Computer Vision

Object Detection

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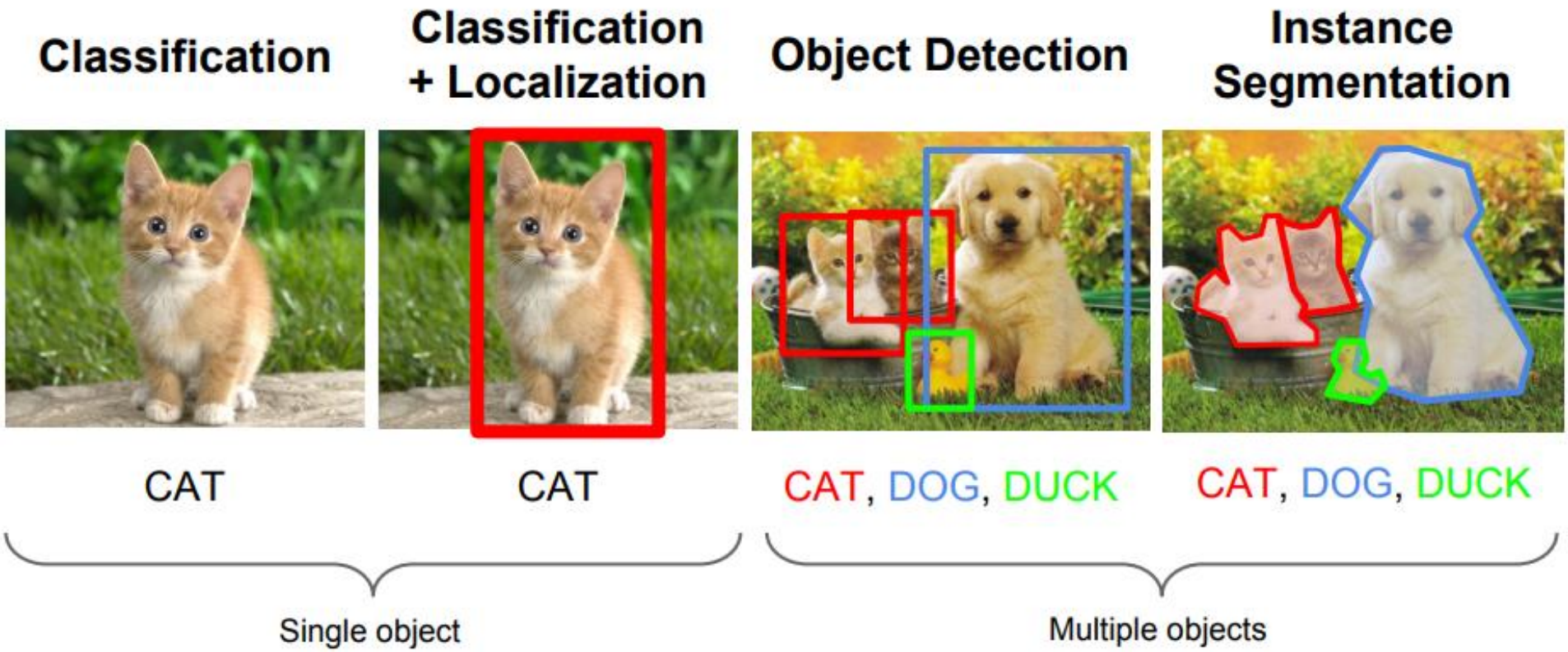
Roadmap



Slide from A. Karpathy

Today's class

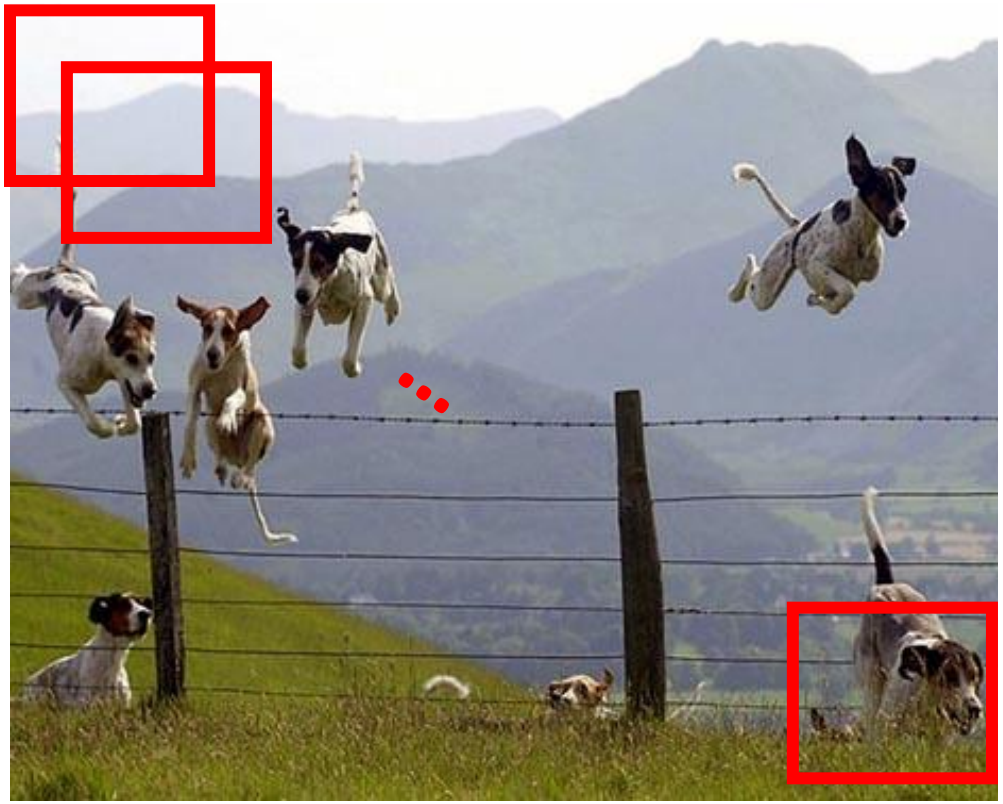
- Overview of object category detection

- Traditional methods
  - Dalal-Triggs detector (basic concept)
  - Viola-Jones detector (cascades, integral images)

- Deep learning methods
  - Two-stage: R-CNN
  - One-stage: YOLO, SSD, Retina Net

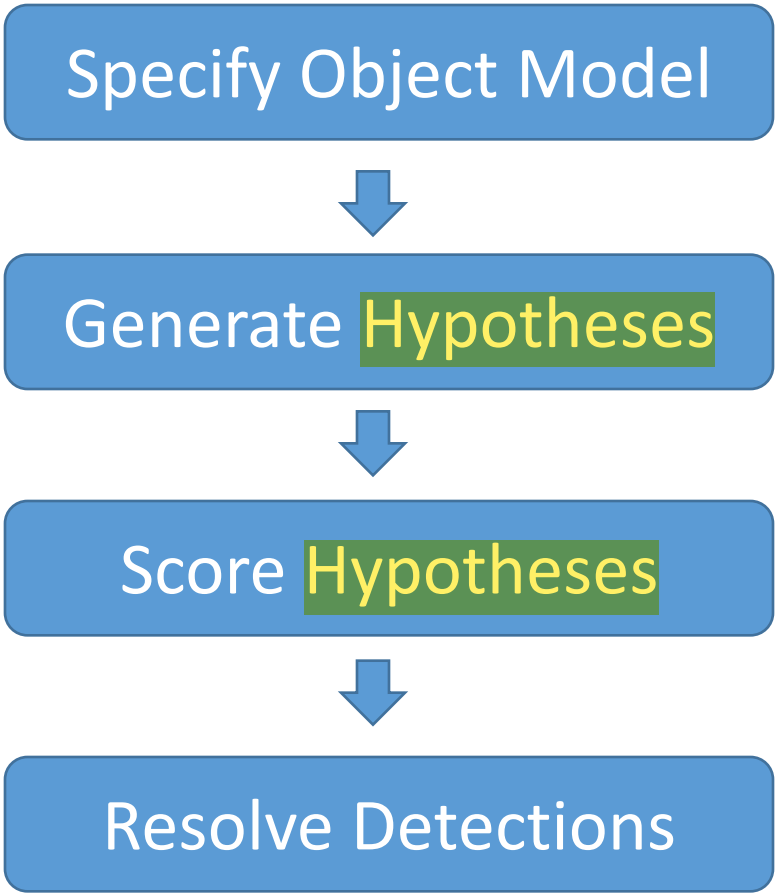
Object Category Detection

- Focus on object search: "Where is it?"
- Build templates that quickly differentiate object patch from background patch



Object or
Non-Object?

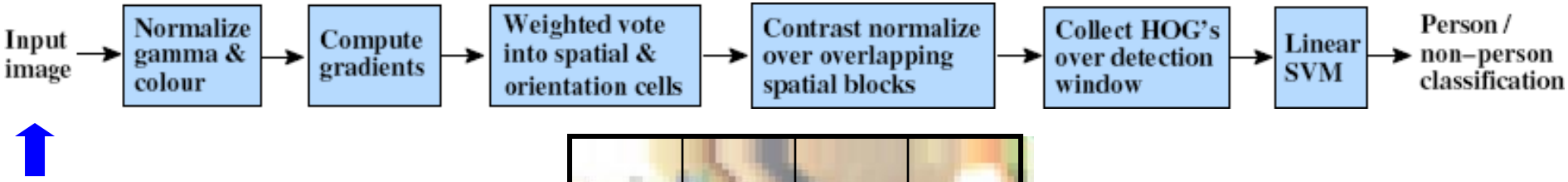
General Process of Object Recognition

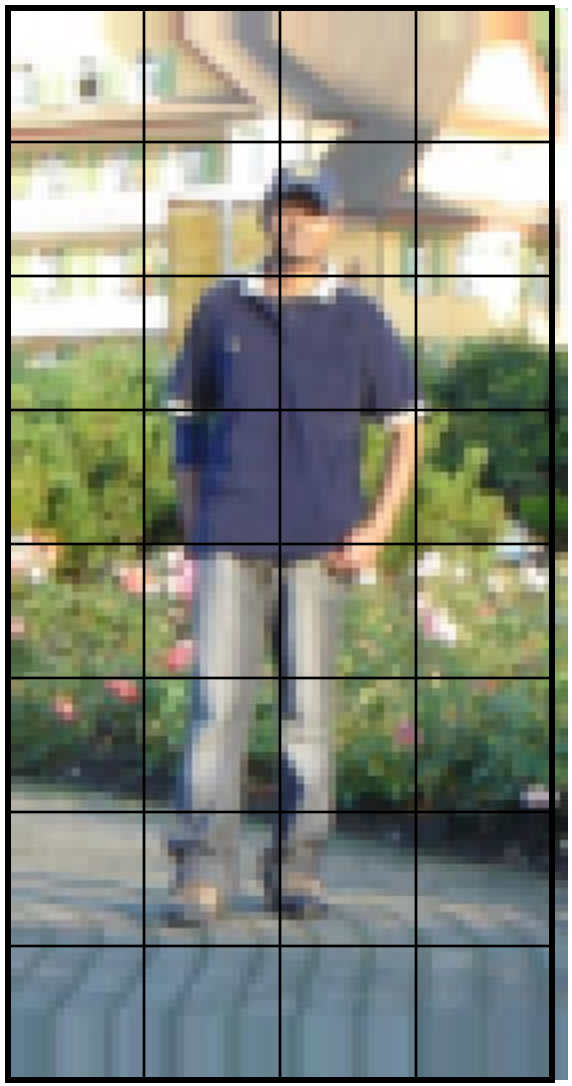


Dalal-Triggs detector: HOG

1. Extract fixed-sized (64x128 pixel) window at each position and scale
2. Compute HOG (histogram of gradient) features within each window
3. Score the window with a linear SVM classifier
4. Perform non-maxima suppression to remove overlapping detections with lower scores

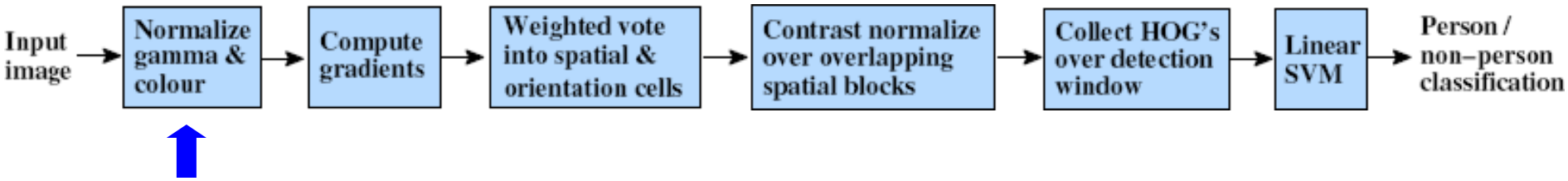
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05





Slides by Pete Barnum

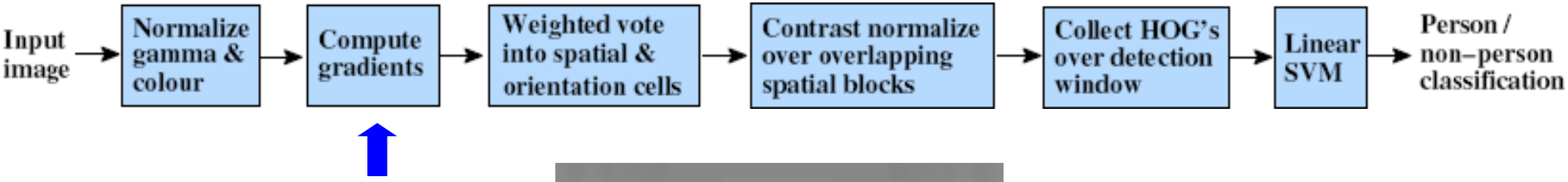
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05



- Tested with
  - Grayscale
  - RGB
  - LAB

  } Slightly better performance vs. grayscale
- Gamma Normalization and Compression
  - Square root
  - Log

  } Superior performance vs. no adjustment



Outperforms

-1	0	1

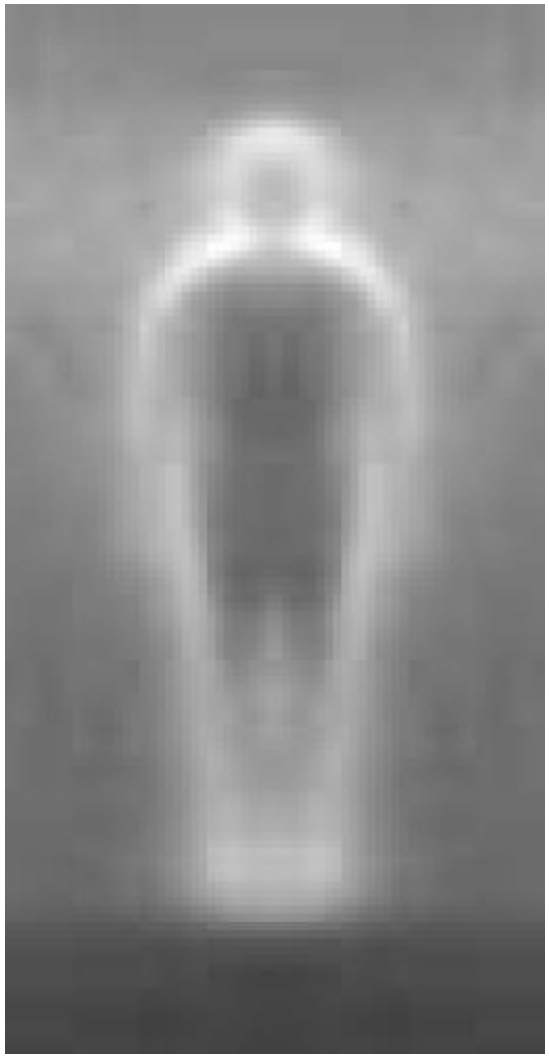
centered

-1	1

uncentered

1	-8	0	8	-1

cubic-corrected



0	1
-1	0

diagonal

-1	0	1
-2	0	2
-1	0	1

Sobel

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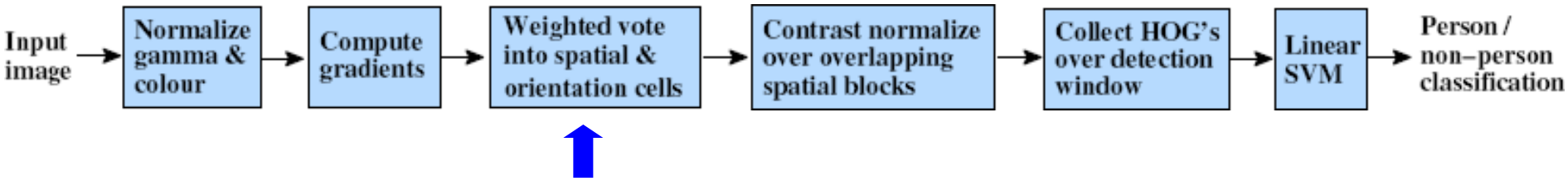
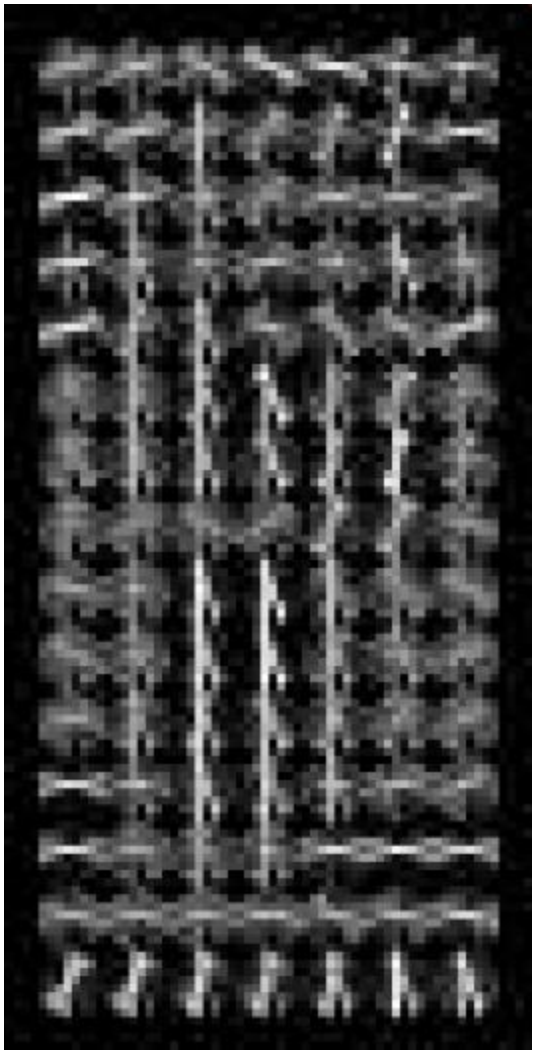
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05



- Histogram of gradient orientations

Orientation: 9 bins
(in 0-180 degree)

Histograms in
8x8 pixel cells



- Votes weighted by magnitude

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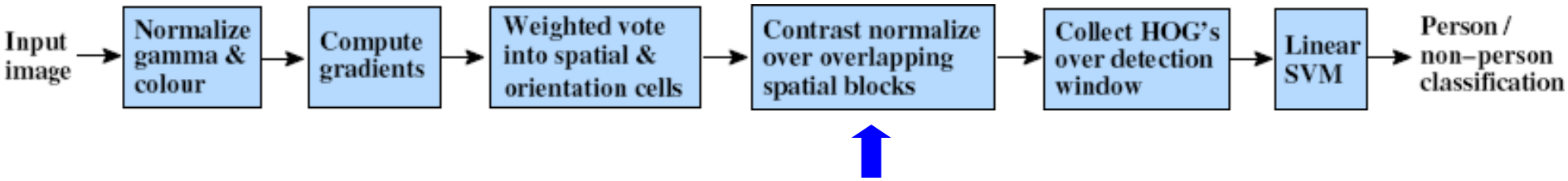
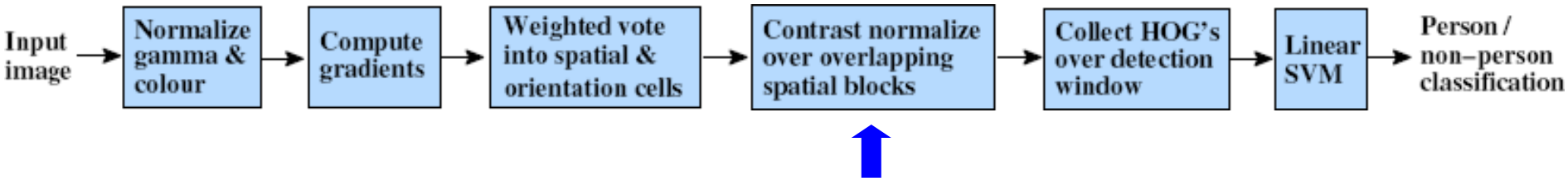


Consider 16×16 pixel blocks (i.e. four 8×8 pixel cells) with block spacing stride of 8 pixels

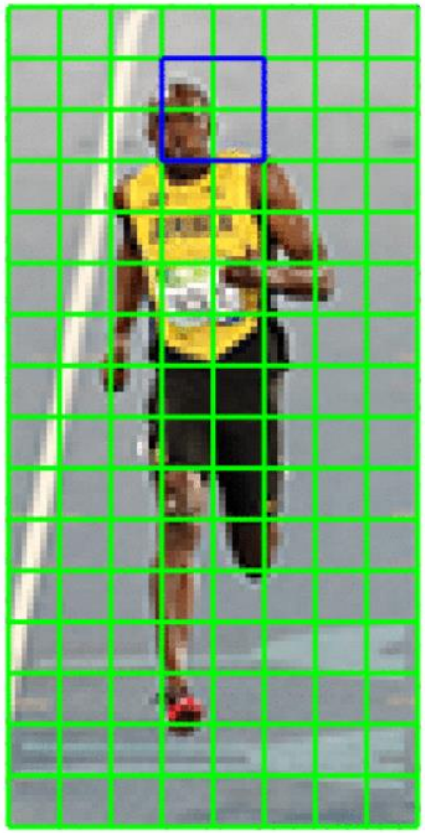
Total: 7×15 blocks (as Window size: 64x128 pixel)



Consider 16×16 pixel blocks (i.e. four 8×8 pixel cells)
with block spacing stride of 8 pixels
Total: 7×15 blocks (as Window size: 64x128 pixel)

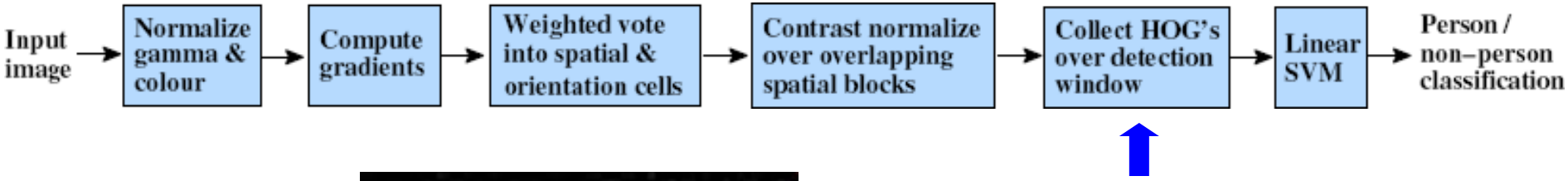
Compute the normalized histograms in a block.

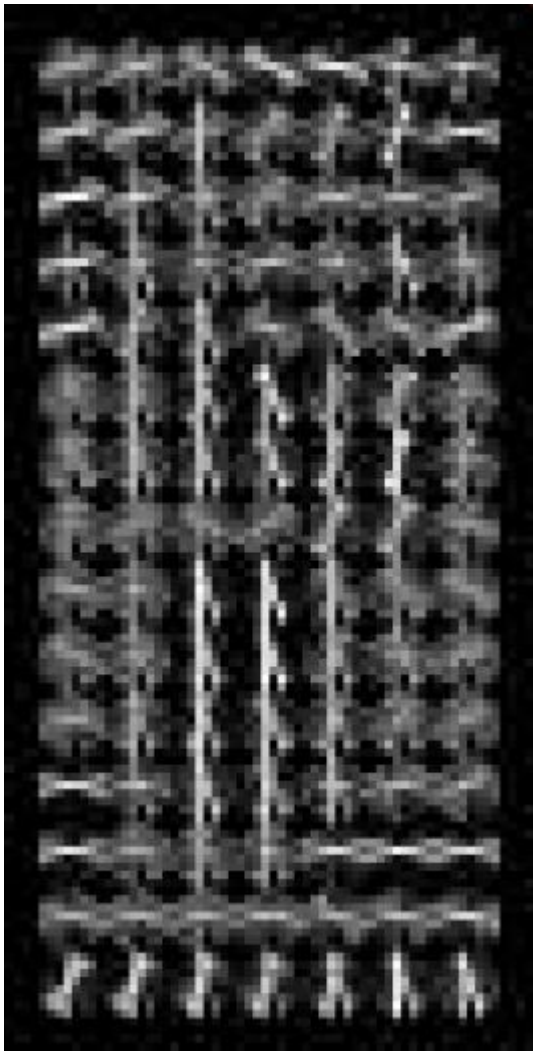
Normalization (different approaches such as
(a) L2-norm,
(b) L2-Hys, L2-norm followed by clipping,
(c) L1-norm,
(d) L1-sqrt, L1-norm followed by square root)



Slide modified from Pete Barnum

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05





orientations

features = 15 x 7 x 9 x 4 = 3780

blocks

cells

Slides by Pete Barnum

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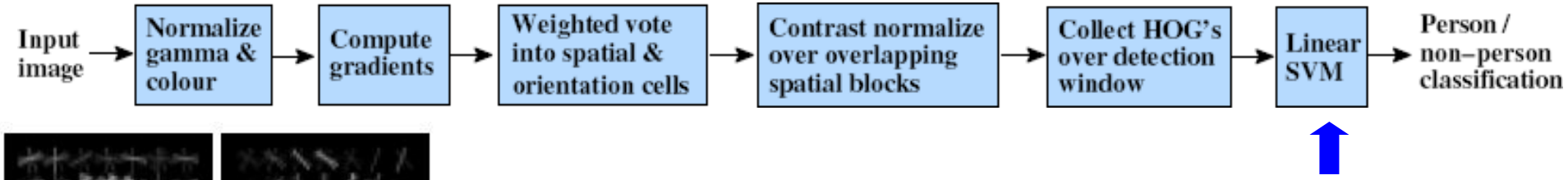
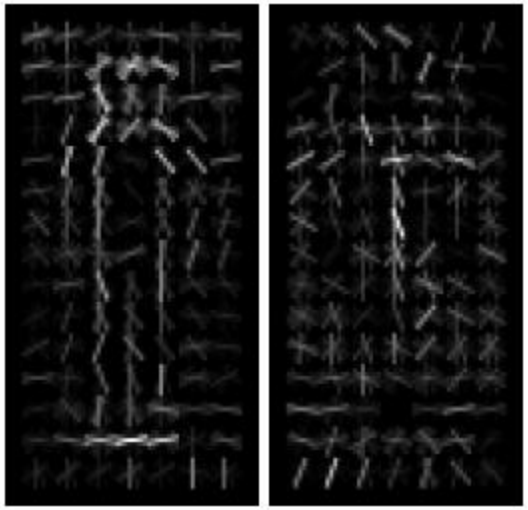
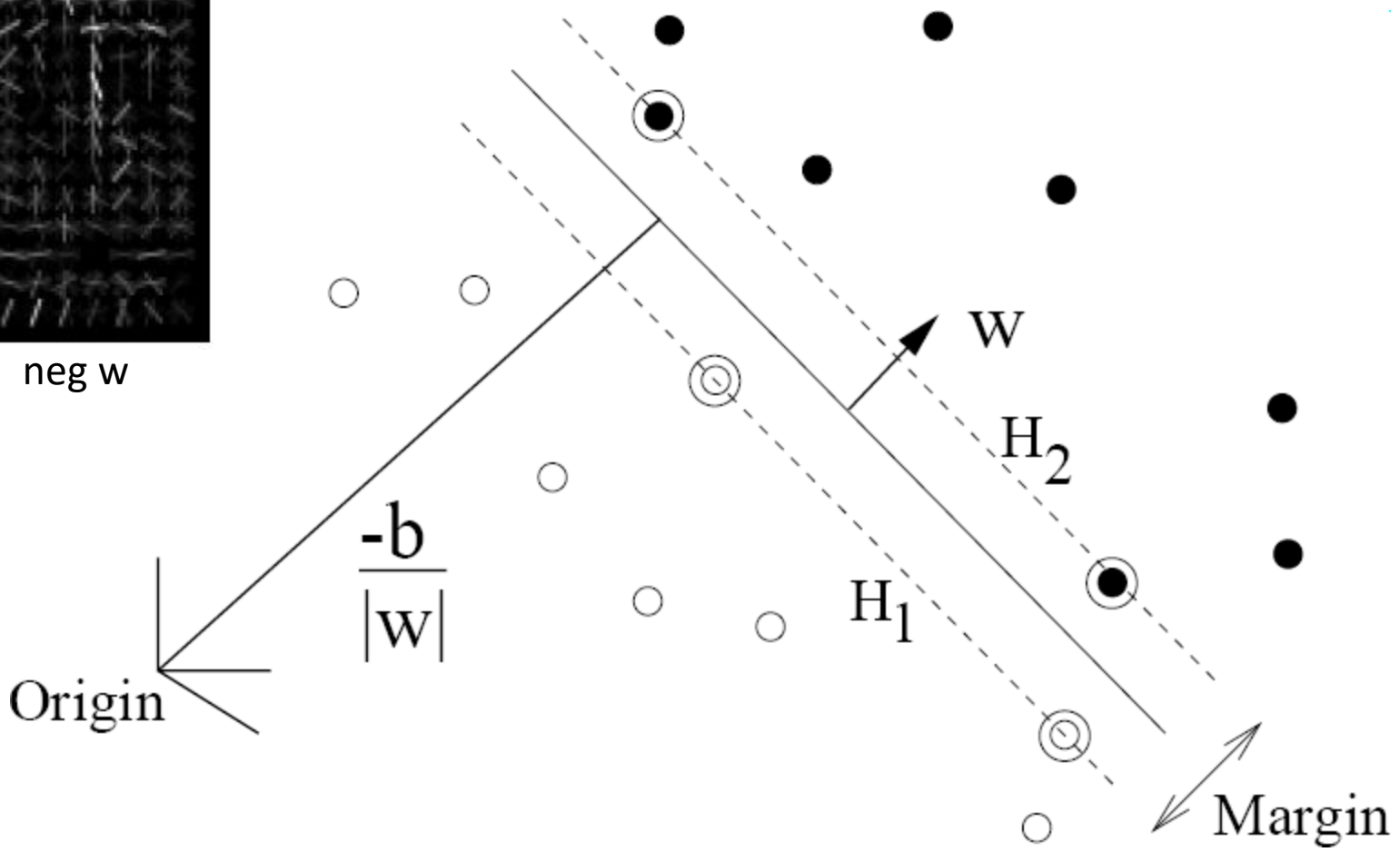




pos w

neg w



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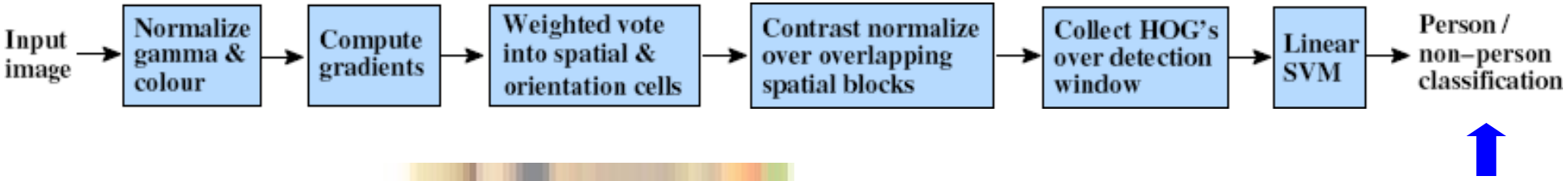


$$0.16 = w^T x - b$$

$$sign(0.16) = 1$$

$$=>$$ pedestrian

Slides by Pete Barnum

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

Detection examples

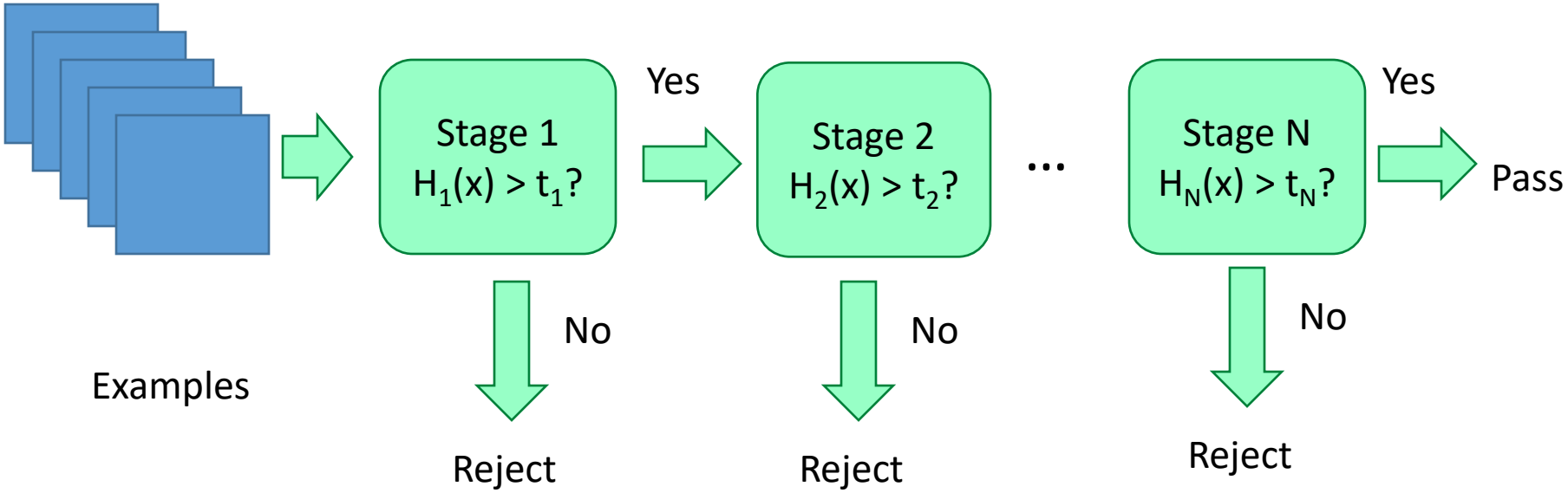
Viola-Jones sliding window detector

Fast detection through two mechanisms

- Quickly eliminate unlikely windows
  - A megapixel image has ~10^6 pixels and a comparable number of candidate object locations
  - Positive instances are rare: 0–10 per image
- Use features that are fast to compute
  - Utilization of integral image

Viola and Jones. Rapid Object Detection using a Boosted Cascade of Simple Features (2001).

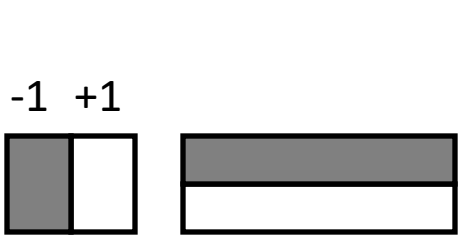
Cascade for Fast Detection



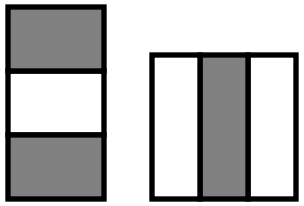
- Choose threshold for low false negative rate
- Fast classifiers early in cascade
- Slow classifiers later, but most examples don't get there

Features that are fast to compute

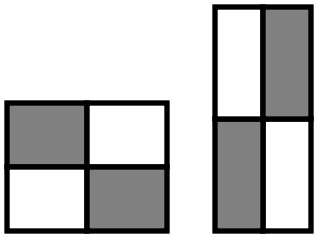
- "Haar-like features"
  - Differences of sums of intensity
  - Thousands, computed at various positions and scales within detection window



Two-rectangle features



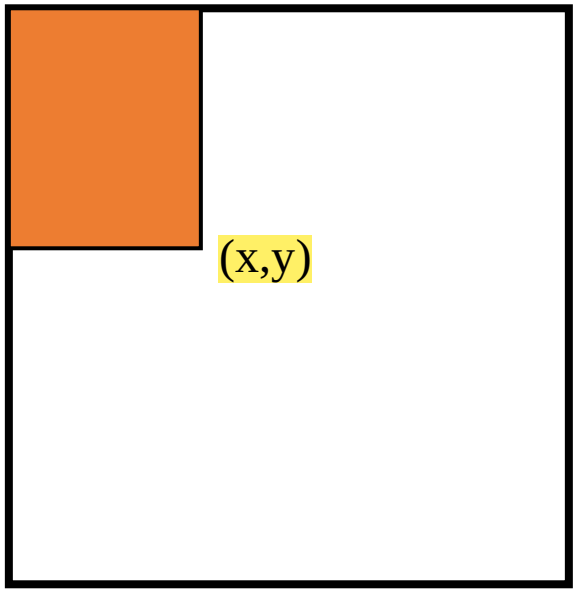
Three-rectangle features



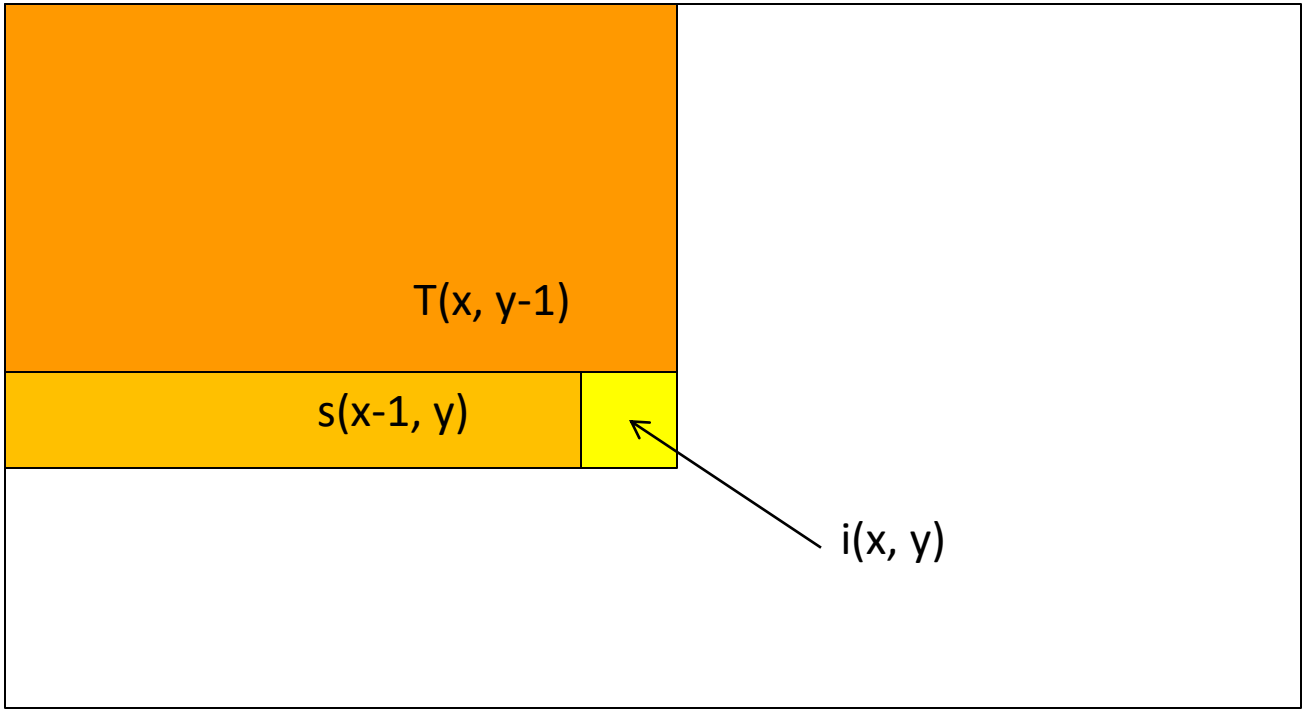
Etc.

Integral Images

- The *integral image* computes a value at each pixel (*x*,*y*) that is the sum of the pixel values above and to the left of (*x*,*y*), inclusive
- This can quickly be computed in one pass through the image



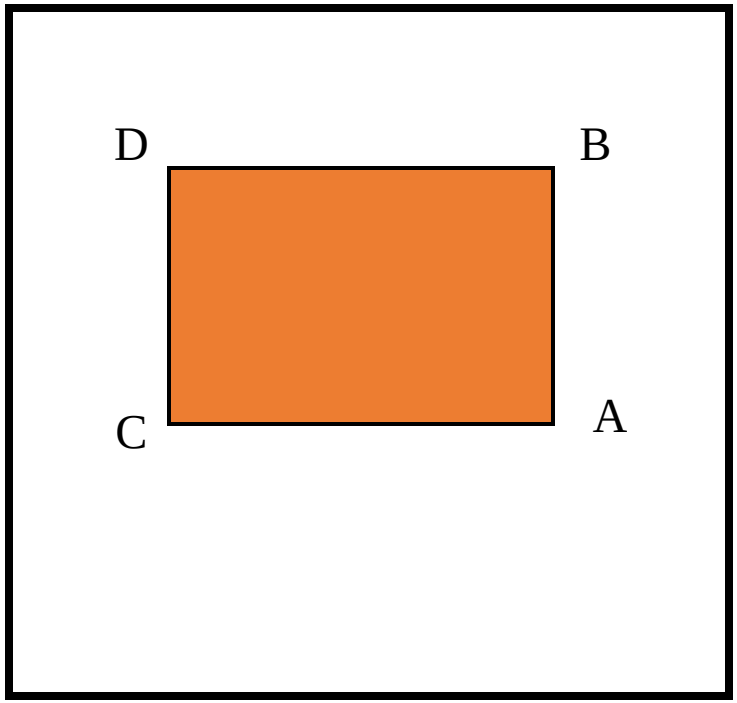
Integral Images



- Cumulative row sum: $s(x, y) = s(x–1, y) + i(x, y)$
- Integral image: $T(x, y) = T(x, y–1) + s(x, y)$

Integral Images

- Let A,B,C,D be the values of the integral image at the corners of a rectangle
- What is the sum of pixel values within the rectangle?

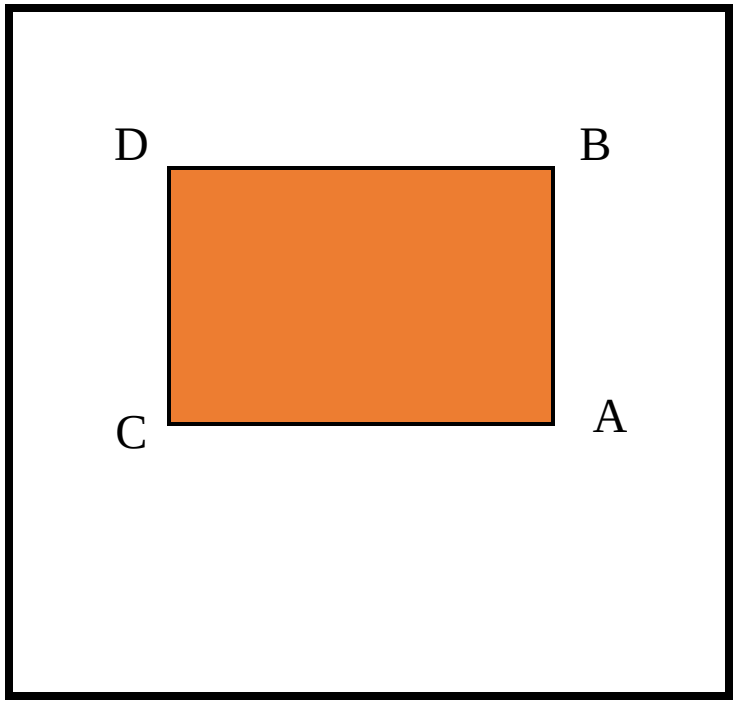


Integral Images

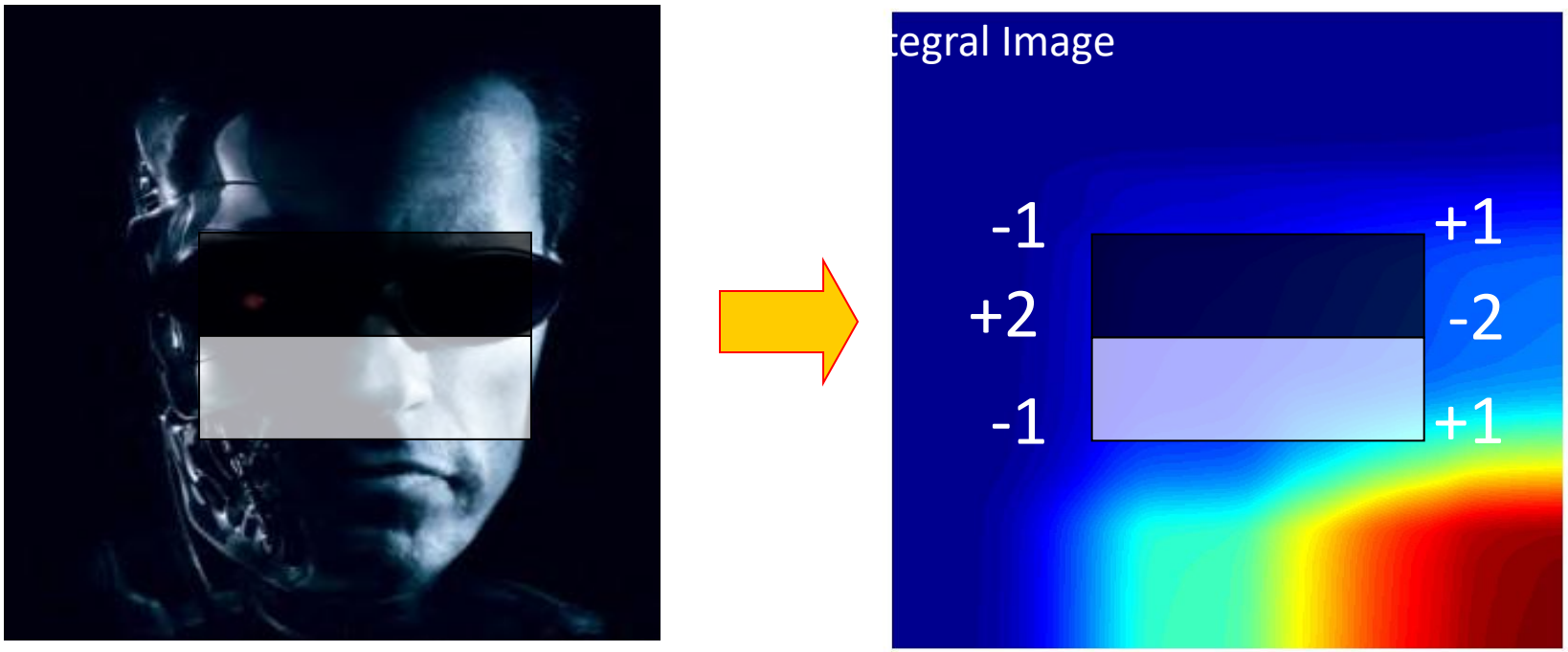
- Let A,B,C,D be the values of the integral image at the corners of a rectangle
- What is the sum of pixel values within the rectangle?

sum = A – B – C + D

- Only 3 additions are required for any size of rectangle!



Integral Images



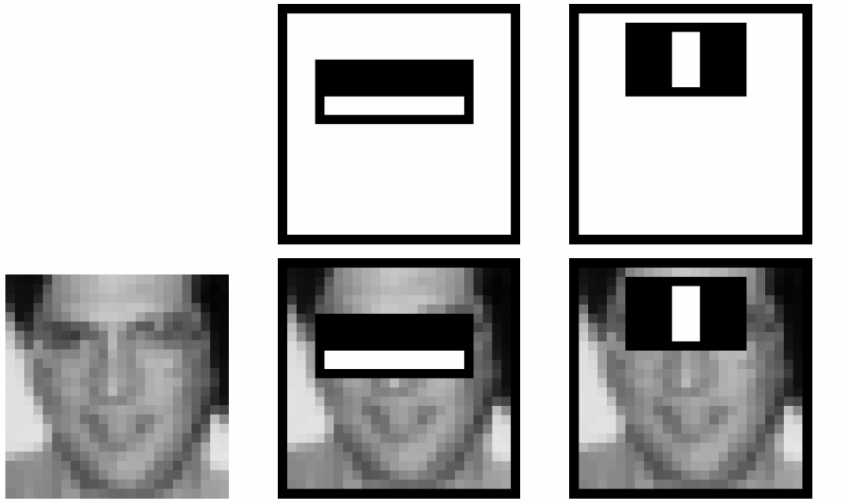
Feature Selection

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- *Boosting* (AdaBoost) is a classification scheme that combines *weak learners* into a more accurate *ensemble classifier*

Feature Selection

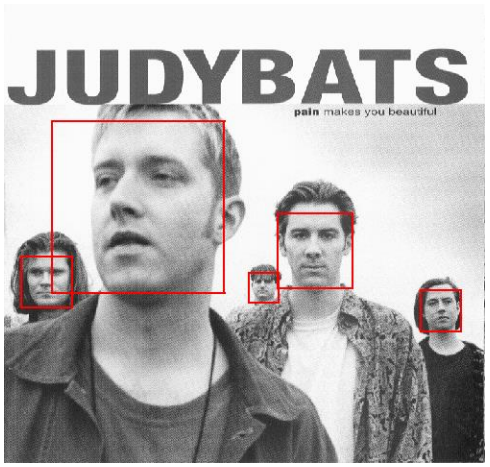
- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- *Boosting* (AdaBoost) is a classification scheme that combines *weak learners* into a more accurate *ensemble classifier*

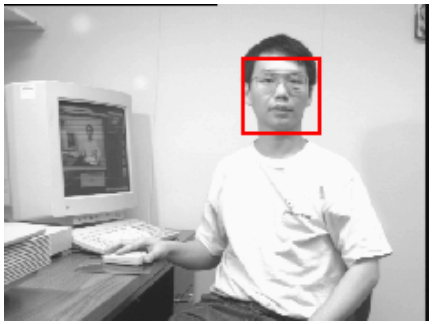
First two features selected by boosting

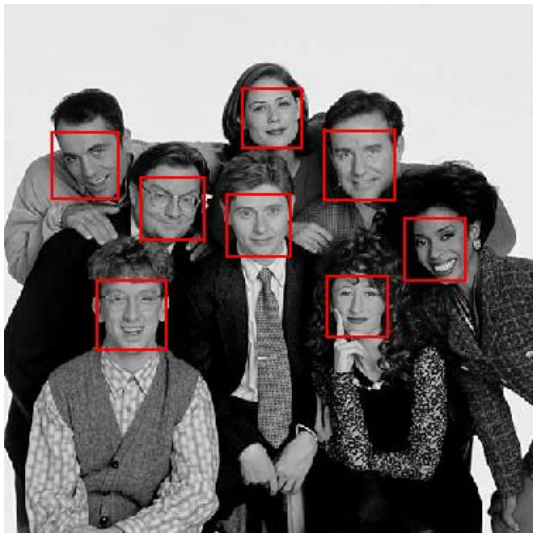


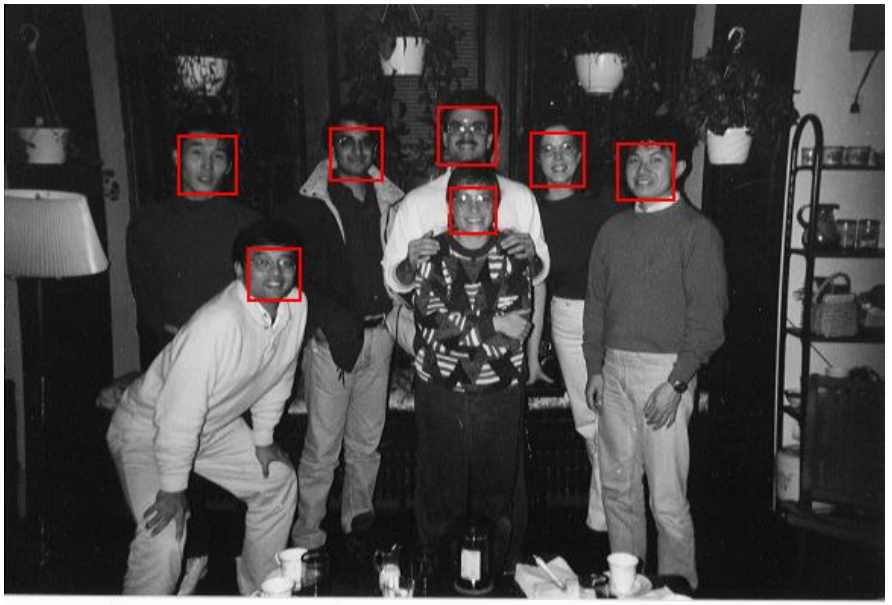
This feature combination can yield 100% detection rate and 50% false positive rate

Viola Jones Face Detection Results





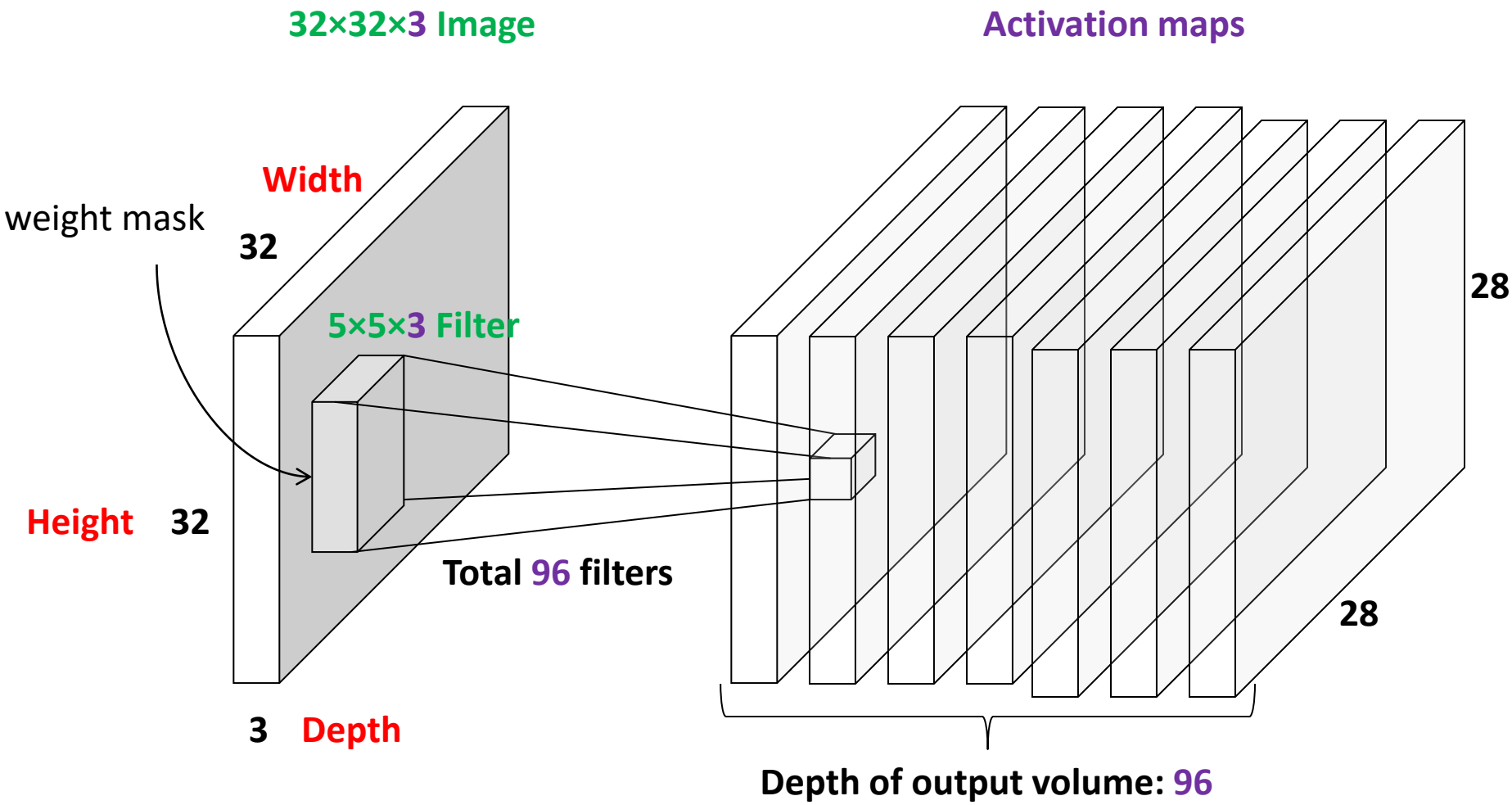




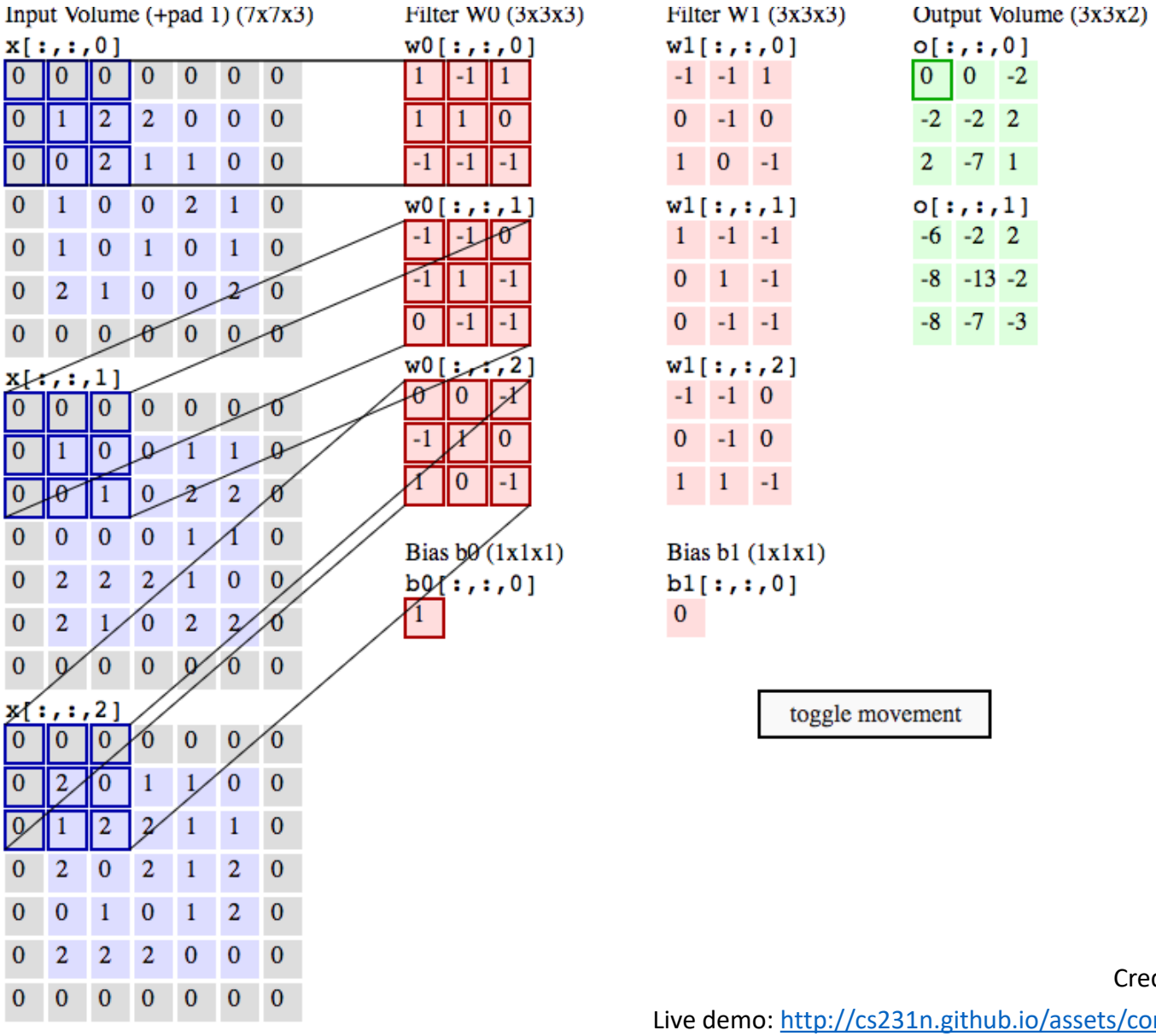
Viola and Jones. Rapid Object Detection using a Boosted Cascade of Simple Features (2001).

Convolutional Neural Network (Quick Recap)

Recap – Convolutional layer



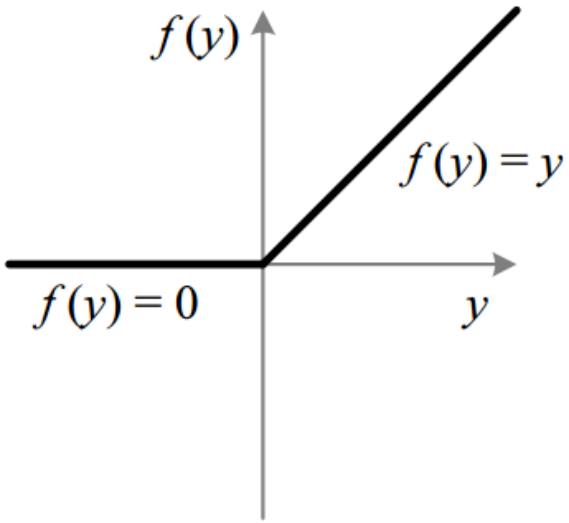
How it works?

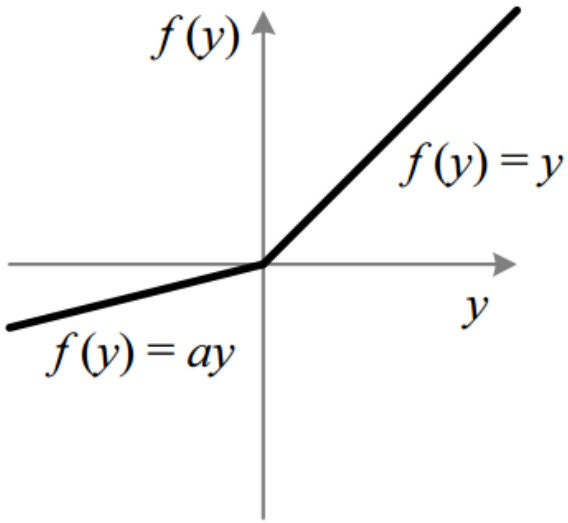


Credit: Andrej Karpathy

Live demo: http://cs231n.github.io/assets/conv-demo/index.html

Recap – Activation

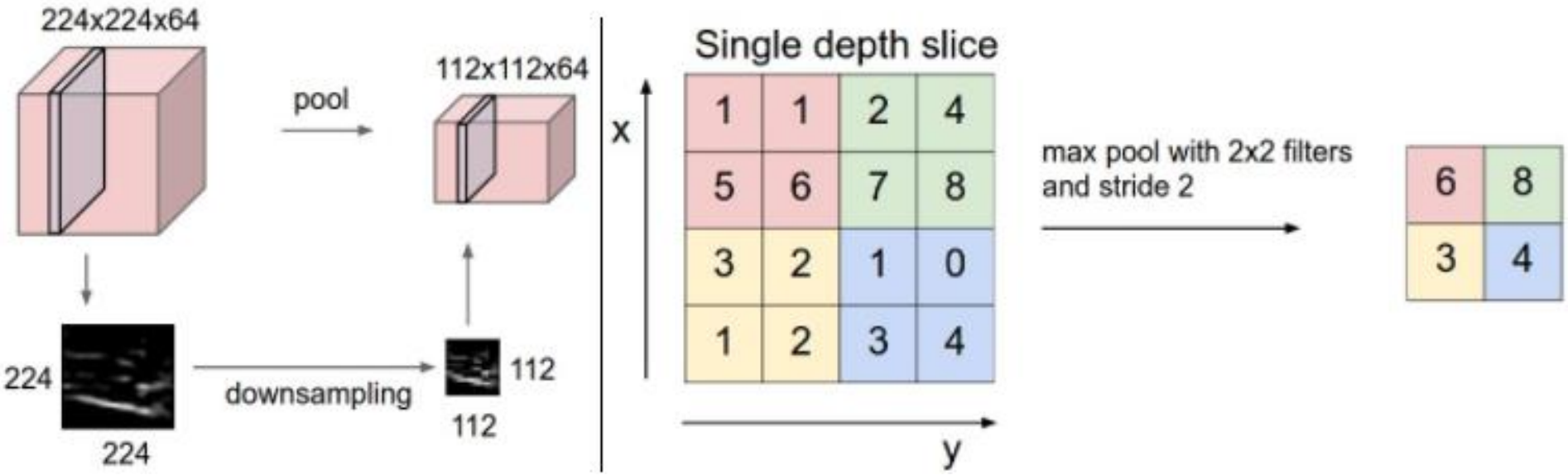




- Introduce the non-linearity

Credit: Andrej Karpathy

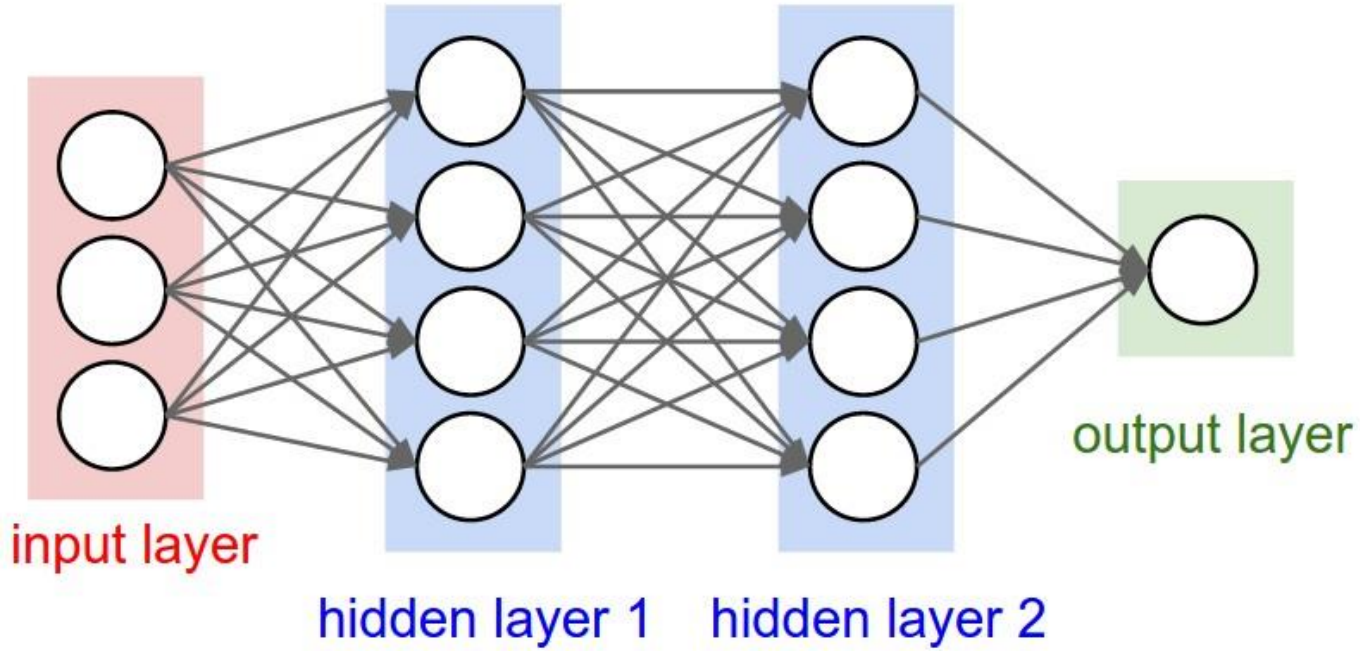
Recap – Pooling layer



- Reduce the feature size
- Introduce a bit invariance (translation, rotation)

Credit: Andrej Karpathy

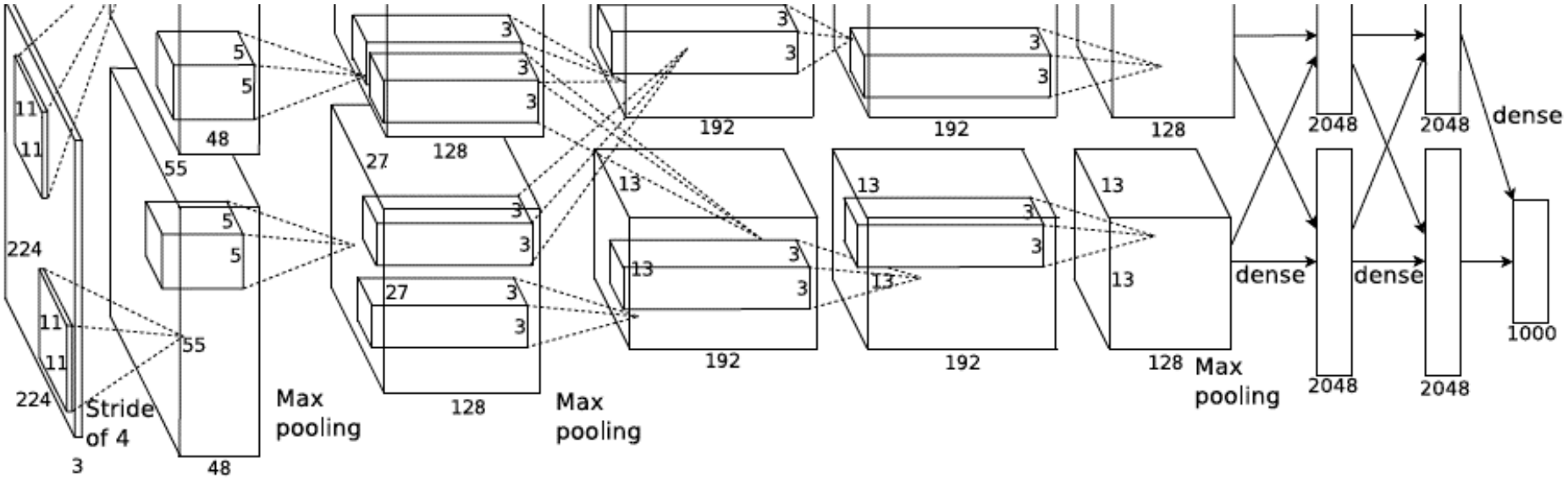
Recap – Fully-connected layer



- Each output node is connected to all the input nodes
- Fixed number of input nodes
- Fixed number of output nodes

Credit: Andrej Karpathy

Put them all together



- Train the deep convolutional neural net with simple chain-rule (a.k.a back propagation)

Credit: Andrej Karpathy

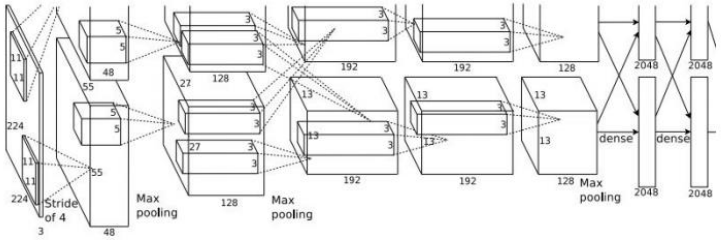
CNN methods for object detection

CNN as feature extractor

Image credit: Justin Johnson

CNN as feature extractor

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

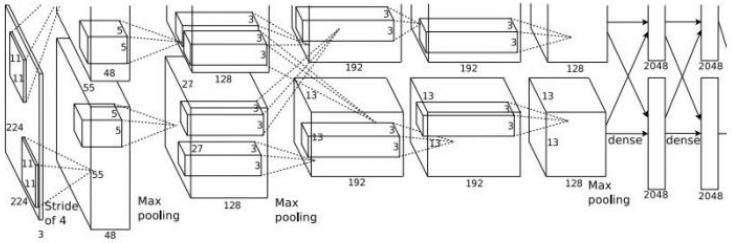


Dog? NO
Cat? NO
Background? YES

Slides by Justin Johnson

CNN as feature extractor

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



Dog? YES
Cat? NO
Background? NO

Slides by Justin Johnson

CNN as feature extractor

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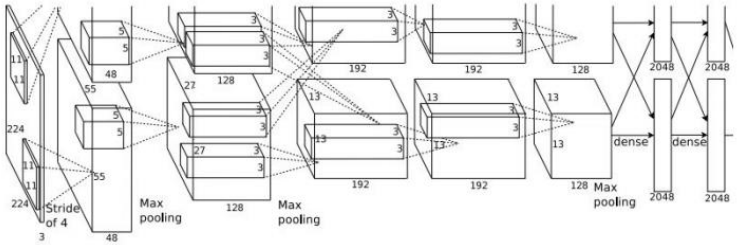

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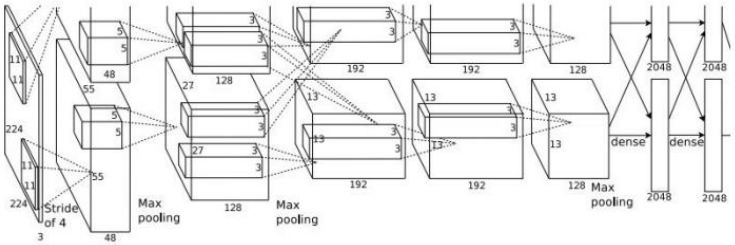

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CNN as feature extractor

- What could be the problems?

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  - Suppose we have a 600 x 600 image, if sliding window size is 20 x 20, then have (600-20+1) x (600-20+1) = ~330,000 windows

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    - Resize image
    - Multi-scale sliding window

CNN as feature extractor

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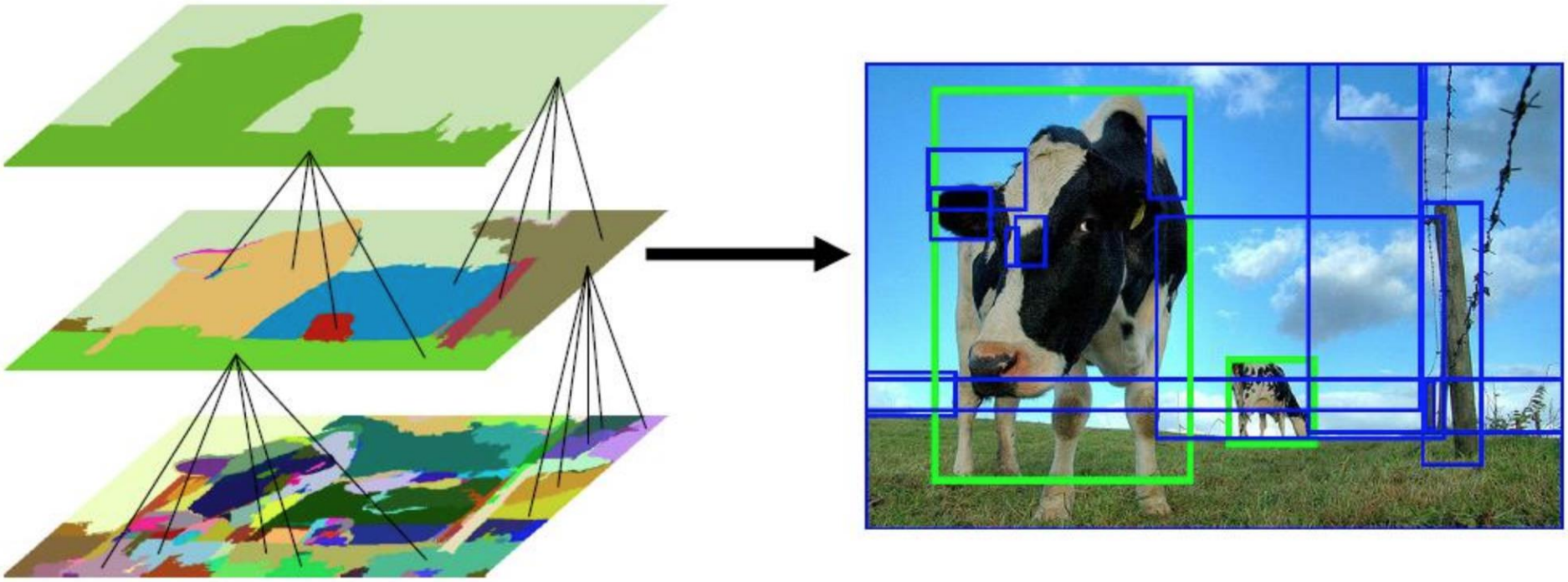
  - Sometimes we want to have more accurate results -> multi-scale detection
    - Resize image
    - Multi-scale sliding window
  - For each image, we need to do the forward pass in the CNN for ~330,000 times. -> Slow!!!

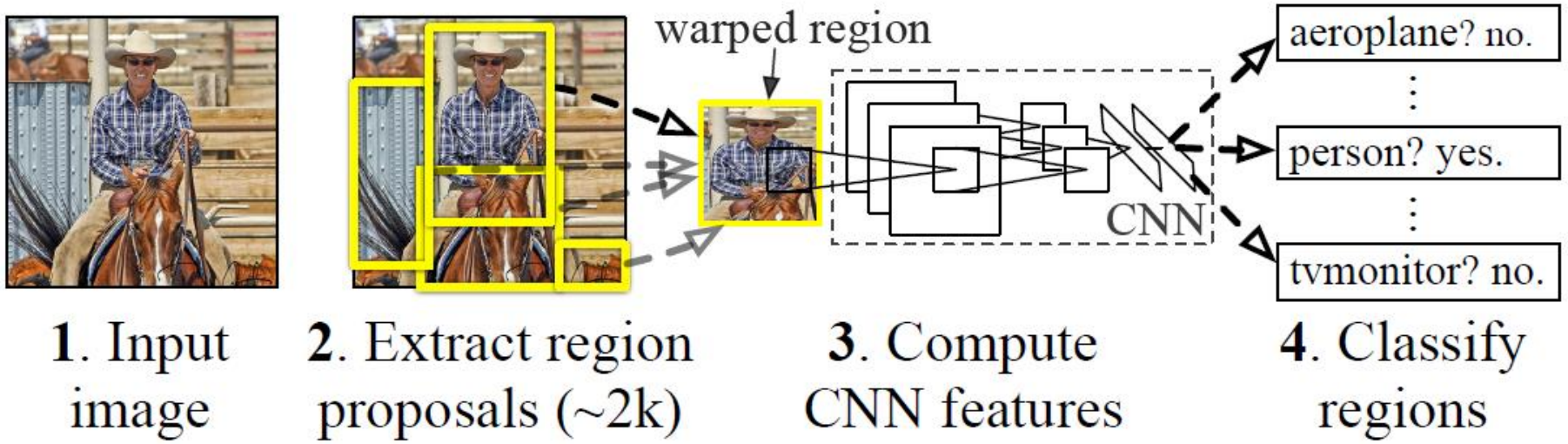
Region Proposal

- Solution
  - Use some fast algorithms to filter out some regions first, only feed the potential region (region proposals) into CNN
  - E.g. selective search



Uijilings et al. IJCV 2013

R-CNN (Girshick et al. CVPR 2014)



- Replace sliding windows with "selective search" region proposals (Uijilings et al. IJCV 2013)
- Extract rectangles around regions and resize to 227x227
- Extract features with fine-tuned CNN (that was initialized with network trained on ImageNet before training)
- Classify last layer of network features with SVM, refine bounding box localization (bbox regression) simultaneously

http://arxiv.org/pdf/1311.2524.pdf

Bounding Box Regression

- Intuition
  - If you observe part of the object, according to the seen examples, you should be able to refine the localization
  - E.g. given the red box below, since you've seen many airplanes, you know this is not a good localization, you will adjust it to the green one

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R-CNN (Girshick et al. CVPR 2014)

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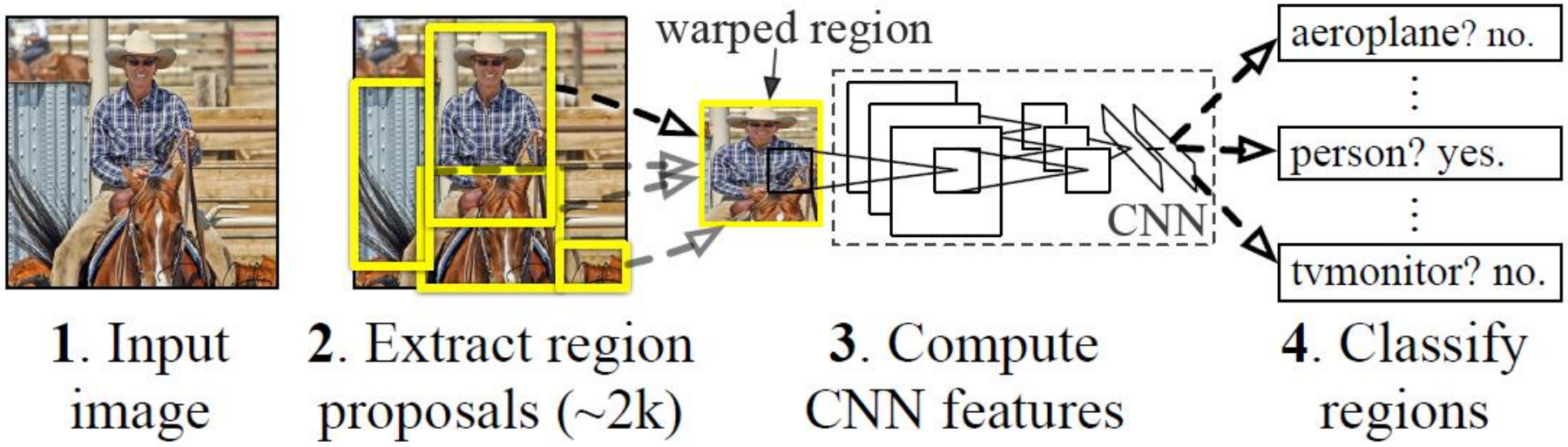
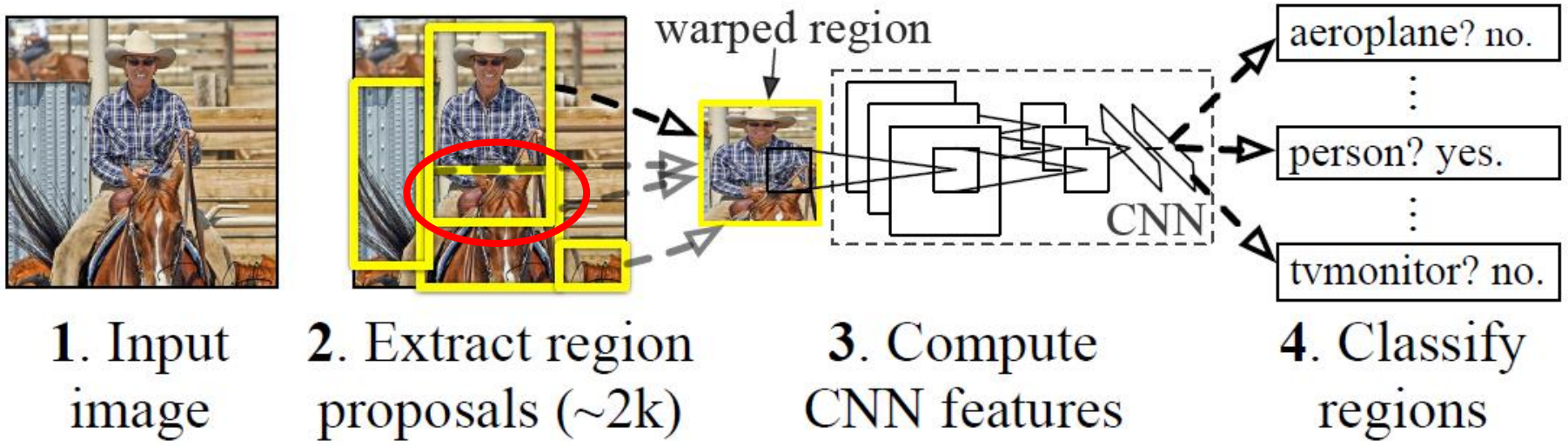


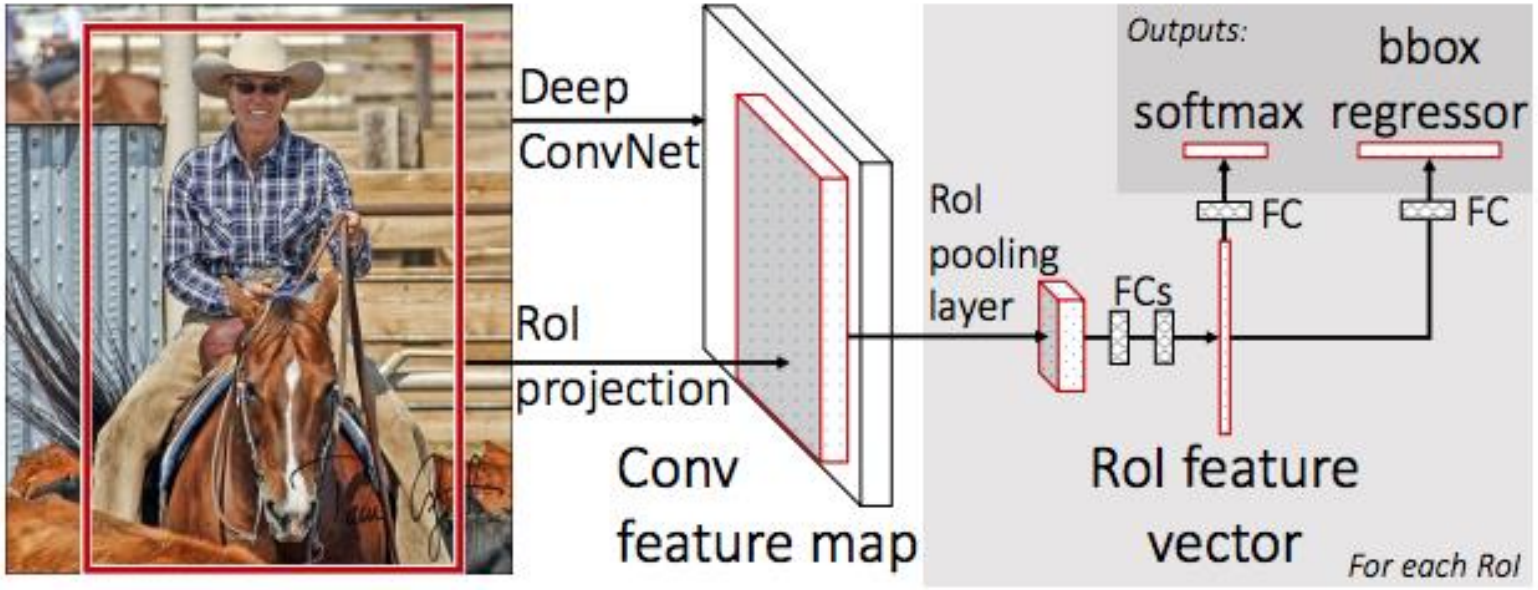
R-CNN (Girshick et al. CVPR 2014)

- What could be the problems?
  - Repetitive computation! For overlapping regions, we feed it multiple times into CNN



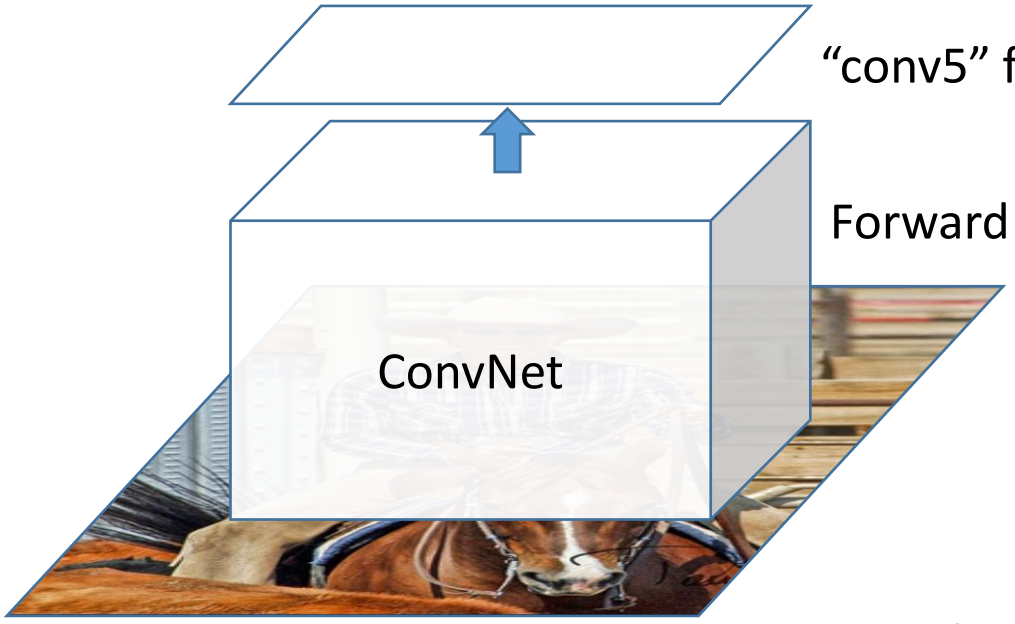
Fast R-CNN (Girshick ICCV 2015)

- Solution
  - Why not feed the whole image into CNN only once! Then crop features instead of image itself



https://arxiv.org/pdf/1504.08083.pdf

Fast R-CNN (Girshick ICCV 2015)



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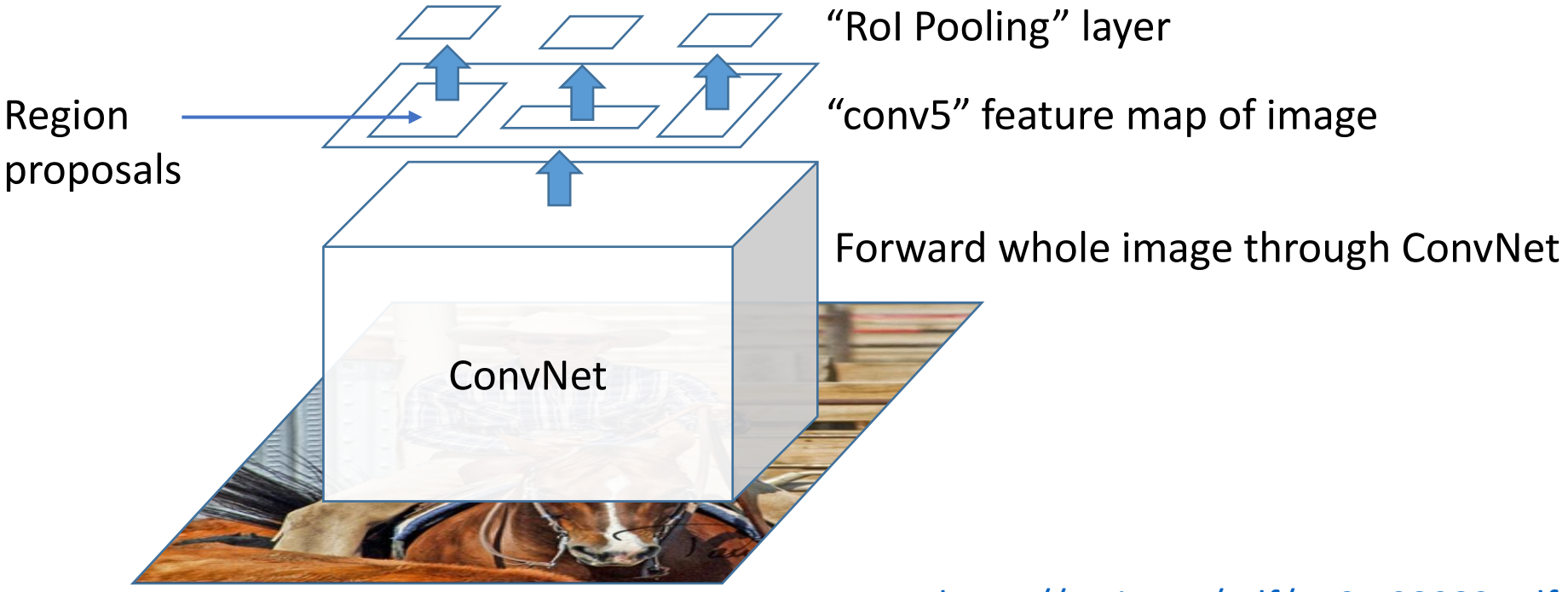

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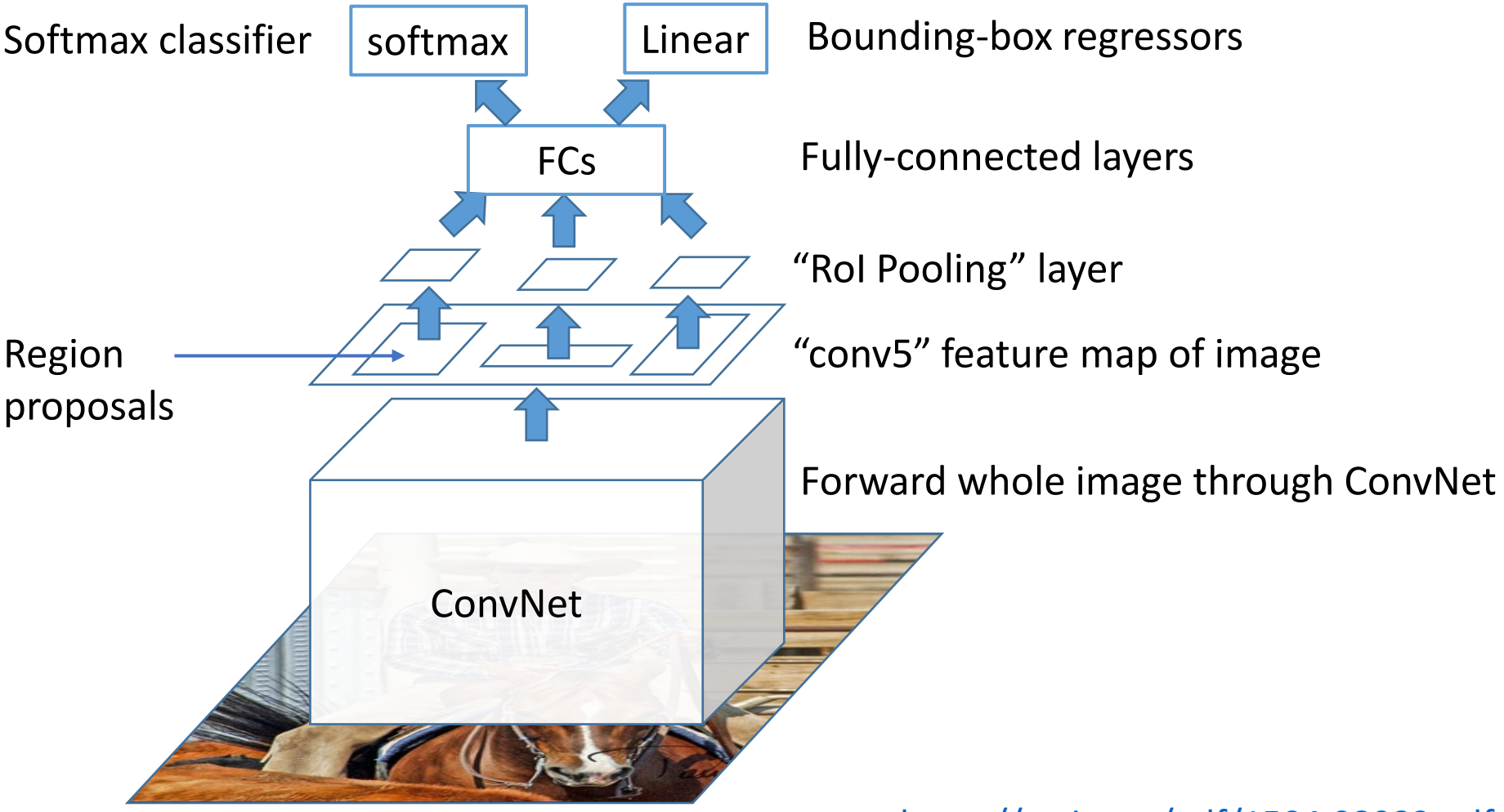
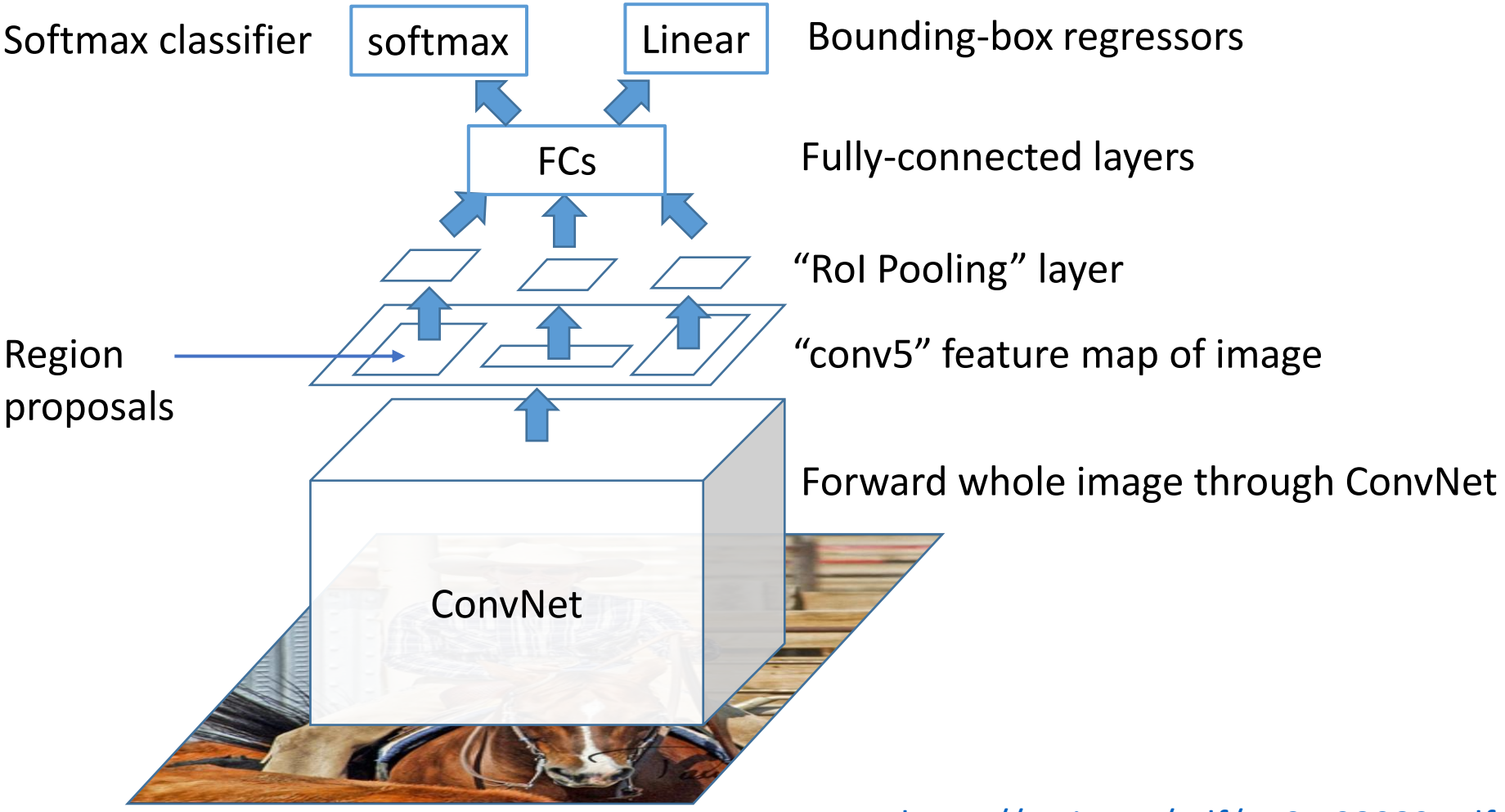


https://arxiv.org/pdf/1504.08083.pdf

Fast R-CNN (Girshick ICCV 2015)

Rather than using post-hoc bounding-box regressors, bounding-box regression is implemented as an additional linear layer in the network



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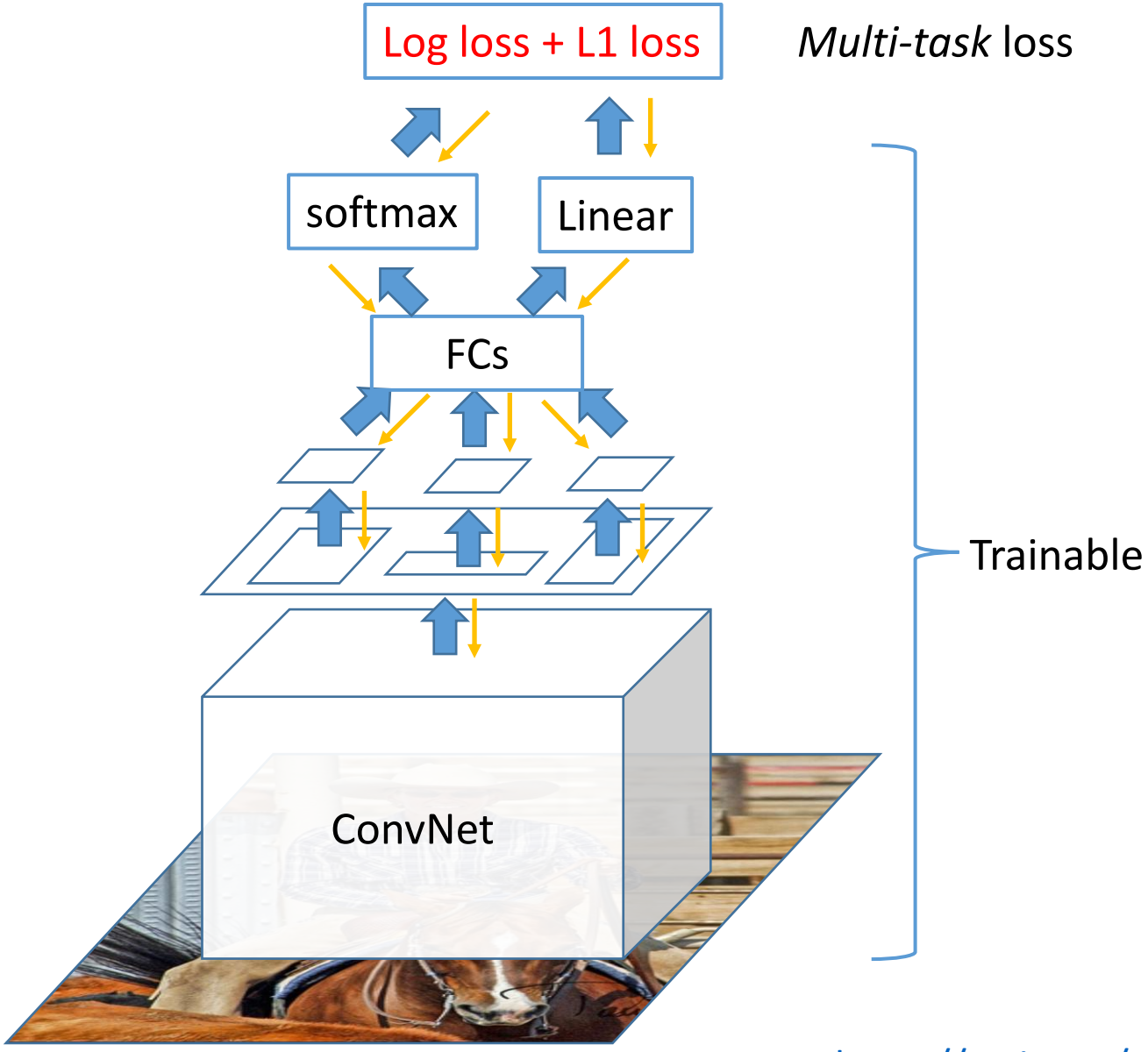
Fast R-CNN (Girshick ICCV 2015)



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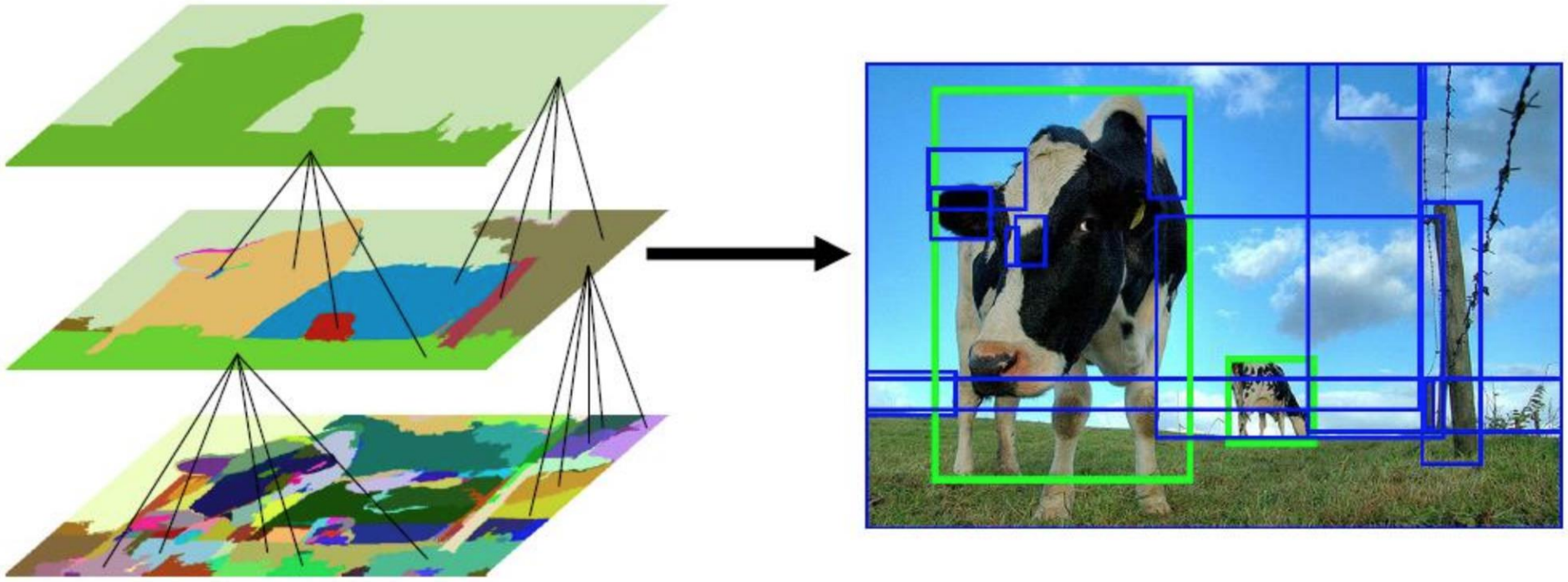
Fast R-CNN (Girshick ICCV 2015)

- What could be the problems?

Fast R-CNN (Girshick ICCV 2015)

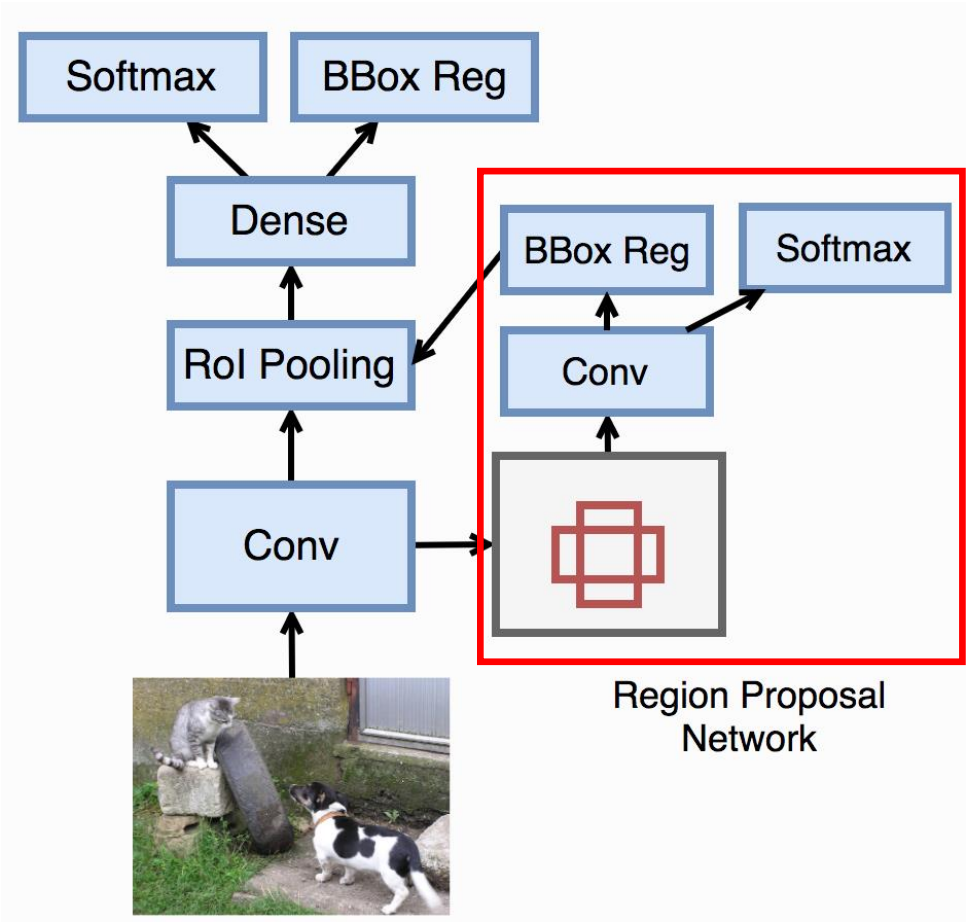
- What could be the problems?
  - Why we need the region proposal pre-processing step? That's not "deep learning" at all. Not cool!



Uijilings et al. IJCV 2013

Faster R-CNN (Ren et al. NIPS 2015)

- Solution
  - Why not generate region proposals using CNN??!
    -> RPN

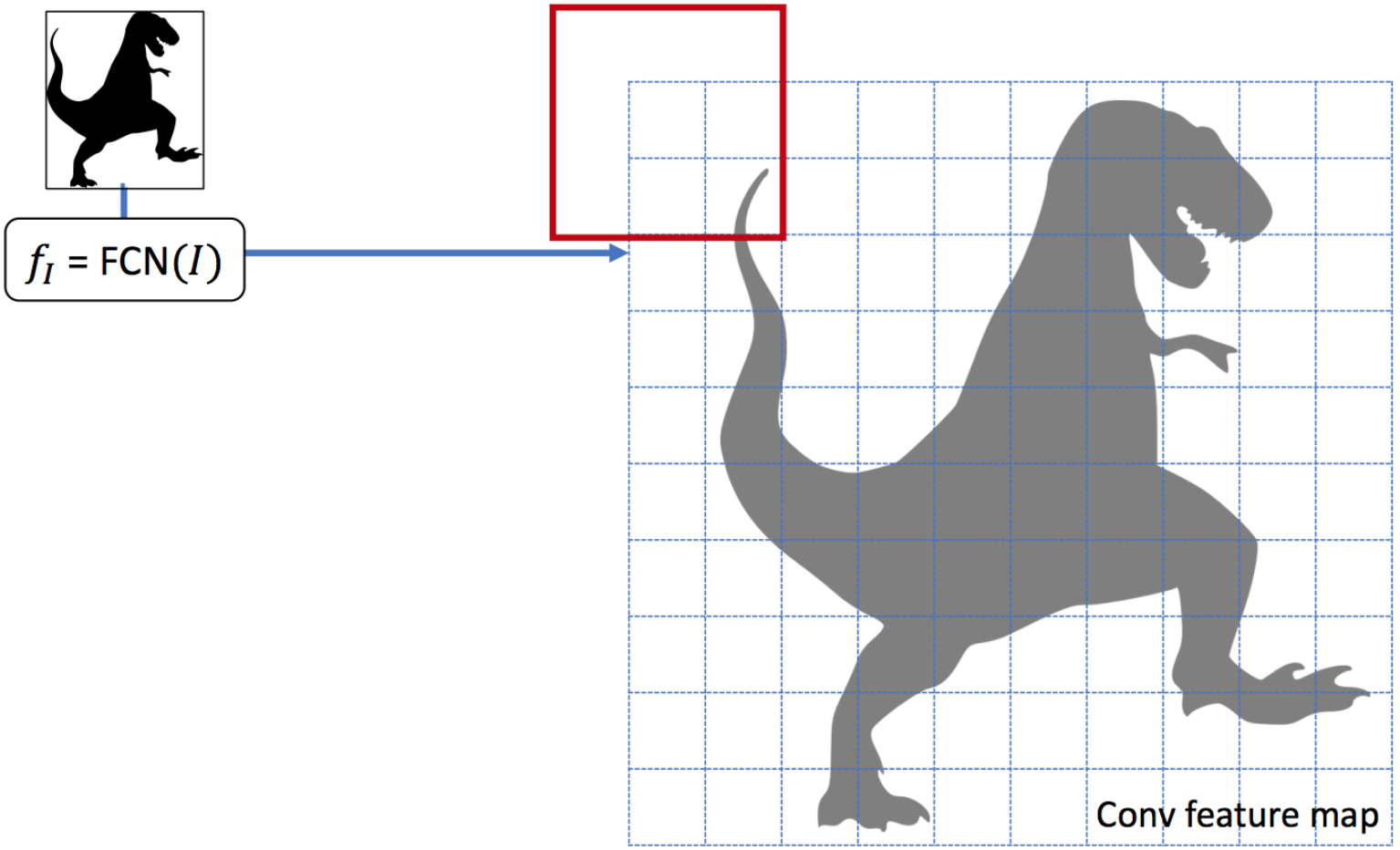


https://arxiv.org/pdf/1506.01497.pdf

Image credit:
http://zh.gluon.ai/chapter_computer-vision/object-detection.html

Faster R-CNN (Ren et al. NIPS 2015)

RPN: Region Proposal Network



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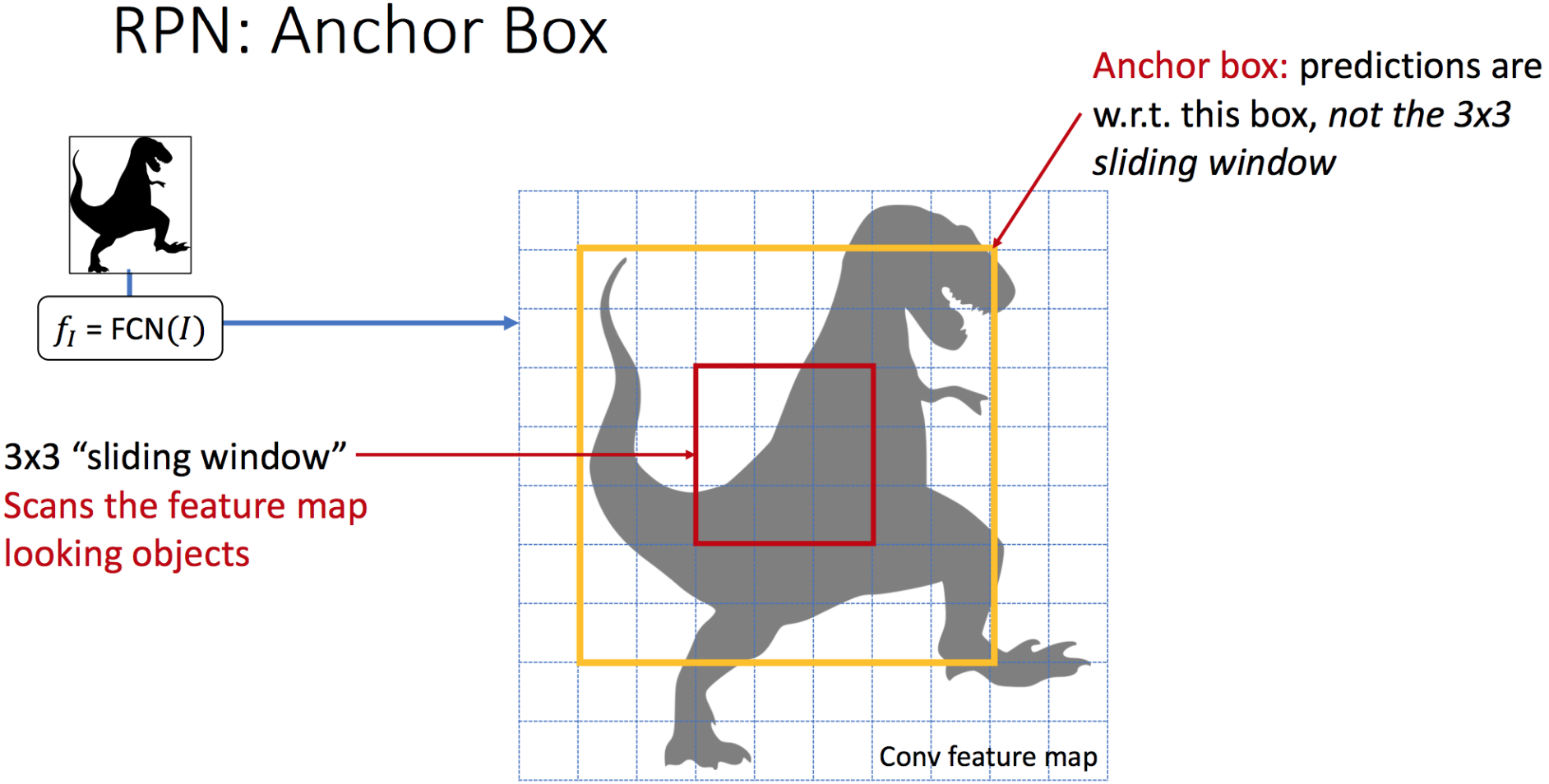
Slides by Ross Girshick

Faster R-CNN (Ren et al. NIPS 2015)

RPN: Anchor Box



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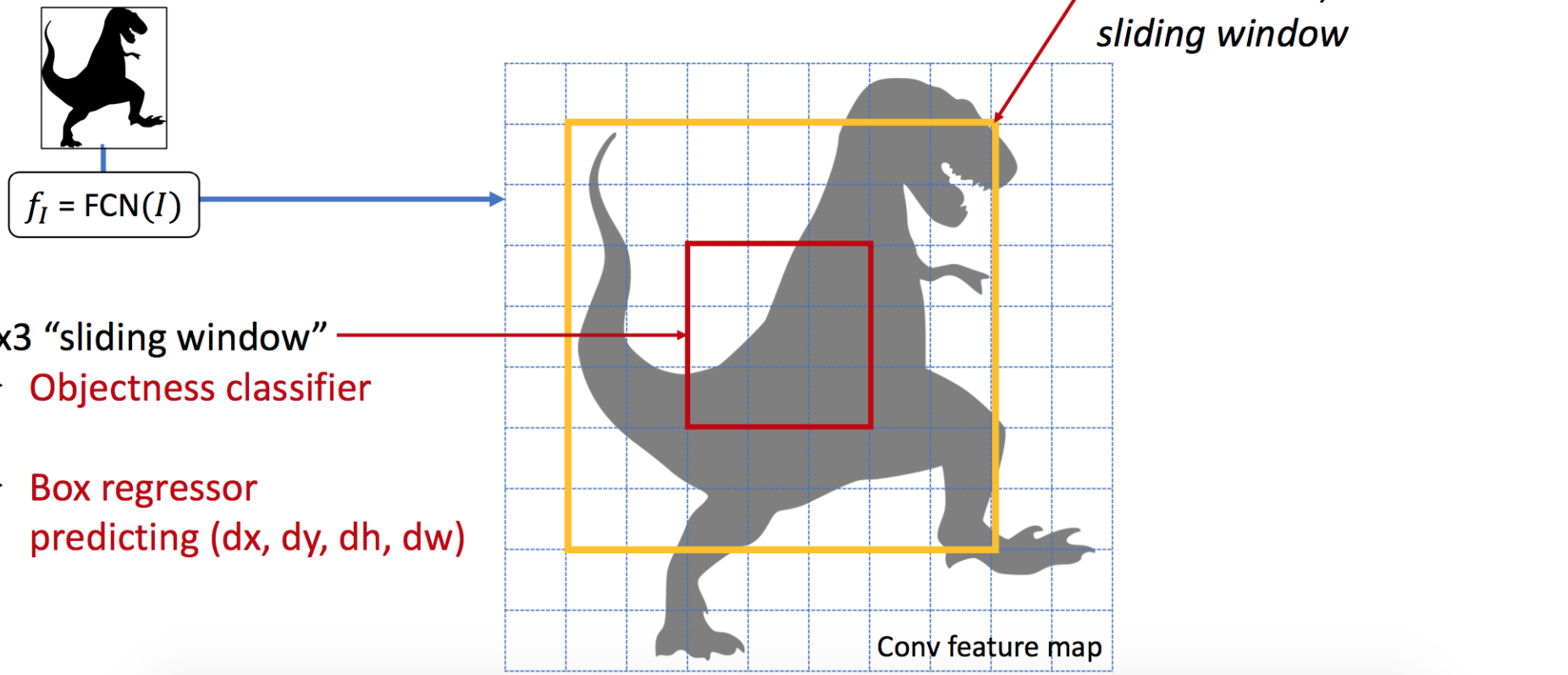

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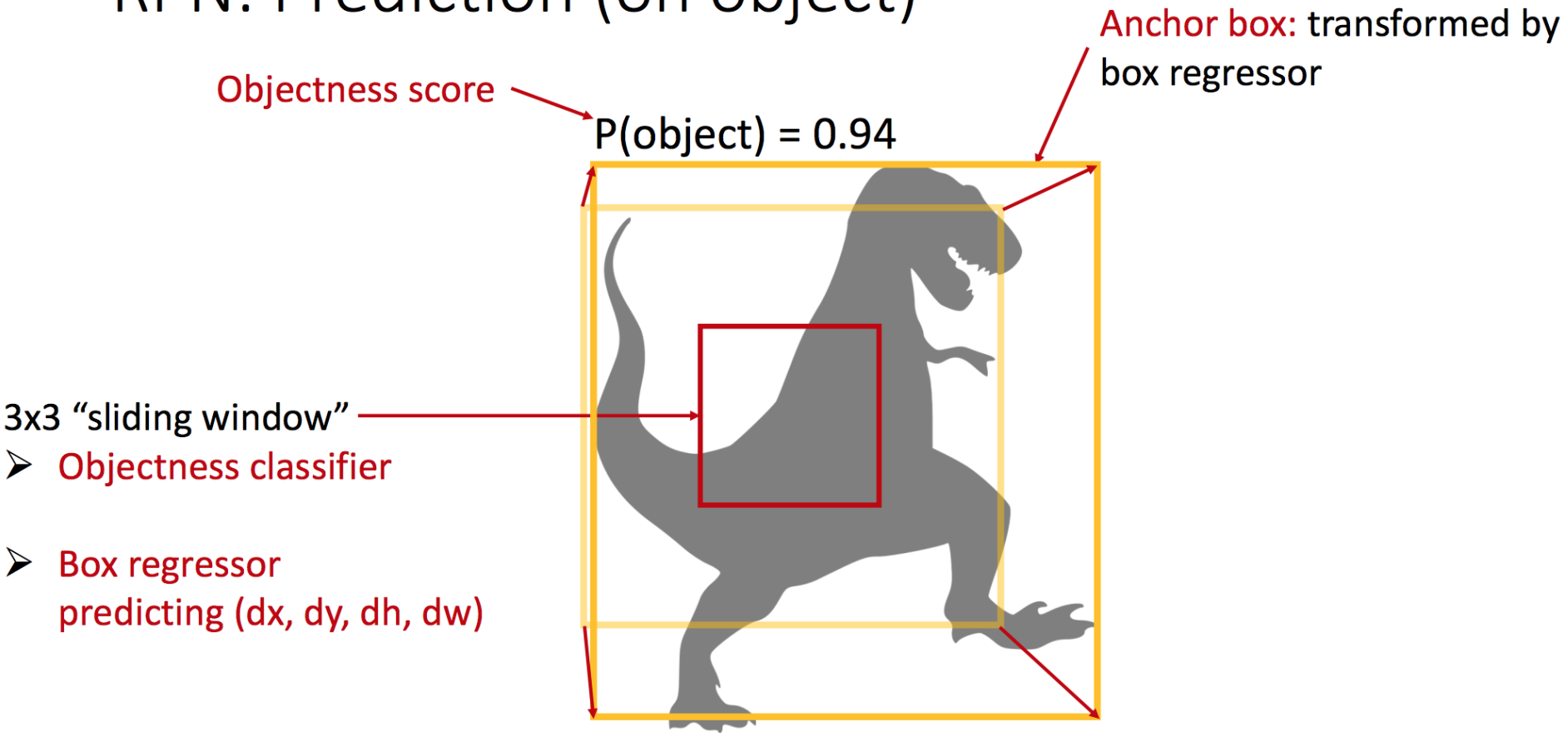
Faster R-CNN (Ren et al. NIPS 2015)

RPN: Prediction (on object)

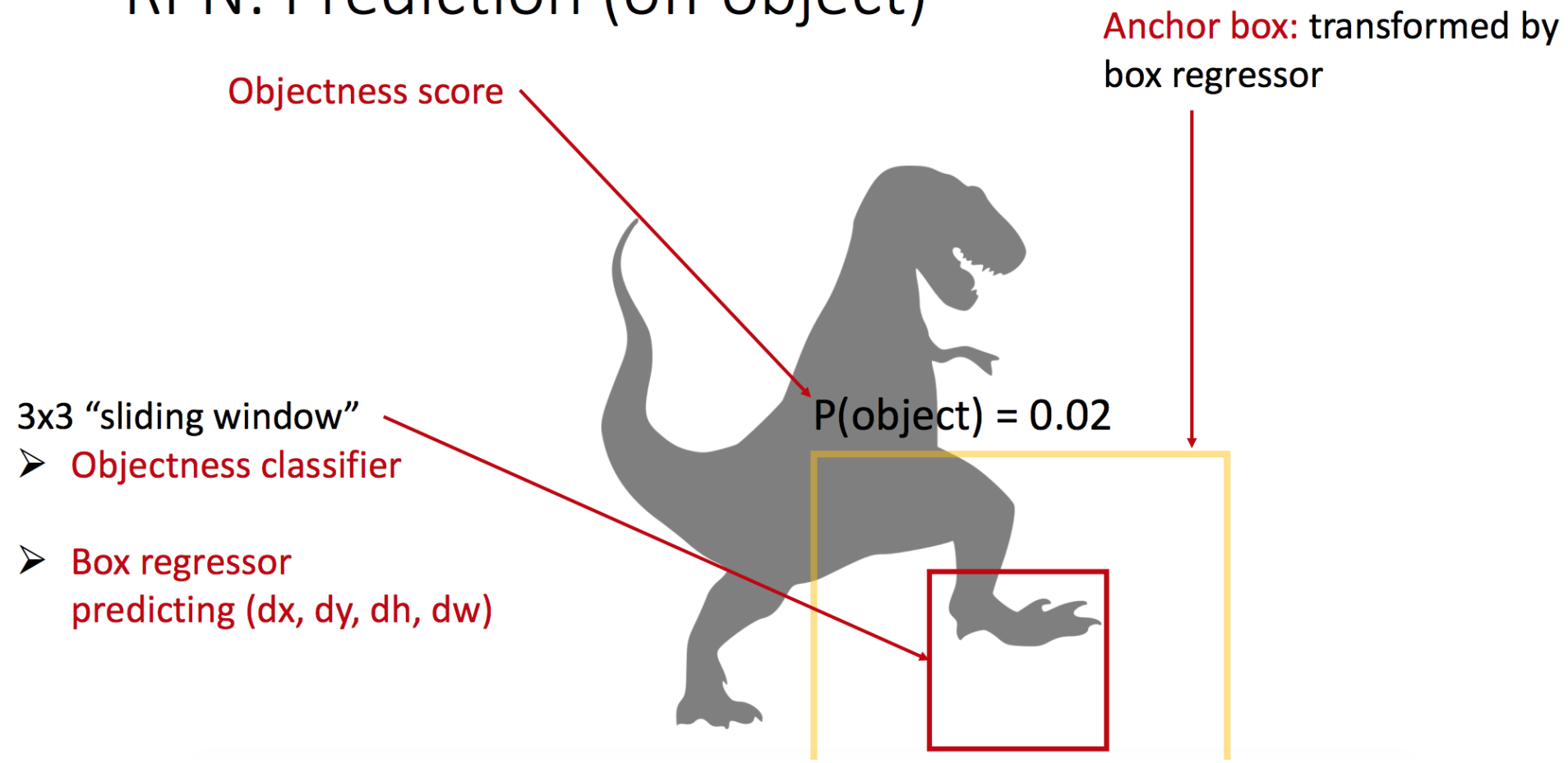


https://arxiv.org/pdf/1506.01497.pdf

Slides by Ross Girshick

Faster R-CNN (Ren et al. NIPS 2015)

RPN: Prediction (off object)



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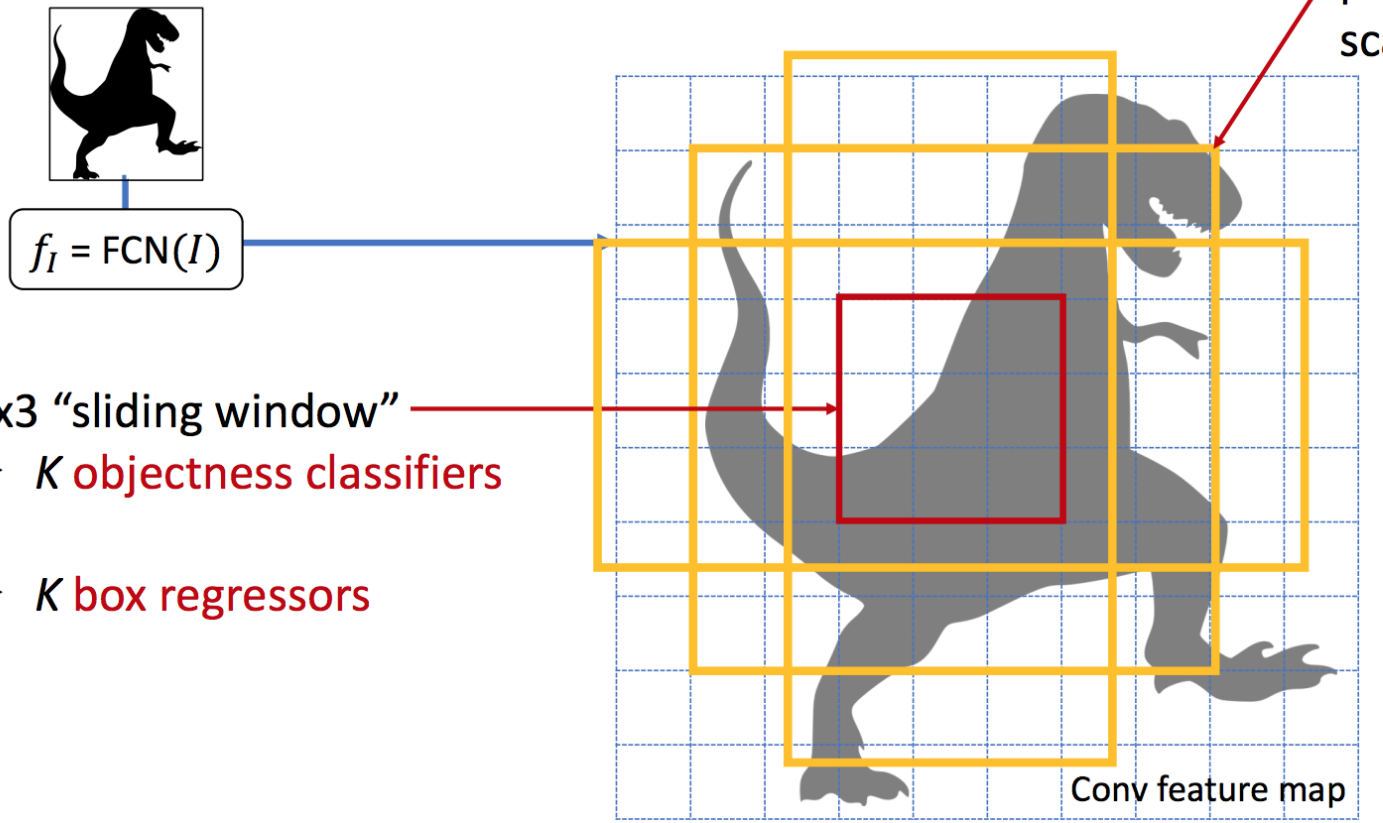
Faster R-CNN (Ren et al. NIPS 2015)

RPN: Multiple Anchors



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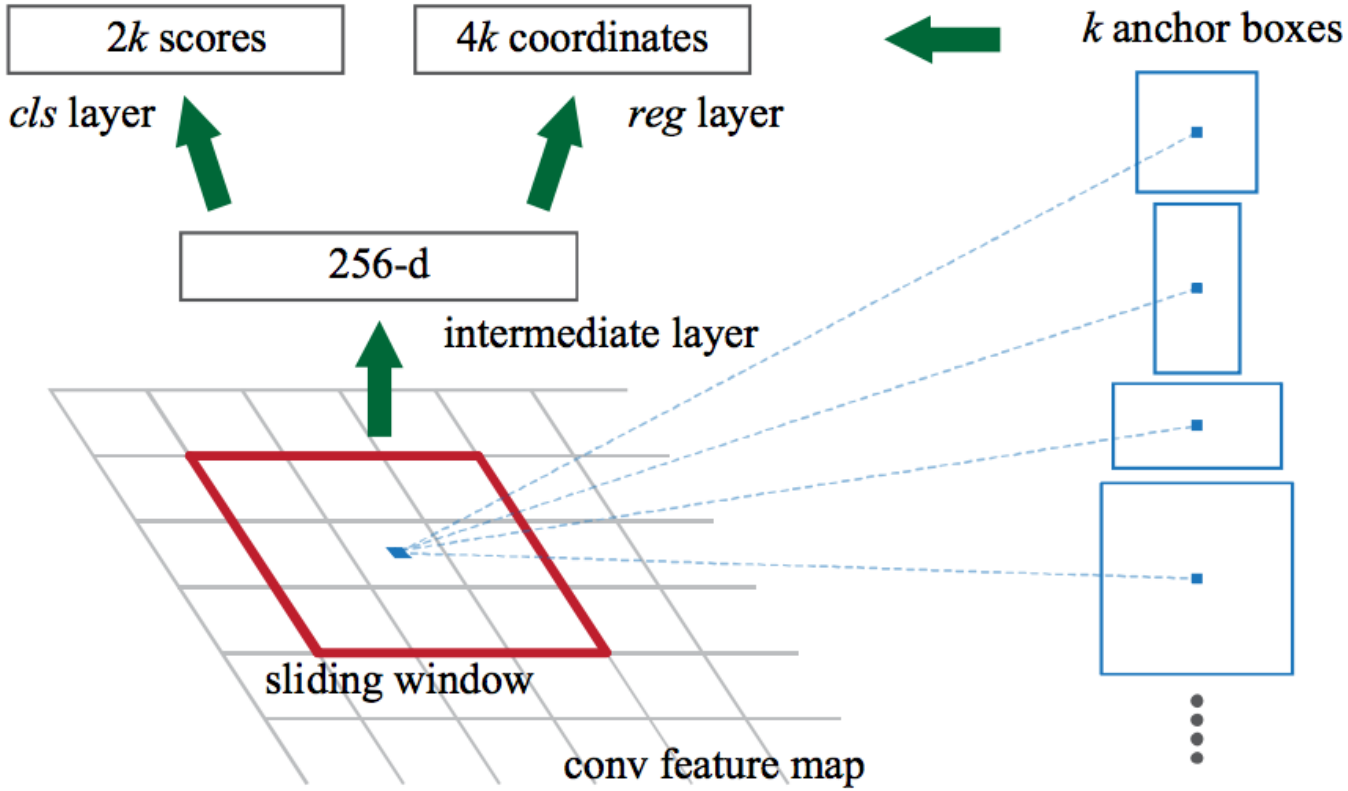
Faster R-CNN (Ren et al. NIPS 2015)

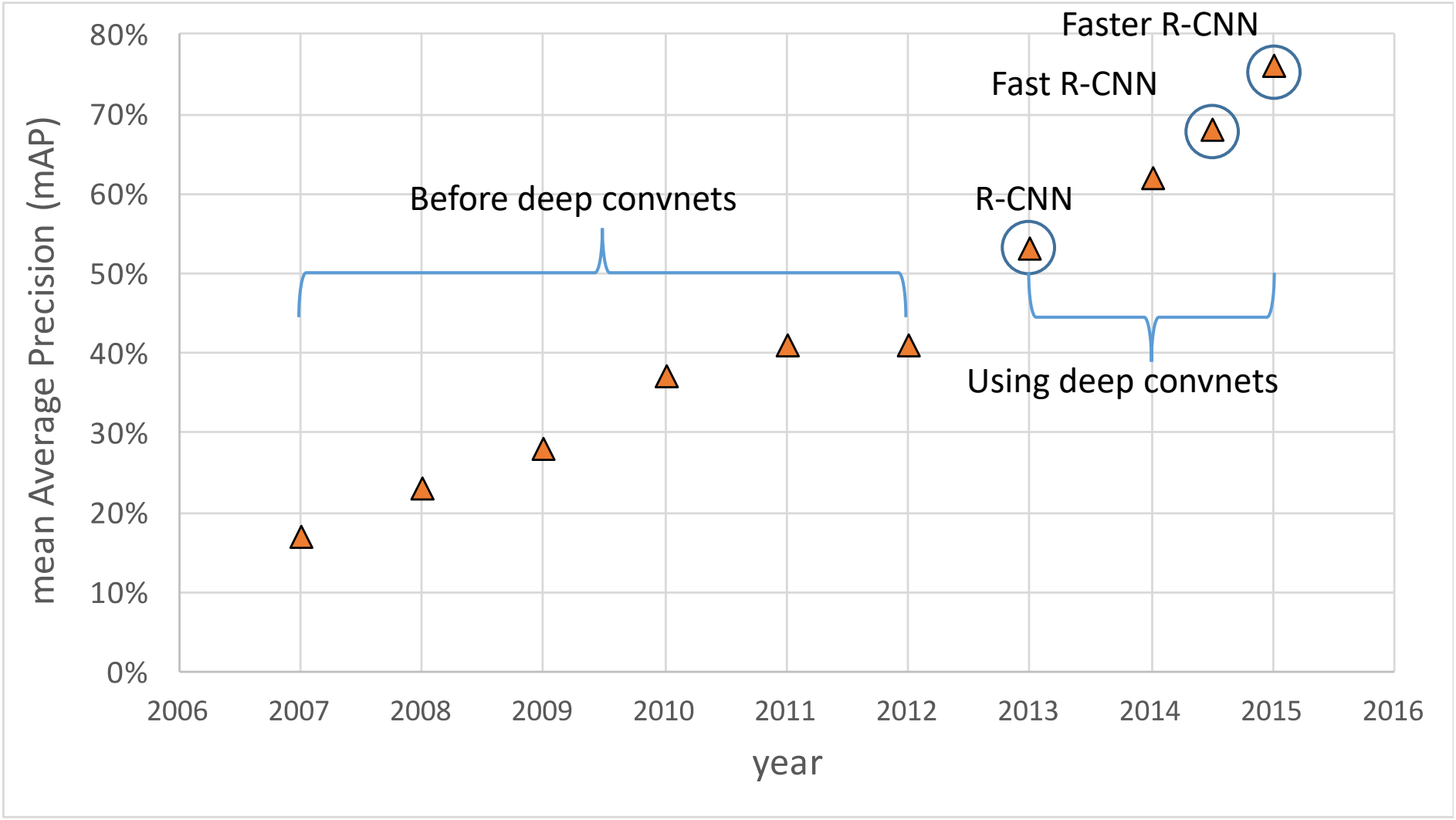
Region proposal network



https://arxiv.org/pdf/1506.01497.pdf

Faster R-CNN (Ren et al. NIPS 2015)

Progress on PASCAL VOC database



Faster R-CNN (Ren et al. NIPS 2015)

- What could be the problems

https://arxiv.org/pdf/1506.01497.pdf

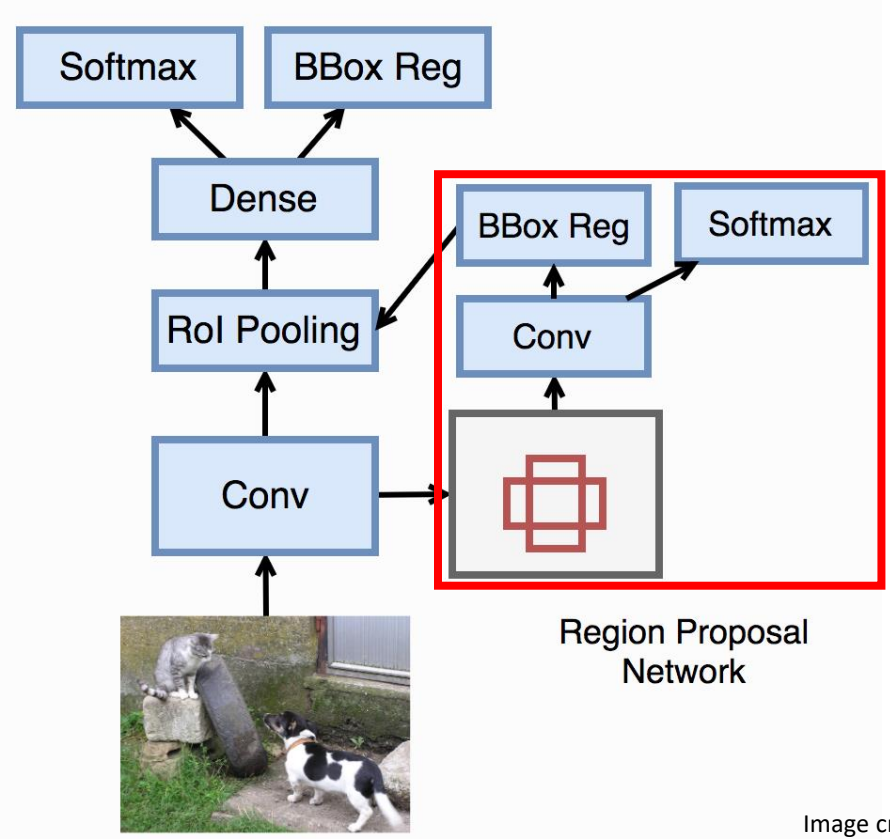
Faster R-CNN (Ren et al. NIPS 2015)

- What could be the problems
  - Two-stage detection pipeline is still too slow to apply on real-time videos

https://arxiv.org/pdf/1506.01497.pdf

One-stage detection

- Solution
  - Don’t generate object proposals!
  - Consider a tiny subset of the output space by design; directly classify this small set of boxes



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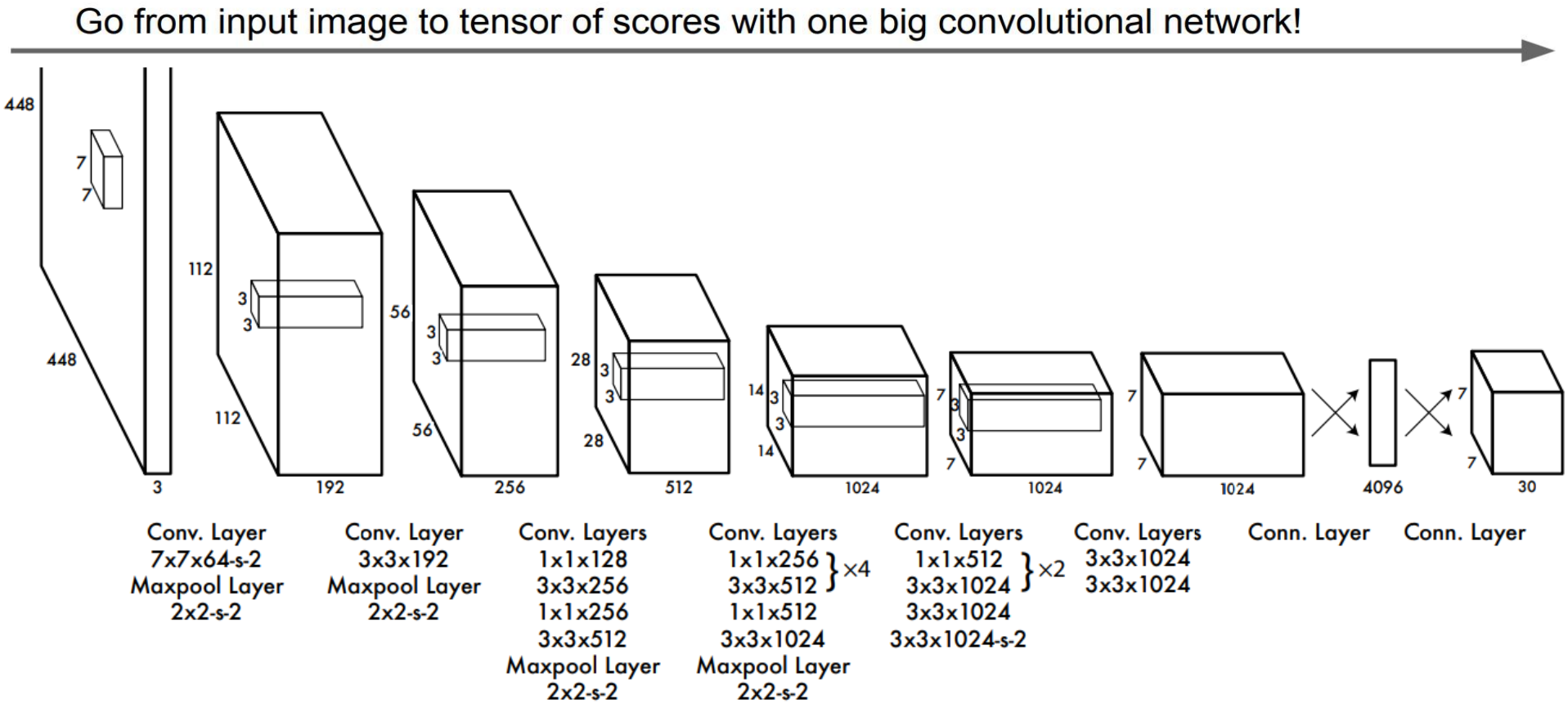
You Only Look Once (YOLO)

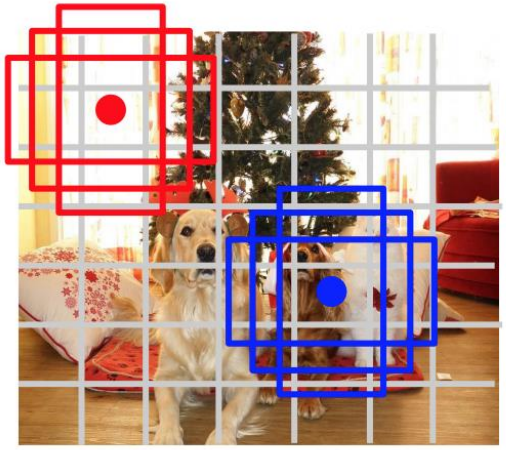


Redmon et al. You only look once: Unified, real-time object detection. CVPR 2016.

You Only Look Once (YOLO)

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

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.

Slides by Justin Johnson

You Only Look Once (YOLO)

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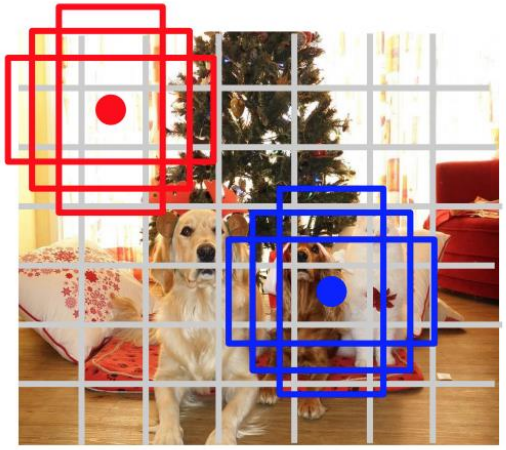

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B = 2 in experiments

C = 20 in PASCAL VOC

Final prediction=7×7×30 tensor.

Redmon et al. You only look once: Unified, real-time object detection. cvpr 2016.

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You Only Look Once (YOLO)

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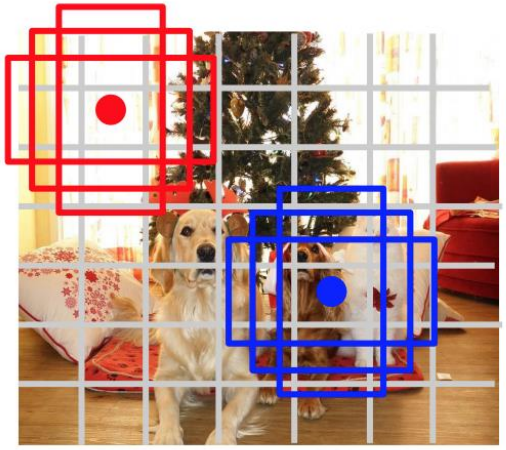

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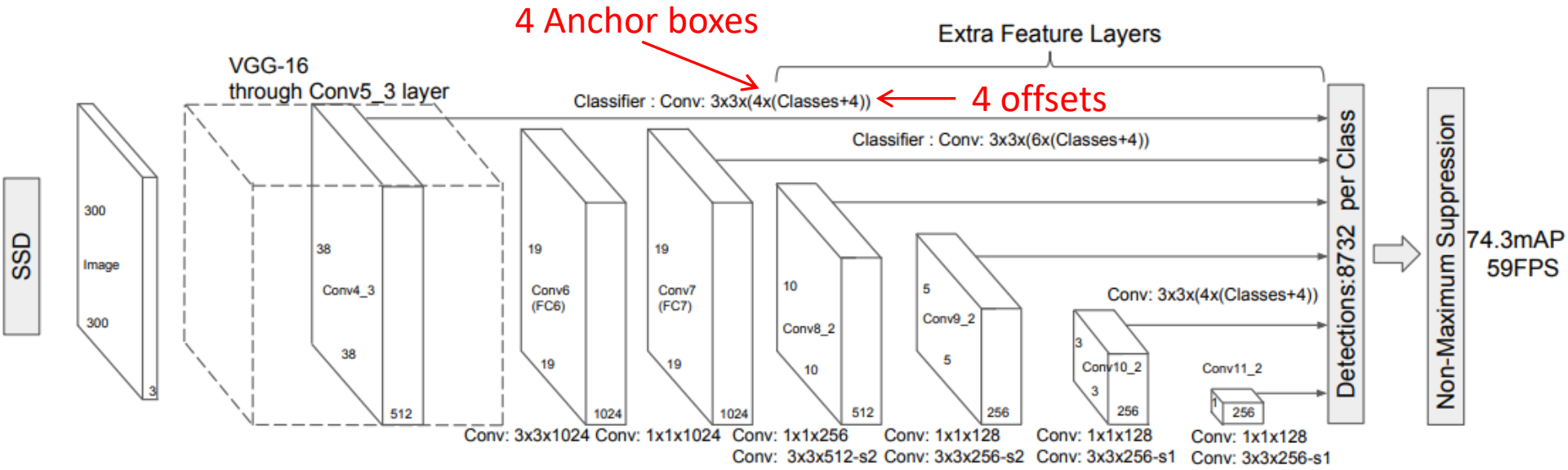
- Very efficient but lower accuracy

Redmon et al. You only look once: Unified, real-time object detection. cvpr 2016.

Slides by Justin Johnson

SSD: Single Shot MultiBox Detector



- Run a small 3×3 sized convolutional kernel to predict the bounding boxes and classification probability.
- SSD also uses anchor boxes at various aspect ratio similar to Faster-RCNN and learns the off-set rather than learning the box.
- In order to handle the scale, SSD predicts bounding boxes after multiple convolutional layers.

Liu et al. SSD: Single Shot MultiBox Detector, ECCV 2016.

SSD: Single Shot MultiBox Detector

Source: http://cv-tricks.com/object-detection/faster-r-cnn-yolo-ssd/

One-stage detection

- What could be the problems?

One-stage detection

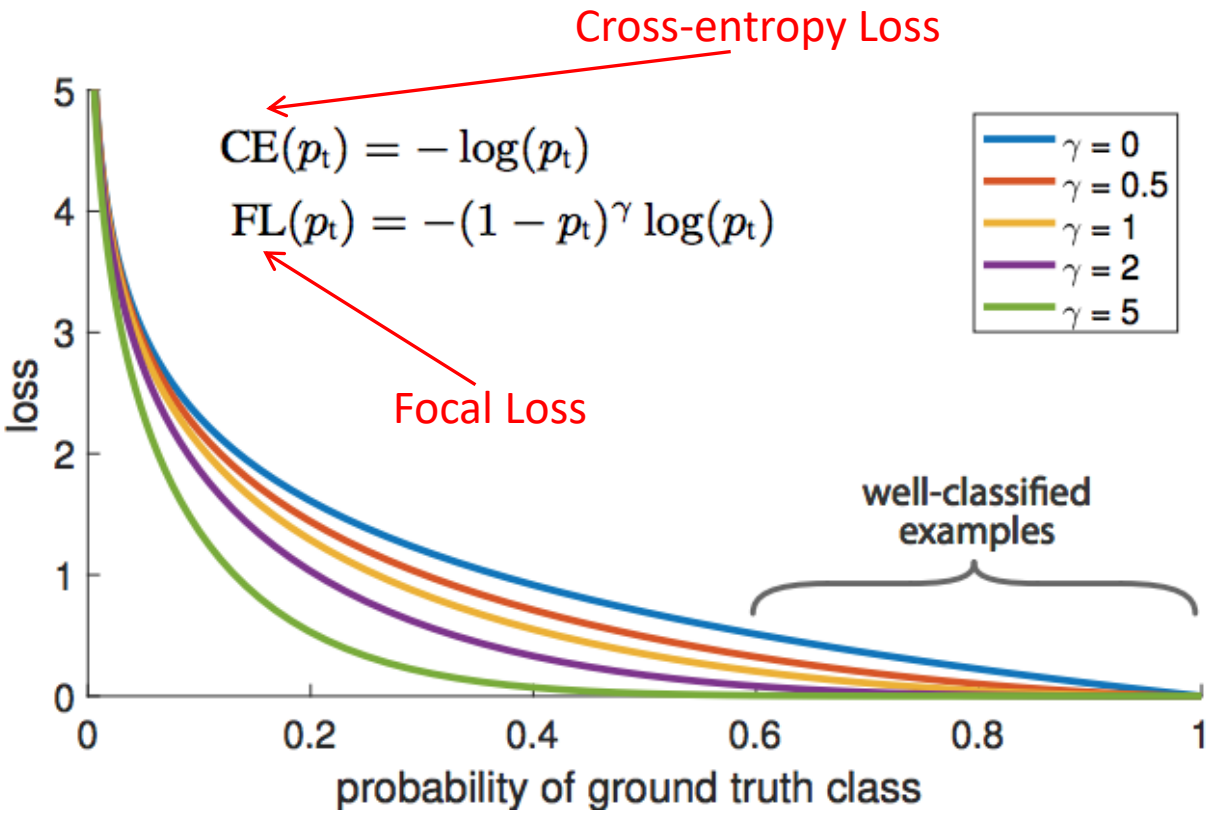
- What could be the problems?
  - The extreme foreground-background class imbalance
    -> we have a lot more negative examples.

One-stage detection

- What could be the problems?
  - The extreme foreground-background class imbalance
    -> we have a lot more negative examples.
  - The vast number of easy negatives overwhelms the detector during training.

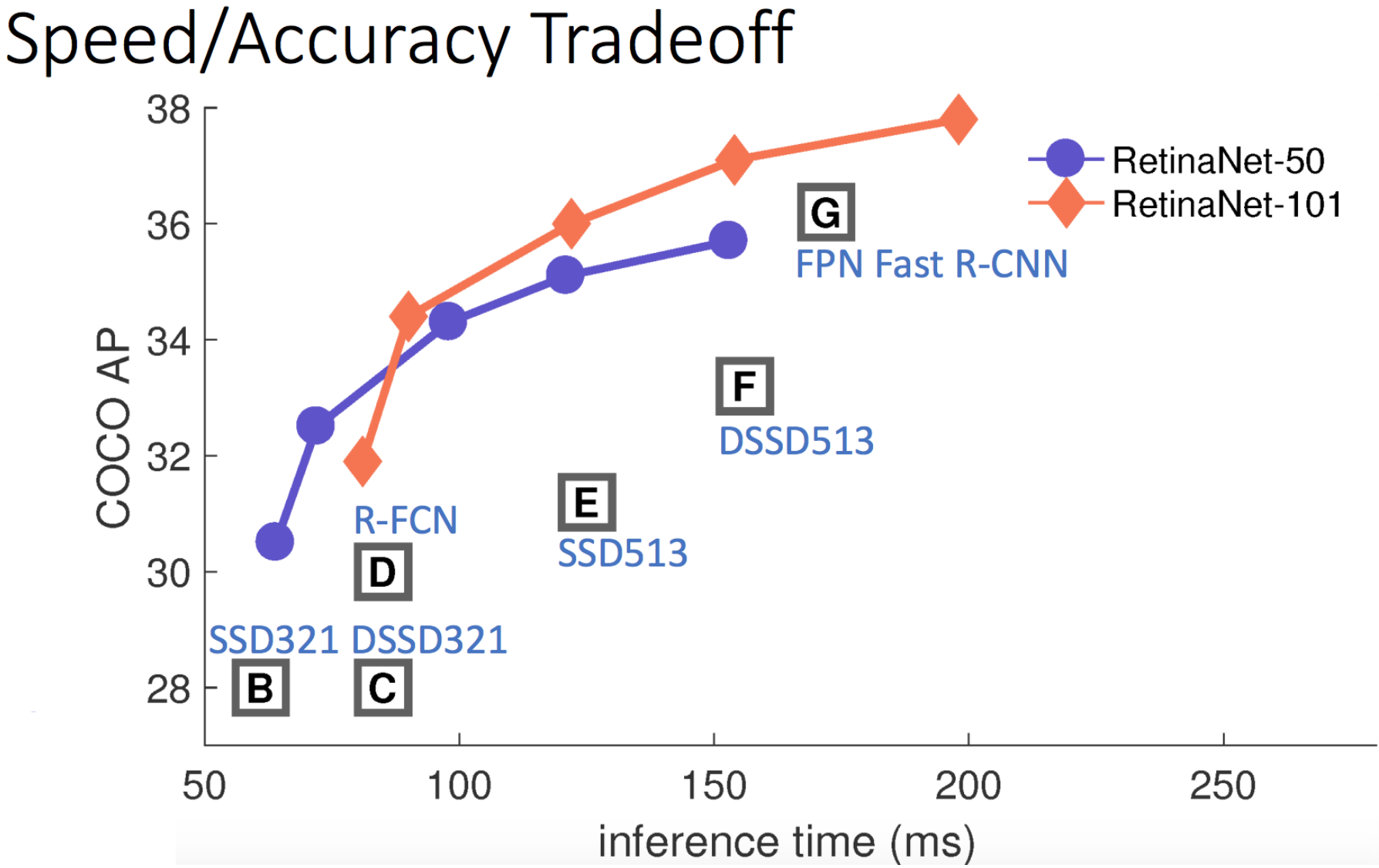
RetinaNet (Lin et al. ICCV 2017)

- Solution
  - For easy negative examples, down-weight the loss, so that the gradients from these example have smaller impact to the model



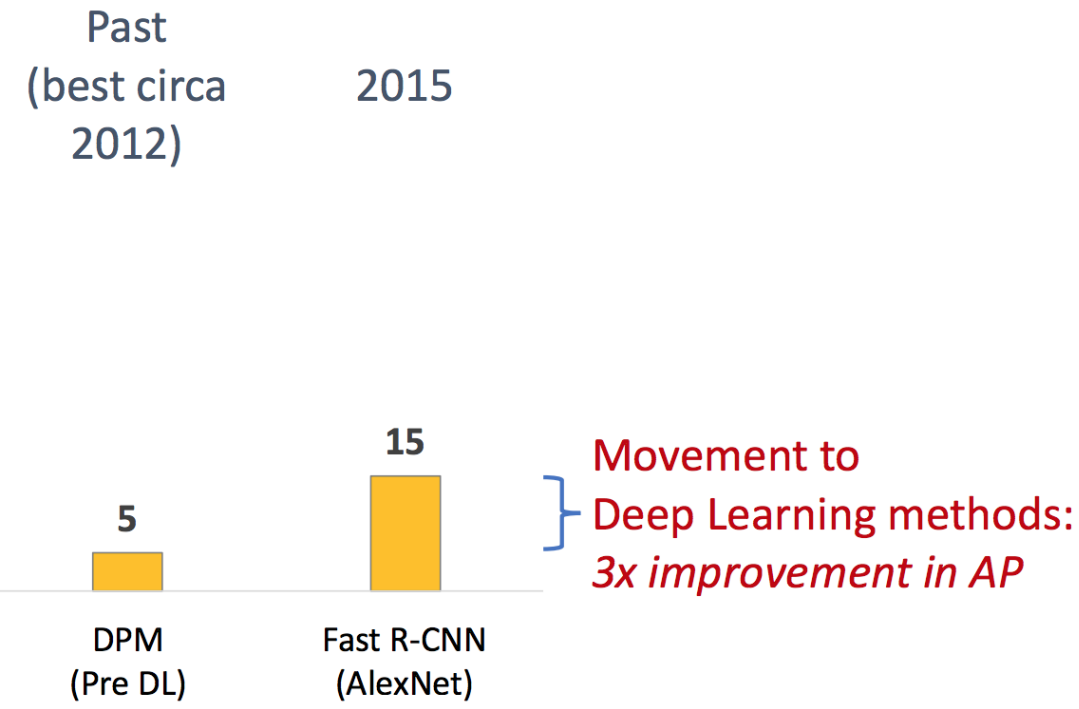
Lin et al. Focal loss for dense object detection. *ICCV* 2017. https://arxiv.org/pdf/1708.02002.pdf

RetinaNet (Lin et al. ICCV 2017)



Lin et al. Focal loss for dense object detection. *ICCV* 2017. https://arxiv.org/pdf/1708.02002.pdf

COCO Object Detection Average Precision (%)



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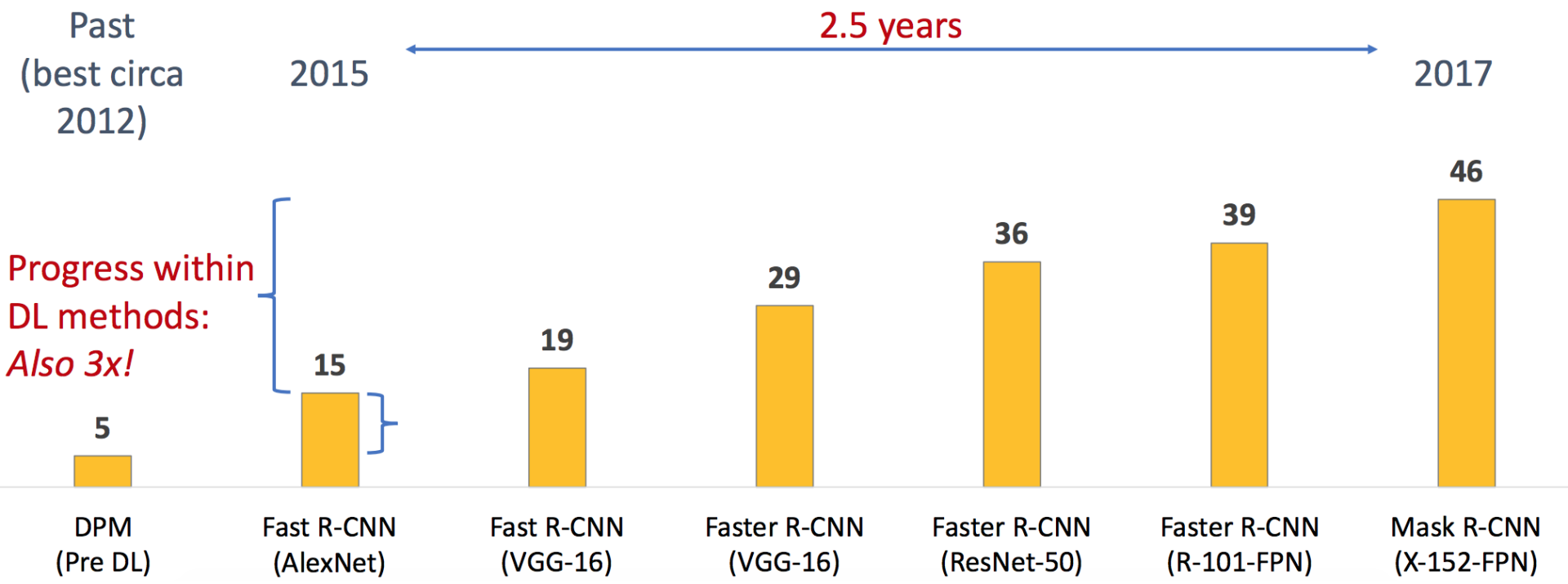
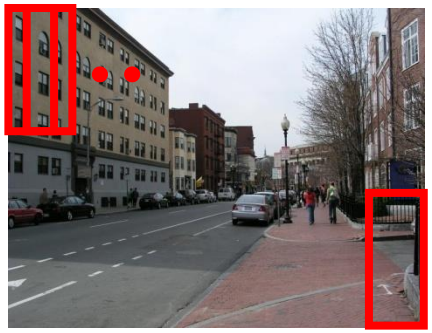
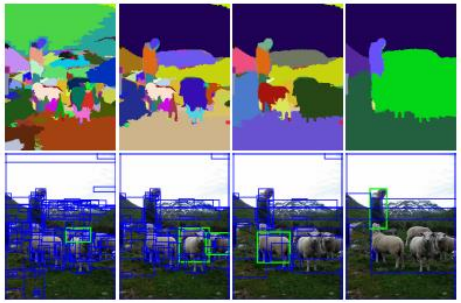


Summary: statistical templates

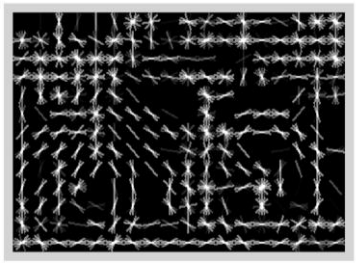
Propose Window → Extract Features → Classify → Post-process



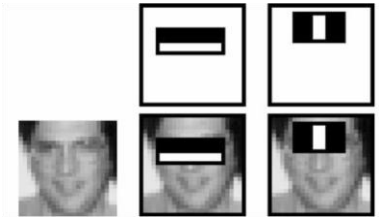
Sliding window: scan image pyramid



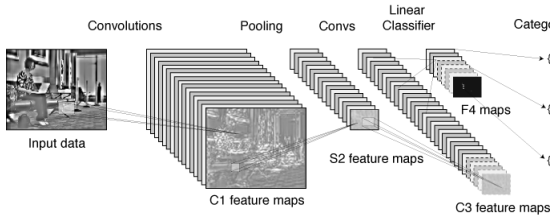
Region proposals: edge/region-based, resize to fixed window



HOG



Fast randomized features



CNN features

SVM

Boosted stubs

Neural network

Non-max suppression

Segment or refine localization

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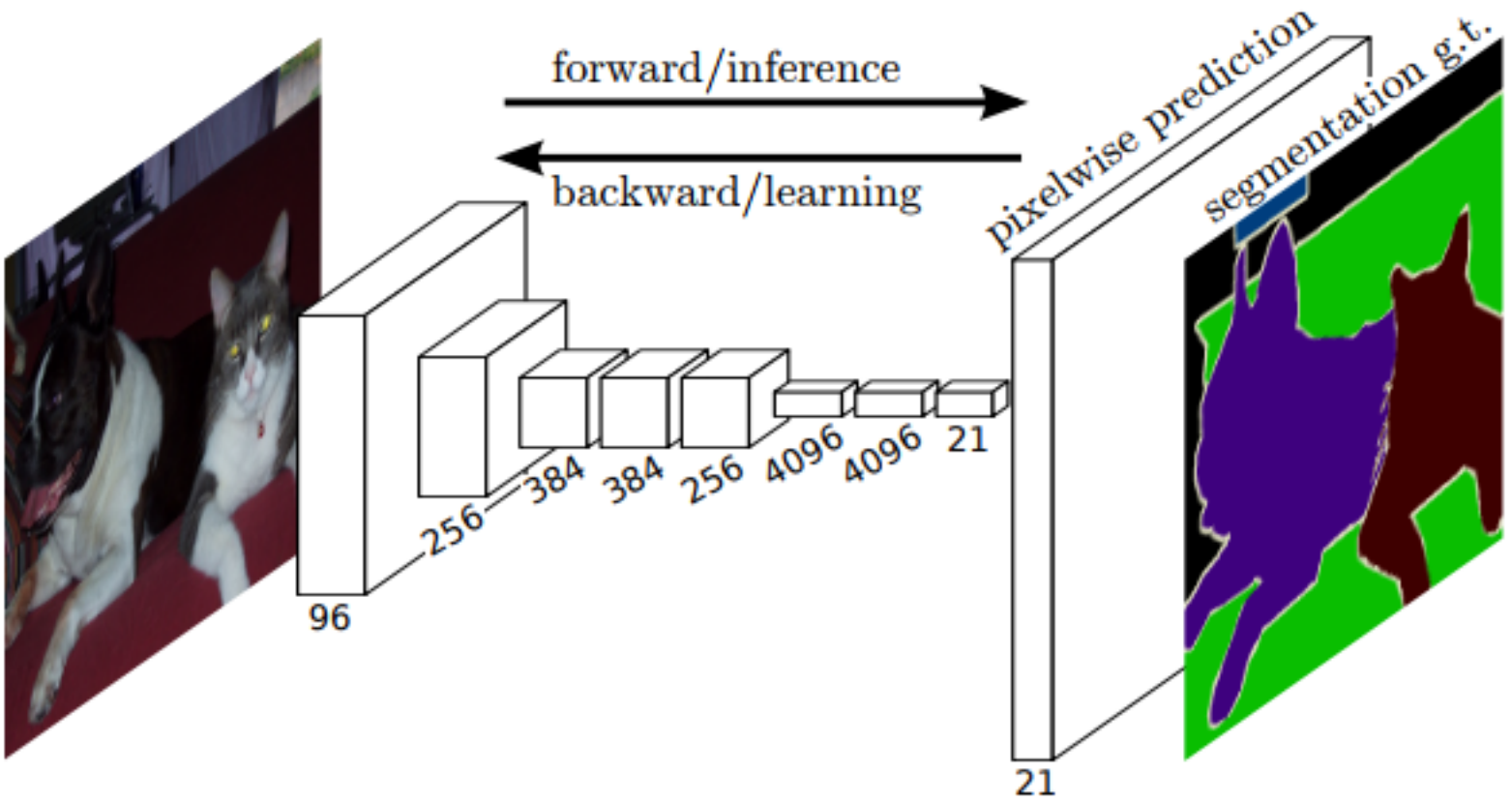
  - S. Lazebnik
  - K. Grauman
  - Antonio Torralba
  - Rob Fergus
  - Leibe
  - And many more …….

Next class

- Image Segmentation



https://people.eecs.berkeley.edu/~jonlong/long_shelhamer_fcn.pdf