Convolutional Feature Maps

Elements of efficient (and accurate) CNN-based object detection

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Overview of this section

- Quick introduction to convolutional feature maps
  - Intuitions: into the "black boxes"
  - How object detection networks & region proposal networks are designed
  - Bridging the gap between "hand-engineered" and deep learning systems
- Focusing on forward propagation (inference)
  - Backward propagation (training) covered by Ross's section

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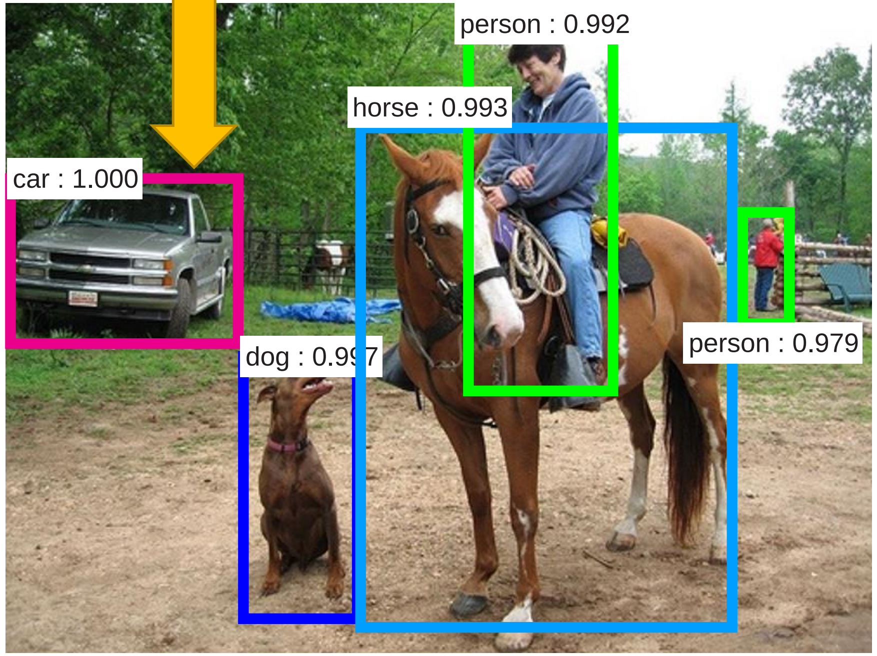
Object Detection = What, and Where

Localization
Where?

Recognition
What?



- We need a building block that tells us “what and where”…

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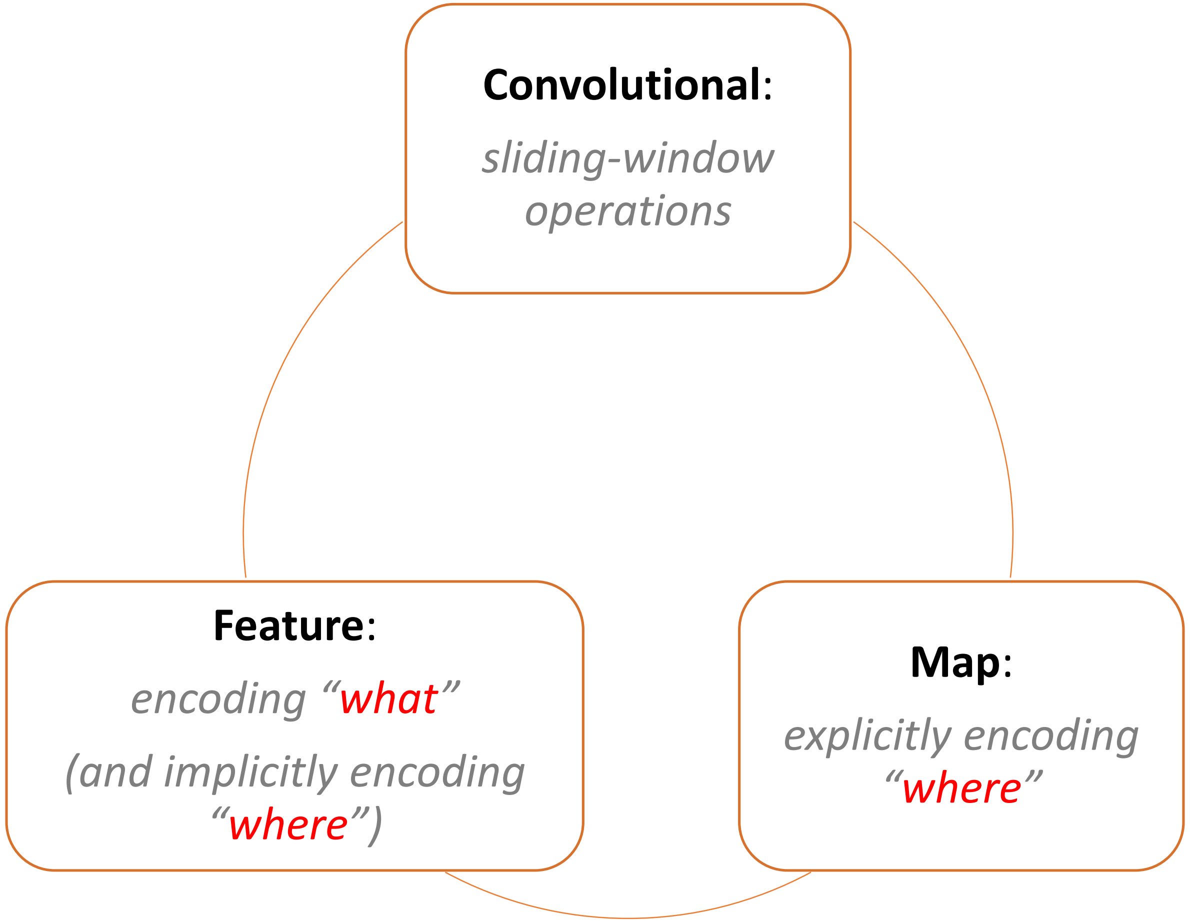
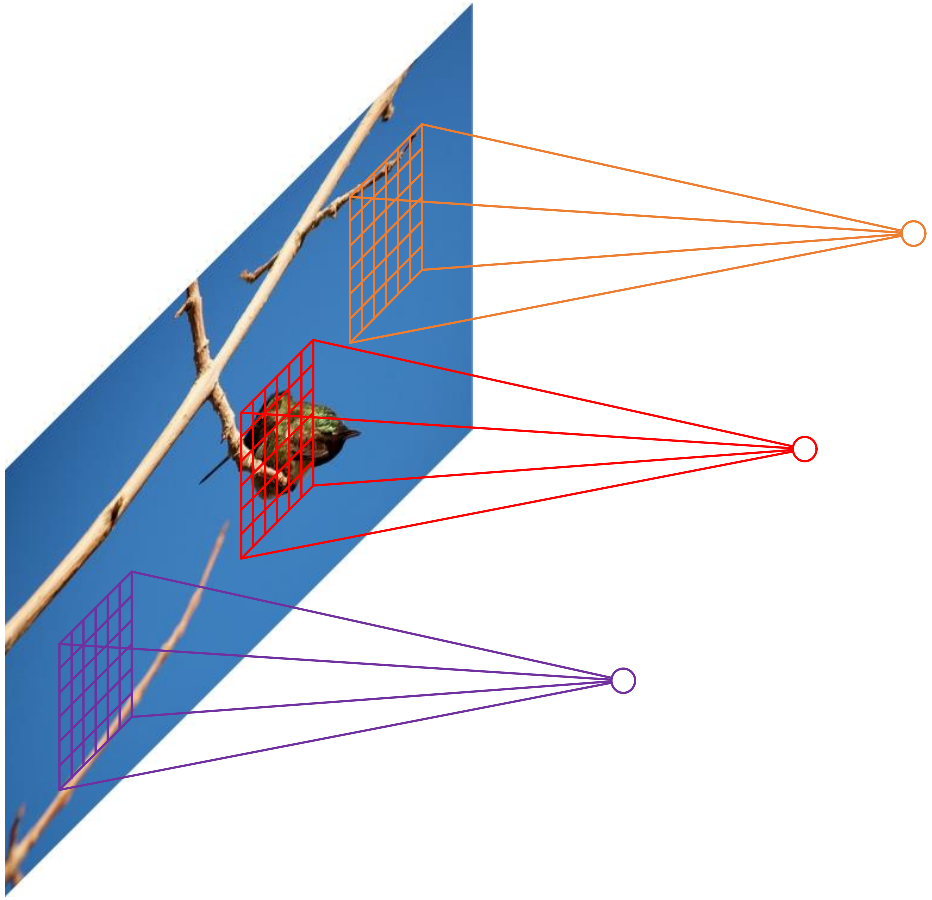
Object Detection = What, and Where



Convolutional Layers

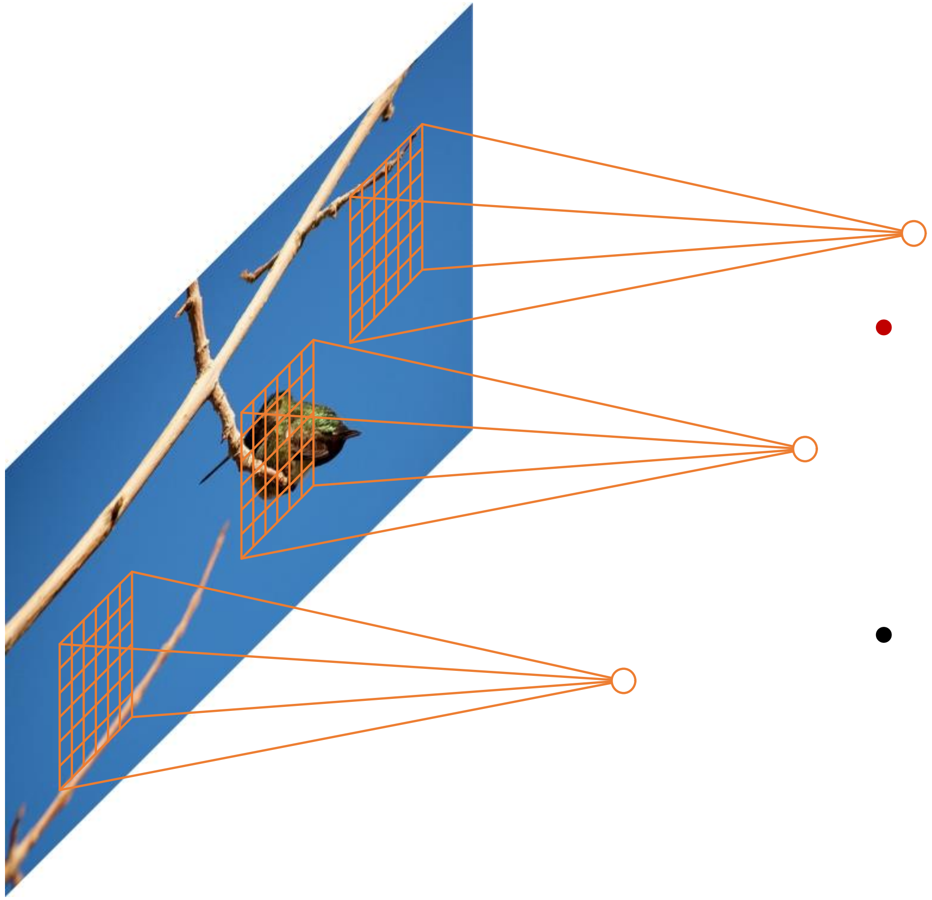
- Convolutional layers are locally connected



- a filter/kernel/window slides on the image or the previous map
- the position of the filter explicitly provides information for localizing
- local spatial information w.r.t. the window is encoded in the channels

Convolutional Layers

- Convolutional layers share weights spatially: translation-invariant

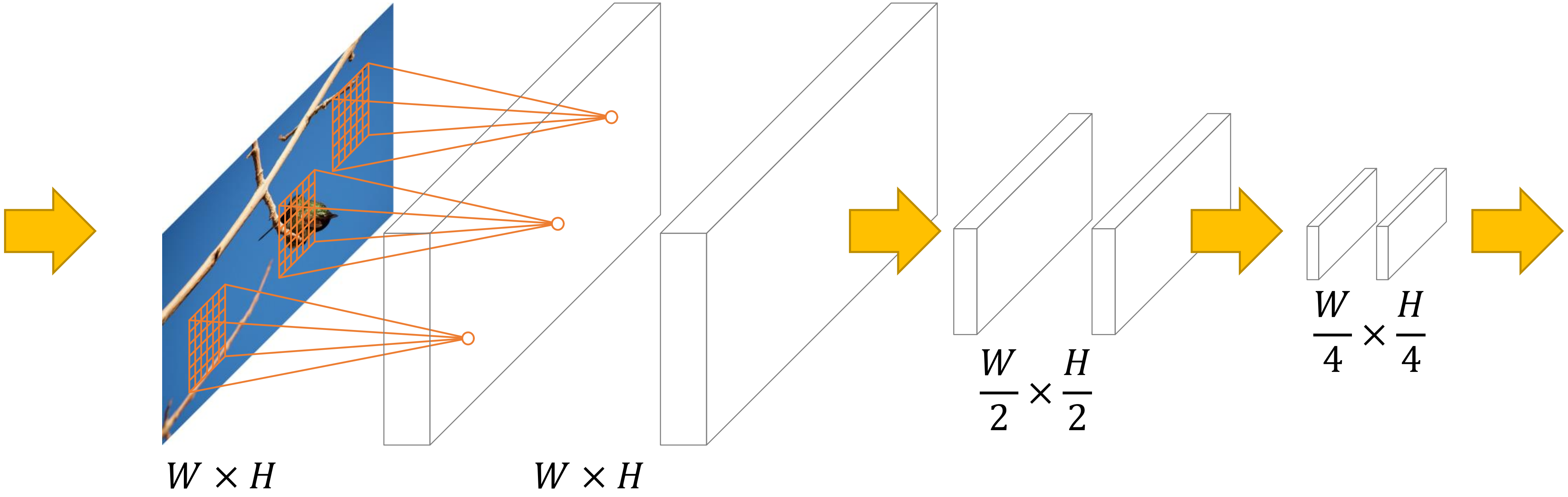


- Translation-invariant: a translated region will produce the same response at the correspondingly translated position

- A local pattern's convolutional response can be re-used by different candidate regions

Convolutional Layers

- Convolutional layers can be applied to images of any sizes, yielding proportionally-sized outputs



HOG by Convolutional Layers

- Steps of computing HOG:
  - Computing image gradients
  - Binning gradients into 18 directions
  - Computing cell histograms
  - Normalizing cell histograms

- Convolutional perspectives:
  - Horizontal/vertical edge filters
  - Directional filters + gating (non-linearity)
  - Sum/average pooling
  - Local response normalization (LRN)

see [Mahendran & Vedaldi, CVPR 2015]

HOG, dense SIFT, and many other "hand-engineered" features are convolutional feature maps.

Aravindh Mahendran & Andrea Vedaldi. "Understanding Deep Image Representations by Inverting Them". CVPR 2015

Feature Maps = features and their locations

Convolutional:

sliding-window operations

Feature:

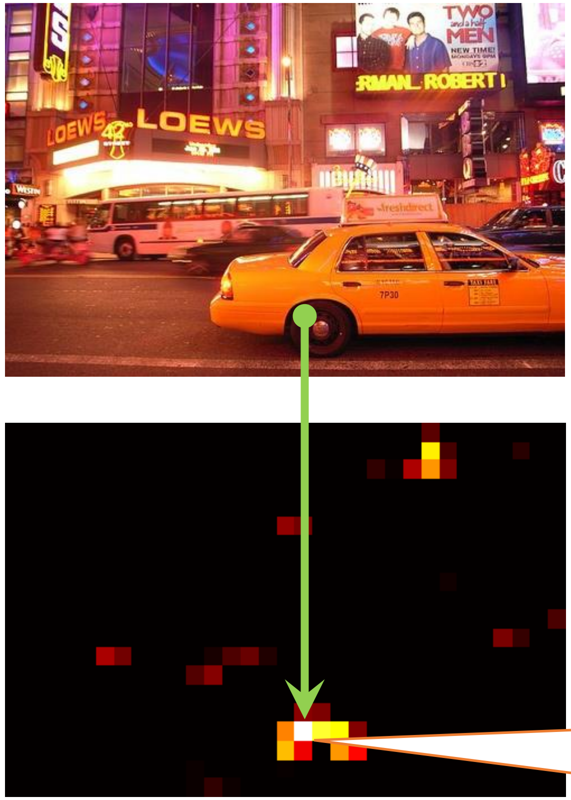
encoding "what"

(and implicitly encoding "where")

Map:

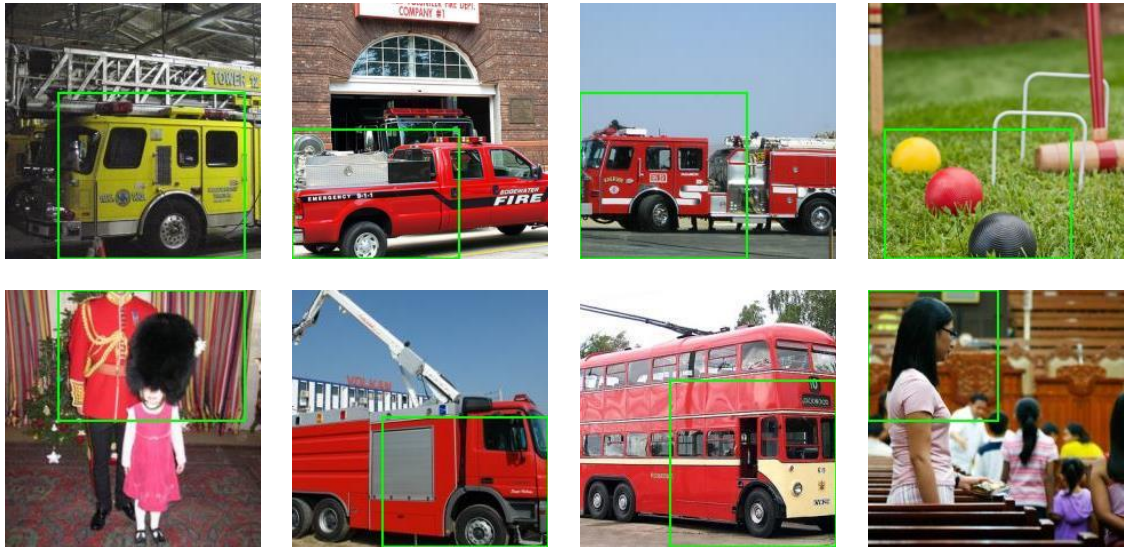
explicitly encoding "where"

Feature Maps = features and their locations



one feature map of conv$_5$
(#55 in 256 channels of a model trained on ImageNet)

ImageNet images with strongest responses of this channel

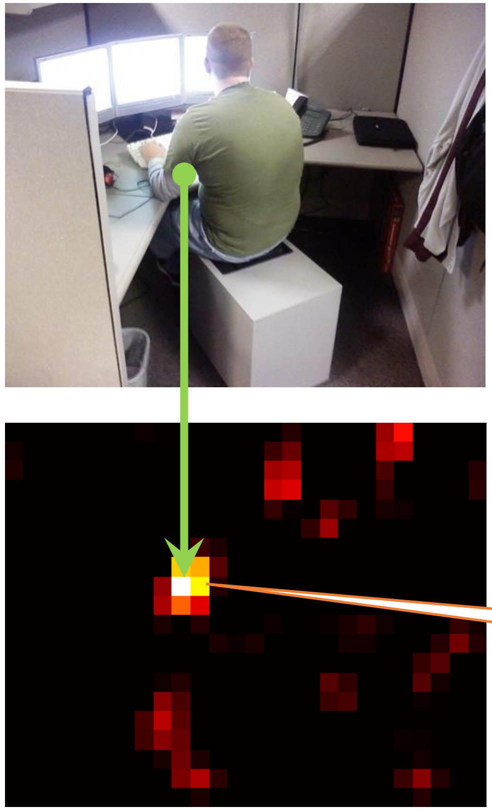


Intuition of *this* response:
There is a "circle-shaped" object (likely a tire) at this position.

What **Where**

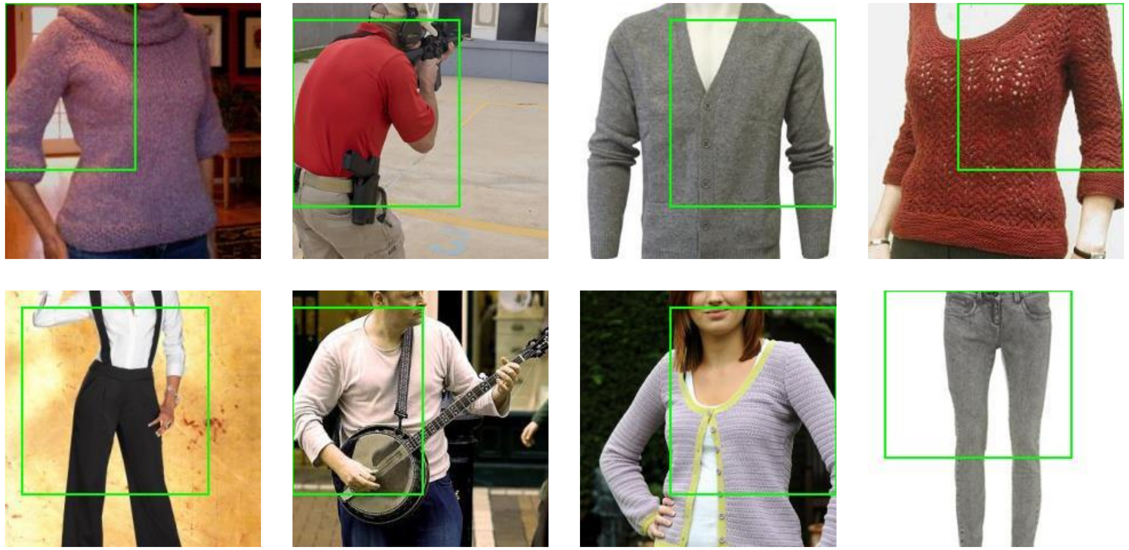
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

Feature Maps = features and their locations



one feature map of $conv_5$
(#66 in 256 channels of a model trained on ImageNet)

ImageNet images with strongest responses of this channel



Intuition of *this* response:
There is a "λ-shaped" object (likely an underarm) at this position.

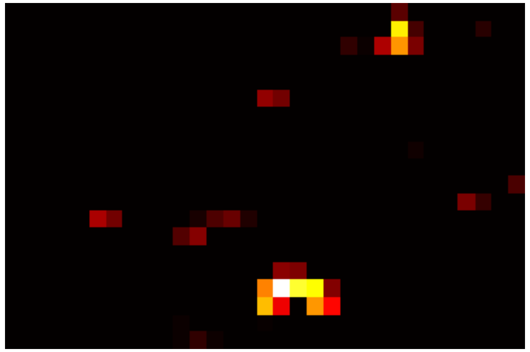
What **Where**

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

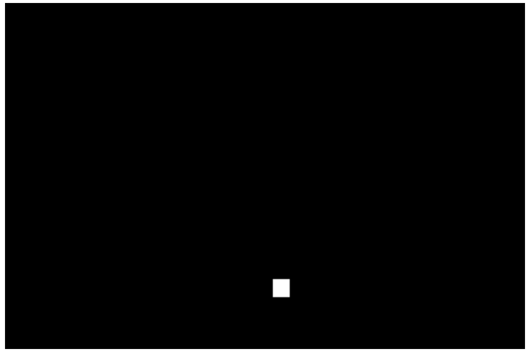
Feature Maps = features and their locations

- Visualizing one response (by Zeiler and Fergus)

image



a feature map



keep one response
(e.g., the strongest)

?

Matthew D. Zeiler & Rob Fergus. "Visualizing and Understanding Convolutional Networks". ECCV 2014.

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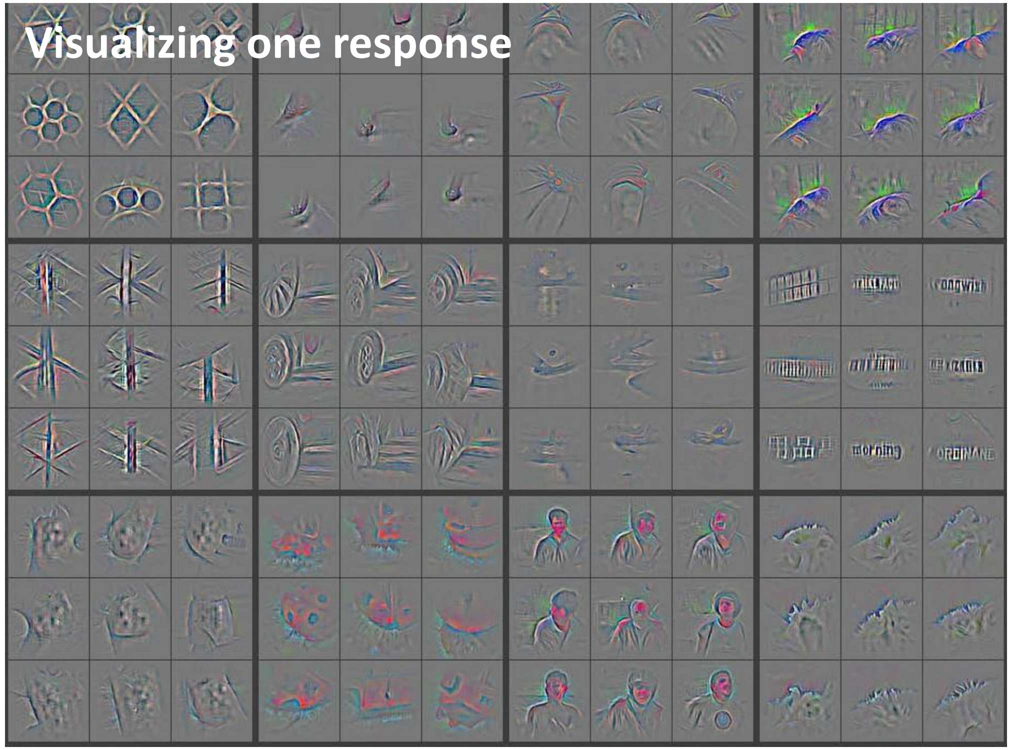
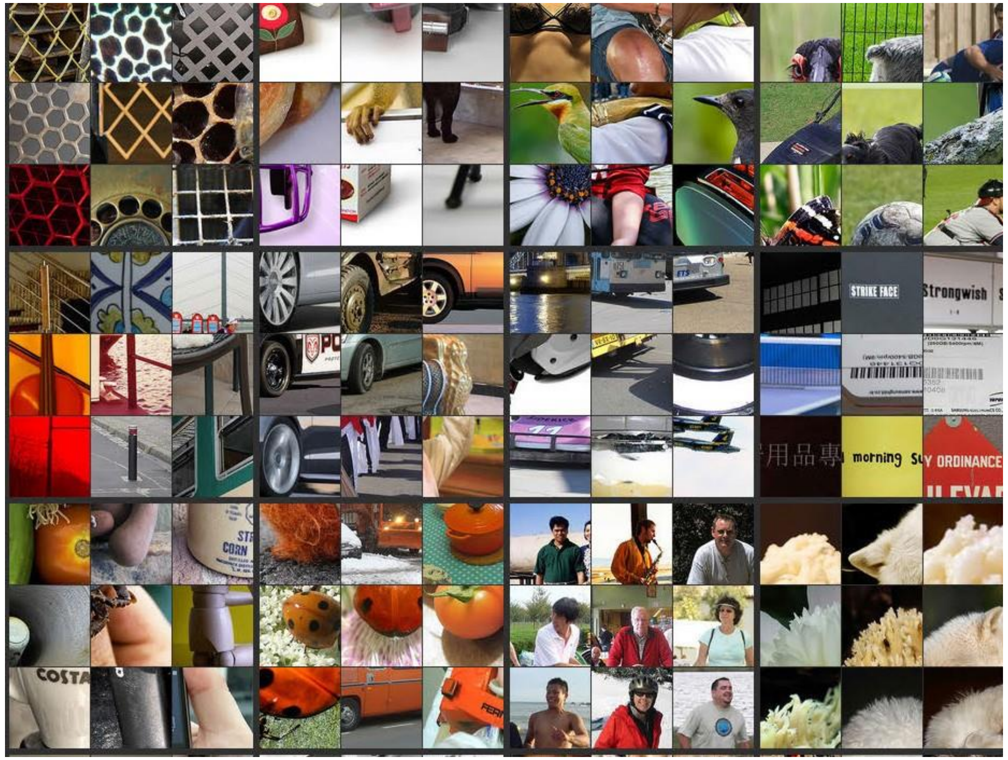
Feature Maps = features and their locations





conv3

image credit: Zeiler & Fergus

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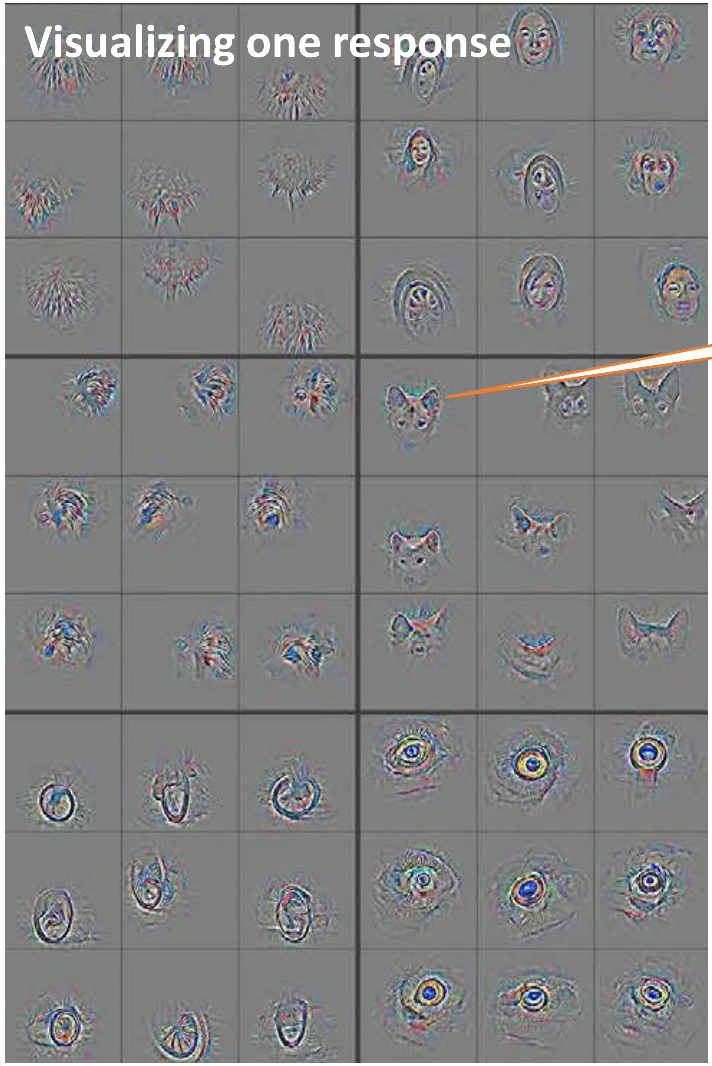
Matthew D. Zeiler & Rob Fergus. "Visualizing and Understanding Convolutional Networks". ECCV 2014.

Feature Maps = features and their locations



conv5

Intuition of *this visualization*:
There is a "dog-head" shape at this position.

- Location of a feature:
explicitly represents *where* it is.

- Responses of a feature:
encode *what* it is, and implicitly encode finer position information –

finer position information is encoded in the channel dimensions (e.g., bbox regression from responses at one pixel as in RPN)

image credit: Zeiler & Fergus

Matthew D. Zeiler & Rob Fergus. "Visualizing and Understanding Convolutional Networks". ECCV 2014.

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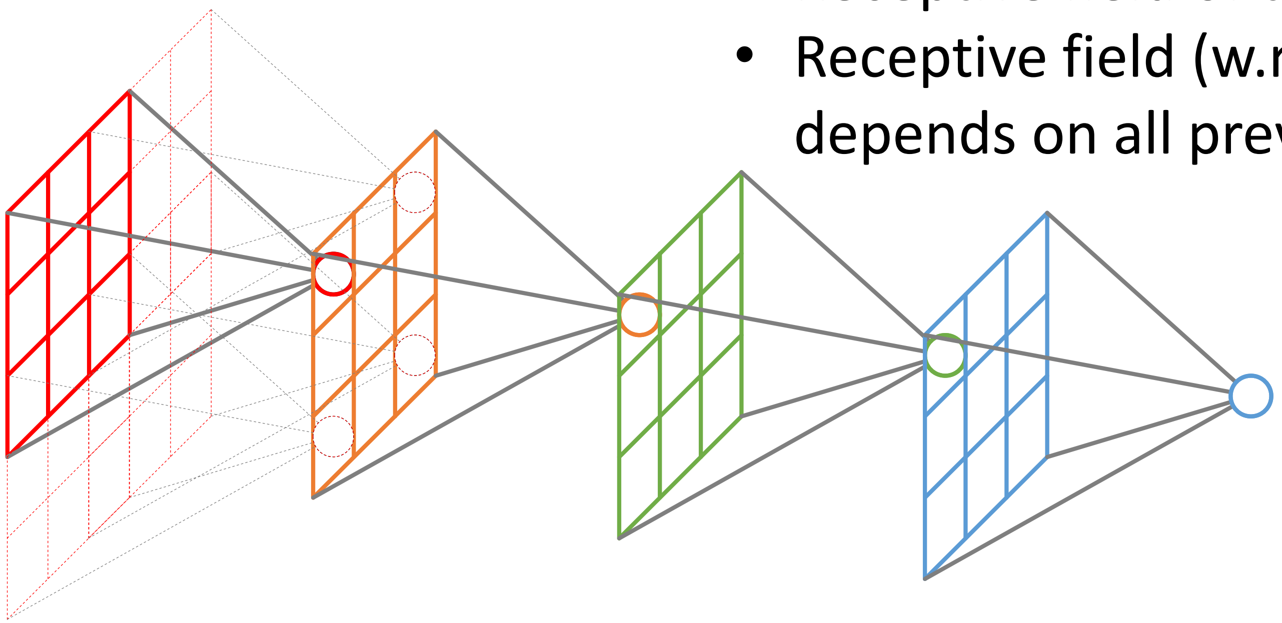
Receptive Field

- Receptive field of the first layer is the filter size
- Receptive field (w.r.t. input image) of a deeper layer depends on all previous layers' filter size and strides



- Correspondence between a feature map pixel and an image pixel is not unique
- Map a feature map pixel to the center of the receptive field on the image in the SPP-net paper

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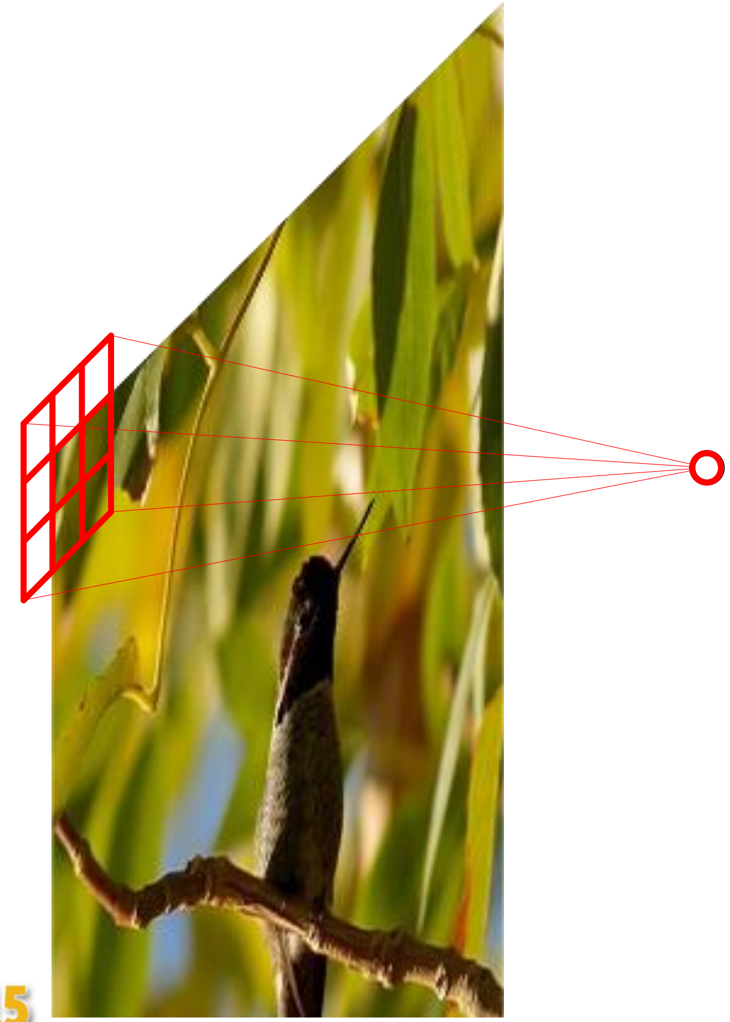
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

Receptive Field



How to compute the center of the receptive field

- A simple solution
  - For each layer, pad $\lfloor F/2 \rfloor$ pixels for a filter size F (e.g., pad 1 pixel for a filter size of 3)
  - On each feature map, the response at (0, 0) has a receptive field centered at (0, 0) on the image
  - On each feature map, the response at (x, y) has a receptive field centered at (Sx, Sy) on the image (stride S)

- A general solution

$$i_0 = g_L(i_L) = \alpha_L(i_L - 1) + \beta_L,$$

$$\alpha_L = \prod_{p=1}^{L} S_p,$$

$$\beta_L = 1 + \sum_{p=1}^{L} \left(\prod_{q=1}^{p-1} S_q \right) \left(\frac{F_p - 1}{2} - P_p \right)$$

See [Karel Lenc & Andrea Vedaldi] "R-CNN minus R". BMVC 2015.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

Region-based CNN Features

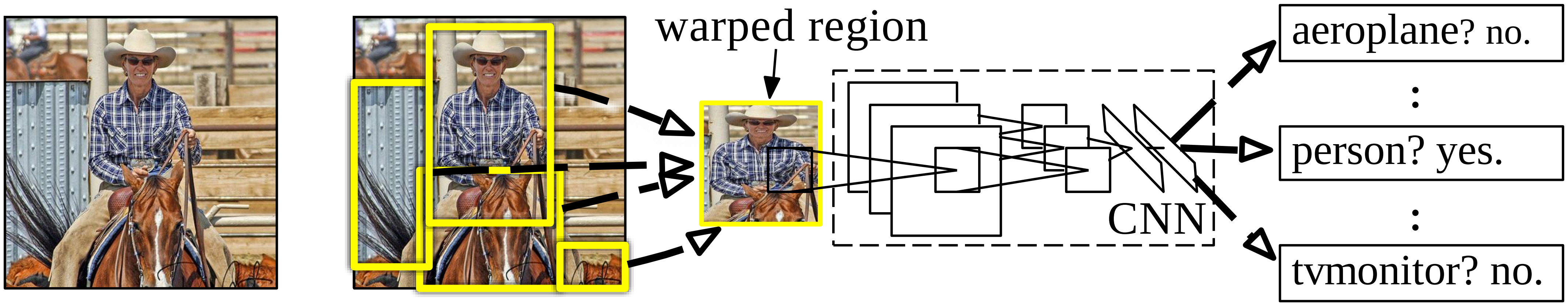


figure credit: R. Girshick et al.

input image

region proposals
~2,000

1 CNN for each region

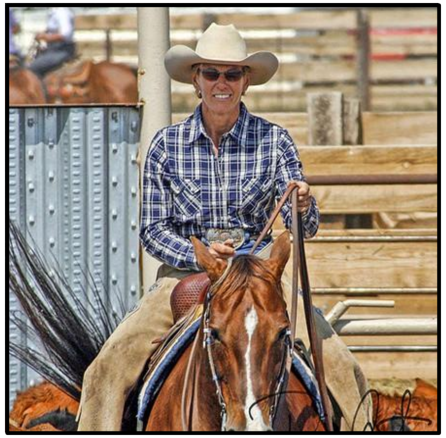
classify regions

R-CNN pipeline

R. Girshick, J. Donahue, T. Darrell, & J. Malik. “Rich feature hierarchies for accurate object detection and semantic segmentation”. CVPR 2014.

Region-based CNN Features

- Given proposal regions, what we need is a feature for each region
- R-CNN: cropping an image region + CNN on region, requires 2000 CNN computations
- What about cropping feature map regions?



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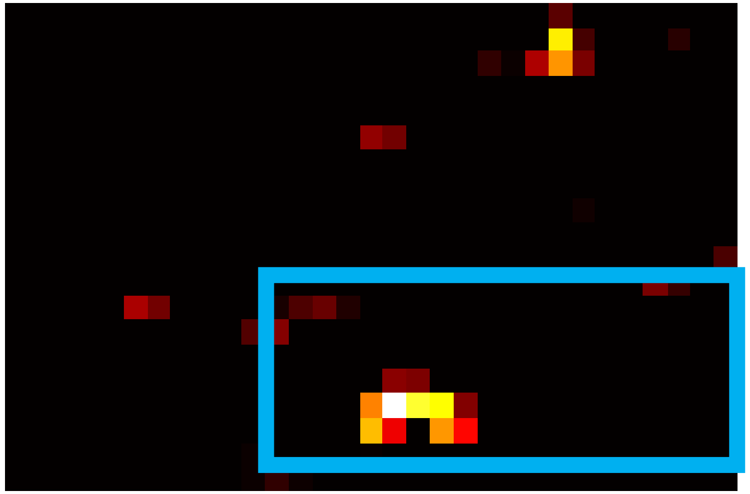
Regions on Feature Maps

image region

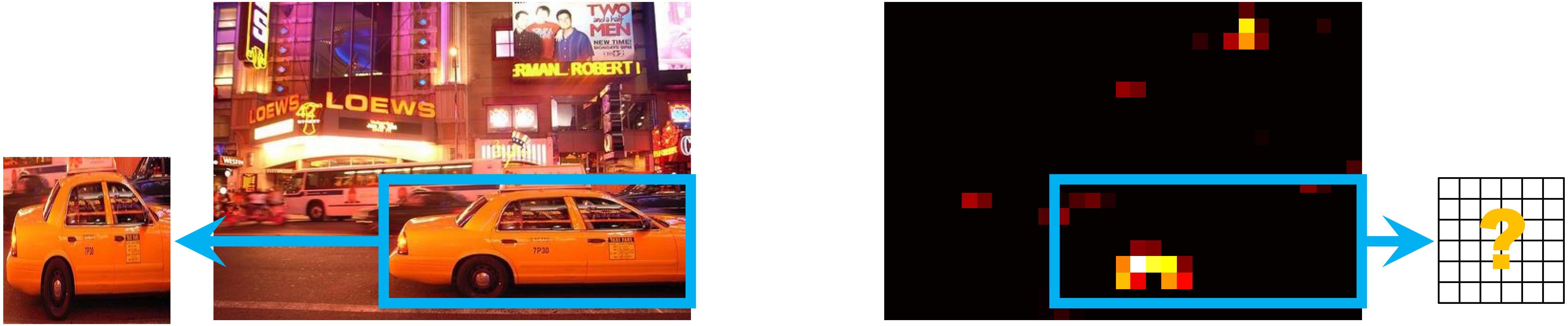


feature map region

- Compute convolutional feature maps on the entire image only once.
- Project an image region to a feature map region (using correspondence of the receptive field center)
- Extract a region-based feature from the feature map region…

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition”. ECCV 2014.

Regions on Feature Maps



warp

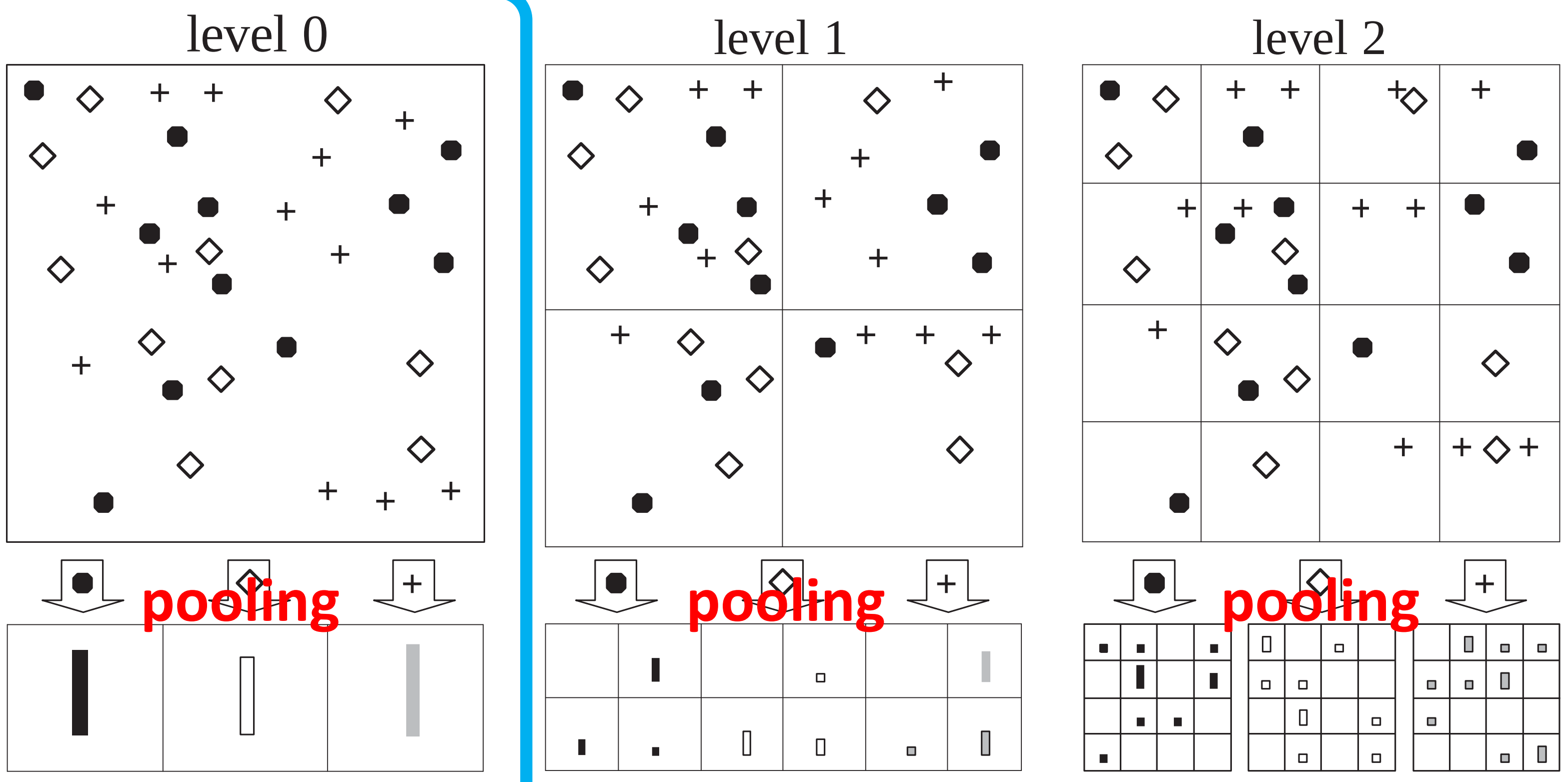
image region

feature map region

- Fixed-length features are required by fully-connected layers or SVM
- But how to produce a fixed-length feature from a feature map region?
- Solutions in traditional compute vision: Bag-of-words, SPM…

Bag-of-words & Spatial Pyramid Matching

SIFT/HOG-based feature maps



Bag-of-words
[J. Sivic & A. Zisserman, ICCV 2003]

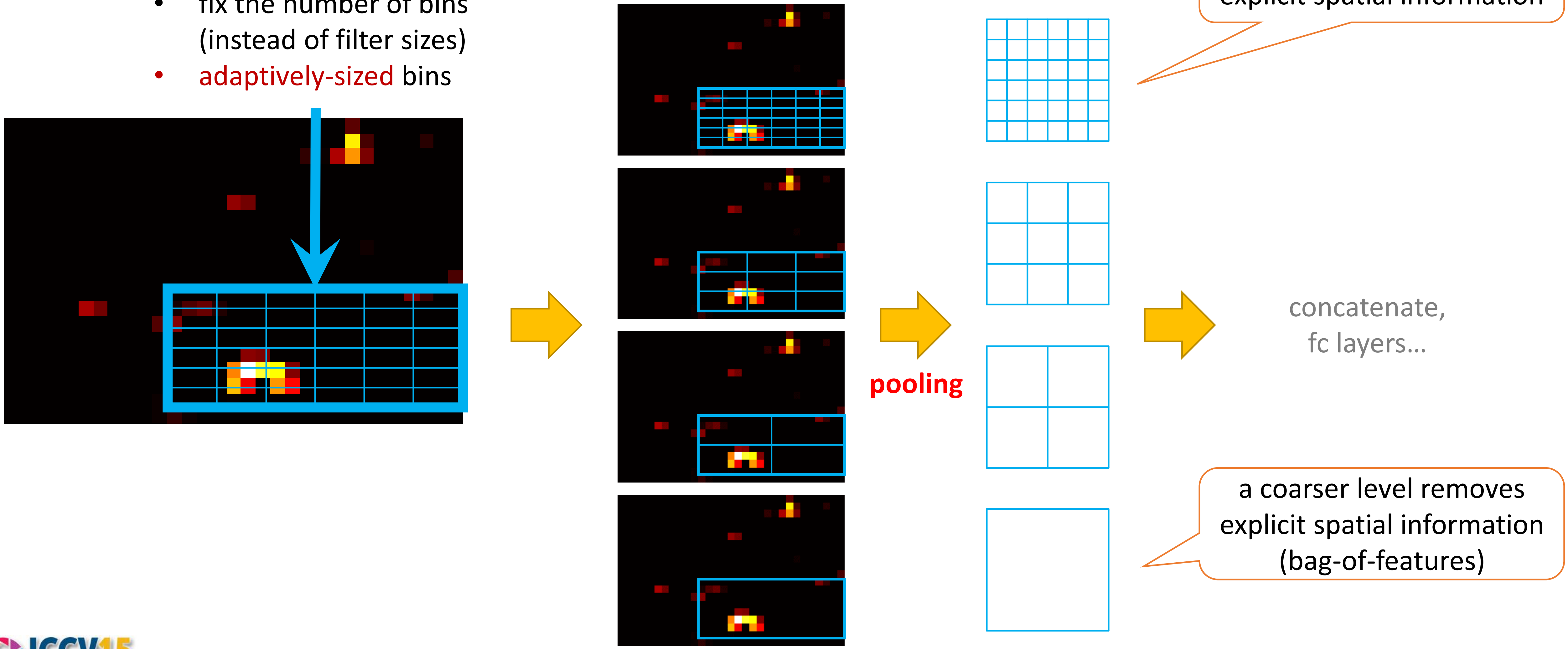
Spatial Pyramid Matching (SPM)
[K. Grauman & T. Darrell, ICCV 2005]
[S. Lazebnik et al, CVPR 2006]

figure credit: S. Lazebnik et al.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

Spatial Pyramid Pooling (SPP) Layer

- fix the number of bins (instead of filter sizes)
- adaptively-sized bins



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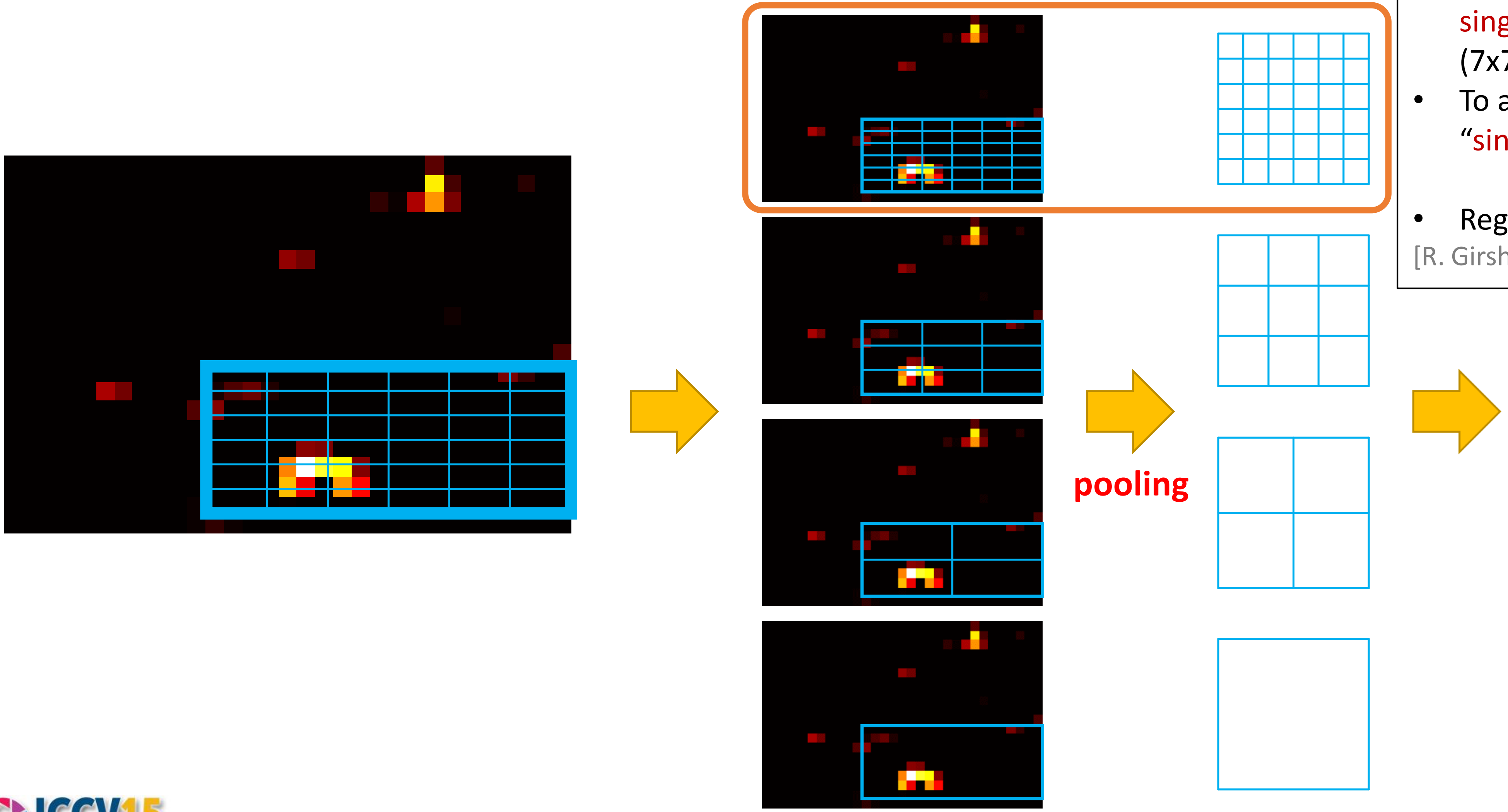
Spatial Pyramid Pooling (SPP) Layer



concatenate,
fc layers…

- Pre-trained nets often have a single-resolution pooling layer (7x7 for VGG nets)
- To adapt to a pre-trained net, a “single-level” pyramid is useable

- Region-of-Interest (RoI) pooling

[R. Girshick, ICCV 2015]

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Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition”. ECCV 2014.

Single-scale and Multi-scale Feature Maps

- Feature Pyramid
  - Resize the input image to multiple scales
  - Compute feature maps for each scale
  - Used for HOG/SIFT features and convolutional features (OverFeat [Sermanet et al. 2013])

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

Single-scale and Multi-scale Feature Maps

- But deep convolutional feature maps perform well at a single scale

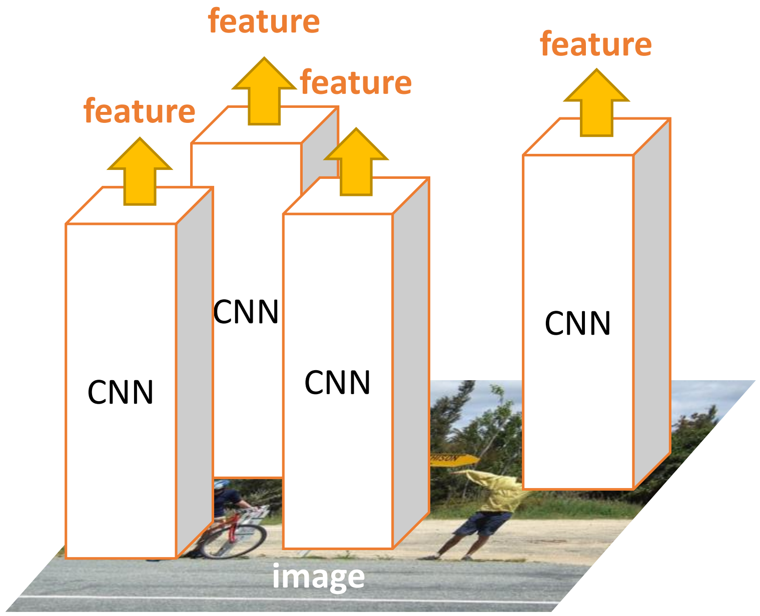
	SPP-net 1-scale	SPP-net 5-scale
pool_5	43.0	44.9
fc_6	42.5	44.8
fine-tuned fc_6	52.3	53.7
fine-tuned fc_7	54.5	55.2
fine-tuned fc_7 bbox reg	58.0	59.2
conv time	0.053s	0.293s
fc time	0.089s	0.089s
total time	0.142s	0.382s

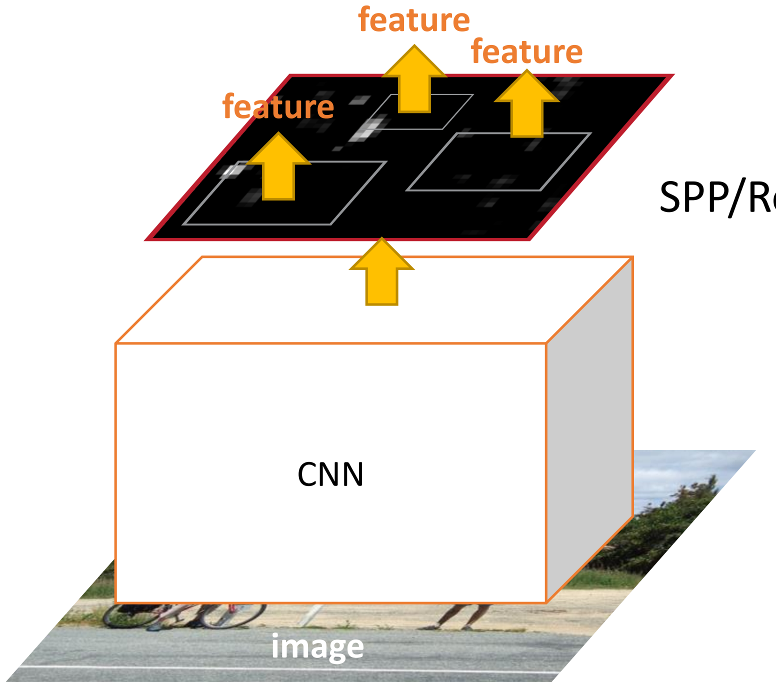
detection mAP on PASCAL VOC 2007, with ZF-net pre-trained on ImageNet
this table is from [K. He, et al. 2014]

- Also observed in Fast R-CNN and VGG nets
- Good speed-vs-accuracy tradeoff
- Learn to be scale-invariant from pre-training data (ImageNet)
- (note: but if good accuracy is desired, feature pyramids are still needed)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition”. ECCV 2014.

R-CNN vs. Fast R-CNN (forward pipeline)





R-CNN

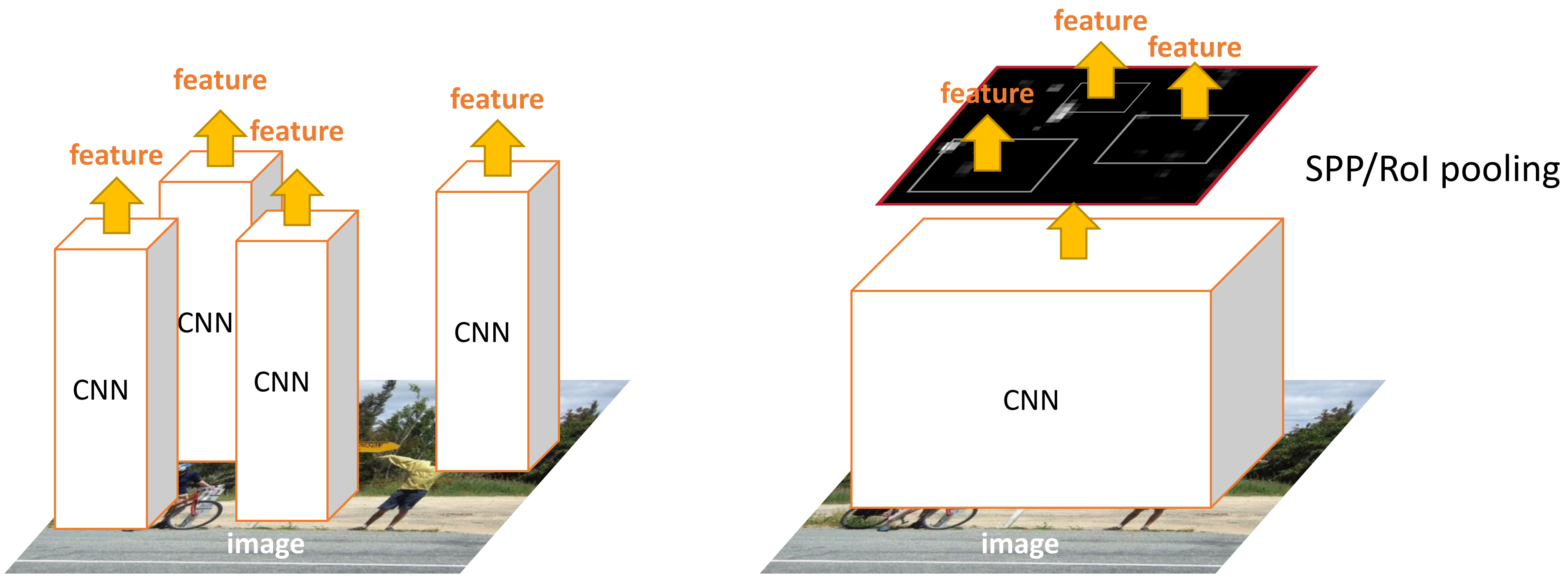
- Extract image regions
- 1 CNN per region (2000 CNNs)
- Classify region-based features

SPP-net & Fast R-CNN (the same forward pipeline)

- 1 CNN on the entire image
- Extract features from feature map regions
- Classify region-based features

Ross Girshick. "Fast R-CNN". ICCV 2015.
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

R-CNN vs. Fast R-CNN (forward pipeline)



R-CNN

- Complexity: $\sim 224 \times 224 \times 2000$

SPP-net & Fast R-CNN (the same forward pipeline)

- Complexity: $\sim 600 \times 1000 \times \mathbf{1}$
- ~ 160**x faster** than R-CNN

Ross Girshick. "Fast R-CNN". ICCV 2015.
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition". ECCV 2014.

Region Proposal from Feature Maps

- Object detection networks are fast (0.2s)…
- but what about region proposal?
  - Selective Search [Uijlings et al. ICCV 2011]: 2s per image
  - EdgeBoxes [Zitnick & Dollar. ECCV 2014]: 0.2s per image

- Can we do region proposal on the same set of feature maps?

Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Feature Maps = features and their locations

Convolutional:

sliding-window operations

Feature:

encoding "what"

(and implicitly encoding "where")

Map:

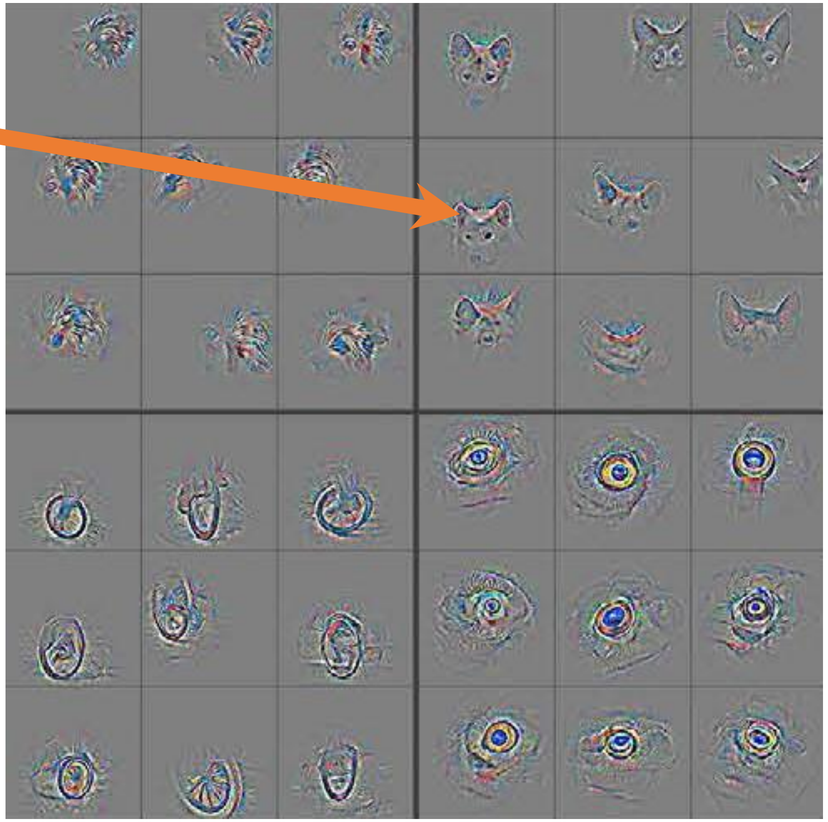
explicitly encoding "where"

Region Proposal from Feature Maps

- By decoding one response at a single pixel, we can still roughly see the object outline*
- Finer localization information has been encoded in the channels of a convolutional feature response
- Extract this information for better localization…

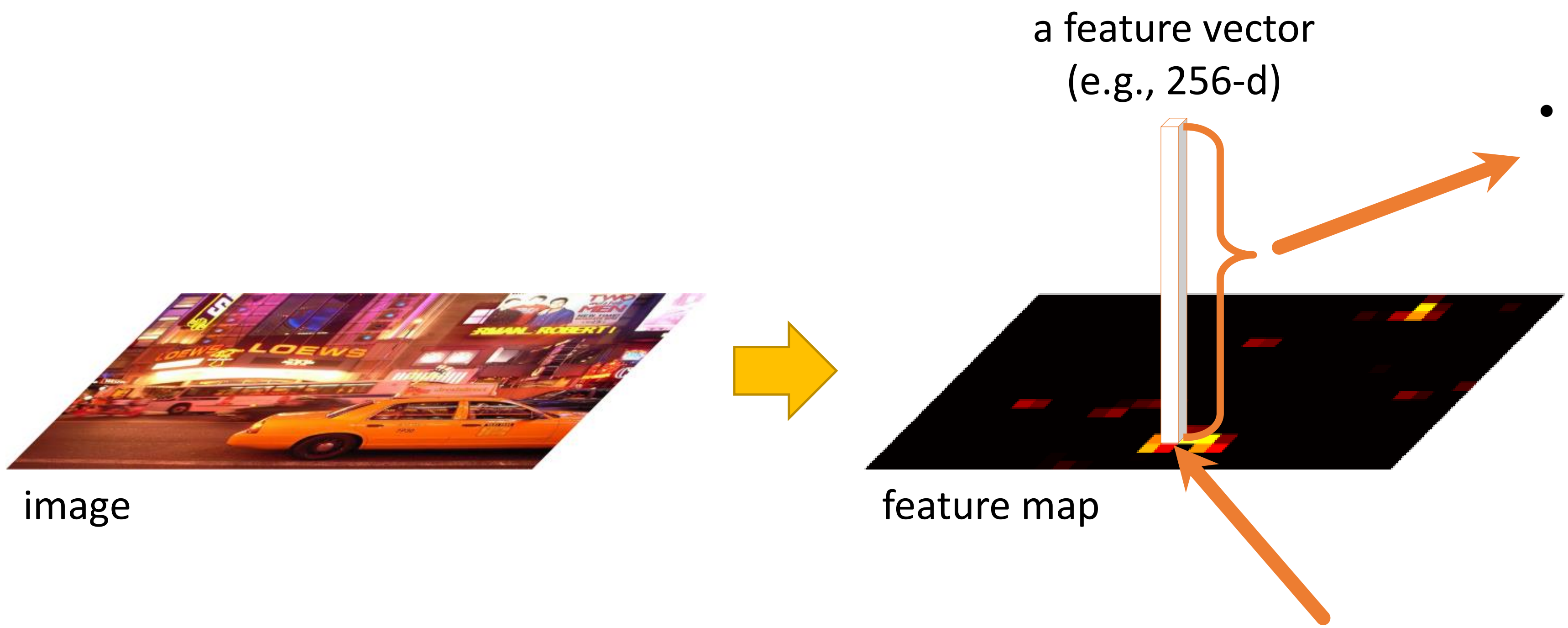
* Zeiler & Fergus's method traces unpooling information so the visualization involves more than a single response. But other visualization methods reveal similar patterns.

Revisiting visualizations from Zeiler & Fergus



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Region Proposal from Feature Maps



- The channels of this feature vector encodes finer localization information

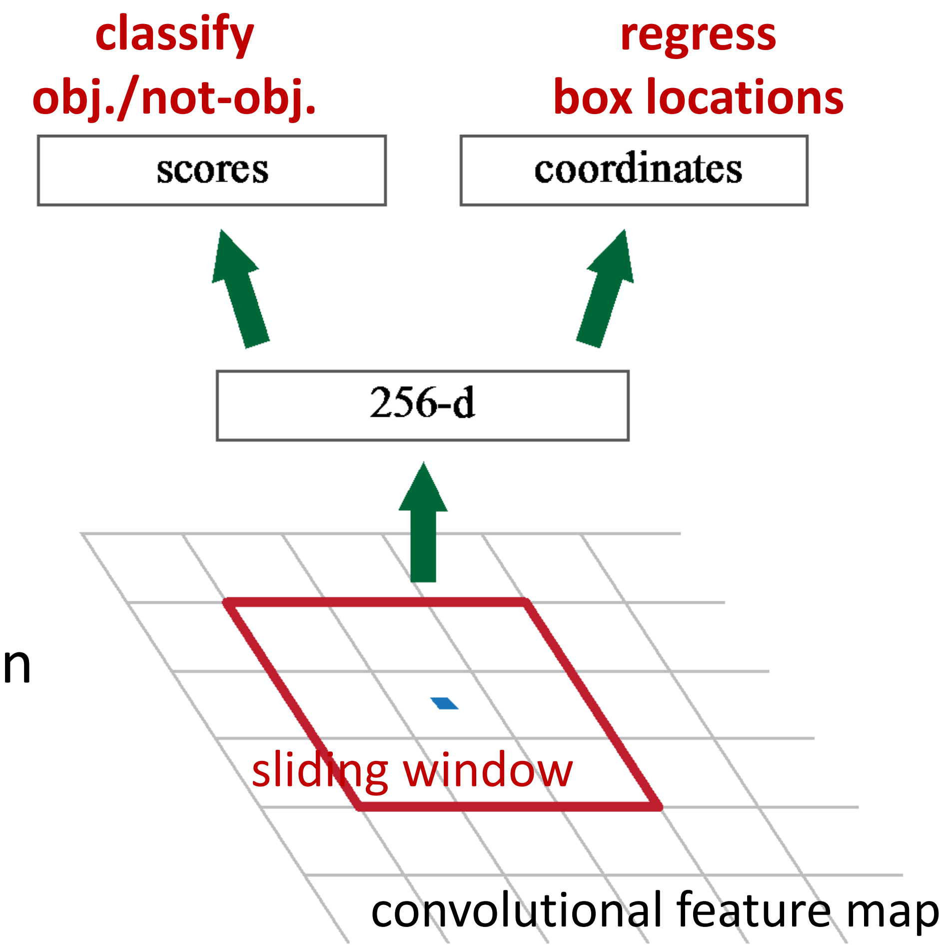
- The spatial position of this feature provides coarse locations

Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.

Region Proposal Network

- Slide a small window on the feature map
- Build a small network for:
  - classifying object or not-object, and
  - regressing bbox locations

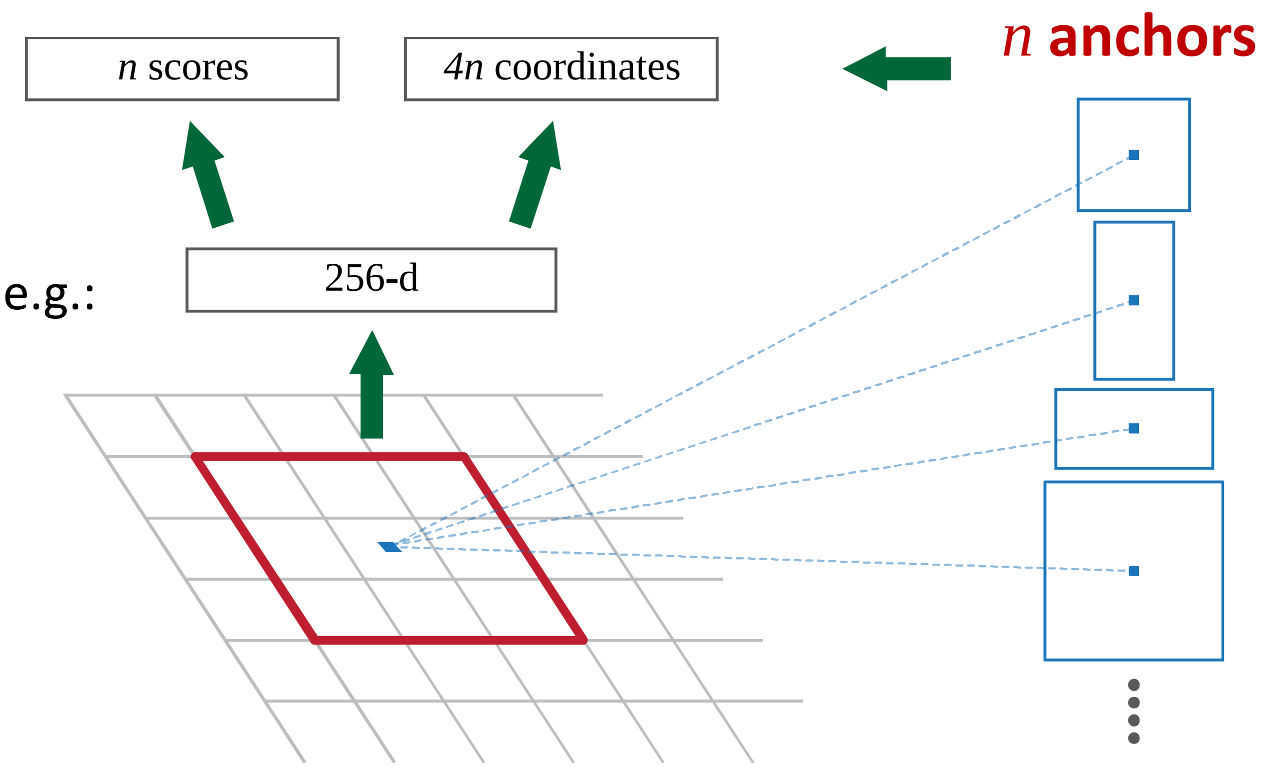
- Position of the sliding window provides localization information with reference to the image
- Box regression provides finer localization information with reference to this sliding window



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.

Anchors as references

- **Anchors**: pre-defined reference boxes
  - Box regression is with reference to anchors:
    regressing an anchor box to a ground-truth box
  - Object probability is with reference to anchors, e.g.:
    - anchors as positive samples: if IoU > 0.7 or IoU is max
    - anchors as negative samples: if IoU < 0.3

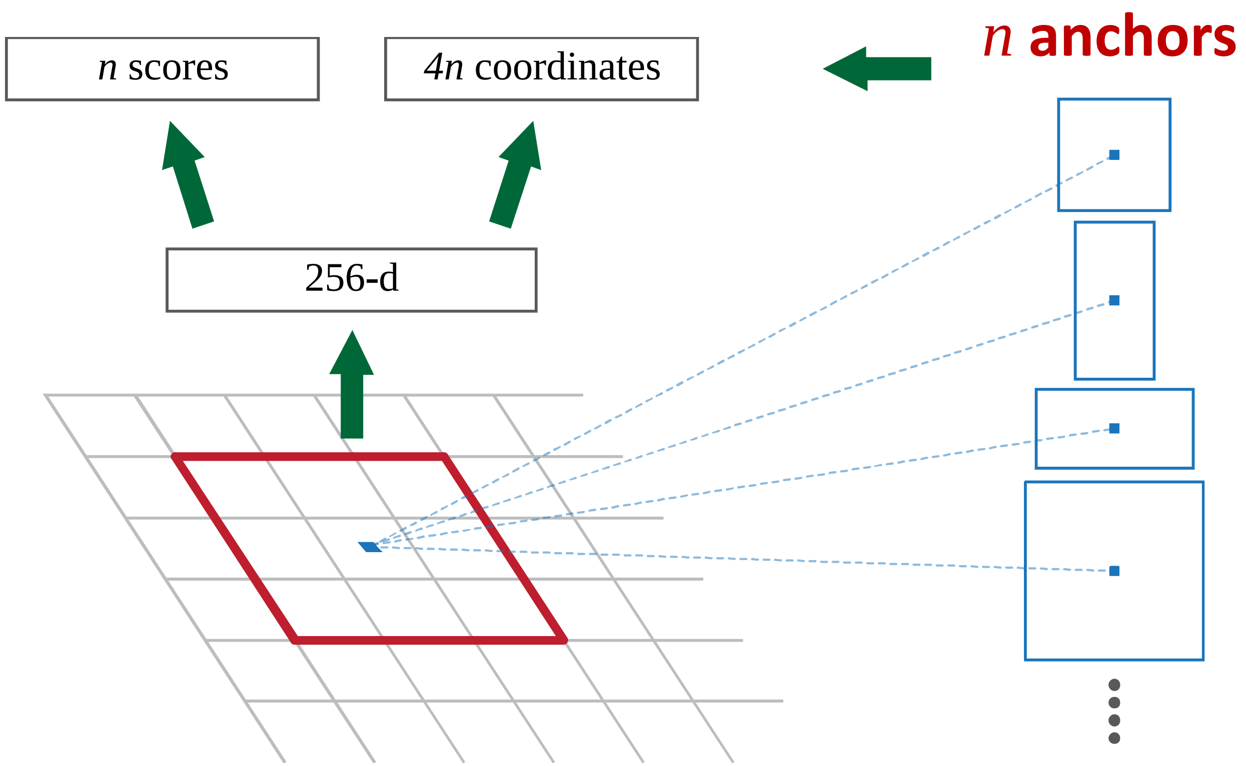


Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Anchors as references

- **Anchors**: pre-defined reference boxes

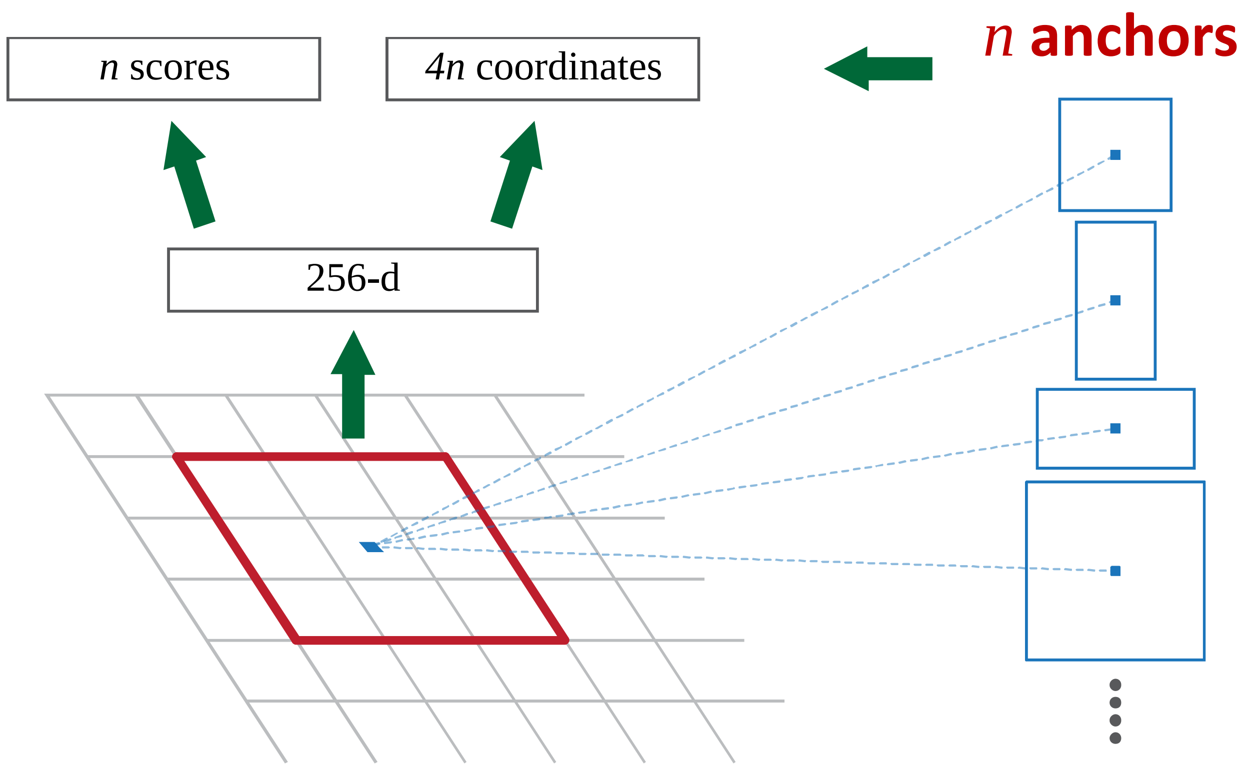
- Translation-invariant anchors:
  - the same set of anchors are used at each sliding position
  - the same prediction functions (with reference to the sliding window) are used
  - a translated object will have a translated prediction



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Anchors as references

- **Anchors**: pre-defined reference boxes
- Multi-scale/size anchors:
  - multiple anchors are used at each position:
    e.g., 3 scales (128^2, 256^2, 512^2) and 3 aspect ratios (2:1, 1:1, 1:2) yield 9 anchors
  - each anchor has its own prediction function
  - single-scale features, multi-scale predictions



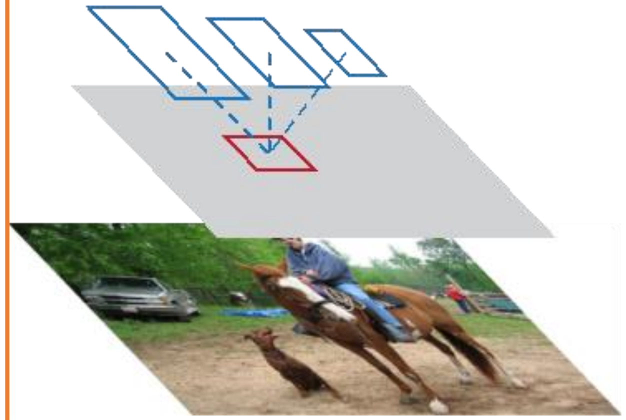
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Anchors as references

- Comparisons of multi-scale strategies

Image/Feature Pyramid

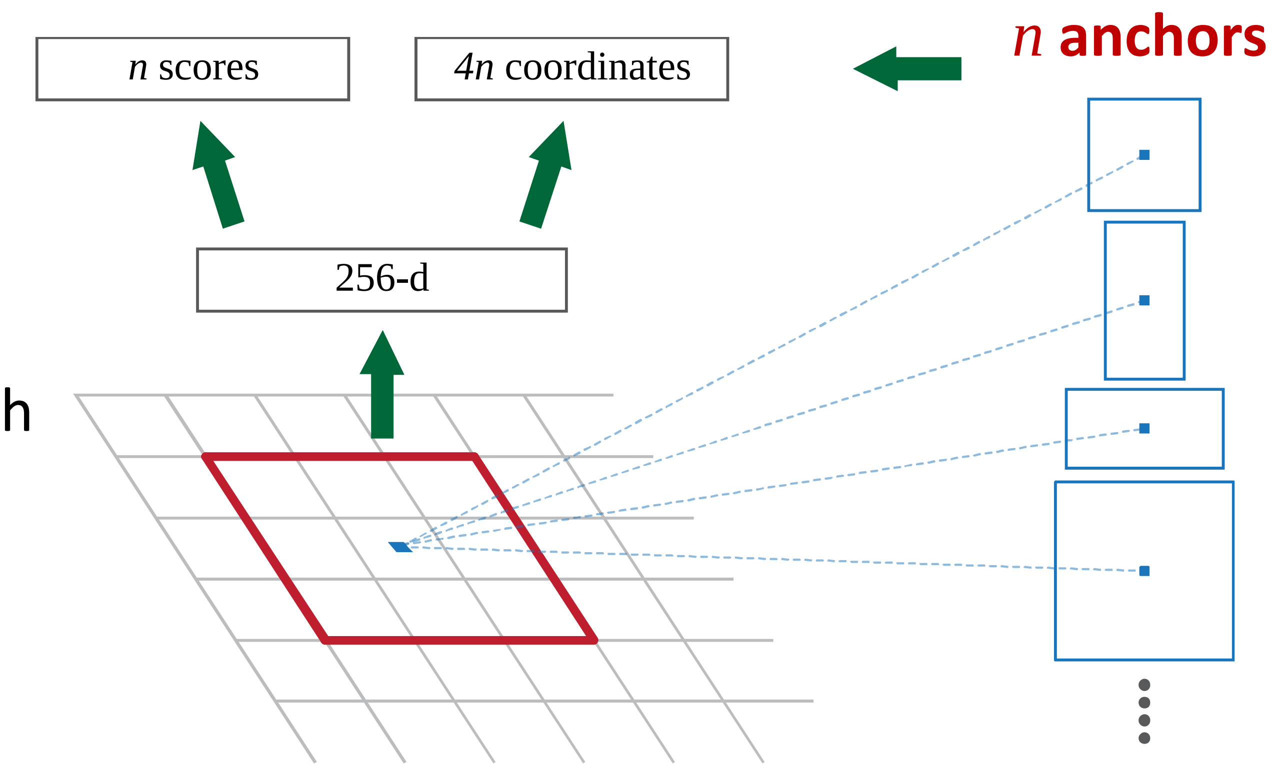
Filter Pyramid



Anchor Pyramid

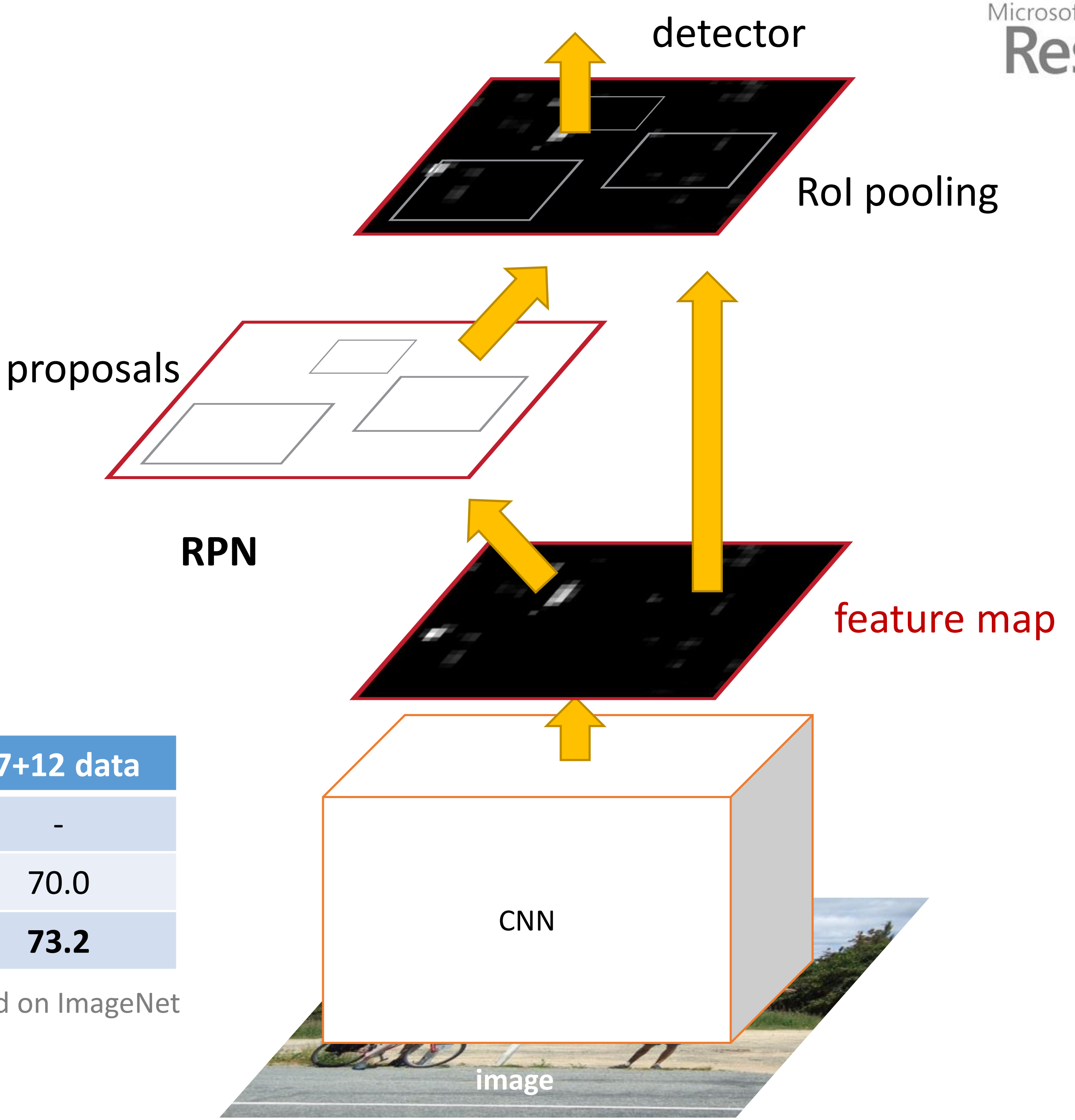
Region Proposal Network

- RPN is fully convolutional [Long et al. 2015]
- RPN is trained end-to-end
- RPN shares convolutional feature maps with the detection network
  (covered in Ross's section)



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Faster R-CNN

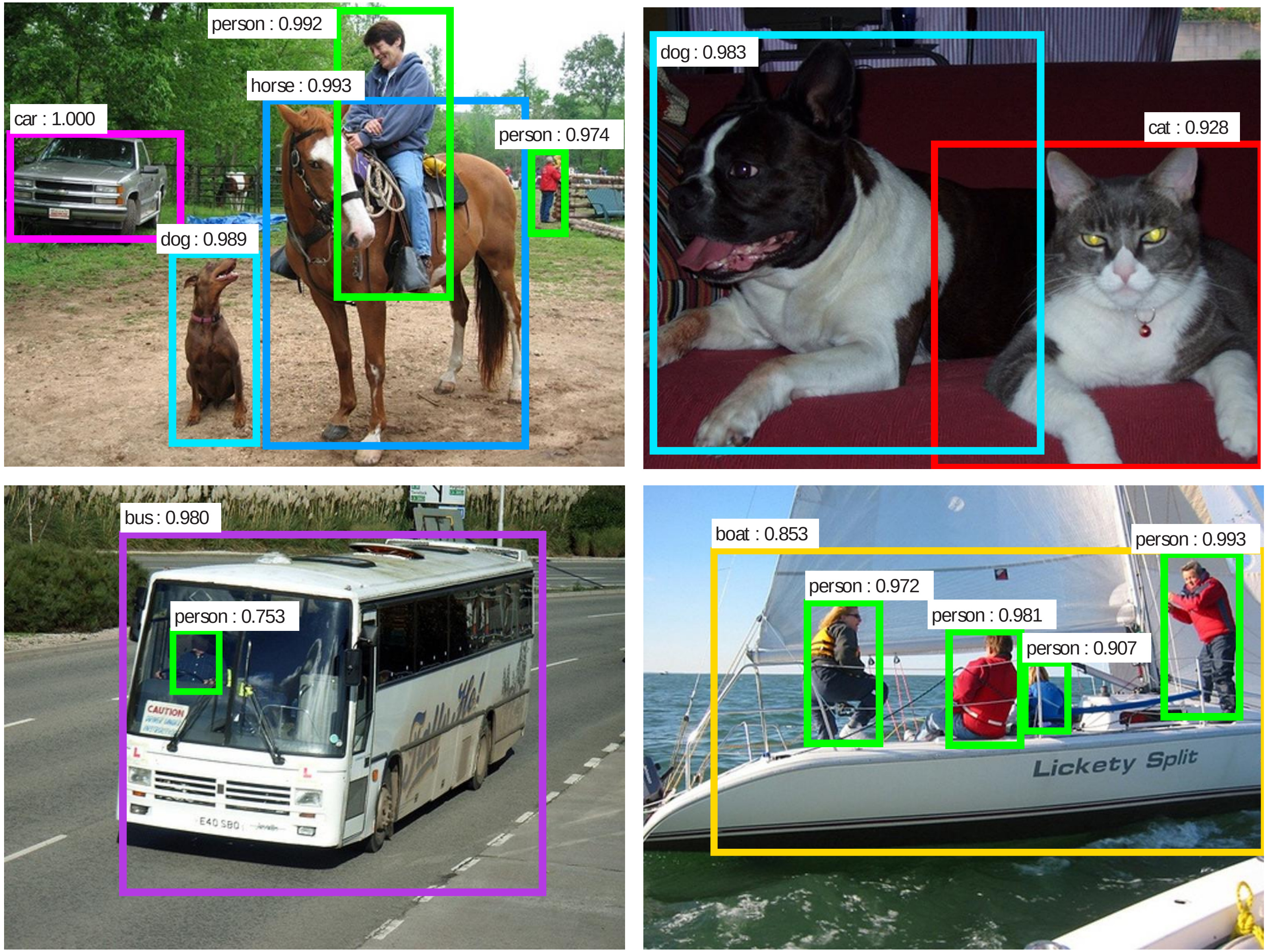


system	time	07 data	07+12 data
R-CNN	~50s	66.0	-
Fast R-CNN	~2s	66.9	70.0
Faster R-CNN	198ms	**69.9**	**73.2**

detection mAP on PASCAL VOC 2007, with VGG-16 pre-trained on ImageNet

Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Example detection results of Faster R-CNN



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.

Keys to efficient CNN-based object detection

- Feature sharing
  - R-CNN => SPP-net & Fast R-CNN: sharing features among proposal regions
  - Fast R-CNN => Faster R-CNN: sharing features between proposal and detection
  - All are done by shared convolutional feature maps

- Efficient multi-scale solutions
  - Single-scale convolutional feature maps are good trade-offs
  - Multi-scale anchors are fast and flexible

Conclusion of this section

- Quick introduction to convolutional feature maps
  - Intuitions: into the "black boxes"
  - How object detection networks & region proposal networks are designed
  - Bridging the gap between "hand-engineered" and deep learning systems

- Focusing on forward propagation (inference)
  - Backward propagation (training) covered by Ross's section