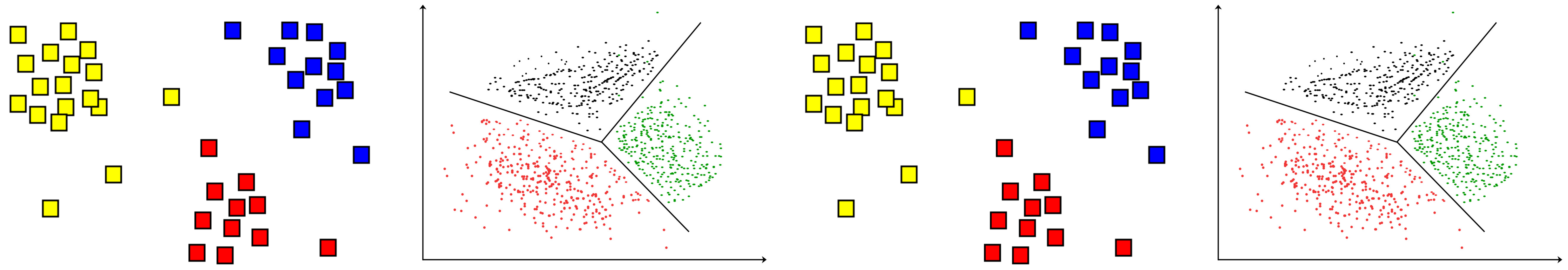
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 17: Classification

Classification

Problem:

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

Key Idea(s):

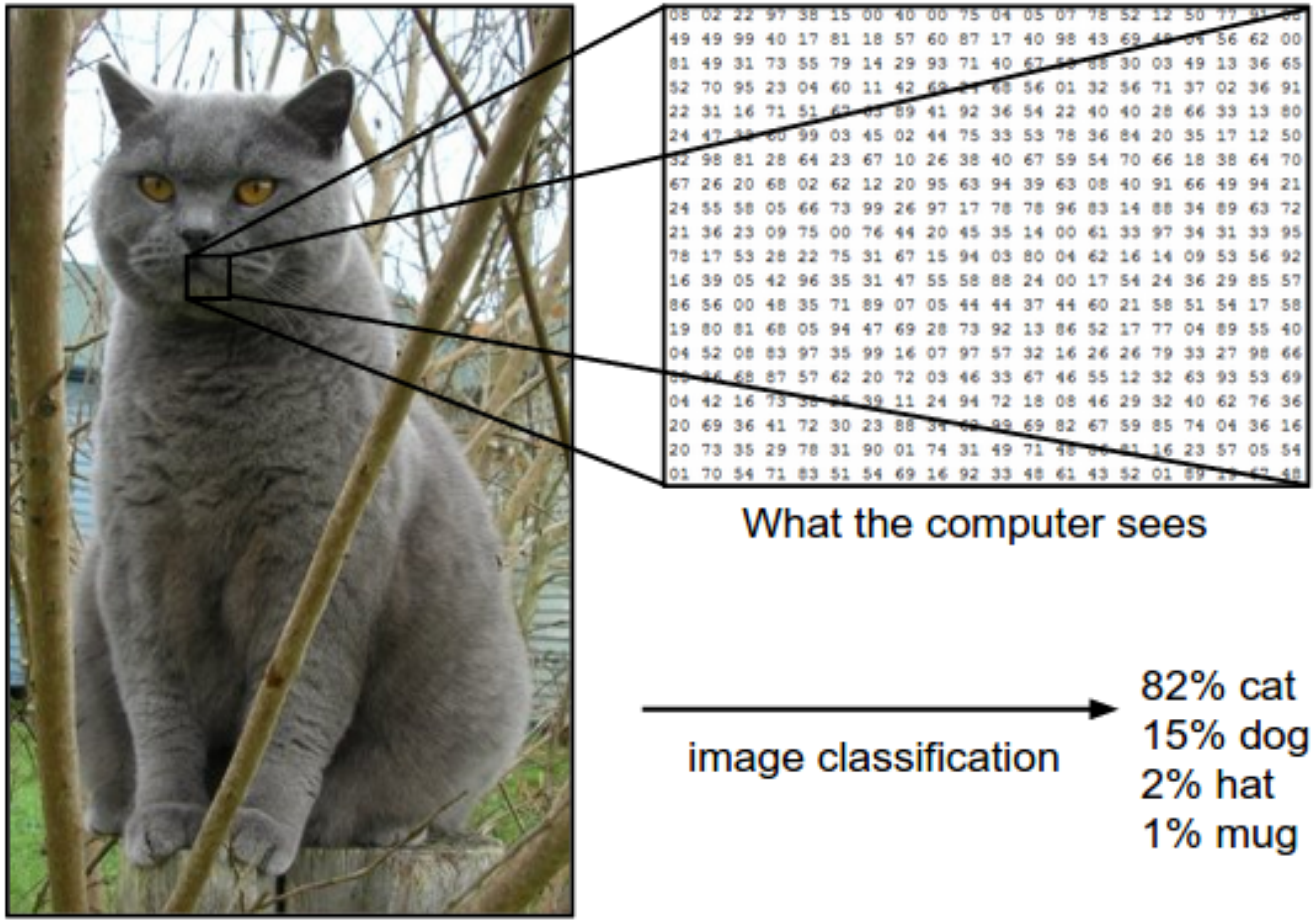
Build a model of data in a given category based on observations of instances in that category

Classification

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

→ cat

Classification



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

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.

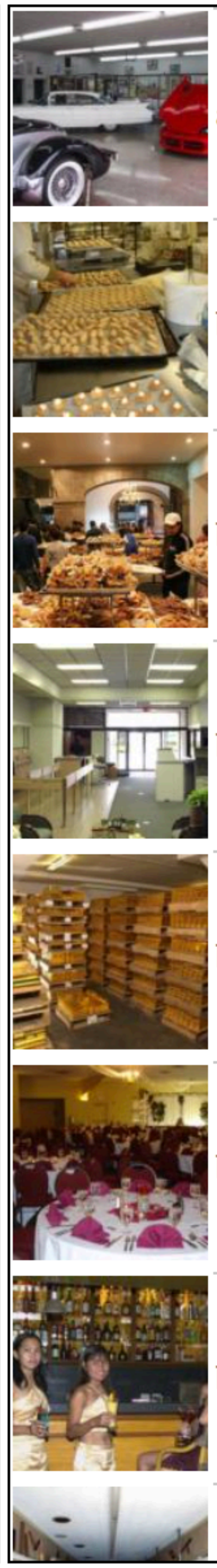
Given a previously unobserved image of a salmon, use the learned classifier to guess whether it is an Atlantic or Pacific salmon

Figure credit: Duda & Hart

Example 2: Real Classification Problem

SUN Dataset

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



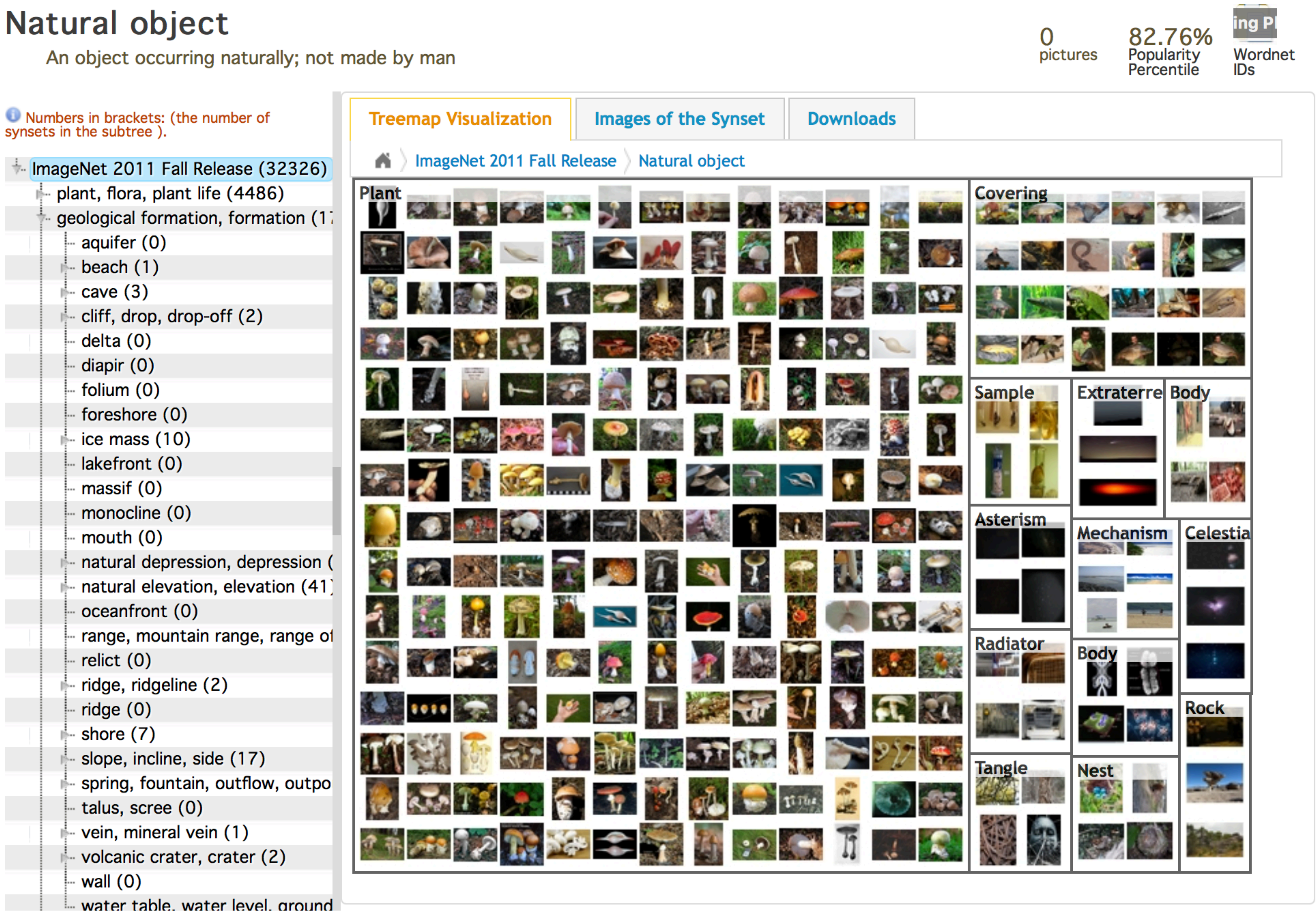
indoor	shopping and dining	auto showroom
outdoor natural	workplace (office building, factory, lab, etc.)	bakery kitchen
outdoor man-made	home or hotel	bakery shop
	transportation (vehicle interiors, stations, etc.)	bank indoor
	sports and leisure	bank vault
	cultural (art, education, religion, millitary,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

Example 3: Real Classification Problem

ImageNet Dataset

- 14 Million images

- 21K **object** categories



Bayes Rule (Review and Definitions)

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

$$\underbrace{P(c|x)}_{\text{posterior probability}} = \frac{\overbrace{P(x|c)}^{\substack{\text{class–conditional probability} \\ \text{(a.k.a. likelihood)}}}\;\overbrace{p(c)}^{\text{prior probability}}}{\underbrace{P(x)}_{\substack{\text{unconditional probability} \\ \text{(a.k.a. marginal likelihood)}}}}$$

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., $c \in \{1, ..., 1000\}$

— features are high-dimensional; i.e., $x \in \mathbb{R}^{2,000+}$

Example: Discrete Bayes Classifier

Assume we have two classes: $c_1 = \textbf{male}$ $c_2 = \textbf{female}$

We have a person who's gender we don't know, who's name is *drew*

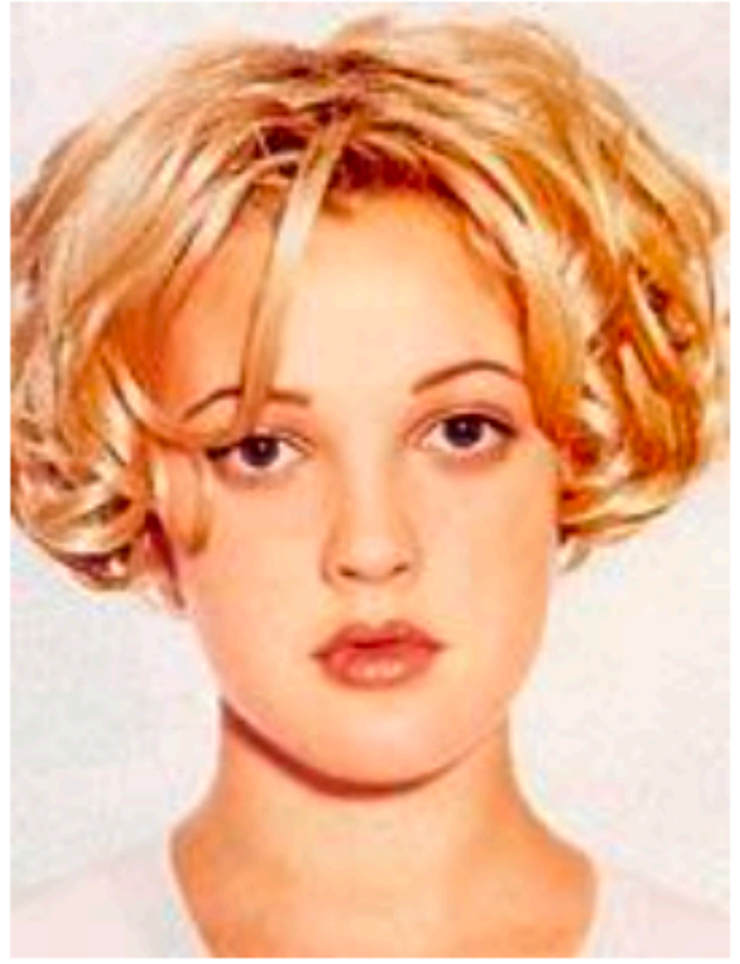
Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Assume we have two classes: $c_1 = \textbf{male}$ $c_2 = \textbf{female}$

We have a person who's gender we don't know, who's name is *drew*

Drew Carey



Drew Barrymore

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

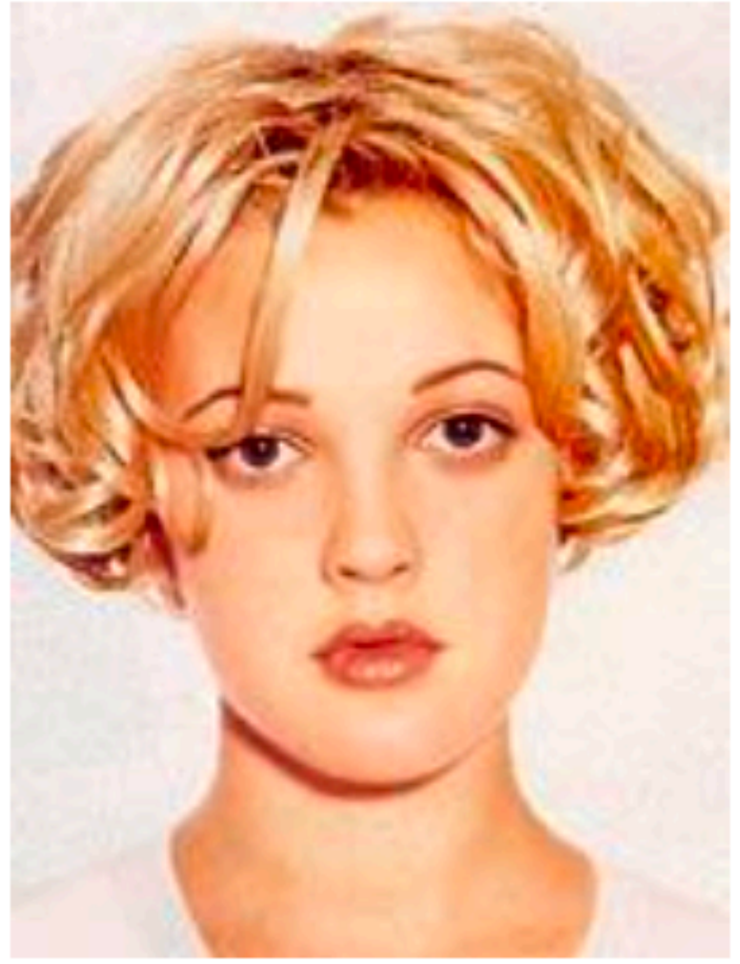
Assume we have two classes: $c_1 = \textbf{male}$ $c_2 = \textbf{female}$

We have a person who's gender we don't know, who's name is *drew*

Classifying drew as being male or female is equivalent to asking is it more probable that *drew* is male or female, i.e. which is greater $p(\textbf{male}|drew)$

$p(\textbf{female}|drew)$

Drew Carey



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Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Assume we have two classes: $c_1 = \textbf{male}$ $c_2 = \textbf{female}$

We have a person who's gender we don't know, who's name is *drew*

Classifying drew as being male or female is equivalent to asking is it more probable that *drew* is male or female, i.e. which is greater $p(\textbf{male}|drew)$

$p(\textbf{female}|drew)$

$$p(\textbf{male}|drew) = \frac{p(drew|\textbf{male})p(\textbf{male})}{p(drew)}$$

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Name	Gender
Drew	Male
Claudia	Female
Drew	Female
Drew	Female
Alberto	Male
Karin	Female
Nina	Female
Sergio	Male

$$p(\mathbf{male}|drew) = \frac{p(drew|\mathbf{male})p(\mathbf{male})}{p(drew)}$$

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Name	Gender
Drew	Male
Claudia	Female
Drew	Female
Drew	Female
Alberto	Male
Karin	Female
Nina	Female
Sergio	Male

$$p(\mathbf{male}) =$$

$$p(drew|\mathbf{male}) =$$

$$p(drew) =$$

$$p(\mathbf{male}|drew) = \frac{p(drew|\mathbf{male})p(\mathbf{male})}{p(drew)}$$

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Name	Gender
Drew	Male
Claudia	Female
Drew	Female
Drew	Female
Alberto	Male
Karin	Female
Nina	Female
Sergio	Male

$$p(\mathbf{male}) = \frac{3}{8}$$

$$p(drew|\mathbf{male}) =$$

$$p(drew) =$$

$$p(\mathbf{male}|drew) = \frac{p(drew|\mathbf{male})p(\mathbf{male})}{p(drew)}$$

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Name	Gender
Drew	Male
Claudia	Female
Drew	Female
Drew	Female
Alberto	Male
Karin	Female
Nina	Female
Sergio	Male

$$p(\mathbf{male}) = \frac{3}{8}$$

$$p(drew|\mathbf{male}) = \frac{1}{3}$$

$$p(drew) =$$

$$p(\mathbf{male}|drew) = \frac{p(drew|\mathbf{male})p(\mathbf{male})}{p(drew)}$$

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

$$p(\mathbf{male}) = \frac{3}{8}$$

$$p(drew|\mathbf{male}) = \frac{1}{3}$$

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$$p(\mathbf{male}|drew) = \frac{p(drew|\mathbf{male})p(\mathbf{male})}{p(drew)}$$

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Drew	Male
Claudia	Female
Drew	Female
Drew	Female
Alberto	Male
Karin	Female
Nina	Female
Sergio	Male

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Name	**Gender**
Drew	Male
Claudia	Female
Drew	Female
Drew	Female
Alberto	Male
Karin	Female
Nina	Female
Sergio	Male

$$p(\mathbf{male}) = \frac{3}{8}$$

$$p(drew|\mathbf{male}) = \frac{1}{3}$$

$$\cancel{p(drew) = \frac{3}{8}}$$

$$p(\mathbf{male}|drew) = \frac{p(drew|\mathbf{male})p(\mathbf{male})}{\cancel{p(drew)}} = 0.125$$

Example from: Eamonn Keogh

Example: Discrete Bayes Classifier

Name	Gender
Drew	Male
Claudia	Female
Drew	Female
Drew	Female
Alberto	Male
Karin	Female
Nina	Female
Sergio	Male

$$p(\mathbf{male}) = \frac{3}{8} \qquad p(\mathbf{female}) = \frac{5}{8}$$

$$p(drew|\mathbf{male}) = \frac{1}{3} \qquad p(drew|\mathbf{female}) = \frac{2}{5}$$

$$\cancel{p(drew) = \frac{3}{8}}$$

$$p(\mathbf{male}|drew) = \frac{p(drew|\mathbf{male})p(\mathbf{male})}{\cancel{p(drew)}} = 0.125$$

$$p(\mathbf{female}|drew) = \frac{p(drew|\mathbf{female})p(\mathbf{female})}{\cancel{p(drew)}} = 0.25$$

Example from: Eamonn Keogh

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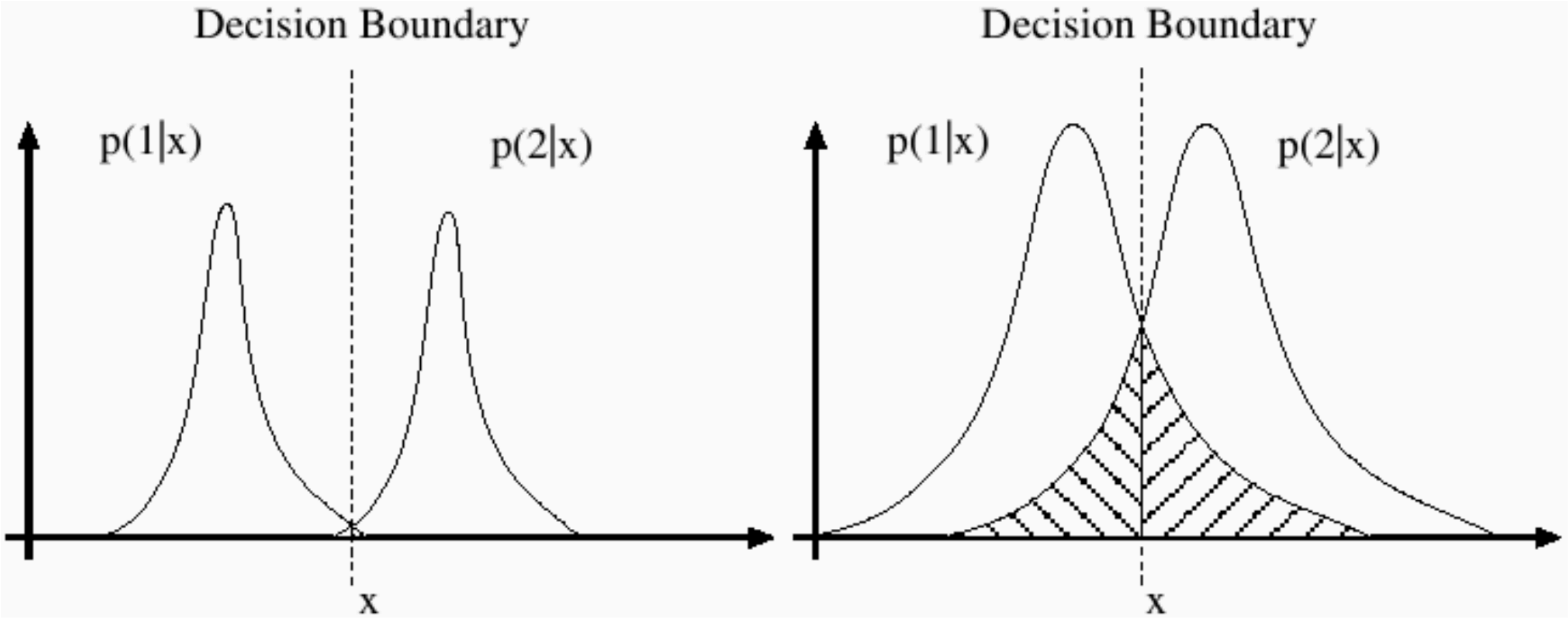
Bayes' Risk

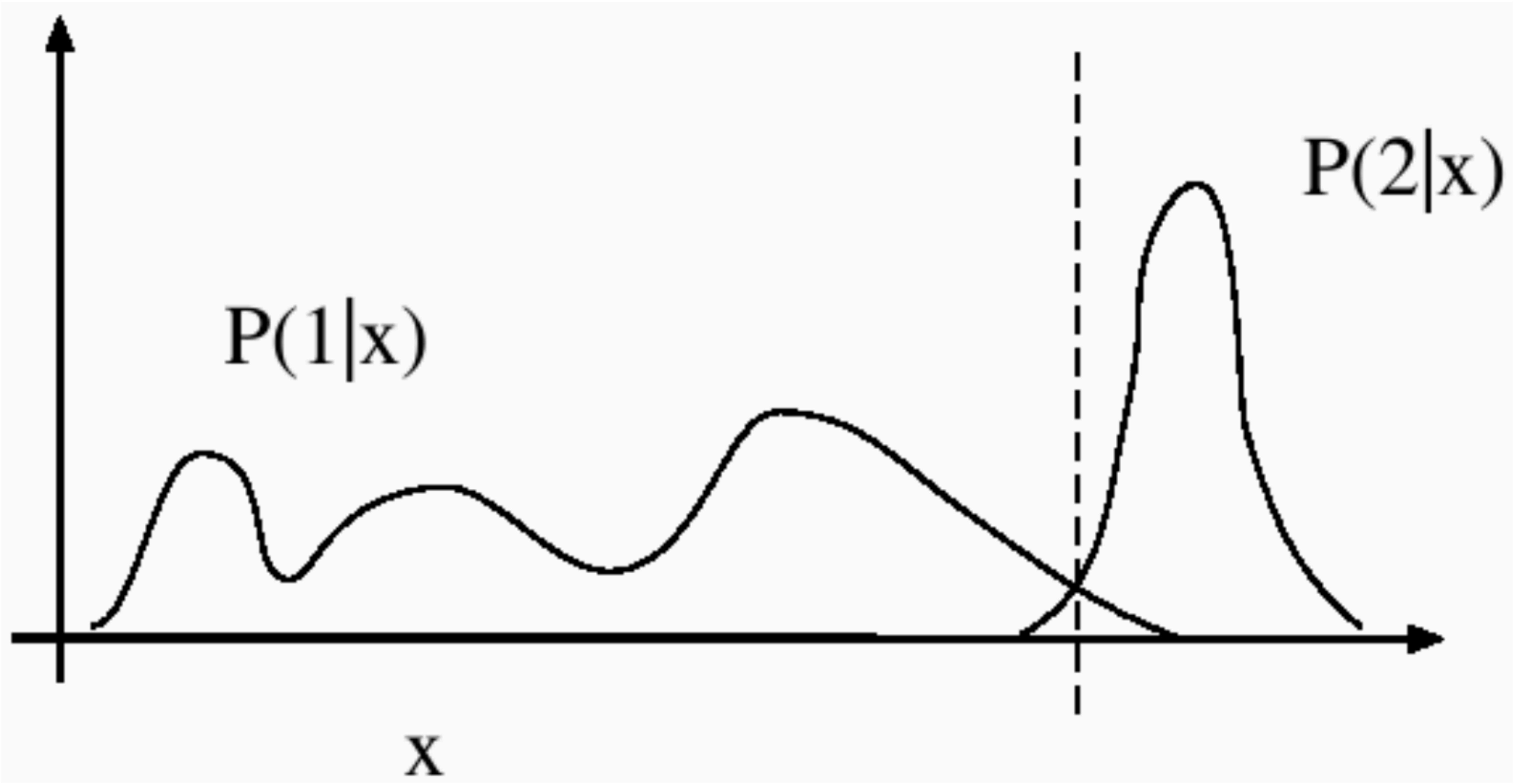
Some errors may be inevitable: the minimum risk (shaded area) is called the **Bayes' risk**



Forsyth & Ponce (2nd ed.) Figure 15.1

Discriminative vs. **Generative**

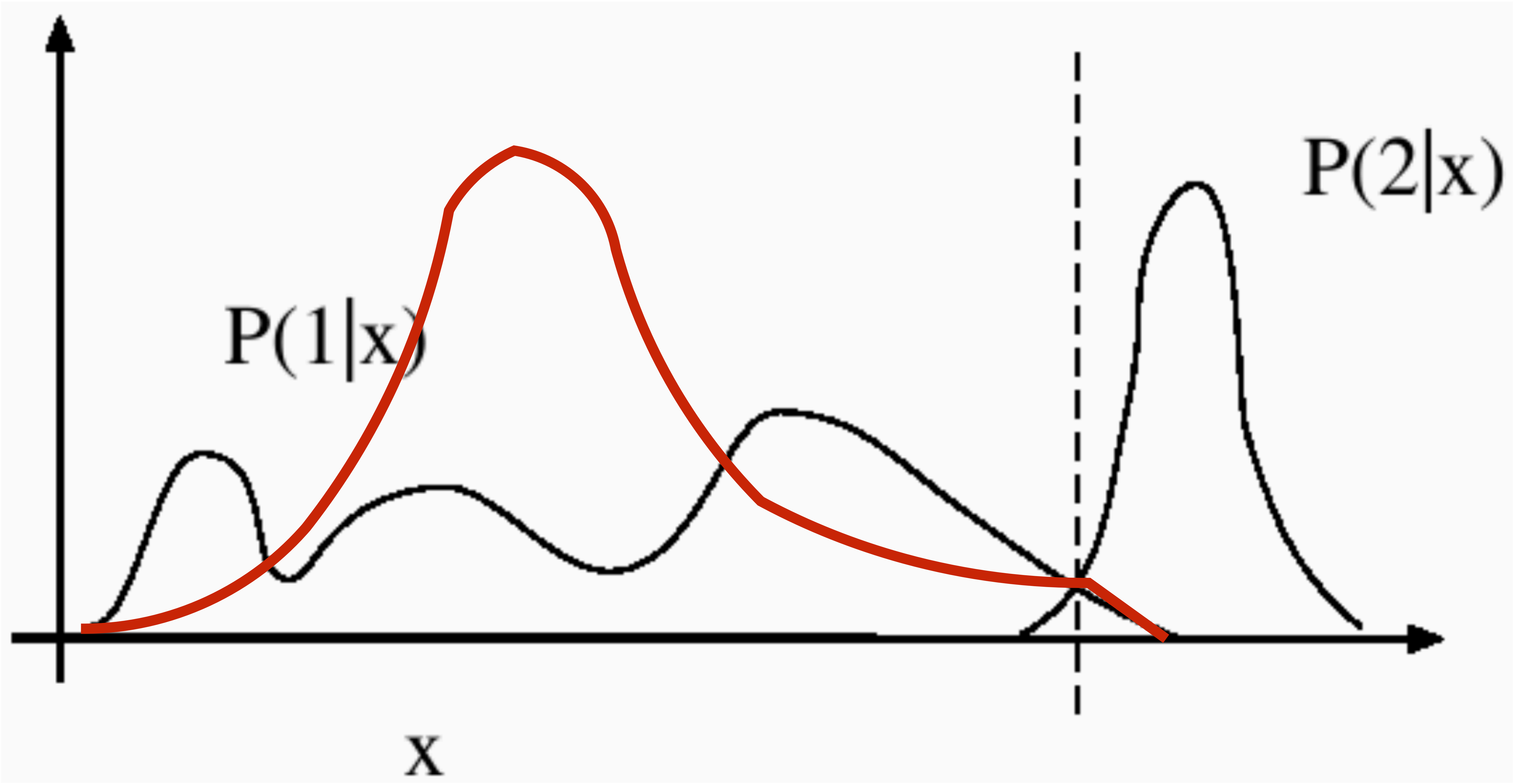
Finding a **decision boundary** is not the same as modeling a **conditional density** — while a normal density here is a poor fit to P(1|x), the quality of the classifier depends only on how well the boundary is positioned



Forsyth & Ponce (2nd ed.) Figure 15.5

Discriminative vs. **Generative**

Finding a **decision boundary** is not the same as modeling a **conditional density** — while a normal density here is a poor fit to P(1|x), the quality of the classifier depends only on how well the boundary is positioned



Forsyth & Ponce (2nd ed.) Figure 15.5