

# Classification using generative models

COMS 4771 Fall 2023

# **Classification problems**

Problem: Create a program that, given an element from the input space  $\mathcal{X}$ , returns the element's corresponding label from the output space  $\mathcal{Y}$

Classification problem:  $\mathcal{Y}$  is discrete (and typically finite) set

Examples:

- ▶ Spam filtering

$$\mathcal{X} = \{\text{all emails}\}, \quad \mathcal{Y} = \{\text{ham, spam}\}$$

- ▶ Intrusion detection

$$\mathcal{X} = \{\text{all network traffic logs}\}, \quad \mathcal{Y} = \{\text{benign, malicious}\}$$

- ▶ News analysis

$$\mathcal{X} = \{\text{all news articles}\}, \quad \mathcal{Y} = \{\text{politics, sports, business, \dots}\}$$

## Model data as random variables

- ▶ Feature vector: random vector  $X = (X_1, X_2, \dots, X_d)$
- ▶ Label: a discrete random variable  $Y$
- ▶  $X$  and  $Y$  may be dependent!

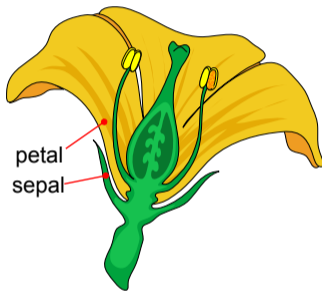
**Typical goal:** create a classifier  $f: \mathcal{X} \rightarrow \mathcal{Y}$  with low error rate

$$\text{err}[f] = \Pr(f(X) \neq Y)$$

**Iris dataset**

## Iris dataset (Fisher, 1936)

- ▶ 3 classes of iris plants  $\mathcal{Y} = \{\text{Setosa}, \text{Versicolor}, \text{Virginica}\}$
- ▶ Take some measurements of each iris plant



- ▶ Training data: 40 examples from each class; test data: 10 examples per class
- ▶ Problem: Create a program that, given the measurements of an iris plant, returns the class that the plant belongs to

## **Generative models for classification**



Generative model (for classification): a family of probability distributions for  $(X, Y)$ , each with the following form:

- ▶ Specify marginal distribution  $p_Y$  of  $Y$  (class prior)
- ▶ For each  $k \in \mathcal{Y}$ , specify conditional distribution of  $X$  given  $Y = k$  (class conditional distributions)

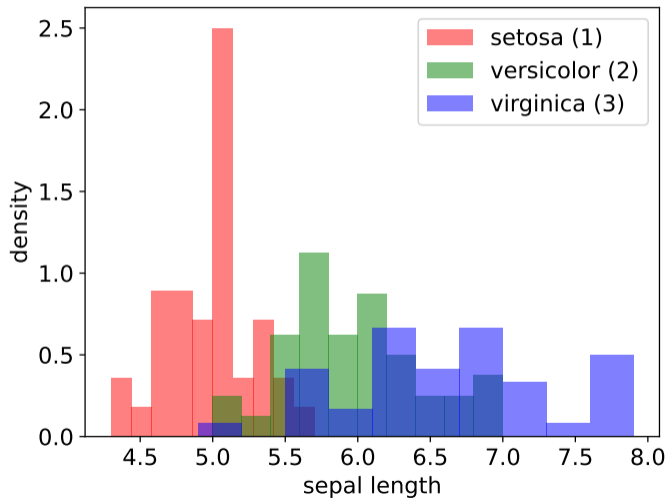
Example: Normal generative model

How to create classifier based on a distribution from the generative model?

- ▶ You have:  $\hat{p}_Y$  and  $\hat{p}_{X|Y=k}$  for each  $k \in \mathcal{Y}$
- ▶ You want:  $\hat{f}: \mathcal{X} \rightarrow \mathcal{Y}$

**Generative model for iris dataset**

# Normal generative model for iris dataset using $x = \text{sepal length}$



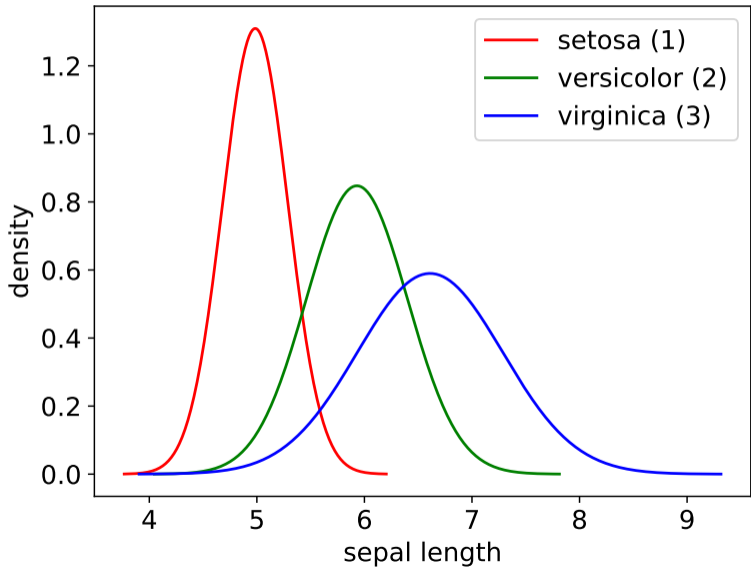
Maximum likelihood estimation (MLE) of  $\pi_k, \mu_k, \sigma_k^2$  for each  $k \in \mathcal{Y}$ :

$$\hat{\pi}_k = \frac{\# \text{ training examples with label } k}{\# \text{ training examples}}$$

$\hat{\mu}_k$  = average value of  $x$  among examples with label  $k$

$\hat{\sigma}_k^2$  = average value of  $(x - \hat{\mu}_k)^2$  among examples with label  $k$

$k$	setosa (1)	versicolor (2)	virginica (3)
$\hat{\pi}_k$	1/3	1/3	1/3
$\hat{\mu}_k$	4.99	5.93	6.61
$\hat{\sigma}_k$	0.31	0.47	0.68

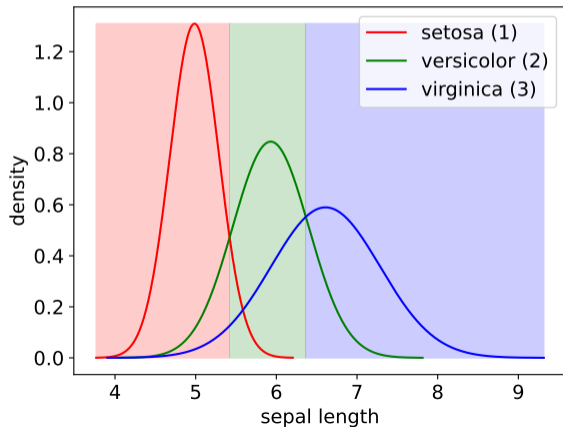


```
def learn(train_x, train_y, num_classes=3):
    return [(np.mean(train_y == k), np.mean(train_x[train_y == k]),
            ↪ np.var(train_x[train_y == k])) for k in range(num_classes)]

def predict(params, test_x):
    log_posterior = np.array([np.log(prior) - np.log(sigma2) / 2 -
    ↪ (test_x - mu) ** 2 / (2*sigma2) for prior, mu, sigma2 in
    ↪ params])
    return np.argmax(log_posterior, axis=0)
```

Resulting classifier:

$$\hat{f}(x) = \arg \max_{k \in \mathcal{Y}} \hat{\pi}_k \cdot \frac{1}{\sqrt{2\pi\hat{\sigma}_k^2}} \exp\left(-\frac{(x - \hat{\mu}_k)^2}{2\hat{\sigma}_k^2}\right)$$

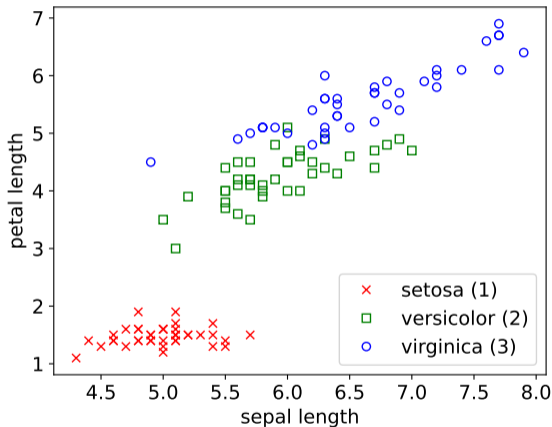


Training error rate of  $\hat{f}$ : 24%  
Test error rate of  $\hat{f}$ : 40%



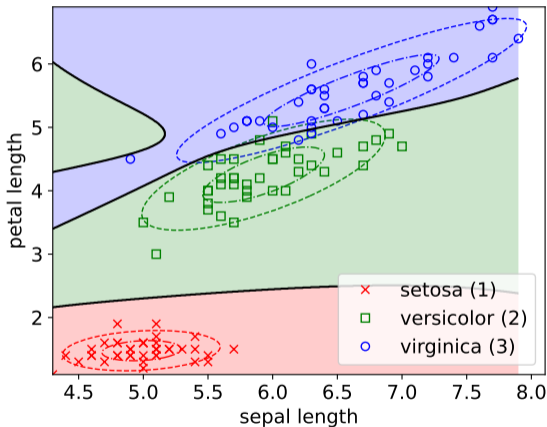
## **Bivariate normal distributions**

Now use two features:  $x = (x_1, x_2) = (\text{sepal length}, \text{petal length})$



Need generative model with class conditional distributions suitable for two-dimensional feature vectors

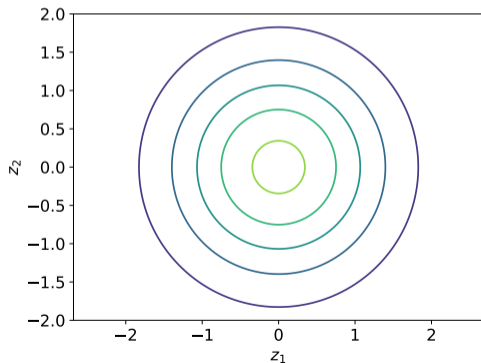
Bivariate normal distribution: 5 parameters (up from 2)



Resulting classifier has test error rate 10% (down from 40%)

If  $Z_1$  and  $Z_2$  are independent random variables and each is a standard normal random variable, then distribution of  $Z = (Z_1, Z_2)$  is [standard bivariate normal](#)

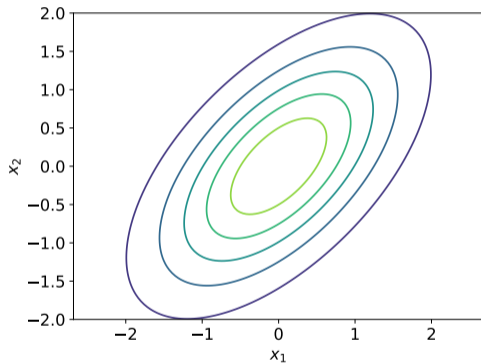
$$p_{(Z_1, Z_2)}(z_1, z_2) = \frac{1}{2\pi} \exp\left(-\frac{z_1^2 + z_2^2}{2}\right) = \phi(z_1)\phi(z_2)$$



What is distribution of  $X = aZ_1 + bZ_2$ ?

What is distribution of  $(X_1, X_2)$ , with  $X_1 = aZ_1 + bZ_2$  and  $X_2 = cZ_1 + dZ_2$ ?

Density function for  $(X_1, X_2)$  where  $X_1 = Z_1 + \frac{1}{3}Z_2$  and  $X_2 = \frac{1}{3}Z_1 + Z_2$ :



## General bivariate normal distribution:

$$p_{(X_1, X_2)}(x_1, x_2) = \frac{1}{2\pi \sqrt{\det(\Sigma)}} \exp\left(-\frac{1}{2} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}^T \Sigma^{-1} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}\right)$$



## Fitting bivariate normal distribution to data using MLE:

$\hat{\mu}_1$  = average value of  $x_1$  in dataset

$\hat{\mu}_2$  = average value of  $x_2$  in dataset

$\hat{\Sigma}_{1,1}$  = average value of  $(x_1 - \hat{\mu}_1)^2$  in dataset

$\hat{\Sigma}_{1,2} = \hat{\Sigma}_{2,1}$  = average value of  $(x_1 - \hat{\mu}_1)(x_2 - \hat{\mu}_2)$  in dataset

$\hat{\Sigma}_{2,2}$  = average value of  $(x_2 - \hat{\mu}_2)^2$  in dataset

(In context of generative models, do this for each class)

# **Multivariate normal distributions**

## General multivariate normal distribution in $d$ -dimensions:

$$p_X(x) = \frac{1}{\sqrt{(2\pi)^d \det(\Sigma)}} \exp\left(-\frac{1}{2}(x - \mu)^\top \Sigma^{-1}(x - \mu)\right)$$

### MLE:

$\hat{\mu}_i$  = average value of  $x_i$  in dataset

$\hat{\Sigma}_{i,j}$  = average value of  $(x_i - \hat{\mu}_i)(x_j - \hat{\mu}_j)$  in dataset