

Lecture 11: Detection and Segmentation

Administrative

Midterms being graded

Please don't discuss midterms until next week - some students not yet taken

A2 being graded

Project milestones due Tuesday 5/16

HyperQuest

HyperQuest

jcjohnss

Justin Johnson

Submit

HyperQuest

Please tell us a little bit about yourself.

What is your current education status?

- Undergraduate student
- Masters student
- PhD student
- Not currently in a degree program

How many years of experience training neural networks have you had?

- This class is my first experience
- Less than 6 months
- 6 months - 1 year
- 1 - 2 years
- 2+ years

How experienced would you consider yourself at training neural networks?

- Very inexperienced
- Some experience
- Moderately experienced
- Expert

What types of networks have you trained before? (Select all that apply.)

- Fully connected networks
- Convolutional neural networks
- Recurrent neural networks
- Networks for vision tasks
- Networks for NLP tasks
- None of the above

Submit

HyperQuest

HyperQuest

Student ID Logout

Instructions:

- You will be provided a random dataset. Your goal is to train a neural network for classification on the dataset, and obtain the **highest validation accuracy** that you can.
- In the first stage, you will choose the initial network configuration.
- In the second stage, you will monitor the training process and have the option of adjusting hyperparameters at every epoch.

You have trained 0 networks so far!

Start a dataset

HyperQuest

HyperQuest

Student ID Logout

Instructions:

- You will be provided a random dataset. Your goal is to train a neural network for classification on the dataset, and obtain the **highest validation accuracy** that you can.
- In the first stage, you will choose the initial network configuration.
- In the second stage, you will monitor the training process and have the option of adjusting hyperparameters at every epoch.

You have trained 0 networks so far!

Start a dataset

Instructions:

- In this stage, choose your initial network configuration. You may refer to the provided dataset statistics for reference. Click on info icons for definitions.

Initial Network Configuration

CNN network width 

- 32
- 64
- 128

Learning rate 

- 0.1
- 0.01
- 0.001

CNN network depth 

- 2
- 4
- 8

Dropout rate 

- 0
- 0.5

Submit

Dataset Statistics

Classes: 10 **Input data size:** [3, 32, 32] **Examples per split:** Train (8500), Val (1500) 

Goal: maximize **best** validation accuracy

Leaderboard: updated periodically [here](#)

Action 1 of max

60

(After training 1 of max 30 epochs)

- Continue
- Done training
- Revert (max 5 consecutive)

Submit

Hyperparameter Adjustment

Weight decay (0)

Same

Next value: 0

CNN Network depth (2)

Same

Next value: 2

Dropout (0.0)

Same

Next value: 0

Learning rate (1.00e-2)

Same

Next value: 1.00e-2

CNN Network width (32)

Same

Next value: 32

Dataset Statistics

Classes: 10

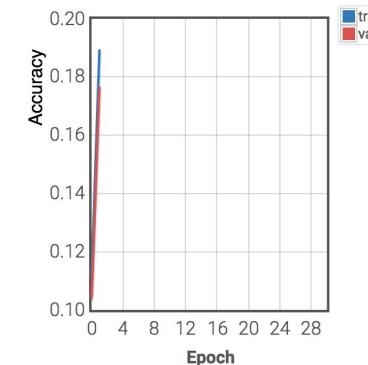
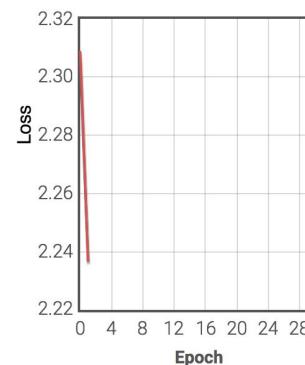
Input data size: [3, 32, 32]

Examples per split: Train (8500), Val (1500)

Configuration History

1. Width = 32, Depth = 2, Learning rate = 0.01, Dropout = 0, Weight decay = 0

Current best training accuracy: 0.190
Current best validation accuracy: 0.177 (Baseline: 0.283)



Goal: maximize **best** validation accuracy

Leaderboard: updated periodically [here](#)

Action 3 of max 60

(After training 3 of max 30 epochs)

- Continue
- Done training
- Revert (max 5 consecutive)

Submit

Hyperparameter Adjustment

Weight decay (0)

Same

Up

Down

Next value: 0

CNN Network depth (2)

Same

Up

Down

Next value: 2

Dropout (0.0)

Same

Up

Down

Next value: 0

Learning rate (1.00e-2)

Same

Up

Down

Next value: 1.00e-2

CNN Network width (32)

Same

Up

Down

Next value: 32

Dataset Statistics

Classes: 10

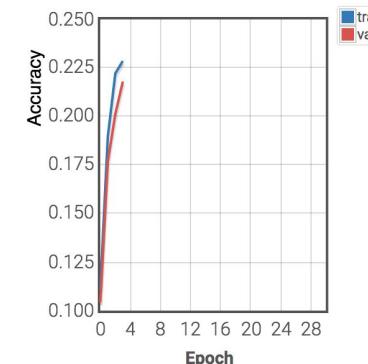
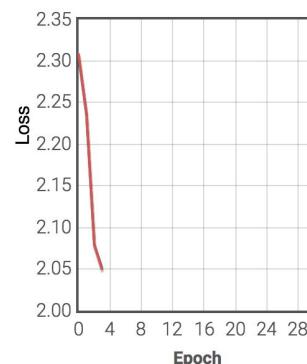
Input data size: [3, 32, 32]

Examples per split: Train (8500), Val (1500)

Configuration History

3. Width = 32, Depth = 2, Learning rate = 0.01, Dropout = 0, Weight decay = 0
2. Width = 32, Depth = 2, Learning rate = 0.01, Dropout = 0, Weight decay = 0
1. Width = 32, Depth = 2, Learning rate = 0.01, Dropout = 0, Weight decay = 0

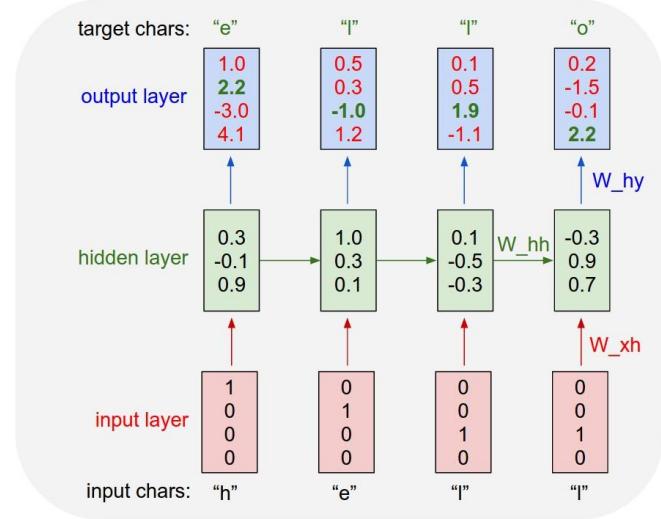
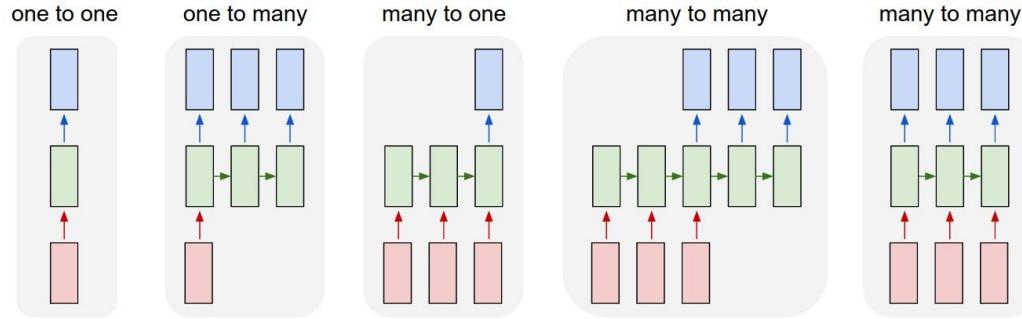
Current best training accuracy: 0.229
Current best validation accuracy: 0.218 (Baseline: 0.283)



HyperQuest

Will post more details on Piazza this afternoon

Last Time: Recurrent Networks



Last Time: Recurrent Networks

For $\bigoplus_{n=1,\dots,m} \mathcal{L}_{m,n} = 0$, hence we can find a closed subset \mathcal{H} in \mathcal{H} and any sets \mathcal{F} on X , U is a closed immersion of S , then $U \rightarrow T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \text{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \rightarrow V$. Consider the maps M along the set of points \mathcal{Sch}_{fppf} and $U \rightarrow U$ is the fibre category of S in U in Section ?? and the fact that any U affine, see Morphisms, Lemma ?? . Hence we obtain a scheme S and any open subset $W \subset U$ in $\mathcal{Sh}(G)$ such that $\text{Spec}(R') \rightarrow S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S . We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \rightarrow \mathcal{O}_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\text{GL}_{S'}(x'/S'')$ and we win. \square

To prove study we see that $\mathcal{F}|_U$ is a covering of \mathcal{X}' , and \mathcal{T}_i is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and \mathcal{F}_p exists and let \mathcal{F}_i be a presheaf of \mathcal{O}_X -modules on \mathcal{C} as a \mathcal{F} -module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\text{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1} \mathcal{F}$$

is a unique morphism of algebraic stacks. Note that

$$\text{Arrows} = (\mathcal{Sch}/S)_{fppf}^{\text{opp}}, (\mathcal{Sch}/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longrightarrow (U, \text{Spec}(A))$$

is an open subset of X . Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S .

Proof. See discussion of sheaves of sets. \square

The result for prove any open covering follows from the less of Example ?? . It may replace S by $X_{\text{spaces},\text{\'etale}}$ which gives an open subspace of X and T equal to S_{Zar} , see Descent, Lemma ?? . Namely, by Lemma ?? we see that R is geometrically regular over S .

PANDARUS:

Alas, I think he shall be come approached and the day
When little strain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord:

They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:

Come, sir, I will make did behold your worship.

VIOLA:

I'll drink it.

```
static void do_command(struct seq_file *m, void *v)
{
    int column = 32 << (cmd[2] & 0x80);
    if (state)
        cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
    else
        seq = 1;
    for (i = 0; i < 16; i++) {
        if (k & (1 << i))
            pipe = (in_use & UMXTTHREAD_UNCCA) +
                ((count & 0x00000000fffffff8) & 0x0000000f) << 8;
        if (count == 0)
            sub(pid, ppc_md.kexec_handle, 0x20000000);
        pipe_set_bytes(i, 0);
    }
    /* Free our user pages pointer to place camera if all dash */
    subsystem_info = &of_changes[PAGE_SIZE];
    rek_controls(offset, idx, &offset);
    /* Now we want to deliberately put it to device */
    control_check_polarity(&context, val, 0);
    for (i = 0; i < COUNTER; i++)
        seq_puts(s, "policy ");
}
```

Last Time: Recurrent Networks

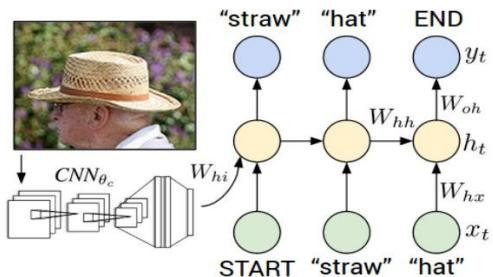


Figure from Karpathy et al, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015; figure copyright IEEE, 2015.

Reproduced for educational purposes.



A cat sitting on a suitcase on the floor



A cat is sitting on a tree branch



A woman is holding a cat in her hand



Two people walking on the beach with surfboards



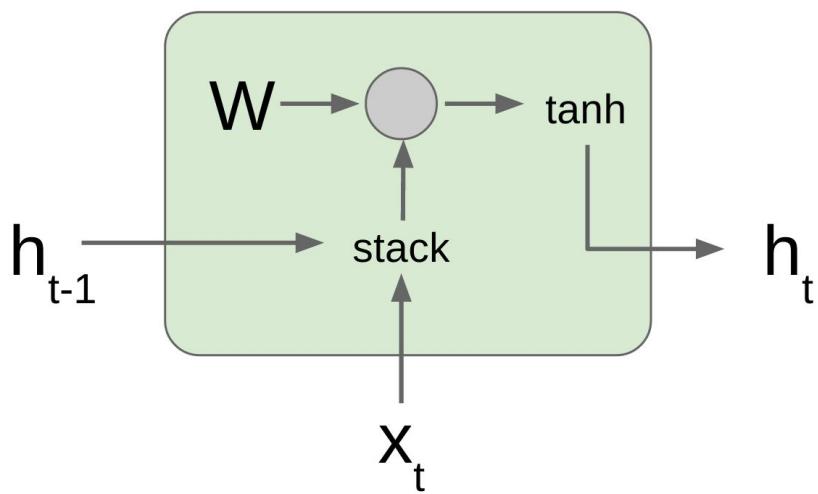
A tennis player in action on the court



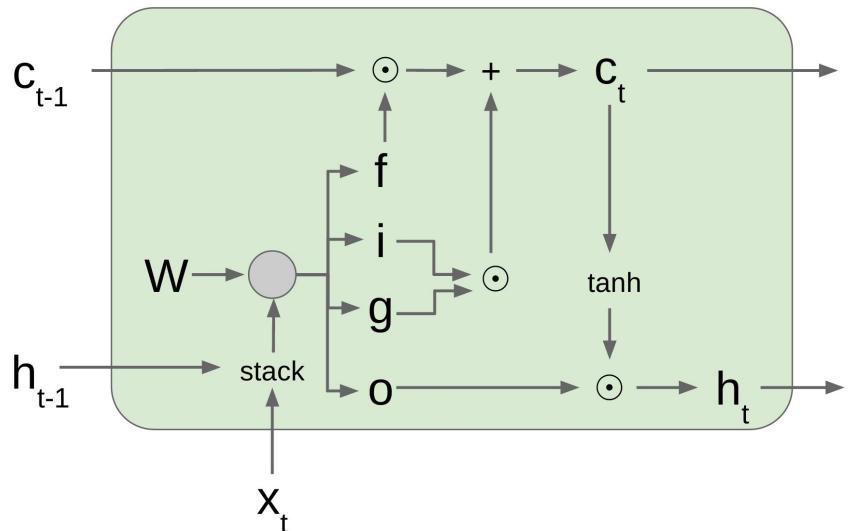
A person holding a computer mouse on a desk

Last Time: Recurrent Networks

Vanilla RNN
Simple RNN
Elman RNN



Long Short Term Memory
(LSTM)



Elman, "Finding Structure in Time", Cognitive Science, 1990.

Hochreiter and Schmidhuber, "Long Short-Term Memory", Neural computation, 1997

Today: Segmentation, Localization, Detection

So far: Image Classification



This image is CC0 public domain

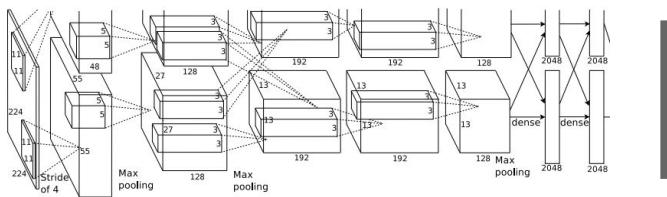


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

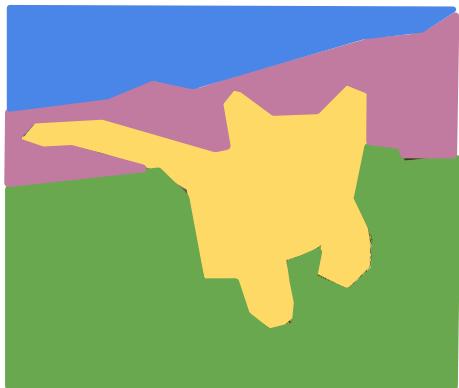
Vector:
4096

Fully-Connected:
4096 to 1000
...

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01

Other Computer Vision Tasks

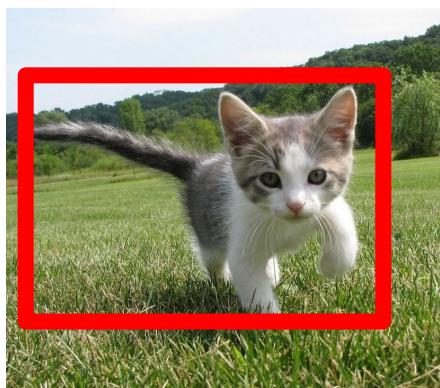
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Classification + Localization



CAT

Single Object

Object Detection



DOG, DOG, CAT

Multiple Object

Instance Segmentation



DOG, DOG, CAT

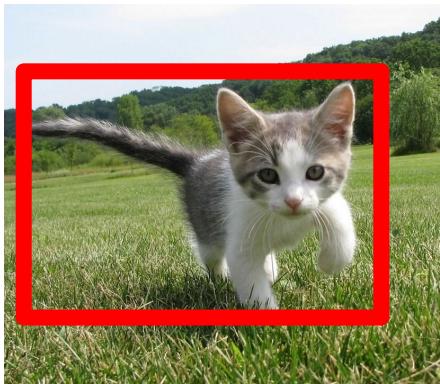
This image is CC0 public domain

Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels



CAT

Single Object



DOG, DOG, CAT

Multiple Object



DOG, DOG, CAT

This image is CC0 public domain

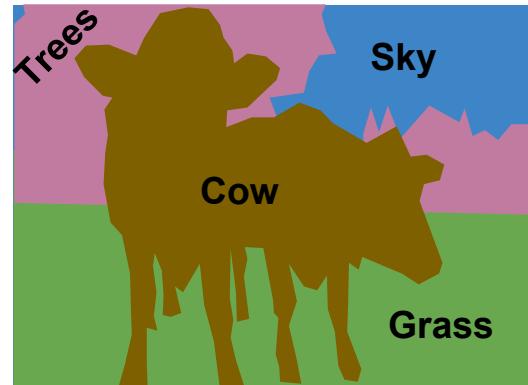
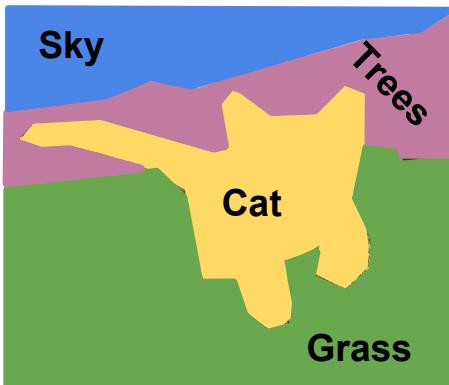
Semantic Segmentation

Label each pixel in the image with a category label

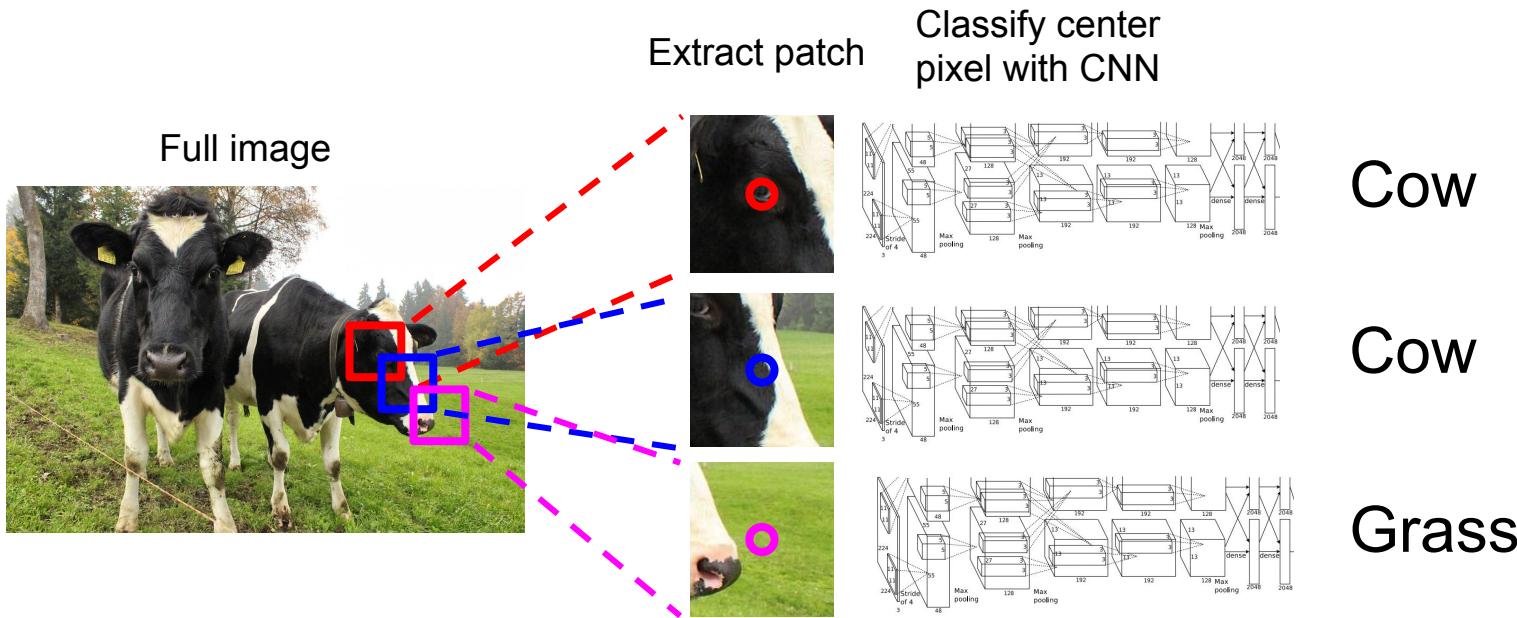
Don't differentiate instances, only care about pixels



[This image is CC0 public domain](#)



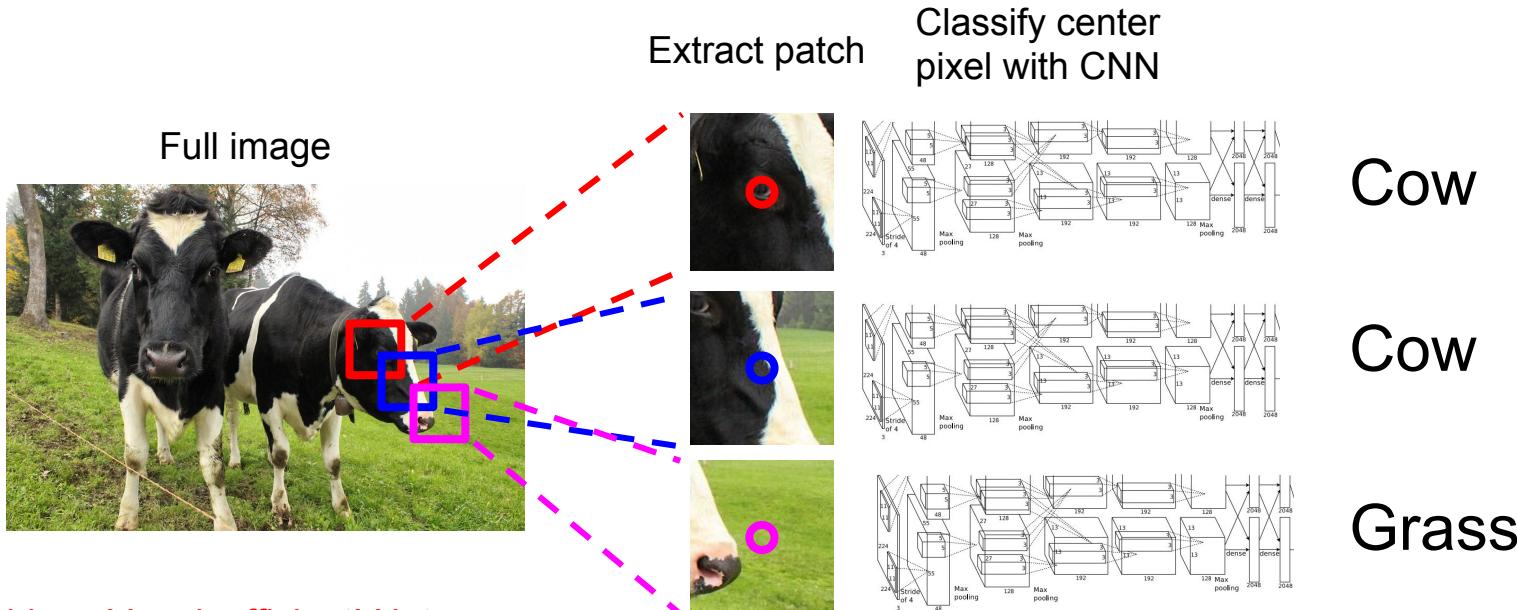
Semantic Segmentation Idea: Sliding Window



Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013

Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

Semantic Segmentation Idea: Sliding Window

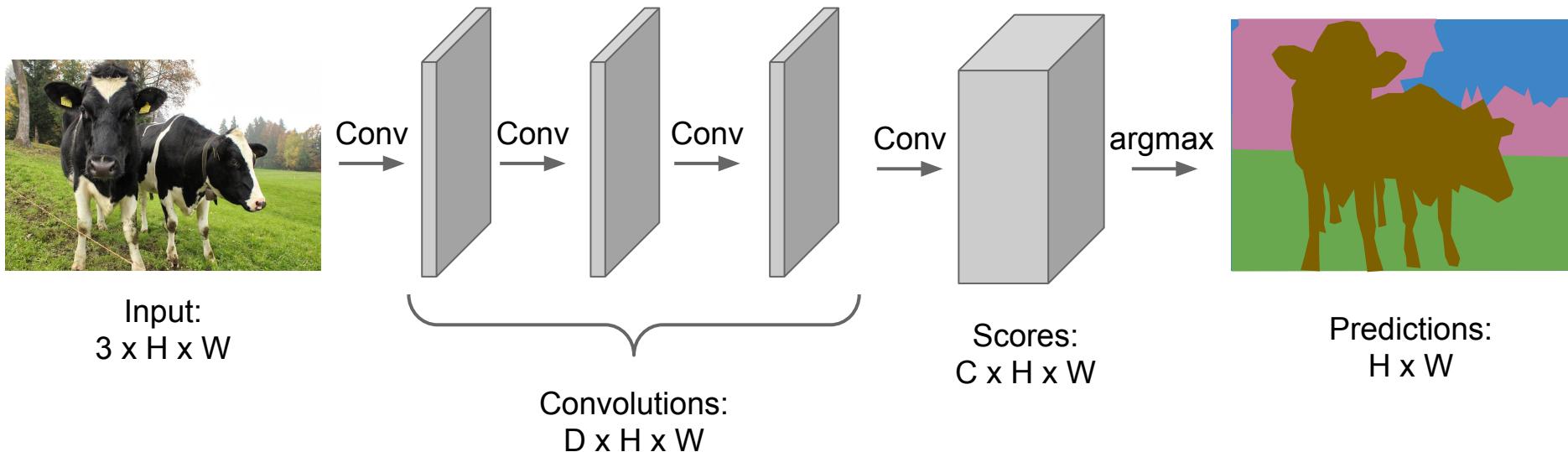


Problem: Very inefficient! Not reusing shared features between overlapping patches

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

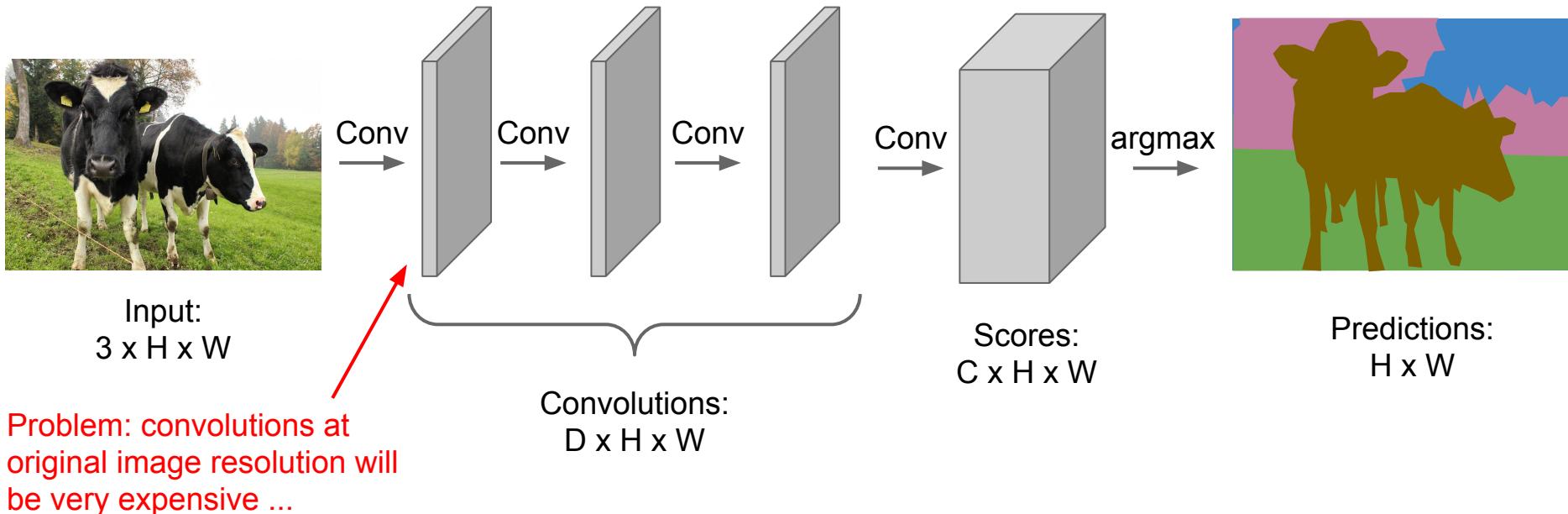
Semantic Segmentation Idea: Fully Convolutional

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



Semantic Segmentation Idea: Fully Convolutional

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

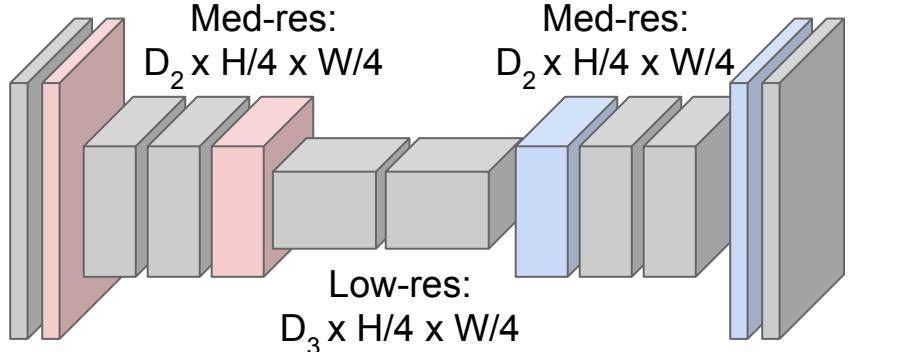


Semantic Segmentation Idea: Fully Convolutional

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



Input:
 $3 \times H \times W$



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

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



Predictions:
 $H \times W$

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

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

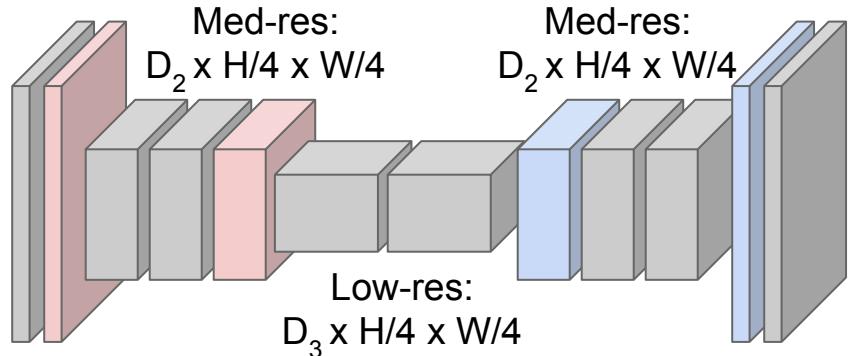
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided
convolution



Input:
 $3 \times H \times W$

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:
???



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

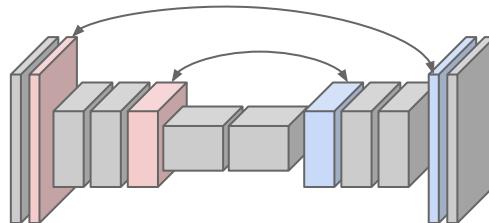
1	2
3	4

Rest of the network

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

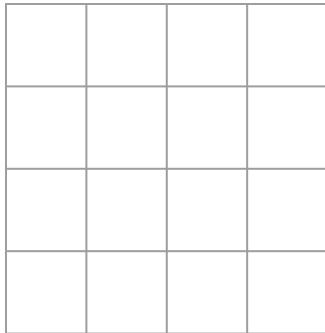
Output: 4 x 4

Corresponding pairs of
downsampling and
upsampling layers

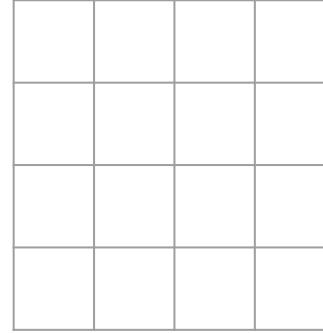


Learnable Upsampling: Transpose Convolution

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



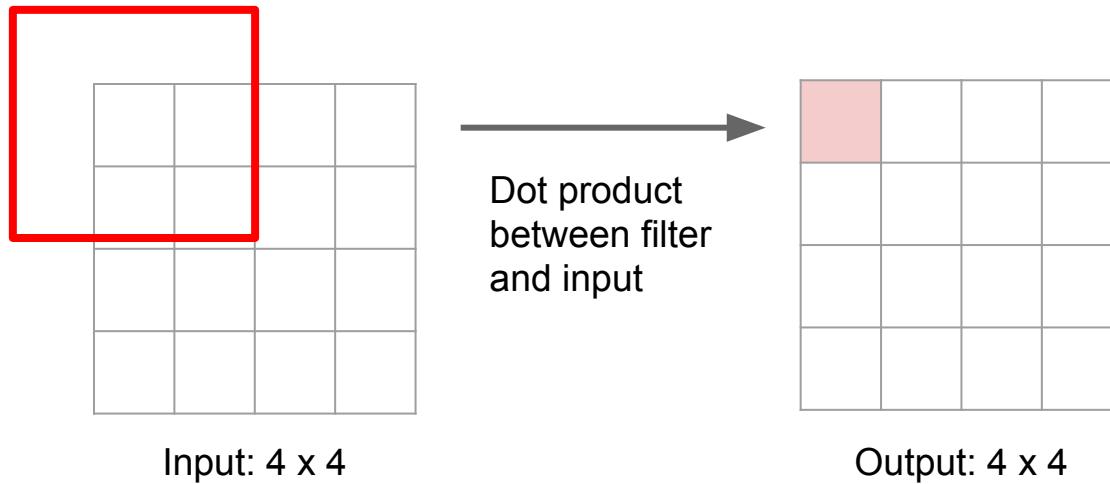
Input: 4×4



Output: 4×4

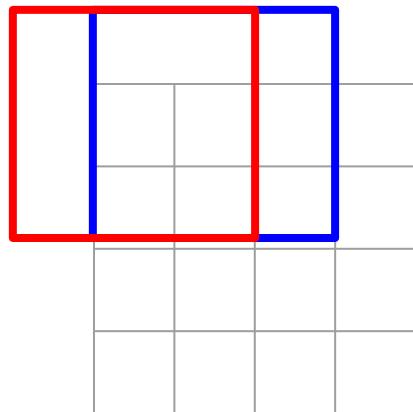
Learnable Upsampling: Transpose Convolution

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



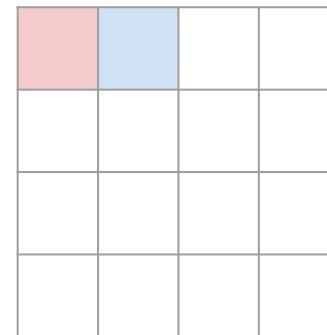
Learnable Upsampling: Transpose Convolution

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



Input: 4×4

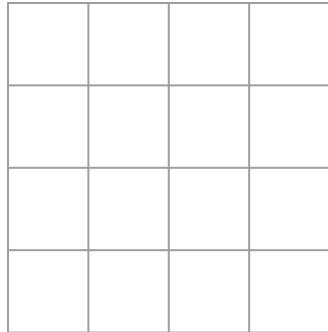
Dot product
between filter
and input



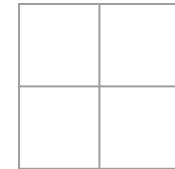
Output: 4×4

Learnable Upsampling: Transpose Convolution

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



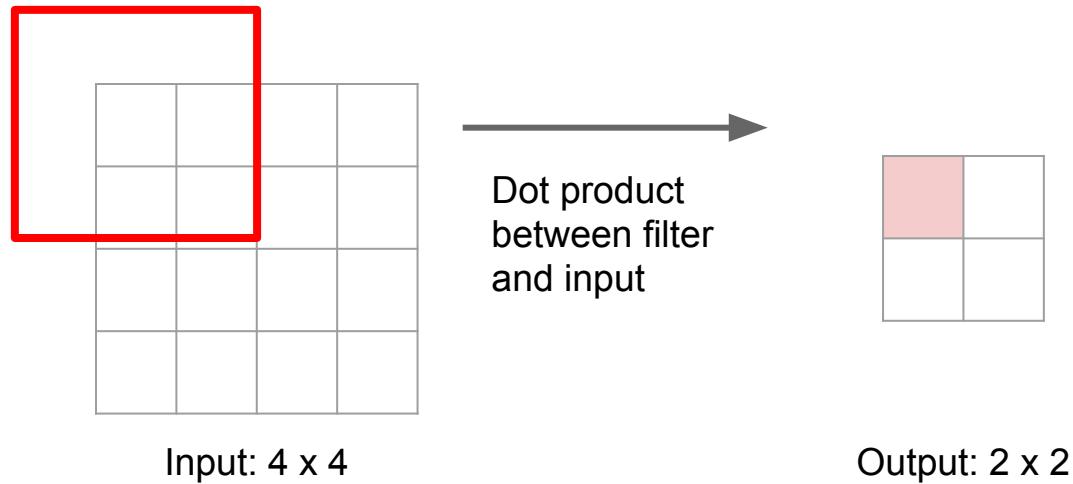
Input: 4×4



Output: 2×2

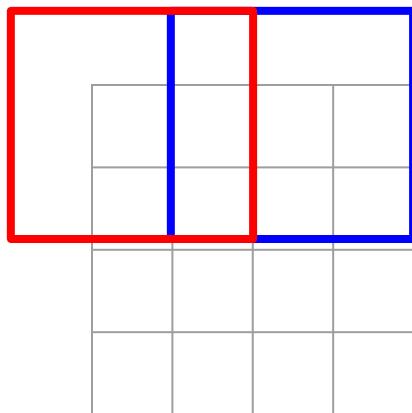
Learnable Upsampling: Transpose Convolution

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



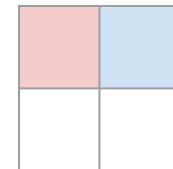
Learnable Upsampling: Transpose Convolution

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



Input: 4×4

Dot product
between filter
and input



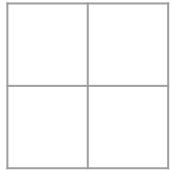
Output: 2×2

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

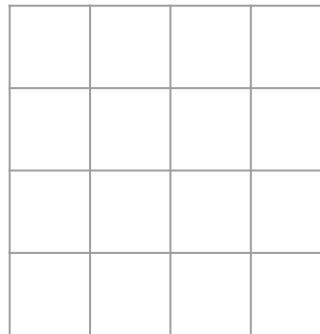
Stride gives ratio between
movement in input and
output

Learnable Upsampling: Transpose Convolution

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



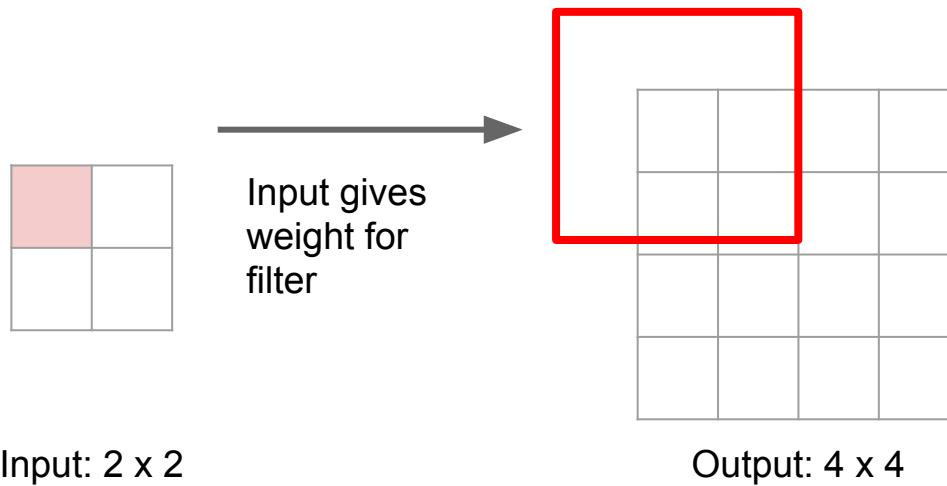
Input: 2×2



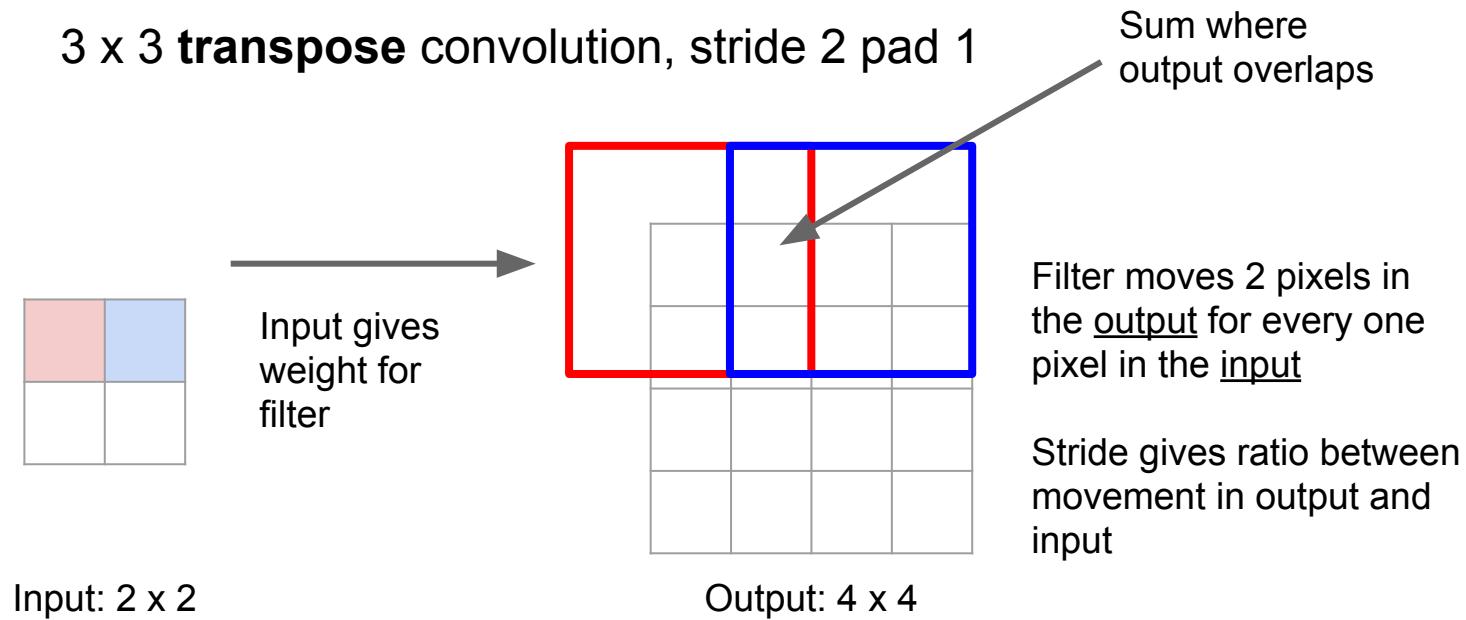
Output: 4×4

Learnable Upsampling: Transpose Convolution

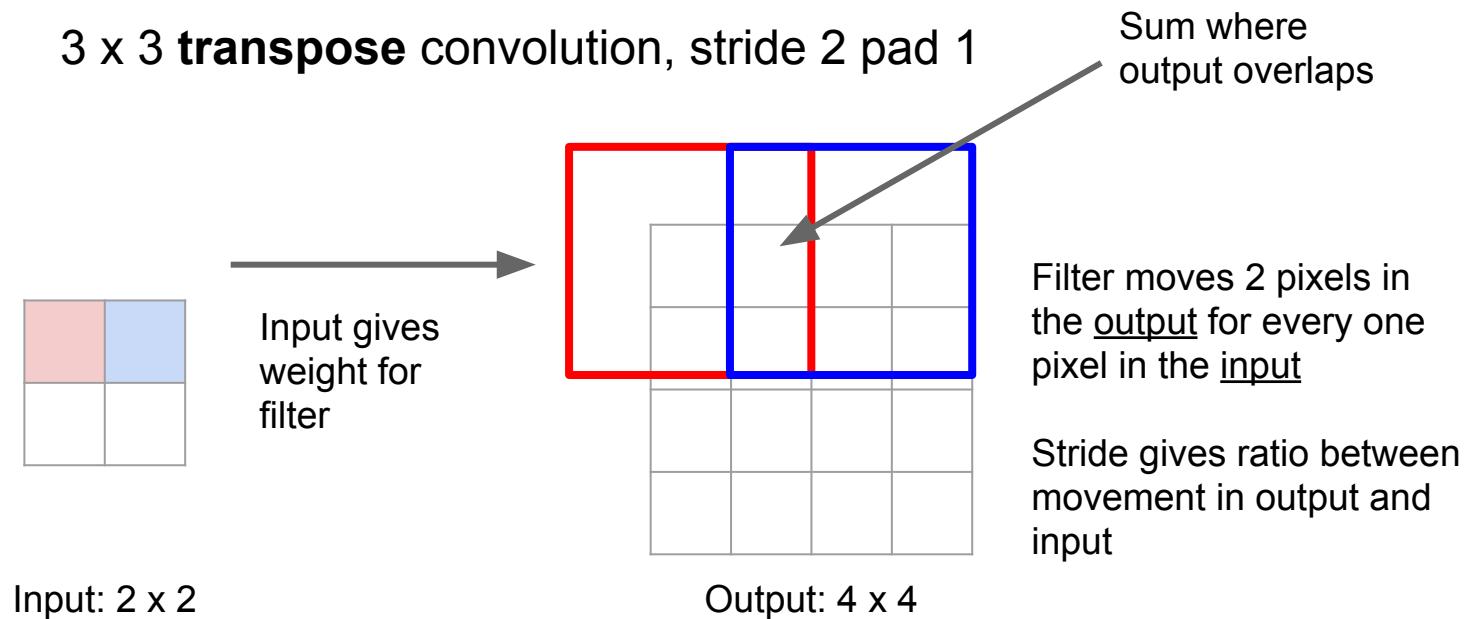
3×3 transpose convolution, stride 2 pad 1



Learnable Upsampling: Transpose Convolution



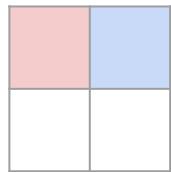
Learnable Upsampling: Transpose Convolution



Learnable Upsampling: Transpose Convolution

Other names:

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

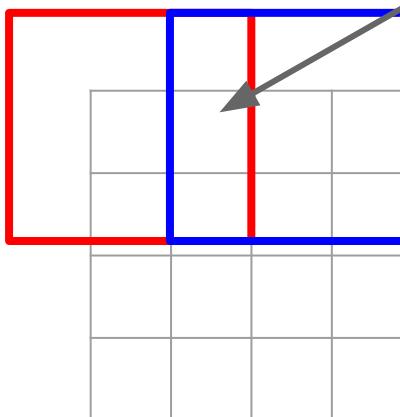


Input: 2 x 2

3 x 3 transpose convolution, stride 2 pad 1



Input gives weight for filter

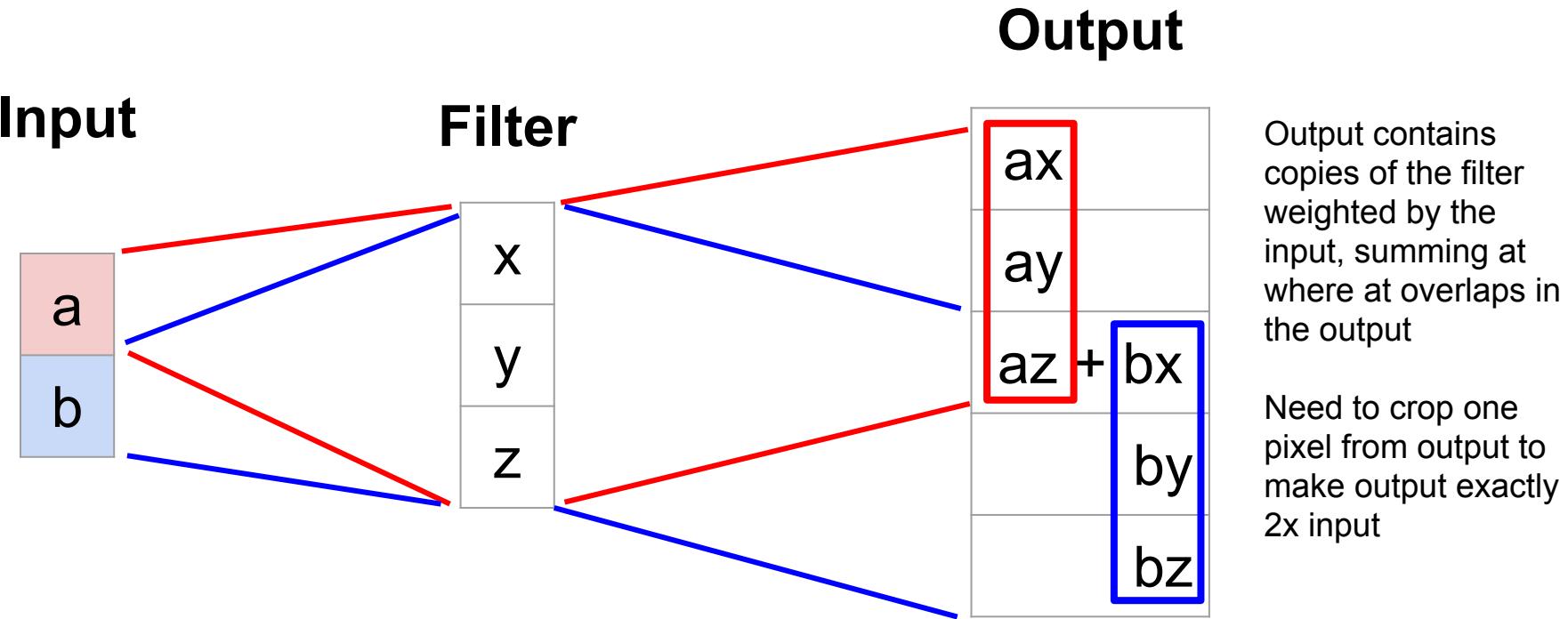


Output: 4 x 4

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

Stride gives ratio between movement in output and input

Transpose Convolution: 1D Example



Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

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

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

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

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

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

Convolution transpose multiplies by the transpose of the same matrix:

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

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

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

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)

We can express convolution in terms of a matrix multiplication

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

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

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

Convolution transpose multiplies by the transpose of the same matrix:

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

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

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

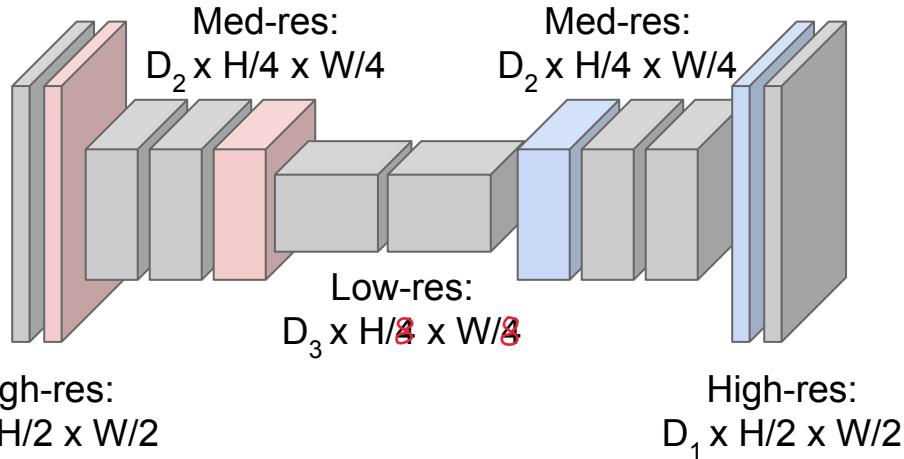
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution



Input:
 $3 \times H \times W$

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



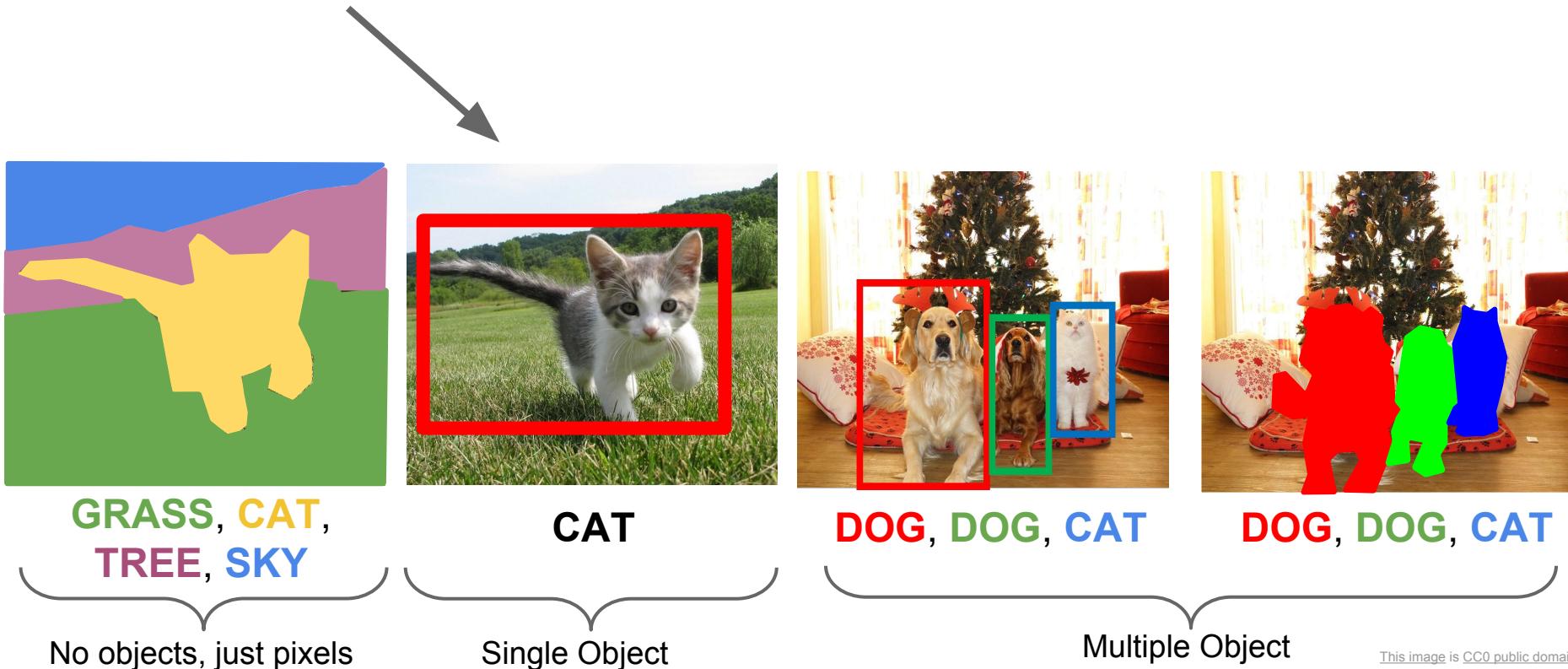
Upsampling:
Unpooling or strided transpose convolution



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

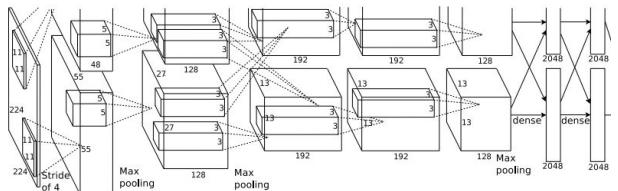
Classification + Localization



Classification + Localization



This image is CC0 public domain



Fully
Connected:
4096 to 1000

Class Scores

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

Vector: Fully
Connected:
4096 to 4

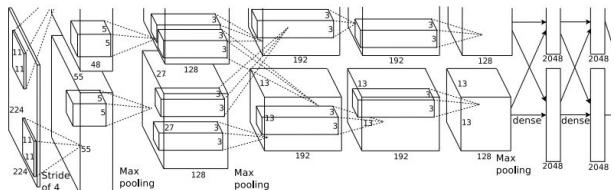
Box Coordinates (x, y, w, h)

Treat localization as a
regression problem!

Classification + Localization



This image is CC0 public domain



Treat localization as a
regression problem!

Fully
Connected:
4096 to 1000

Vector: Fully
Connected:
4096 to 4

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

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

Correct label:
Cat

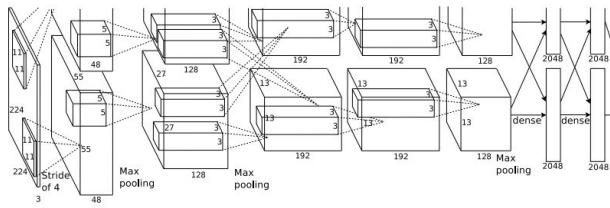
Softmax
Loss

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

Classification + Localization



This image is CC0 public domain



Treat localization as a
regression problem!

Vector: Fully
Connected:
4096 to 4

Class Scores

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

Multitask Loss

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

Correct label:
Cat

Softmax
Loss

+

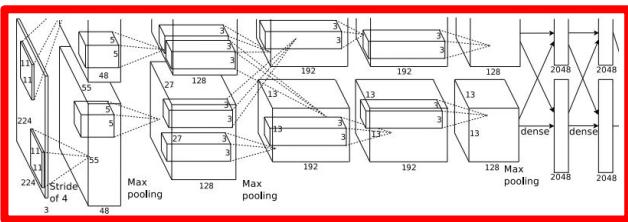
Loss

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

Classification + Localization



This image is CC0 public domain



Often pretrained on ImageNet
(Transfer learning)

Treat localization as a
regression problem!

Vector: 4096
Fully Connected: 4096 to 4

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

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

Correct label:
Cat

Softmax
Loss

+

Loss

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

Aside: Human Pose Estimation



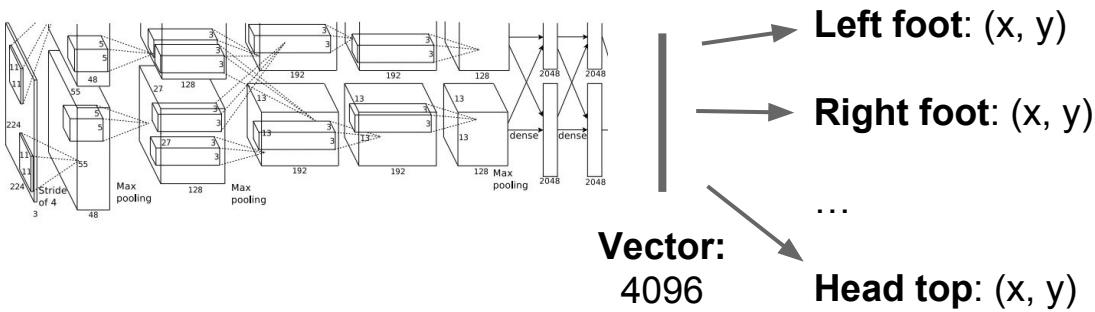
Represent pose as a set of 14 joint positions:

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

This image is licensed under CC-BY 2.0.

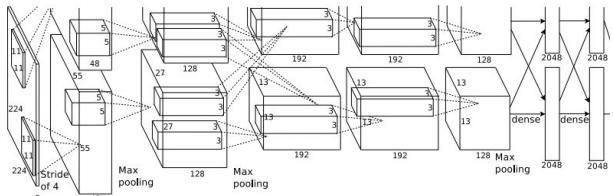
Johnson and Everingham, "Clustered Pose and Nonlinear Appearance Models for Human Pose Estimation", BMVC 2010

Aside: Human Pose Estimation



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

Aside: Human Pose Estimation



Vector:
4096

Correct left
foot: (x', y')

Left foot: (x, y) \rightarrow L2 loss

Right foot: (x, y) \rightarrow L2 loss

...

Head top: (x, y) \rightarrow L2 loss

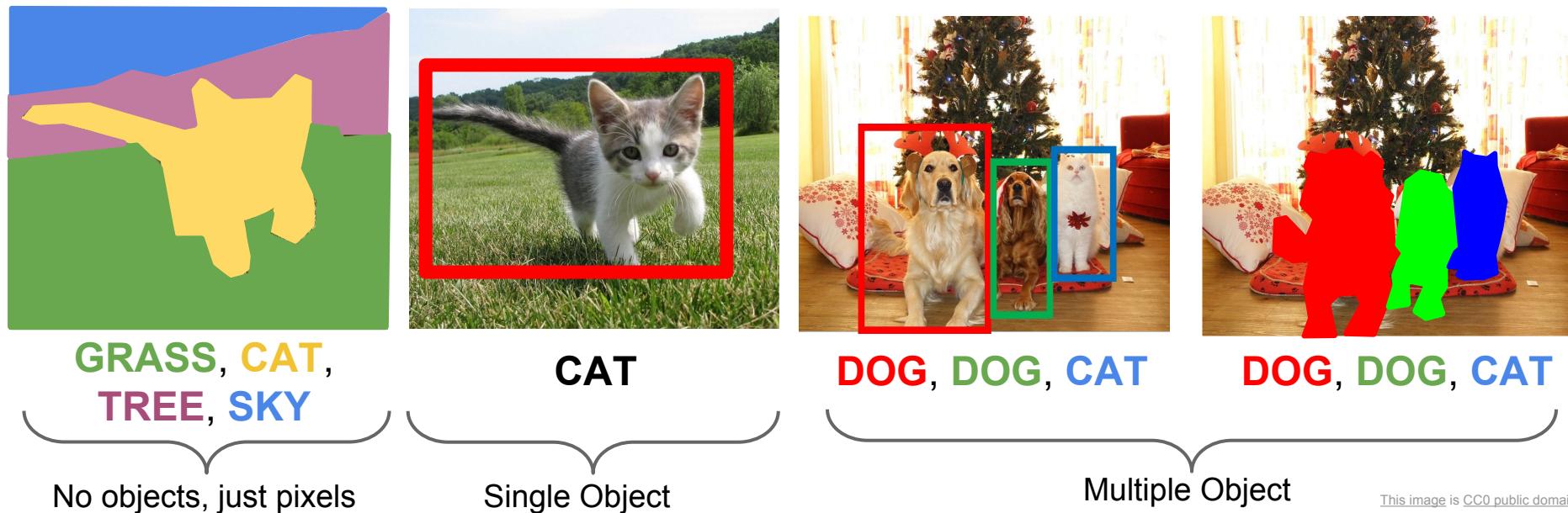
Correct head
top: (x', y')

+

Loss

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

Object Detection



This image is CC0 public domain

Object Detection: Impact of Deep Learning

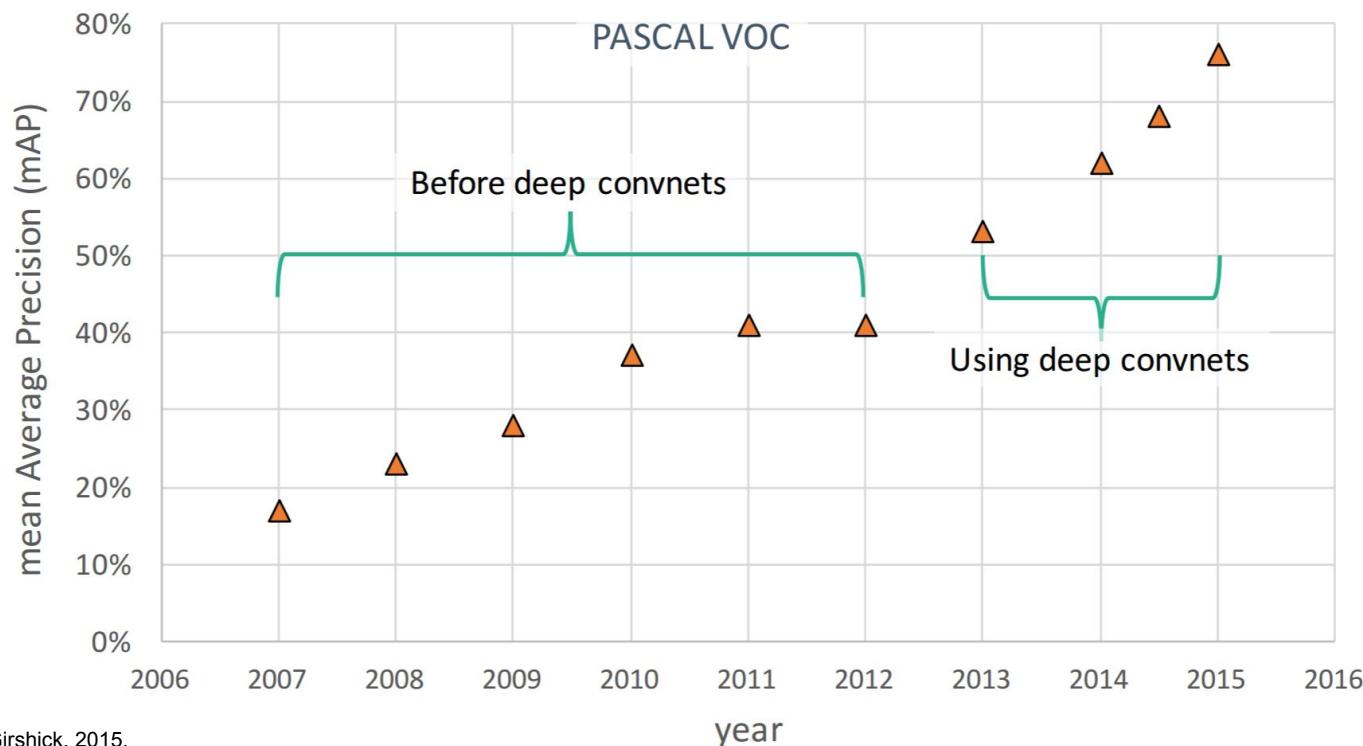
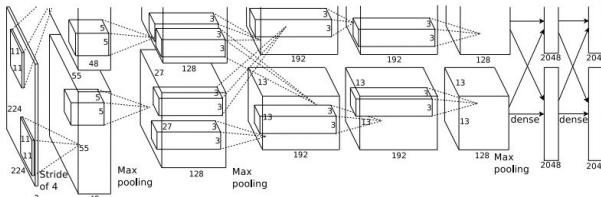
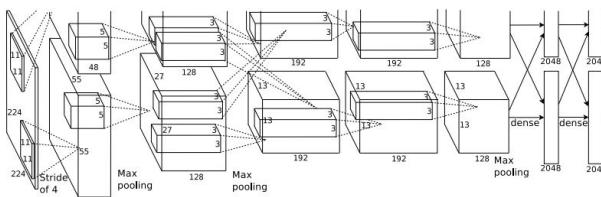


Figure copyright Ross Girshick, 2015.
Reproduced with permission.

Object Detection as Regression?



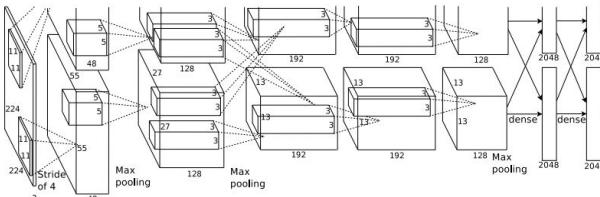
CAT: (x, y, w, h)



DOG: (x, y, w, h)

DOG: (x, y, w, h)

CAT: (x, y, w, h)



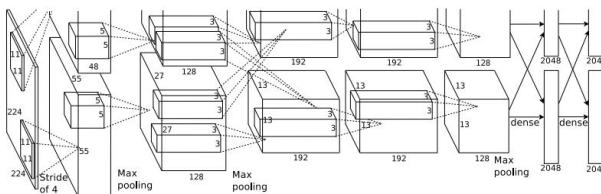
DUCK: (x, y, w, h)

DUCK: (x, y, w, h)

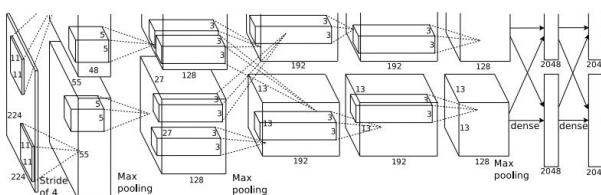
...

Object Detection as Regression?

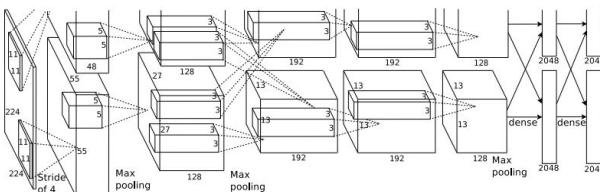
Each image needs a different number of outputs!



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



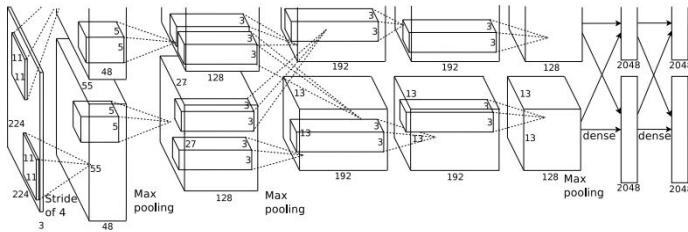
DOG: (x, y, w, h)
DOG: (x, y, w, h) 16 numbers
CAT: (x, y, w, h)



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

Object Detection as Classification: Sliding Window

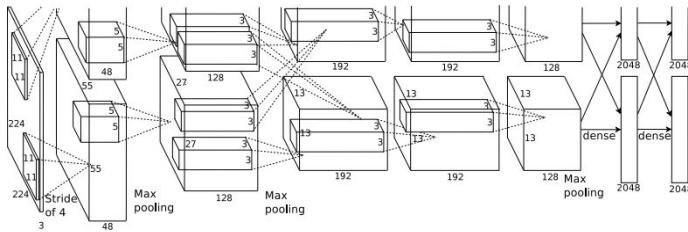
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection as Classification: Sliding Window

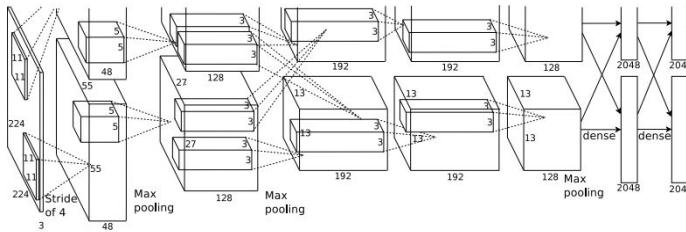
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection as Classification: Sliding Window

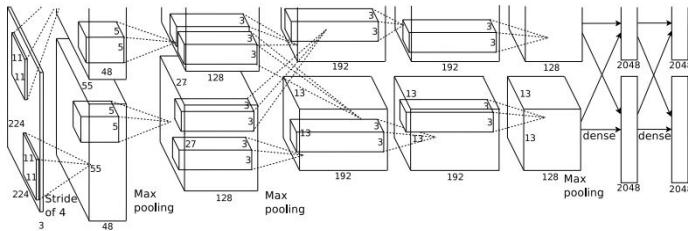
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection as Classification: Sliding Window

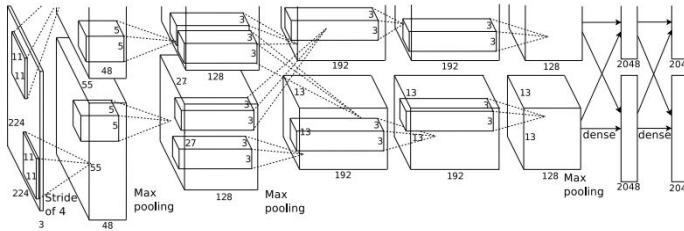
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



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

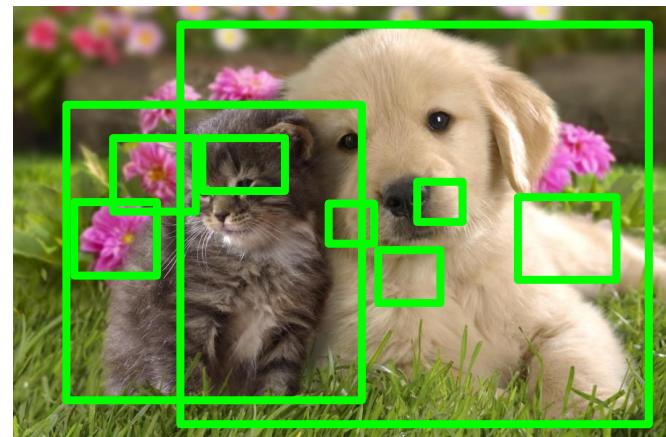


Dog? NO
Cat? YES
Background? NO

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

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



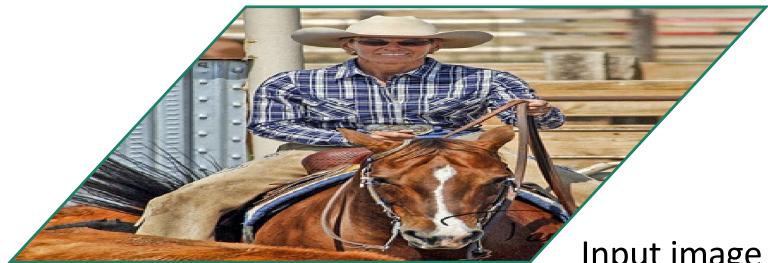
Alexe et al, "Measuring the objectness of image windows", TPAMI 2012

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

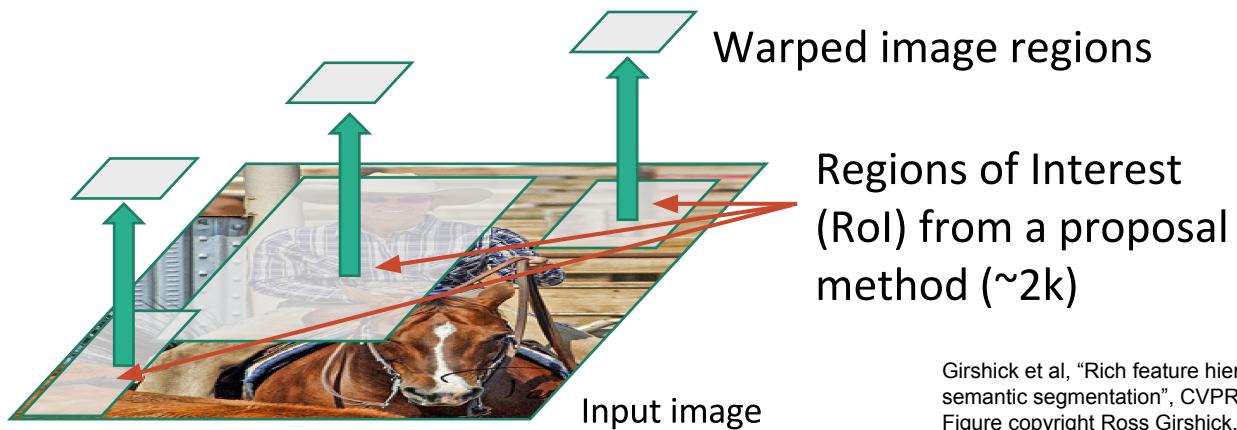


Input image

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

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

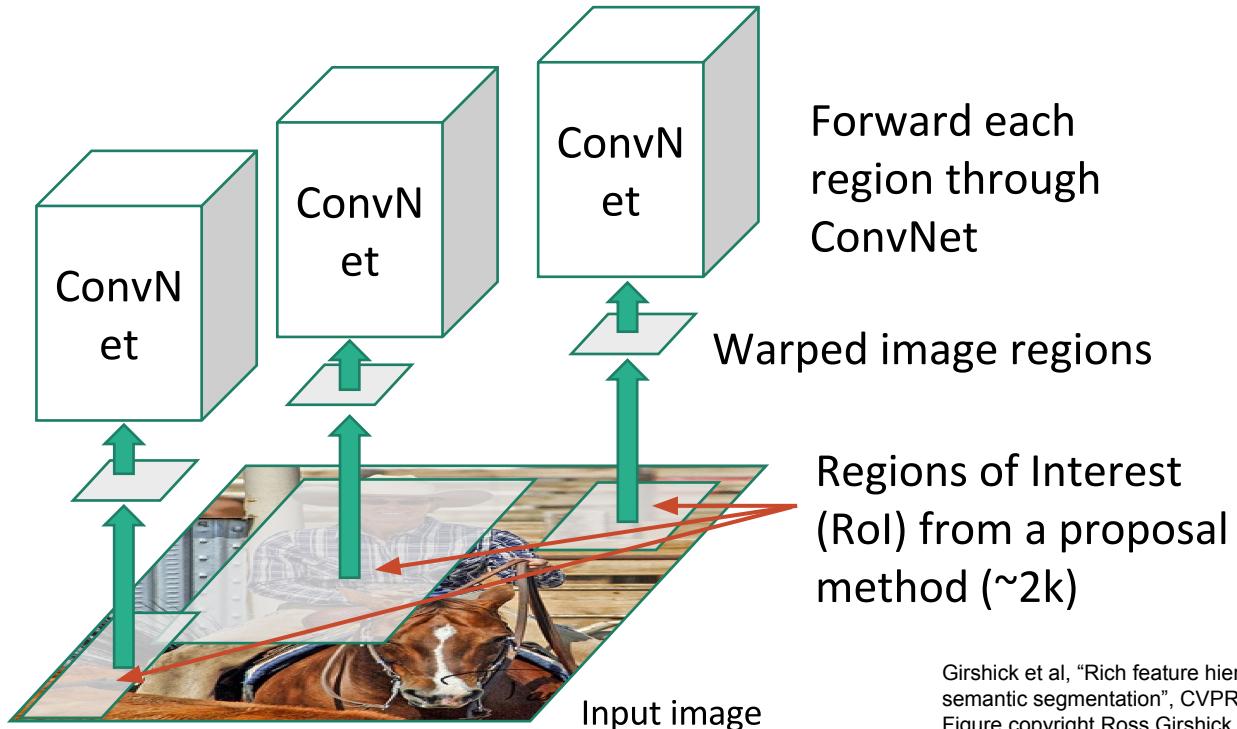
R-CNN



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

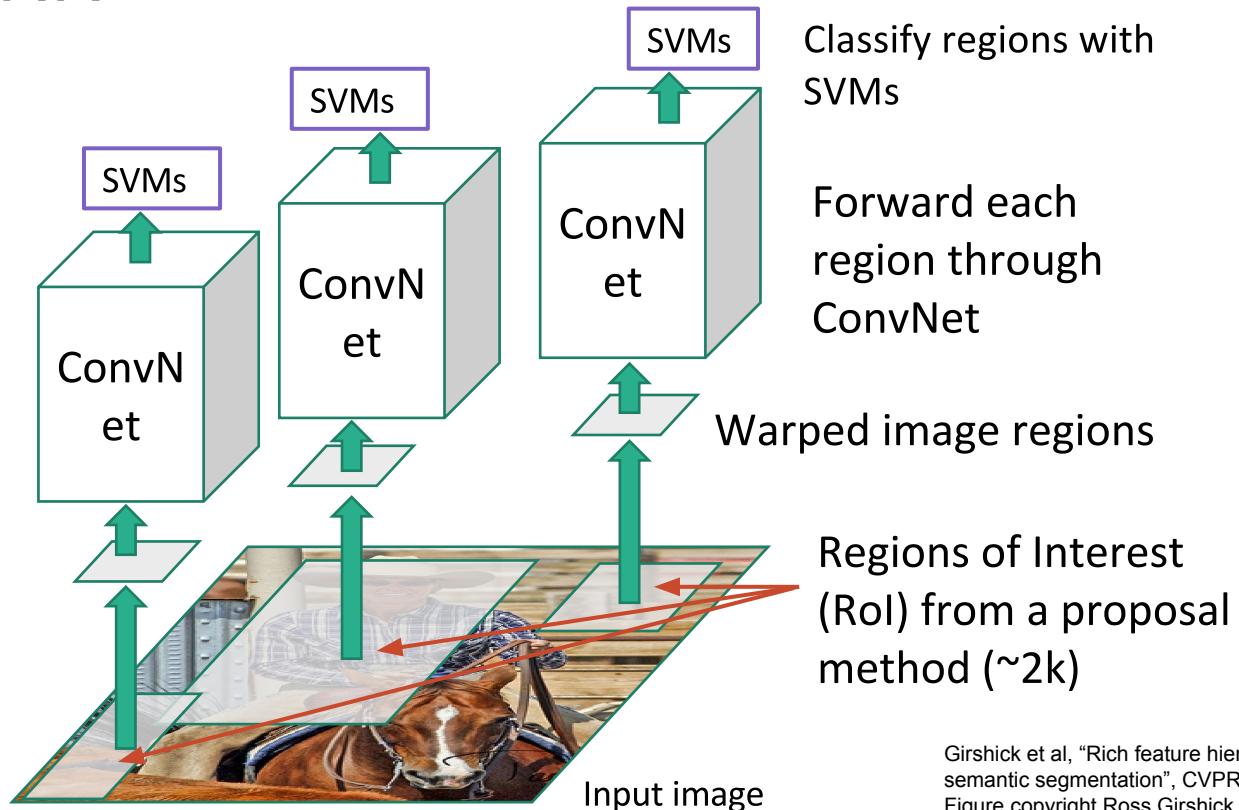
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

R-CNN



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

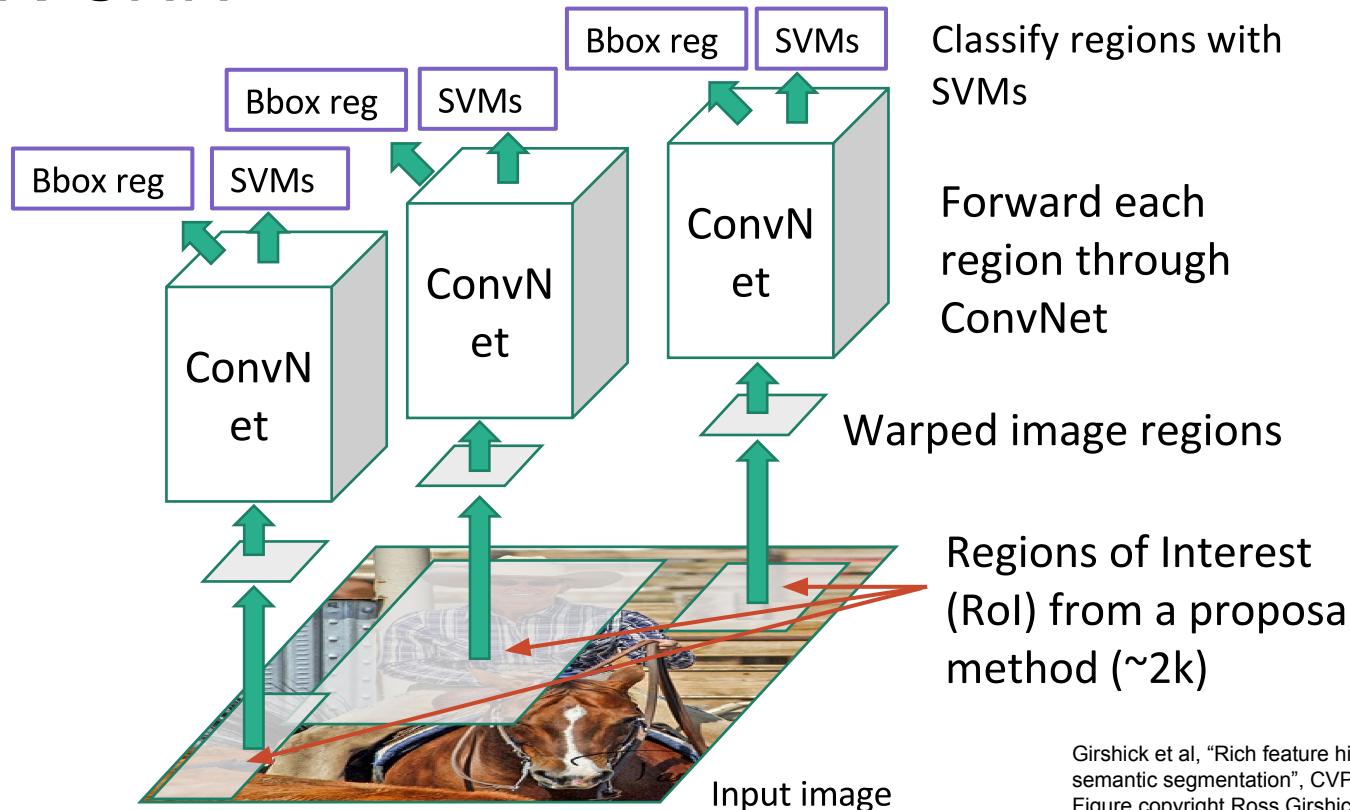
R-CNN



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

R-CNN

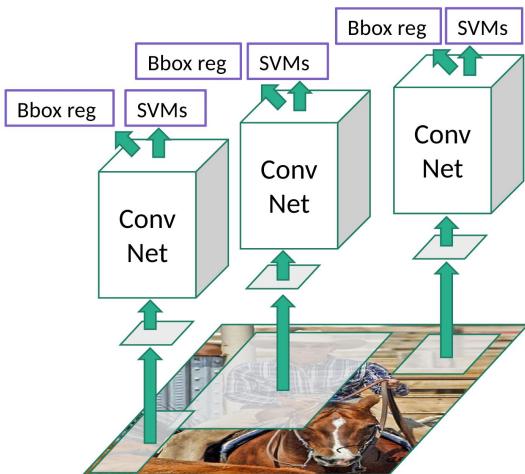
Linear Regression for bounding box offsets



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: Problems

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



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

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

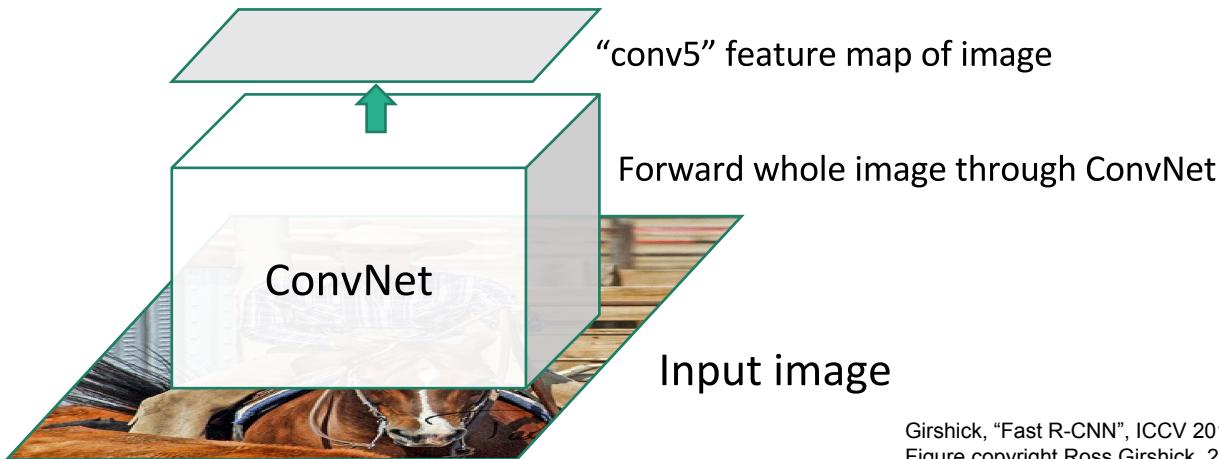
Fast R-CNN



Input image

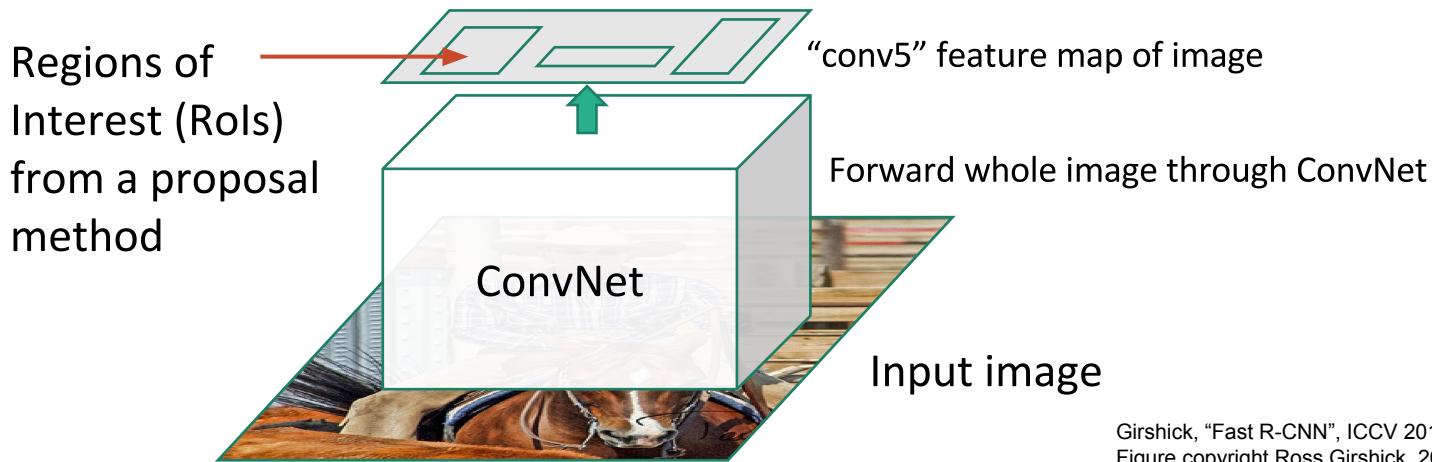
Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



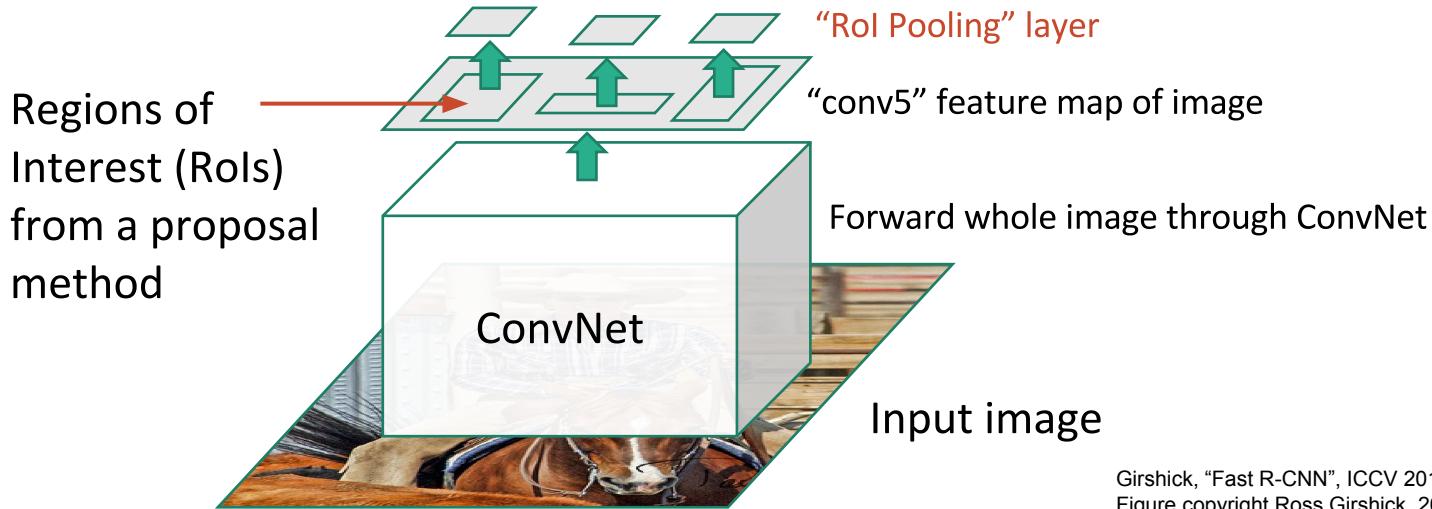
Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



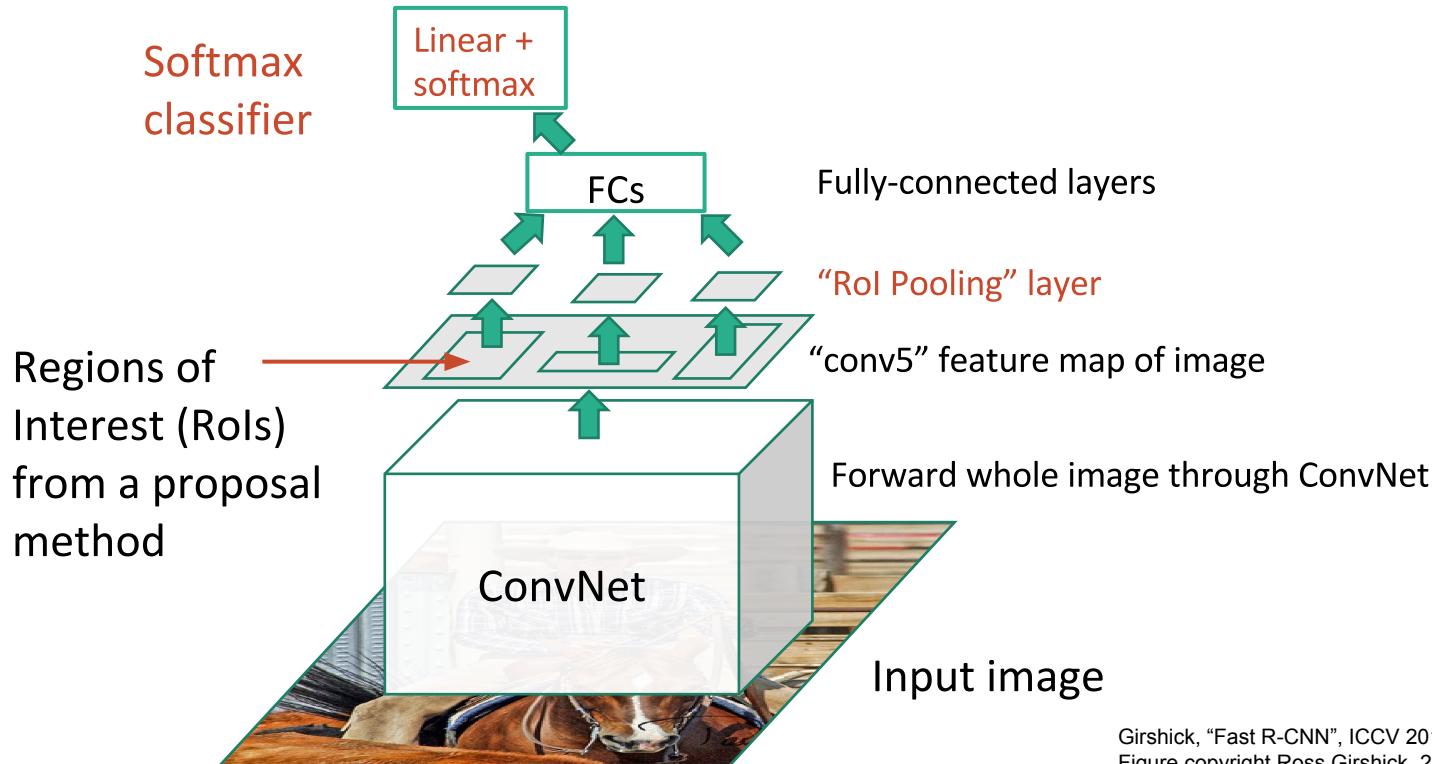
Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



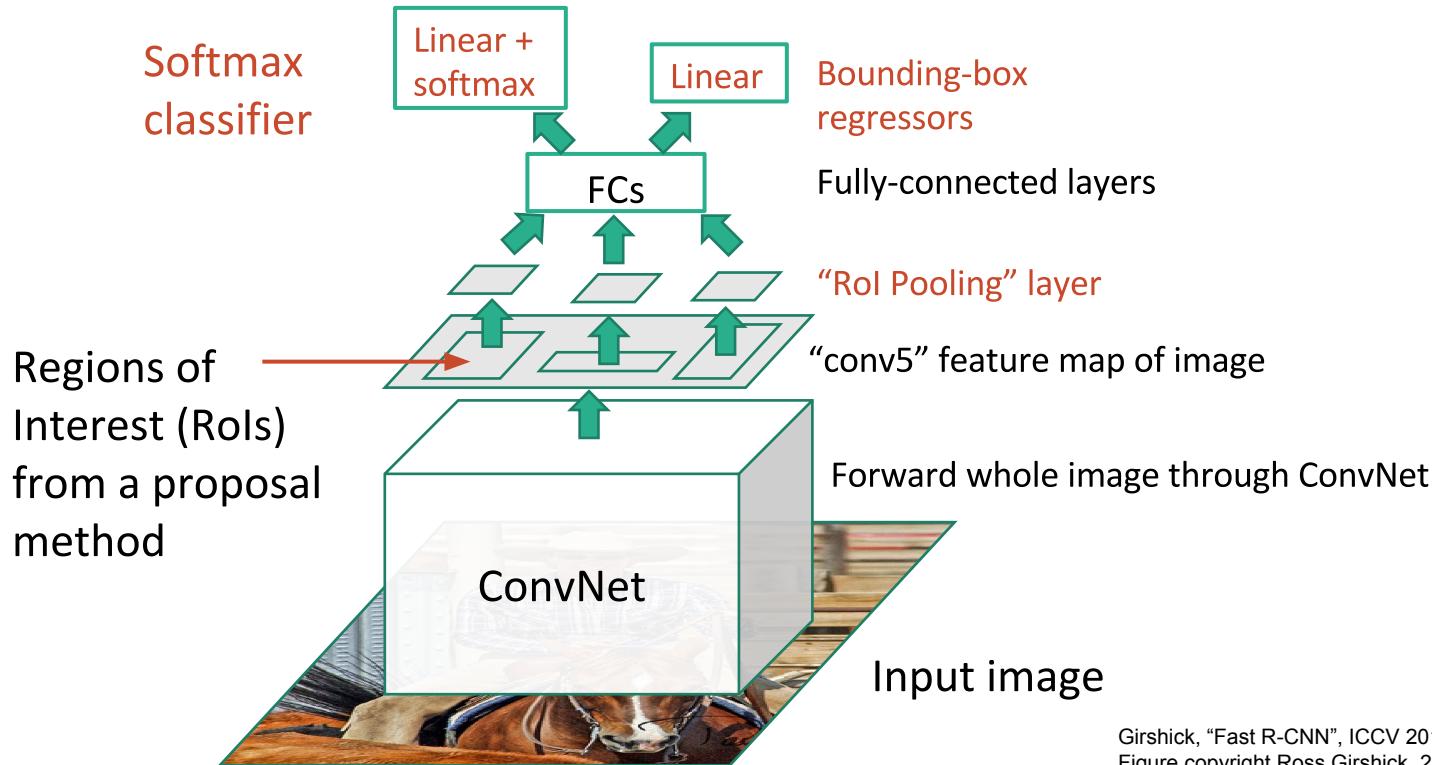
Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



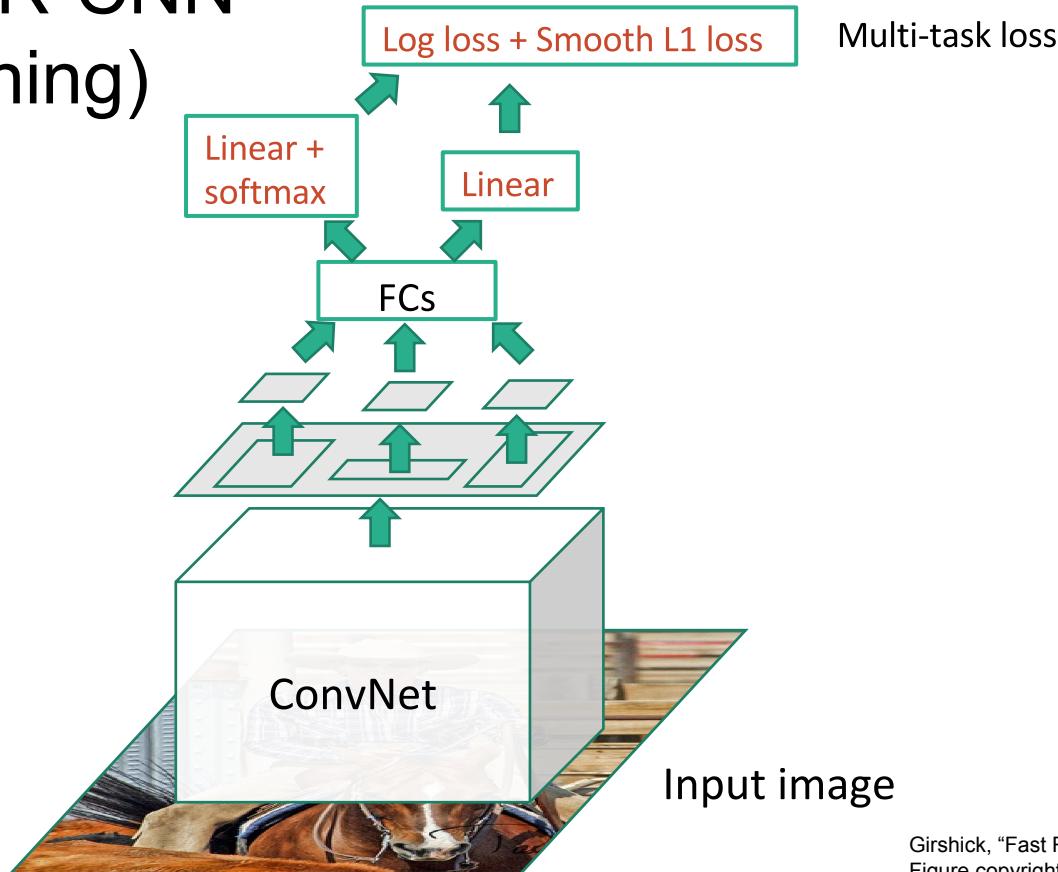
Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

Fast R-CNN



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

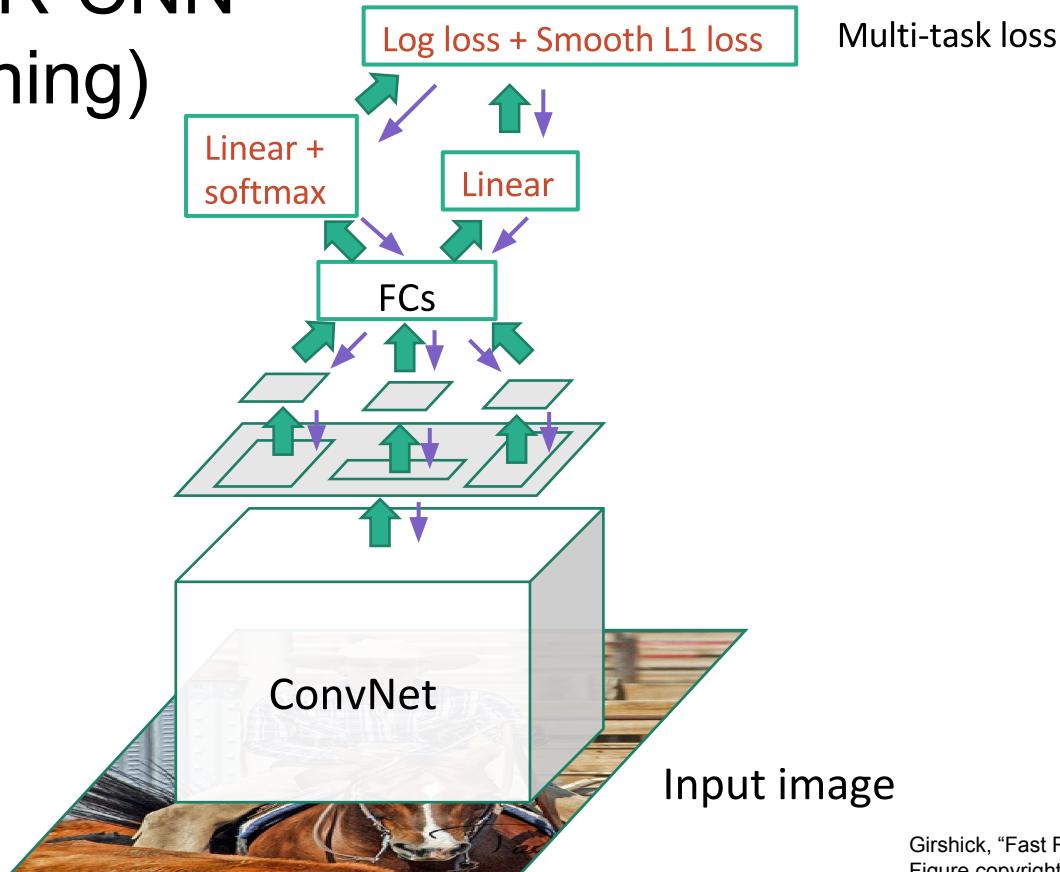
Fast R-CNN (Training)



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

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

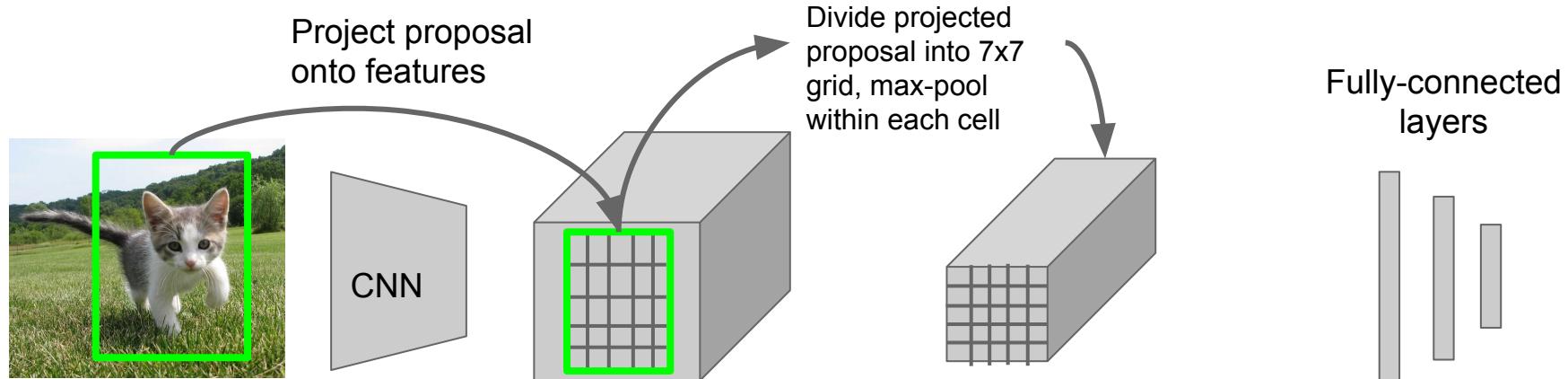
Fast R-CNN (Training)



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

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

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)

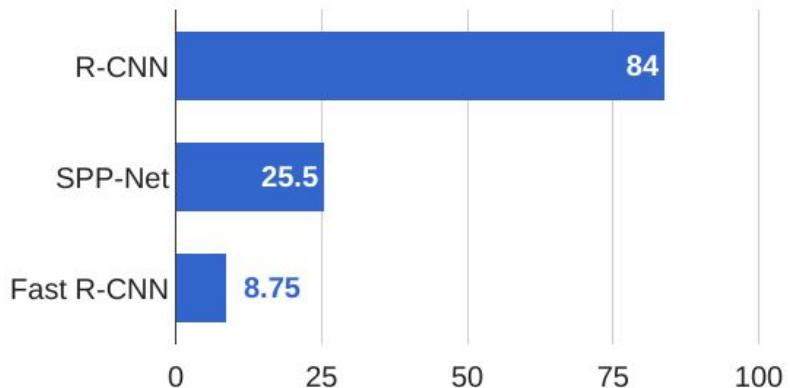
RoI conv features:
512 x 7 x 7
for region proposal

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

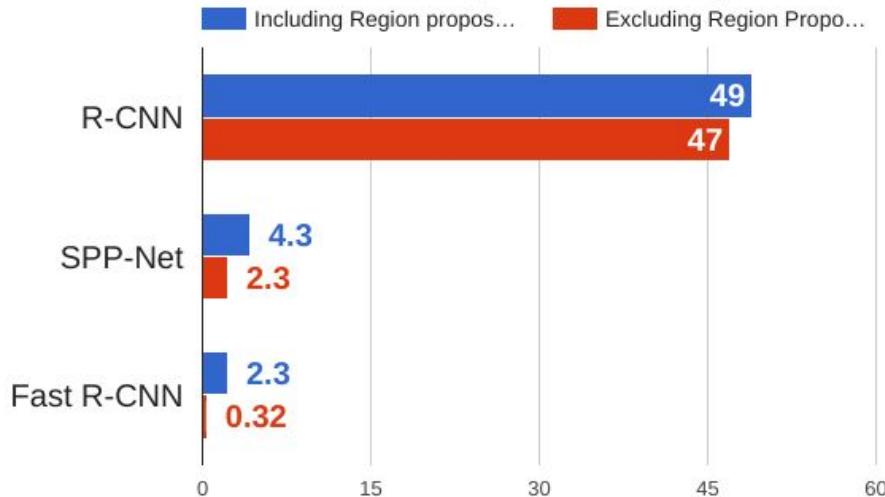
Girshick, "Fast R-CNN", ICCV 2015.

R-CNN vs SPP vs Fast R-CNN

Training time (Hours)



Test time (seconds)



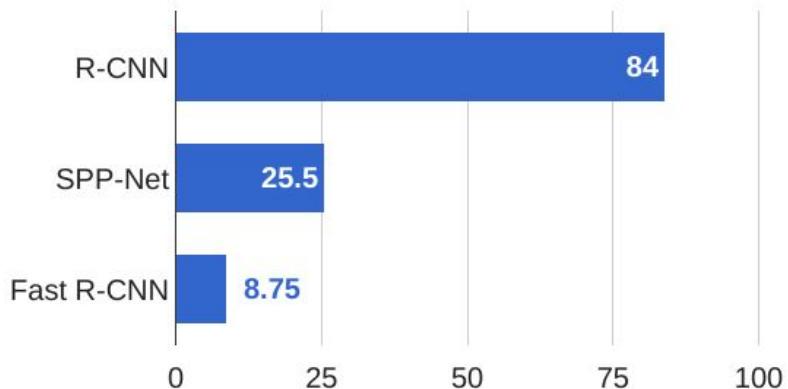
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

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

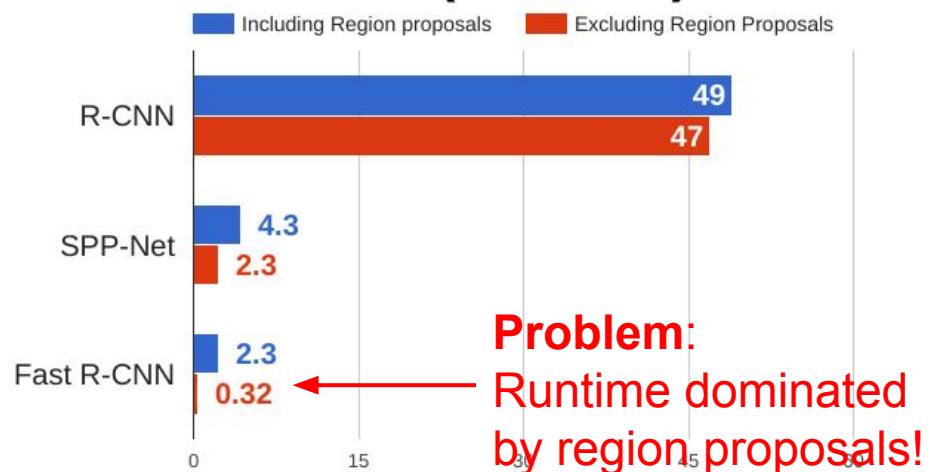
Girshick, "Fast R-CNN", ICCV 2015

R-CNN vs SPP vs Fast R-CNN

Training time (Hours)



Test time (seconds)



Problem:
Runtime dominated
by region proposals!

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

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

Girshick, "Fast R-CNN", ICCV 2015

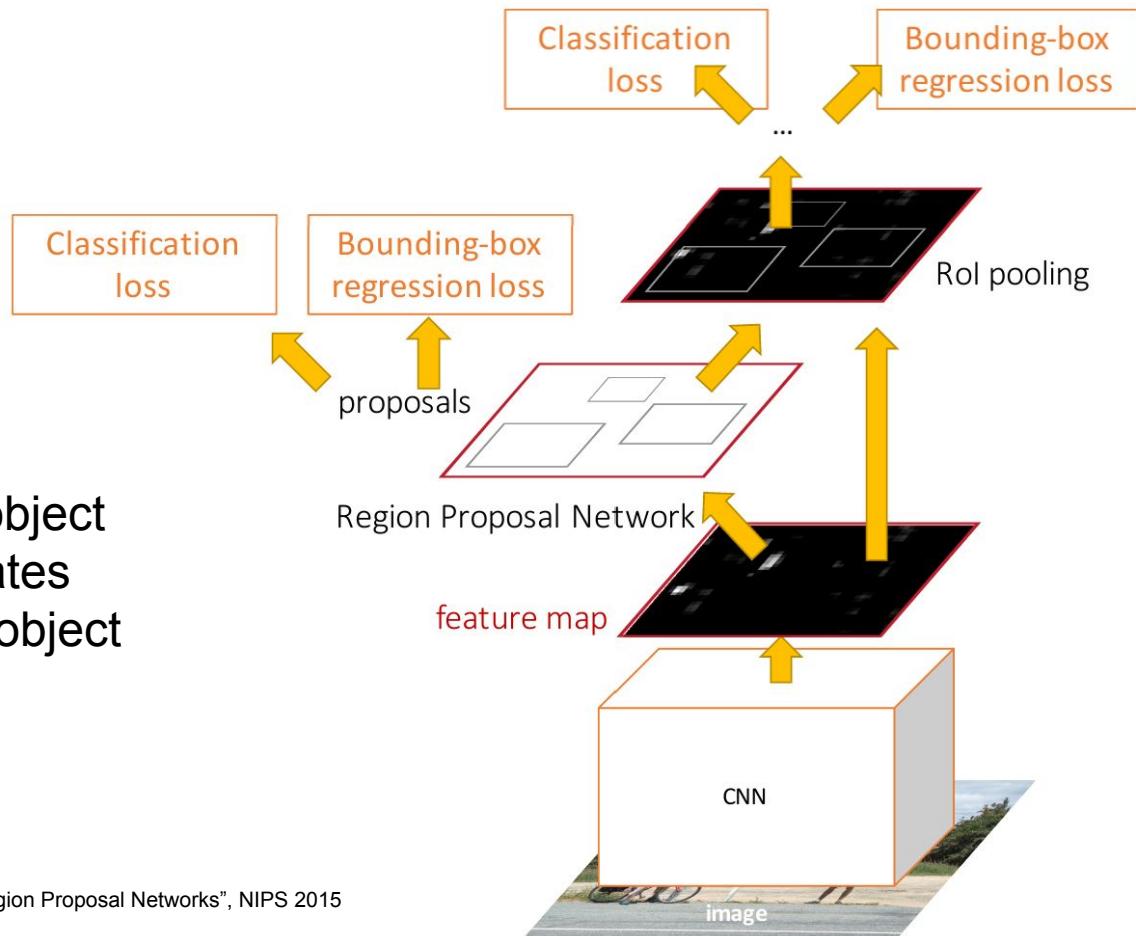
Faster R-CNN:

Make CNN do proposals!

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

Jointly train with 4 losses:

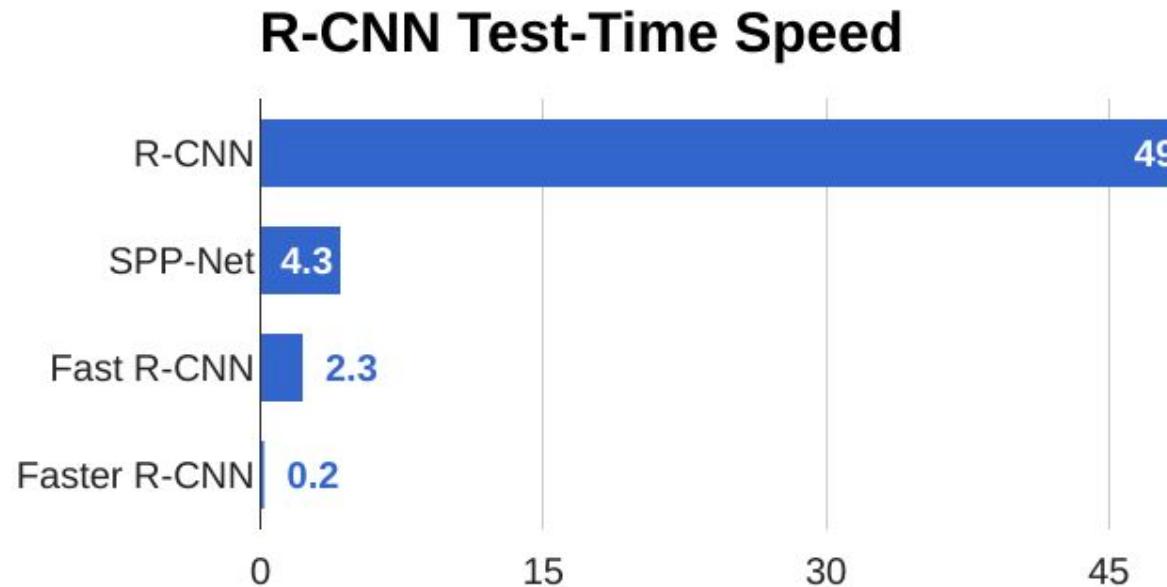
1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates



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

Faster R-CNN:

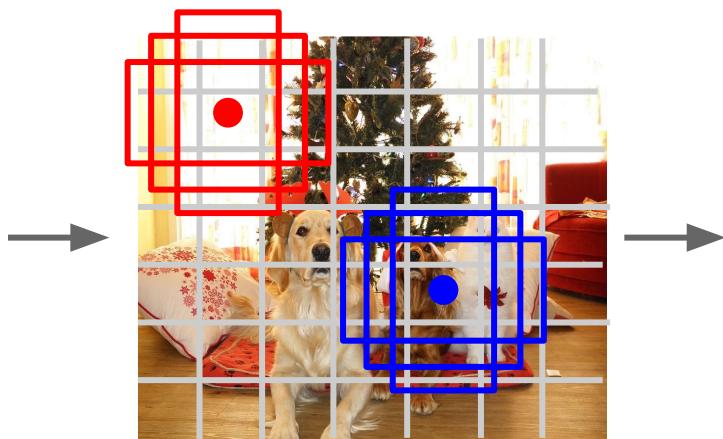
Make CNN do proposals!



Detection without Proposals: YOLO / SSD



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)

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

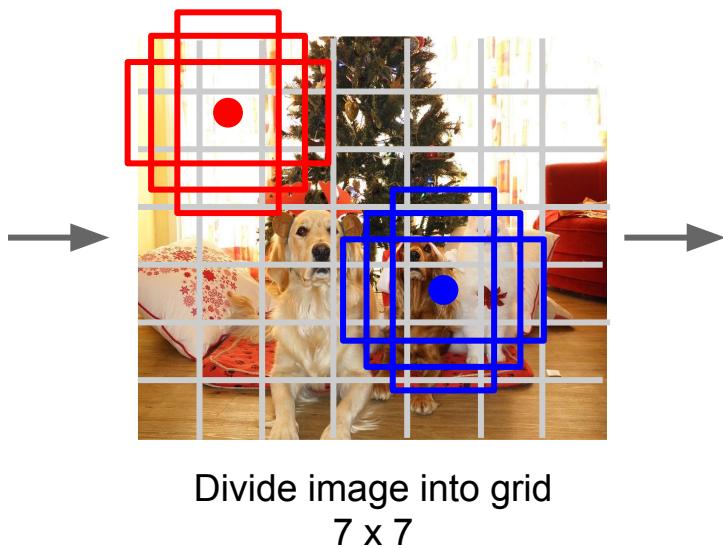
Redmon et al, "You Only Look Once:
Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016

Detection without Proposals: YOLO / SSD

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



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)

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

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

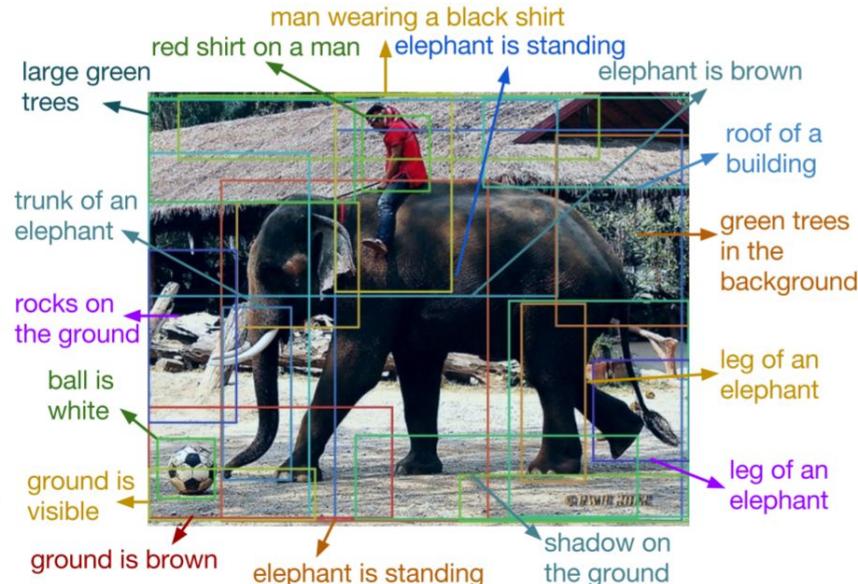
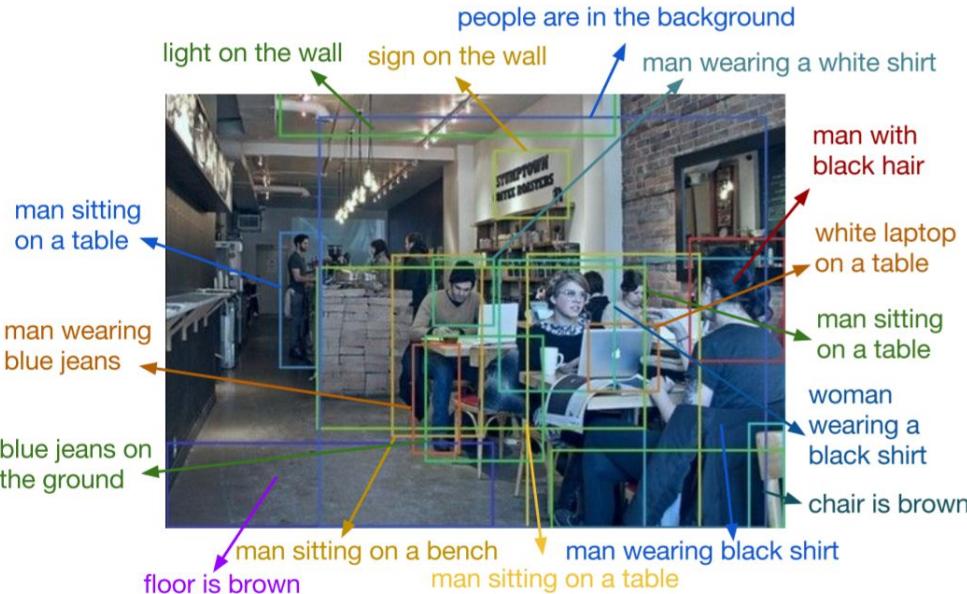
Inception-V2: Ioffe and Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015

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

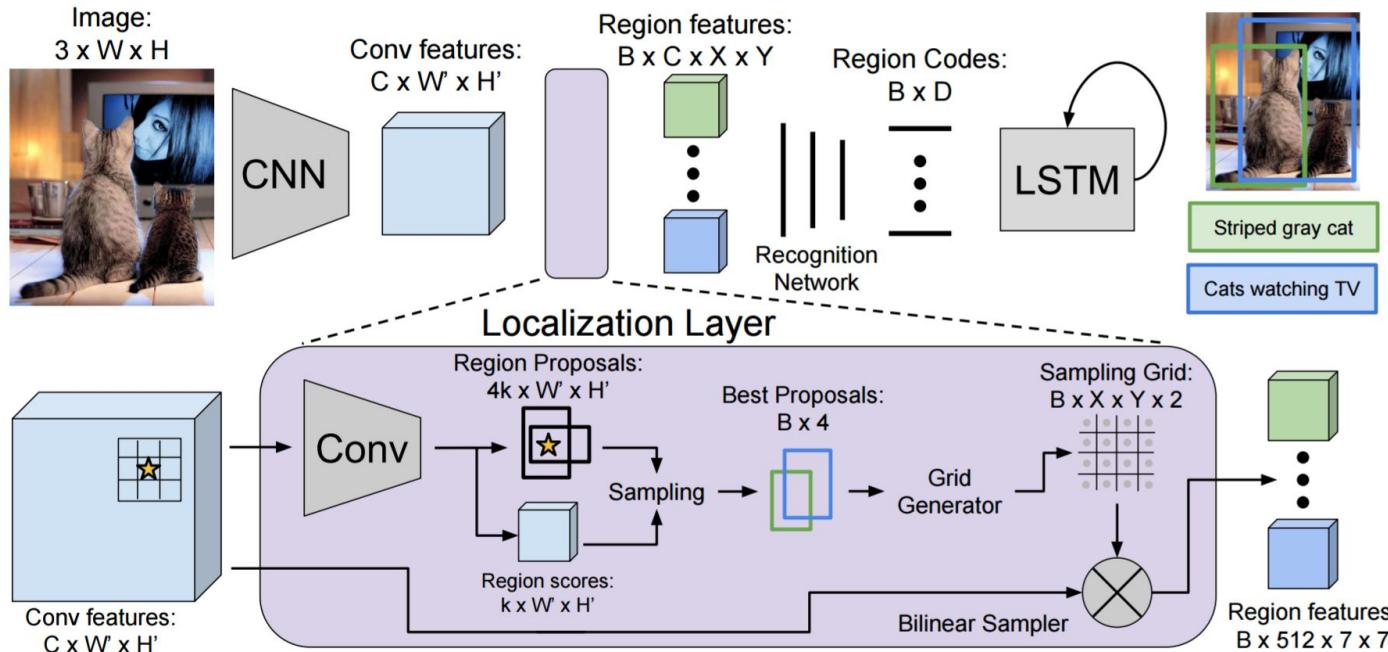
MobileNet: Howard et al, "Efficient Convolutional Neural Networks for Mobile Vision Applications", arXiv 2017

Aside: Object Detection + Captioning = Dense Captioning

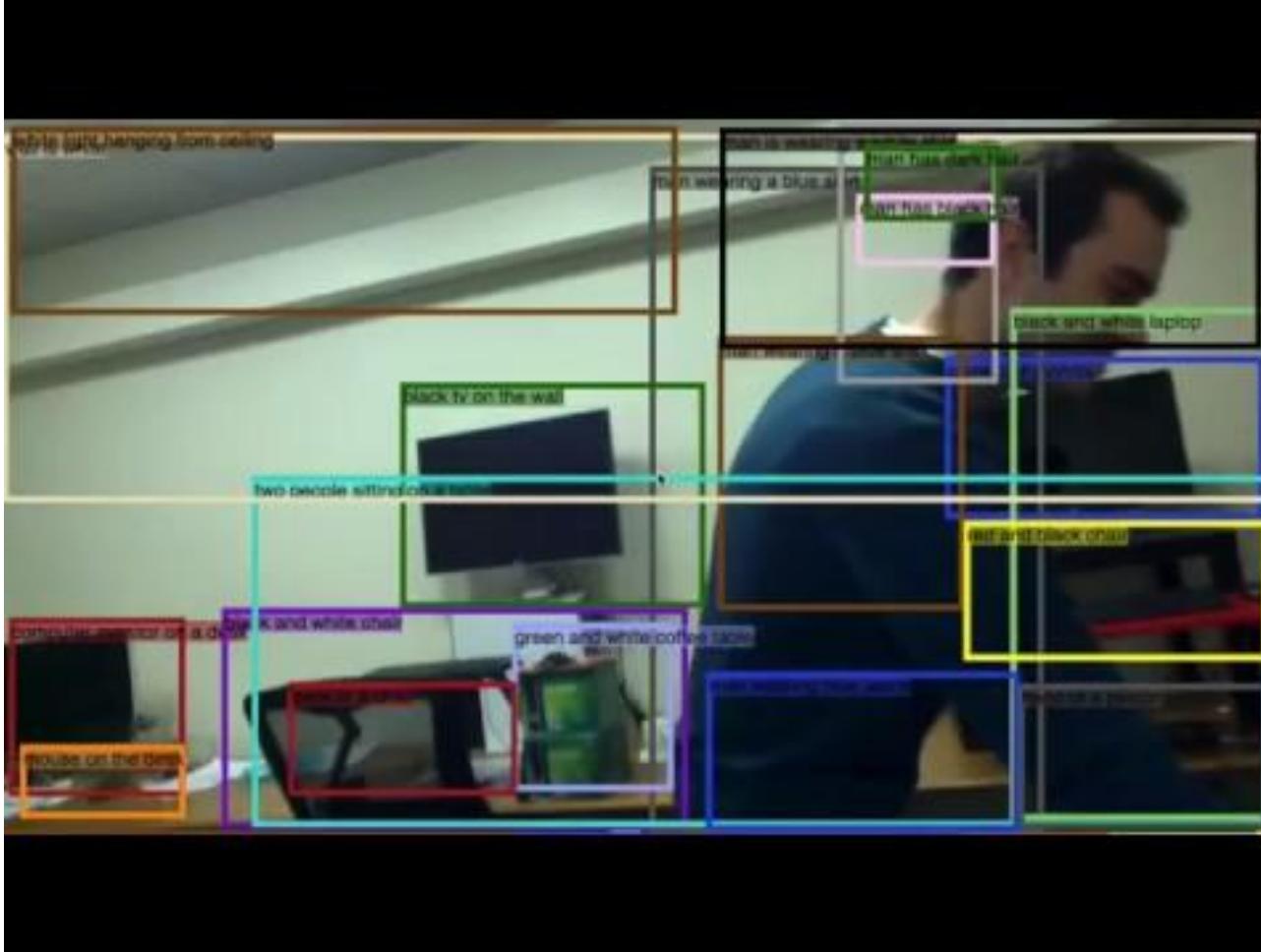


Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016
Figure copyright IEEE, 2016. Reproduced for educational purposes.

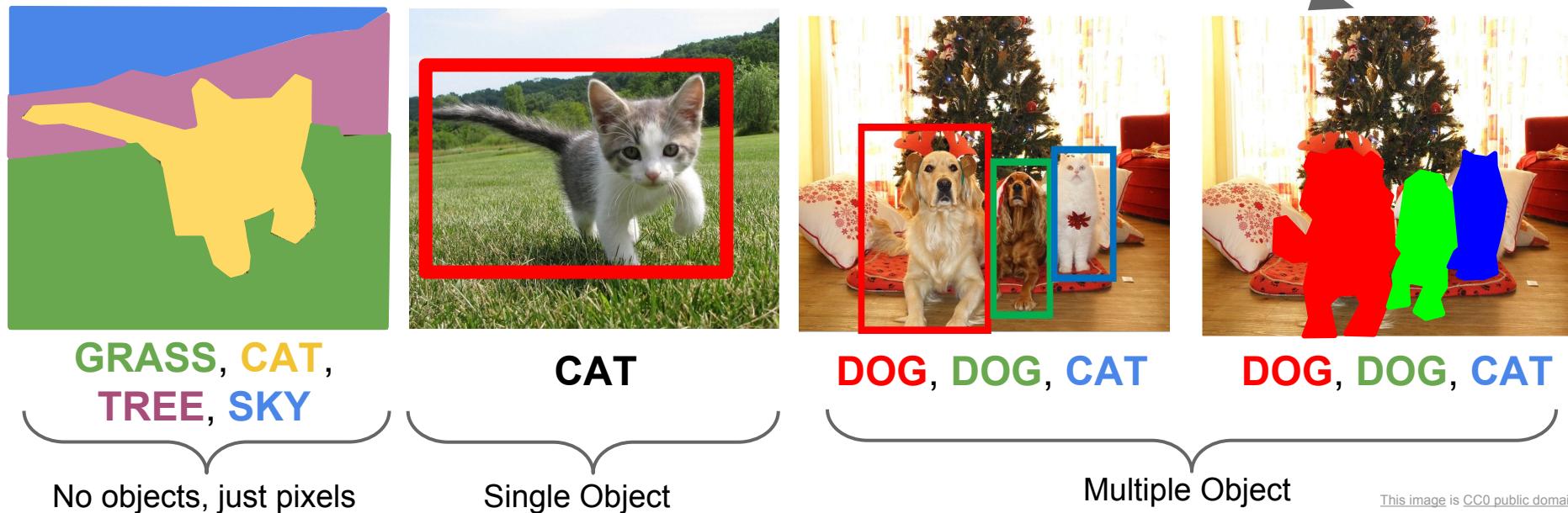
Aside: Object Detection + Captioning = Dense Captioning



Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016
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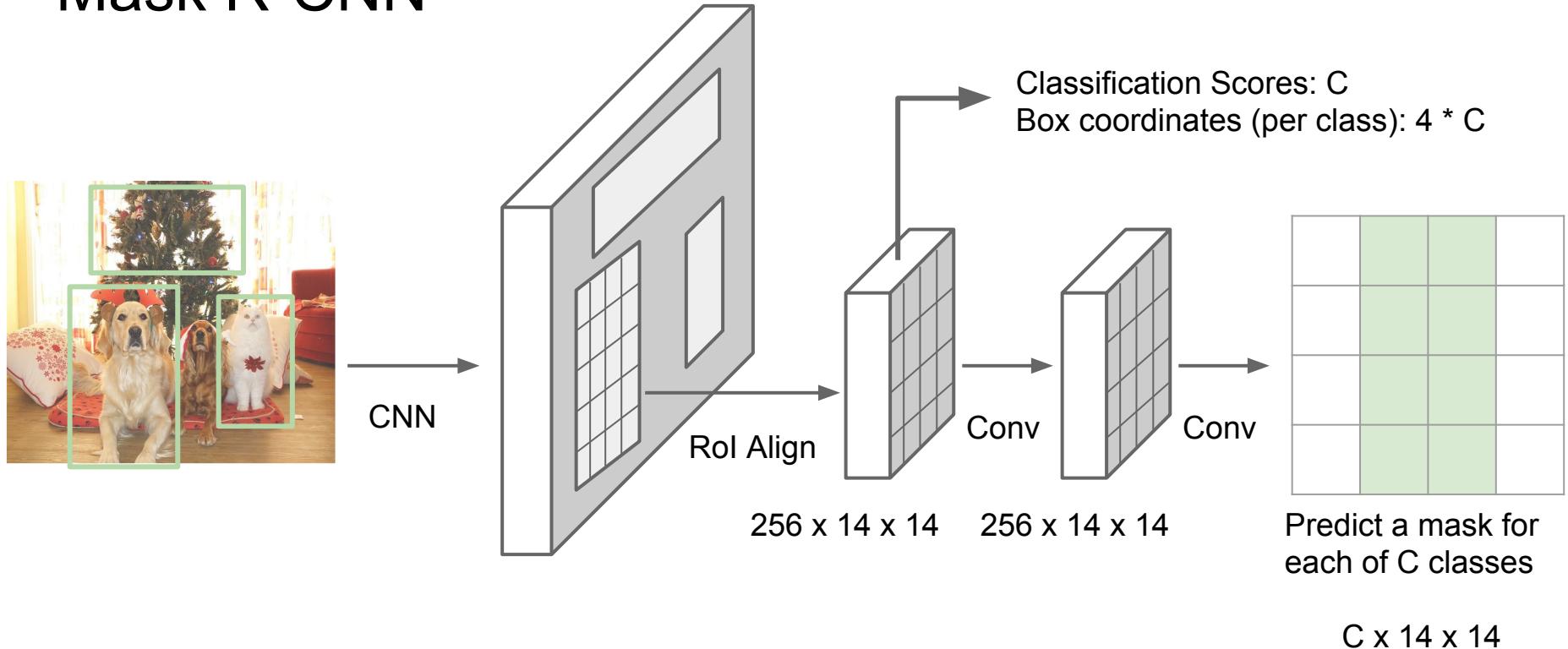


Instance Segmentation



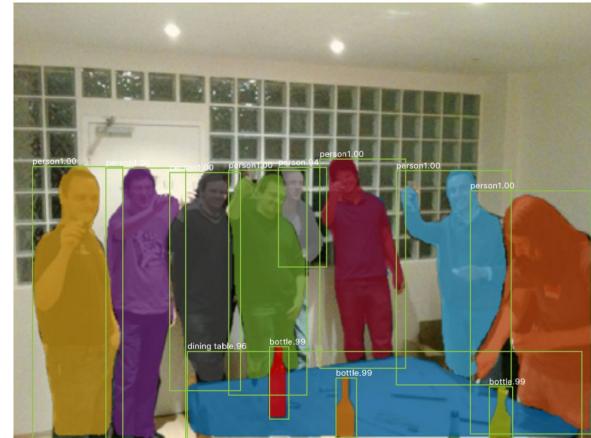
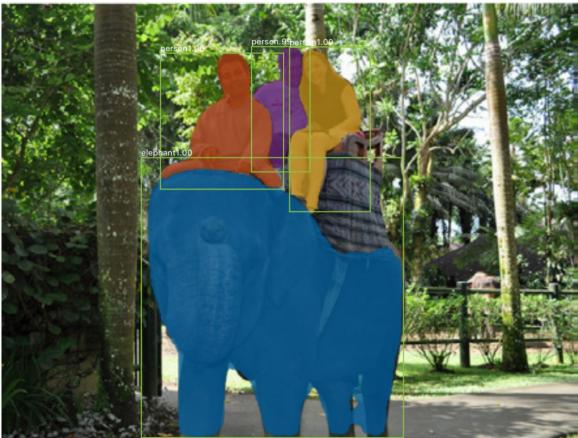
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Mask R-CNN



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

Mask R-CNN: Very Good Results!

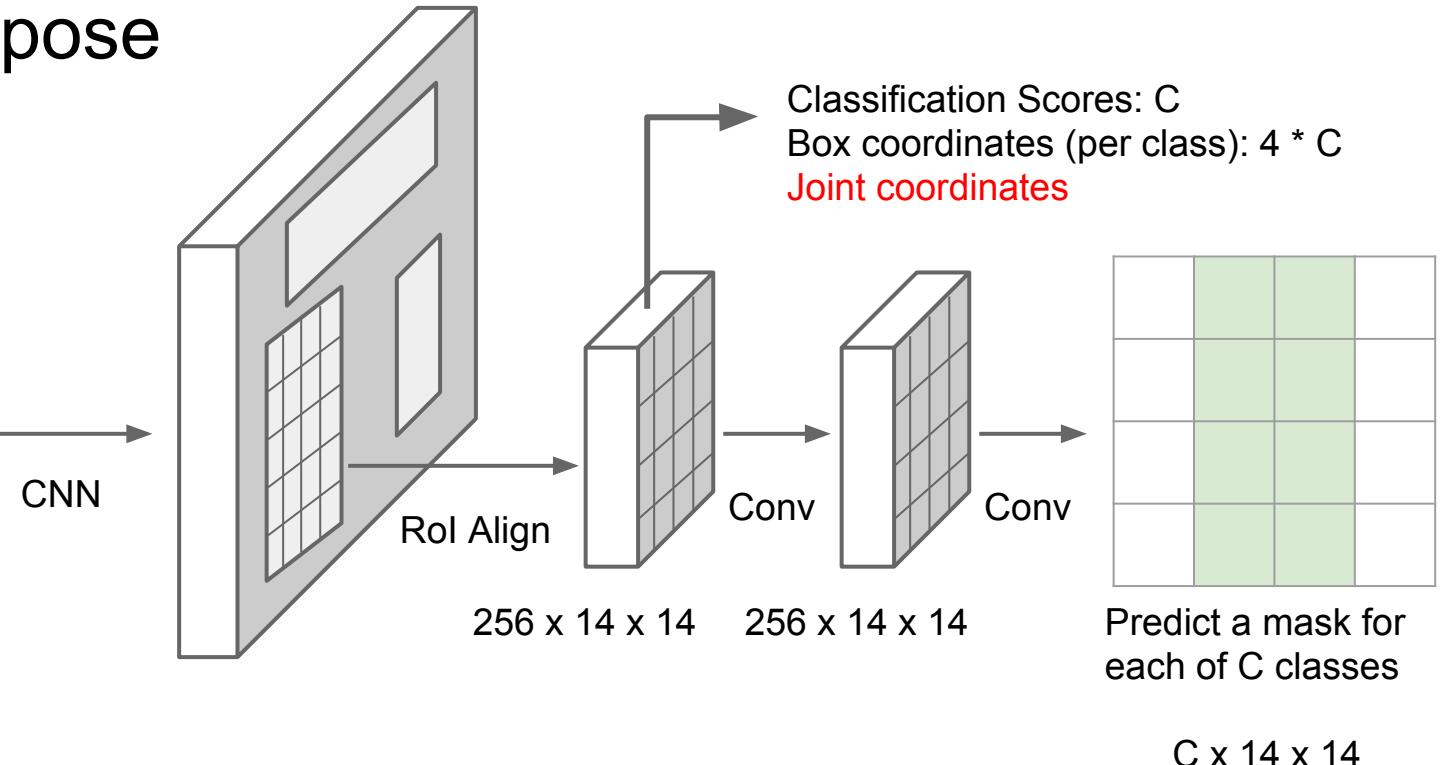
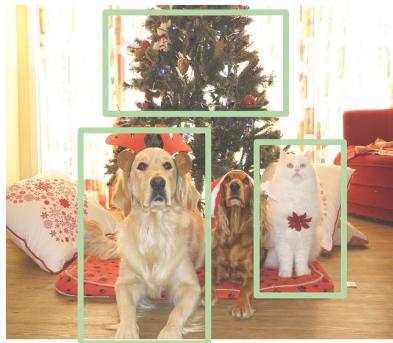


He et al, "Mask R-CNN", arXiv 2017

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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

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Recap:

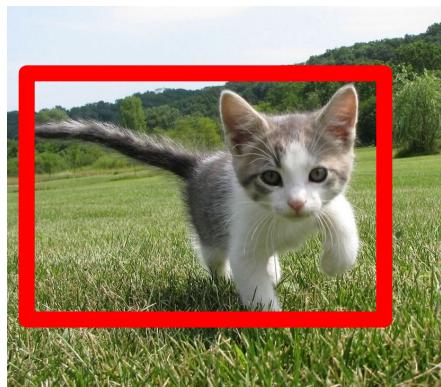
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Classification + Localization



CAT

Single Object

Object Detection



DOG, DOG, CAT

Multiple Object

Instance Segmentation



DOG, DOG, CAT

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Next time:
Visualizing CNN features
DeepDream + Style Transfer