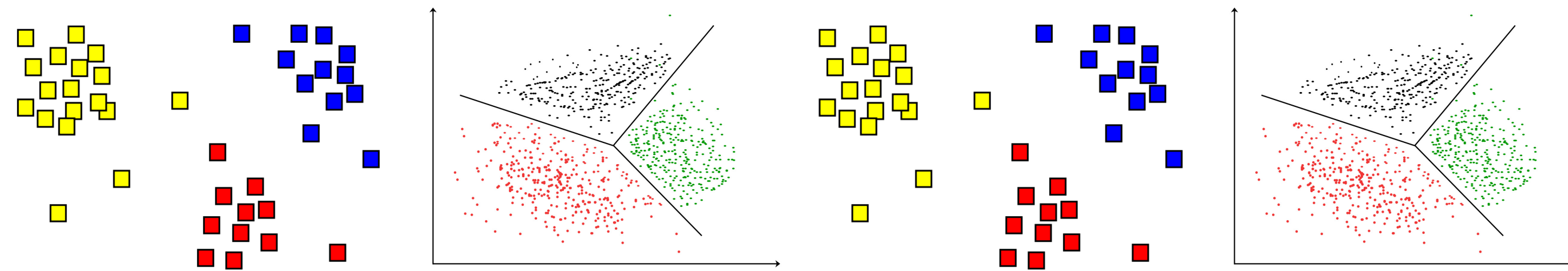




CPSC 425: Computer Vision



Lecture 27: Classification

Classification

Problem:

Assign new observations into one of a fixed set of categories (classes)

Key Idea(s):

Build a model of data in a given category based on observations of instances in that category

Classification

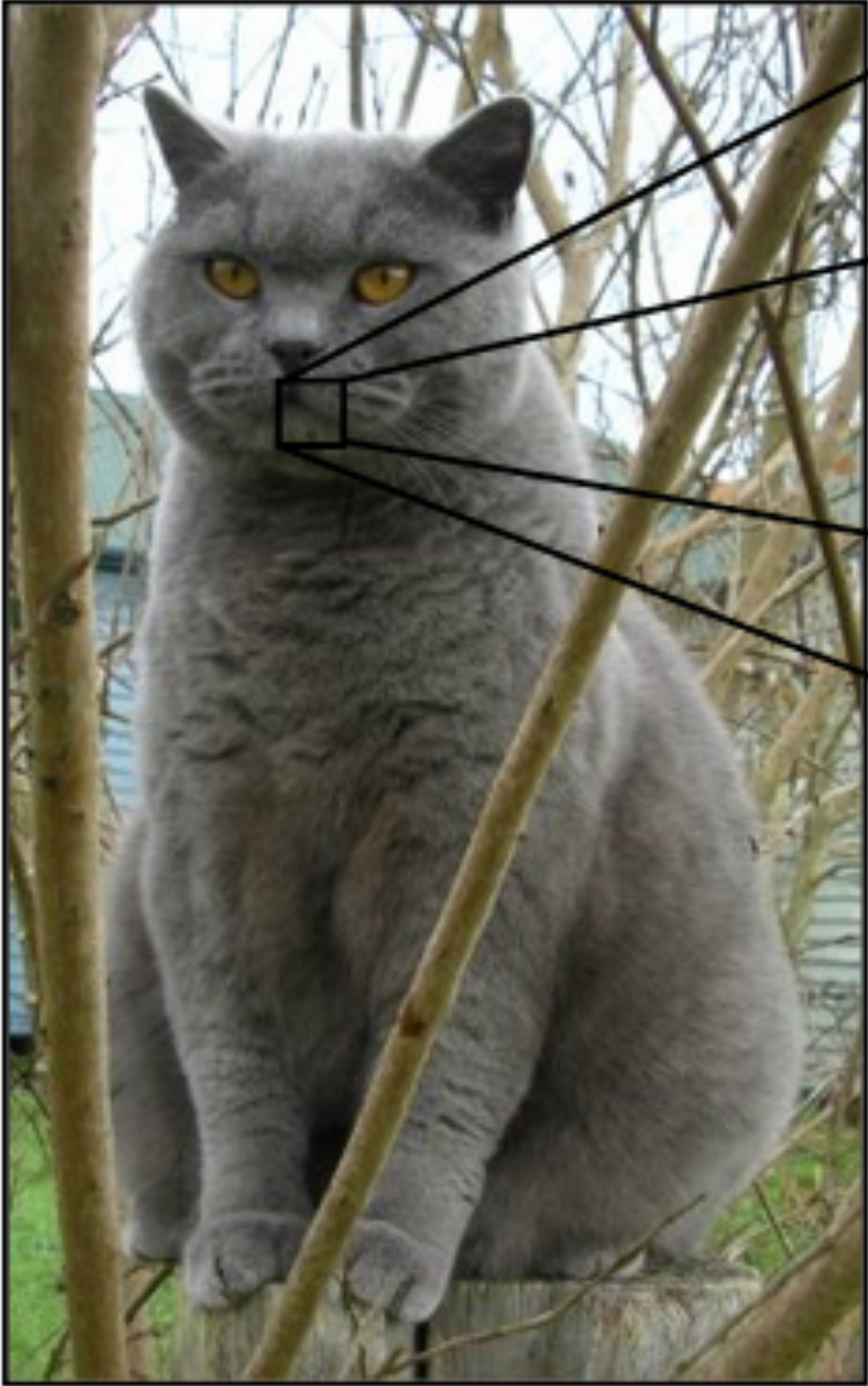


(assume given set of discrete labels)
{dog, cat, truck, plane, ...}



cat

Classification



| | | | | | | | | | | | | | | | | | | | |
|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 08 | 02 | 22 | 97 | 38 | 15 | 00 | 40 | 00 | 75 | 04 | 05 | 07 | 78 | 52 | 12 | 50 | 77 | 81 | 88 |
| 49 | 49 | 99 | 40 | 17 | 81 | 18 | 57 | 60 | 87 | 17 | 40 | 98 | 43 | 69 | 48 | 04 | 56 | 62 | 00 |
| 81 | 49 | 31 | 73 | 55 | 79 | 14 | 29 | 93 | 71 | 40 | 67 | 52 | 88 | 30 | 03 | 49 | 13 | 36 | 65 |
| 52 | 70 | 95 | 23 | 04 | 60 | 11 | 42 | 69 | 21 | 68 | 56 | 01 | 32 | 56 | 71 | 37 | 02 | 36 | 91 |
| 22 | 31 | 16 | 71 | 51 | 67 | 05 | 59 | 41 | 92 | 36 | 54 | 22 | 40 | 40 | 28 | 66 | 33 | 13 | 80 |
| 24 | 47 | 38 | 80 | 99 | 03 | 45 | 02 | 44 | 75 | 33 | 53 | 78 | 36 | 84 | 20 | 35 | 17 | 12 | 50 |
| 32 | 98 | 81 | 28 | 64 | 23 | 67 | 10 | 26 | 38 | 40 | 67 | 59 | 54 | 70 | 66 | 18 | 38 | 64 | 70 |
| 67 | 26 | 20 | 68 | 02 | 62 | 12 | 20 | 95 | 63 | 94 | 39 | 63 | 08 | 40 | 91 | 66 | 49 | 94 | 21 |
| 24 | 55 | 58 | 05 | 66 | 73 | 99 | 26 | 97 | 17 | 78 | 78 | 96 | 83 | 14 | 88 | 34 | 89 | 63 | 72 |
| 21 | 36 | 23 | 09 | 75 | 00 | 76 | 44 | 20 | 45 | 35 | 14 | 00 | 61 | 33 | 97 | 34 | 31 | 33 | 95 |
| 78 | 17 | 53 | 28 | 22 | 75 | 31 | 67 | 15 | 94 | 03 | 80 | 04 | 62 | 16 | 14 | 09 | 53 | 56 | 92 |
| 16 | 39 | 05 | 42 | 96 | 35 | 31 | 47 | 55 | 58 | 88 | 24 | 00 | 17 | 54 | 24 | 36 | 29 | 85 | 57 |
| 86 | 56 | 00 | 48 | 35 | 71 | 89 | 07 | 05 | 44 | 44 | 37 | 44 | 60 | 21 | 58 | 51 | 54 | 17 | 58 |
| 19 | 80 | 81 | 68 | 05 | 94 | 47 | 69 | 28 | 73 | 92 | 13 | 86 | 52 | 17 | 77 | 04 | 89 | 55 | 40 |
| 04 | 52 | 08 | 83 | 97 | 35 | 99 | 16 | 07 | 97 | 57 | 32 | 16 | 26 | 26 | 79 | 33 | 27 | 98 | 66 |
| 89 | 36 | 68 | 87 | 57 | 62 | 20 | 72 | 03 | 46 | 33 | 67 | 46 | 55 | 12 | 32 | 63 | 93 | 53 | 69 |
| 04 | 42 | 16 | 73 | 35 | 35 | 39 | 11 | 24 | 94 | 72 | 18 | 08 | 46 | 29 | 32 | 40 | 62 | 76 | 36 |
| 20 | 69 | 36 | 41 | 72 | 30 | 23 | 88 | 34 | 82 | 99 | 69 | 82 | 67 | 59 | 85 | 74 | 04 | 36 | 16 |
| 20 | 73 | 35 | 29 | 78 | 31 | 90 | 01 | 74 | 31 | 49 | 71 | 48 | 86 | 81 | 16 | 23 | 57 | 05 | 54 |
| 01 | 70 | 54 | 71 | 83 | 51 | 54 | 69 | 16 | 92 | 33 | 48 | 61 | 43 | 52 | 01 | 89 | 12 | 67 | 48 |

What the computer sees

image classification

- 82% cat
- 15% dog
- 2% hat
- 1% mug

Classification

A **classifier** is a procedure that accepts as input a set of features and outputs a class **label**

Classifiers can be binary (face vs. not-face) or multi-class (cat, dog, horse, ...).

We build a classifier using a **training set** of labelled examples $\{(\mathbf{x}_i, y_i)\}$, where each \mathbf{x}_i is a feature vector and each y_i is a class label.

Given a previously unseen observation, we use the classifier to predict its class label.

Classification

- Collect a database of images with labels
- Use ML to train an image classifier
- Evaluate the classifier on test images

Example training set

Label →

Feature vector
computed from
the image →



Example 1: A Classification Problem

Categorize images of fish

— “Atlantic salmon” vs “Pacific salmon”

Use **features** such as length, width, lightness, fin shape & number, mouth position, etc.

Given a previously unobserved image of a salmon, use the learned classifier to guess whether it is an Atlantic or Pacific salmon

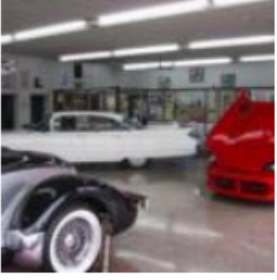


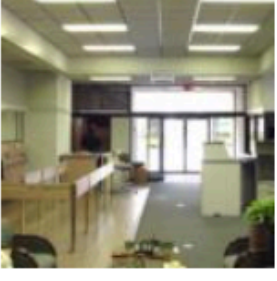






Figure credit: Duda & Hart

Example 2: Real Classification Problem

SUN Dataset

- 131K images
- 908 **scene** categories

| | | | |
|---------------------|---|---|----------------|
| indoor | shopping and dining |  | auto showroom |
| outdoor natural | workplace (office building, factory, lab, etc.) |  | bakery kitchen |
| outdoor man-made | home or hotel |  | bakery shop |
| | transportation (vehicle interiors, stations, etc.) |  | bank indoor |
| | sports and leisure |  | bank vault |
| | cultural (art, education, religion, military, law, politics, etc.) |  | banquet hall |
| | |  | bar |
| | |  | |

Example 3: Real Classification Problem

ImageNet Dataset

- 14 Million images
- 21K **object** categories

Natural object

An object occurring naturally; not made by man

0 pictures
82.76% Popularity Percentile
Wordnet IDs

Numbers in brackets: (the number of synsets in the subtree).

- ImageNet 2011 Fall Release (32326)
 - plant, flora, plant life (4486)
 - geological formation, formation (1)
 - aquifer (0)
 - beach (1)
 - cave (3)
 - cliff, drop, drop-off (2)
 - delta (0)
 - diapir (0)
 - folium (0)
 - foreshore (0)
 - ice mass (10)
 - lakefront (0)
 - massif (0)
 - monocline (0)
 - mouth (0)
 - natural depression, depression (0)
 - natural elevation, elevation (41)
 - oceanfront (0)
 - range, mountain range, range of (0)
 - relict (0)
 - ridge, ridgeline (2)
 - ridge (0)
 - shore (7)
 - slope, incline, side (17)
 - spring, fountain, outflow, outpouring, talus, scree (0)
 - vein, mineral vein (1)
 - volcanic crater, crater (2)
 - wall (0)
 - water table, water level, ground

Treemap Visualization Images of the Synset Downloads

ImageNet 2011 Fall Release Natural object

Plant

Covering

Sample Extraterrestrial Body

Asterism Mechanism Celestial

Radiator Body Rock

Tangle Nest

Bayes Rule (Review and Definitions)

Let c be the class label and let x be the measurement (i.e., evidence)

The diagram illustrates the Bayes Rule equation with color-coded labels for each term:

- class-conditional probability (a.k.a. likelihood)**: $P(x|c)$ (blue box)
- prior probability**: $p(c)$ (green box)
- posterior probability**: $P(c|x)$ (purple box)
- unconditional probability (a.k.a. marginal likelihood)**: $P(x)$ (cyan box)

$$P(c|x) = \frac{P(x|c)p(c)}{P(x)}$$

Bayes Rule (Review and Definitions)

Let c be the **class label** and let x be the **measurement** (i.e., evidence)

Simple case:

- binary classification; i.e., $c \in \{1, 2\}$
- features are 1D; i.e., $x \in \mathbb{R}$

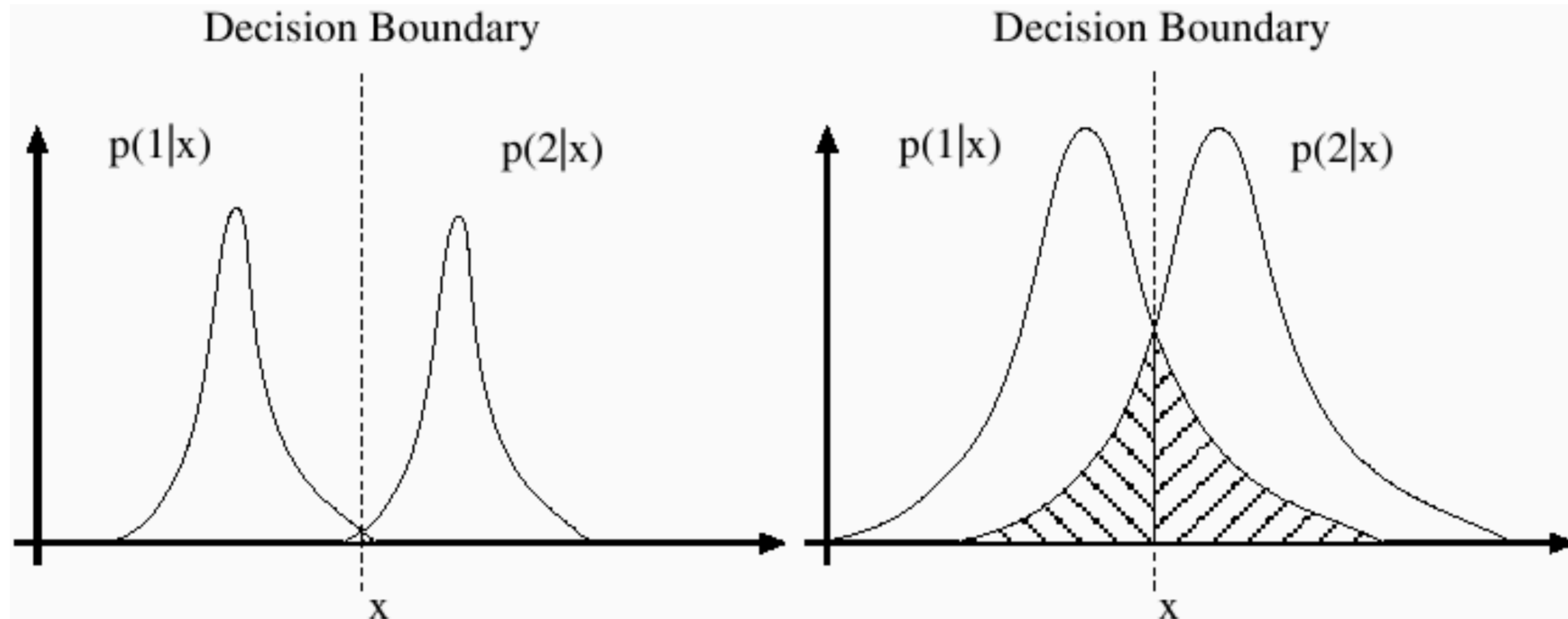
$$P(c|x) = \frac{P(x|c)p(c)}{P(x)}$$

General case:

- multi-class; i.e., $c \in \{1, \dots, 1000\}$
- features are high-dimensional; i.e., $x \in \mathbb{R}^{2,000+}$

Bayes' Risk

Some errors may be inevitable: the minimum risk (shaded area) is called the **Bayes' risk**



Forsyth & Ponce (2nd ed.) Figure 15.1