Object Category Recognition

Computer Vision

CS 543 / ECE 549

University of Illinois

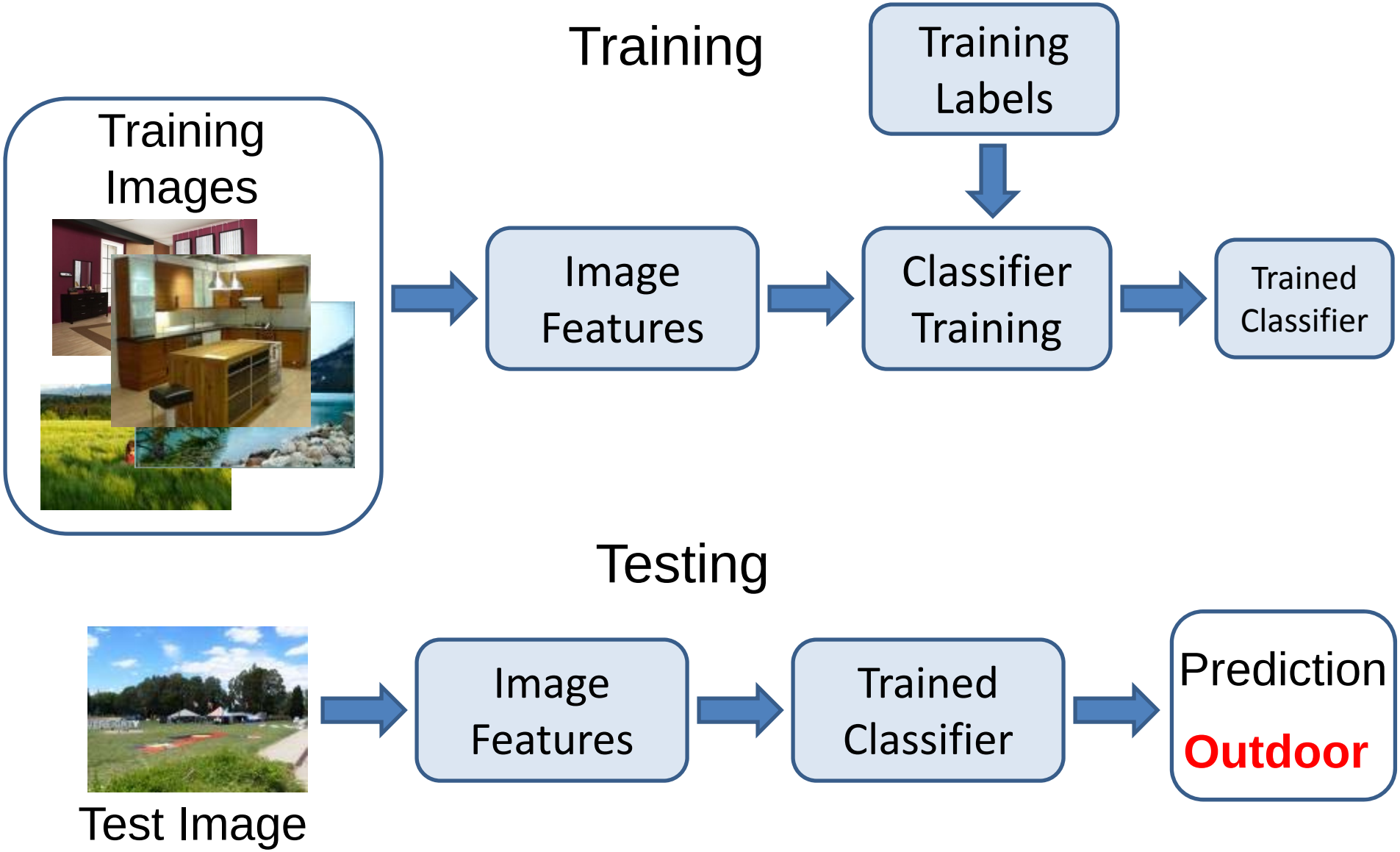
Derek Hoiem

(Plus leftover material from image categorization)

Today’s class: categorization

- More about classifiers
- Overview of object category detection
- More about categorization in general

Image Categorization

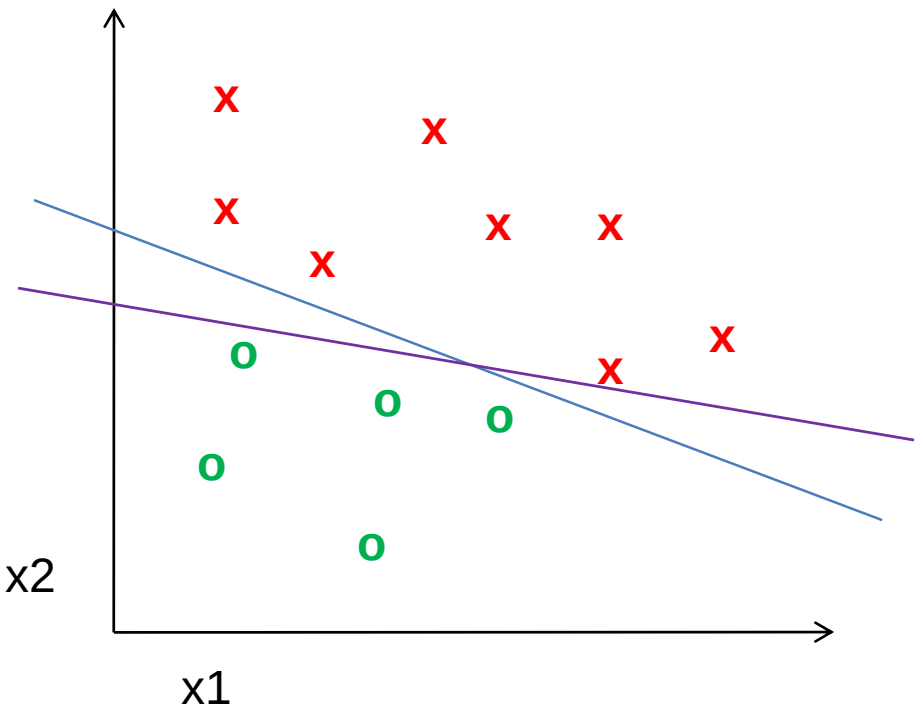


Many classifiers to choose from

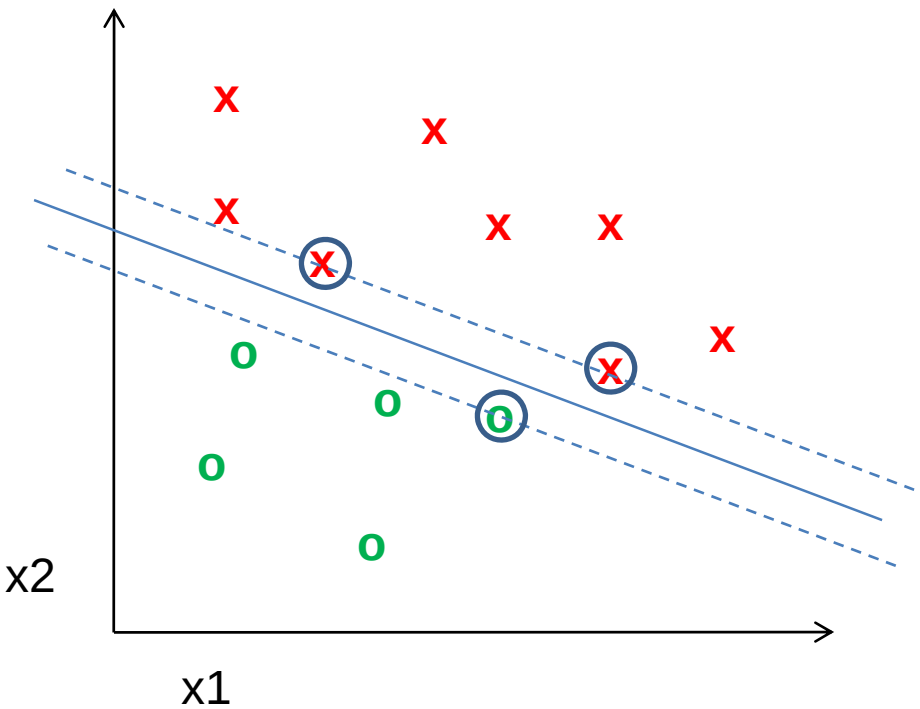
- SVM
- Neural networks
- Naïve Bayes
- Bayesian network
- Logistic regression
- Randomized Forests
- Boosted Decision Trees
- K-nearest neighbor
- RBMs
- Etc.

No Free Lunch Theorem

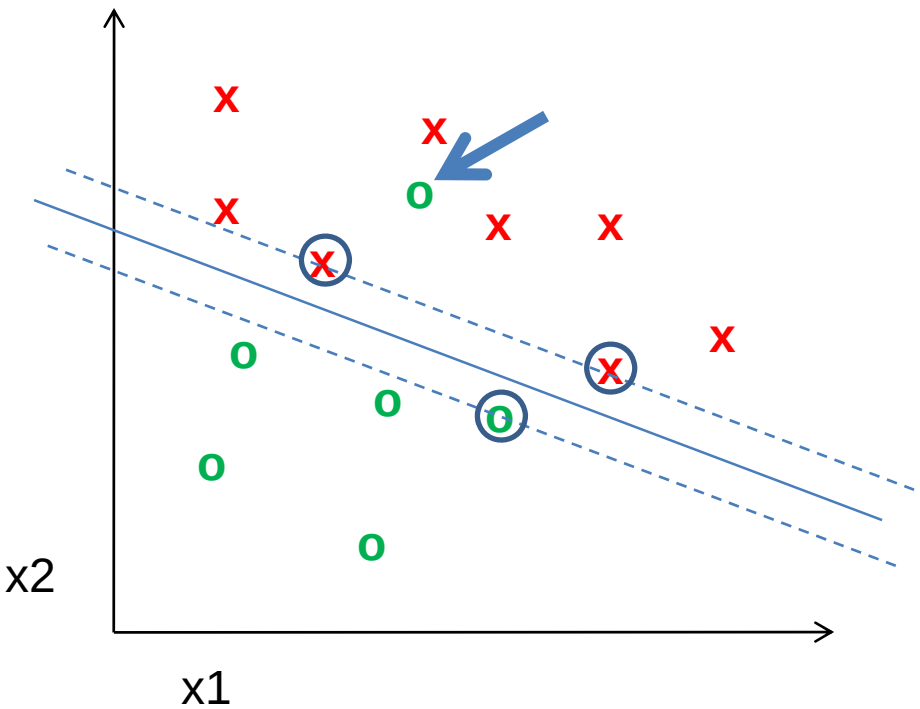
Classifiers: Linear SVM



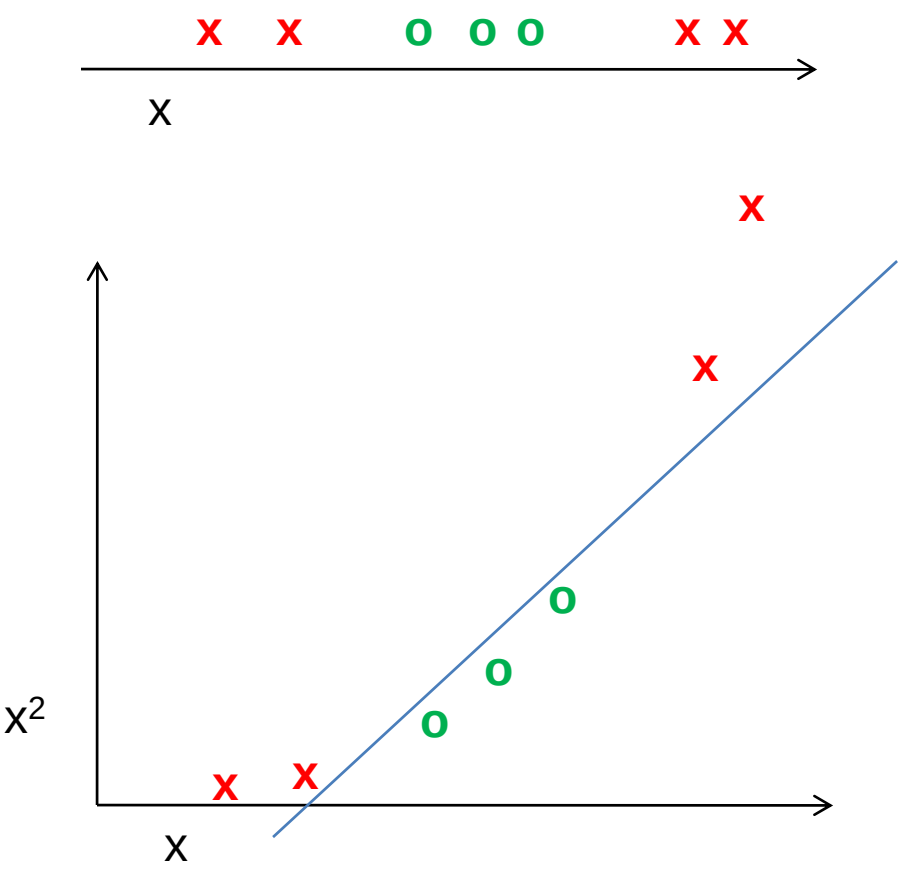
Classifiers: Linear SVM



Classifiers: Linear SVM



Classifiers: Kernelized SVM

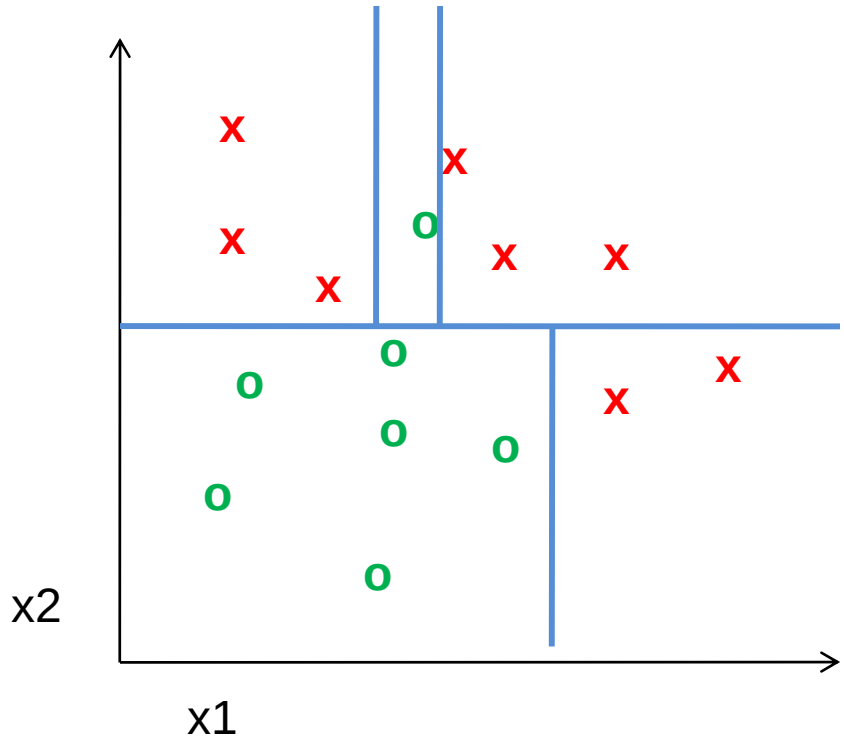


Using SVMs

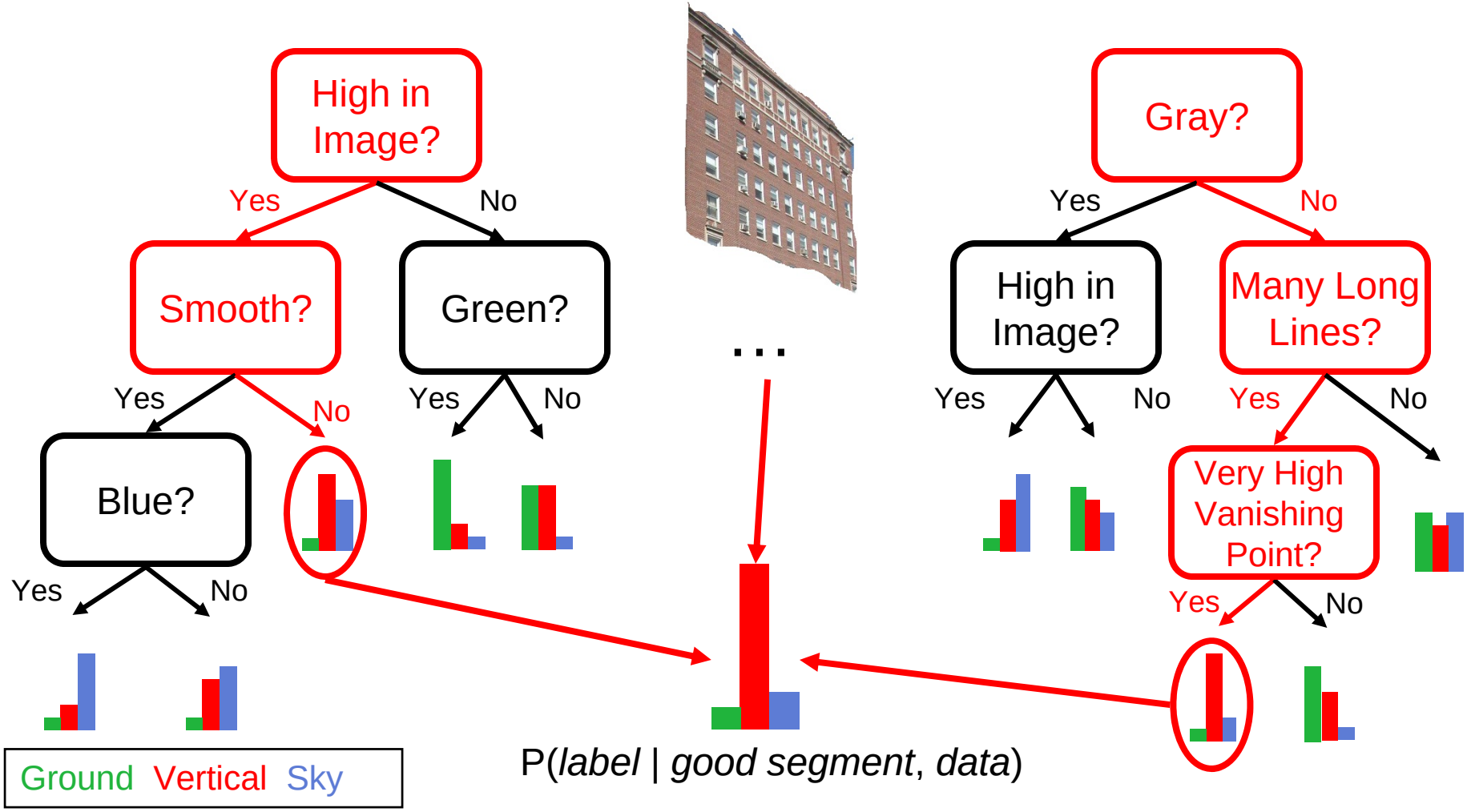
- Good general purpose classifier
  - Generalization depends on margin, so works well with many weak features
  - No feature selection
  - Usually requires some parameter tuning

- Choosing kernel
  - Linear: fast training/testing – start here
  - RBF: related to neural networks, nearest neighbor
  - Chi-squared, histogram intersection: good for histograms (but slower, esp. chi-squared)
  - Can learn a kernel function

Classifiers: Decision Trees



Boosted Decision Trees



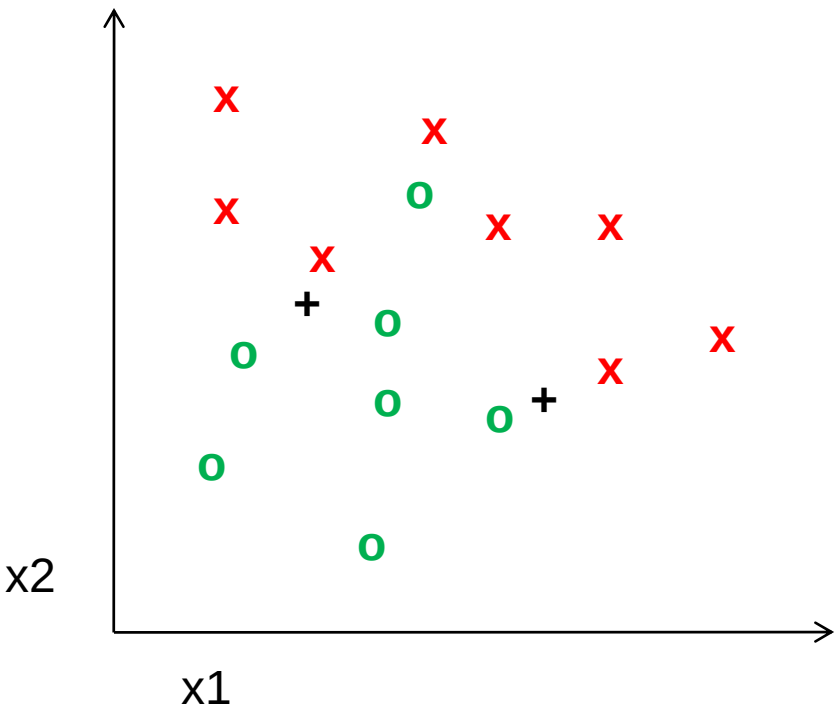
P(*label* | *good segment*, *data*)

[Collins et al. 2002]

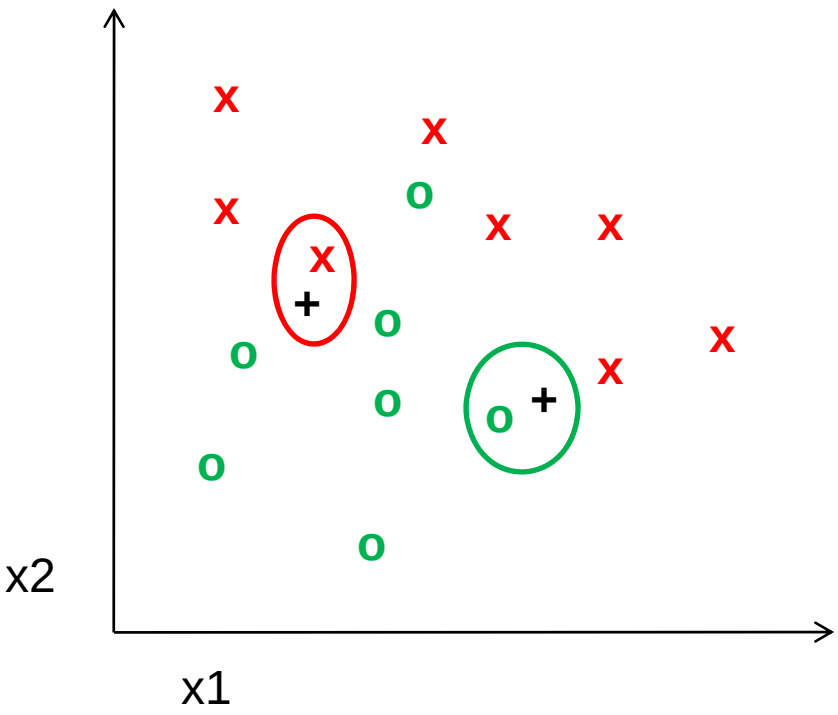
Using Boosted Decision Trees

- Flexible: can deal with both continuous and categorical variables
- How to control bias/variance trade-off
  - Size of trees
  - Number of trees
- Boosting trees often works best with a small number of well-designed features
- Boosting “stubs” can give a fast classifier

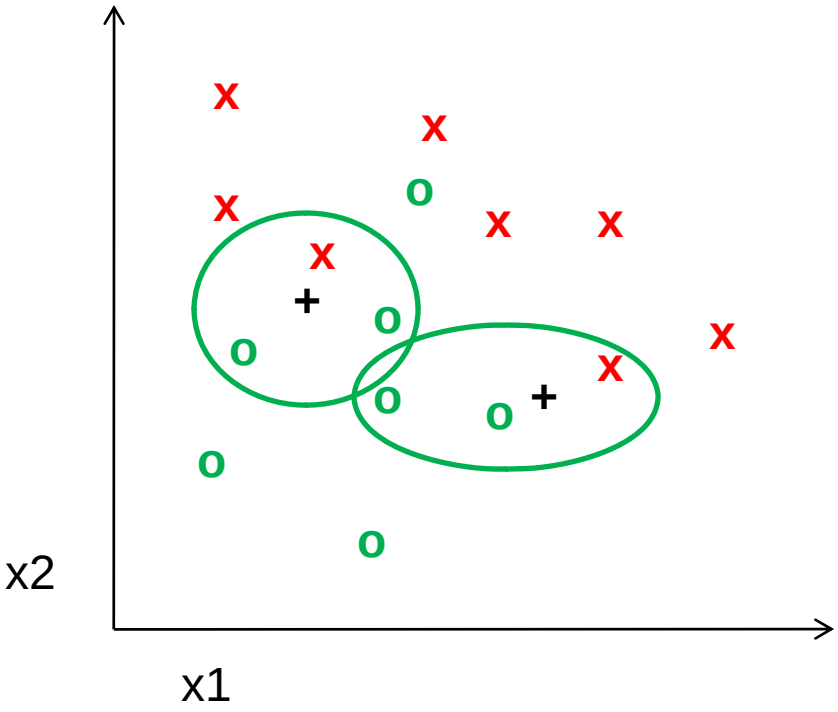
K-nearest neighbor



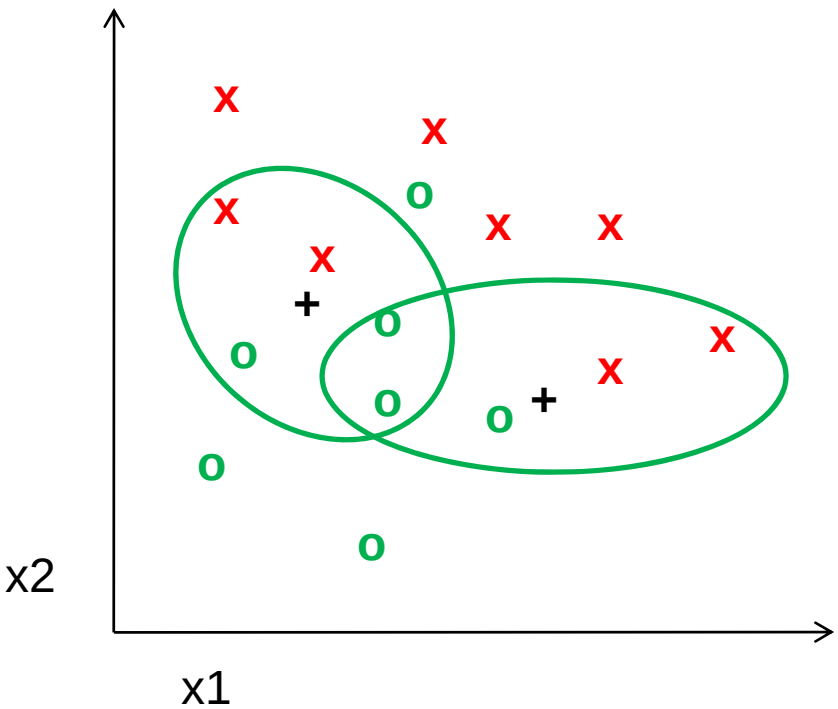
1-nearest neighbor



3-nearest neighbor



5-nearest neighbor



Using K-NN

- Simple, so another good one to try first
- With infinite examples, 1-NN provably has error that is at most twice Bayes optimal error

What to remember about classifiers

- No free lunch: machine learning algorithms are tools, each well-suited to some purposes but not others
- Try simple classifiers first
- Better to have smart features and simple classifiers than simple features and smart classifiers
- Use increasingly powerful classifiers with more training data (bias-variance tradeoff)

Some Machine Learning References

- General
  - Tom Mitchell, *Machine Learning*, McGraw Hill, 1997
  - Christopher Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, 1995
- Adaboost
  - Friedman, Hastie, and Tibshirani, “Additive logistic regression: a statistical view of boosting”, Annals of Statistics, 2000
- SVMs
  - http://www.support-vector.net/icml-tutorial.pdf

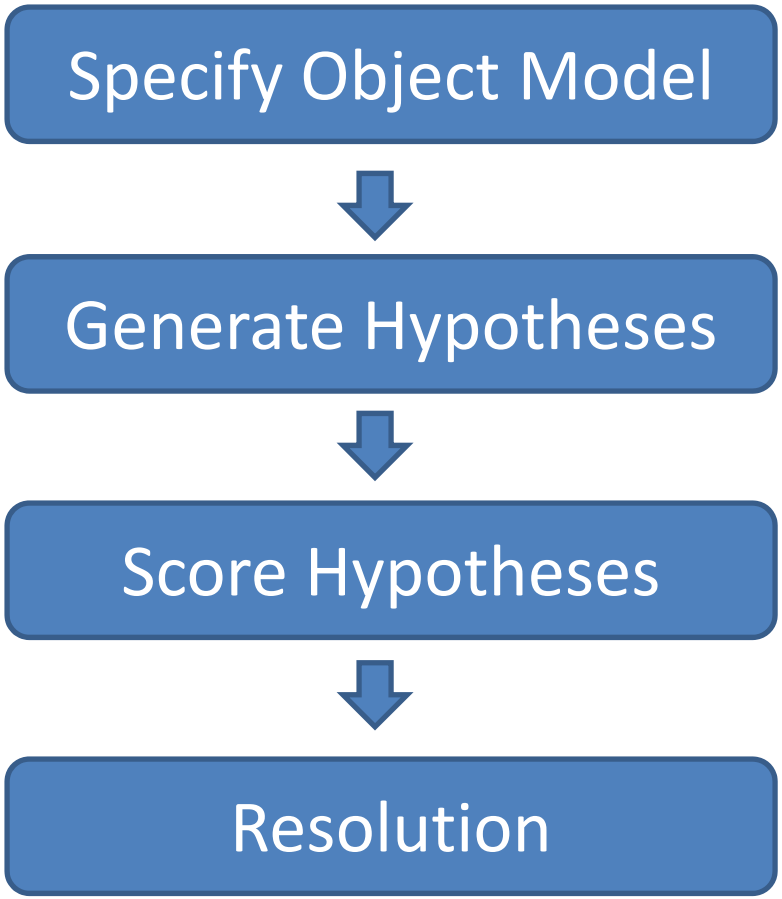
Moving on…

Object Categories

Object category detection in computer vision

Goal: detect all pedestrians, cars, monkeys, etc in image

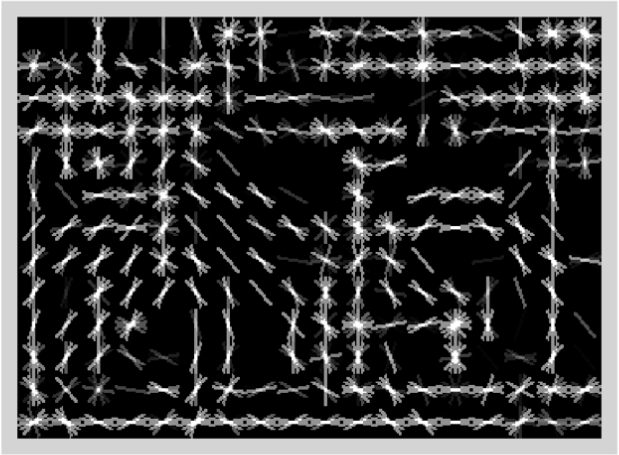
General Process of Object Recognition



Specifying an object model

1. Statistical Template in Bounding Box
   - Object is some (x,y,w,h) in image
   - Features defined wrt bounding box coordinates

Image

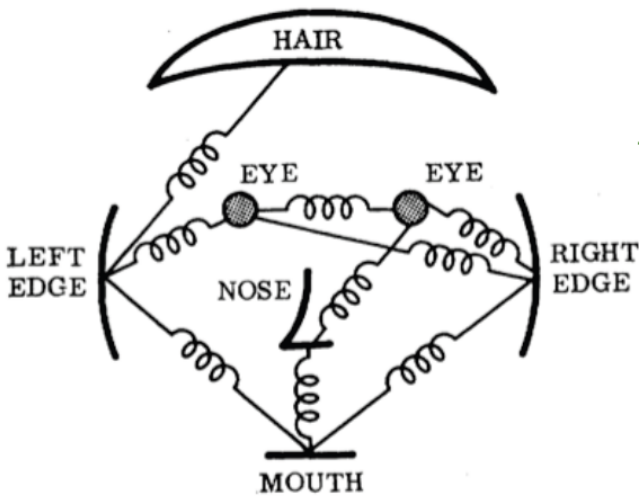


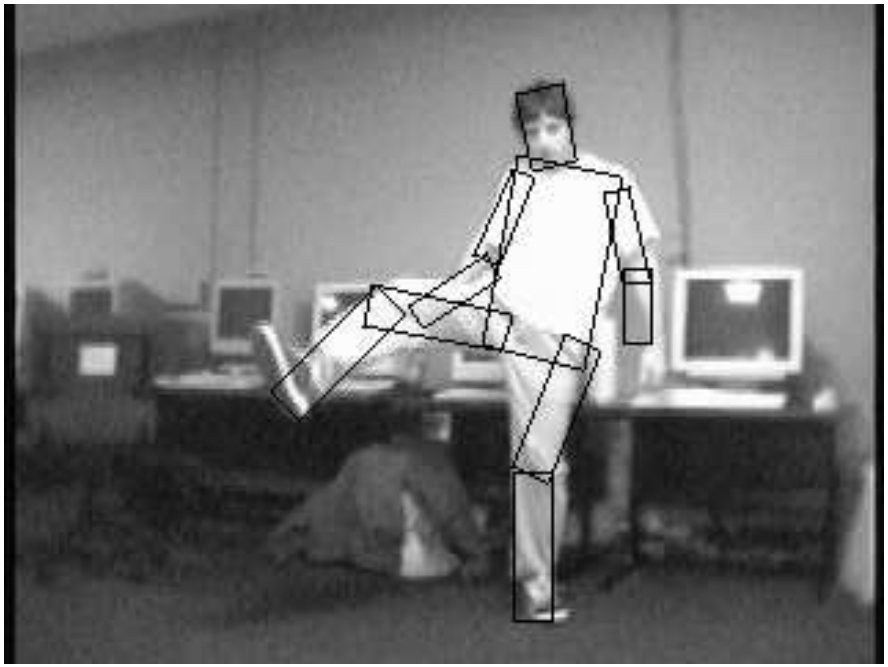
Template Visualization

Images from Felzenszwalb

Specifying an object model

2. Articulated parts model
   - Object is configuration of parts
   - Each part is detectable



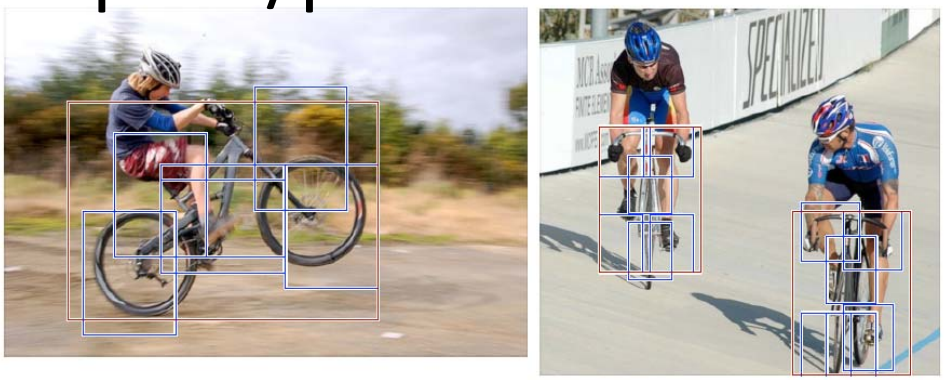


Images from Felzenszwalb

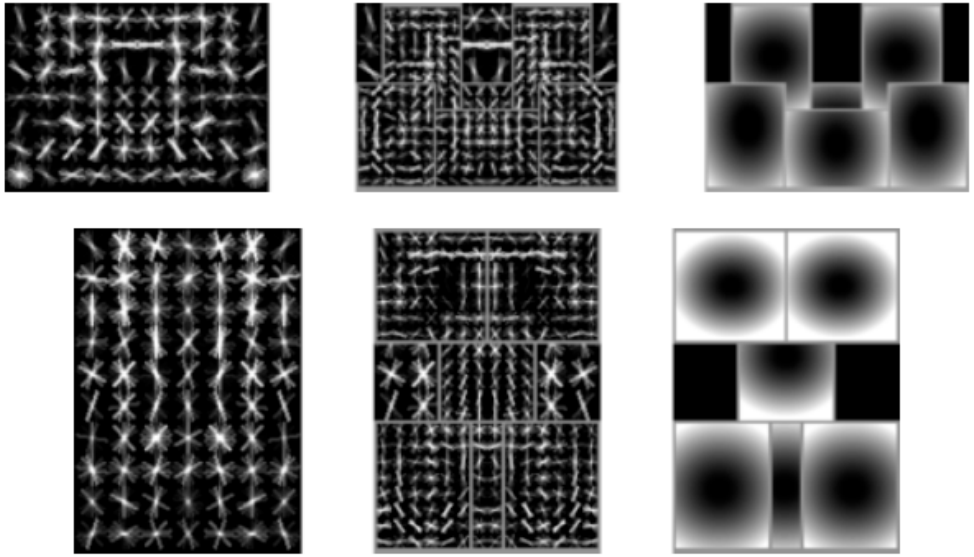
Specifying an object model

3. Hybrid template/parts model

Detections



Template Visualization



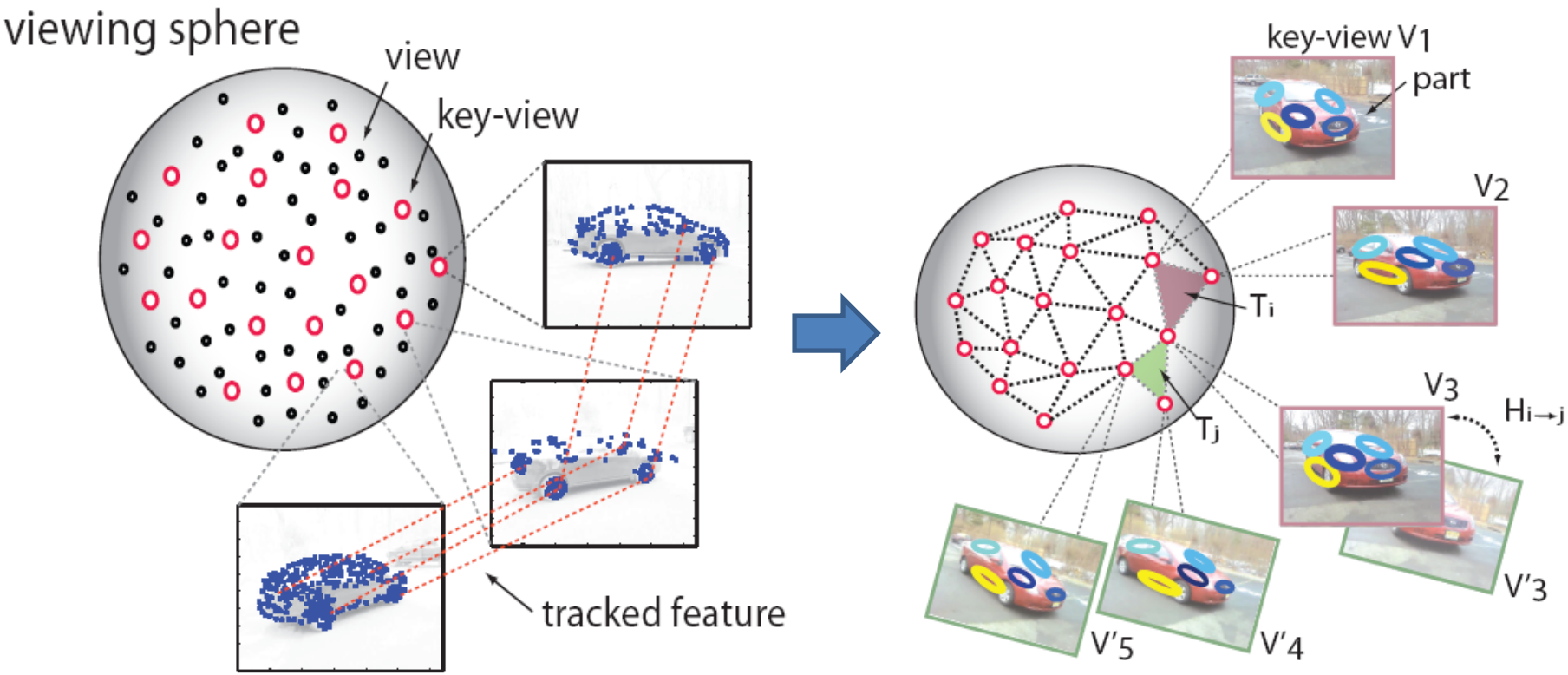
root filters coarse resolution | part filters finer resolution | deformation models

Felzenszwalb et al. 2008

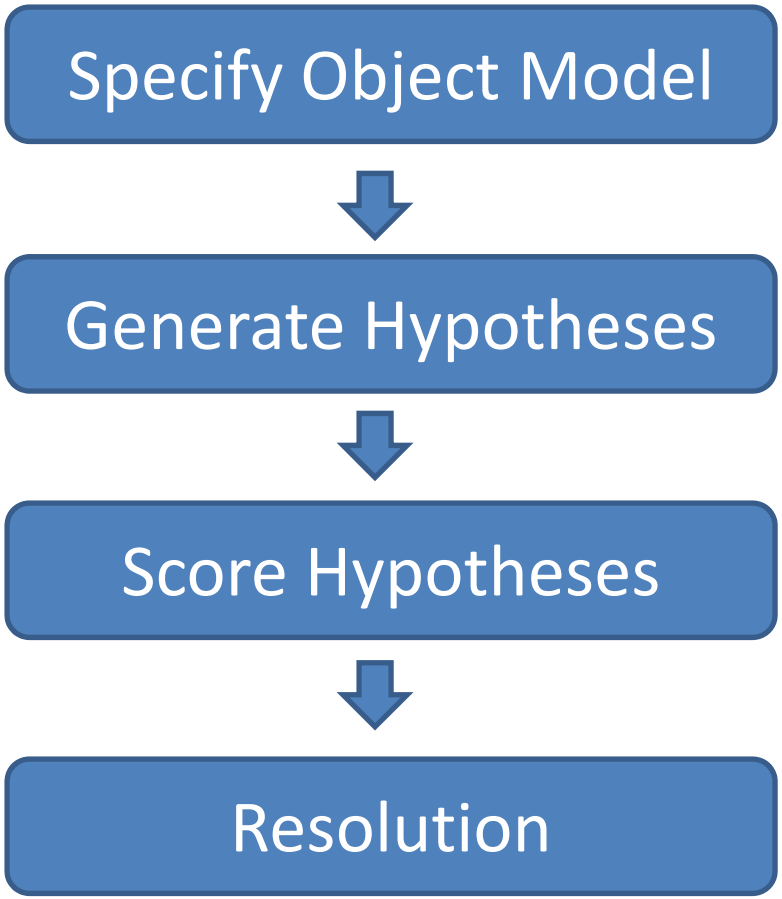
Specifying an object model

4. 3D-ish model

- Object is collection of 3D planar patches under affine transformation



General Process of Object Recognition



Generating hypotheses

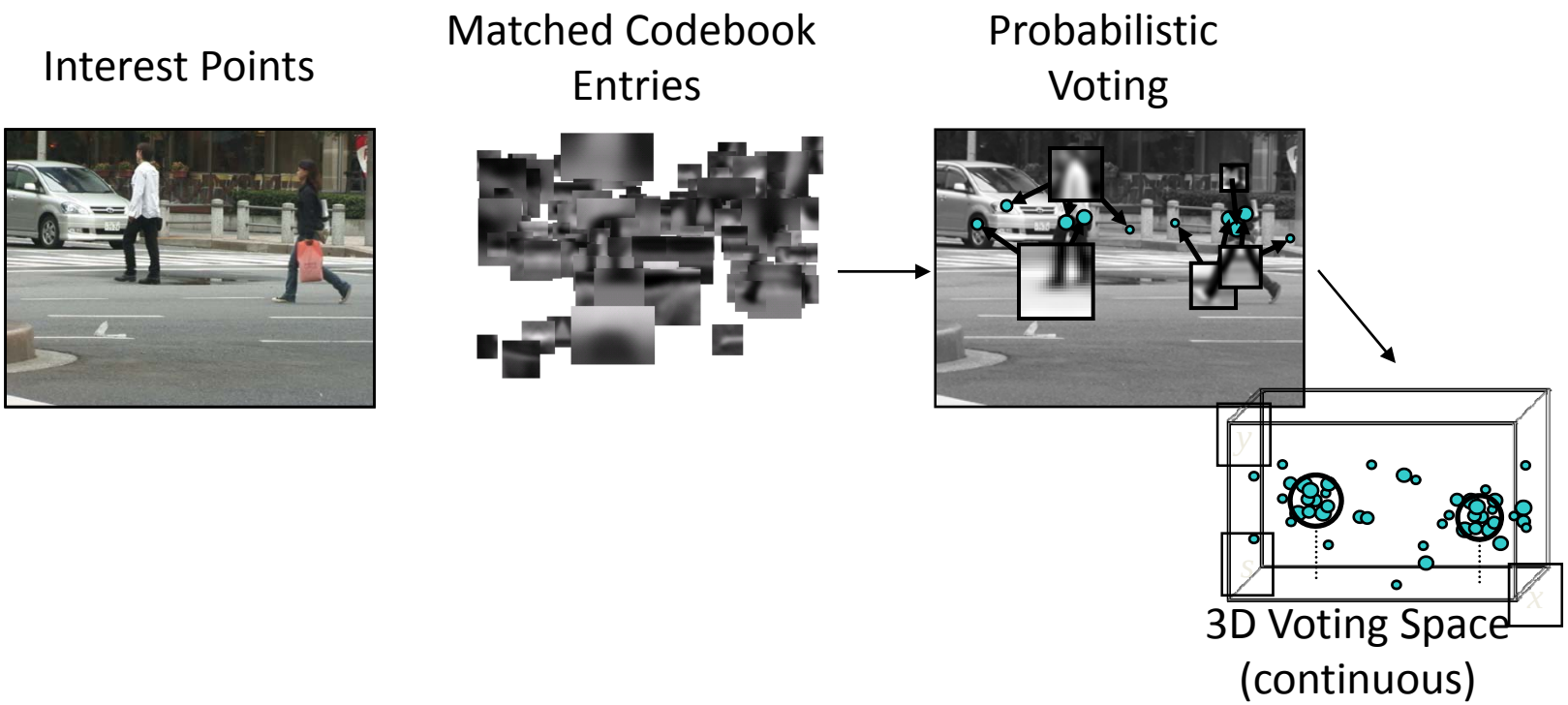
1. Sliding window
   - Test patch at each location and scale

Generating hypotheses

1. Sliding window
   - Test patch at each location and scale

Generating hypotheses

2. Voting from patches/keypoints

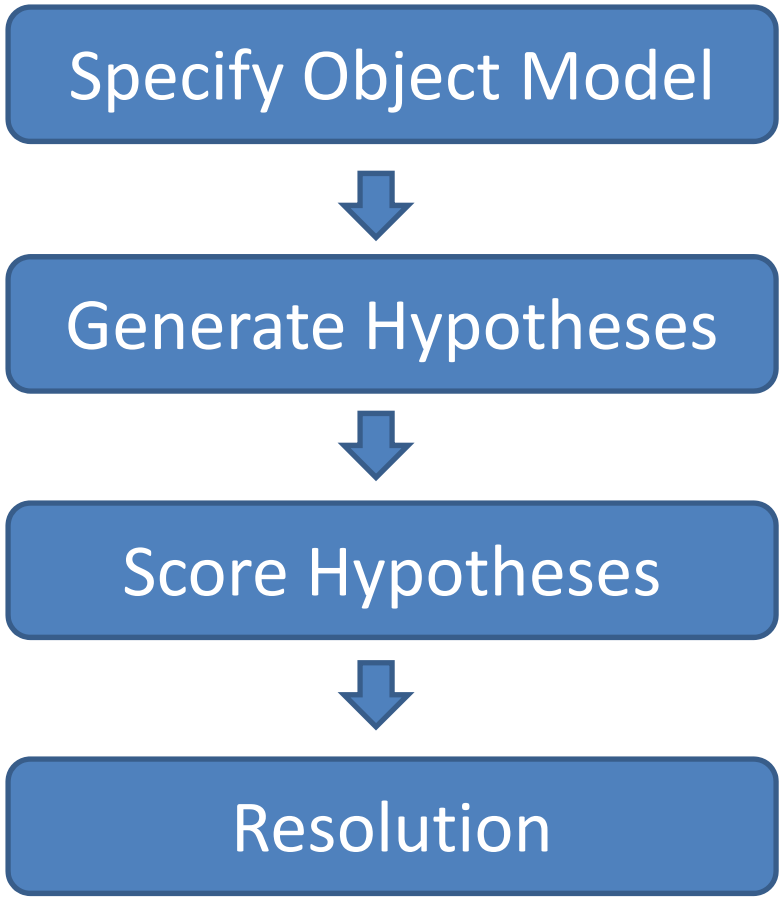


ISM model by Leibe et al.

Generating hypotheses

3. Region-based proposal

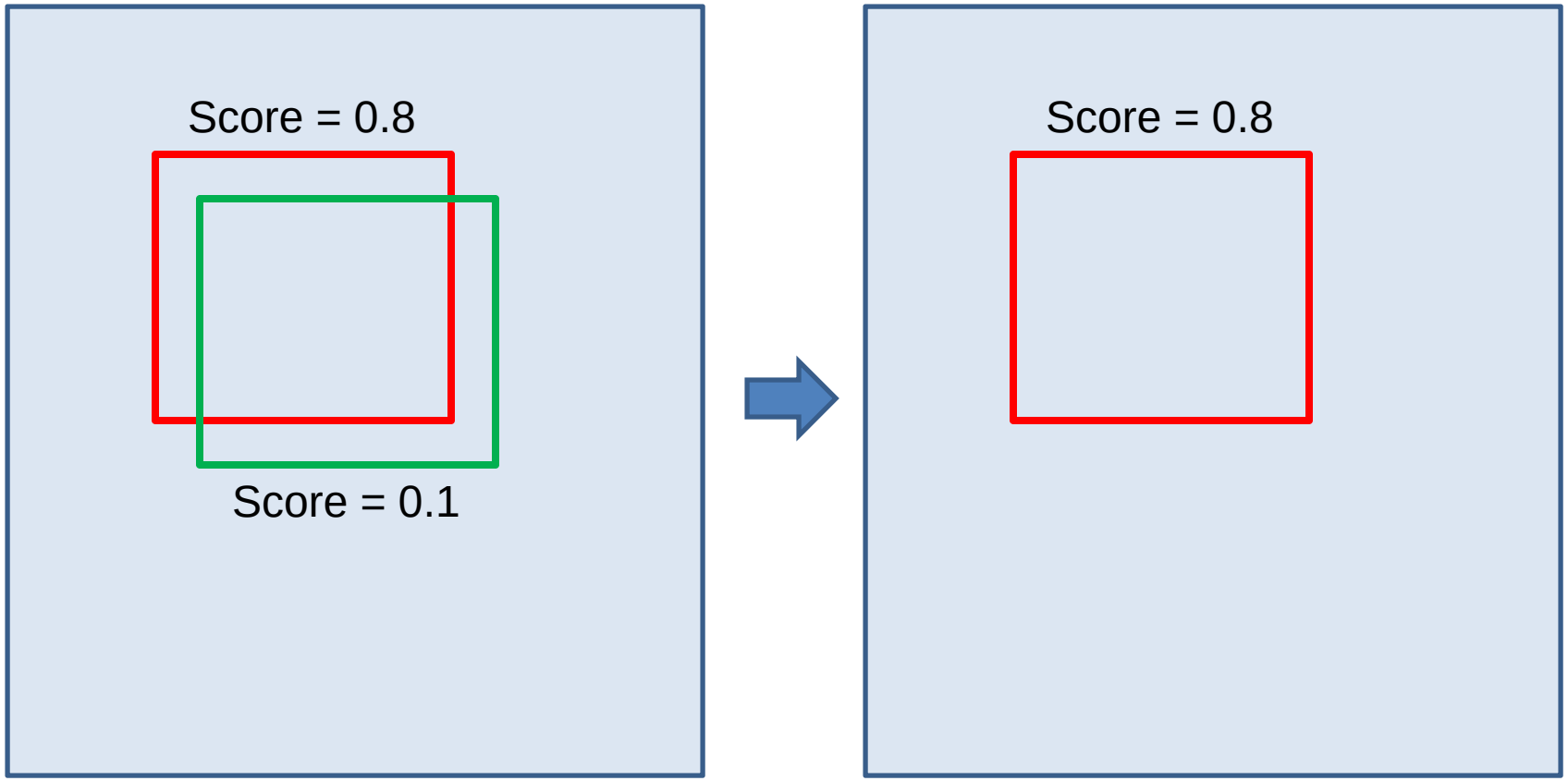
General Process of Object Recognition



Many types of classifiers, features

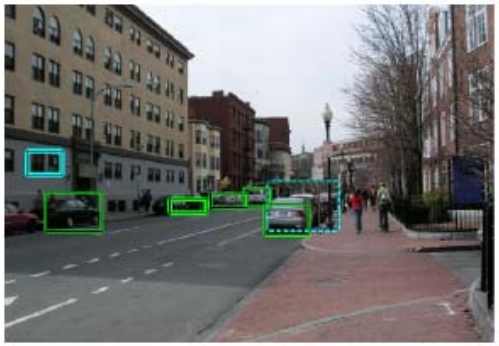
Resolving detection scores

1. Non-max suppression



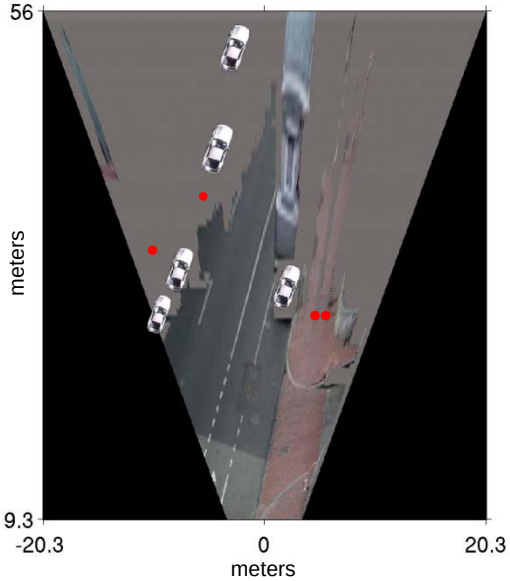
Resolving detection scores

2. Context/reasoning



(g) Car Detections: Local

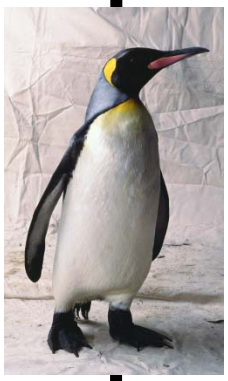
(h) Ped Detections: Local



More thoughts on categories…

Object Categorization

Object Categorization



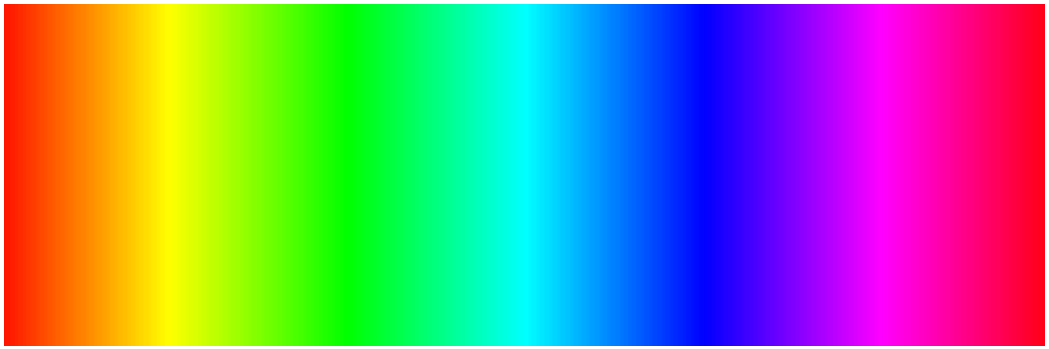
?

Slide Credit: Torralba

An example of categorical perception

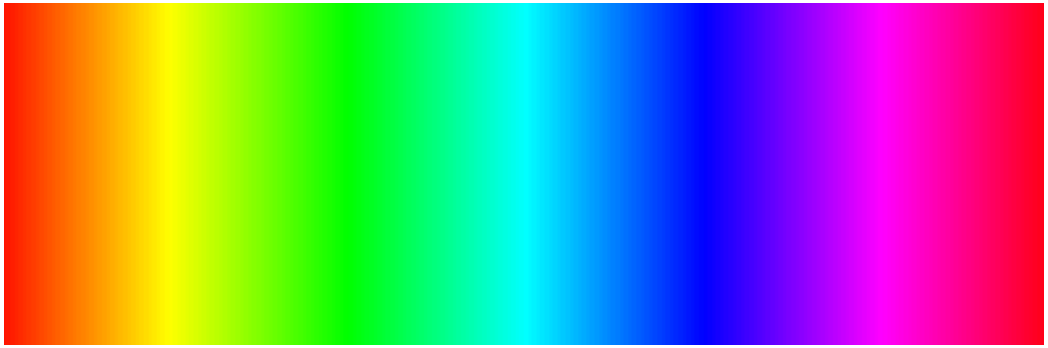
Continuous perception: graded response

Categorical perception: “sharp” boundaries



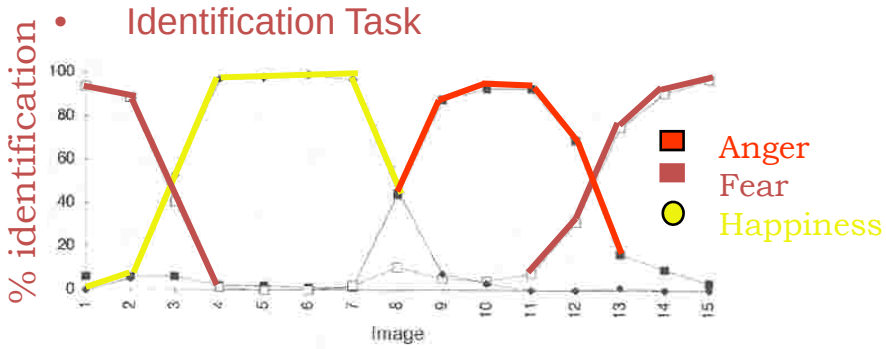
Many perceptual phenomena are a mixture of the two: categorical at an everyday level of magnification, but continuous at a more microscopic level.

Categorical perception: “sharp” boundaries



Red vs. yellow vs. green vs. blue

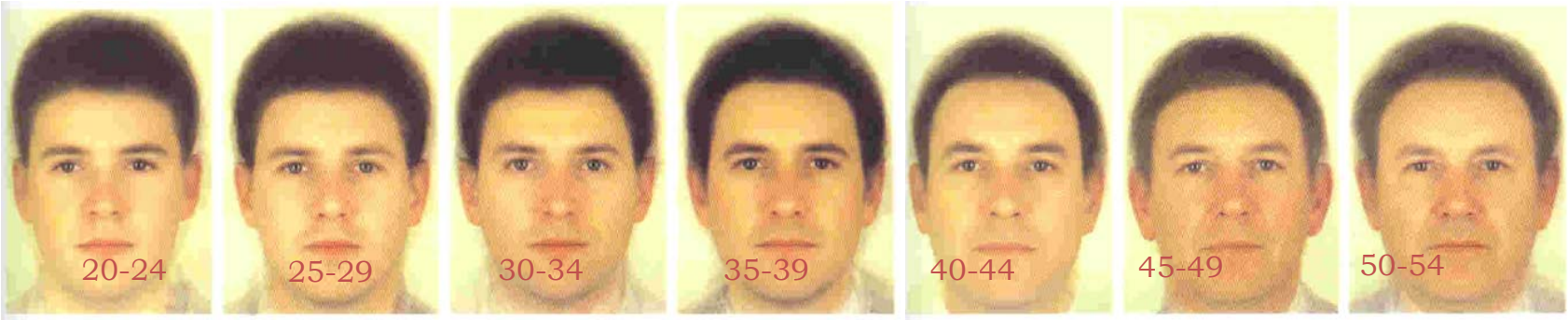
fear  happiness



Slide Credit: Torralba

Continuous perception: graded response

Dark vs. Light



Young vs. Old

Slide Credit: Torralba

Slide Credit: Torralba

Why do we care about categories?

Perception of function: We can perceive the 3D shape, texture, material properties, without knowing about objects. But, the concept of category encapsulates also information about what can we do with those objects.

"We therefore include the perception of function as a proper – indeed, crucial – subject for vision science", *from Vision Science, chapter 9, Palmer*.

Why do we care about categories?

When we recognize an object we can make predictions about its behavior in the future, beyond of what is immediately perceived.

Slide Credit: Torralba

Slide Credit: Torralba

The perception of function

- Direct perception (affordances): Gibson

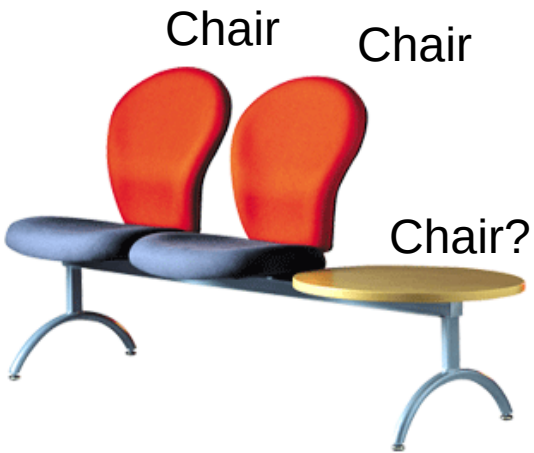
Flat surface
Horizontal
Knee-high
…

→ Sittable upon

- Mediated perception (Categorization)

Flat surface
Horizontal
Knee-high
…

→ Chair → Sittable upon



Slide Credit: Torralba

Direct perception

Some aspects of an object function can be perceived directly

– Functional form: Some forms clearly indicate to a function ("sittable-upon", container, cutting device, …)

Sittable-upon Sittable-upon

Sittable-upon

It does not seem easy to sit-upon this…

Slide Credit: Torralba

Direct perception

Some aspects of an object function can be perceived directly

– Observer relativity: Function is observer dependent

Limitations of Direct Perception

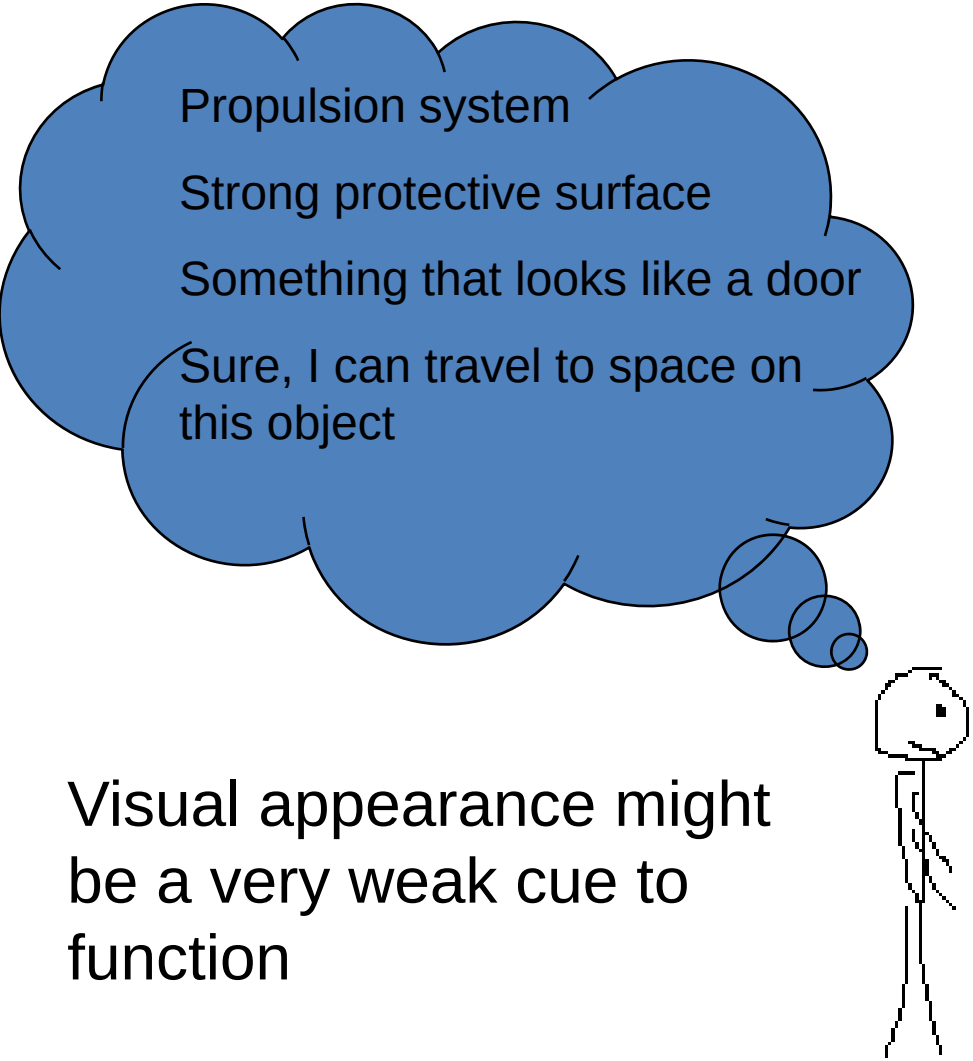
Objects of similar structure might have very different functions

Figure 9.1.2 Objects with similar structure but different functions. Mailboxes afford letter mailing, whereas trash cans do not, even though they have many similar physical features, such as size, location, and presence of an opening large enough to insert letters and medium-sized packages.

Not all functions seem to be available from direct visual information only.

Slide Credit: Torralba

Limitations of Direct Perception



Visual appearance might be a very weak cue to function

Slide Credit: Torralba

So categorize or not?

"It seems exceedingly unlikely (though logically possible) that we categorize everything in our visual fields", Palmer.

Hypothesis: we categorize the objects that are relevant for a specific task that we have at hand, but we only extract affordances from the others.

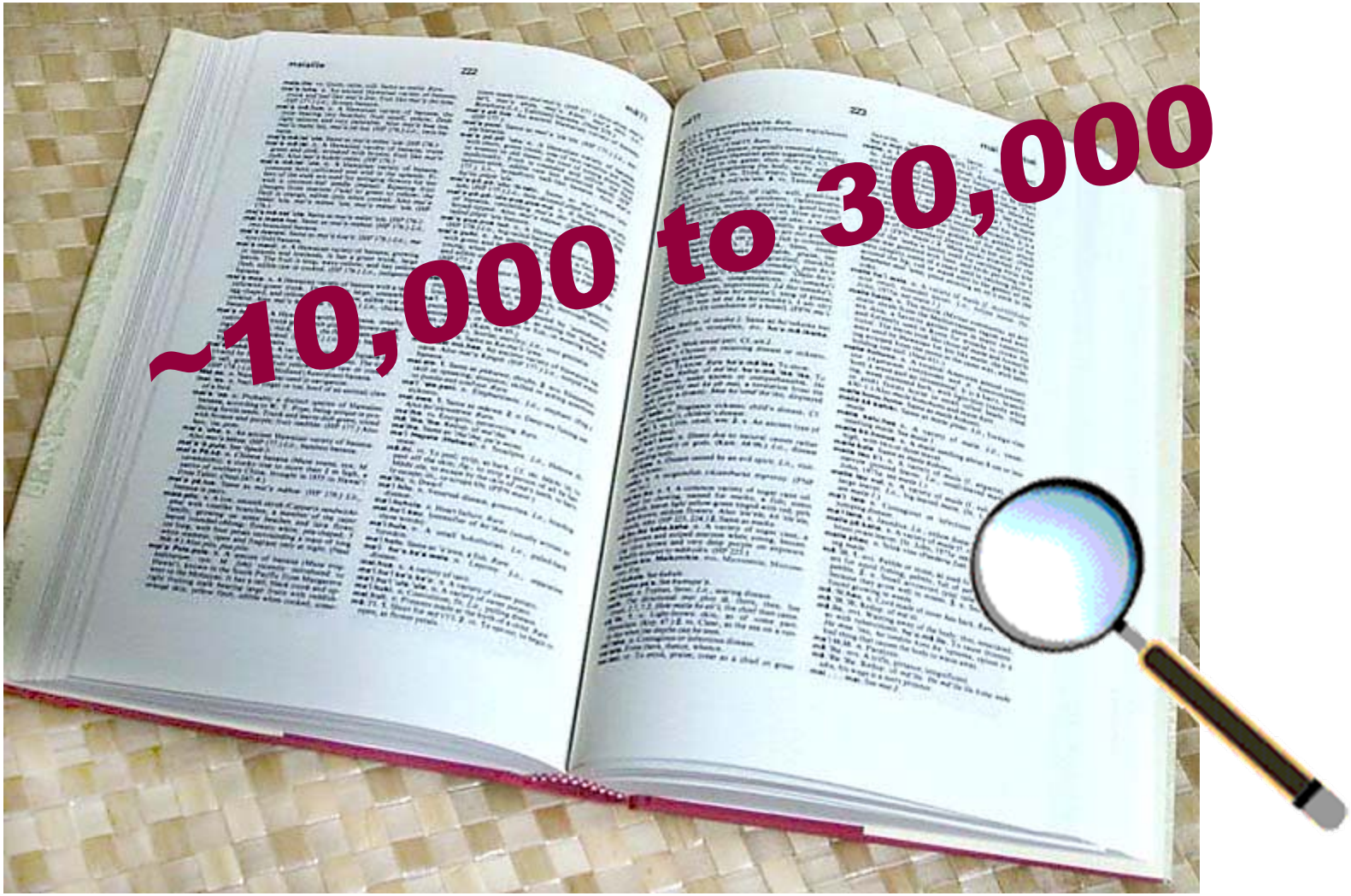
How many categories?

Many

Slide by Aude Oliva

Slide Credit: Torralba

How many object categories are there?



Biederman 1987

How many categories?

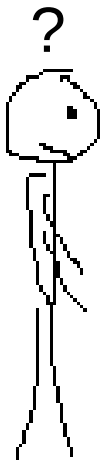
- Probably this question is not even specific enough to have an answer

Slide Credit: Torralba

Which level of categorization is the right one?

Car is an object composed of:

a few doors, four wheels (not all visible at all times), a roof, front lights, windshield



How do you define a category?

Slide Credit: Torralba

Prototype or Sum of Exemplars ?

Prototype Model

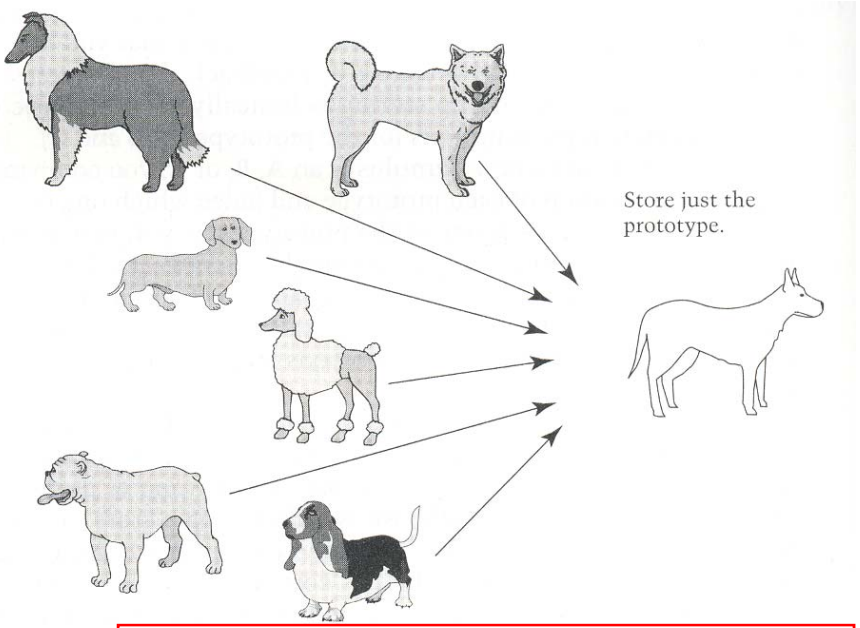


Figure 7.3. *Schematic of the prototype model. Although many exemplars are seen, only the prototype is stored. The prototype is updated continually to incorporate more experience with new exemplars.*

Category judgments are made by comparing a new exemplar to the prototype.

Exemplars Model

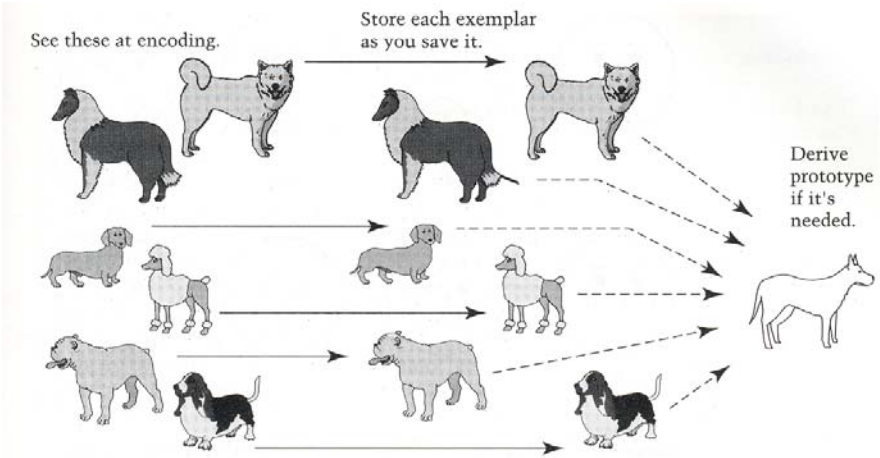


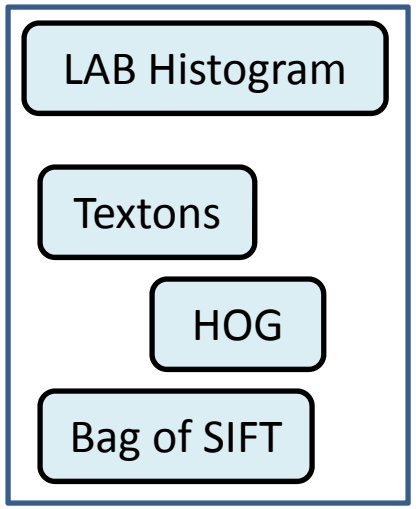
Figure 7.4. *Schematic of the exemplar model. As each exemplar is seen, it is encoded into memory. A prototype is abstracted only when it is needed, for example, when a new exemplar must be categorized.*

Category judgments are made by comparing a new exemplar to all the old exemplars of a category or to the exemplar that is the most appropriate

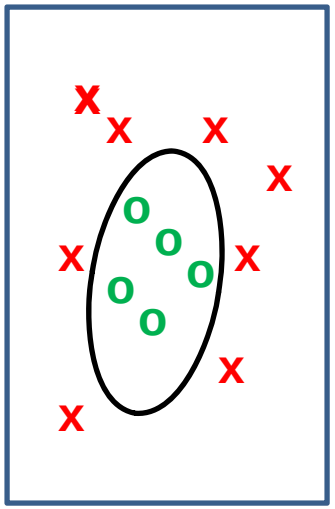
How do you define a category?

In computer vision:

Examples



+ Image Features



+ Classifier

= Object Definition

Levels of Categorization

SUPERORDINATE LEVEL CATEGORIES

↑

BASIC-LEVEL CATEGORIES

↓

SUBORDINATE LEVEL CATEGORIES

Table 7.3. ***Examples of Nested Category Structures***

Superordinate Level	Basic Level	Subordinate Level	
Musical instrument	Guitar	Folk guitar	Classical guitar
	Piano	Grand piano	Upright piano
Fruit	Peach	Freestone peach	Cling peach
	Grapes	Concord grapes	Green seedless grapes
Tree	Maple	Silver maple	Sugar maple
	Birch	River birch	White birch
	Oak	White oak	Red oak

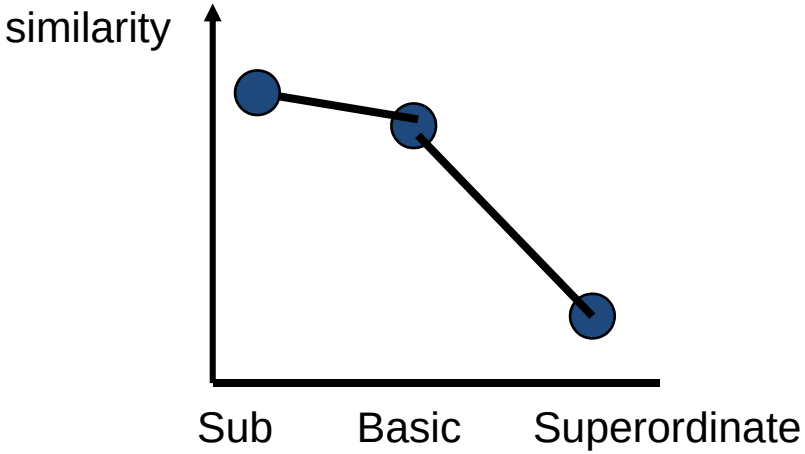
Rosch's Levels of Categorization

Definition of Basic Level:

• **Similar shape**: Basic level categories are the highest-level category for which their members have similar shapes.

• **Similar motor interactions**: … for which people interact with its members using similar motor sequences.

• **Common attributes**: … there are a significant number of attributes in common between pairs of members.



Similarity declines only slightly going from subordinate to basic level, and then drops dramatically.

Levels of Categorization

- Rosch et al (1976) found that when people are shown pictures of objects, they identify objects at a basic level more quickly than they identified objects at higher or lower levels.
- Objects appear to be recognized first at their basic level, and only afterwards they are classified in terms of higher or lowers level categories

Typicality effects

- Typicality: how good or common an item is a member of a given category.
- The typical exemplar is like a representation of the average (or central tendency)
- But, the <u>representation of a category varies with experience</u>, so does the "typical" exemplar

Table 7.1. Some Results of Rosch's (1973) Typicality Ratings

Category	Member	Rating
Fruit	Apple	1.3
	Plum	2.3
	Pineapple	2.3
	Strawberry	2.3
	Fig	4.7
	Olive	6.2
Sport	Football	1.2
	Hockey	1.8
	Wrestling	3.0
	Archery	3.9
	Gymnastics	2.6
	Weight-lifting	4.7
Bird	Robin	1.1
	Eagle	1.2
	Wren	1.4
	Chicken	3.8
	Ostrich	3.3
	Bat	5.8
Vehicle	Car	1.0
	Boat	2.7
	Scooter	2.5
	Tricycle	3.5
	Horse	5.9
	Skis	5.7

Entry-level categories
(Jolicoeur, Gluck, Kosslyn 1984)

- Typical member of a basic-level category are categorized at the expected level
- Atypical members tend to be classified at a subordinate level.

A bird


An ostrich

We do not need to recognize the exact category

A new class can borrow information from similar categories

Next class

- Sliding window detectors