

Recognition

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CMPSCI 670: Computer Vision

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Agenda for the next few lectures

- ◆ Overview of recognition
- ◆ Image representations
- ◆ Machine learning
- ◆ Deep learning

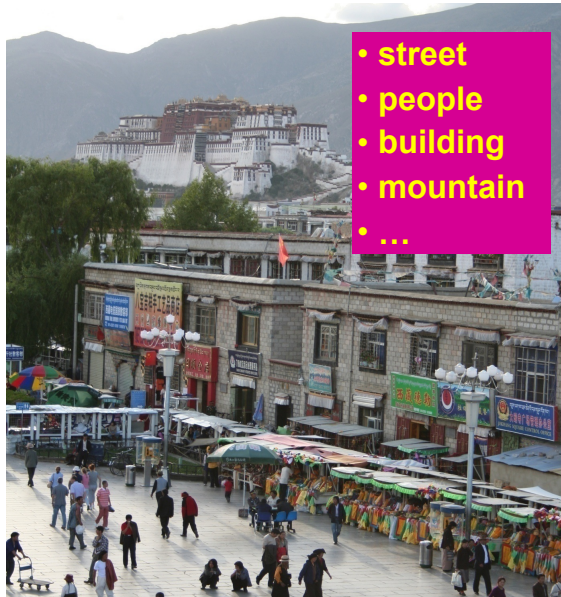


Scene categorization

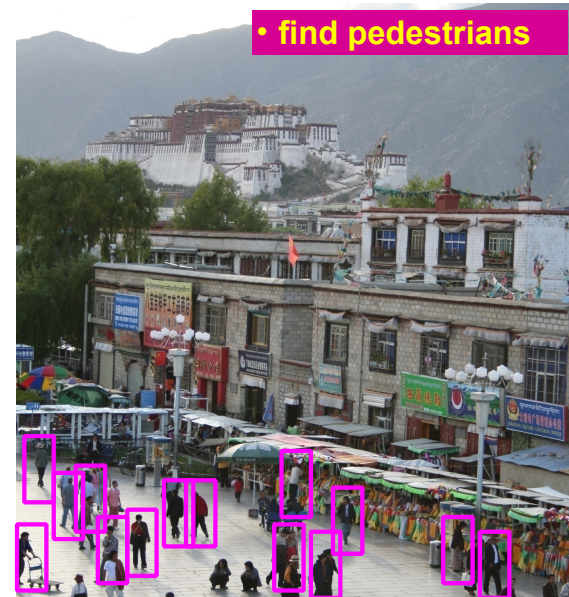


- outdoor/indoor
- city/forest/factory/etc.

Image annotation/tagging



Object detection



Activity recognition



Image parsing

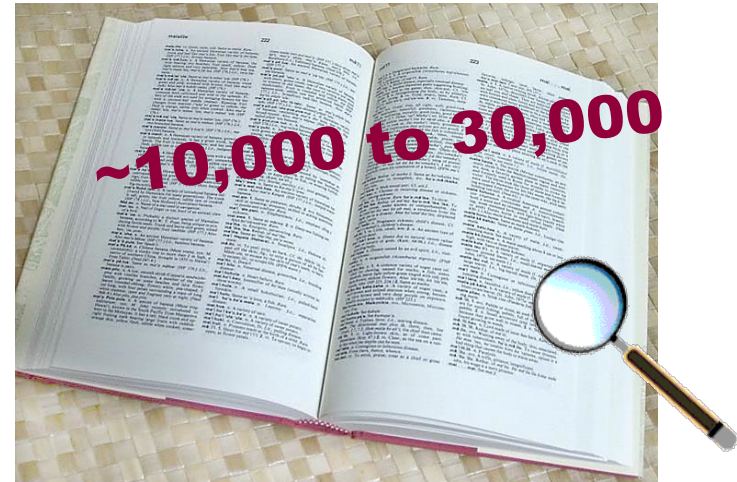


Visual question answering

How many people are waking on the street?
Where was this picture taken? (external knowledge)



How many visual object categories?



[http://wexler.free.fr/library/files/biederman%20\(1987\)%20recognition-by-components.%20a%20theory%20of%20human%20image%20understanding.pdf](http://wexler.free.fr/library/files/biederman%20(1987)%20recognition-by-components.%20a%20theory%20of%20human%20image%20understanding.pdf)

Biederman 1987



Categorization spectrum

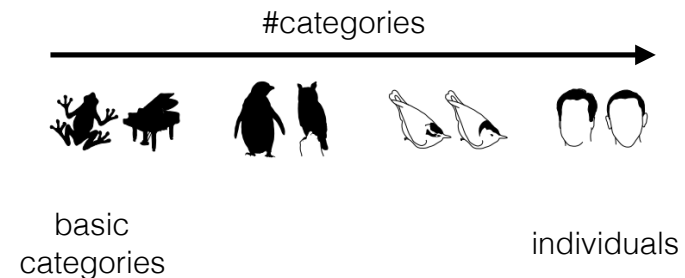


Figure credit: Ryan Farrell

History of ideas in recognition

1960s – early 1990s: the geometric era

1990s: appearance-based models

Late 1990s: local features

Early 2000s: parts-and-shape models

Mid-2000s: bags-of-features, learning-based techniques

Present trends: big data, recognition + X (X=geometry, robotics, language), deep learning, getting AI to work, many applications: health care, autonomous driving, face recognition, image/video search, etc.

Recognition by learning



The machine learning framework

Apply a prediction function to a feature representation of the image to get the desired output:

$f(\text{apple image}) = \text{"apple"}$

$f(\text{tomato image}) = \text{"tomato"}$

$f(\text{cow image}) = \text{"cow"}$

The machine learning framework

$$y = f(x)$$

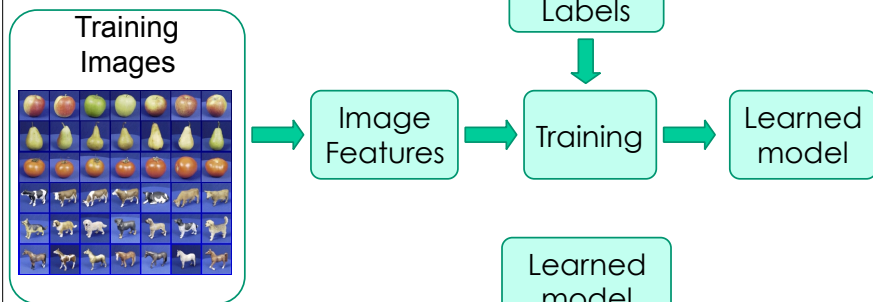
output prediction function Image feature

Training: given a *training set* of labeled examples $\{(x_1, y_1), \dots, (x_N, y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set

Testing: apply f to a never before seen *test example* x and output the predicted value $y = f(x)$

Steps

Training



Testing



Slide credit: D. Hoiem

Ingredients for learning

♦ **Whole idea:** Inject *your* knowledge into a learning system

♦ **Sources of knowledge:**

1. Feature representation

- Not typically a focus of machine learning
- Typically seen as “problem specific”
- However, it’s hard to learn from bad representations

2. Training data: labeled examples

- Often expensive to label lots of data
- Sometimes data is available for “free”

3. Model

- No single learning algorithm is always good (“no free lunch”)
- Different learning algorithms work with different ways of representing the learned classifier

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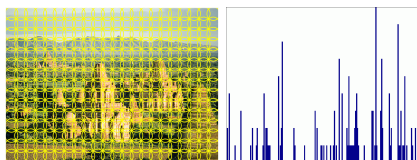
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Features (examples)

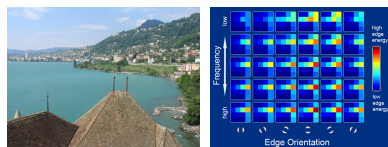
Raw pixels (and simple functions of raw pixels)



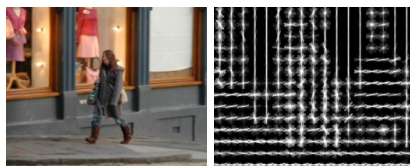
bags of features



GIST descriptors



Gradient histograms



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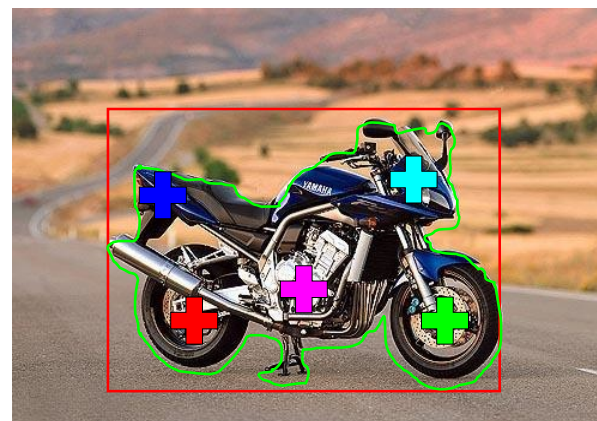
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Recognition task and supervision

Images in the training set must be annotated with the “correct answer” that the model is expected to produce

Contains a motorbike

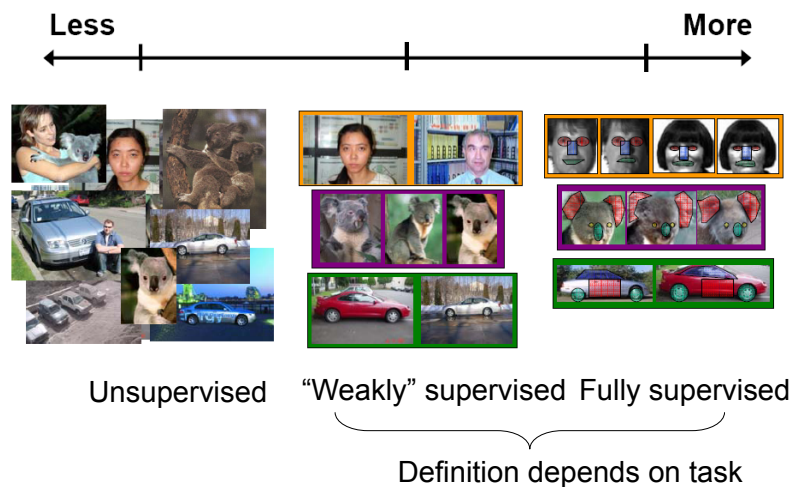


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Spectrum of supervision



Generalization

How well does a learned model *generalize* from the data it was trained on to a new test set?



Training set (labels known)



Test set (labels unknown)

Datasets

Circa 2001: five categories, hundreds of images per category

Circa 2004: 101 categories

Today: up to thousands of categories, millions of images

Caltech 101 & 256

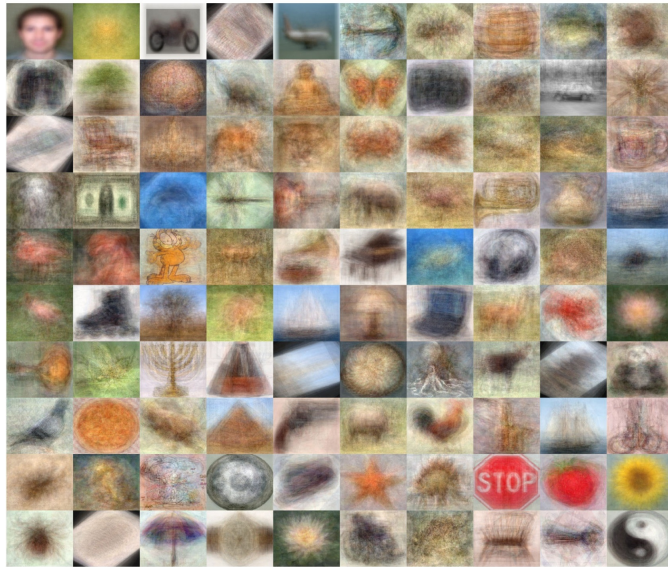
http://www.vision.caltech.edu/Image_Datasets/Caltech101/
http://www.vision.caltech.edu/Image_Datasets/Caltech256/



Griffin, Holub, Perona, 2007

Fei-Fei, Fergus, Perona, 2004

Caltech-101: Intra-class variability



PASCAL Visual Object Classes Challenge (2005-12)

<http://pascallin.ecs.soton.ac.uk/challenges/VOC/>

• Challenge classes:

Person: person

Animal: bird, cat, cow, dog, horse, sheep

Vehicle: aeroplane, bicycle, boat, bus, car, motorbike, train

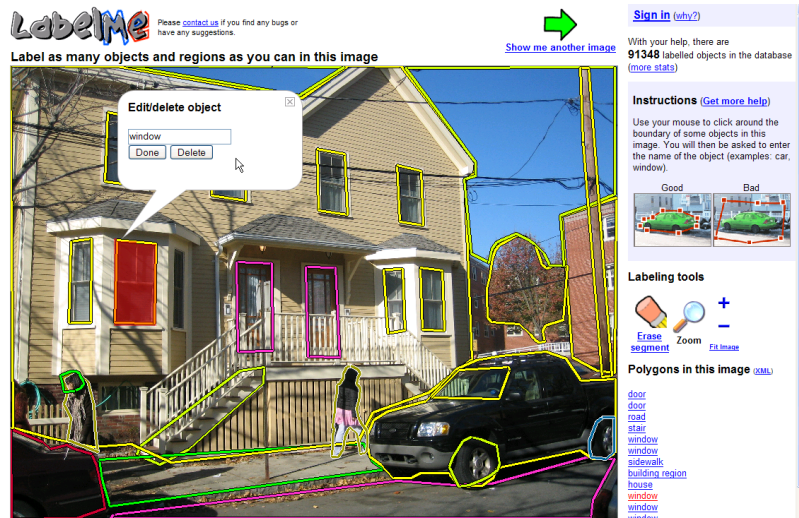
Indoor: bottle, chair, dining table, potted plant, sofa, tv/monitor

• Dataset size (by 2012):

11.5K training/validation images, 27K bounding boxes, 7K segmentations



LabelMe Dataset <http://labelme.csail.mit.edu/>



Russell, Torralba, Murphy, Freeman, 2008

ImageNet

<http://www.image-net.org>

IMAGENET

14,197,122 images, 21841 synsets indexed

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