# CNN applications

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(Slide credits: Fei-Fei Li, Andrej Karpathy, Justin Johnson, Serena Yeung)

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University of Oklahoma

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# Overview

- We will look into several applications of CNNs besides image recognition
  - Semantic segmentation
  - Object localization
  - Object detection
  - Instance segmentation

# So far: Image Classification

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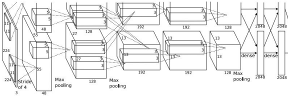


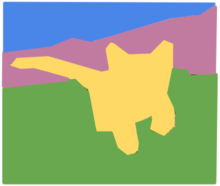
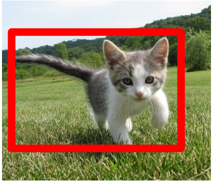
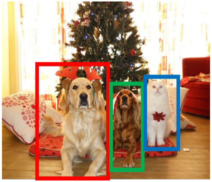
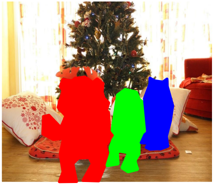
Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

**Vector:** 4096

**Fully-Connected**: 4096 to 1000

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

# Other Computer Vision Tasks

| Semantic Segmentation | Classification + Localization | Object Detection | Instance Segmentation |
|---|---|---|---|
|  |  |  |  |
| GRASS, CAT, TREE, SKY | CAT | DOG, DOG, CAT | DOG, DOG, CAT |
| No objects, just pixels | Single Object | Multiple Object | |

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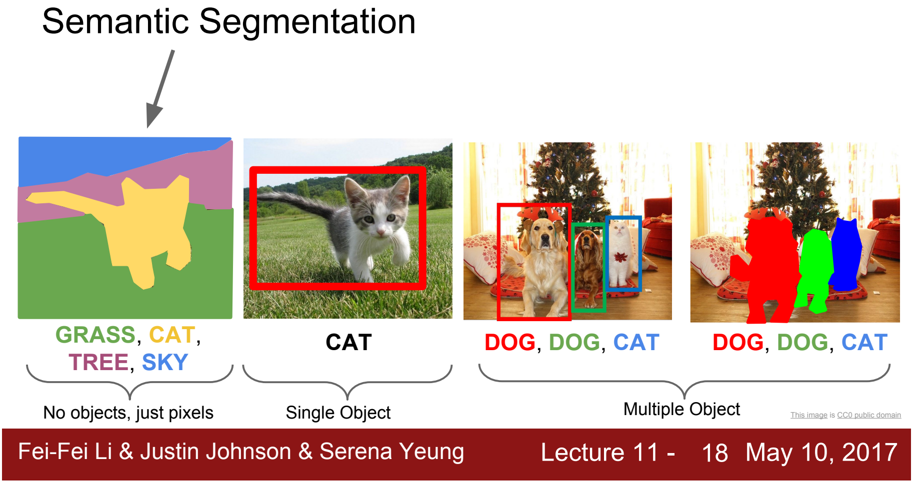
Semantic Segmentation
GRASS, CAT, TREE, SKY
CAT
DOG, DOG, CAT
DOG, DOG, CAT
No objects, just pixels
Single Object
Multiple Object
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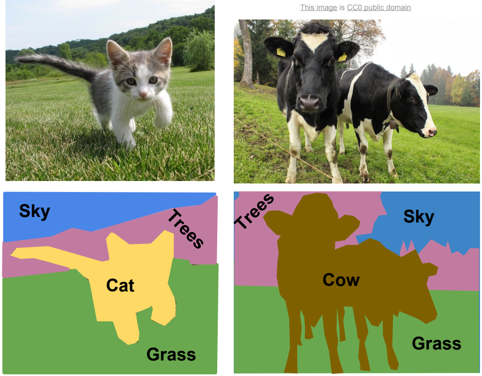
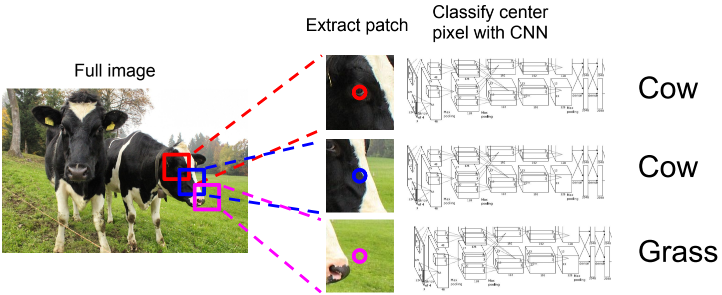
# Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

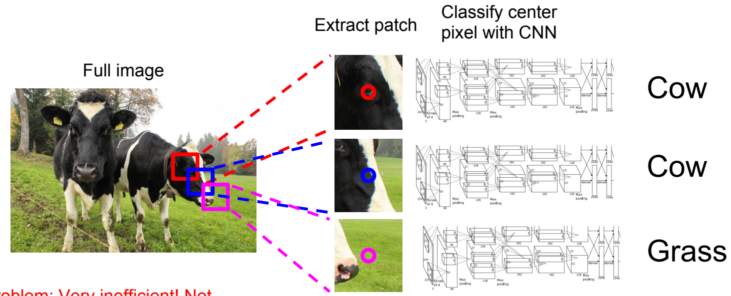


# Semantic Segmentation Idea: Sliding Window




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

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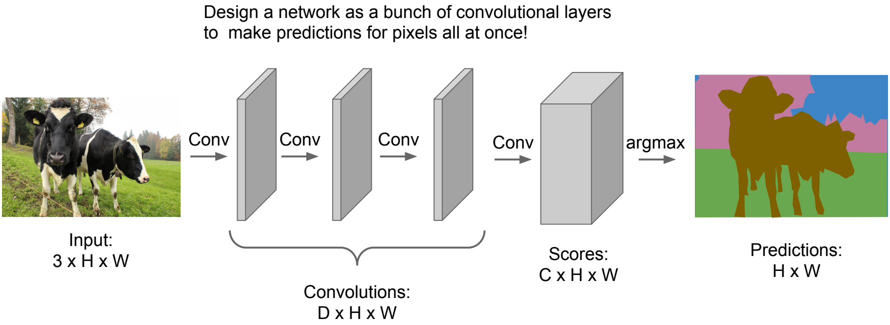
# Semantic Segmentation Idea: Fully Convolutional

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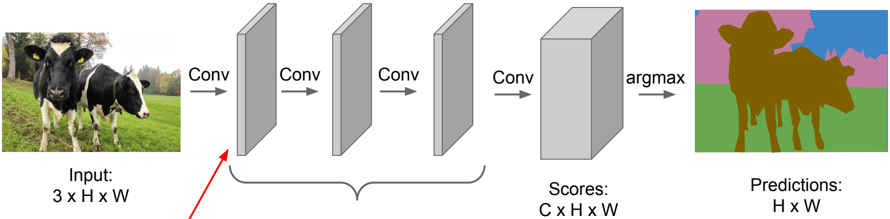
# Semantic Segmentation Idea: Fully Convolutional

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




Convolutions:
D x H x W

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

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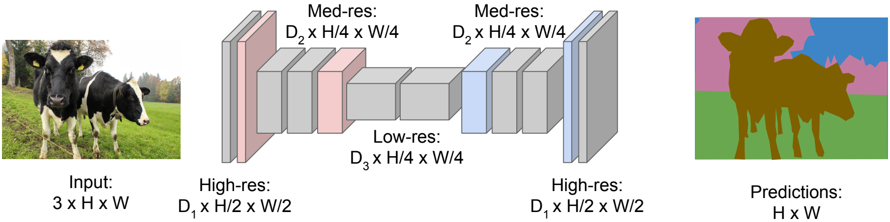
# Semantic Segmentation Idea: Fully Convolutional

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

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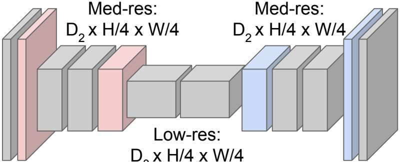
# Semantic Segmentation Idea: Fully Convolutional

**Downsampling**: Pooling, strided convolution

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

**Upsampling**: ???

Input:
3 x H x W



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

Med-res:
$D_2$ x H/4 x W/4

Low-res:
$D_3$ x H/4 x W/4

Med-res:
$D_2$ x H/4 x W/4

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

Predictions:
H x W

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

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# 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”

**Max Pooling**
Remember which element was max!

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

Input: 4 x 4

| | |
|---|---|
| 5 | 6 |
| 7 | 8 |

Output: 2 x 2

…

Rest of the network

**Max Unpooling**
Use positions from pooling layer

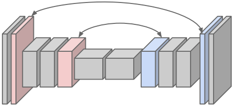
| | |
|---|---|
| 1 | 2 |
| 3 | 4 |

Input: 2 x 2

| | | | |
|---|---|---|---|
| 0 | 0 | 2 | 0 |
| 0 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 4 |

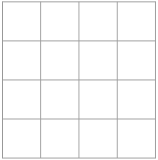
Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

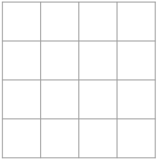


# Learnable Upsampling: Transpose Convolution

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



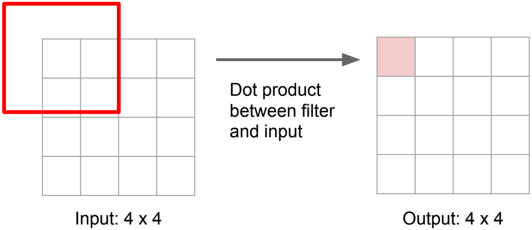
Input: 4 x 4



Output: 4 x 4

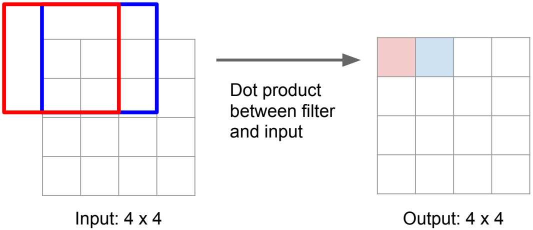
# Learnable Upsampling: Transpose Convolution

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



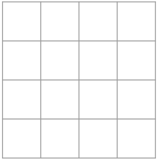
# Learnable Upsampling: Transpose Convolution

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

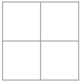


# Learnable Upsampling: Transpose Convolution

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



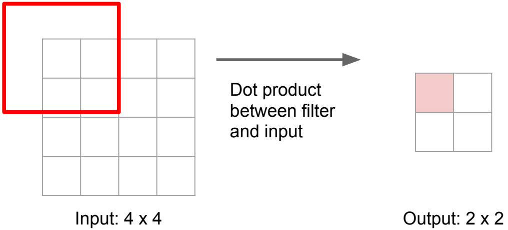
Input: 4 x 4



Output: 2 x 2

# Learnable Upsampling: Transpose Convolution

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

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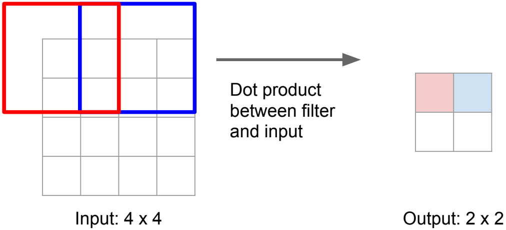
# Learnable Upsampling: Transpose Convolution

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




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

Stride gives ratio between movement in input and output

# Learnable Upsampling: Transpose Convolution

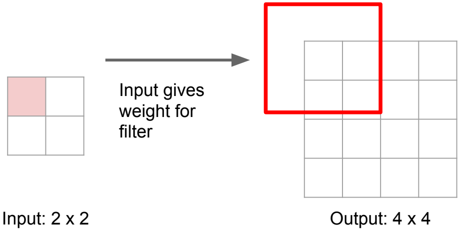
3 x 3 **transpose** convolution, stride 2 pad 1

Input: 2 x 2

Output: 4 x 4

# Learnable Upsampling: Transpose Convolution

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

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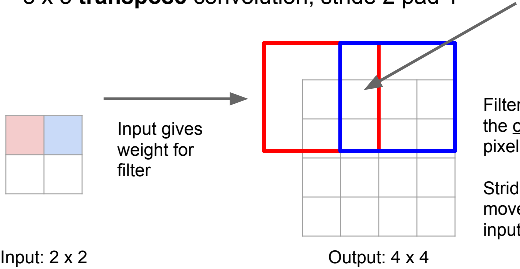
# Learnable Upsampling: Transpose Convolution

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

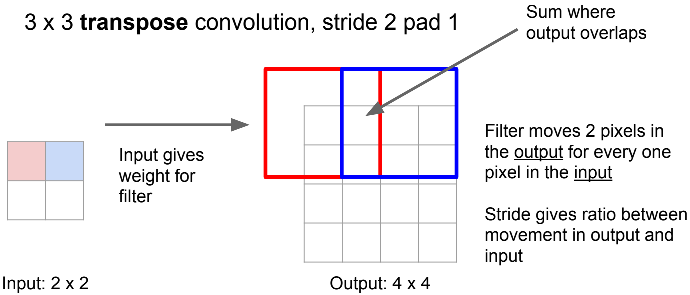
Sum where output overlaps




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

Stride gives ratio between movement in output and input

# Learnable Upsampling: Transpose Convolution

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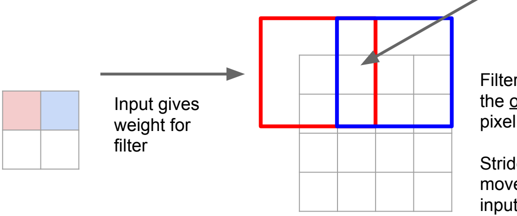
# Learnable Upsampling: Transpose Convolution

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

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

Sum where output overlaps



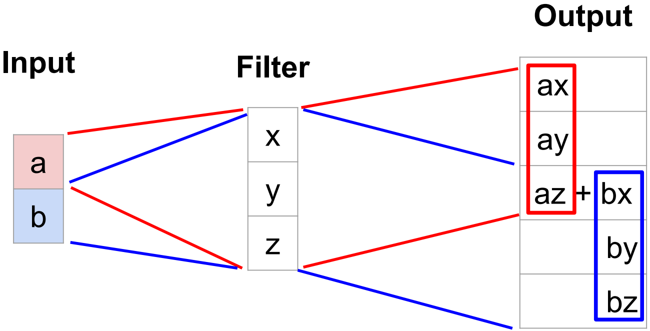

Input: 2 x 2

Output: 4 x 4

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

Stride gives ratio between movement in output and input

# Transpose Convolution: 1D Example




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

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

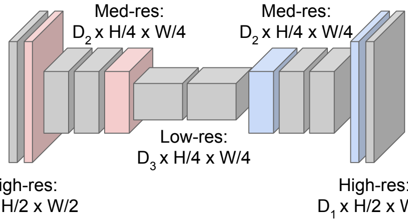
# Semantic Segmentation Idea: Fully Convolutional

**Downsampling**:
Pooling, strided convolution

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

**Upsampling**:
Unpooling or strided transpose convolution

Input:
3 x H x W




Predictions:
H x W

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

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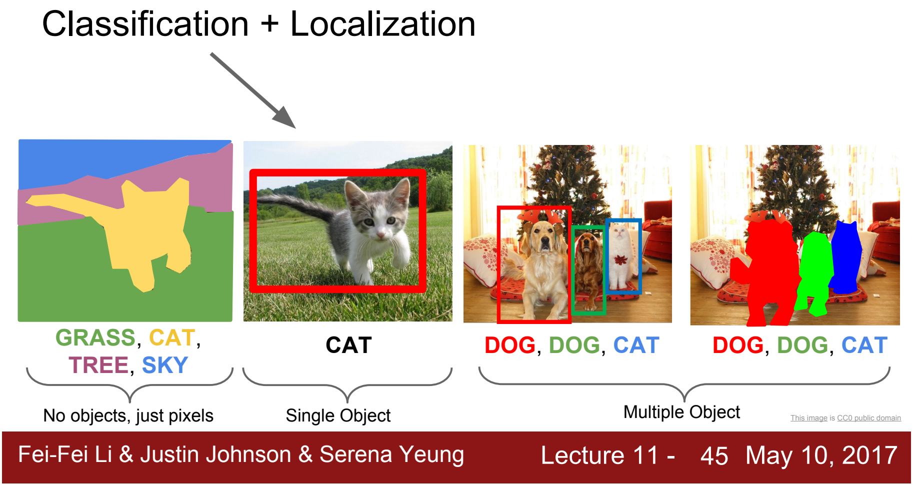
Classification + Localization
GRASS, CAT, TREE, SKY
No objects, just pixels
CAT
Single Object
DOG, DOG, CAT
DOG, DOG, CAT
Multiple Object
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# Classification + Localization

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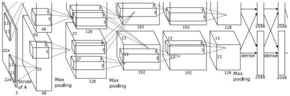

**Vector:** 4096

**Fully Connected:** 4096 to 1000

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

**Fully Connected:** 4096 to 4

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

Treat localization as a regression problem!

# Classification + Localization

**Correct label:**
Cat

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

**Softmax Loss**

**Fully Connected:**
4096 to 1000

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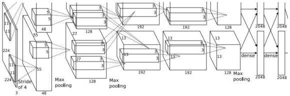

**Vector:** 4096

**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!

# Classification + Localization

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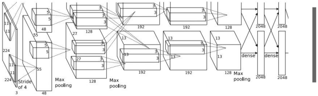


**Vector:** 4096

**Fully Connected**: 4096 to 1000

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

**Correct label:** Cat

**Softmax Loss**

**Fully Connected**: 4096 to 4

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

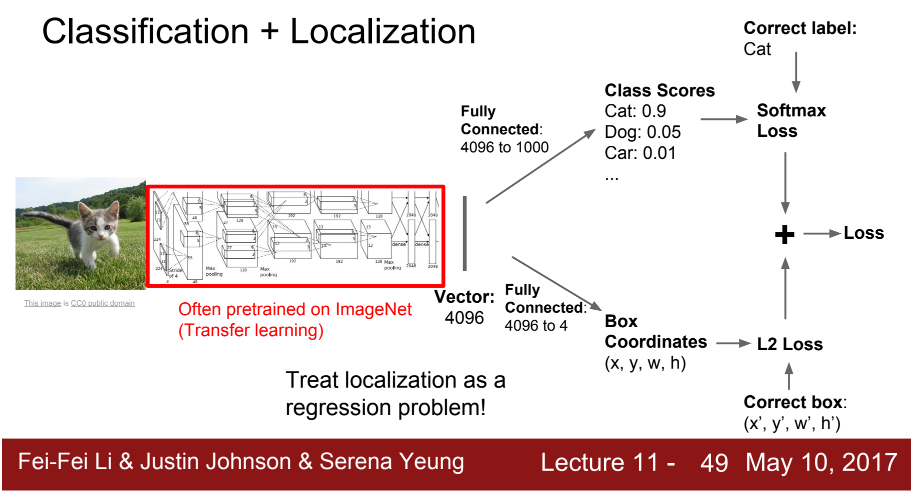
**L2 Loss**

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

Multitask Loss

**+** → **Loss**

Treat localization as a regression problem!


Classification + Localization
Correct label:
Cat
Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...
Softmax
Loss
Fully
Connected:
4096 to 1000
Loss
This image is CC0 public domain
Often pretrained on ImageNet
(Transfer learning)
Vector:
4096
Fully
Connected:
4096 to 4
Box
Coordinates
(x, y, w, h)
L2 Loss
Treat localization as a
regression problem!
Correct box:
(x', y', w', h')
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# Aside: Human Pose Estimation

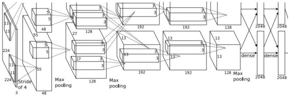
Represent pose as a set of 14 joint positions:

Left / right foot
Left / right knee
Left / right hip
Left / right shoulder
Left / right elbow
Left / right hand
Neck
Head top



Johnson and Everingham, "Clustered Pose and Nonlinear Appearance Models for Human Pose Estimation", BMVC 2010

# Aside: Human Pose Estimation



**Vector:** 4096

**Left foot**: (x, y)

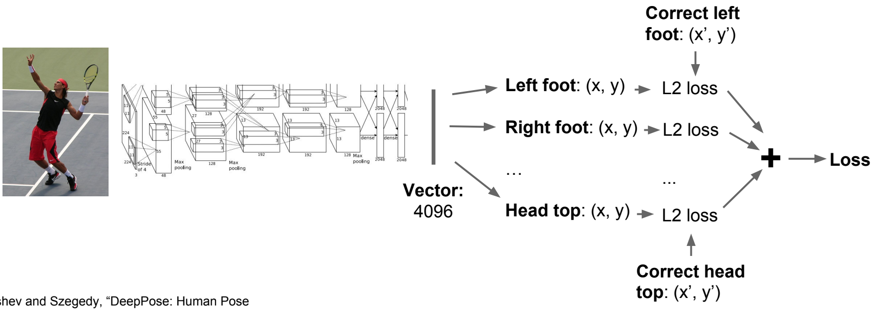
**Right foot**: (x, y)

…

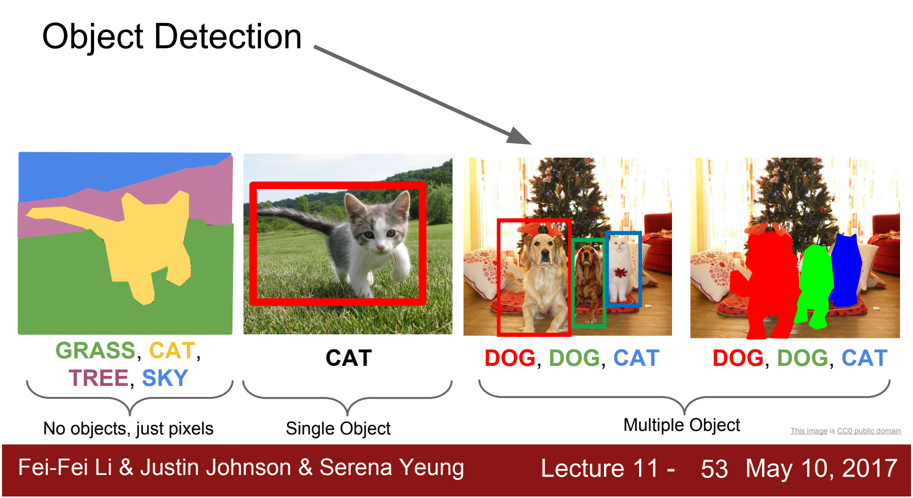
**Head top**: (x, y)

Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014

# Aside: Human Pose Estimation




Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014


Object Detection
GRASS, CAT, TREE, SKY
CAT
DOG, DOG, CAT
DOG, DOG, CAT
No objects, just pixels
Single Object
Multiple Object
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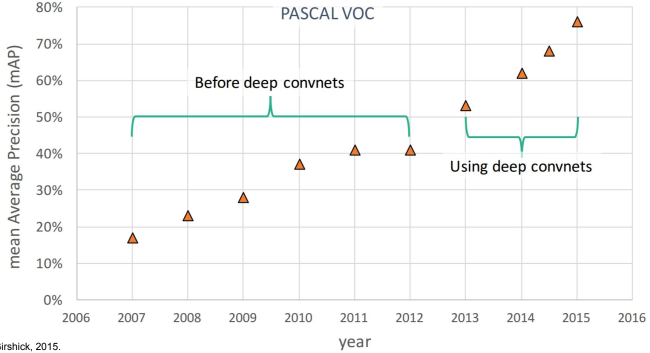
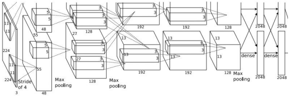
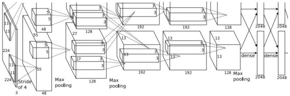
# Object Detection: Impact of Deep Learning



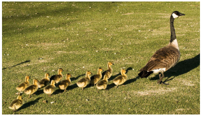
# Object Detection as Regression?

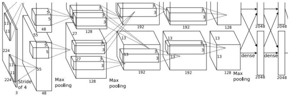



CAT: (x, y, w, h)




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






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

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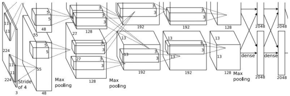
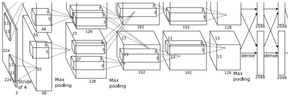
# Object Detection as Regression?

Each image needs a different number of outputs!

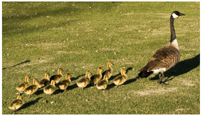
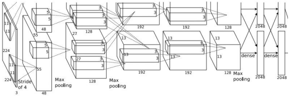
CAT: (x, y, w, h)

4 numbers

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

16 numbers

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

Many numbers!

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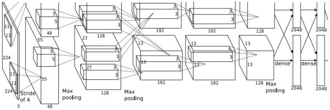
# Object Detection as Classification: Sliding Window

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




Dog? NO
Cat? NO
Background? YES

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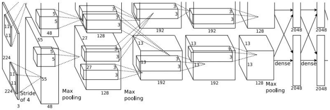
# Object Detection as Classification: Sliding Window

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



Dog? YES
Cat? NO
Background? NO

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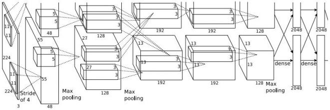
# Object Detection as Classification: Sliding Window

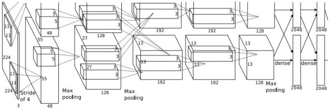
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background




Dog? YES
Cat? NO
Background? NO

# Object Detection as Classification: Sliding Window

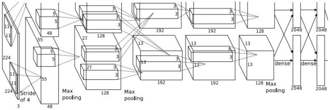
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background




Dog? NO
Cat? YES
Background? NO

# Object Detection as Classification: Sliding Window

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



Dog? NO
Cat? YES
Background? NO

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

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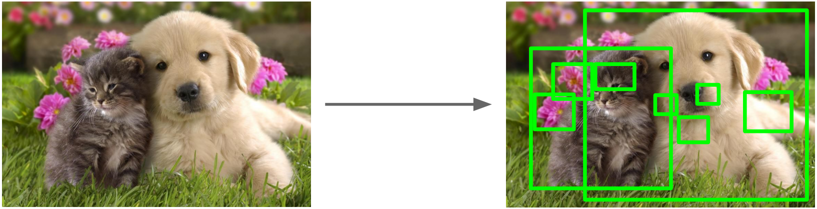
# Region Proposals

- Find “blobby” image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 1000 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

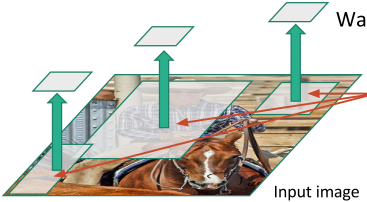
Input image

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


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

## 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.

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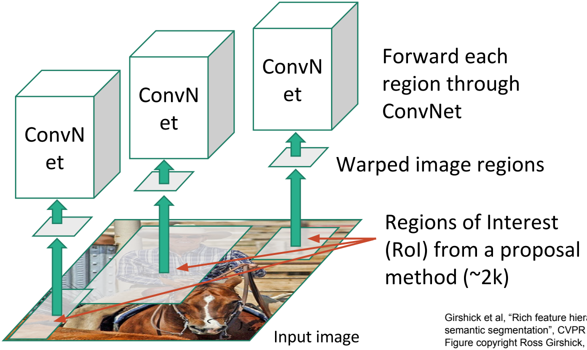
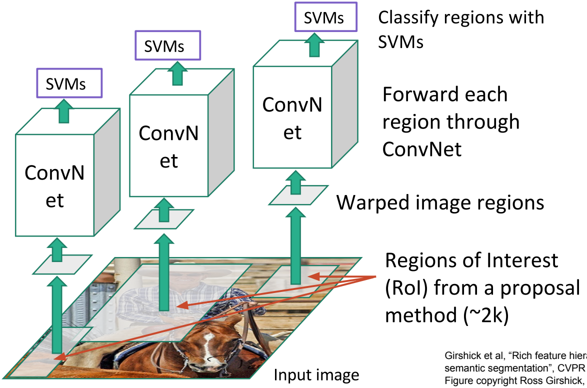
## R-CNN



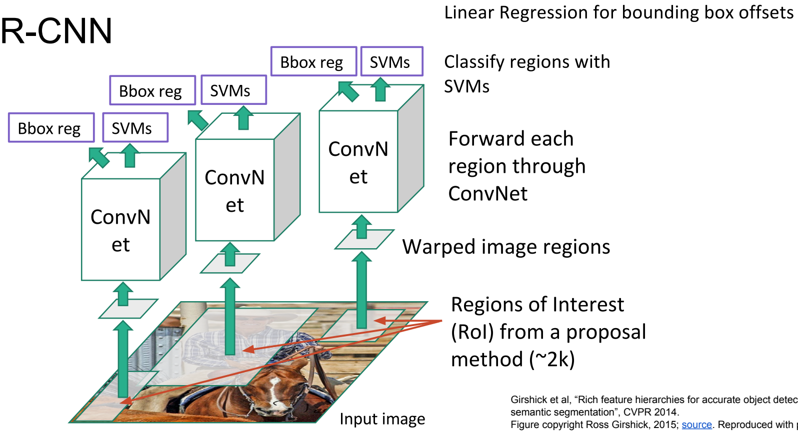

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

# R-CNN




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

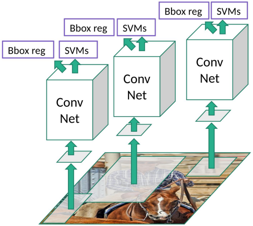
# R-CNN




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

# R-CNN: Problems

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



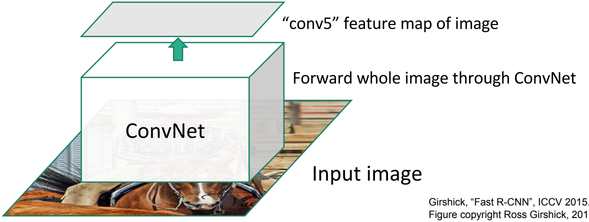

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

# Fast R-CNN

Input image

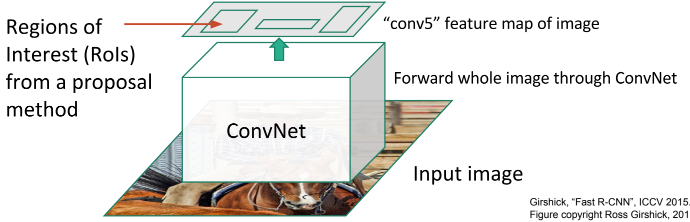
Girshick, "Fast R-CNN", ICCV 2015.

# Fast R-CNN



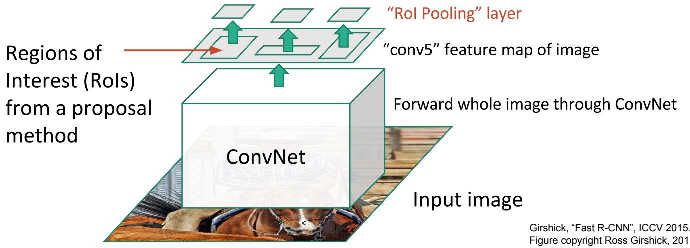

Girshick, "Fast R-CNN", ICCV 2015.

# Fast R-CNN



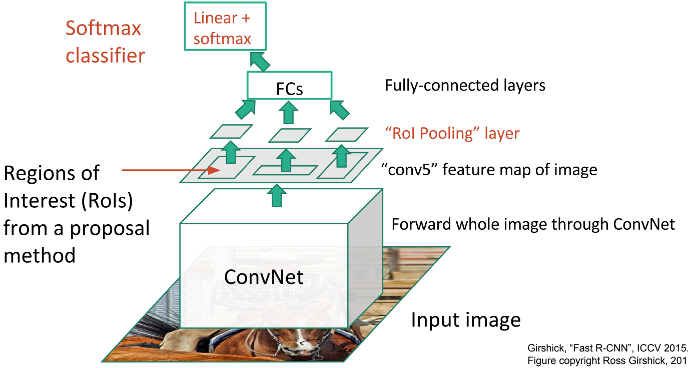

Girshick, "Fast R-CNN", ICCV 2015.

# Fast R-CNN



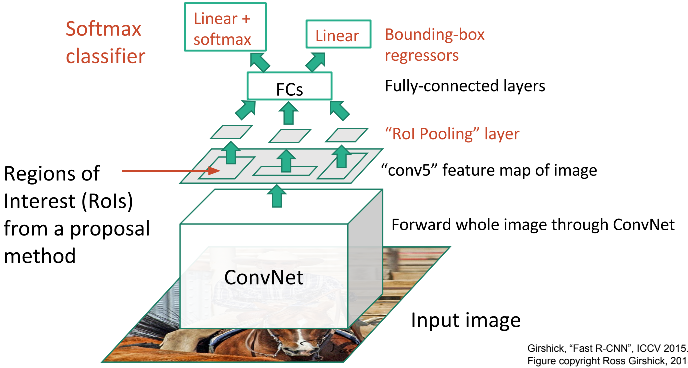

Girshick, "Fast R-CNN", ICCV 2015.

# Fast R-CNN



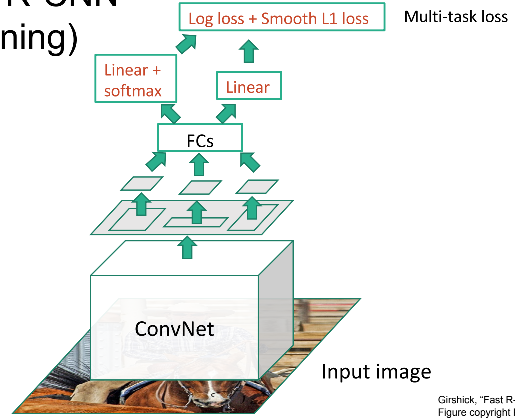

Girshick, "Fast R-CNN", ICCV 2015.

# Fast R-CNN




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

# Fast R-CNN (Training)




Girshick, "Fast R-CNN", ICCV 2015.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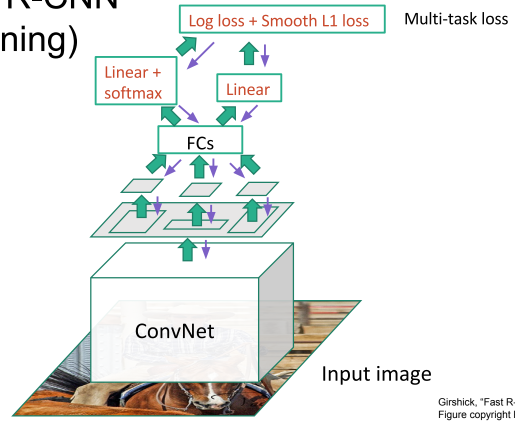
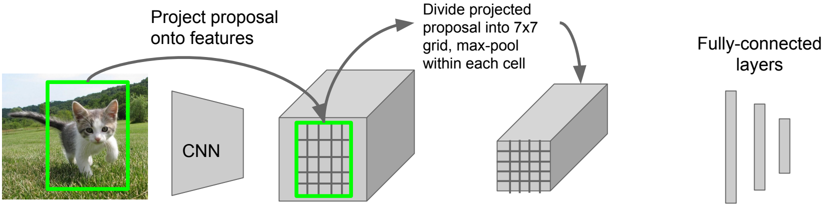
# Fast R-CNN (Training)




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

# Faster R-CNN: RoI Pooling




Hi-res input image:
3 x 640 x 480
with region
proposal

Hi-res conv features:
512 x 20 x 15;

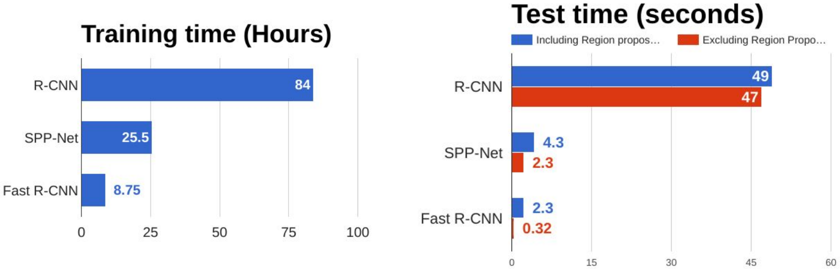
Projected region
proposal is e.g.
512 x 18 x 8
(varies per proposal)

RoI conv features:
512 x 7 x 7
for region proposal

Fully-connected layers expect
low-res conv features:
512 x 7 x 7

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

# R-CNN vs SPP vs Fast R-CNN




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

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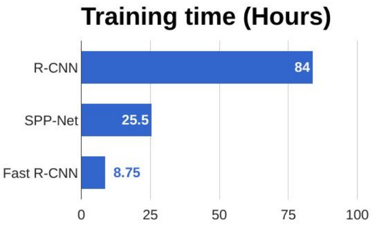
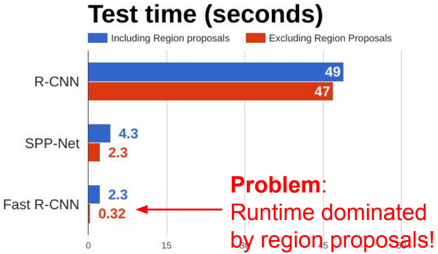
# R-CNN vs SPP vs Fast R-CNN




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

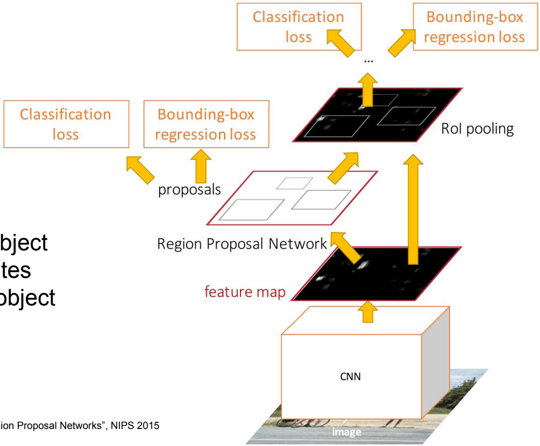
# Faster R-CNN:

Make CNN do proposals!

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

Jointly train with 4 losses:

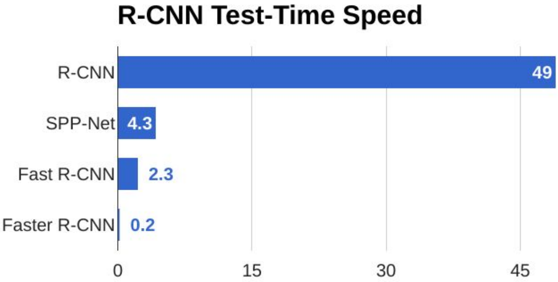
1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates




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

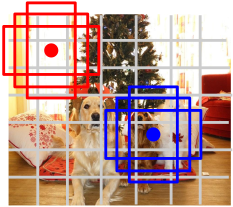
# Fast**er** R-CNN:

Make CNN do proposals!



# Detection without Proposals: YOLO / SSD

Input image
3 x H x W



Divide image into grid
7 x 7

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

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

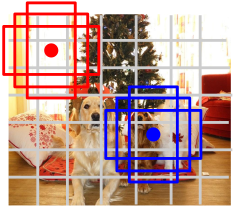
Output:
7 x 7 x (5 * B + C)

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

# Detection without Proposals: YOLO / SSD

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

Input image
3 x H x W



Divide image into grid
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7 x 7 x (5 * B + C)

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

# Object Detection: Lots of variables ...

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

**Object Detection architecture**
Faster R-CNN
R-FCN
SSD

**Image Size**
**# Region Proposals**
…

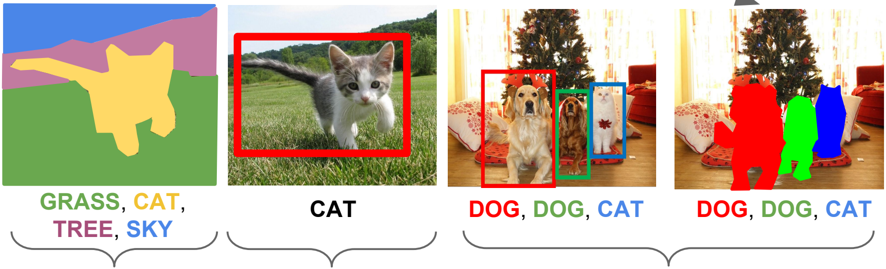
**Takeaways**
Faster R-CNN is slower but more accurate

SSD is much faster but not as accurate

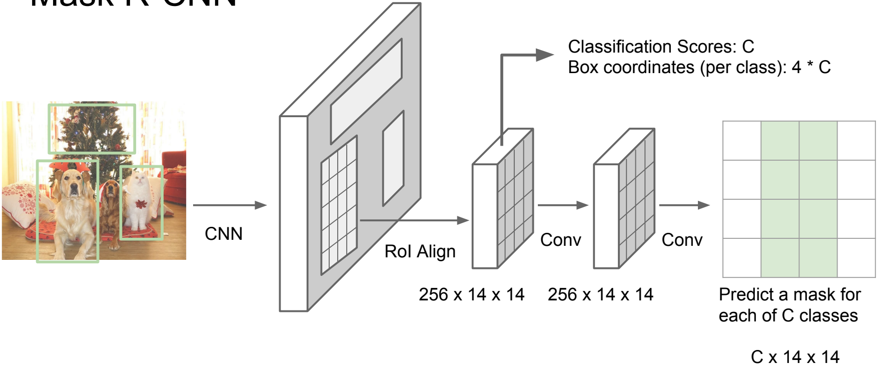
Huang et al, "Speed/accuracy trade-offs for modern convolutional object detectors", CVPR 2017

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

# Instance Segmentation

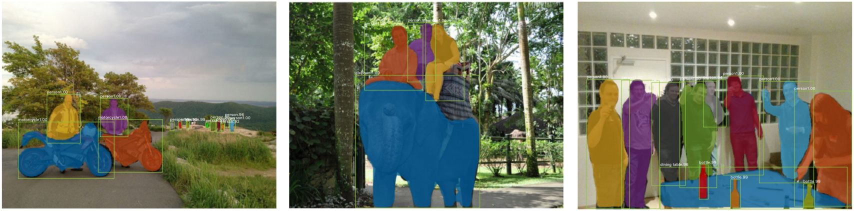


# Mask R-CNN



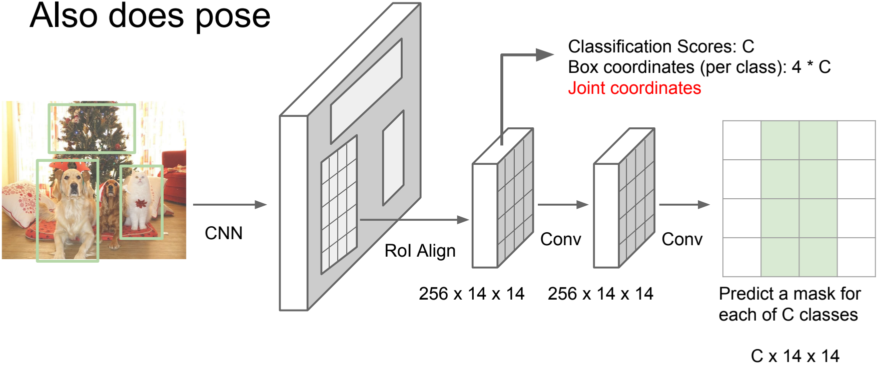

He et al, "Mask R-CNN", arXiv 2017

# Mask R-CNN: Very Good Results!



He et al, “Mask R-CNN”, arXiv 2017

# Mask R-CNN
# Also does pose




He et al, “Mask R-CNN”, arXiv 2017

# Mask R-CNN
# Also does pose


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