Object Detection

- The goal of object detection is to localize objects in an image and tell their class
- Localization: **place a tight bounding box around object**
- Most approaches find only objects of one or a few specific classes, e.g. car or cow

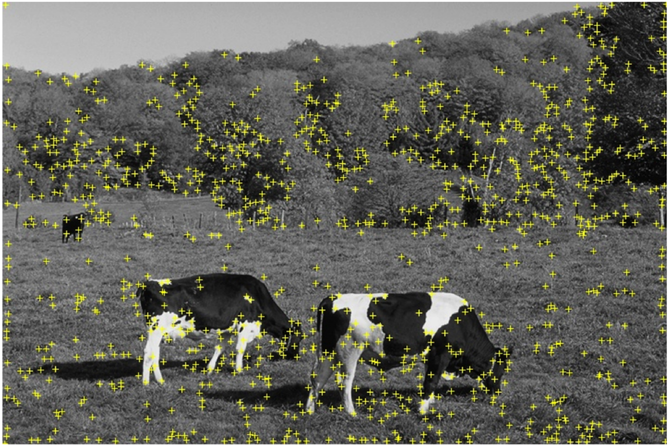
Type of Approaches

Different approaches tackle detection differently. They can roughly be categorized into three main types:

- Find **interest points**, followed by Hough voting

Interest Point Based Approaches

- Compute interest points (e.g., Harris corner detector is a popular choice)
- Vote for where the object could be given the content around interest points



Interest points

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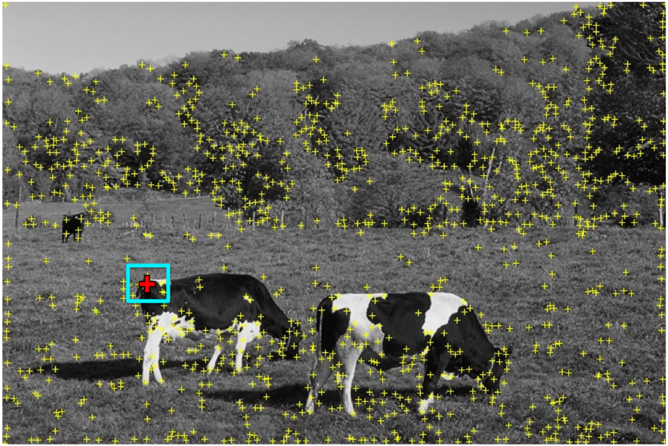

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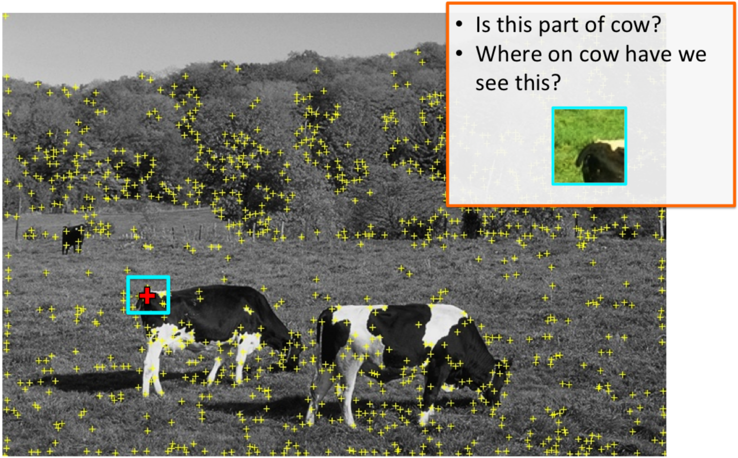

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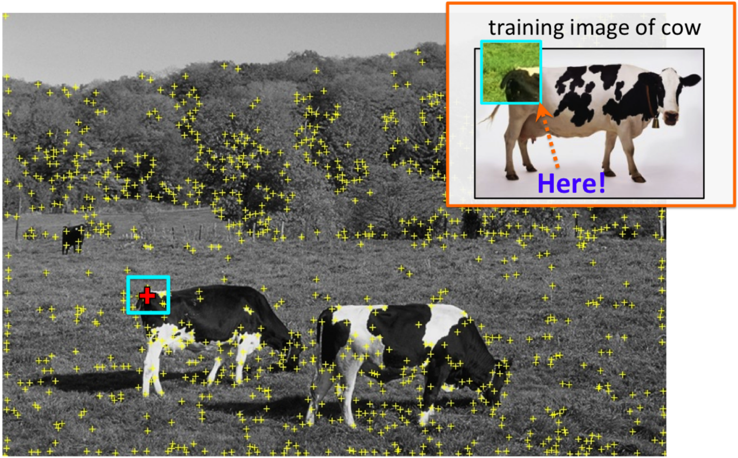

Interest points

Interest Point Based Approaches

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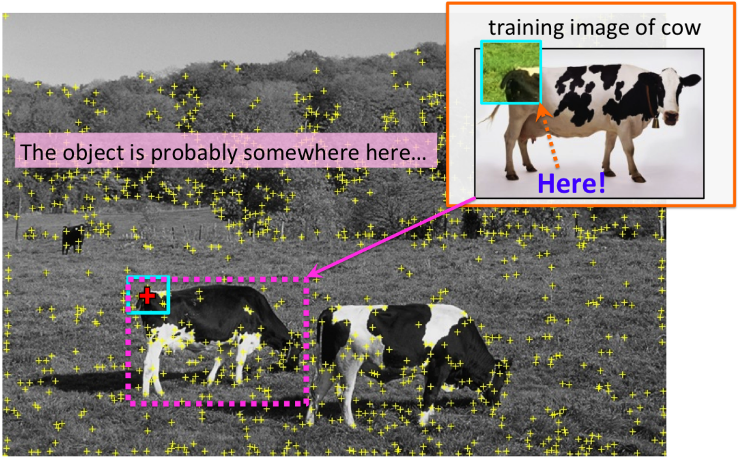

Interest points

Type of Approaches

Different approaches tackle detection differently. They can roughly be categorized into three main types:

- Find **interest points**, followed by Hough voting
- **Sliding windows**: "slide" a box around image and classify each image crop inside a box (contains object or not?)

Sliding Window Approaches

- Slide window and ask a classifier: "Is sheep in window or not?"

0.1
confidence

[Slide: R. Urtasun]

Sliding Window Approaches

- Slide window and ask a classifier: "Is sheep in window or not?"

-0.2

[Slide: R. Urtasun]

Sliding Window Approaches

- Slide window and ask a classifier: "Is sheep in window or not?"

-0.1

[Slide: R. Urtasun]

Sliding Window Approaches

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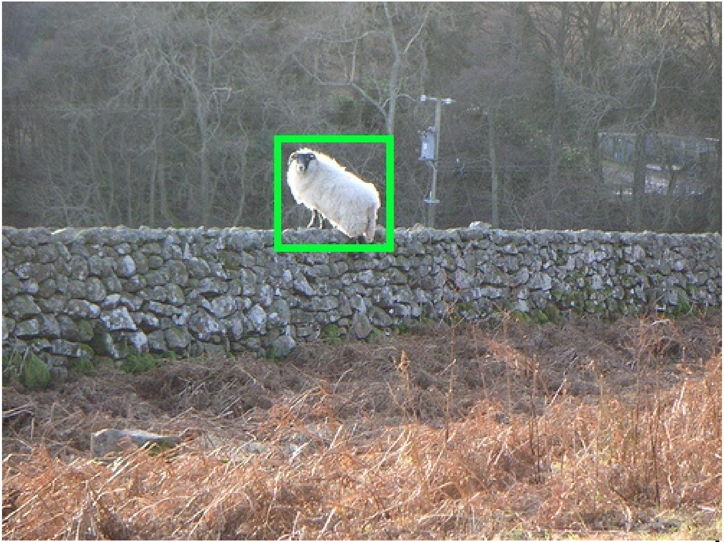


. . .
1.5
. . .

[Slide: R. Urtasun]

Sliding Window Approaches

- Slide window and ask a classifier: "Is sheep in window or not?"

0.5

[Slide: R. Urtasun]

Sliding Window Approaches

- Slide window and ask a classifier: "Is sheep in window or not?"

0.4

[Slide: R. Urtasun]

Sliding Window Approaches

- Slide window and ask a classifier: "Is sheep in window or not?"

0.3

[Slide: R. Urtasun]

Sliding Window Approaches

- Slide window and ask a classifier: "Is sheep in window or not?"

0.1
confidence-
0.2
-0.1
0.1
...
1.5
...
0.5
0.4
0.3

[Slide: R. Urtasun]

Type of Approaches

Different approaches tackle detection differently. They can roughly be categorized into three main types:

- Find **interest points**, followed by Hough voting
- **Sliding windows**: "slide" a box around image and classify each image crop inside a box (contains object or not?)
- Generate **region (object) proposals**, and classify each region

Region Proposal Based Approaches

- Group pixels into object-like regions

Region Proposal Based Approaches

- Group pixels into object-like regions

Region Proposal Based Approaches

- Group pixels into object-like regions

Region Proposal Based Approaches

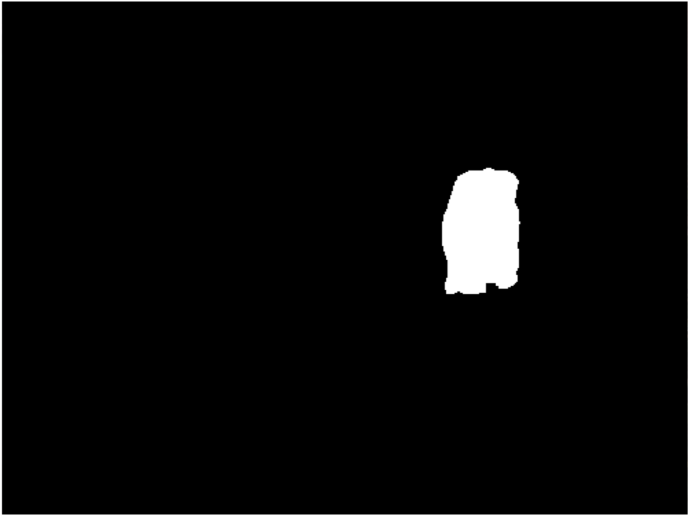
- Generate **many** different regions

Region Proposal Based Approaches

- Generate **many** different regions

Region Proposal Based Approaches

- Generate **many** different regions



Region Proposal Based Approaches

- The hope is that at least a few will cover real objects

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Region Proposal Based Approaches

- Select a region

Region Proposal Based Approaches

- Crop out an image patch around it, throw to classifier (e.g., Neural Net)

classifier
``dog'' or not?

confidence: -2.5

Region Proposal Based Approaches

- Do this for every region

Region Proposal Based Approaches

- Do this for every region

Region Proposal Based Approaches

- Do this for every region

classifier
``dog'' or not?

confidence: 1.5

Dog!!!

Type of Approaches

Different approaches tackle detection differently. They can roughly be categorized into three main types:

- Find **interest points**, followed by Hough voting $\leftarrow$ **Let's first look at one example method for this**
- **Sliding windows**: "slide" a box around image and classify each image crop inside a box (contains object or not?)
- Generate **region (object) proposals**, and classify each region

Object Detection via Hough Voting:

Implicit Shape Model

B. Leibe, A. Leonardis, B. Schiele

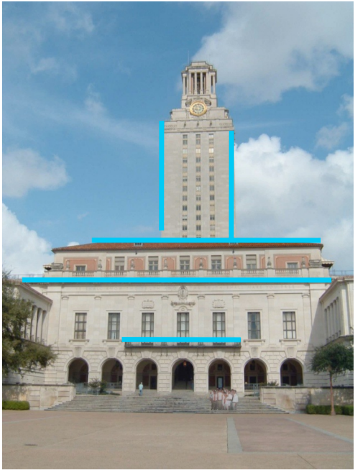
Robust Object Detection with Interleaved Categorization and Segmentation

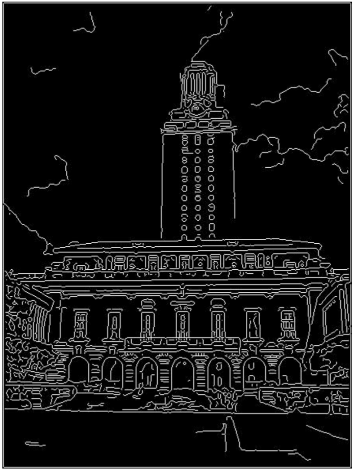
IJCV, 2008

Paper: http://www.vision.rwth-aachen.de/publications/pdf/leibe-interleaved-ijcv07final.pdf

Start with Simple: Line Detection

- How can I find lines in this image?





[Source: K. Grauman]

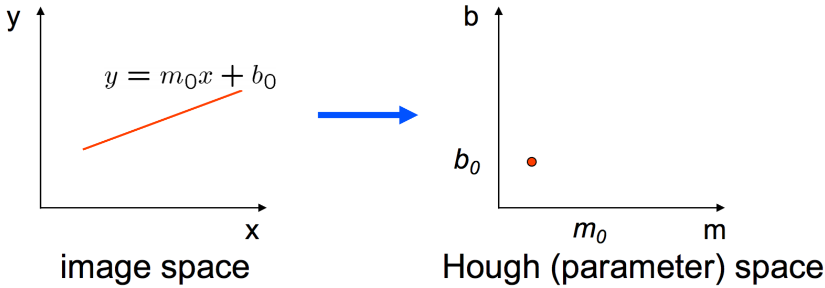
Hough Transform

- Idea: Voting (Hough Transform)
- Voting is a general technique where we let the features vote for all models that are compatible with it.
  - Cycle through features, cast votes for model parameters.
  - Look for model parameters that receive a lot of votes.

[Source: K. Grauman]

Hough Transform: Line Detection

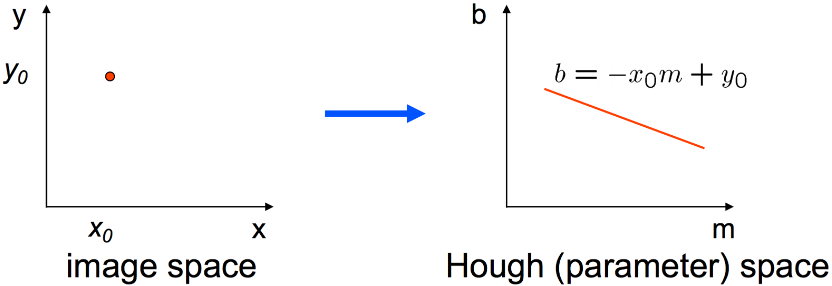
- Hough space: parameter space



- Connection between image (x, y) and Hough (m, b) spaces
  - A line in the image corresponds to a point in Hough space
  - What does a point (x_0, y_0) in the image space map to in Hough space?

[Source: S. Seitz]

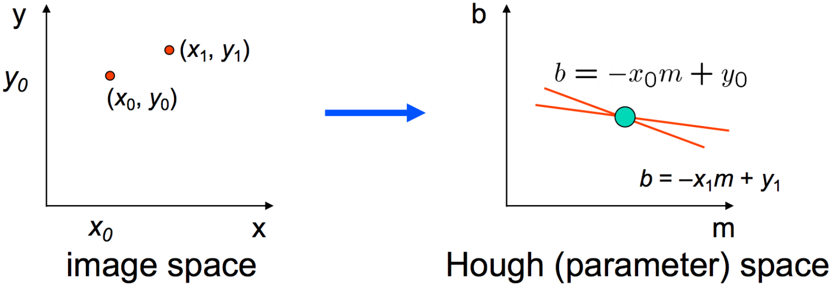
- Hough space: parameter space



- Connection between image (x, y) and Hough (m, b) spaces
  - A line in the image corresponds to a point in Hough space
  - A point in image space votes for all the lines that go through this point. This votes are a line in the Hough space.

[Source: S. Seitz]

- Hough space: parameter space

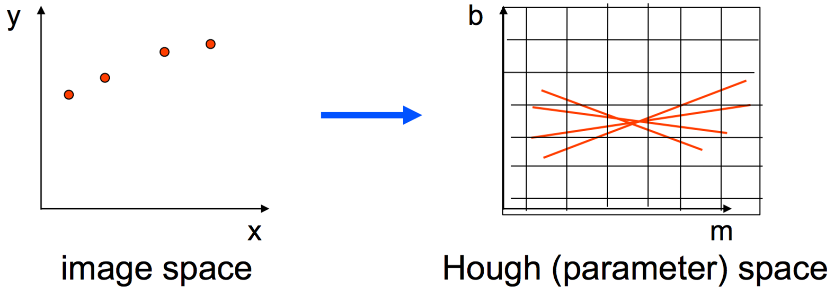


- Two points: Each point corresponds to a line in the Hough space
- A point where these two lines meet defines a line in the image!

[Source: S. Seitz]

Hough Transform: Line Detection

- Hough space: parameter space

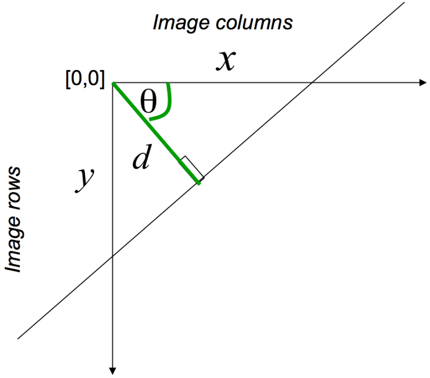


- Vote with each image point
- Find peaks in Hough space. Each peak is a line in the image.

[Source: S. Seitz]

Hough Transform: Line Detection

- Issues with usual (m, b) parameter space: undefined for vertical lines
- A better representation is a polar representation of lines



d: perpendicular distance from line to origin

θ: angle the perpendicular makes with the x-axis

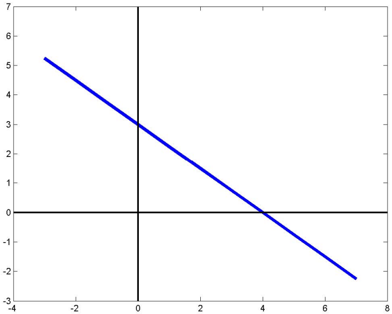
$$x \cos\theta - y \sin\theta = d$$

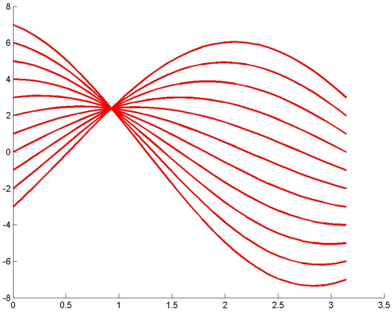
Point in image space → sinusoid segment in Hough space

[Source: S. Seitz]

With the parameterization $x \cos\theta + y \sin\theta = d$

- Points in picture represent sinusoids in parameter space
- Points in parameter space represent lines in picture
- Example $0.6x + 0.4y = 2.4$, Sinusoids intersect at $d = 2.4$, $\theta = 0.9273$





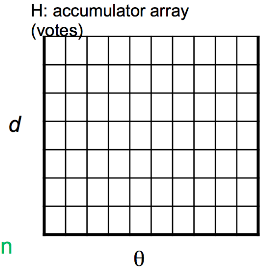
[Source: M. Kazhdan, slide credit: R. Urtasun]

Hough Transform: Line Detection

- **Hough Voting algorithm**

Using the polar parameterization:

$$x\cos\theta - y\sin\theta = d$$



Basic Hough transform algorithm

1. Initialize H[d, θ]=0
2. for each edge point I[x,y] in the image

   for $\theta = [\theta_{min}$ to $\theta_{max}]$ // some quantization

   $$d = x\cos\theta - y\sin\theta$$

   H[d, θ] += 1
3. Find the value(s) of (d, θ) where H[d, θ] is maximum
4. The detected line in the image is given by $d = x\cos\theta - y\sin\theta$

[Source: S. Seitz]

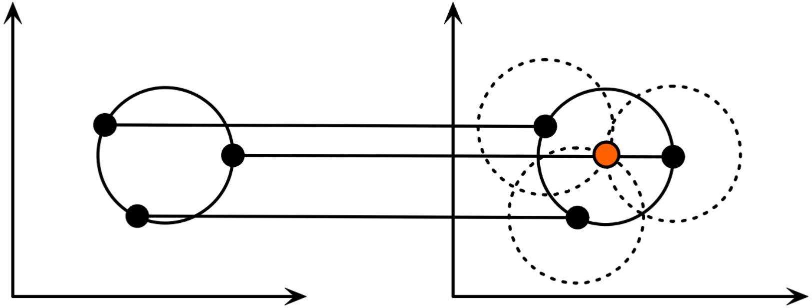
Hough Transform: Circle Detection

- What about circles? How can I fit circles around these coins?

Hough Transform: Circle Detection

Assume we are looking for a circle of known radius r

- Circle: $(x - a)^2 + (y - b)^2 = r^2$
- Hough space (a, b): A point (x_0, y_0) maps to $(a - x_0)^2 + (b - y_0)^2 = r^2 \;\rightarrow\;$ a circle around (x_0, y_0) with radius r
- Each image point votes for a circle in Hough space



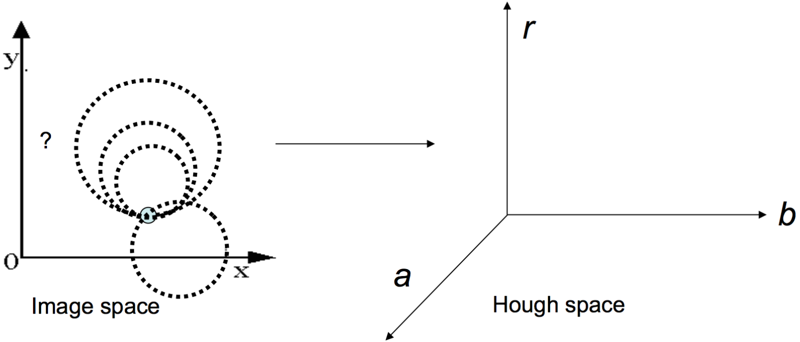
Each point in geometric space (left) generates a circle in parameter space (right). The circles in parameter space intersect at the (a, b) that is the center in geometric space.

[Source: H. Rhody]

Hough Transform: Circle Detection

What if we don't know r?

- Hough space: ?

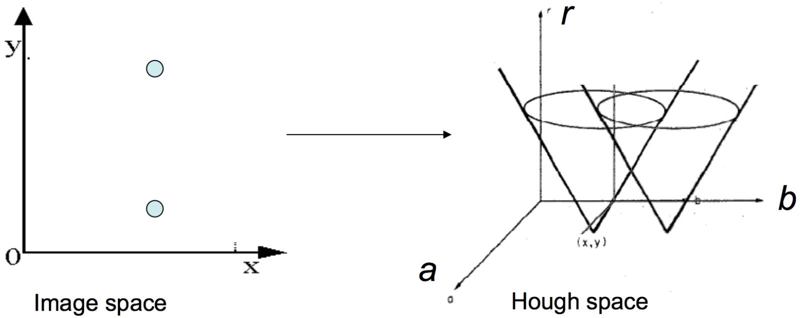


[Source: K. Grauman]

Hough Transform: Circle Detection

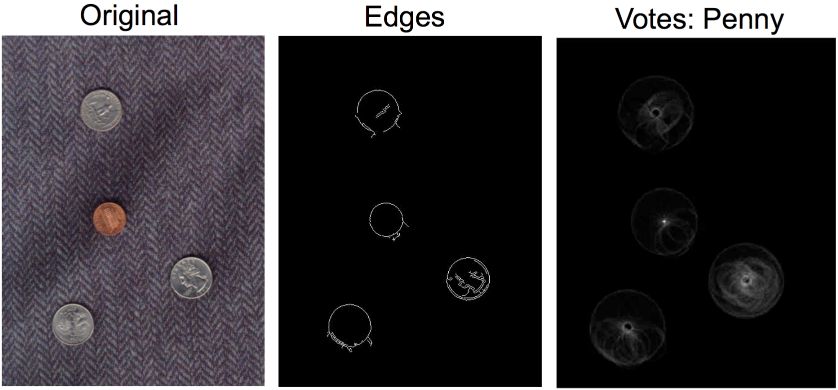
What if we don't know r?

- Hough space: conics



[Source: K. Grauman]

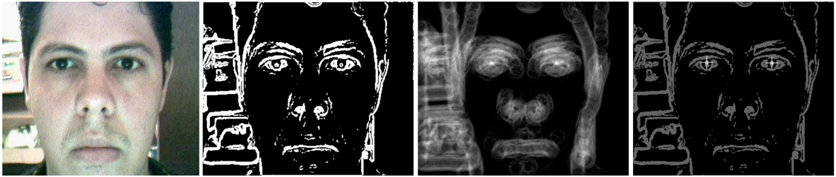
- Find the coins



[Source: K. Grauman]

Hough Transform: Circle Detection

- Iris detection

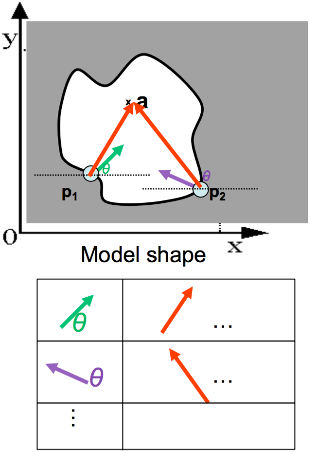


Gradient+threshold | Hough space (fixed radius) | Max detections

[Source: K. Grauman]

Generalized Hough Voting

- Hough Voting for general shapes



Offline procedure:

At each boundary point, compute displacement vector: $\mathbf{r} = \mathbf{a} - \mathbf{p}_i$.

Store these vectors in a table indexed by gradient orientation θ.

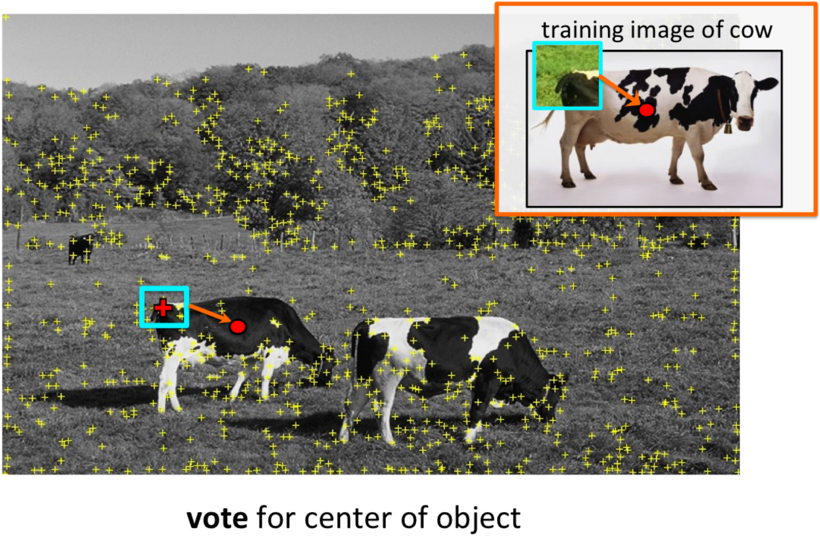
Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980

Implicit Shape Model

- Implicit Shape Model adopts the idea of voting
- Basic idea:
  - Find interest points in an image
  - Match patch around each interest point to a training patch
  - Vote for object center given that training instance

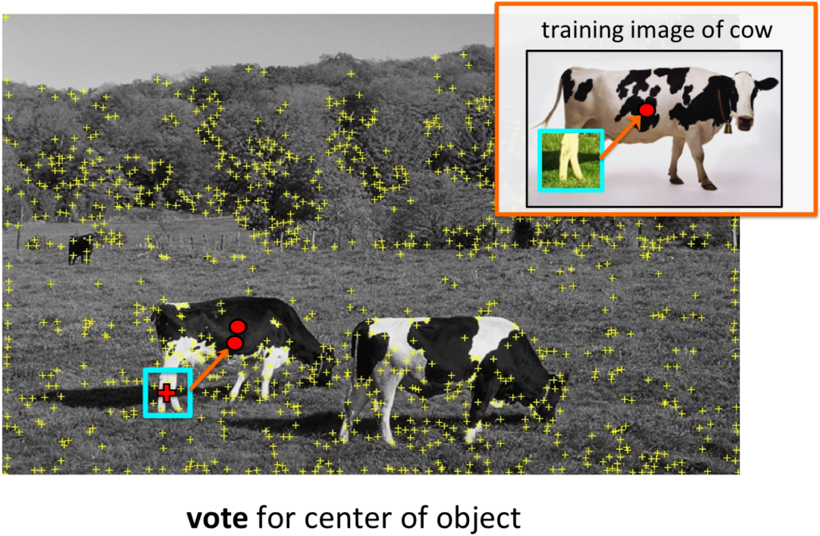
Implicit Shape Model: Basic Idea

- Vote for object center



Implicit Shape Model: Basic Idea

- Vote for object center



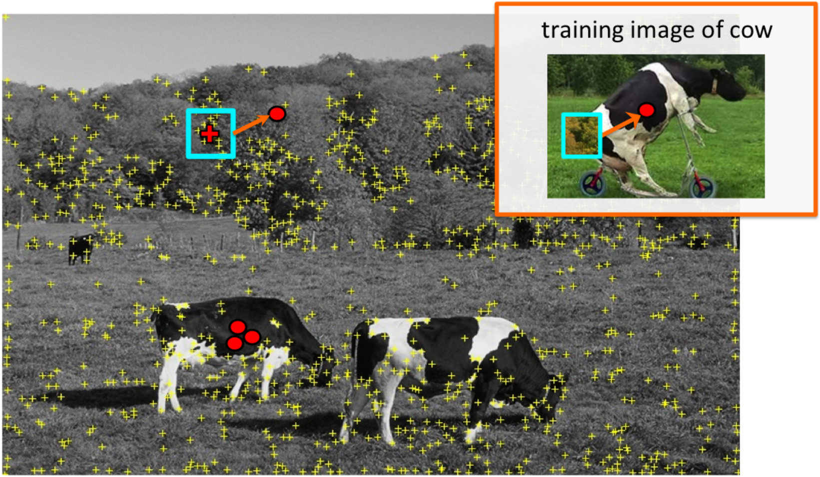
Implicit Shape Model: Basic Idea

- Vote for object center

vote for center of object

Implicit Shape Model: Basic Idea

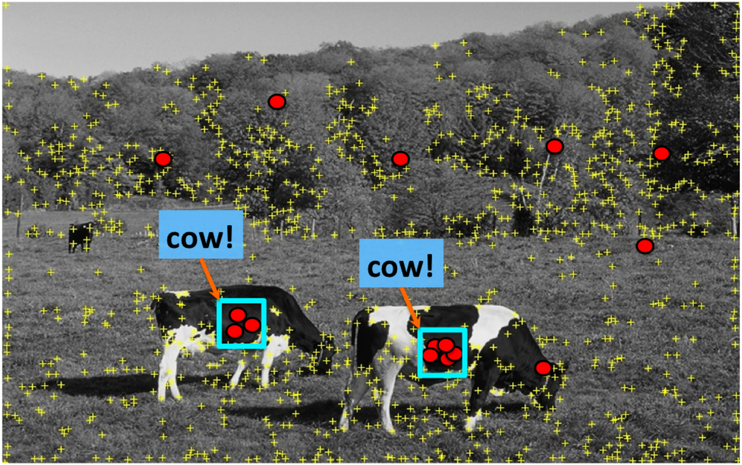
- Vote for object center



of course some wrong votes are bound to happen...

Implicit Shape Model: Basic Idea

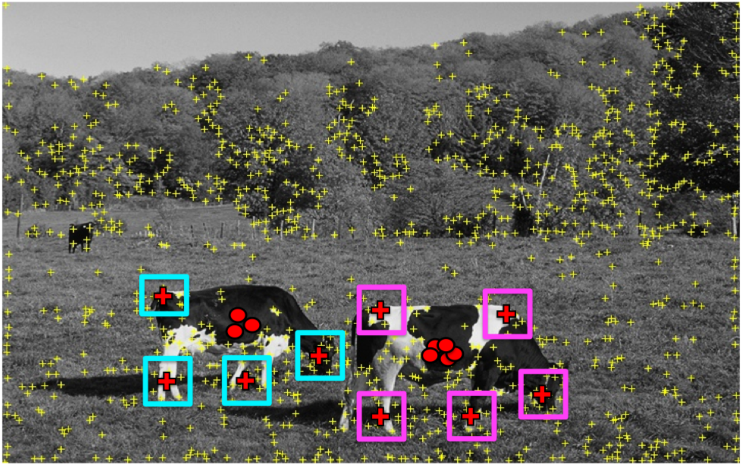
- Vote for object center



But that's ok. We want only **peaks** in voting space.

Implicit Shape Model: Basic Idea

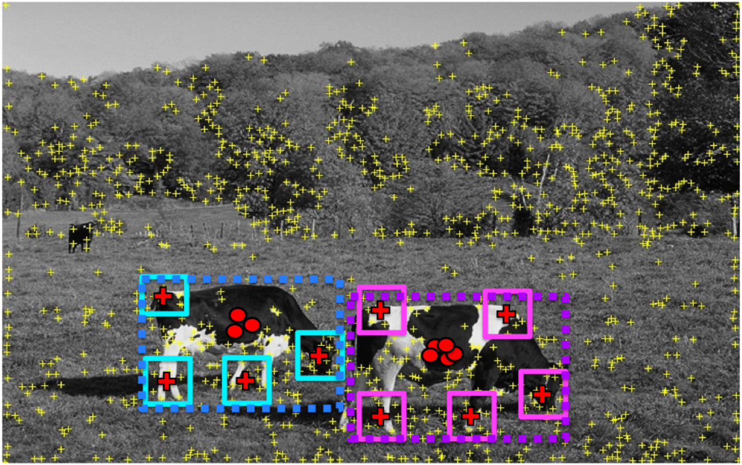
- Find the patches that produced the peak



Find patches that voted for the peaks (back-projection).

Implicit Shape Model: Basic Idea

- Place a box around these patches $\rightarrow$ objects!



Find full objects based on the back-projected patches.

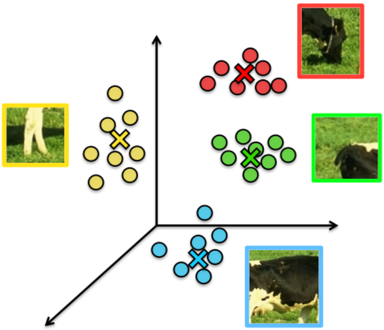
Implicit Shape Model: Basic Idea

- Really easy. Only one problem... Would be slow... How do we make it fast?

we need to match a patch around each yellow + to all patches in all training images $\rightarrow$ **SLOW**

Implicit Shape Model: Basic Idea

- **Visual vocabulary** (we saw this for retrieval)
- Compare each patch to a small set of visual words (clusters)



Visual words (visual codebook)!

Implicit Shape Model: Basic Idea

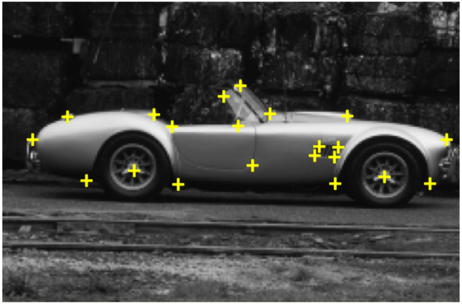
- Training: Getting the vocabulary

training image

Implicit Shape Model: Basic Idea

- Find interest points in each training image

training image

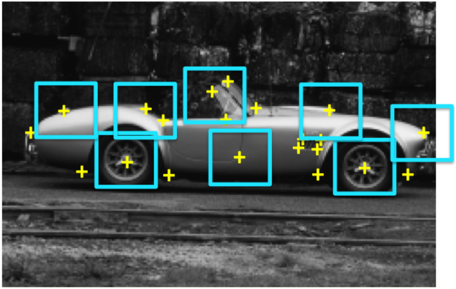


detect interest points (e.g. Harris)

Implicit Shape Model: Basic Idea

- Collect patches around each interest point

training image

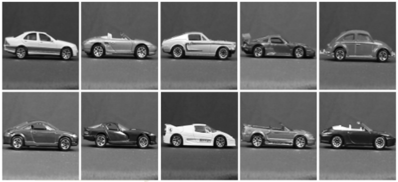


extract an image patch around each interest point

Implicit Shape Model: Basic Idea

- Collect patches across all training examples

training images

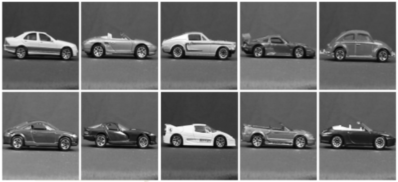


collect all patches

Implicit Shape Model: Basic Idea

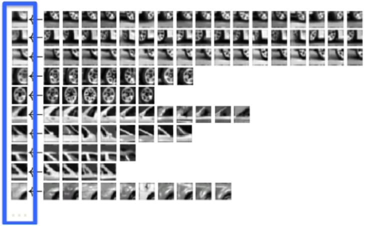
- Cluster the patches to get a small set of "representative" patches

training images



collect all patches

visual codebook

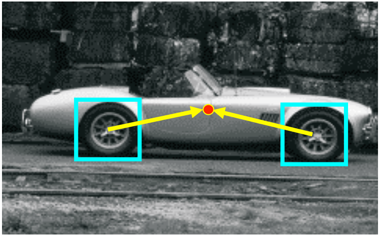


clusters

- cluster the patches to get a few ``representative'' patches
- each cluster represented as the average of all patches that belong to the cluster

Implicit Shape Model: Training

- Represent each training patch with the closest visual word.
- Record the displacement vectors for each word across all training examples.



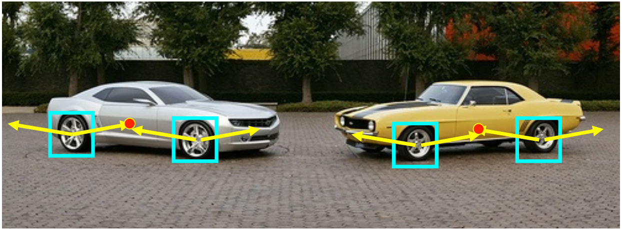
Training image

Visual codeword with displacement vectors

[Leibe et al. IJCV 2008]

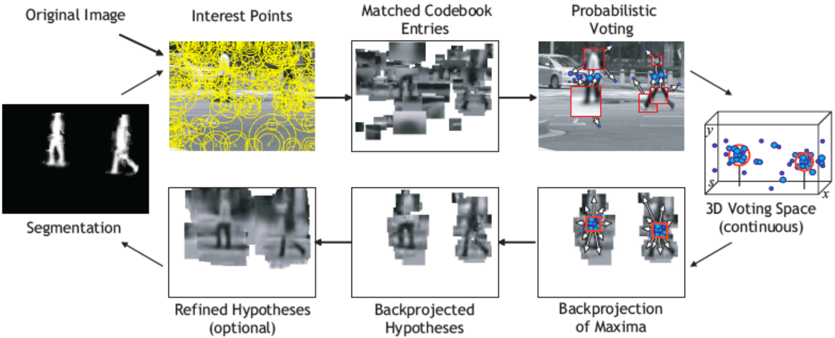
Implicit Shape Model: Test

- At test times detect interest points
- Assign each patch around interest point to closes visual word
- Vote with all displacement vectors for that word



[Source: B. Leibe]

Recognition Pipeline



[Source: B. Leibe]

Recognition Summary

- Apply interest points and extract features around selected locations.
- Match those to the codebook.
- Collect consistent configurations using Generalized Hough Transform.
- Each entry votes for a set of possible positions and scales in continuous space.
- Extract maxima in the continuous space using Mean Shift.
- Refinement can be done by sampling more local features.

[Source: R. Urtasun]

Example

Original image

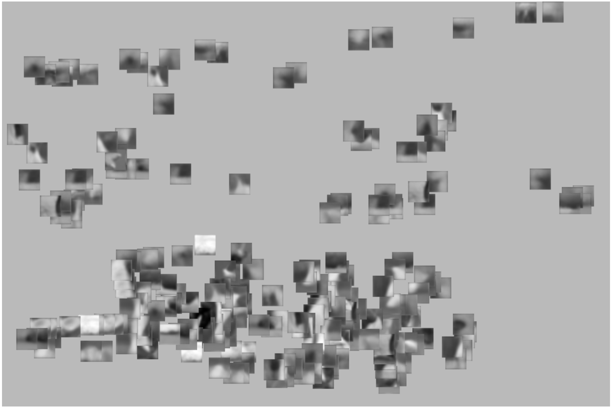
[Source: B. Leibe, credit: R. Urtasun]

Example

Interest points

[Source: B. Leibe, credit: R. Urtasun]

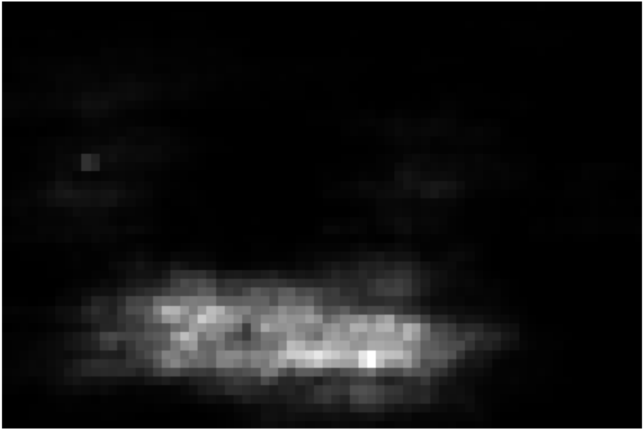
Example



Matched patches

[Source: B. Leibe, credit: R. Urtasun]

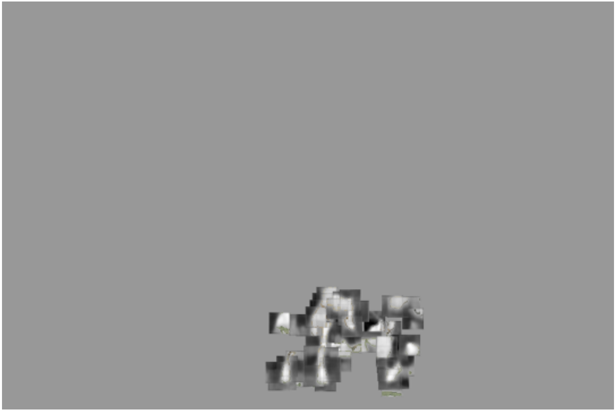
Example



Voting space

[Source: B. Leibe, credit: R. Urtasun]

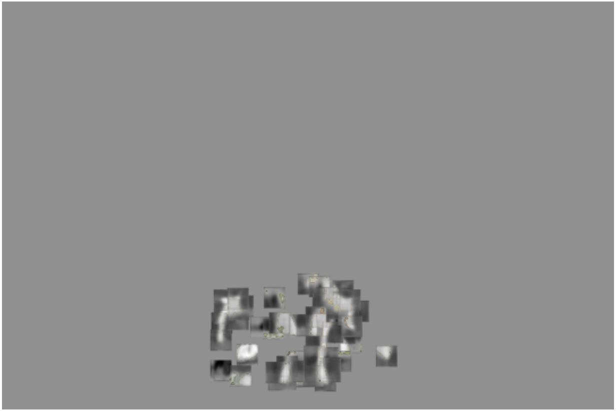
Example



1st hypothesis

[Source: B. Leibe, credit: R. Urtasun]

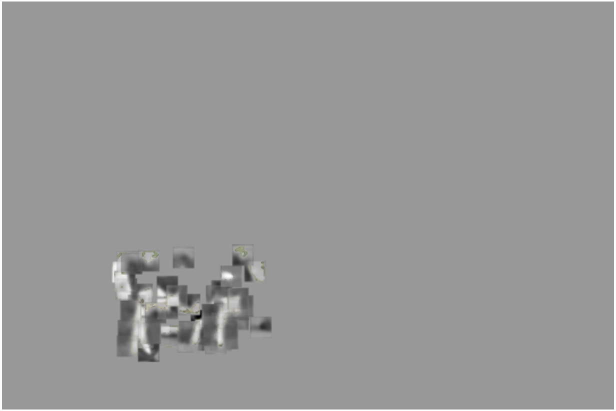
Example



2nd hypothesis

[Source: B. Leibe, credit: R. Urtasun]

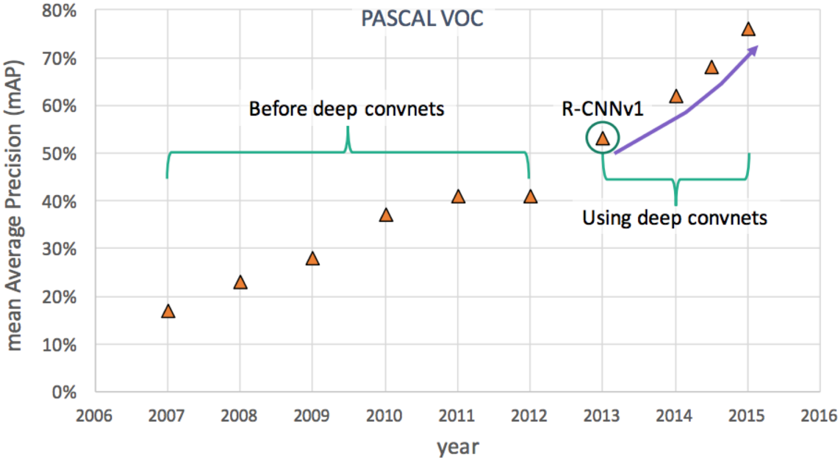
Example



3rd hypothesis

[Source: B. Leibe, credit: R. Urtasun]

The CNN Era



[Slide credit: Renjie Liao]

Deep Object Detection

Object Detection

Published: 09 Oct 2015 Category: deep_learning

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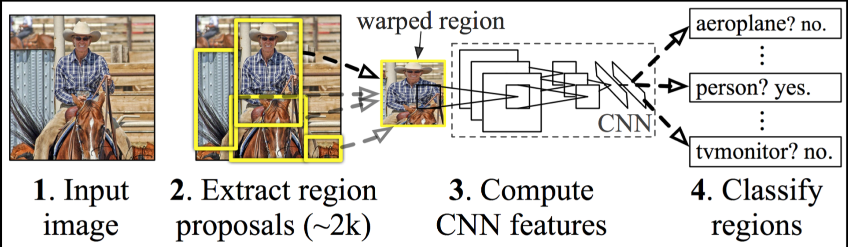
- DSSD

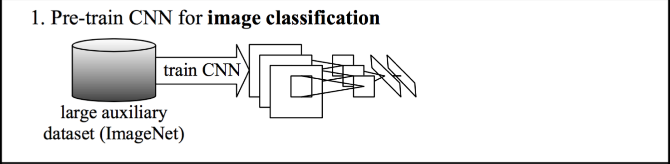
https://handong1587.github.io/deep_learning/2015/10/09/object-detection.html

RCNN: Regions with CNN Features

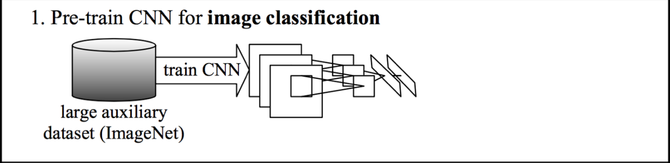


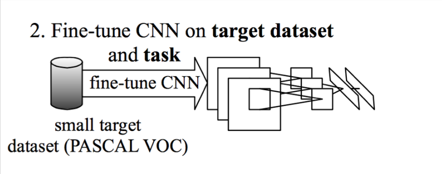
[Slide credit: Ross Girshick]

Training


1. Pre-train CNN for **image classification**
train CNN
large auxiliary
dataset (ImageNet)

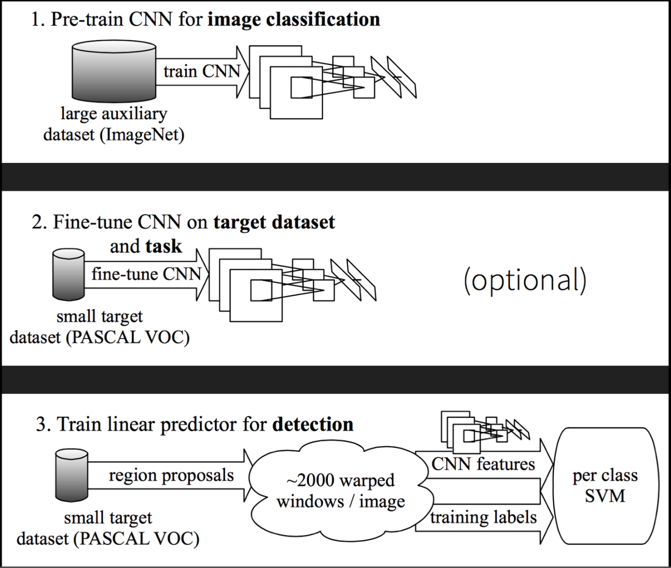
Training





(optional)

Training



(optional)

RCNN: Performance

	VOC2007
DPM v5 (Girshick et al. 2011)	33.7%
Regionlets (Wang et al. 2013)	41.7%
R-CNN (AlexNet)	54.2%
R-CNN (AlexNet) + BB	58.5%
R-CNN (VGGNet)	62.2%
R-CNN (VGGNet) + BB	66.0%

RCNN: Performance

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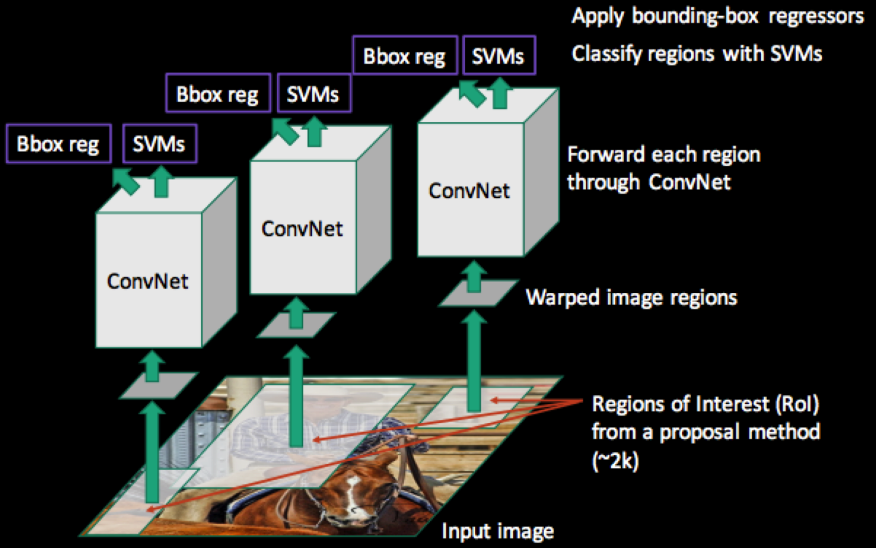
R-CNN (VGGNet)	62.2%
R-CNN (VGGNet) + BB	66.0%

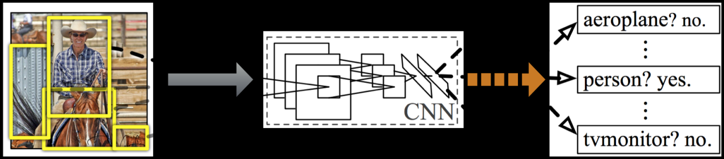
R-CNN (VGGNet)	Time
Train	84 hours
Test	47 s/im

RCNN Pipeline



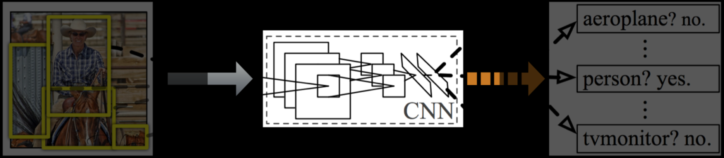
[Slide credit: Ross Girshick]

Object Detection



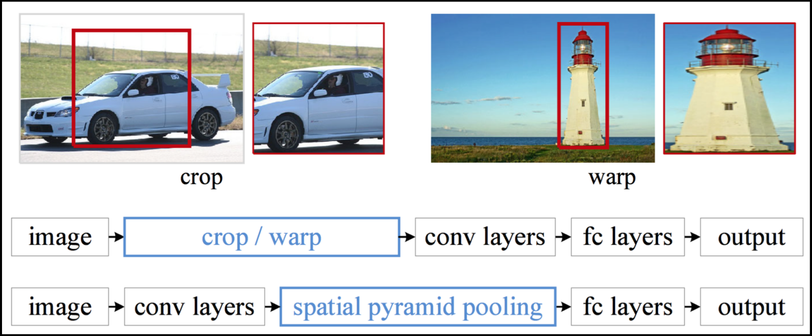
Getting Proposals Feature Extraction Classifier

Object Detection



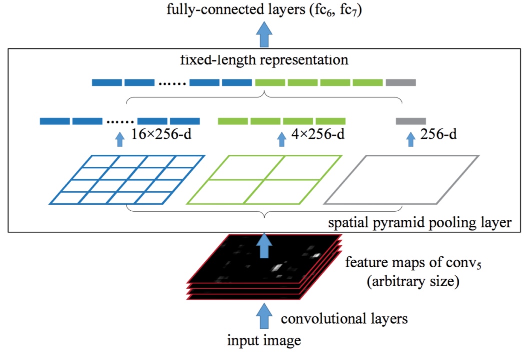
Getting Proposals **Feature Extraction** Classifier

Spatial Pyramid Pooling



Slide credit: K. He, et al. Spatial pyramid pooling in deep convolutional networks for visual recognition. ECCV2014

Spatial Pyramid Pooling

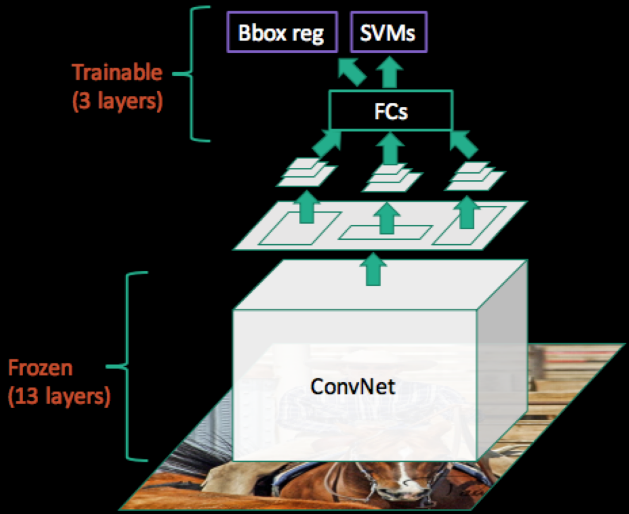



```
[pool3x3]        [pool2x2]        [pool1x1]
type=pool        type=pool        type=pool
pool=max         pool=max         pool=max
inputs=conv5     inputs=conv5     inputs=conv5
sizeX=5          sizeX=7          sizeX=13
stride=4         stride=6         stride=13

[fc6]
type=fc
outputs=4096
inputs=pool3x3,pool2x2,pool1x1
```

Slide credit: K. He, et al. Spatial pyramid pooling in deep convolutional networks for visual recognition. ECCV2014

SPP-Net

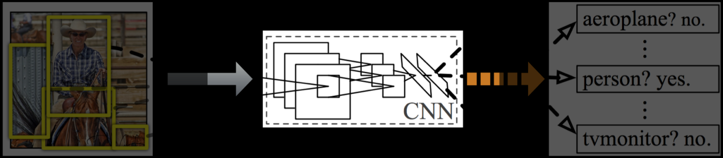


[Slide credit: Ross Girshick]

SPP-Net: Performance

	VOC2007	Speed
R-CNN (ZFNet)	59.2%	14.5 s/im
R-CNN (VGGNet)	66.0%	47.0 s/im
SPP (ZFNet)	59.2%	0.38 s/im
SPP (VGGNet)	63.1%	2.3 s/im

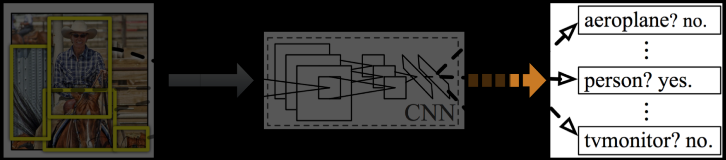
Object Detection



Getting Proposals **Feature Extraction** Classifier

SPP

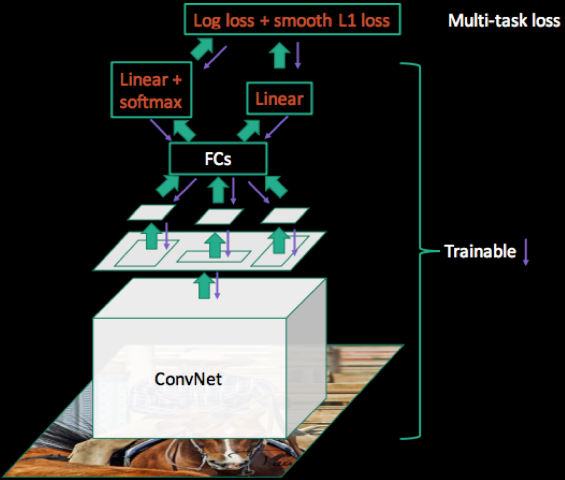
Object Detection



Getting Proposals Feature Extraction **Classifier**

Fast R-CNN

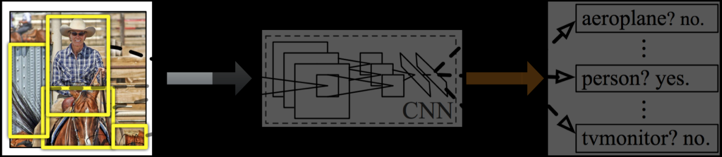
Totally end-to-end!



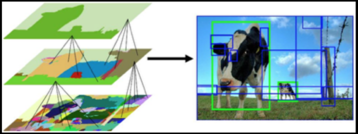
Fast R-CNN: Performance

	VOC2007
SPPNet BB	63.1%
R-CNN BB	66.0%
Fast RCNN	66.9%
Fast RCNN (07+12)	70.0%

Object Detection

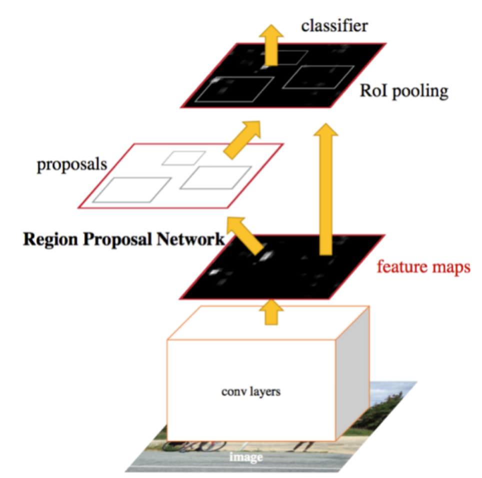


Getting Proposals Feature Extraction Classifier



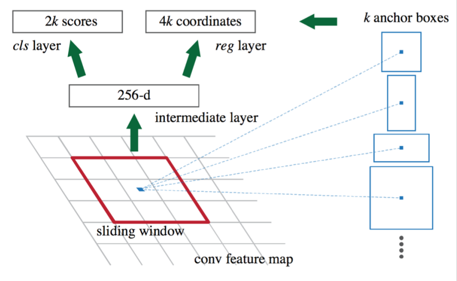
(e.g. selective search)

Faster R-CNN



Ren S, et al. Faster r-cnn: Towards real-time object detection with region proposal networks. NIPS2015

Region Proposal Network (RPN)



- Sliding window style
- Multi-scale predictions on fix-sized window for efficiency (take advantage of the large receptive field of CNN features)
- Same loss as R-CNN (cls+bbox)

anchor	128^2, 2:1	128^2, 1:1	128^2, 1:2	256^2, 2:1	256^2, 1:1	256^2, 1:2	512^2, 2:1	512^2, 1:1	512^2, 1:2
proposal	188×111	113×114	70×92	416×229	261×284	174×332	768×437	499×501	355×715

Region Proposal Network (RPN)

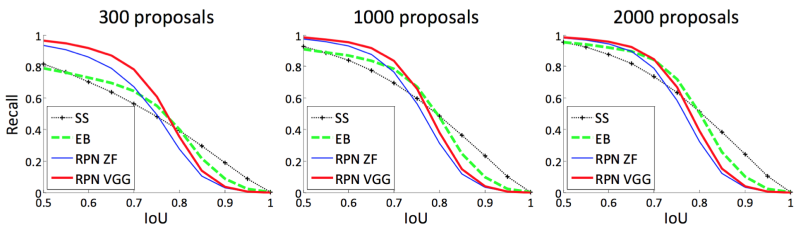


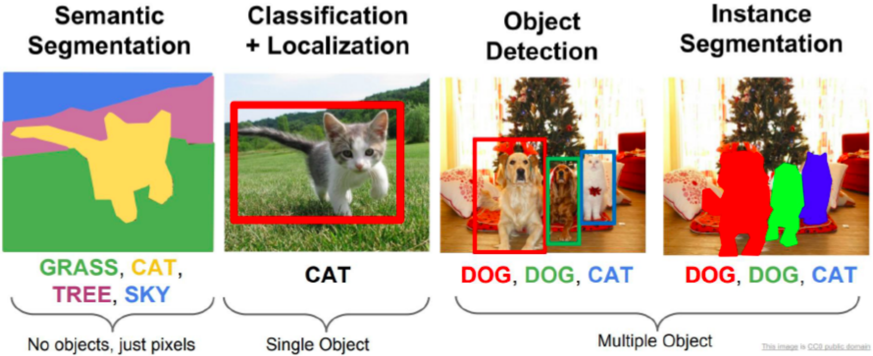
Figure 2: Recall *vs.* IoU overlap ratio on the PASCAL VOC 2007 test set.

Faster R-CNN: Performance

- Fewer and better proposals not only bring speed-up, but also detection performance boost.

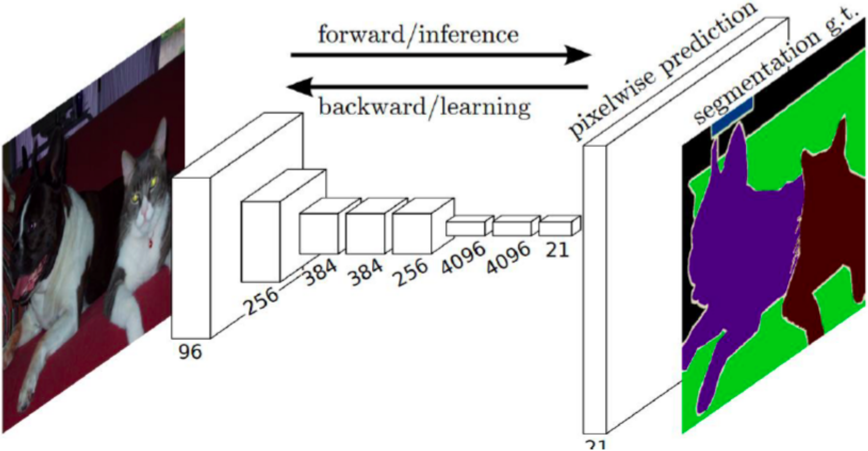
method	# proposals	data	mAP (%)	time (ms)
SS	2k	07	66.9	1830
SS	2k	07+12	70.0	1830
RPN+VGG, unshared	300	07	68.5	342
RPN+VGG, shared	300	07	69.9	**196**
RPN+VGG, shared	300	07+12	**73.2**	**196**

Recognition Tasks

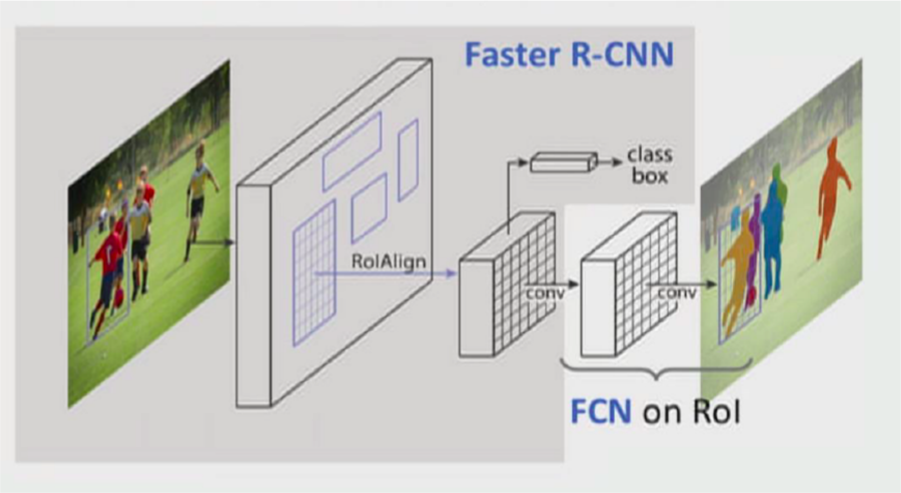


Mask-RCNN

Segmentation via FCN

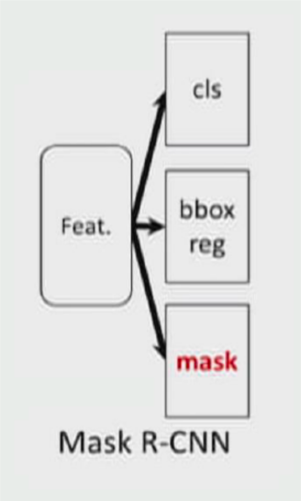


Mask-RCNN

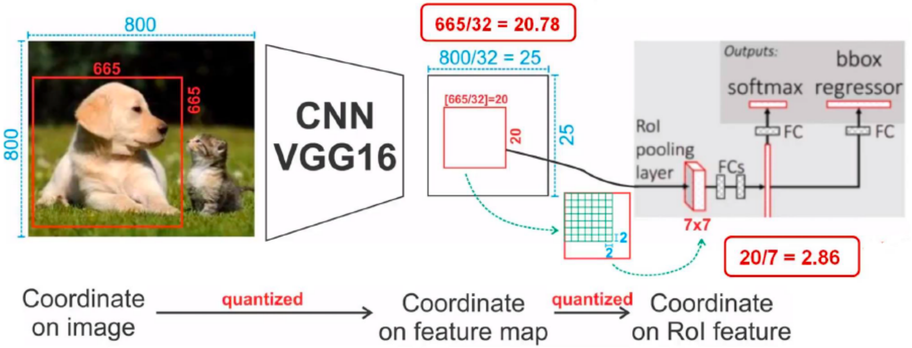


Mask-RCNN: Multiple Heads

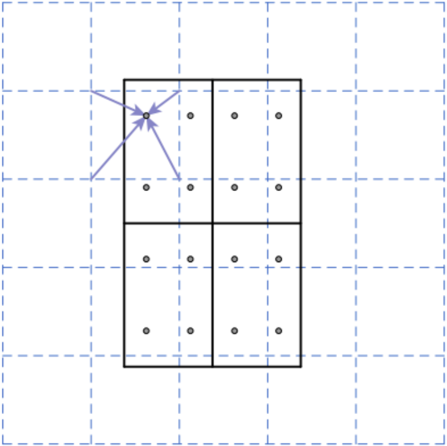
- Loss for each proposal is:
  $L = L\_cls + L\_box + L\_mask$



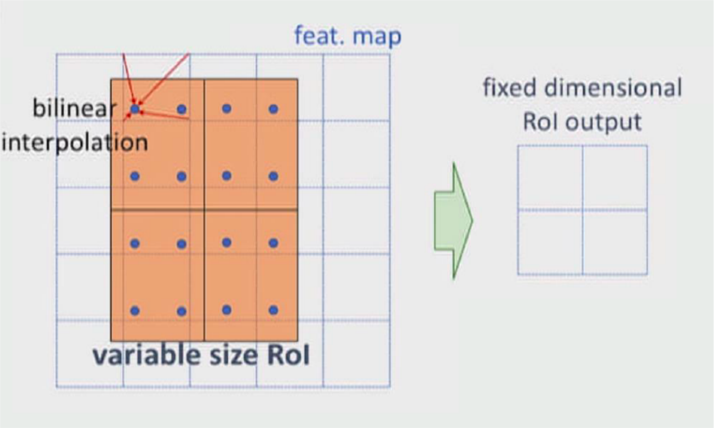
Mask-RCNN: RoI Align



Mask-RCNN: RoI Align



Mask-RCNN: RoI Align



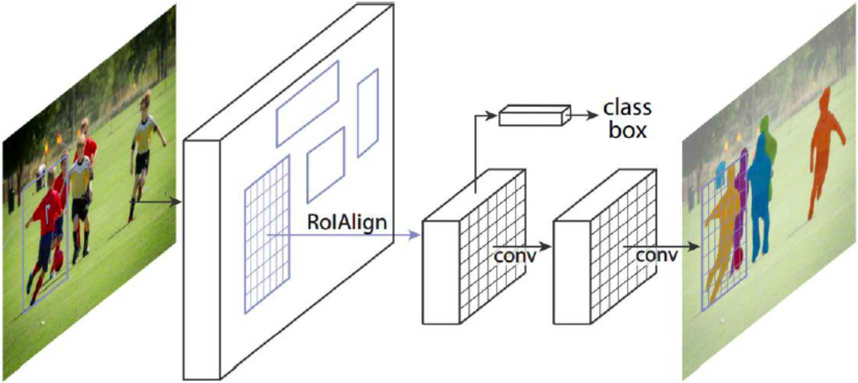
Mask-RCNN: RoI Align

	align?	bilinear?	agg.	AP	AP_{50}	AP_{75}
RoIPool [12]			max	26.9	48.8	26.4
RoIWarp [10]		✓	max	27.2	49.2	27.1
		✓	ave	27.1	48.9	27.1
RoIAlign	✓	✓	max	**30.2**	**51.0**	**31.8**
	✓	✓	ave	**30.3**	**51.2**	**31.5**

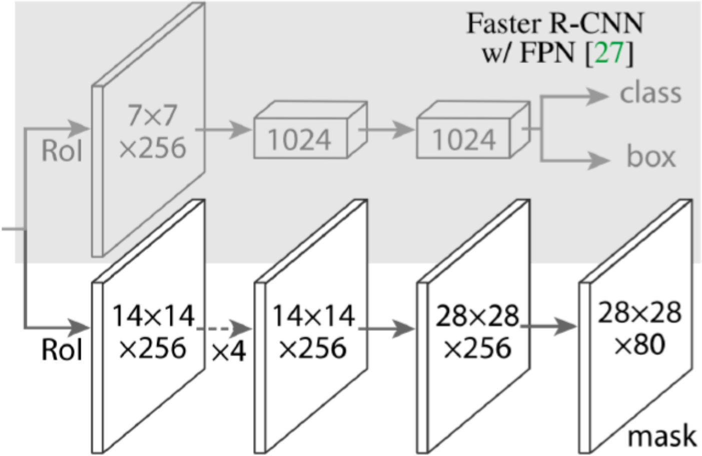
(a) RoIAlign (ResNet-50-C4) comparison

	AP	AP_{50}	AP_{75}	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}
RoIPool	23.6	46.5	21.6	28.2	52.7	26.9
RoIAlign	**30.9**	**51.8**	**32.1**	**34.0**	**55.3**	**36.4**
	+7.3	*+ 5.3*	*+10.5*	*+5.8*	*+2.6*	*+9.5*

Mask-RCNN: Mask Head



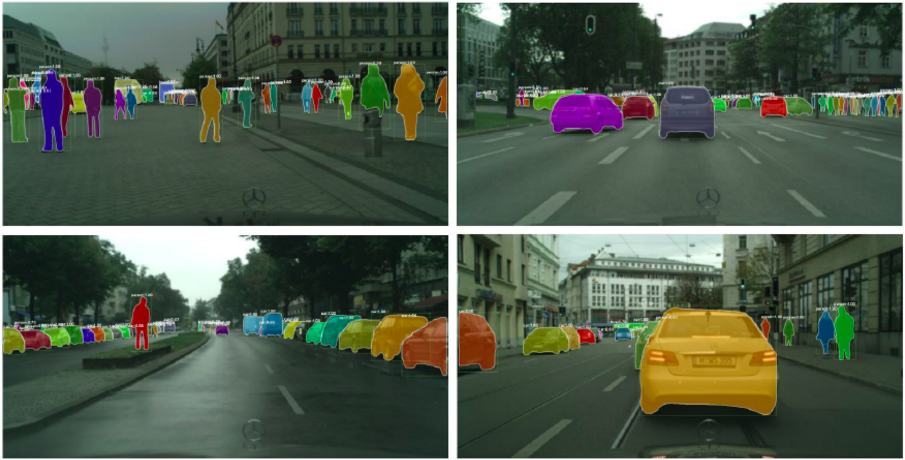
Mask-RCNN: Mask Head



Mask-RCNN: Detection Results

	backbone	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{bb}_{S}	AP^{bb}_{M}	AP^{bb}_{L}
Faster R-CNN+++ [19]	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN [27]	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI [21]	Inception-ResNet-v2 [41]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [39]	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
Faster R-CNN, RoIAlign	ResNet-101-FPN	37.3	59.6	40.3	19.8	40.2	48.8
Mask R-CNN	ResNet-101-FPN	38.2	60.3	41.7	20.1	41.1	50.2
Mask R-CNN	ResNeXt-101-FPN	**39.8**	**62.3**	**43.4**	**22.1**	**43.2**	51.2

Mask-RCNN: Instance Segmentation

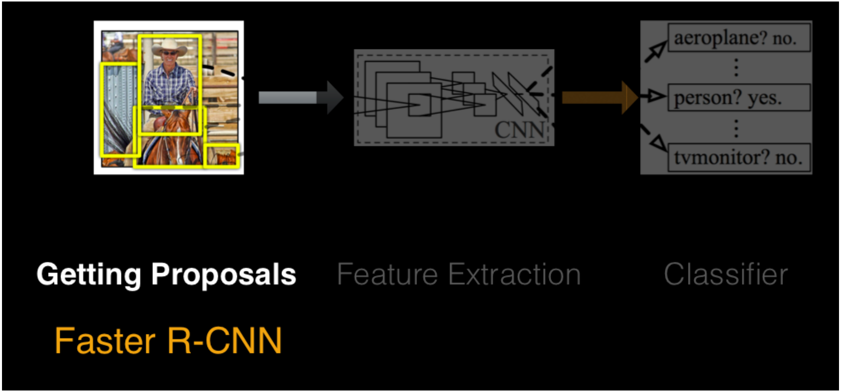


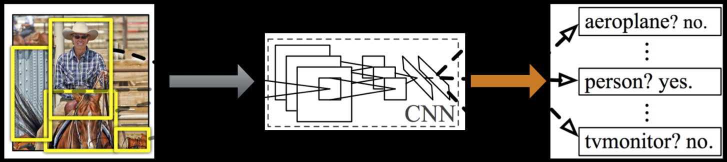
Mask-RCNN: Instance Segmentation

	training data	AP [val]	AP	AP_{50}	person	rider	car	truck	bus	train	mcycle	bicycle
InstanceCut [23]	fine + coarse	15.8	13.0	27.9	10.0	8.0	23.7	14.0	19.5	15.2	9.3	4.7
DWT [4]	fine	19.8	15.6	30.0	15.1	11.7	32.9	17.1	20.4	15.0	7.9	4.9
SAIS [17]	fine	-	17.4	36.7	14.6	12.9	35.7	16.0	23.2	19.0	10.3	7.8
DIN [3]	fine + coarse	-	20.0	38.8	16.5	16.7	25.7	20.6	30.0	23.4	17.1	10.1
SGN [29]	fine + coarse	29.2	25.0	44.9	21.8	20.1	39.4	24.8	33.2	30.8	17.7	12.4
Mask R-CNN	fine	31.5	26.2	49.9	30.5	23.7	46.9	22.8	32.2	18.6	19.1	16.0
Mask R-CNN	fine + COCO	**36.4**	**32.0**	**58.1**	**34.8**	**27.0**	**49.1**	**30.1**	**40.9**	**30.9**	**24.1**	**18.7**

Mask-RCNN: Pose

Object Detection





Getting Proposals | Feature Extraction | Classifier

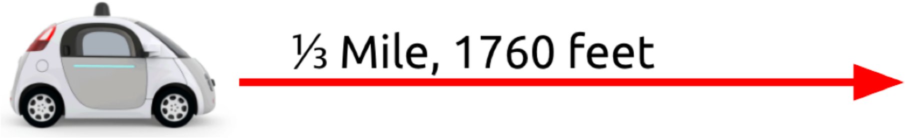
Faster R-CNN | SPP | Fast R-CNN

66.0% —> 73.2%

47 s/im —> 0.2 s/im

Car Example

	Pascal 2007 mAP	Speed	
DPM v5	33.7	.07 FPS	14 s/img
R-CNN	66.0	.05 FPS	20 s/img



[Slide credit: Joseph Chet Redmon]

Car Example

	Pascal 2007 mAP	Speed	
DPM v5	33.7	.07 FPS	14 s/img
R-CNN	66.0	.05 FPS	20 s/img
Fast R-CNN	70.0	.5 FPS	2 s/img

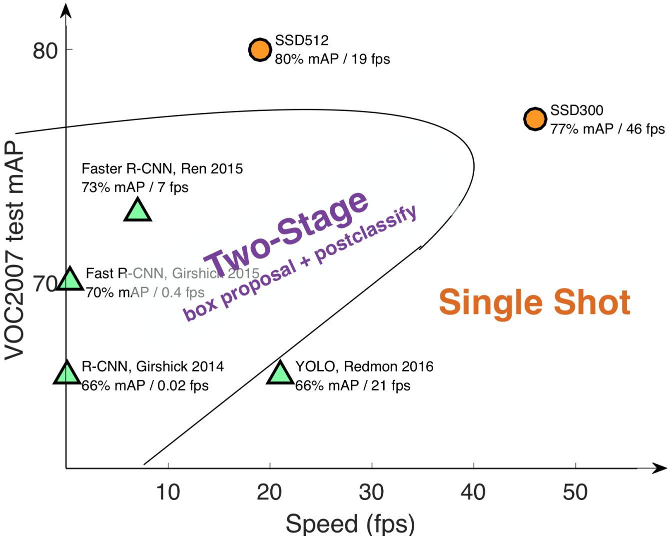
[Slide credit: Joseph Chet Redmon]

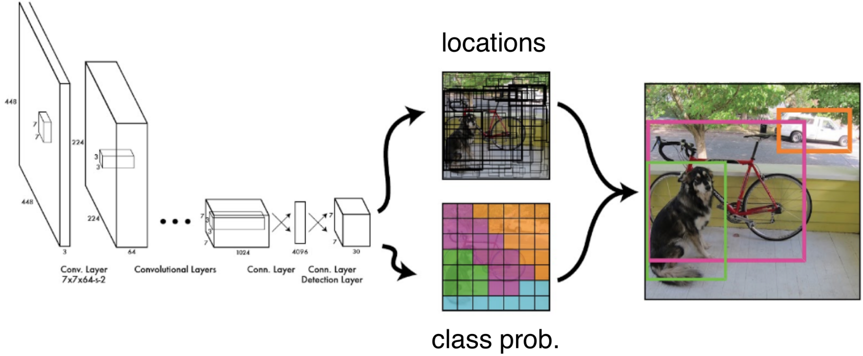
Car Example

	Pascal 2007 mAP	Speed	
DPM v5	33.7	.07 FPS	14 s/img
R-CNN	66.0	.05 FPS	20 s/img
Fast R-CNN	70.0	.5 FPS	2 s/img
Faster R-CNN	73.2	7 FPS	140 ms/img

[Slide credit: Joseph Chet Redmon]

Real Time Object Detection?



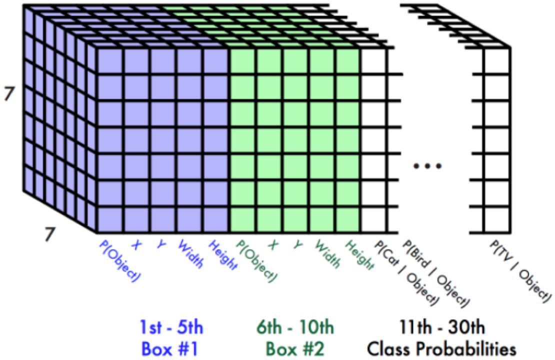


[Slide credit: Redmon J et al. You only look once: Unified, real-time object detection. CVPR'16]

YOLO: Output Parametrization

Each cell predicts:

- For each bounding box:
  - 4 coordinates (x, y, w, h)
  - 1 confidence value
- Some number of class probabilities



For Pascal VOC:

- 7x7 grid
- 2 bounding boxes / cell
- 20 classes

7 x 7 x (2 x 5 + 20) = 7 x 7 x 30 tensor = **1470 outputs**

[Slide credit: Redmon J et al. You only look once: Unified, real-time object detection. CVPR'16]

YOLO Limitations

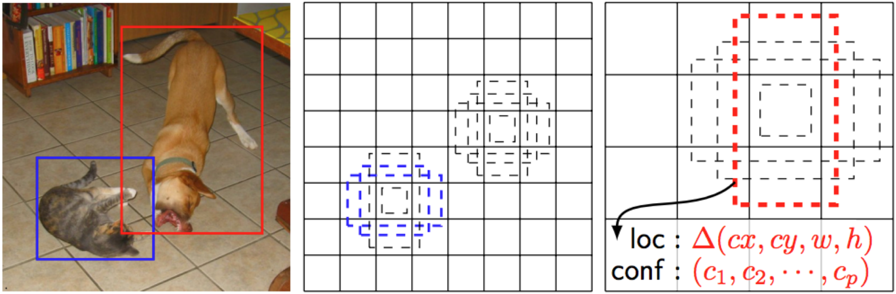
- Small objects
- Objects with different shapes and sizes
- Occluded objects

SSD: Single Shot MultiBox Detector

[Slide credit: Wei Liu et al., SSD: Single Shot MultiBox Detector, ECCV'16]

SSD: Single Shot MultiBox Detector

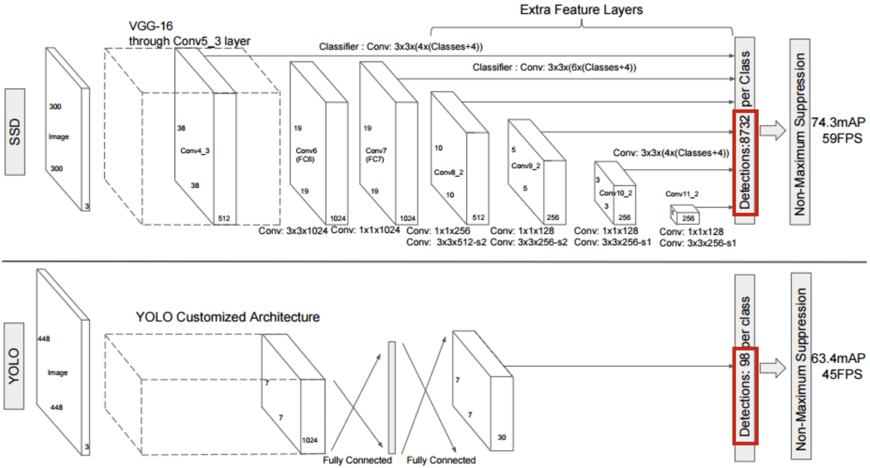
- SSD: YOLO + default box shape + multi-scale



(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

[Slide credit: Wei L, et al. SSD: Single Shot MultiBox Detector. ECCV'16]

SSD: Single Shot MultiBox Detector



[Slide credit: Wei L, et al. SSD: Single Shot MultiBox Detector. ECCV'16]

Thank you and good luck!