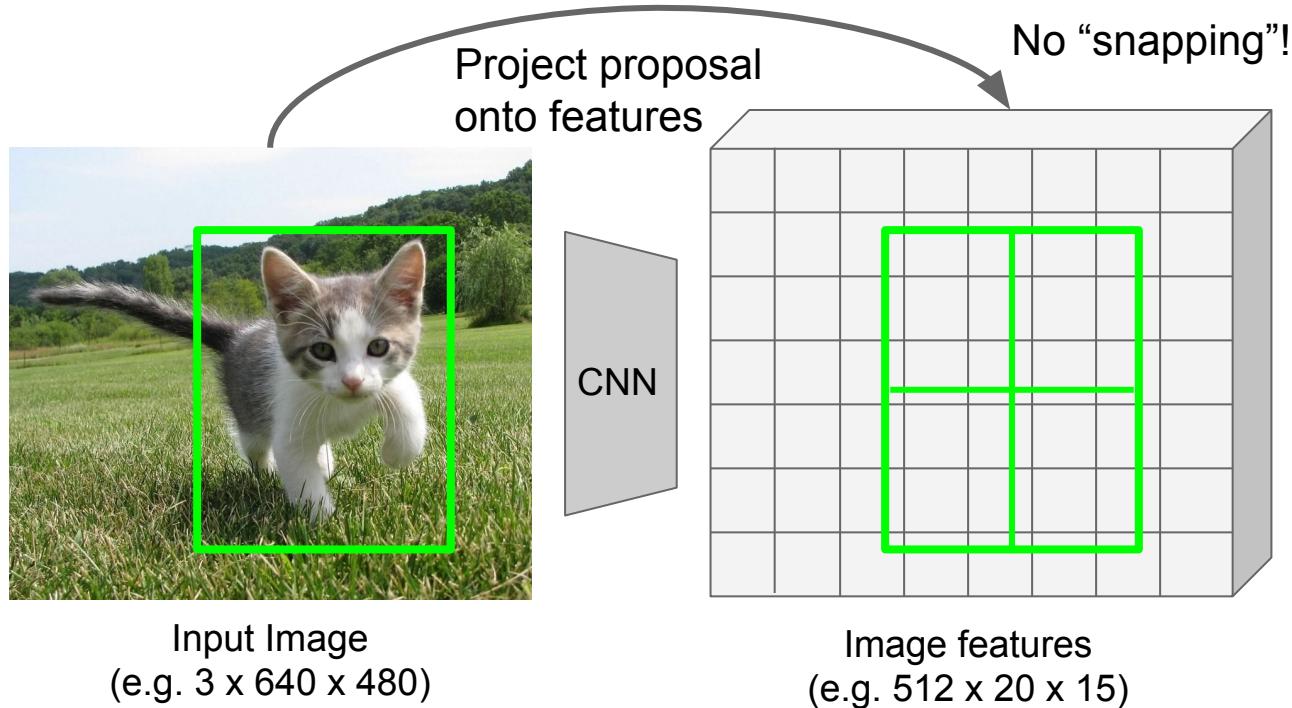
Region features
(here $512 \times 2 \times 2$;
In practice e.g $512 \times 7 \times 7$)

Region features always the
same size even if input
regions have different sizes!

Problem: Region features slightly misaligned

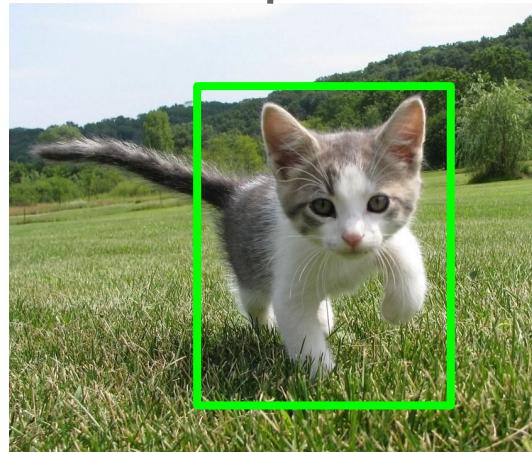
Girshick, “Fast R-CNN”, ICCV 2015.

Cropping Features: RoI Align



He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align



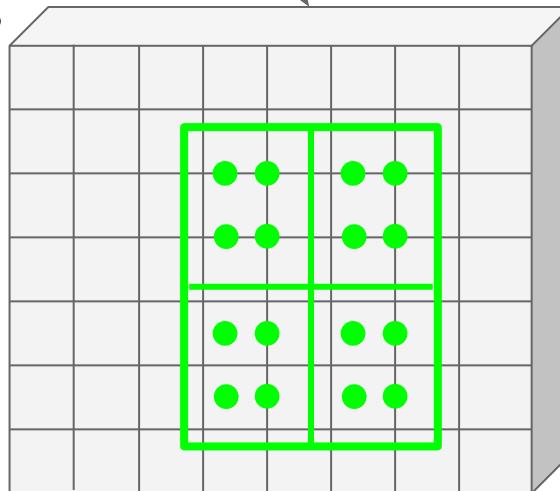
Input Image
(e.g. $3 \times 640 \times 480$)

Project proposal
onto features



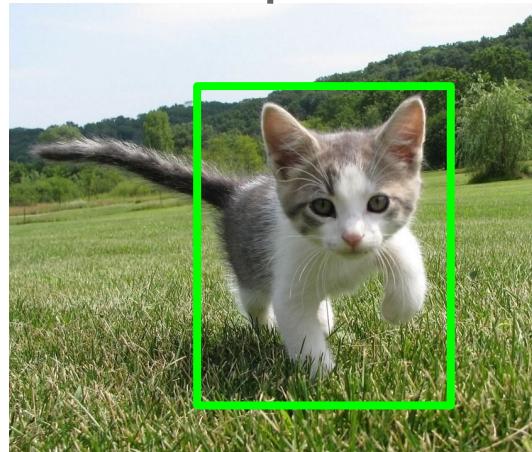
Image features
(e.g. $512 \times 20 \times 15$)

No “snapping”!



Sample at regular points
in each subregion using
bilinear interpolation

Cropping Features: RoI Align



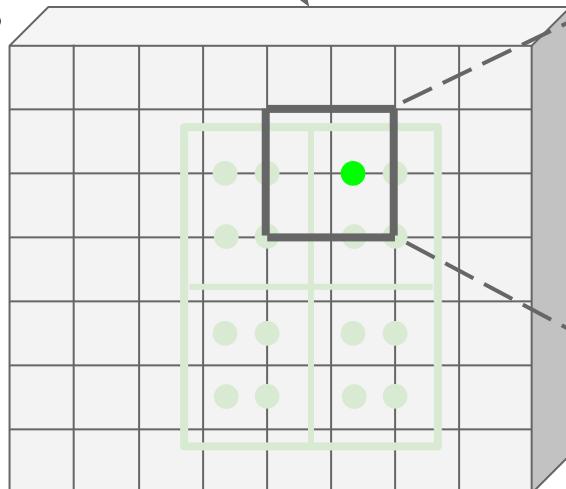
Input Image
(e.g. $3 \times 640 \times 480$)

Project proposal
onto features

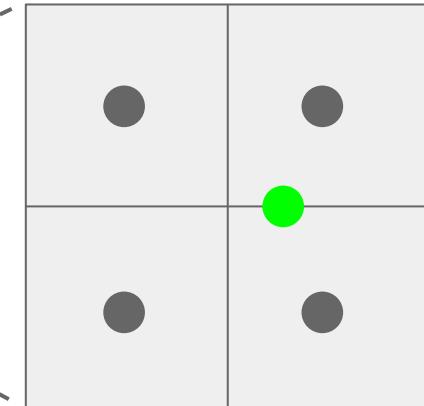


Image features
(e.g. $512 \times 20 \times 15$)

No “snapping”!

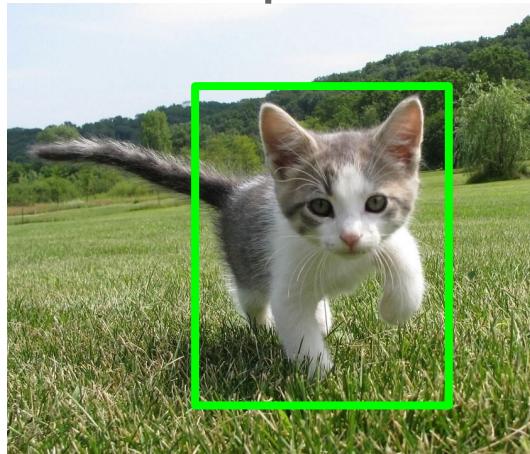


Sample at regular points
in each subregion using
bilinear interpolation



Feature f_{xy} for point (x, y)
is a linear combination of
features at its four
neighboring grid cells:

Cropping Features: RoI Align



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

Project proposal
onto features



No “snapping”!

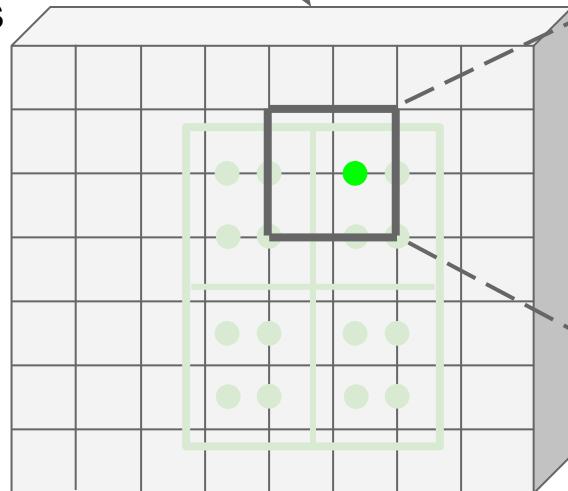
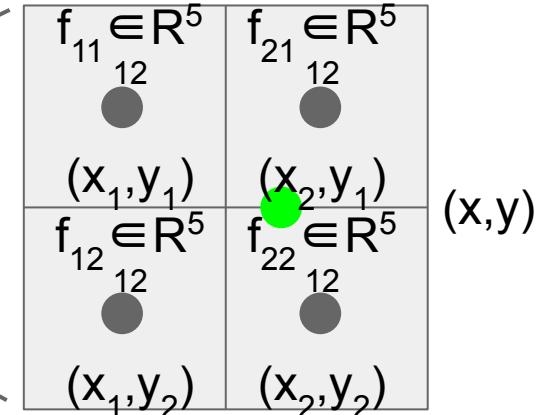


Image features
(e.g. $512 \times 20 \times 15$)

Sample at regular points
in each subregion using
bilinear interpolation

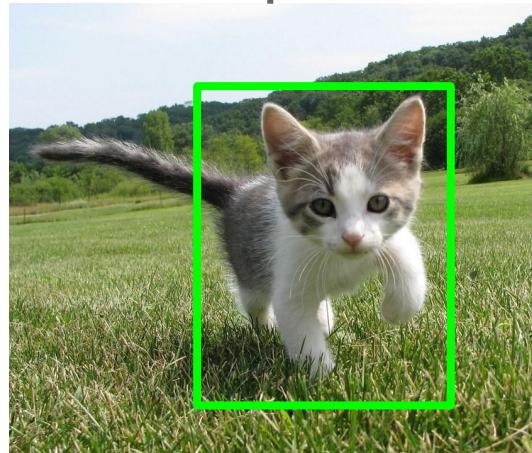


Feature f_{xy} for point (x, y)
is a linear combination of
features at its four
neighboring grid cells:

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

He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align



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

Project proposal
onto features



No “snapping”!

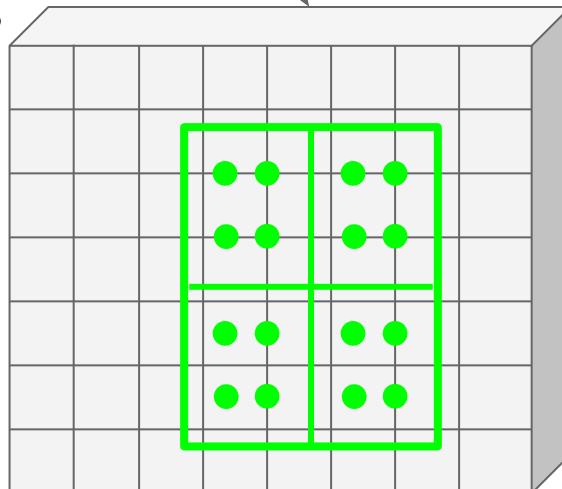
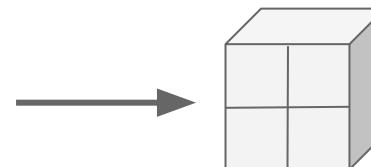


Image features
(e.g. $512 \times 20 \times 15$)

Sample at regular points
in each subregion using
bilinear interpolation

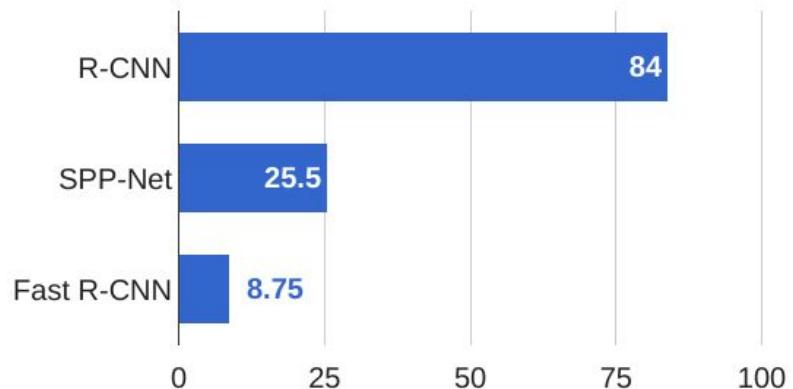
Max-pool within
each subregion



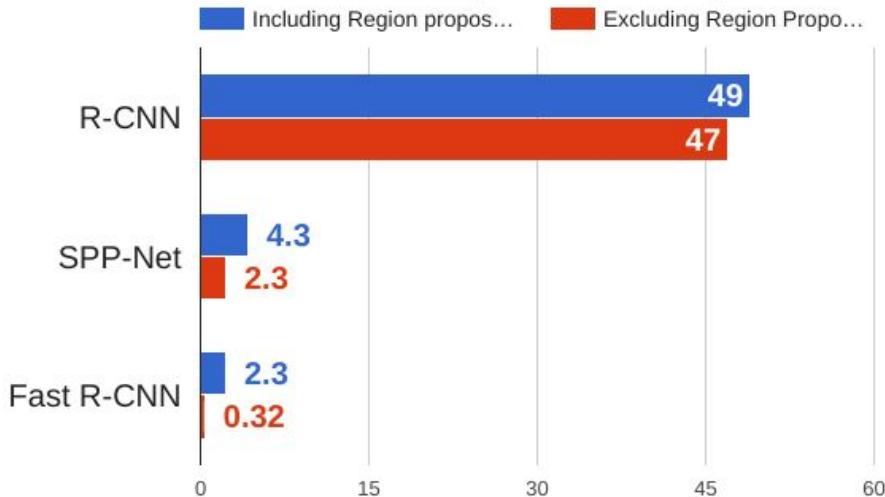
Region features
(here $512 \times 2 \times 2$;
In practice e.g $512 \times 7 \times 7$)

R-CNN vs Fast R-CNN

Training time (Hours)



Test time (seconds)



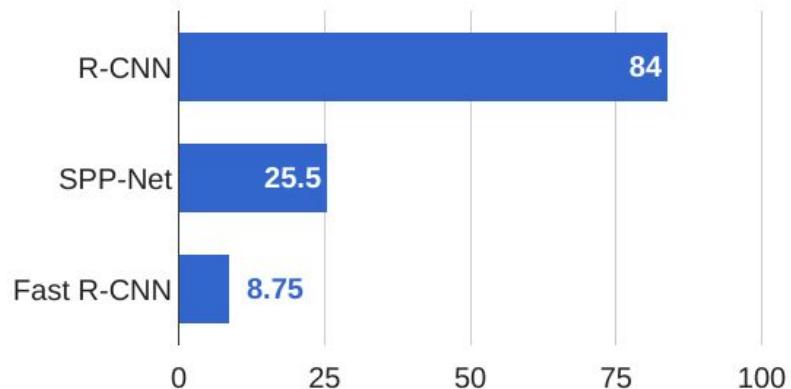
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

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

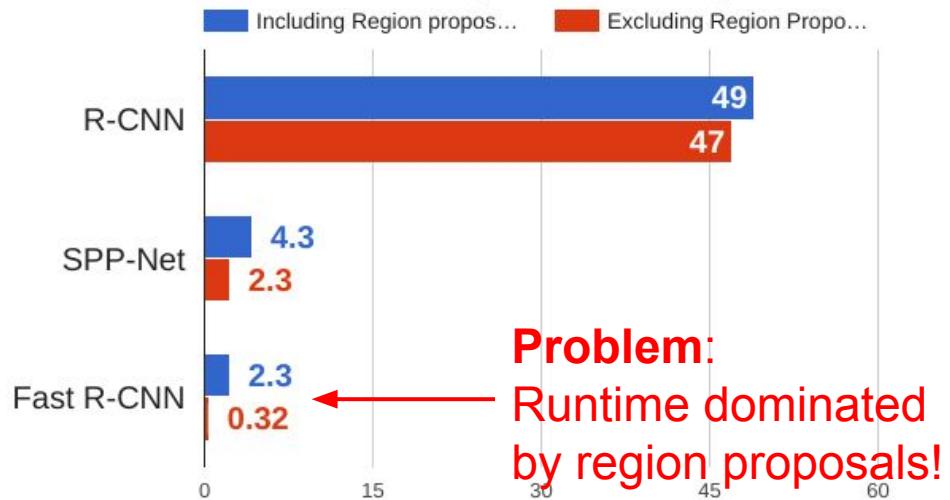
Girshick, "Fast R-CNN", ICCV 2015

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

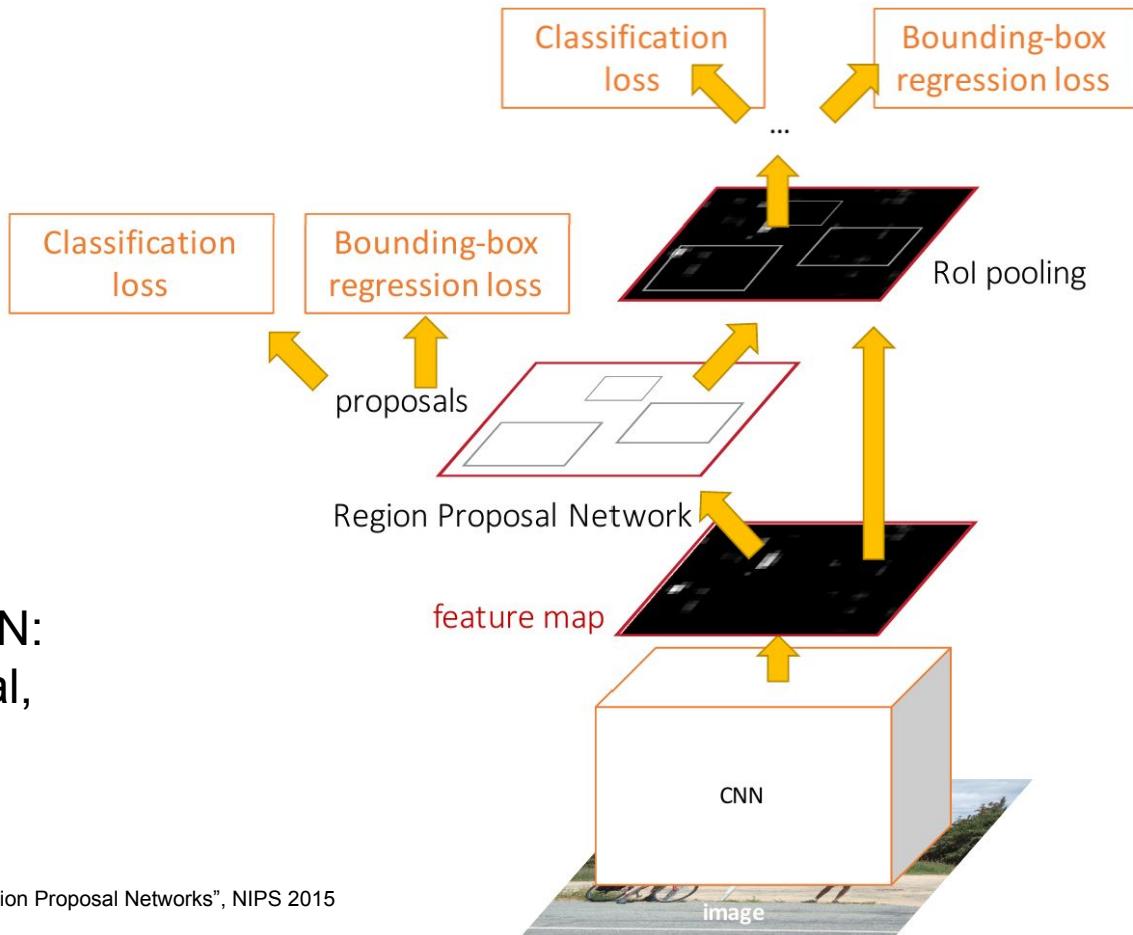
Girshick, "Fast R-CNN", ICCV 2015

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. $3 \times 640 \times 480$)

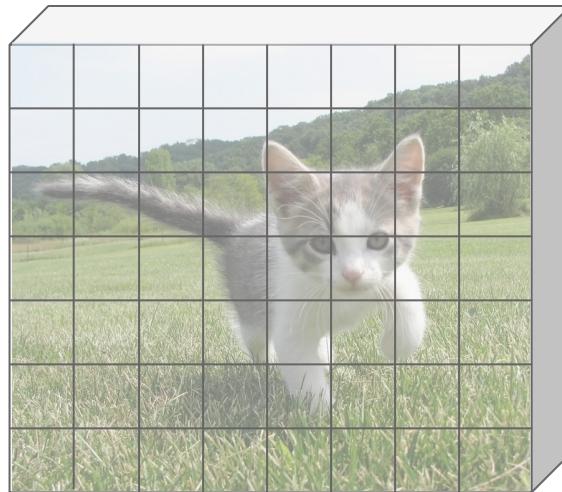
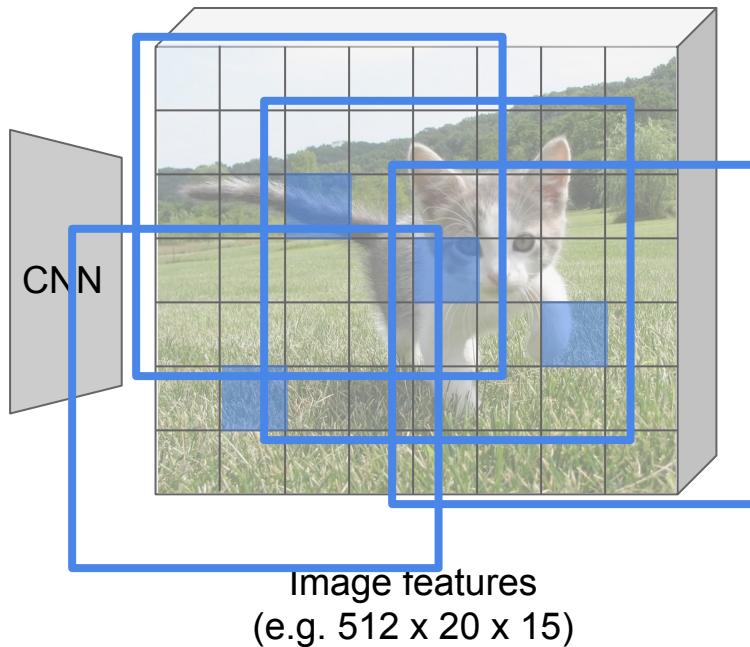


Image features
(e.g. $512 \times 20 \times 15$)

Region Proposal Network



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

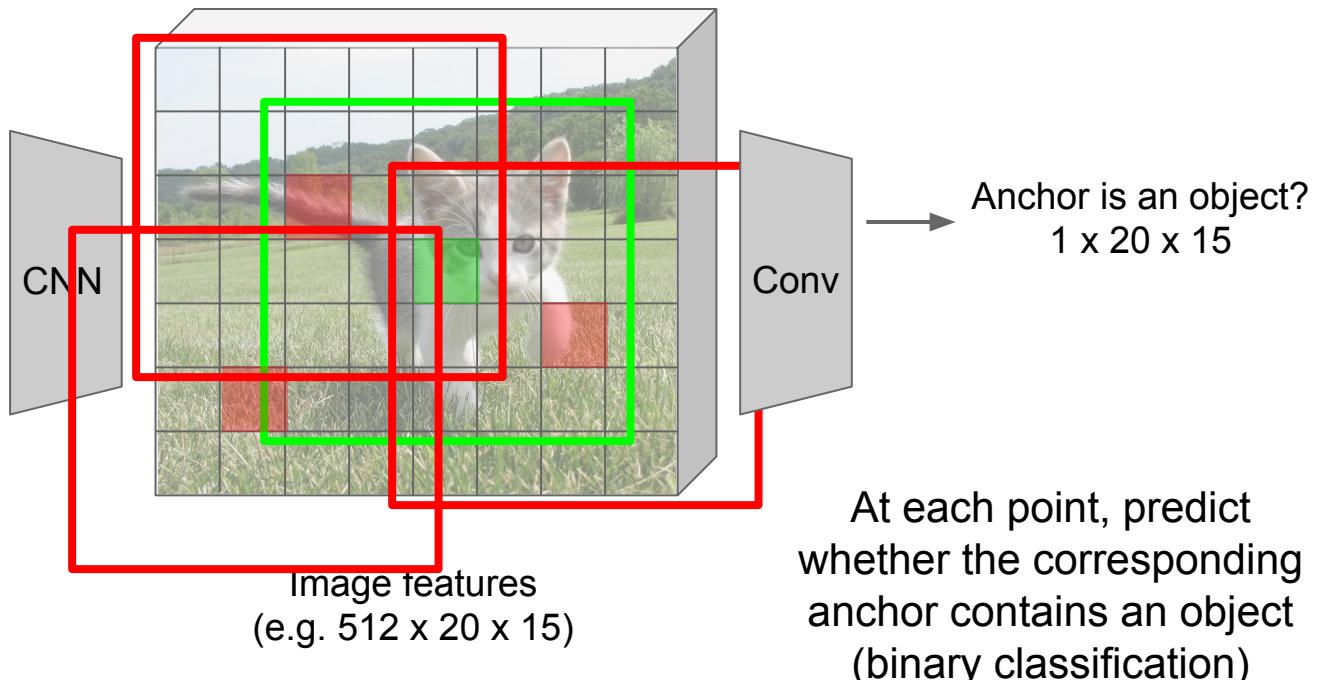


Imagine an **anchor box** of fixed size at each point in the feature map

Region Proposal Network



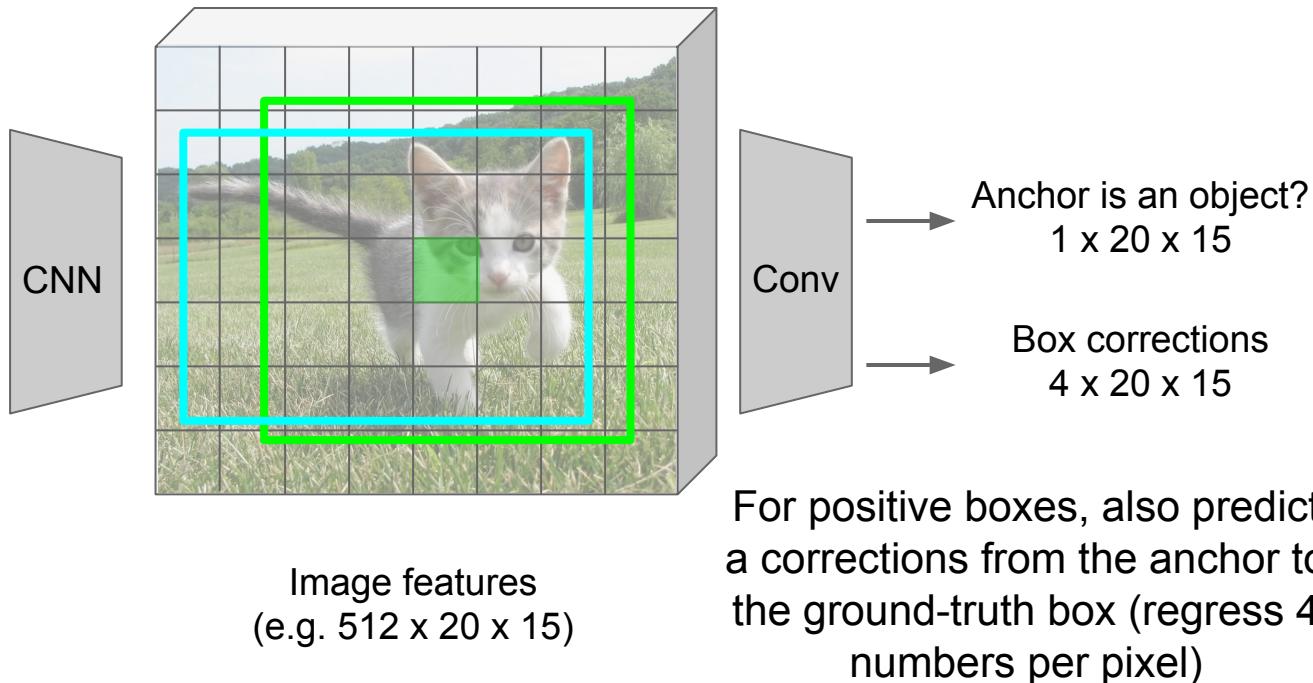
Input Image
(e.g. $3 \times 640 \times 480$)



Region Proposal Network



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

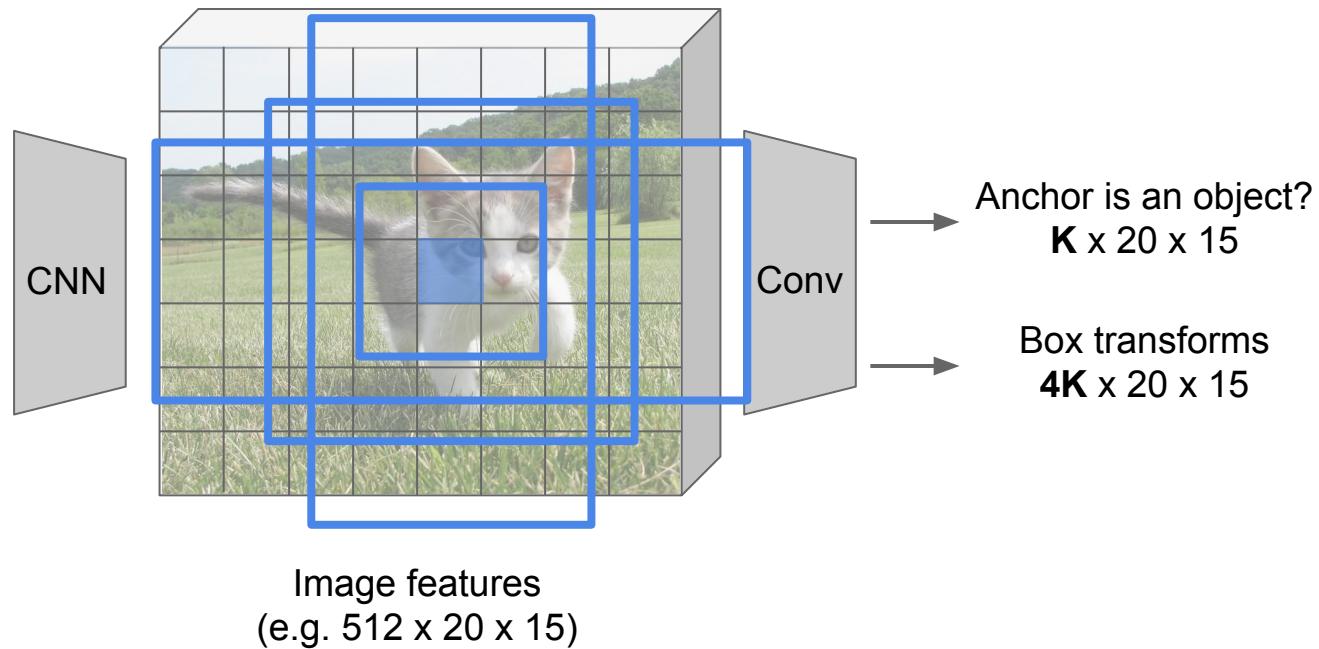


Region Proposal Network

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



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

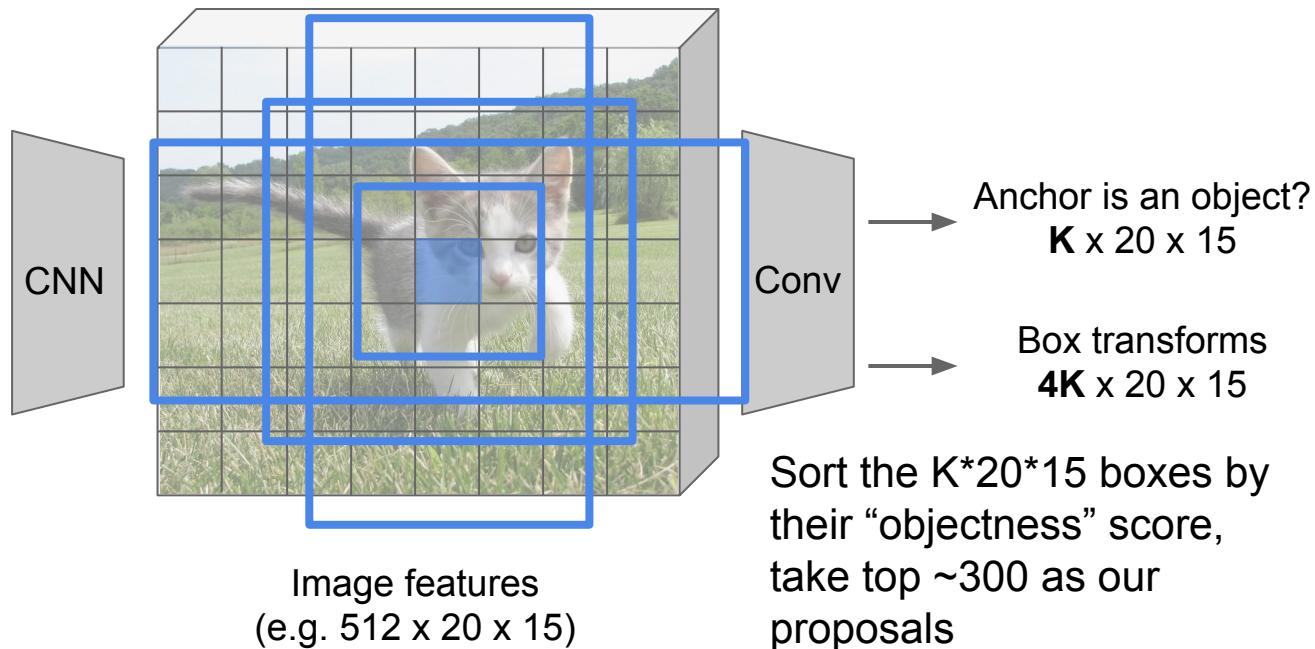


Region Proposal Network

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



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

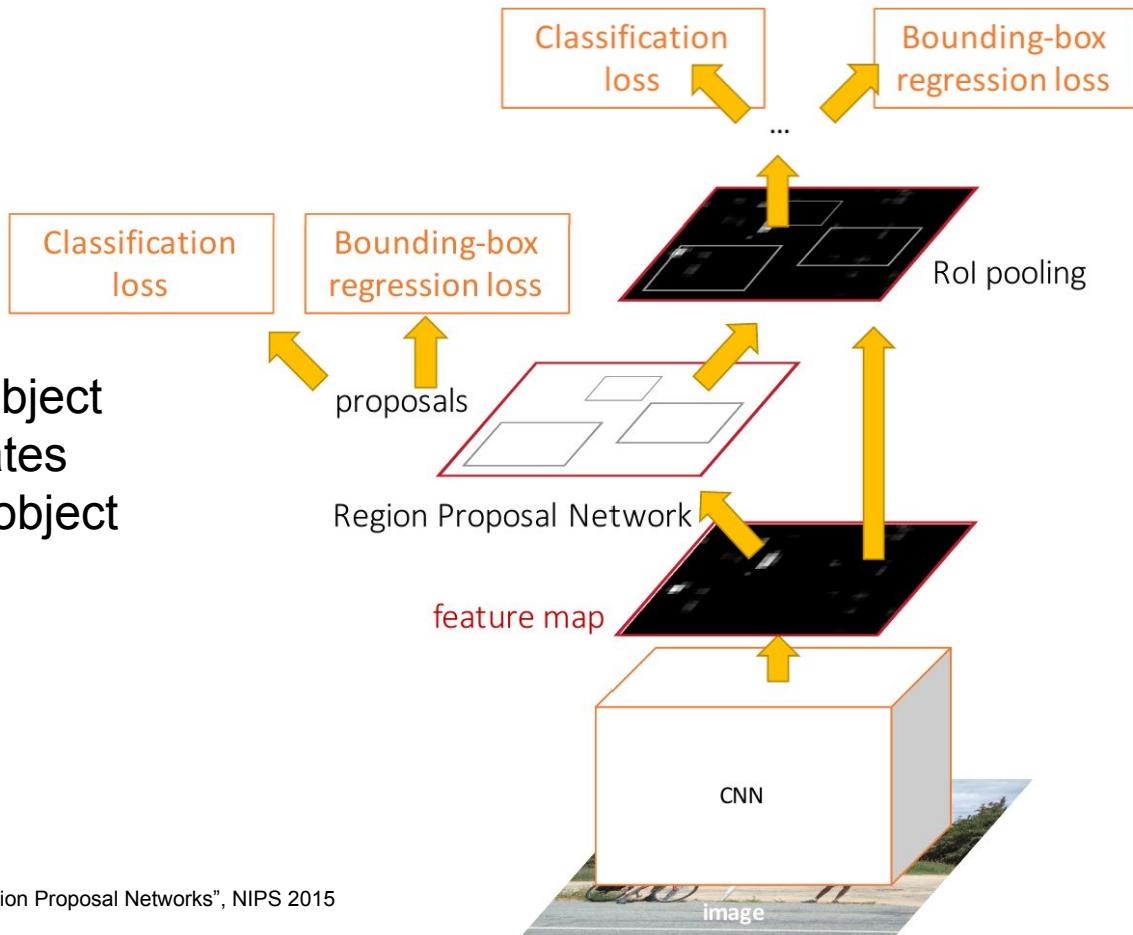


Faster R-CNN:

Make CNN do proposals!

Jointly train with 4 losses:

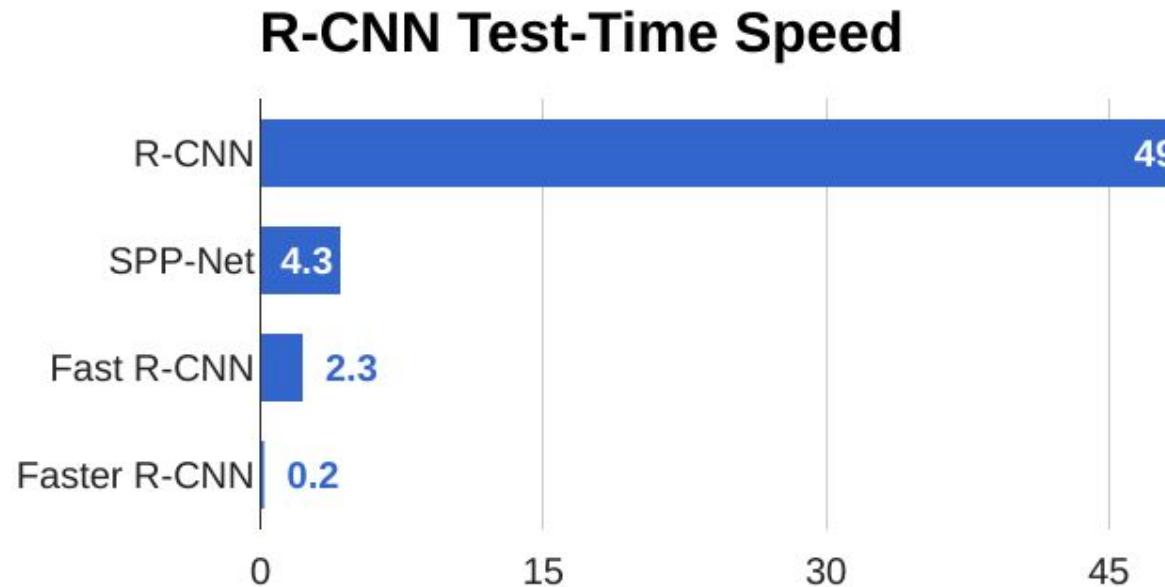
1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates



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!

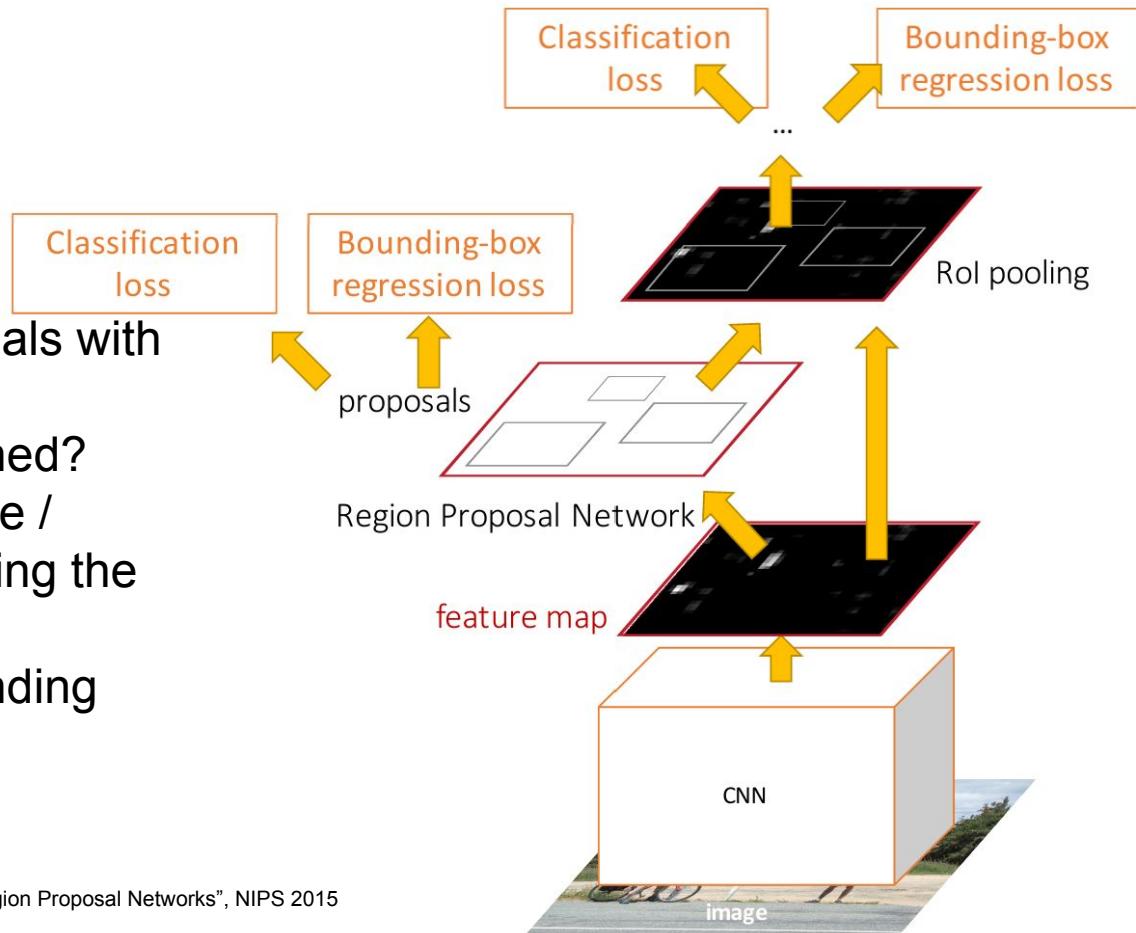


Faster R-CNN:

Make CNN do proposals!

Glossing over many details:

- Ignore overlapping proposals with **non-max suppression**
- How 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!

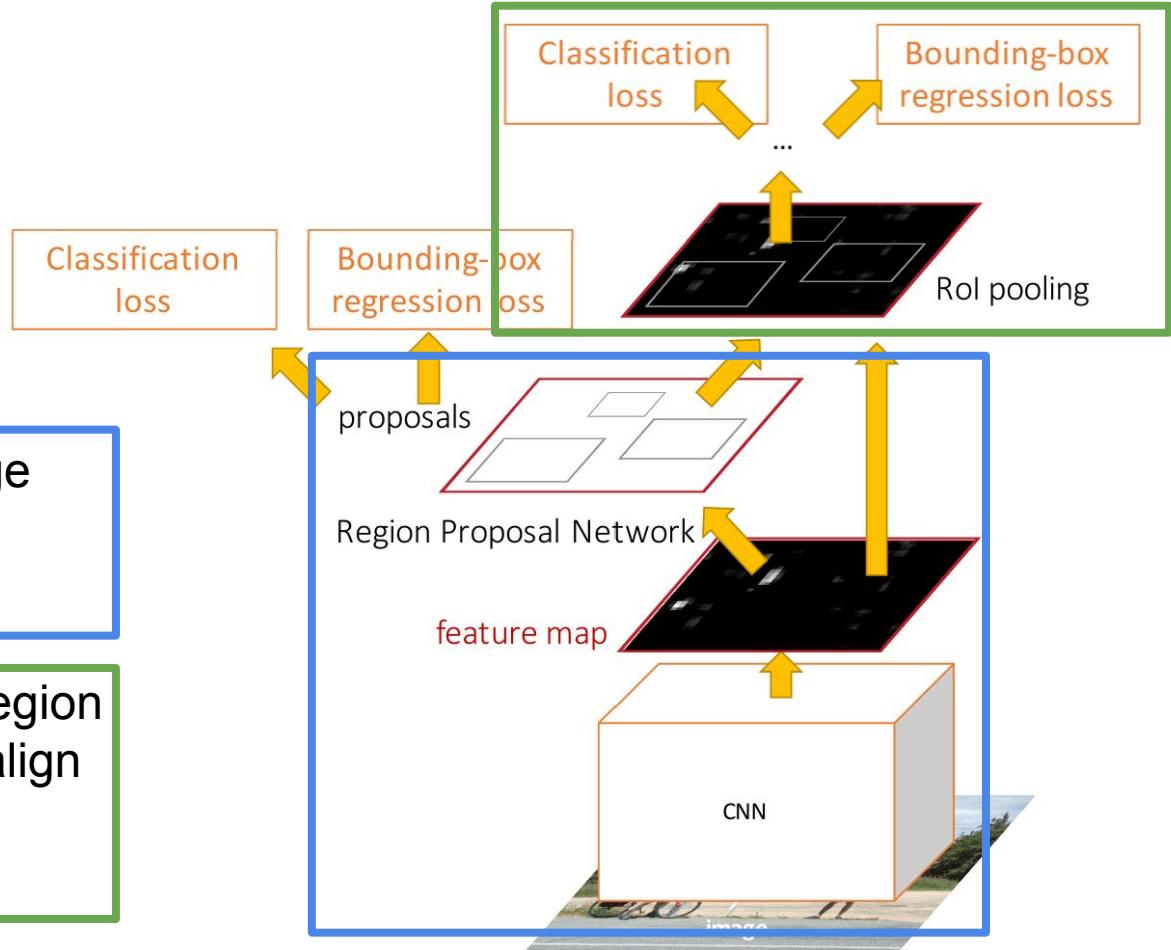
Faster R-CNN is a
Two-stage object detector

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

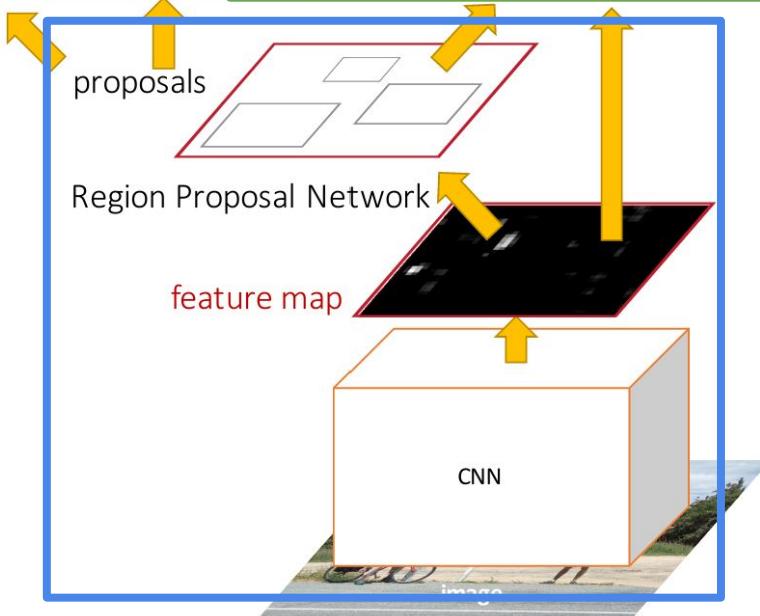
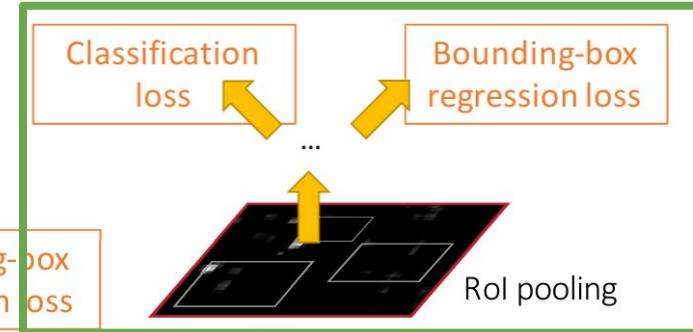
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- Crop features: RoI pool / align
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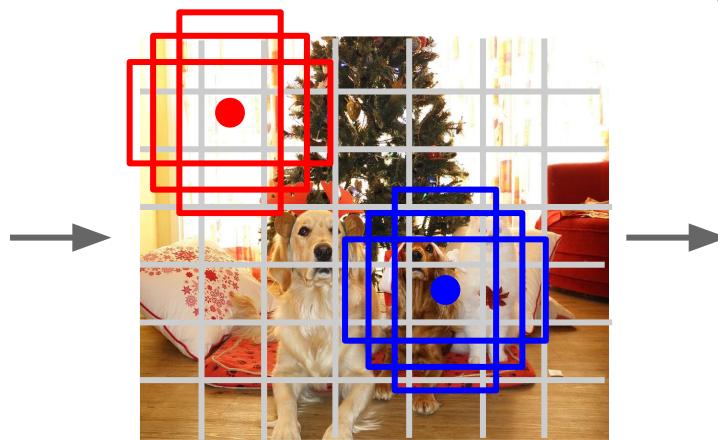
Do we really need
the second stage?



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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VGG16
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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

R-FCN: Dai et al, “R-FCN: Object Detection via Region-based Fully Convolutional Networks”, NIPS 2016

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MobileNet: Howard et al, “Efficient Convolutional Neural Networks for Mobile Vision Applications”, arXiv 2017

Instance Segmentation

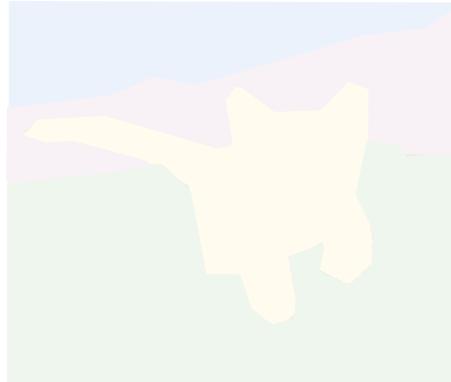
Classification



CAT

No spatial extent

Semantic
Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Object
Detection



DOG, DOG, CAT

Multiple Object

Instance
Segmentation



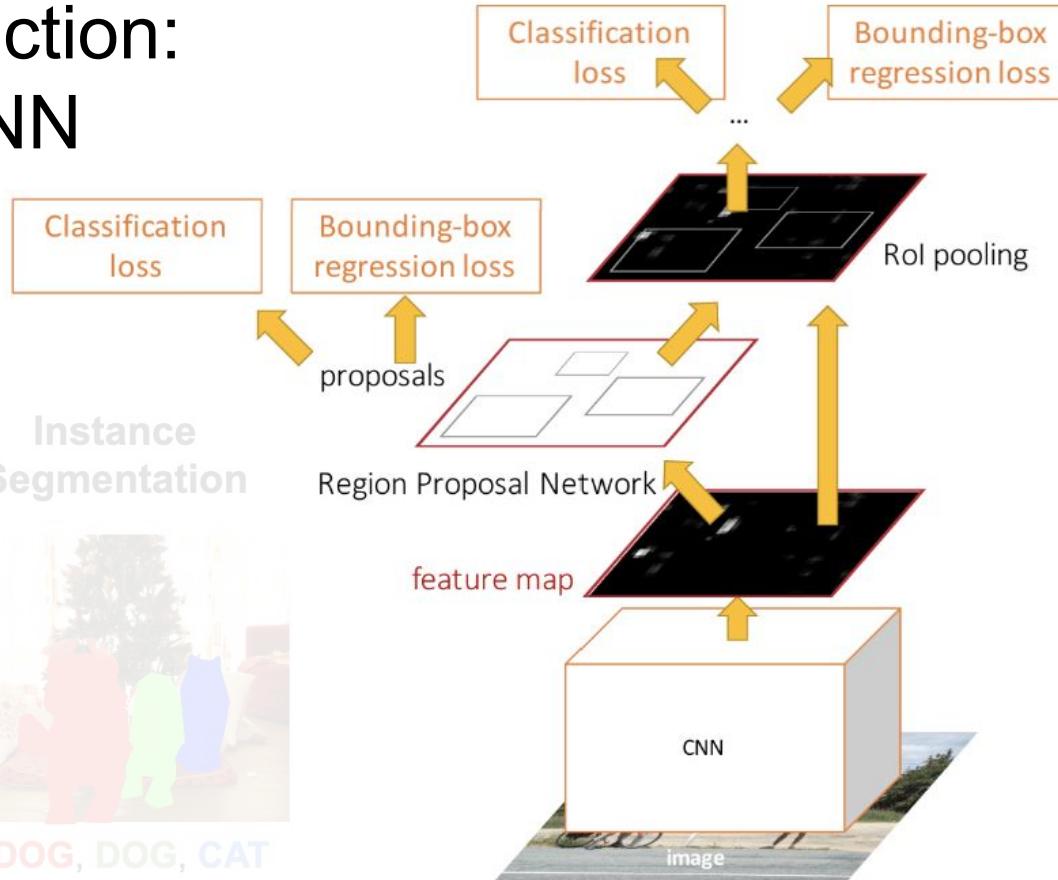
DOG, DOG, CAT

Object Detection: Faster R-CNN

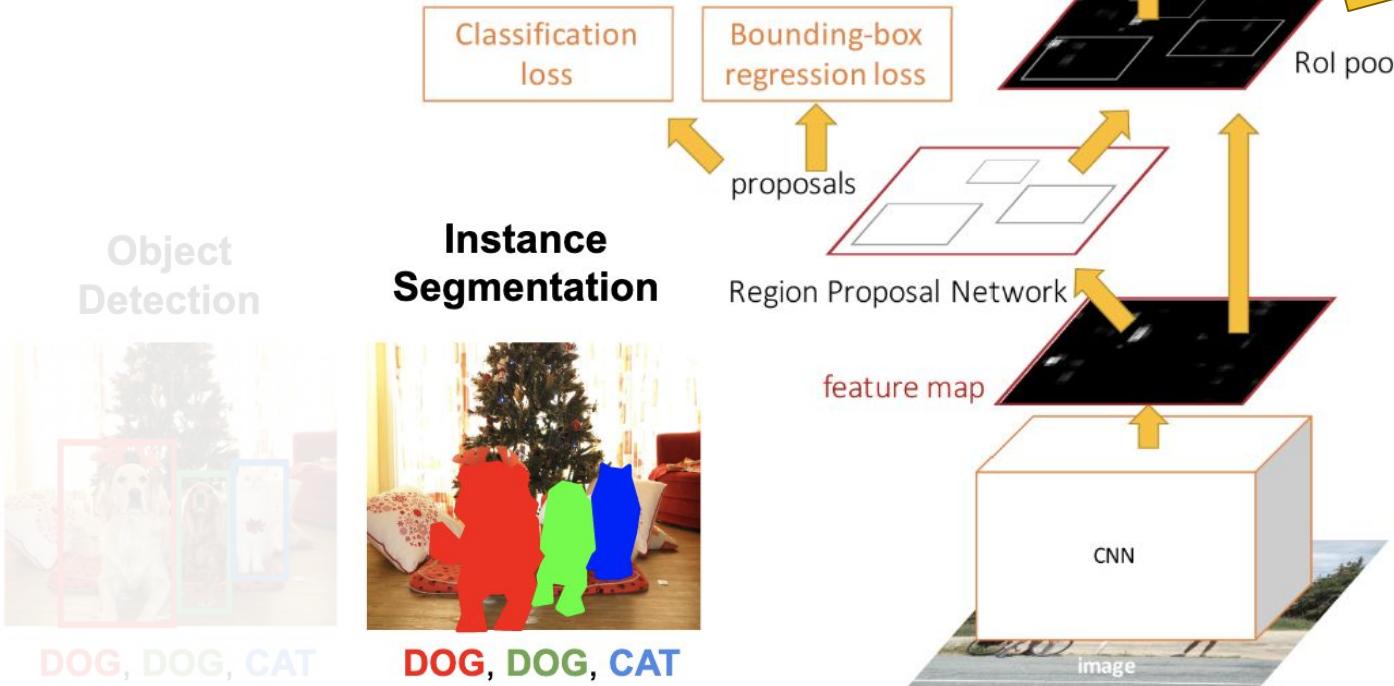
Object Detection



Instance Segmentation



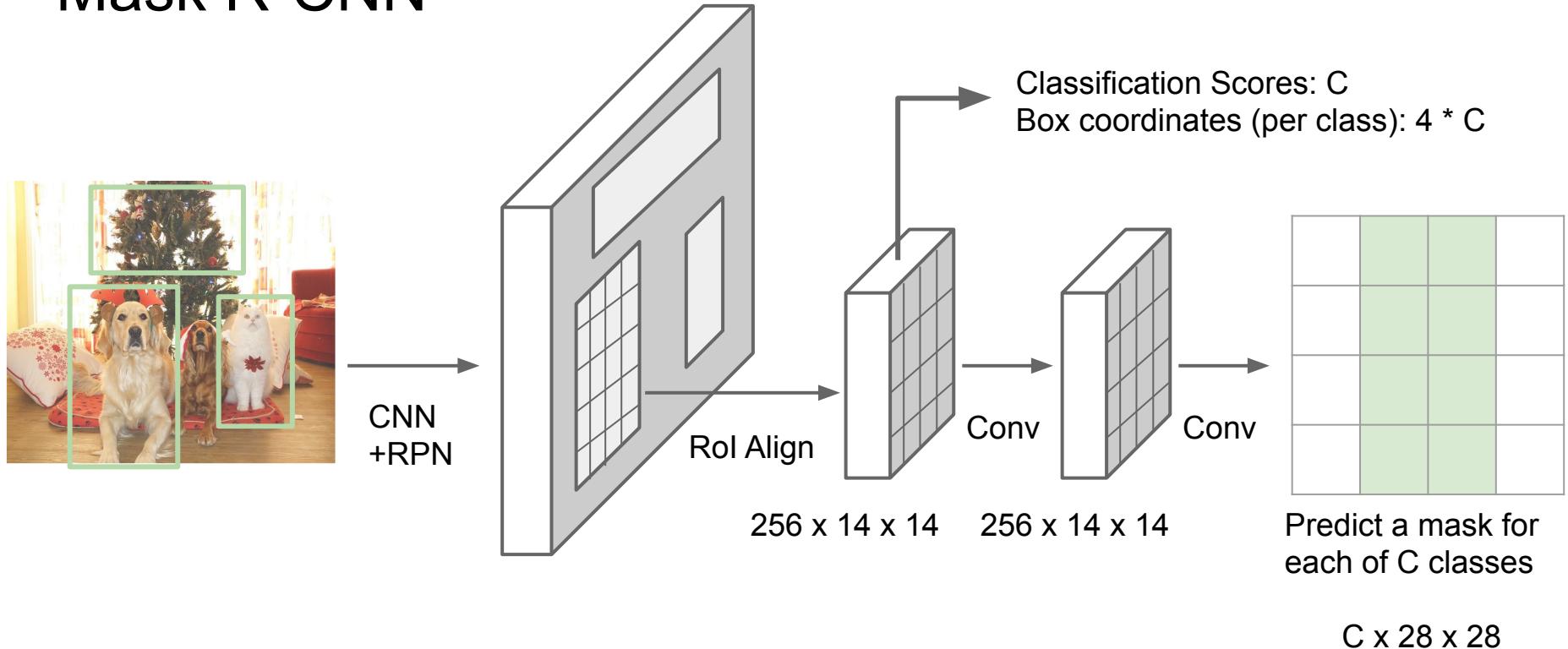
Instance Segmentation: Mask R-CNN



Add a small mask network that operates on each RoI and predicts a 28x28 binary mask

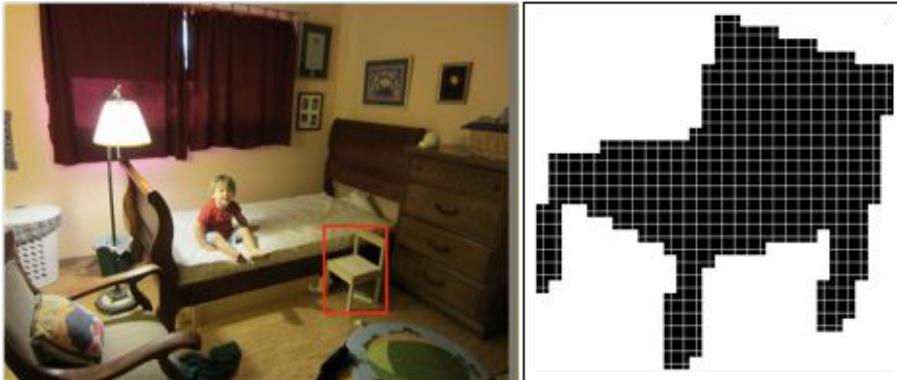
He et al., "Mask R-CNN", ICCV 2017

Mask R-CNN



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

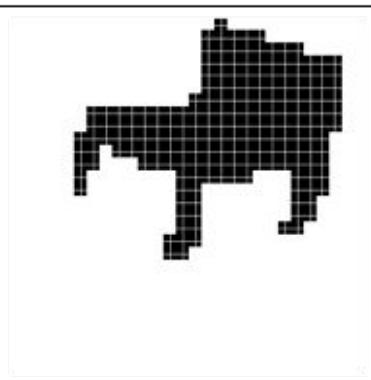
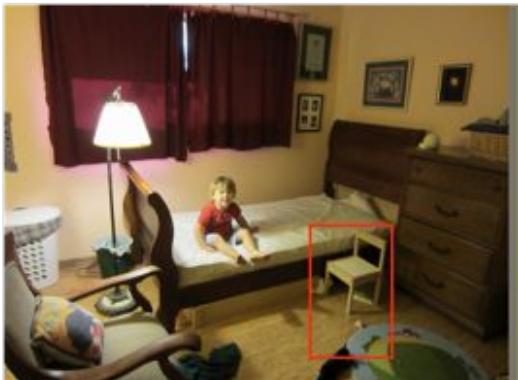
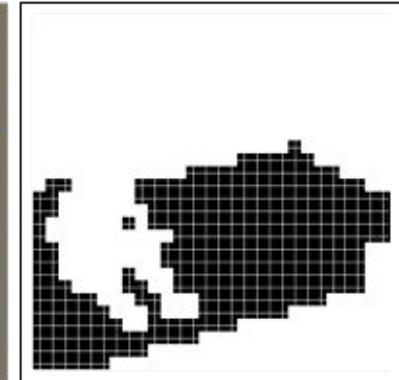
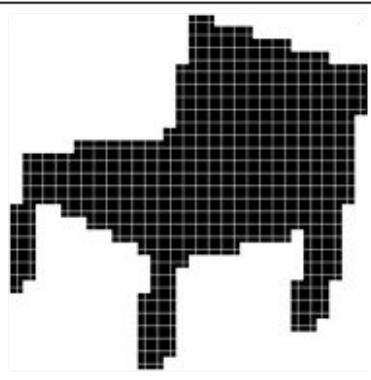
Mask R-CNN: Example Mask Training Targets



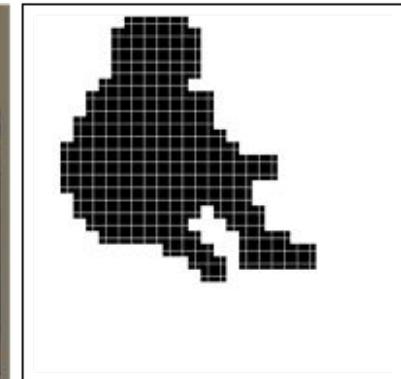
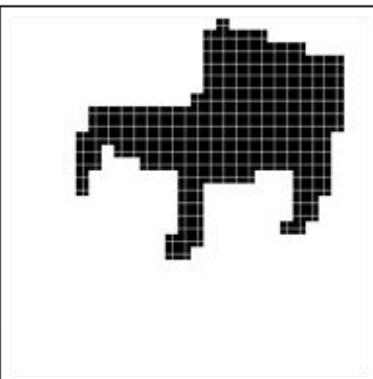
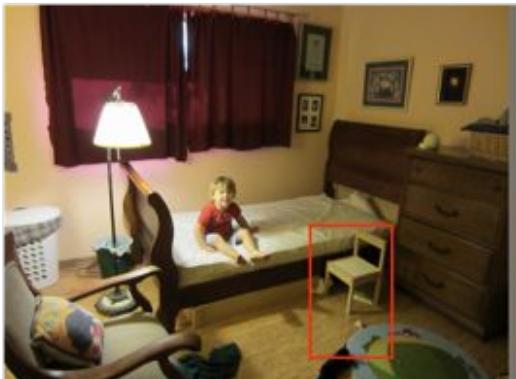
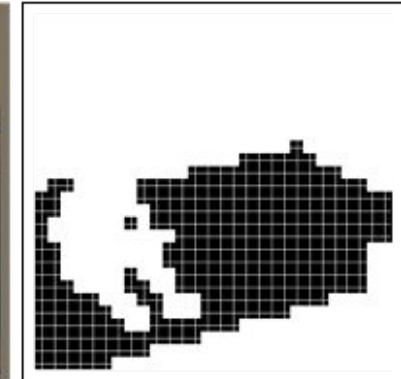
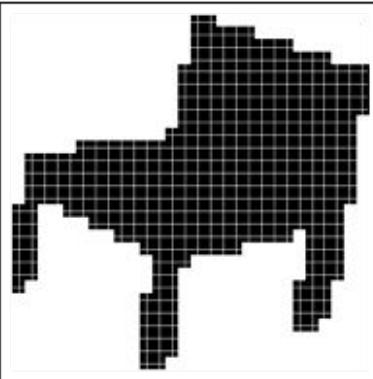
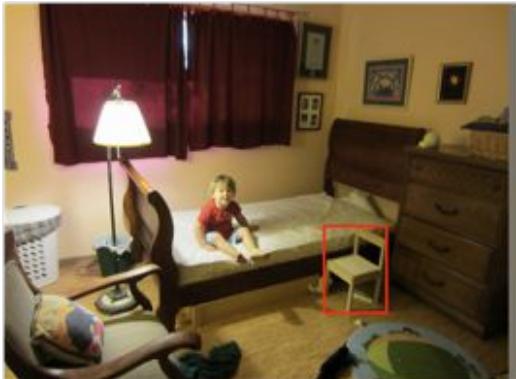
Mask R-CNN: Example Mask Training Targets



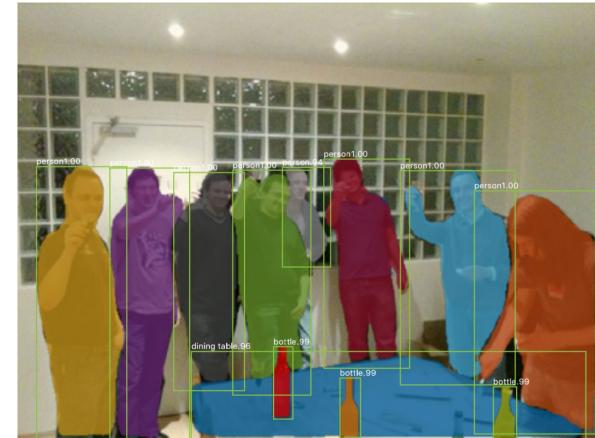
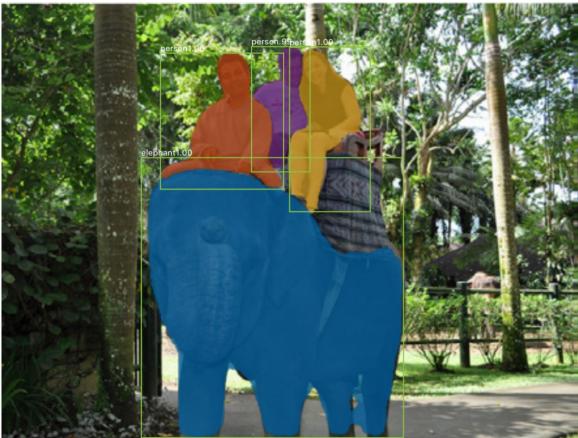
Mask R-CNN: Example Mask Training Targets



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)

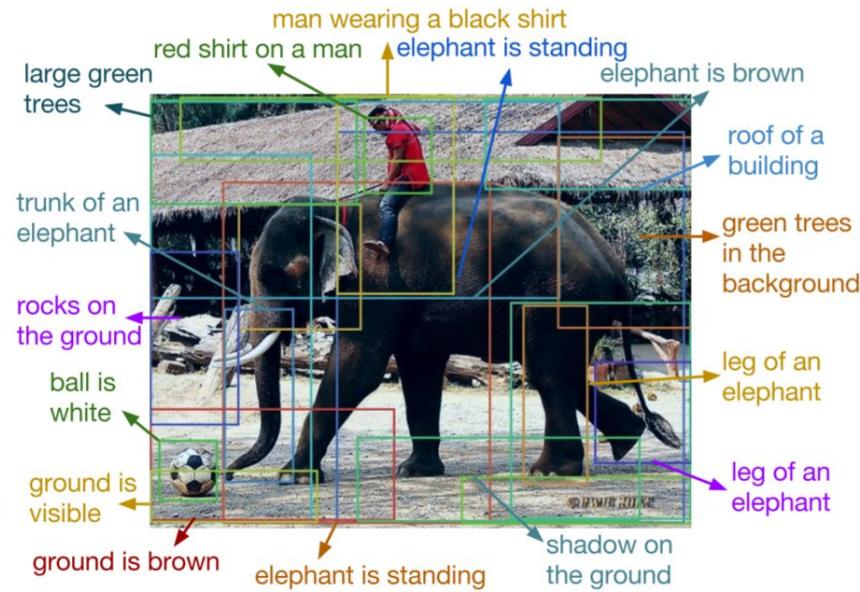
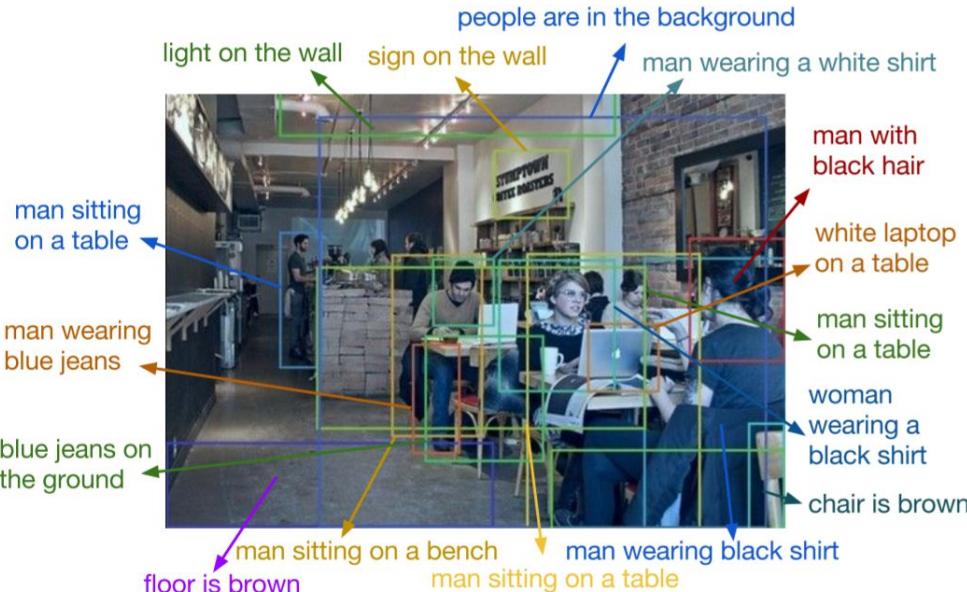
<https://github.com/facebookresearch/detectron2>

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

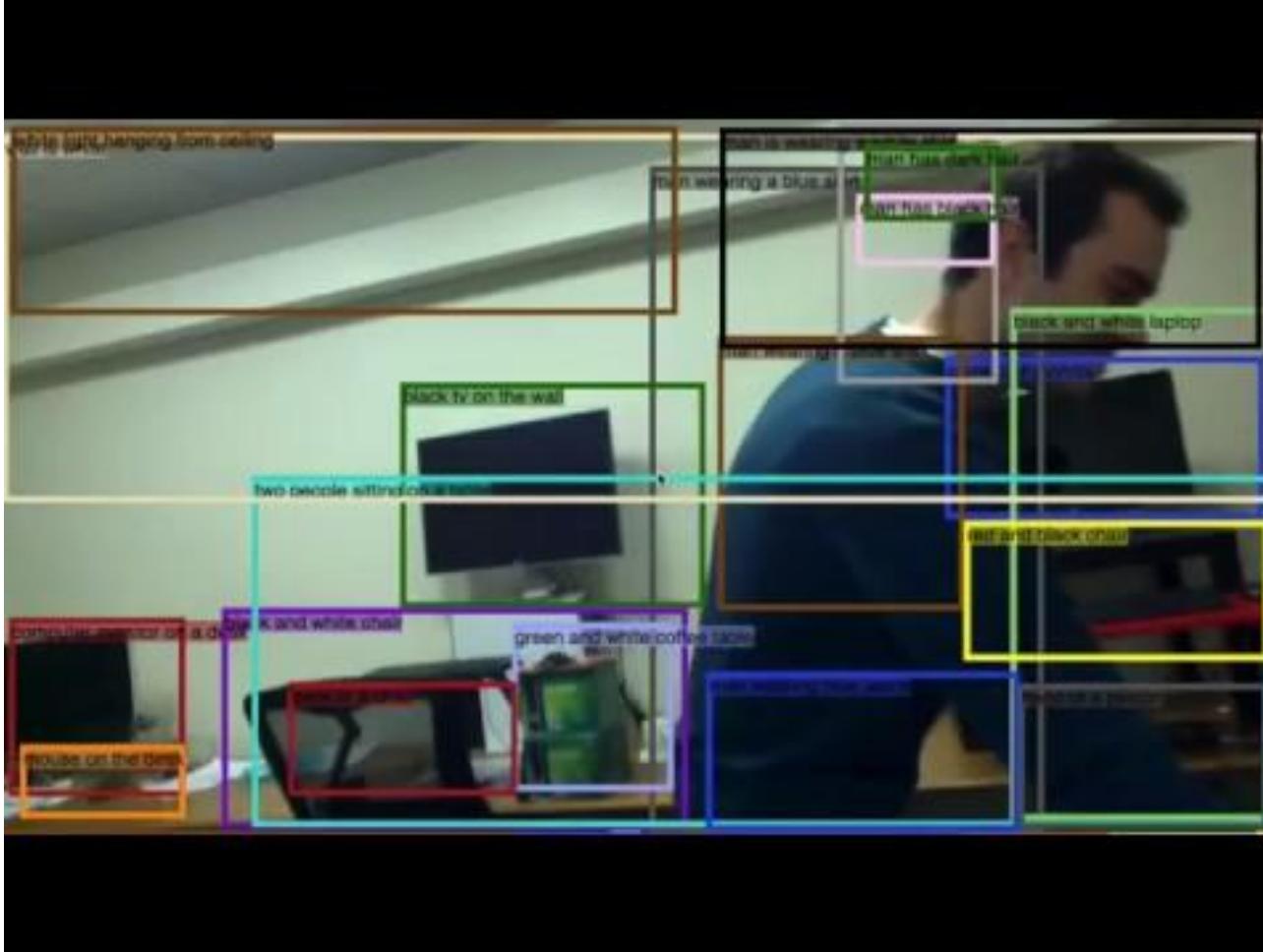
Finetune on your own dataset with pre-trained models

Beyond 2D Object Detection...

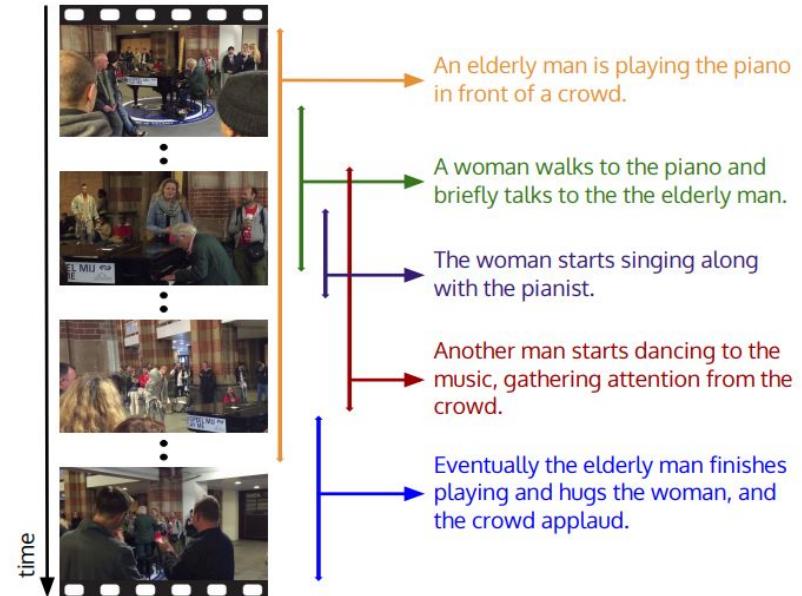
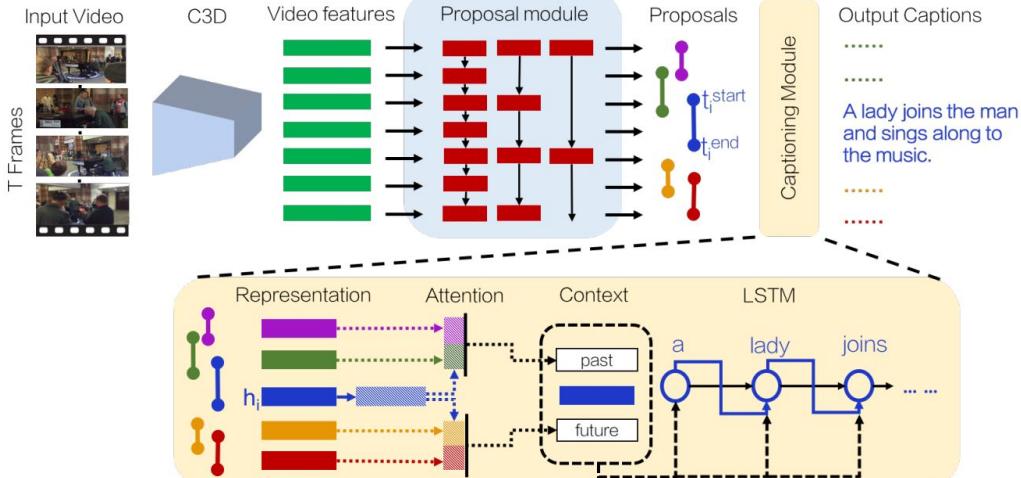
Object Detection + Captioning = Dense Captioning



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

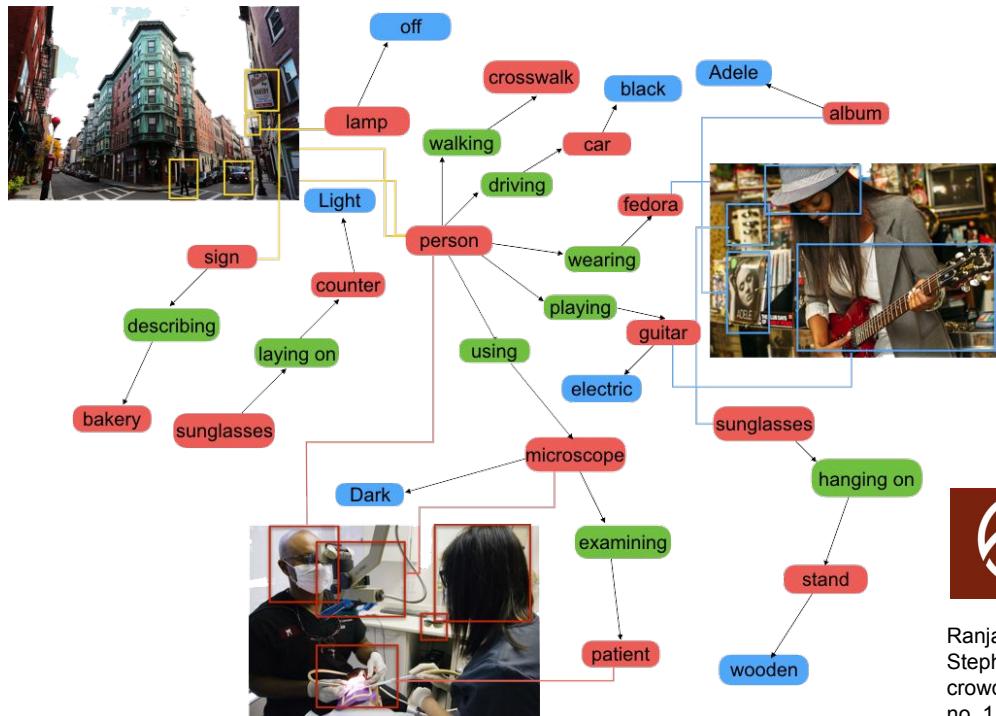


Dense Video Captioning



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

next to

5.4 Million Region Descriptions

1.7 Million Visual Question Answers

3.8 Million Object Instances

2.8 Million Attributes

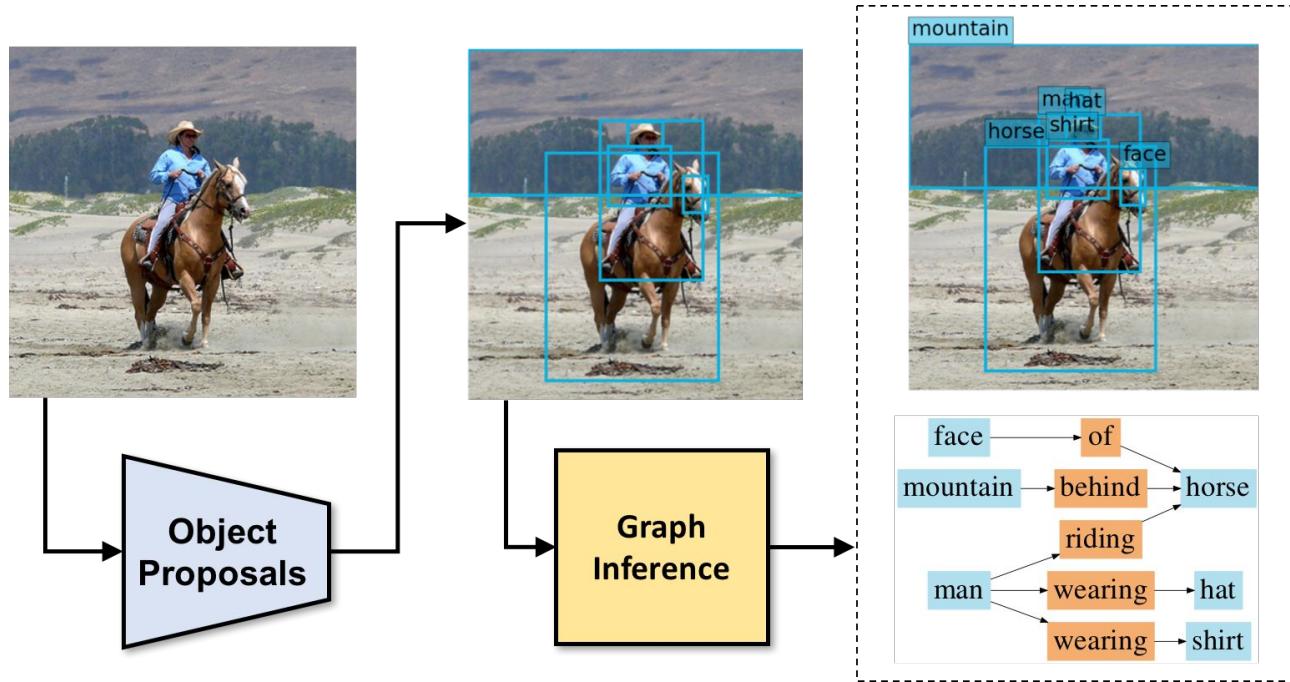
2.3 Million Relationships

Everything Mapped to Wordnet Synsets

 **VISUALGENOME**

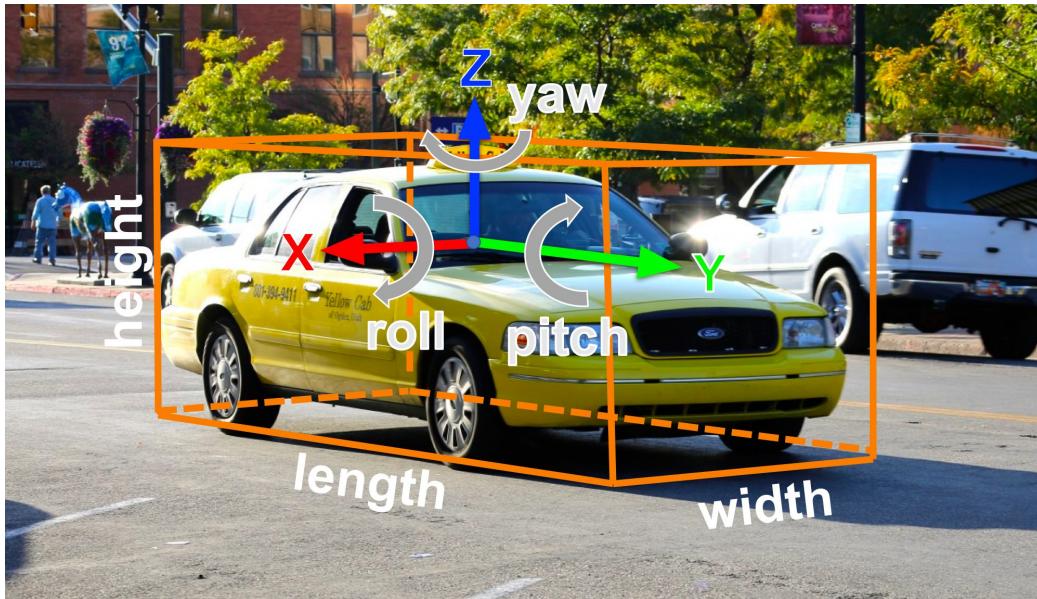
Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "Visual genome: Connecting language and vision using crowdsourced dense image annotations." International Journal of Computer Vision 123, no. 1 (2017): 32-73.

Scene Graph Prediction



Xu, Zhu, Choy, and Fei-Fei, "Scene Graph Generation by Iterative Message Passing", CVPR 2017
Figure copyright IEEE, 2018. Reproduced for educational purposes.

3D Object Detection



2D Object Detection:

2D bounding box
(x, y, w, h)

3D Object Detection:

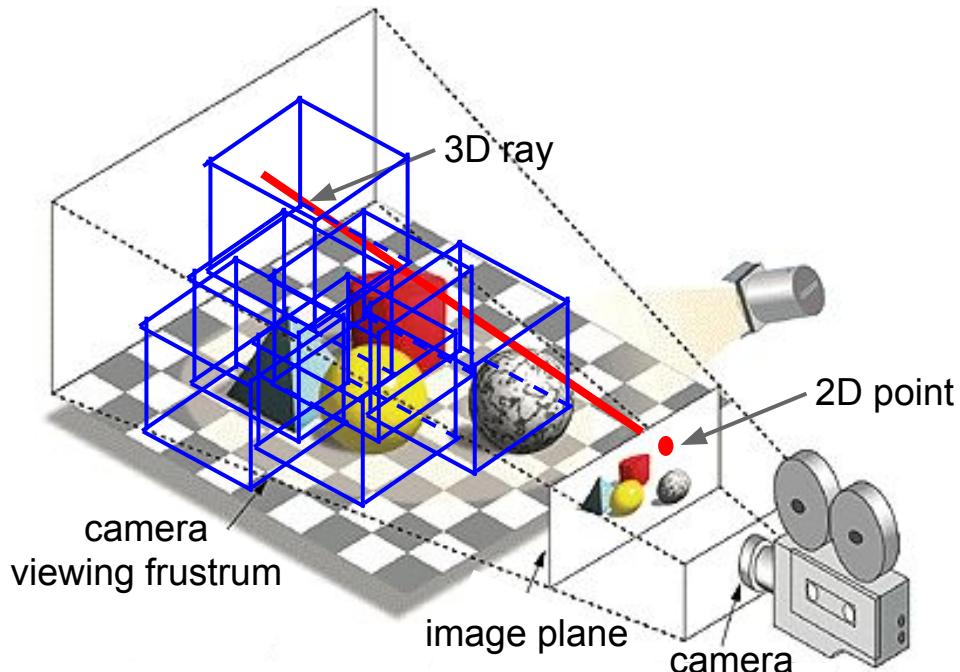
3D oriented bounding box
($x, y, z, w, h, l, r, p, y$)

Simplified bbox: no roll & pitch

Much harder problem than 2D object detection!

This image is CC0 public domain

3D Object Detection: Simple Camera Model



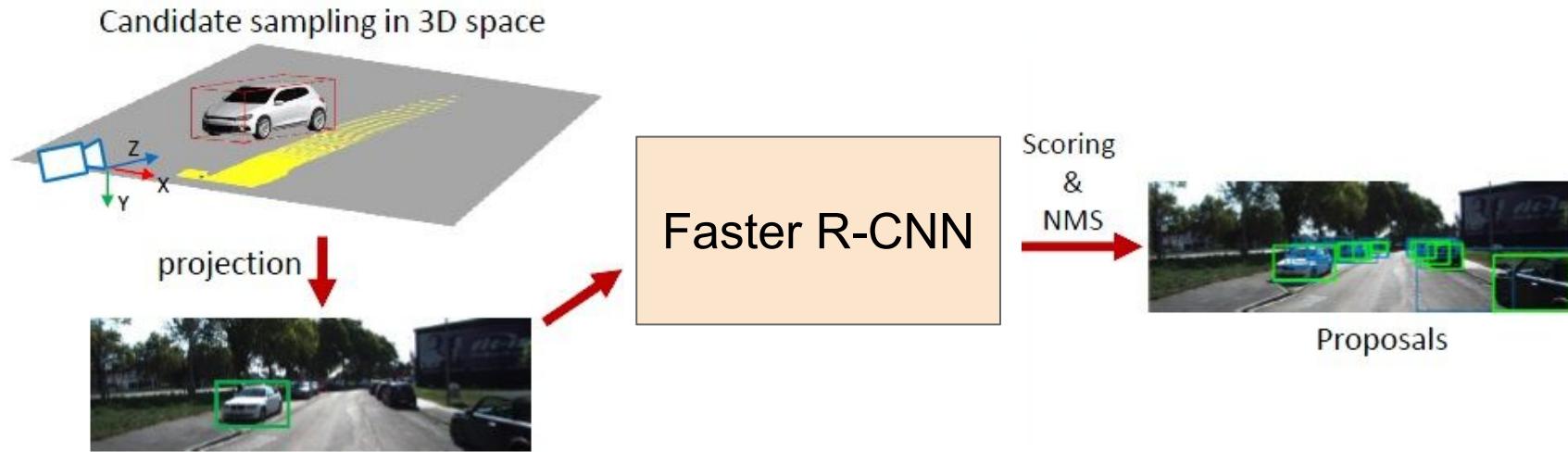
A point on the image plane corresponds to a **ray** in the 3D space

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

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

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

3D Object Detection: Monocular Camera

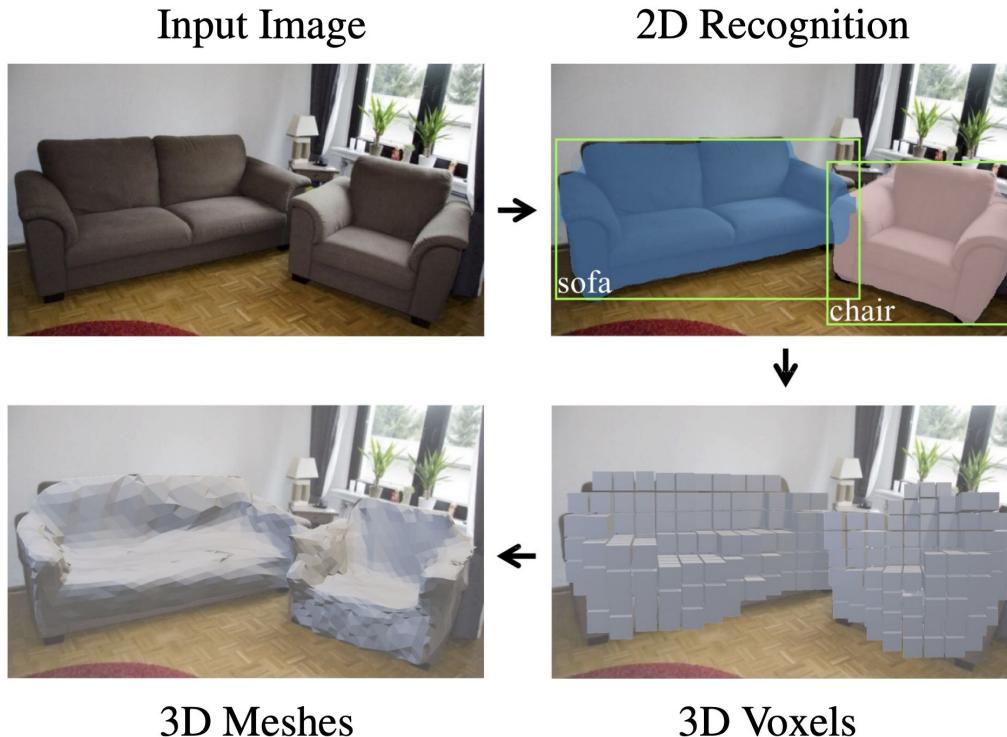


2D candidate boxes

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

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

3D Shape Prediction: Mesh R-CNN



Gkioxari et al., Mesh RCNN, ICCV 2019

Recap: Lots of computer vision tasks!

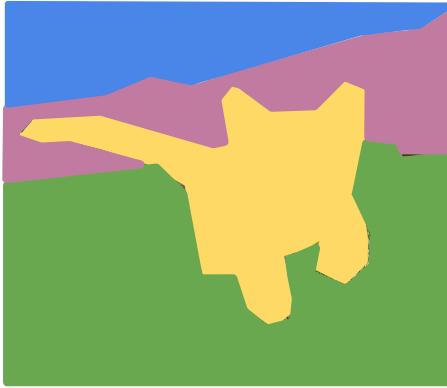
Classification



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:
Visualizing CNN features
DeepDream + Style Transfer