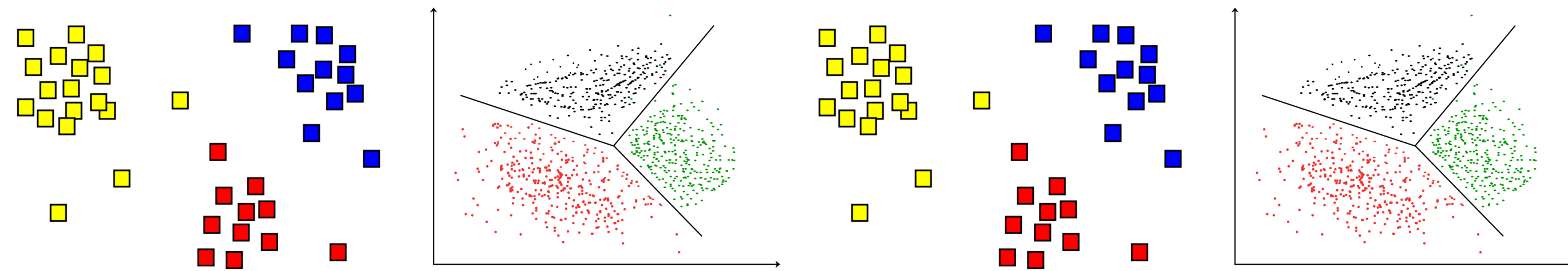


CPSC 425: Computer Vision



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



08	02	22	97	38	15	00	40	00	75	04	05	07	78	52	12	50	77	91	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	55	88	30	03	49	13	36	65
52	70	95	23	04	60	11	42	69	24	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	39	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
59	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	63	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	13	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

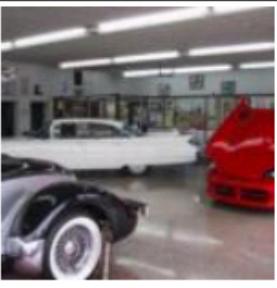


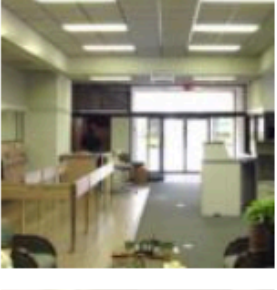
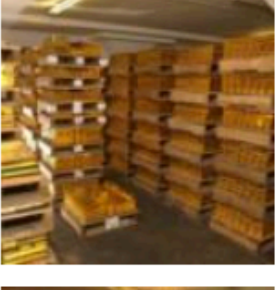





Figure credit: Duda & Hart

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, outpo (0)
 - talus, scree (0)
 - vein, mineral vein (1)
 - volcanic crater, crater (2)
 - wall (0)
 - water table, water level, ground (0)

Treemap Visualization | Images of the Synset | Downloads

ImageNet 2011 Fall Release > Natural object

Plant

Covering

Sample

Extraterre

Body

Asterism

Mechanism

Celestia

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., $x \in \mathbb{R}^{2,000+}$

Example: Discrete Bayes Classifier

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

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

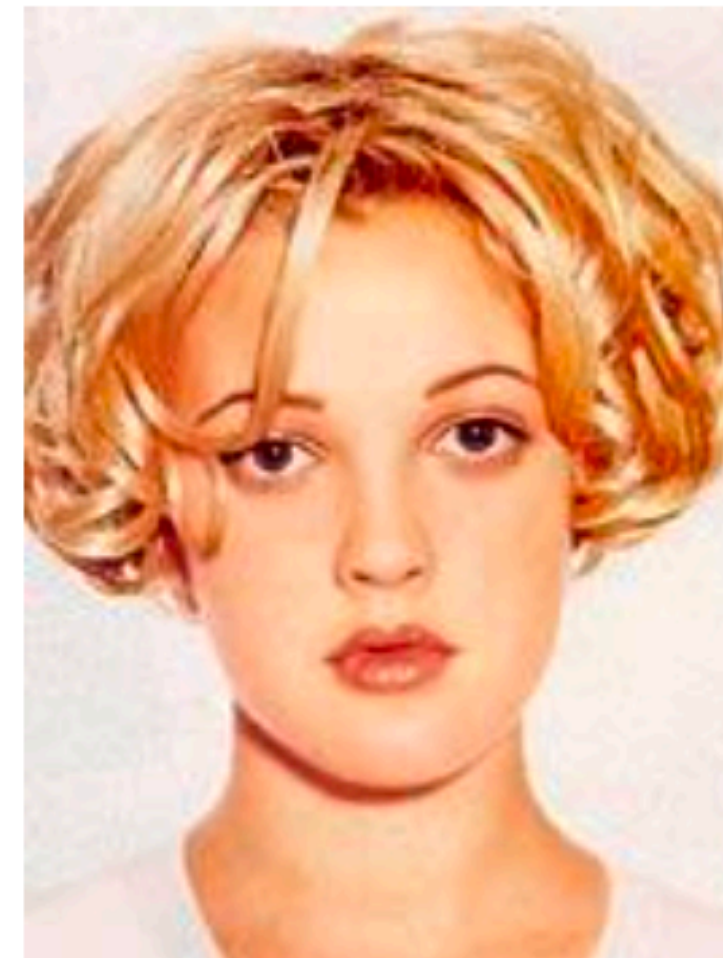
Example: Discrete Bayes Classifier

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

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



Drew Carey



Drew Barrymore

Example: Discrete Bayes Classifier

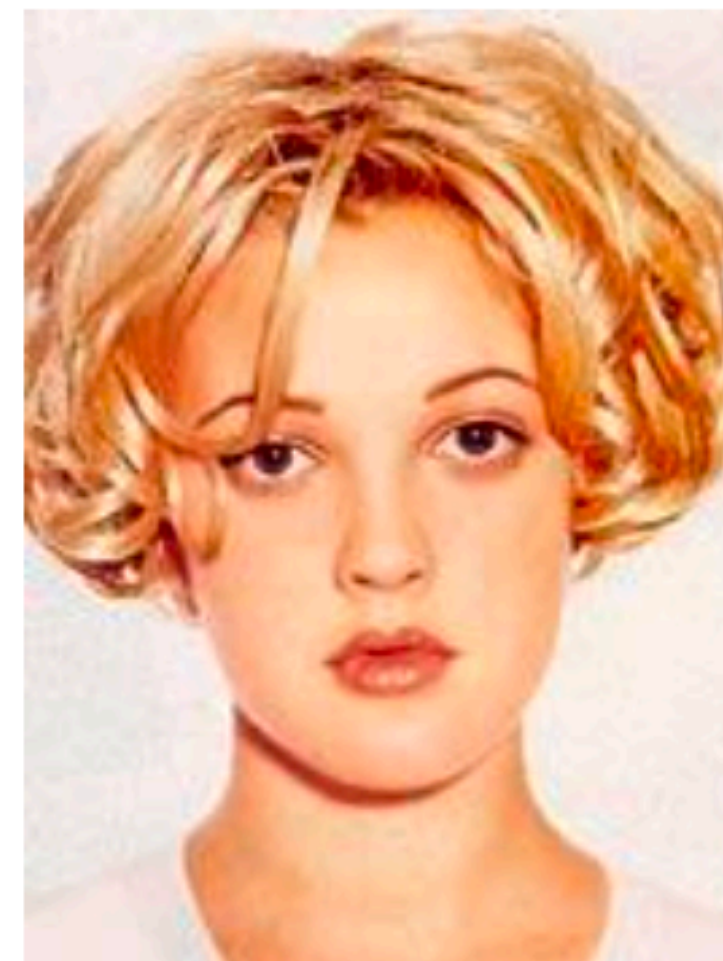
Assume we have two classes: $c_1 = \mathbf{male}$ $c_2 = \mathbf{female}$

We have a person whose gender we don't know, whose 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 $p(\mathbf{male}|drew)$
 $p(\mathbf{female}|drew)$



Drew Carey



Drew Barrymore

Example: Discrete Bayes Classifier

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

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

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

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: Discrete Bayes Classifier

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

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

$$p(drew) =$$

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

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

Example: Discrete Bayes Classifier

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

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

$$p(drew) =$$

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

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

Example: Discrete Bayes Classifier

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

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

$$p(drew) =$$

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

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

Example: Discrete Bayes Classifier

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

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

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

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

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

Example: Discrete Bayes Classifier

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

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

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

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

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

Example: Discrete Bayes Classifier

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

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

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

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

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

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

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., $x \in \mathbb{R}$

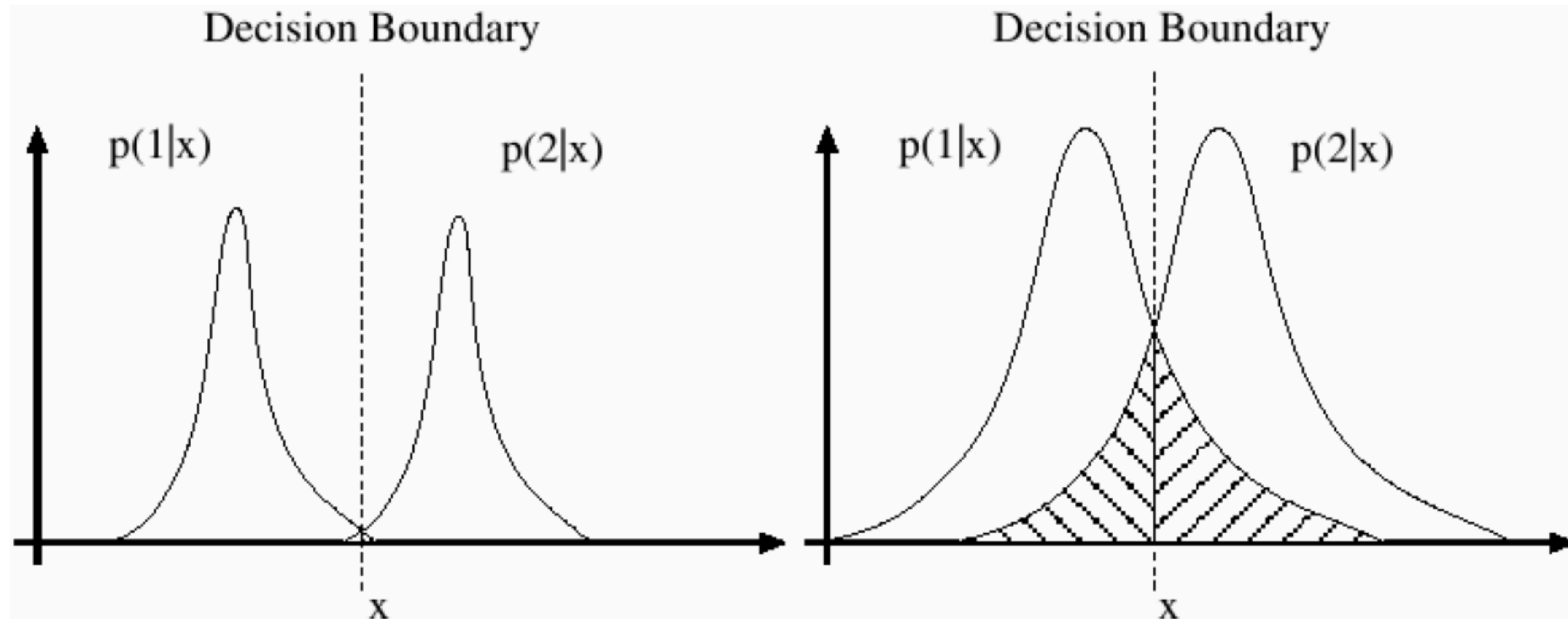
$$P(c|x) = \frac{P(x|c)p(c)}{P(x)}$$

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

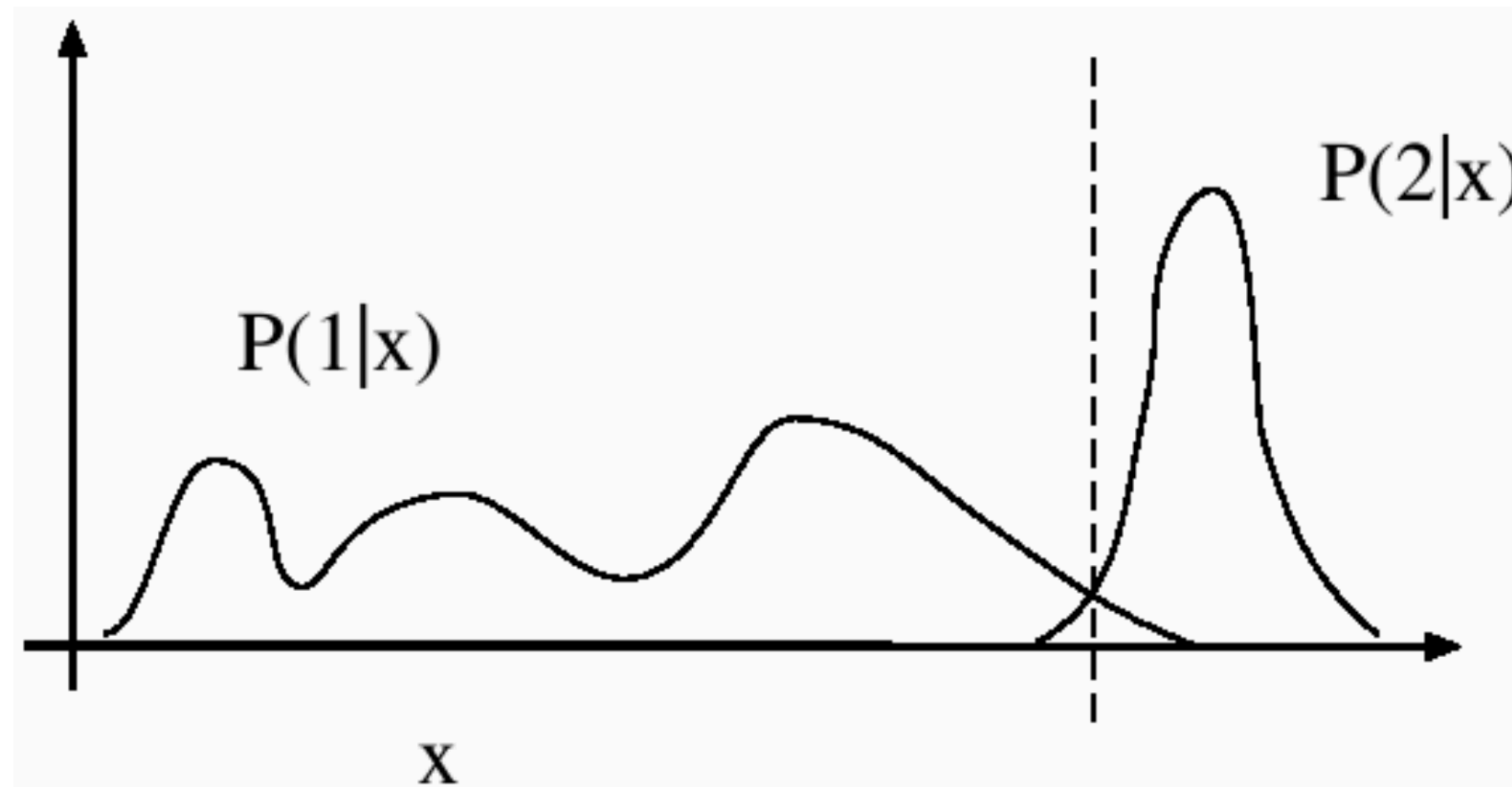
Some errors may be inevitable: the minimum risk (shaded area) is called the **Bayes' risk**



Forsyth & Ponce (2nd ed.) Figure 15.1

Discriminative vs. Generative

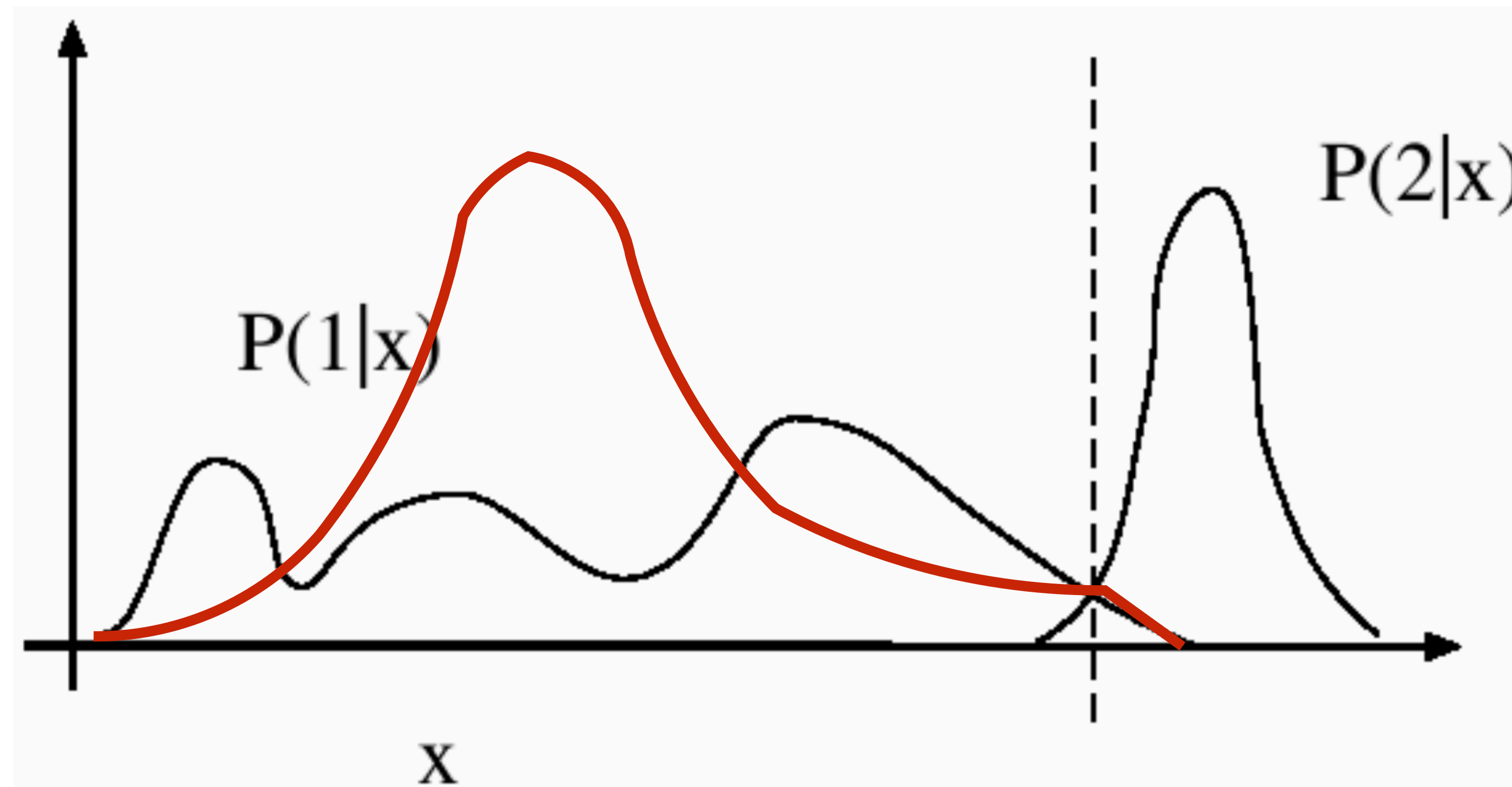
Finding a **decision boundary** is not the same as modeling a **conditional density** — while a normal density here is a poor fit to $P(1|x)$, the quality of the classifier depends only on how well the boundary is positioned



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