Сверточные нейронные сети для задачи распознавания

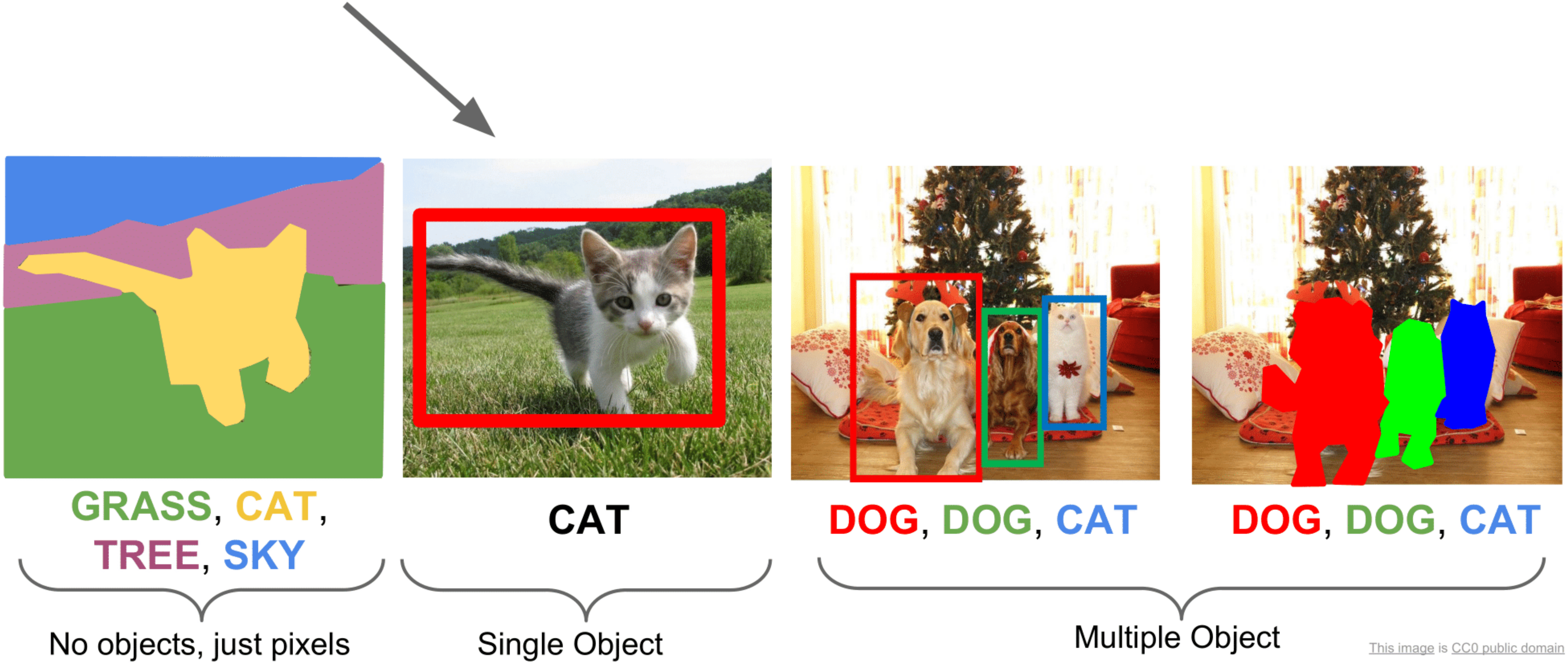
ЛИТПМ

МФТИ

Кафедра технологий проектирования сложных технических систем

2022

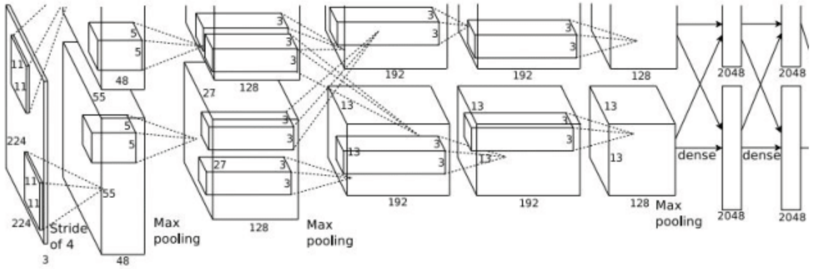
Classification + Localization



Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Classification + Localization

This image is CC0 public domain



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!

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Classification + Localization

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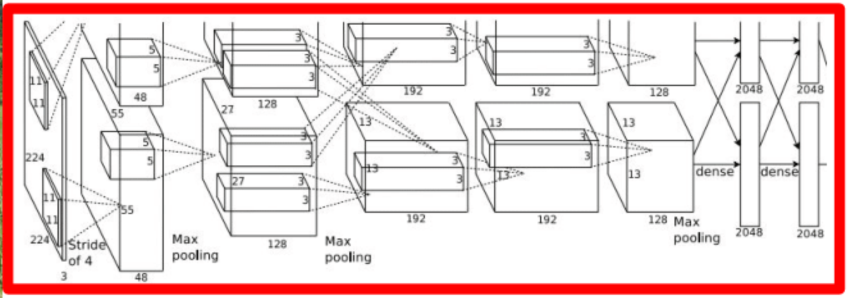


Often pretrained on ImageNet
(Transfer learning)

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’)

+ → **Loss**

Treat localization as a regression problem!

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Aside: Human Pose Estimation

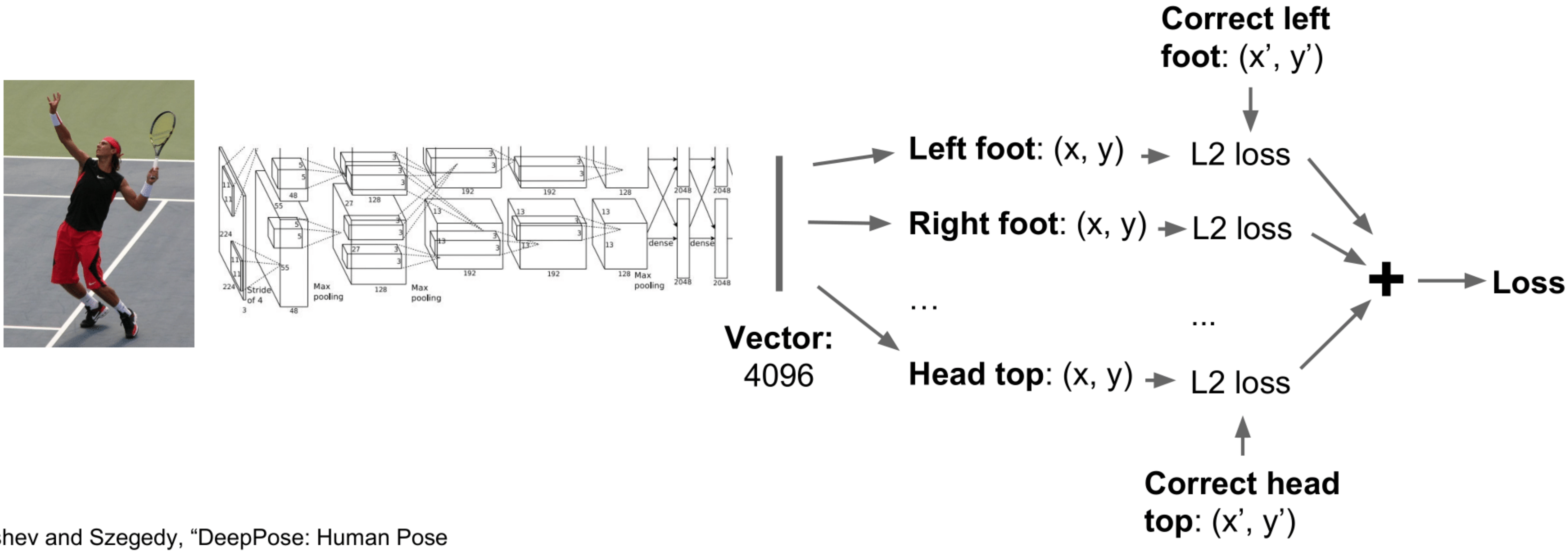
Represent pose as a set of 14 joint positions:

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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

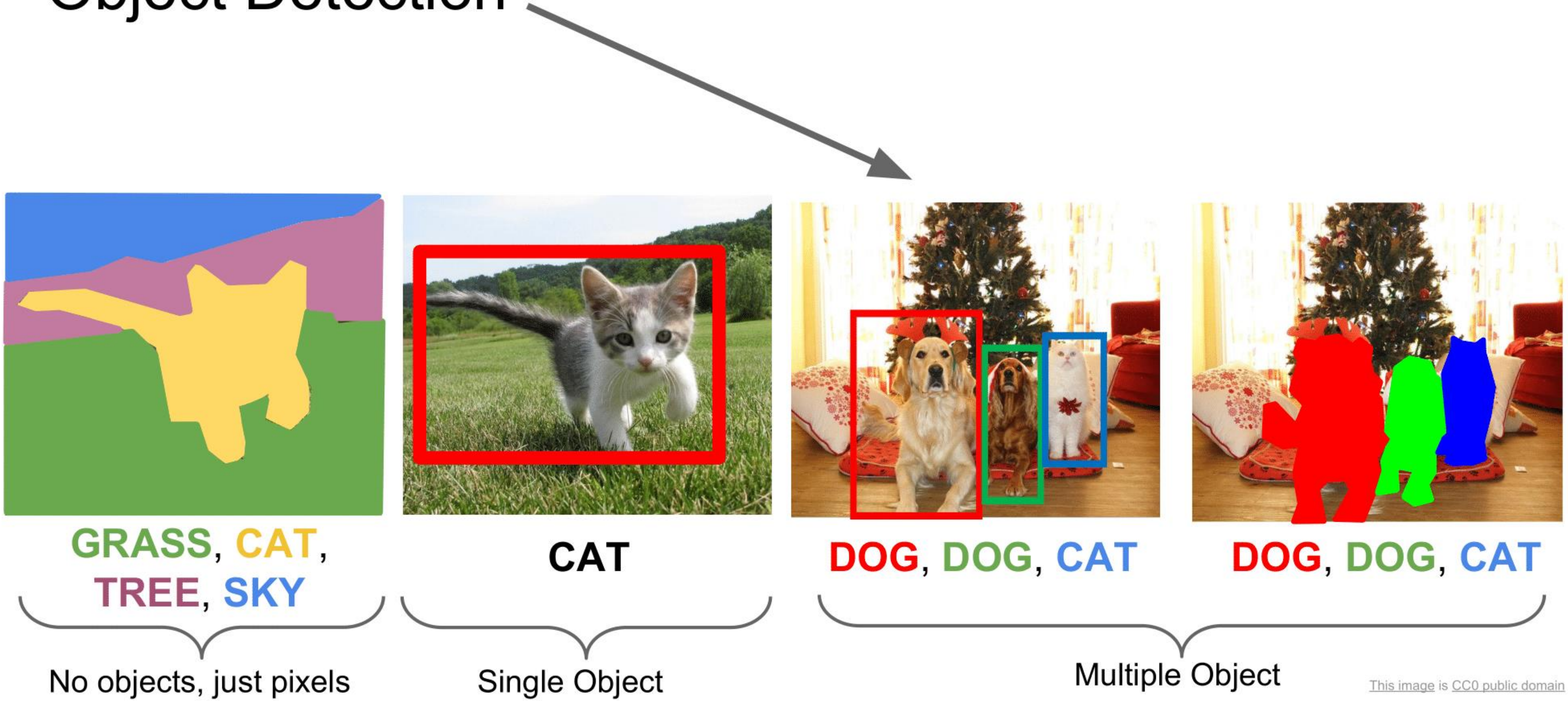
Aside: Human Pose Estimation



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

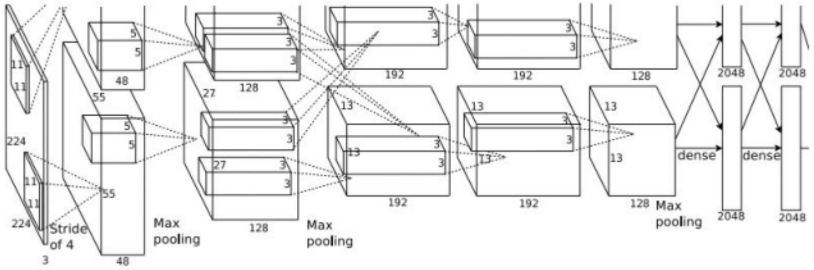
Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Object Detection

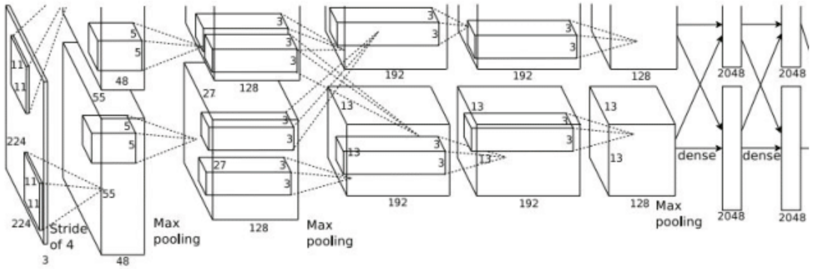


Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

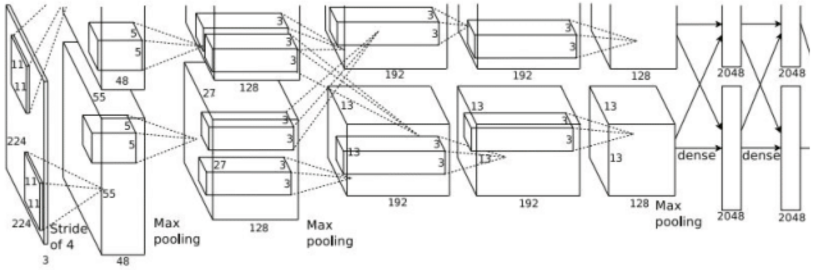
Object Detection as Regression?



CAT: (x, y, w, h)



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

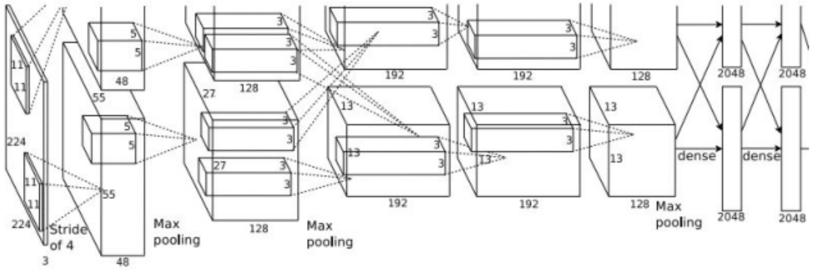


DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

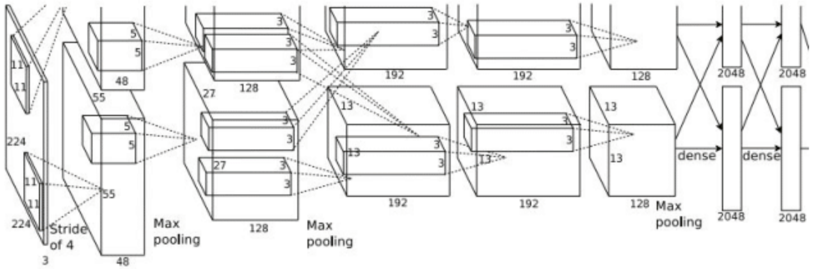
Object Detection as Regression?

Each image needs a different number of outputs!



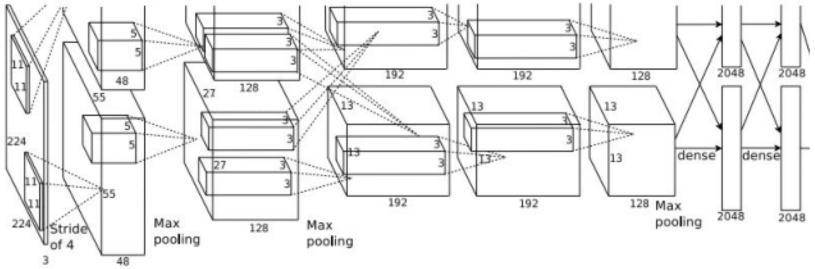
CAT: (x, y, w, h)

4 numbers



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

16 numbers



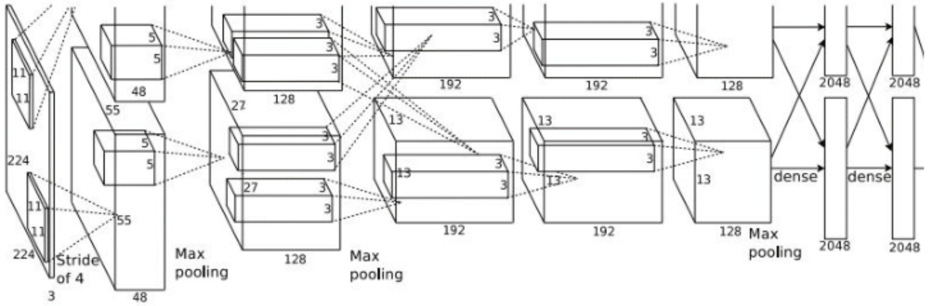
DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

Many numbers!

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Object Detection as Classification: Sliding Window

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

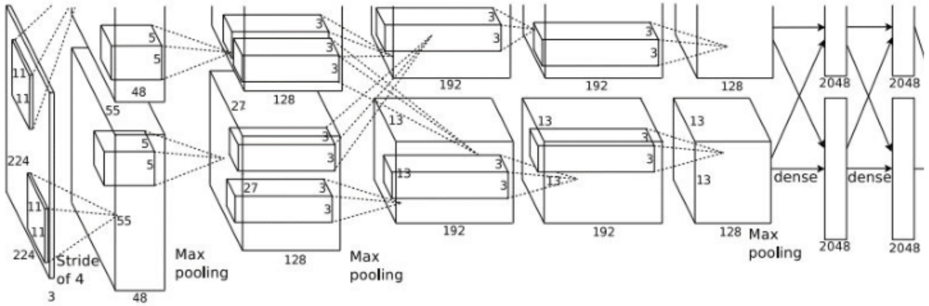


Dog? NO
Cat? NO
Background? YES

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

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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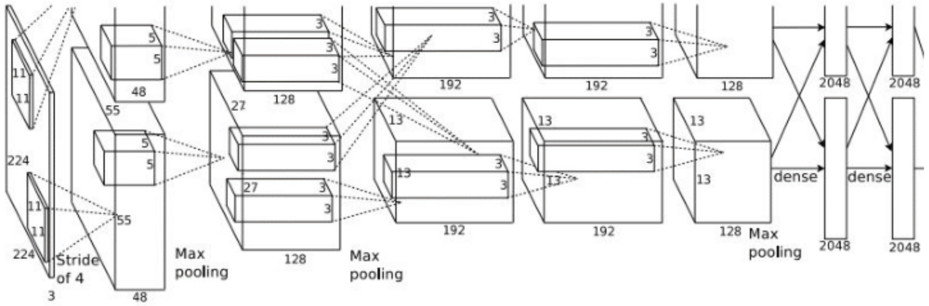

Dog? YES
Cat? NO
Background? NO

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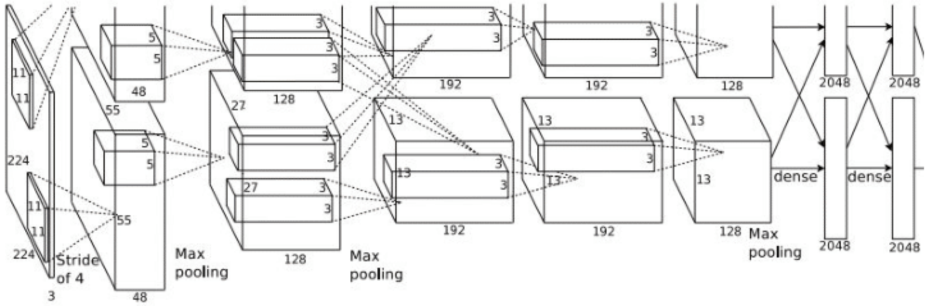

Dog? NO
Cat? YES
Background? NO

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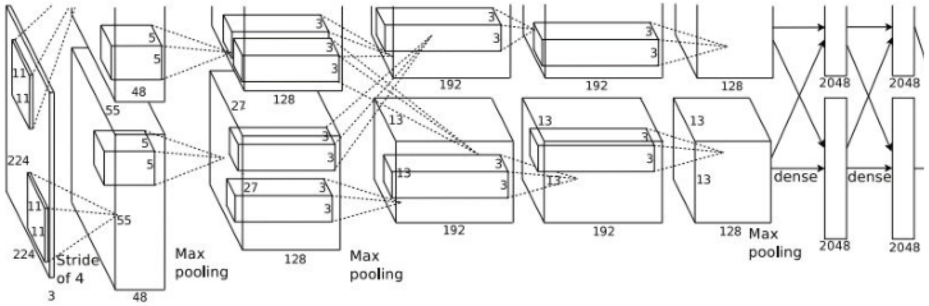
Object Detection as Classification: Sliding Window

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



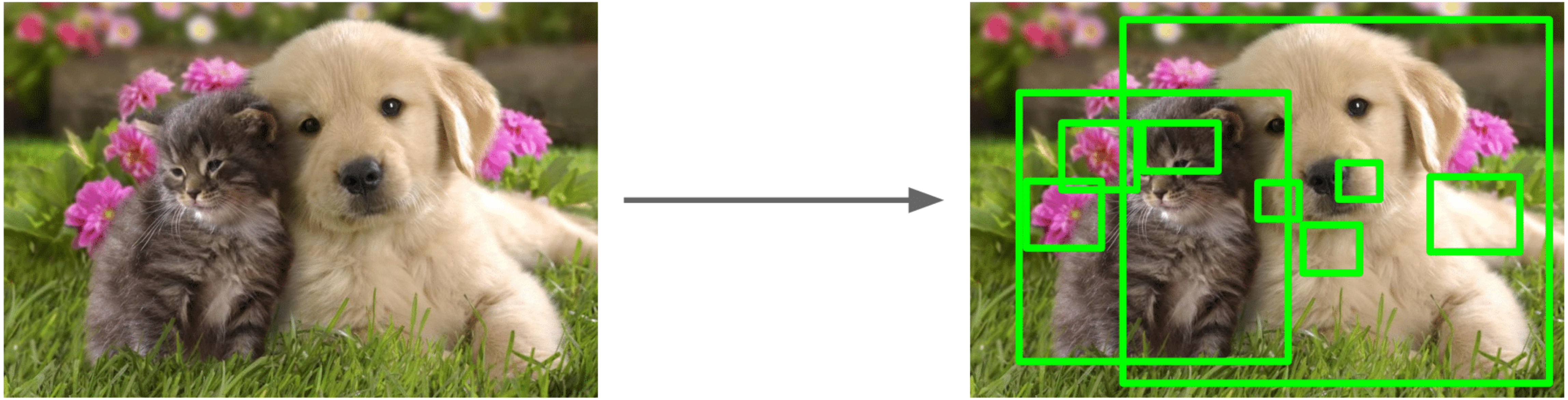
Dog? NO
Cat? YES
Background? NO

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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

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

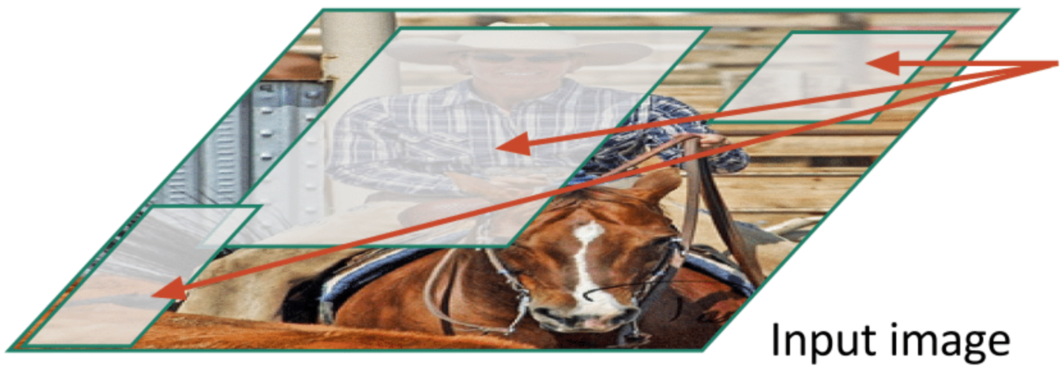
Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

R-CNN

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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

R-CNN



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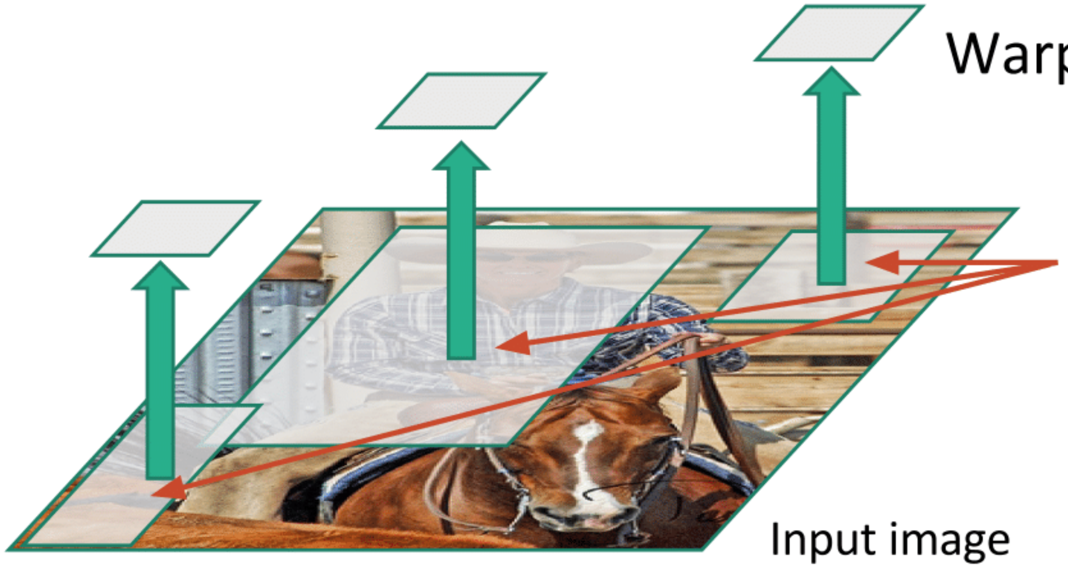
R-CNN



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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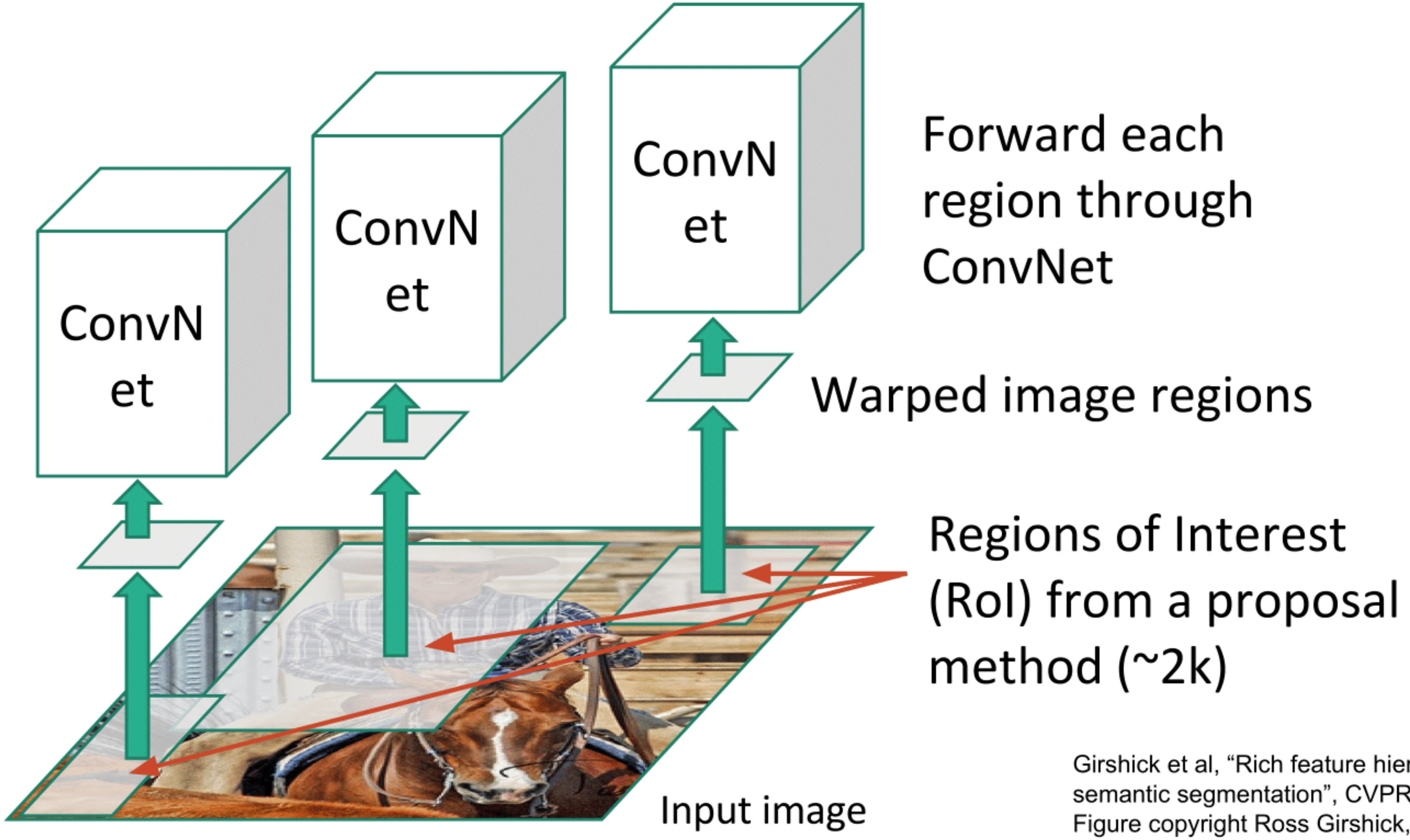
R-CNN



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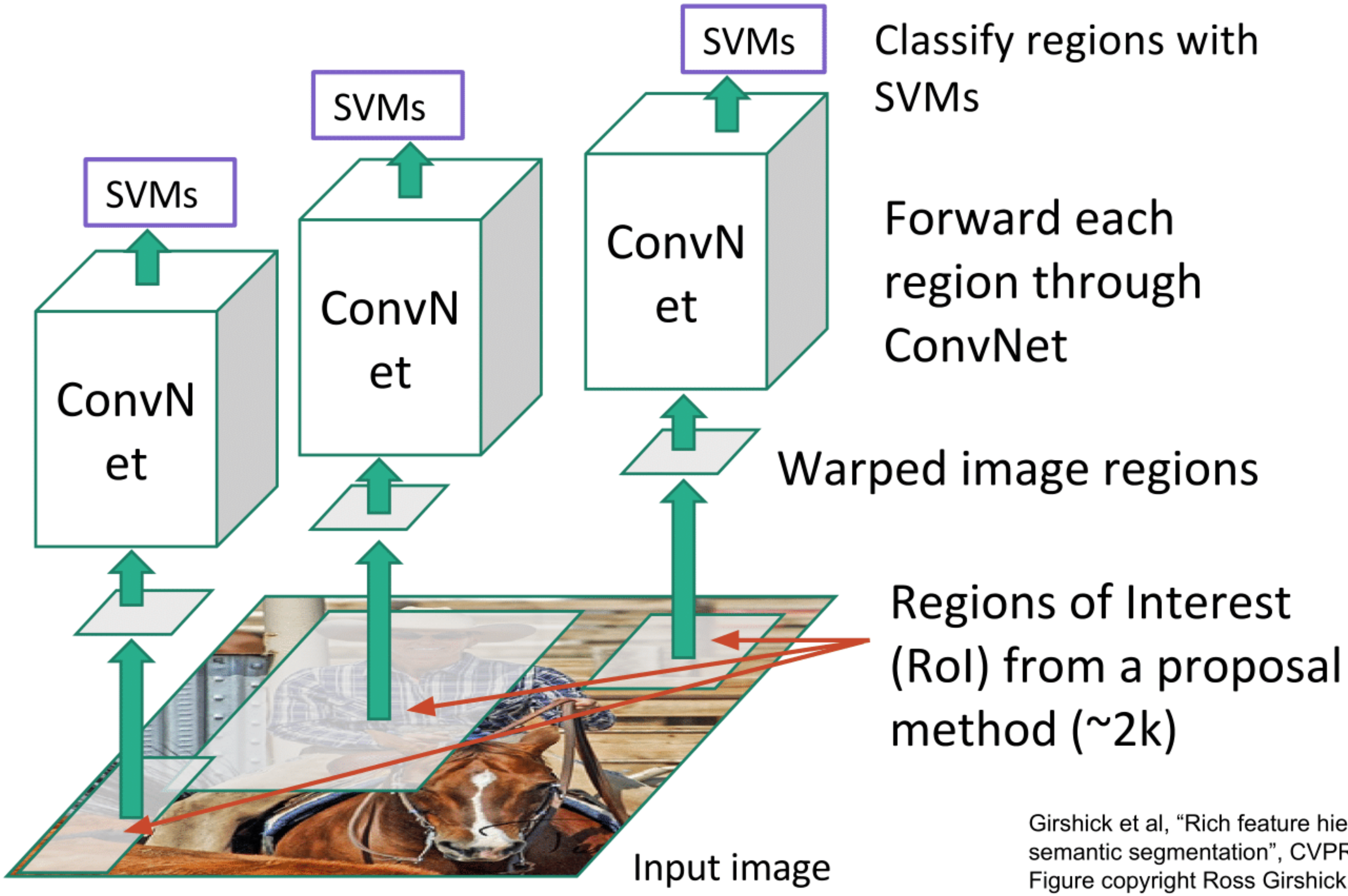
R-CNN



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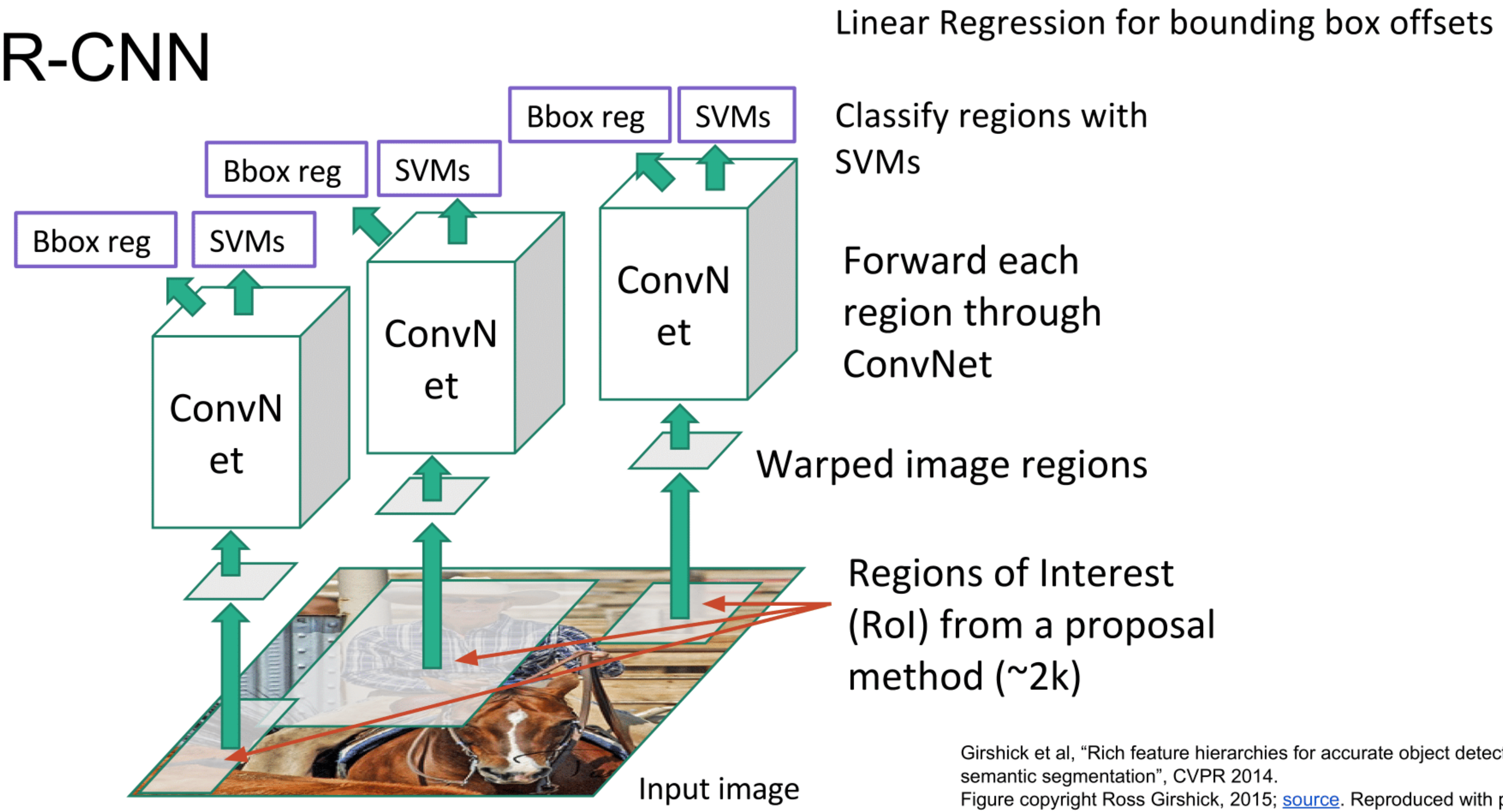
R-CNN

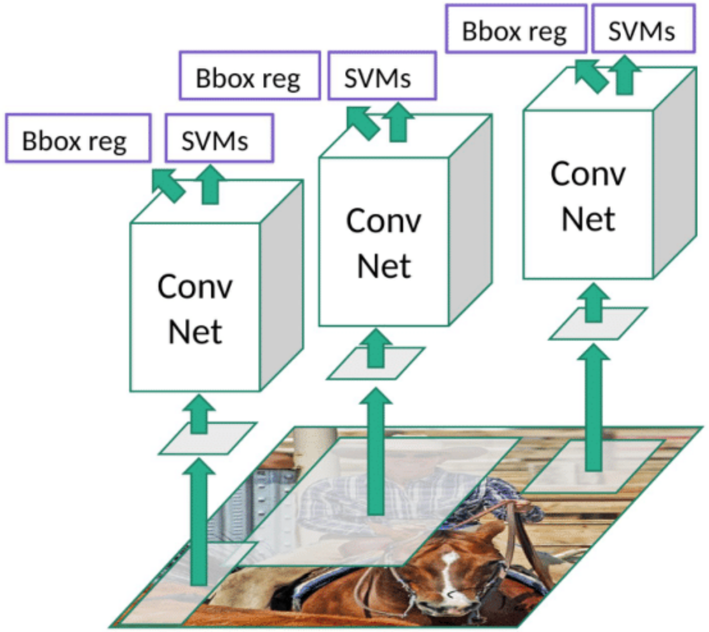


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

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]



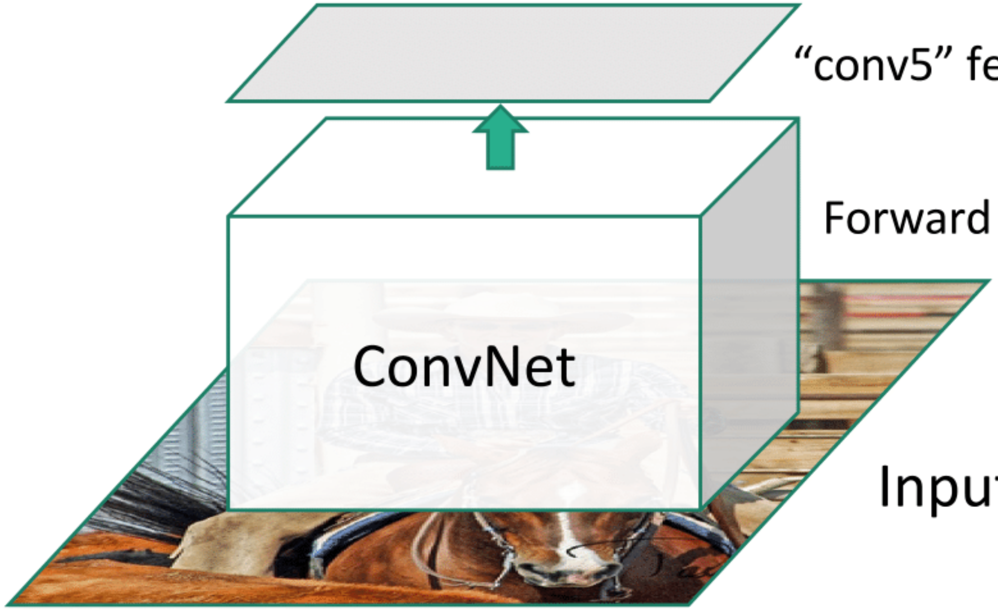
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

Fast R-CNN

Input image

Girshick, “Fast R-CNN”, ICCV 2015.

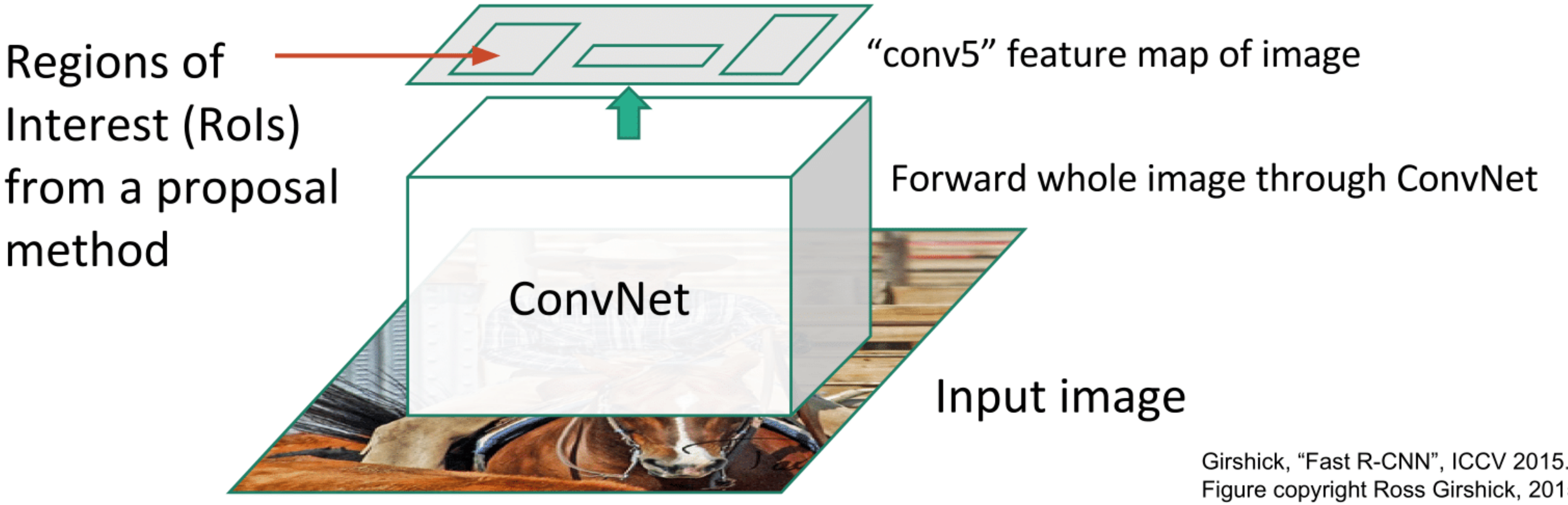
Fast R-CNN



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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Fast R-CNN



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

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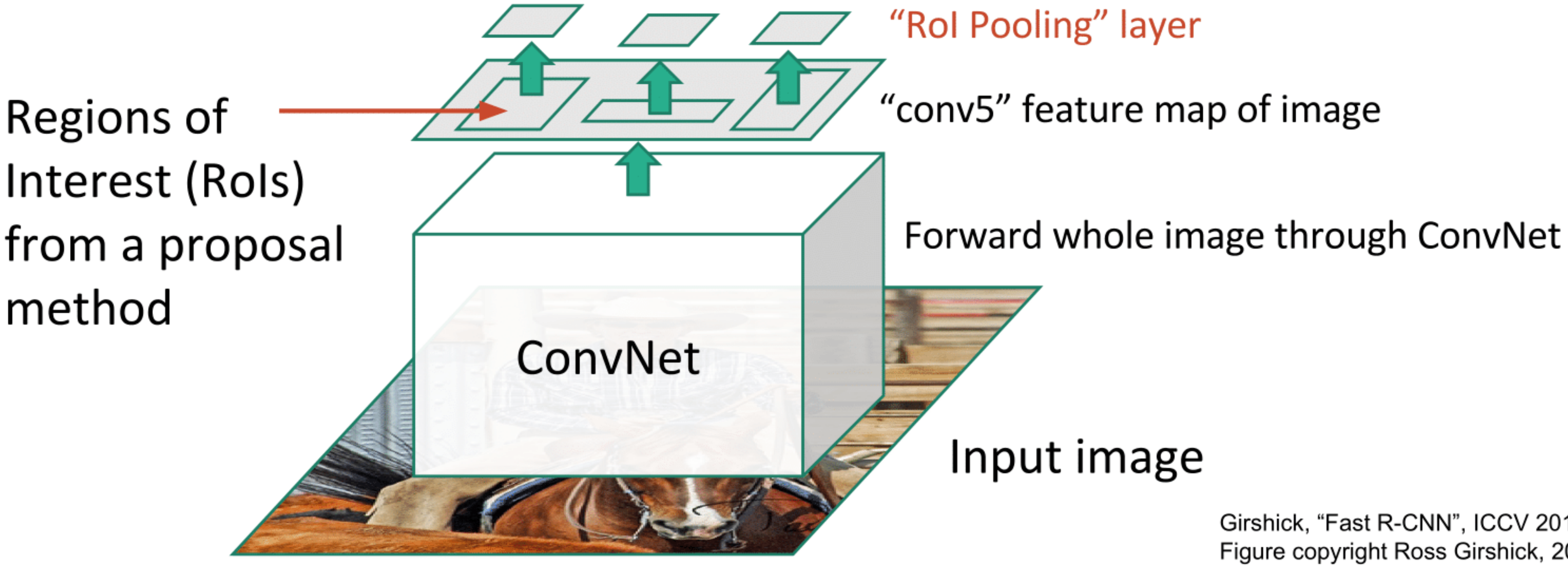
Fast R-CNN



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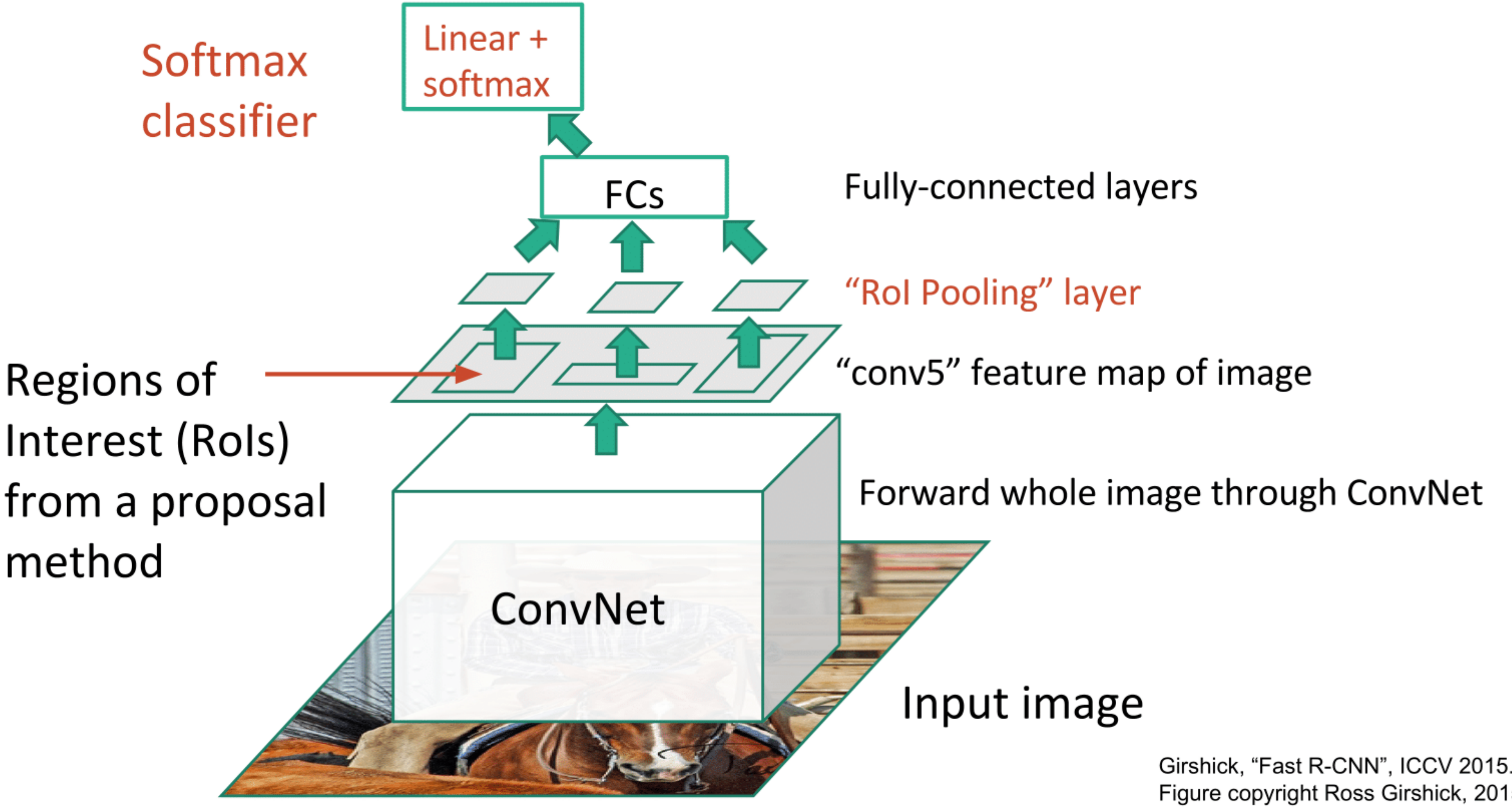
Fast R-CNN



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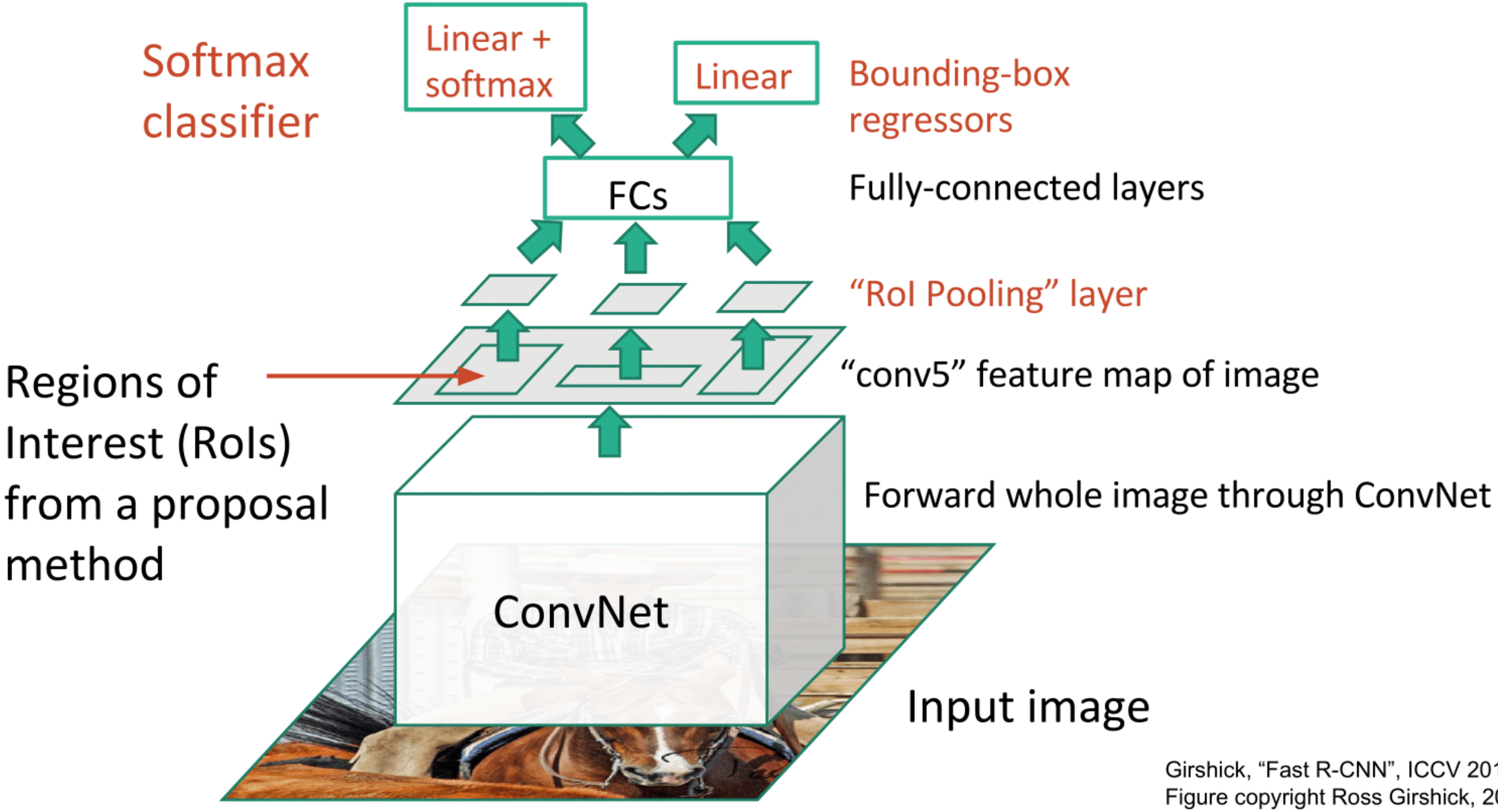
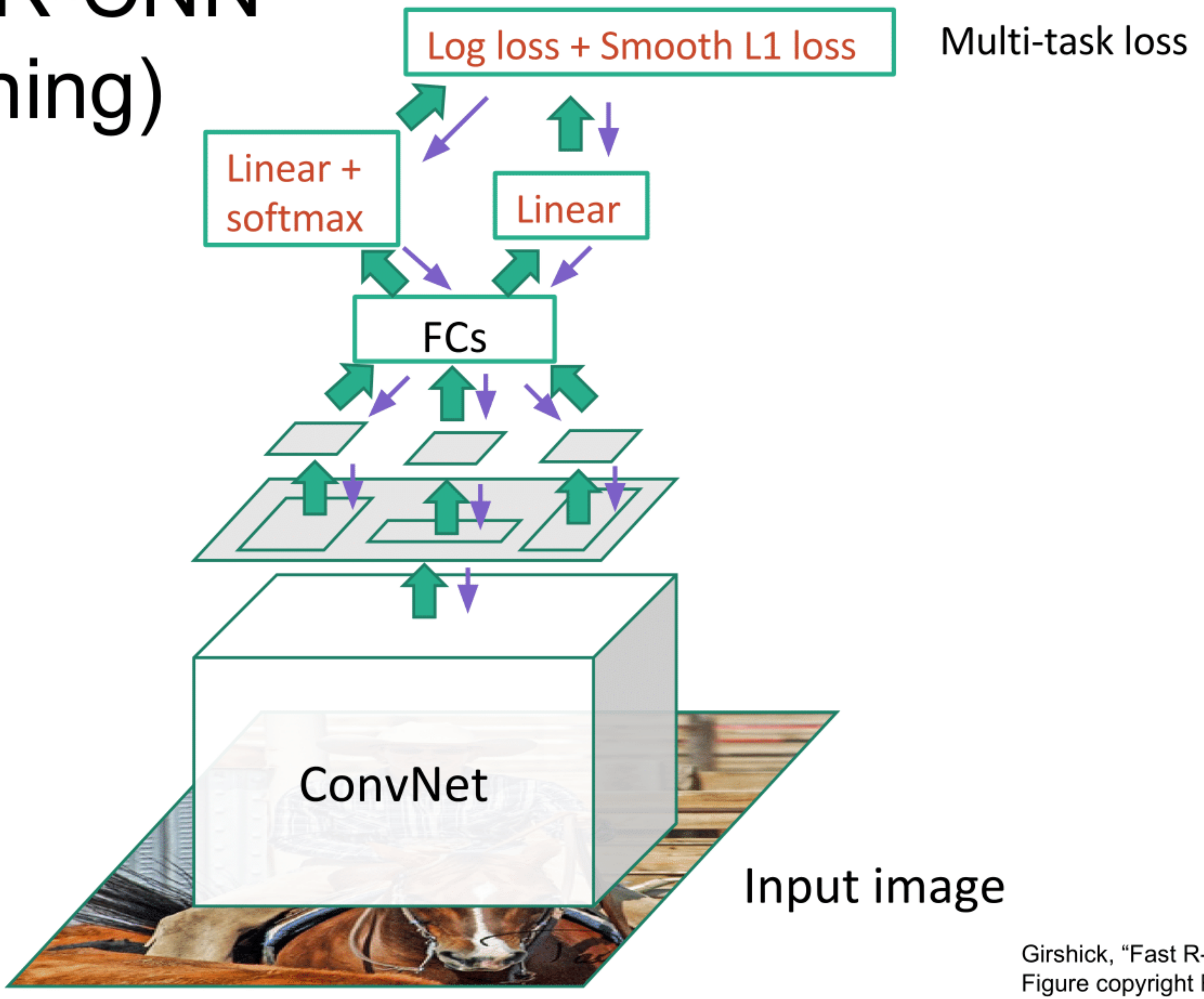
Fast R-CNN



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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Fast R-CNN (Training)



Girshick, “Fast R-CNN”, ICCV 2015.
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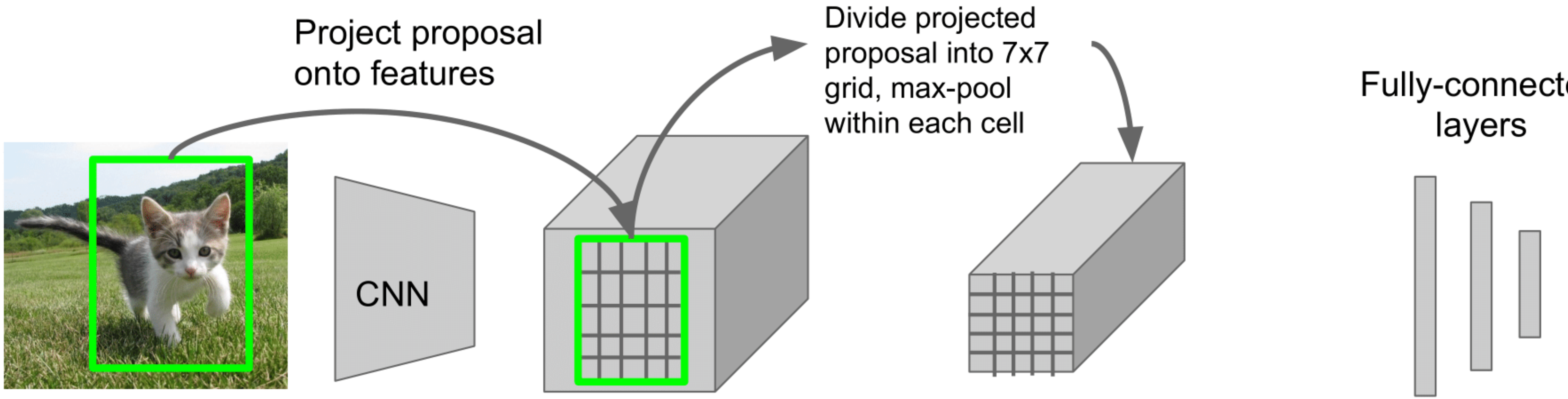
Faster R-CNN: RoI Pooling



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)

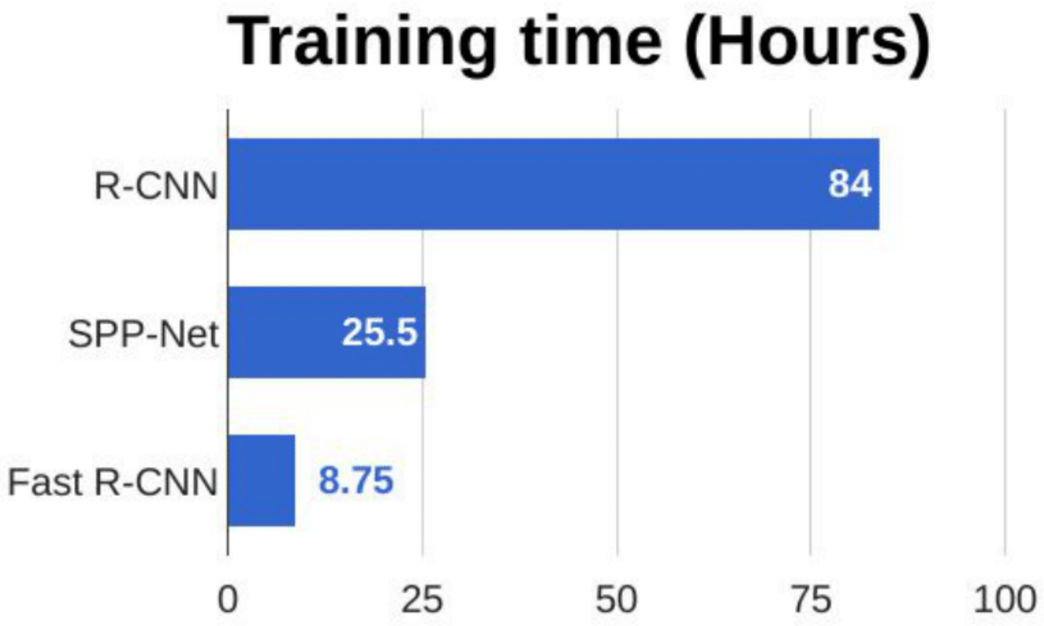
RoI conv features:
512 x 7 x 7
for region proposal

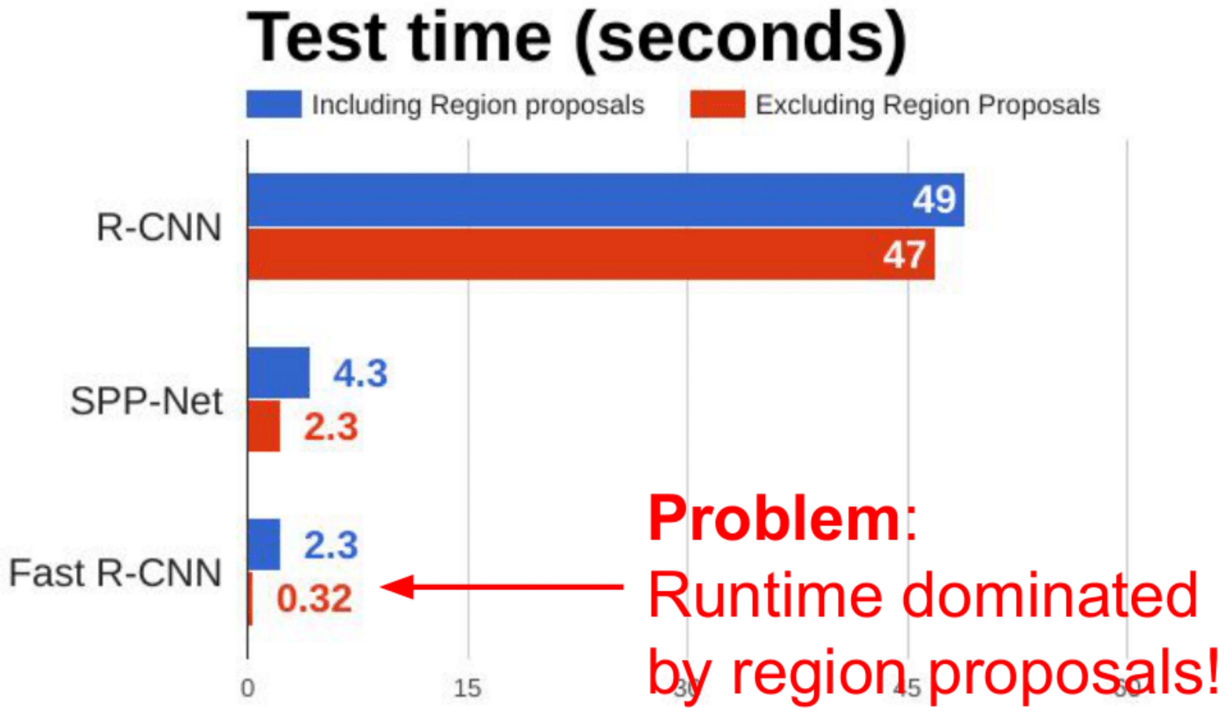
Fully-connected layers expect
low-res conv features:
512 x 7 x 7

Girshick, “Fast R-CNN”, ICCV 2015.

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

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

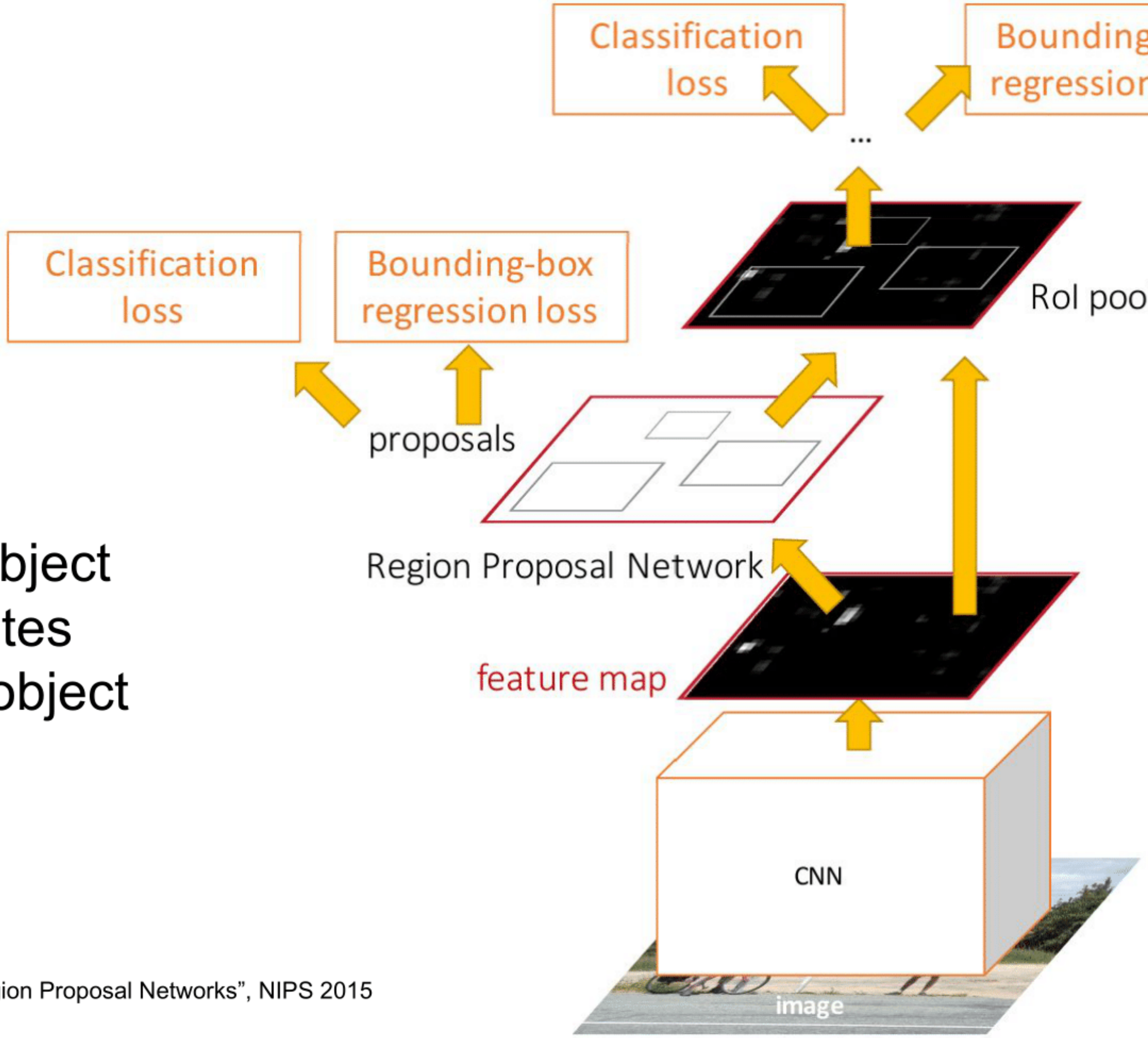
Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

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

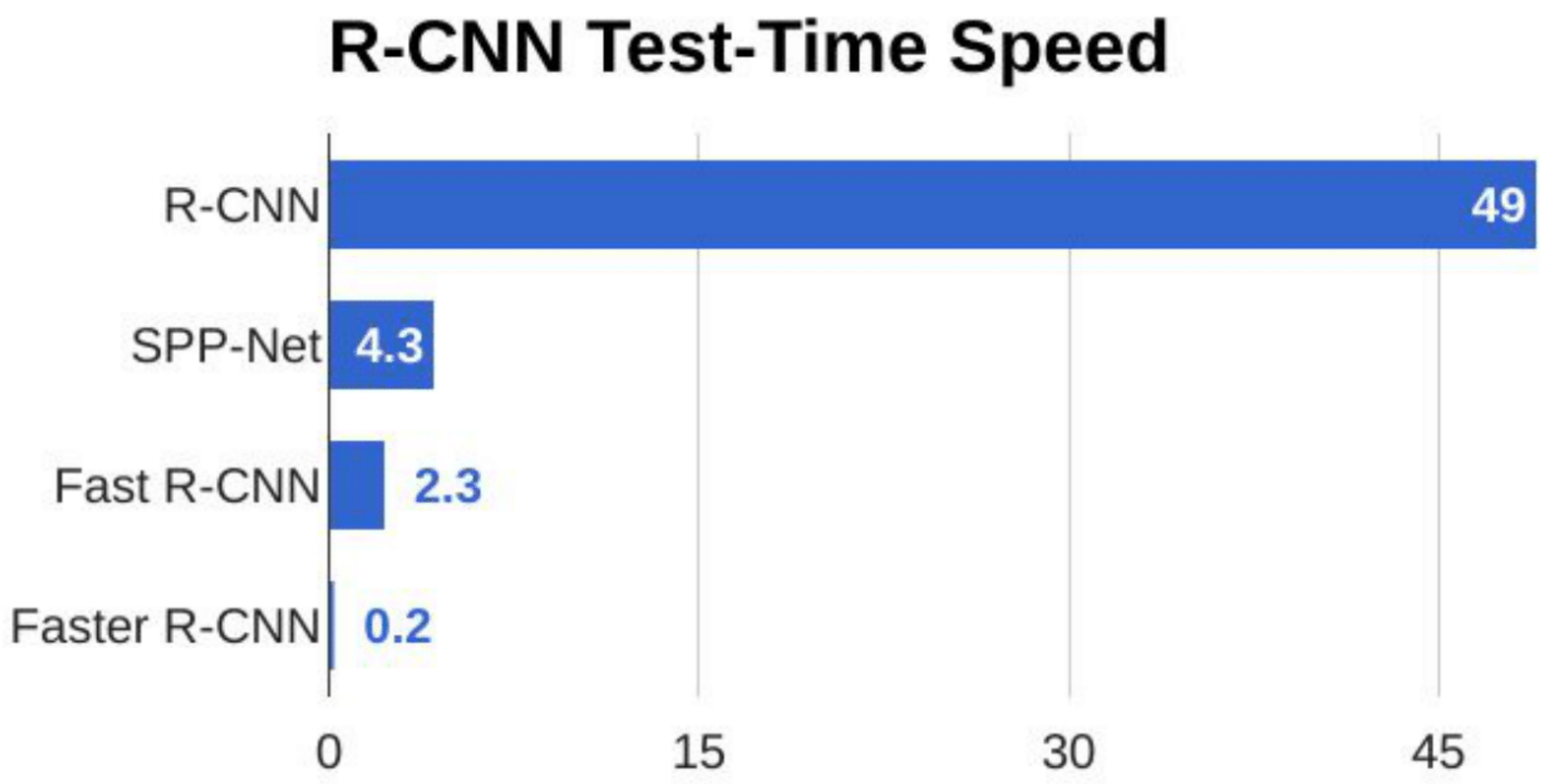


Ren et al, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”, NIPS 2015

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Fast**er** R-CNN:

Make CNN do proposals!

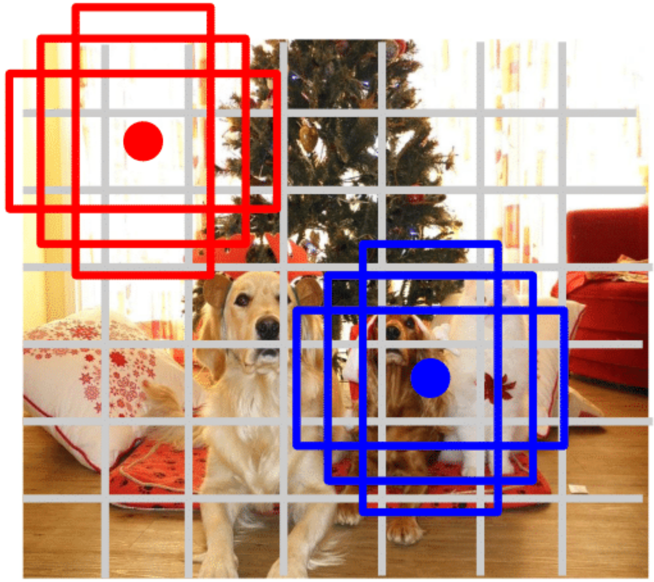


Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

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
7 x 7

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

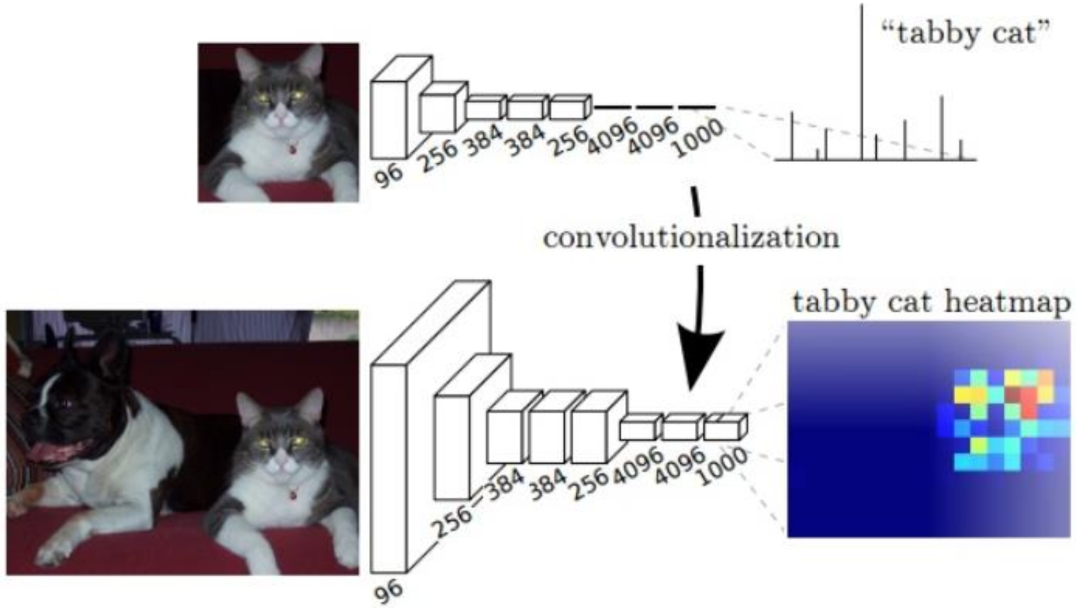
Within each grid cell:
- Regress from each of the B base boxes to a final box with 5 numbers:
(dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)

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

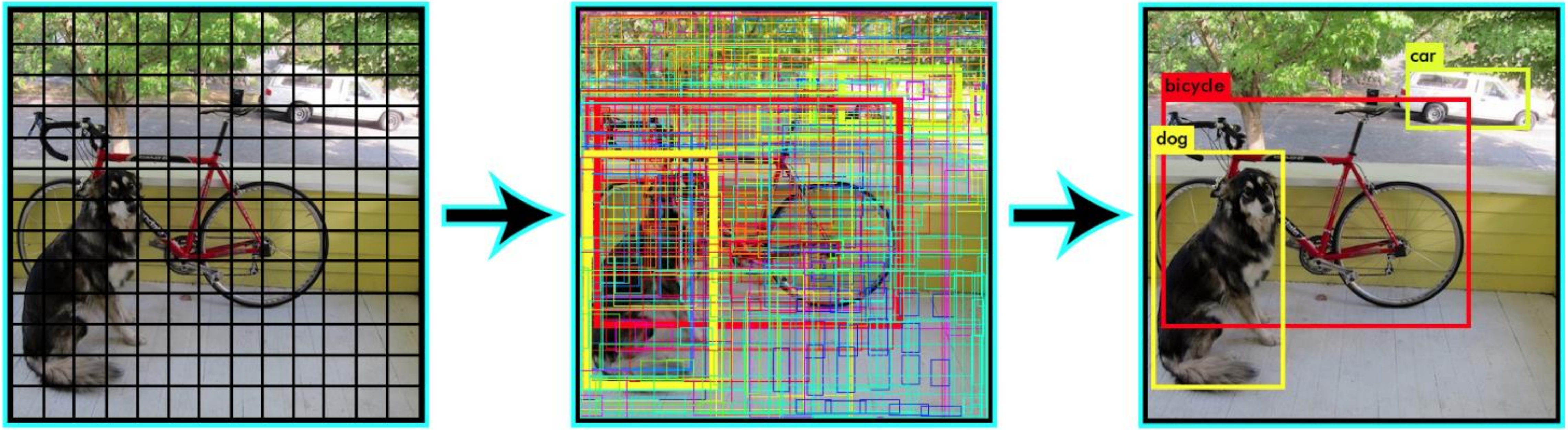
Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

One Shot Detection



Для каждой ячейки в последнем conv слое предказываем координаты бокса и класс объекта с центром в ячейке.

One Shot Detector: YOLO



Для каждой ячейки в последнем conv слое предказываем координаты боксa и класс объекта с центром в ячейке.

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

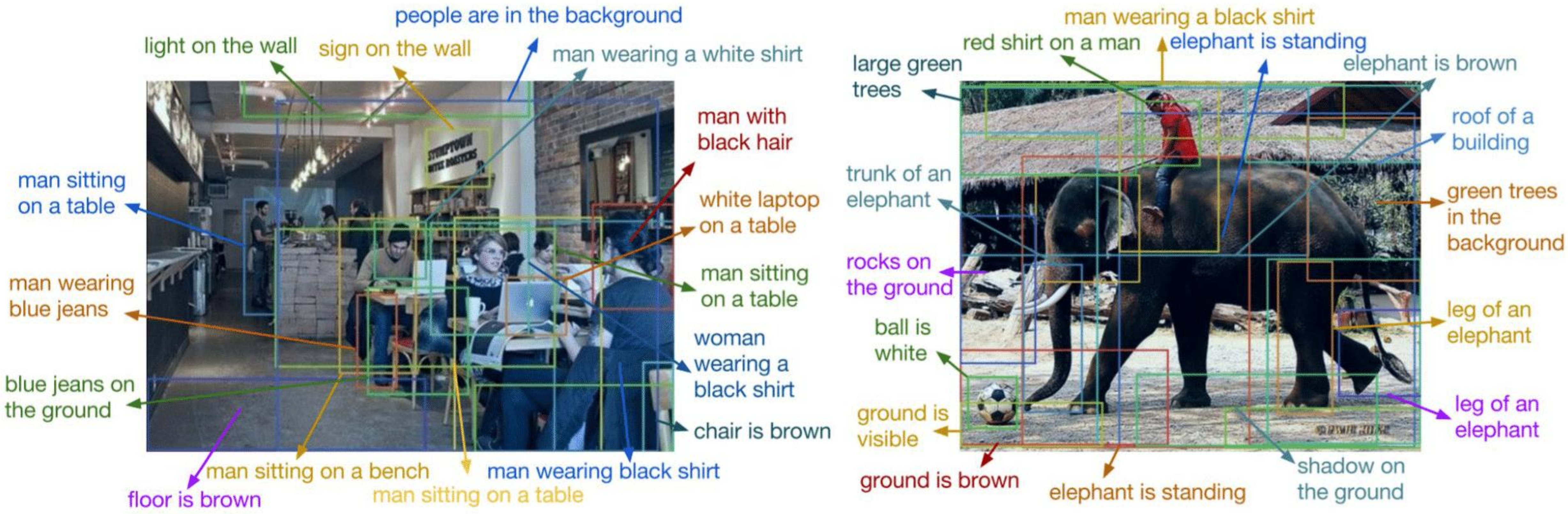
SSD is much faster but not as accurate

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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

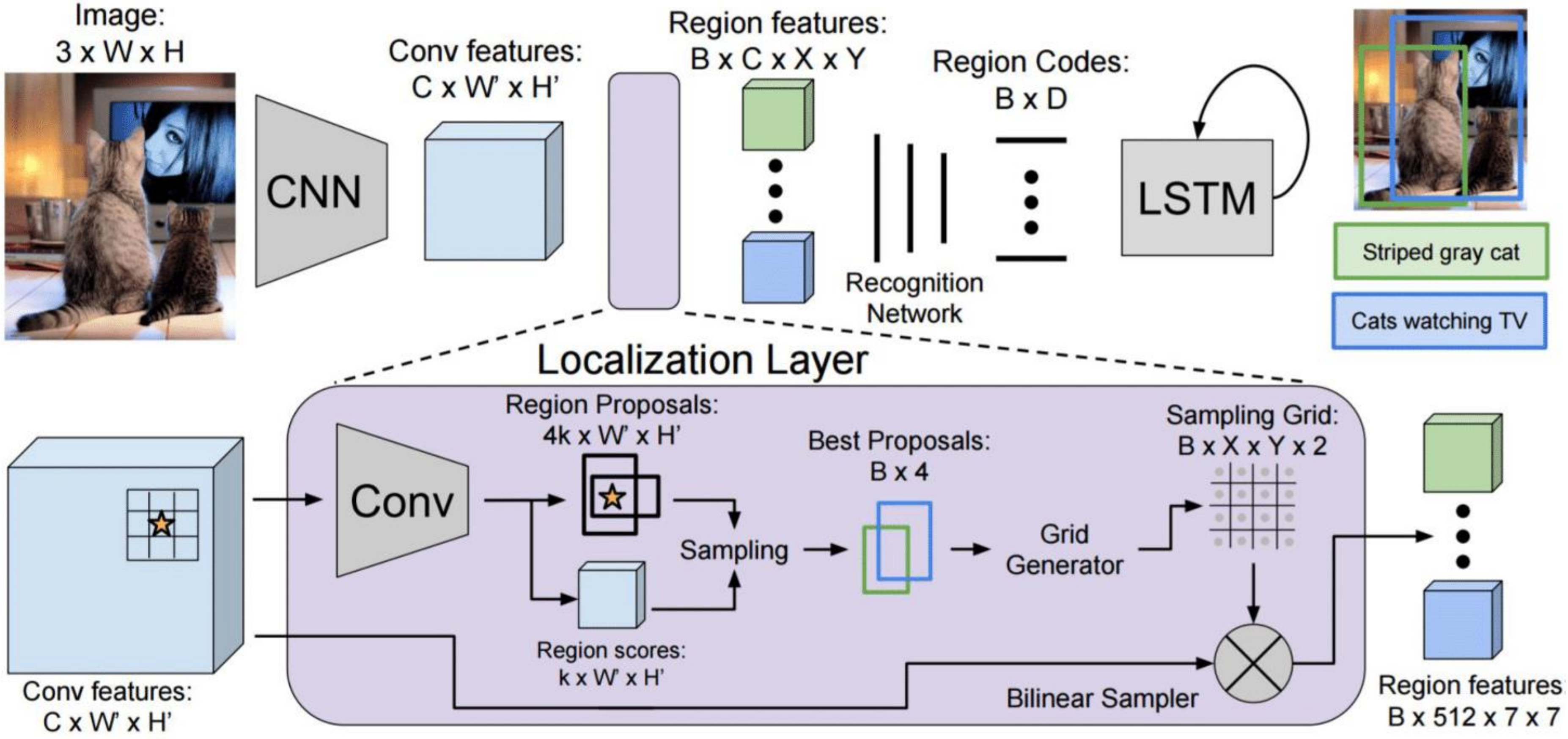
Aside: Object Detection + Captioning = Dense Captioning



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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

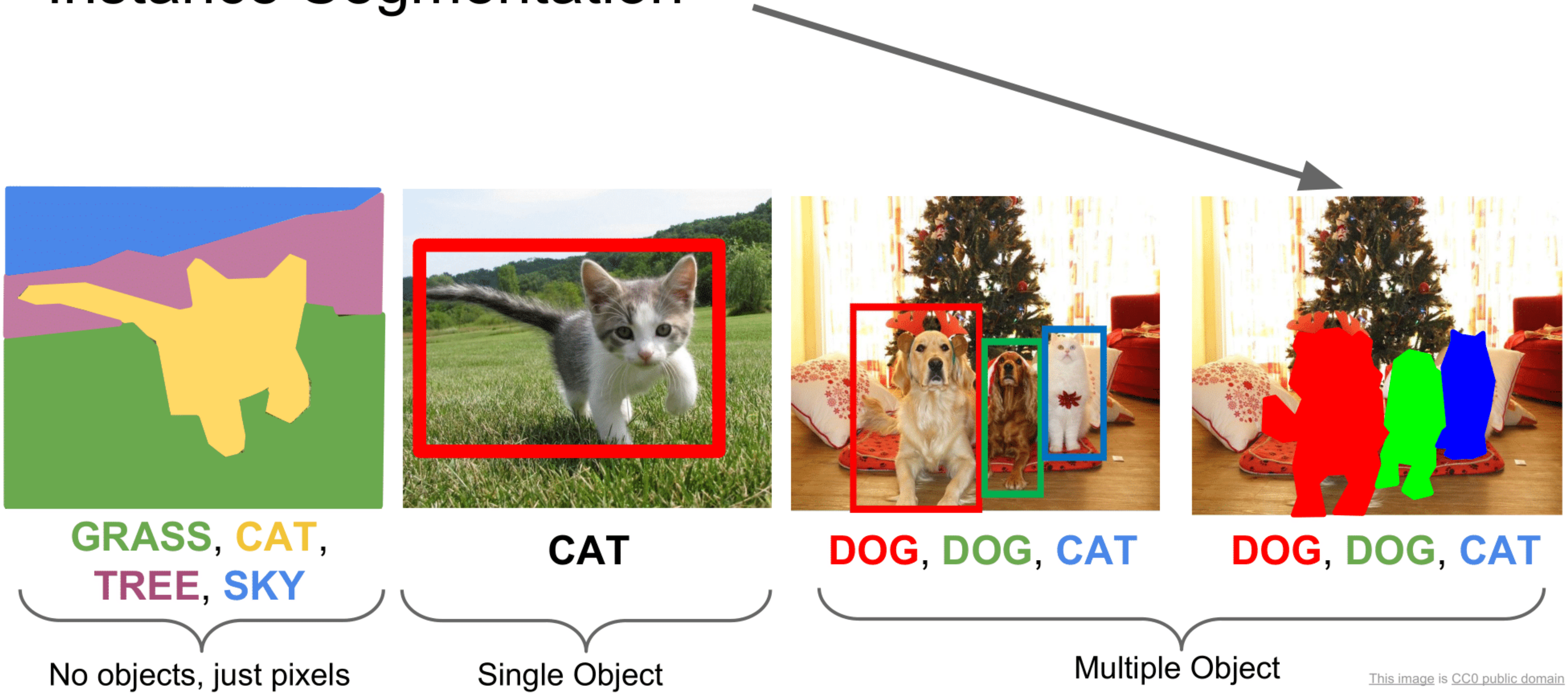
Aside: Object Detection + Captioning = Dense Captioning



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

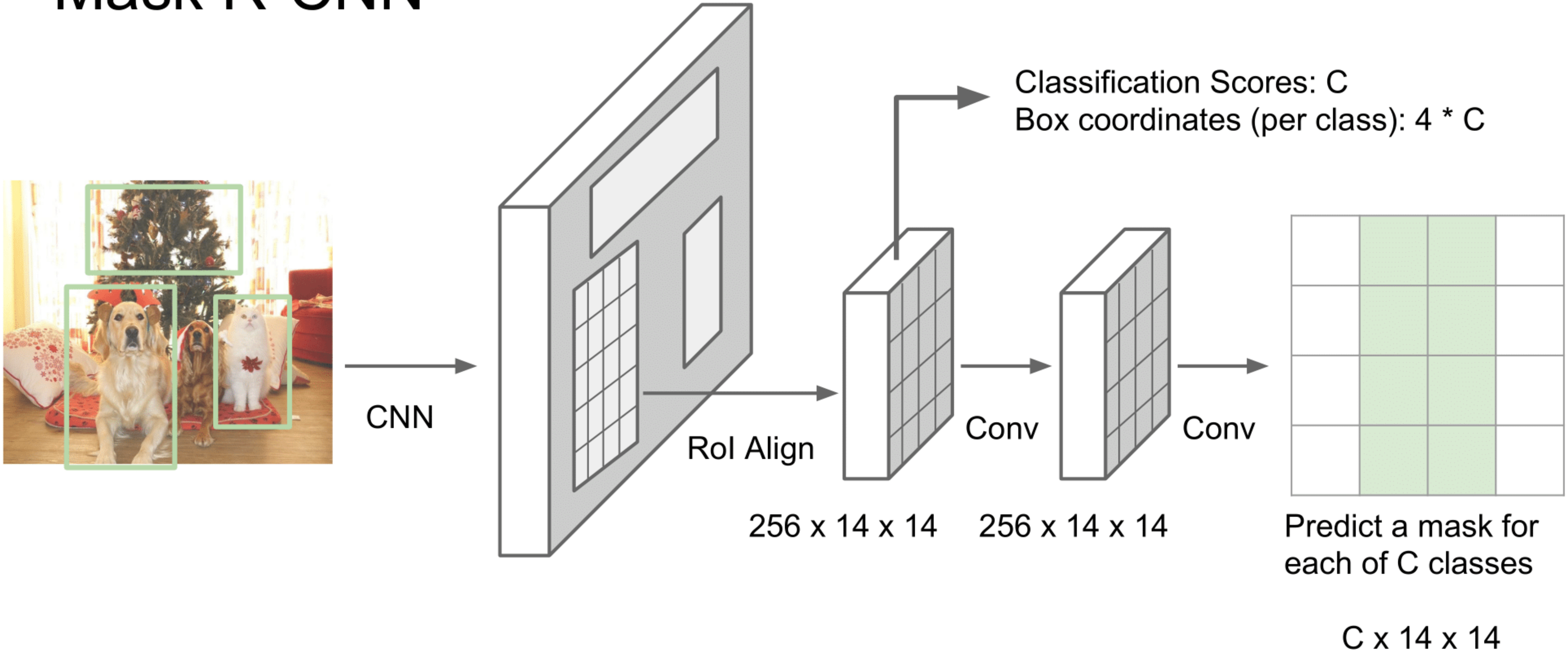
Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Instance Segmentation



Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

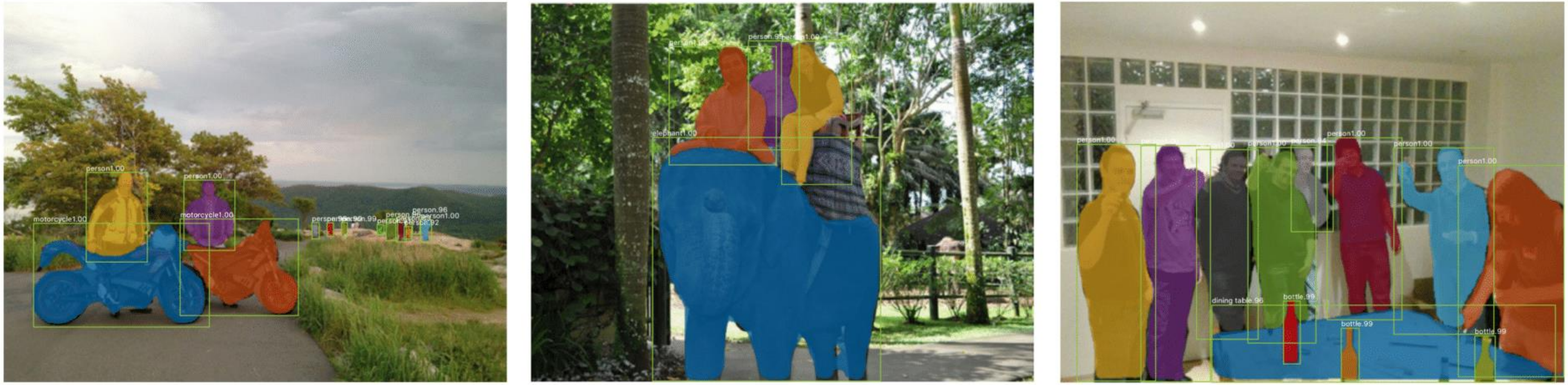
Mask R-CNN



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

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Mask R-CNN: Very Good Results!

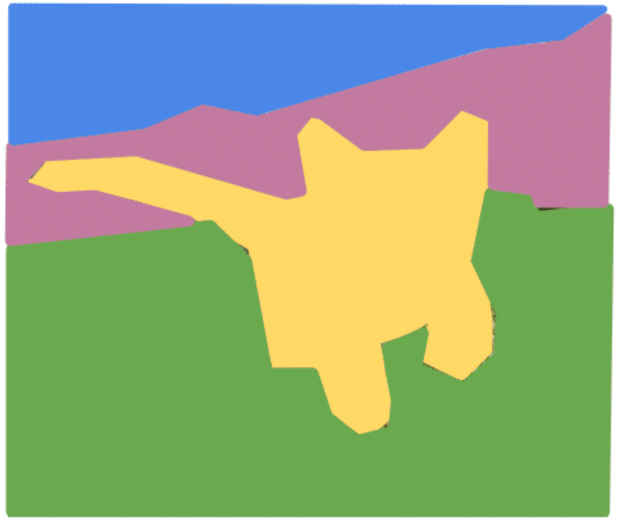


He et al, “Mask R-CNN”, arXiv 2017

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung

Recap:

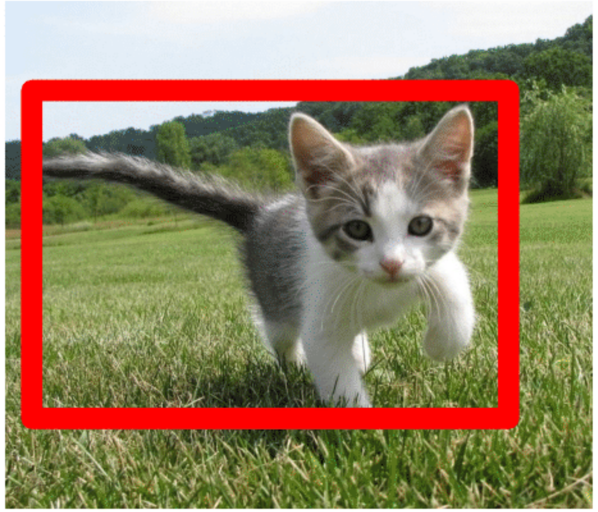
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

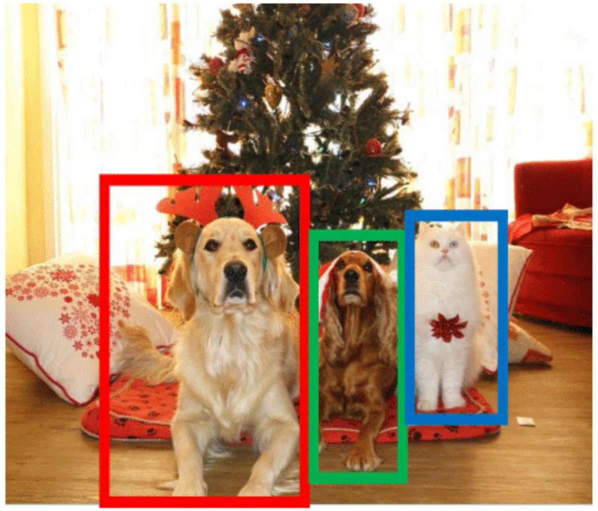
Classification + Localization



CAT

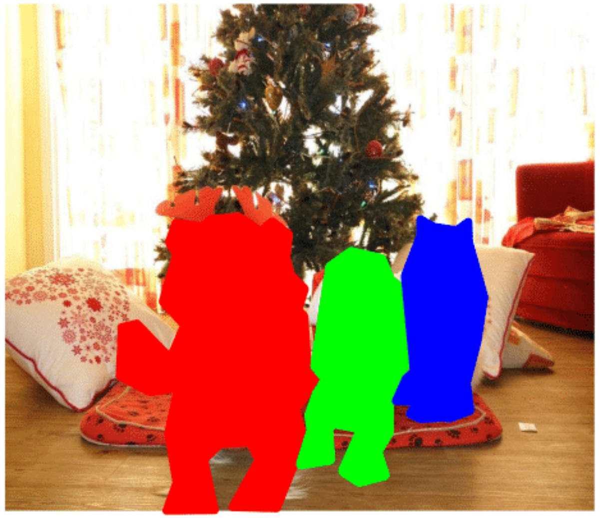
Single Object

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

Source: Stanford CS231n Lecture 11 2017 by Fei-Fei Li & Justin Johnson & Serena Yeung