

Lecture 21

Missing Data Problem

ECEN 5283 Computer Vision

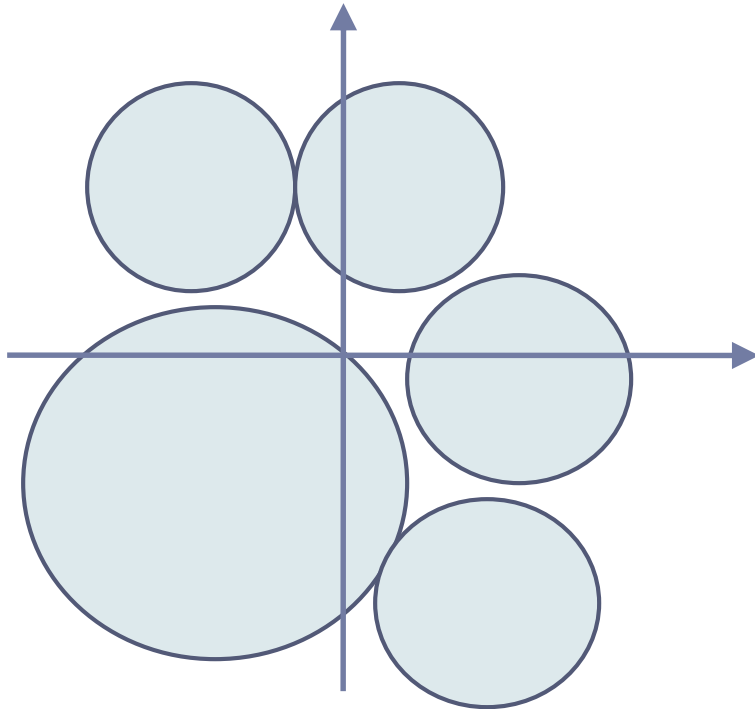
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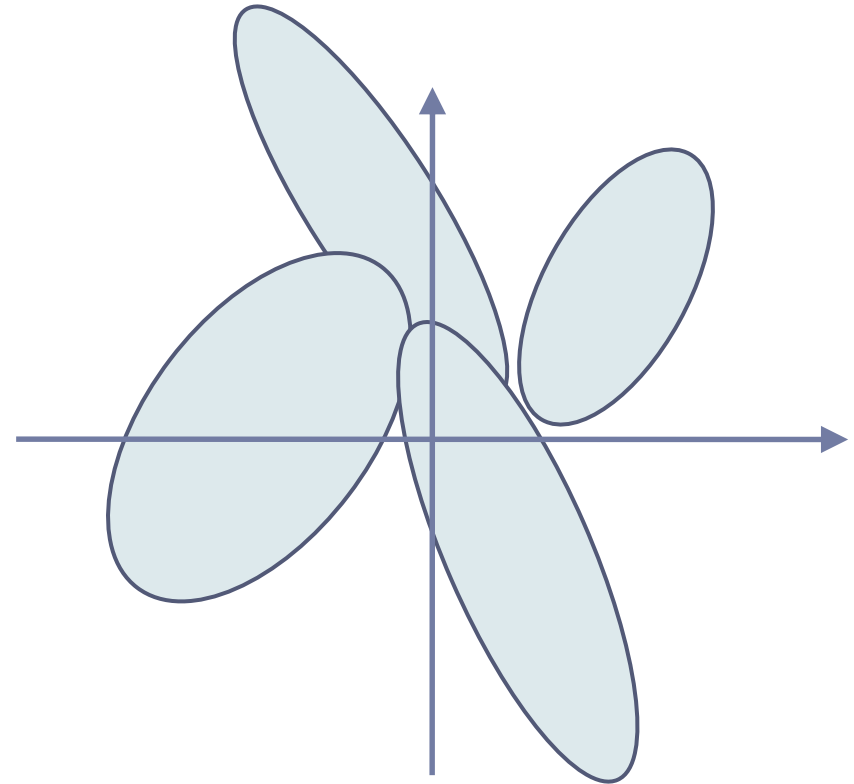
Goals

- ▶ To re-visit some basic issues of clustering.
- ▶ To introduce the missing data problem for classification.
- ▶ To formulate the missing data problem probabilistically with two basic issues, *parameter estimation* and *data classification*.

Underlying Assumption of K-means



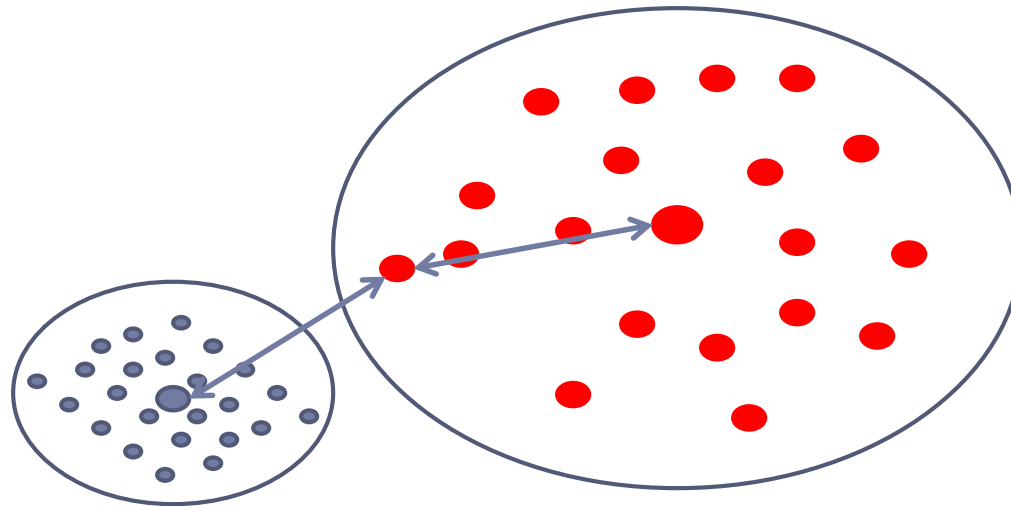
All feature distributions are isotropic due to the nature of Euclidean distance



K-means does not work for the case of non-isotropic feature distributions

K-means: Limitations

- ▶ There are three major limitations in K-means
 - ▶ Does NOT consider the spread (variance) of different clusters.
 - ▶ Does NOT consider the structure of each cluster
 - ▶ Does NOT consider the proportion (prior) of different clusters.



Missing Data Problem: Example

- ▶ Let us consider a missing data problem example
 - ▶ Assume that people can be classified into three groups according to the physical size, **big**, **median**, and **small people**.
 - ▶ Each group is characterized by the population percentage and a 2-D Gaussian showing the distribution of weight-height.
 - ▶ The reason for using Gaussian distributions instead of hard-thresholds is due to the uncertainty or error for weight-height measurement.



$$N(\mu_1, \Sigma_1)$$

$$\alpha_1 = 25\%$$



$$N(\mu_2, \Sigma_2)$$

$$\alpha_2 = 60\%$$



$$N(\mu_3, \Sigma_3)$$

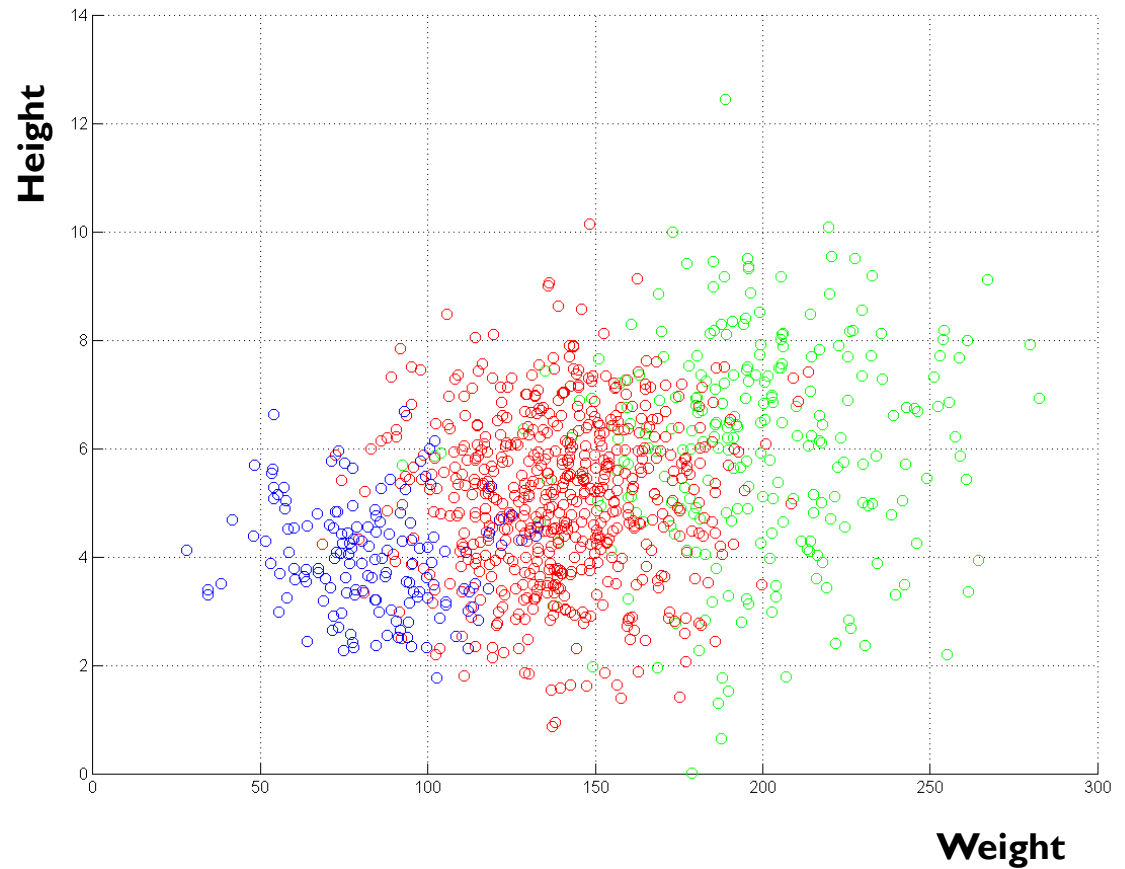
$$\alpha_3 = 15\%$$

If we don't miss anything ...

$N(\boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1), \alpha_1 = 25\%$
(big people)

$N(\boldsymbol{\mu}_2, \boldsymbol{\Sigma}_2), \alpha_2 = 60\%$
(median people)

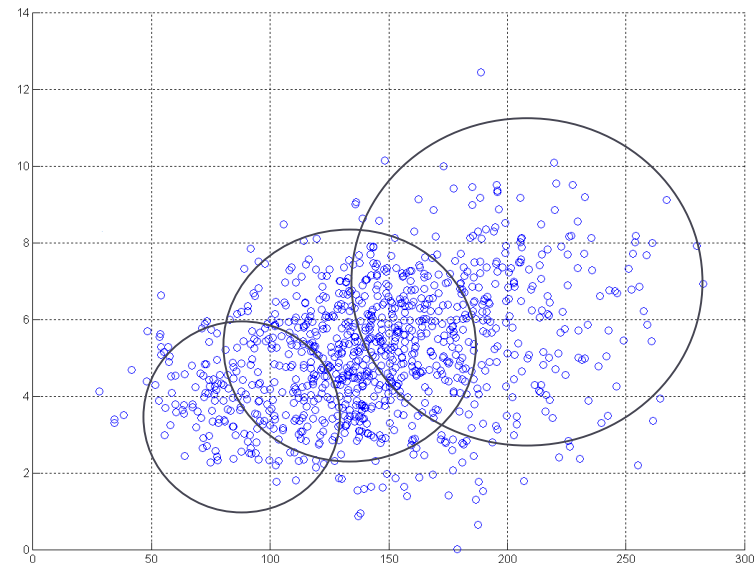
$N(\boldsymbol{\mu}_3, \boldsymbol{\Sigma}_3), \alpha_3 = 15\%$
(small people)



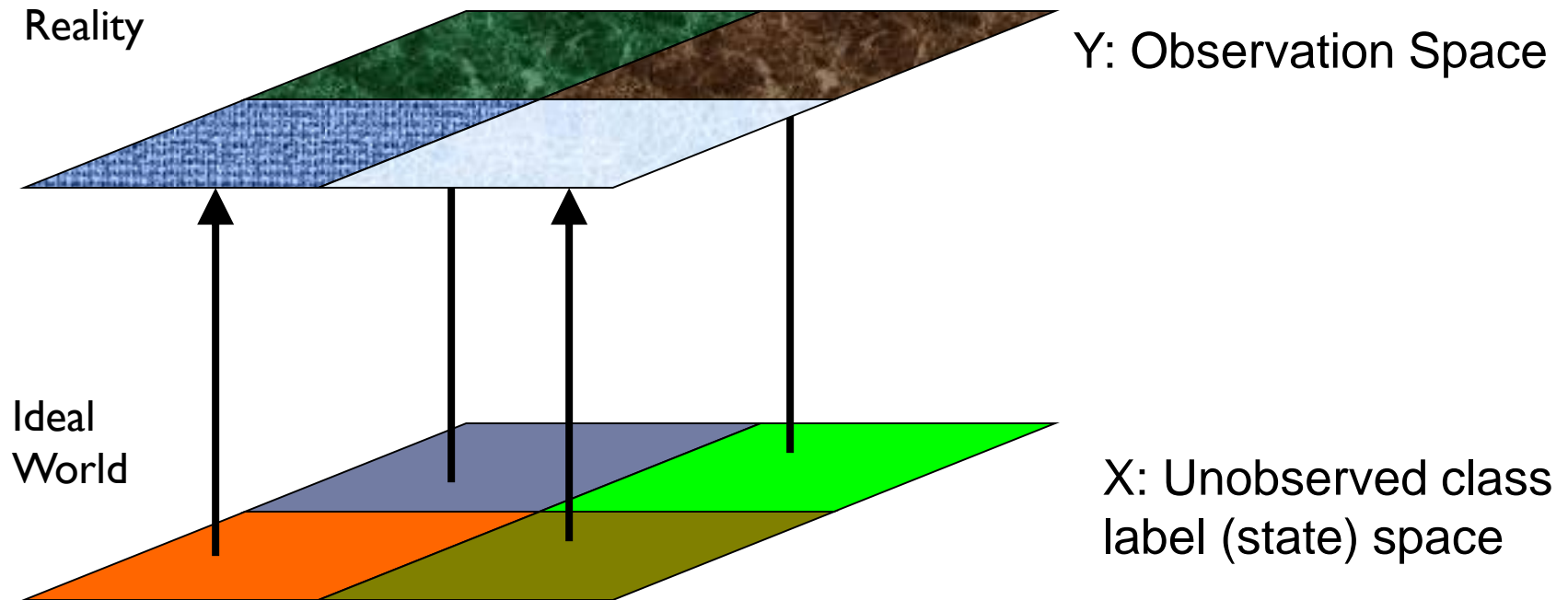
However, in reality we have ...

- ▶ Now you are given the statistics of a certain population, and you are given two tasks:
 - ▶ Estimate the model parameters for each class
 - ▶ Classify each data point into one of three classes
- ▶ That means the class labels are missing in the data we have collected, and we need to find them.

$$\{\alpha_i, \mu_i, \Sigma_i \mid i = 1, 2, 3\}$$



Missing Data Problem Restatement



Mapping $X \rightarrow Y$ loses the class label information.

Inference $Y \rightarrow X$ is needed.

Probabilistic Formulation

- ▶ **Prior probability:** something you know before you even see the data or the observation. **It is like your prior knowledge.**

$$\alpha_i = p(x = i) \text{ (prior probability)}$$

- ▶ **Likelihood function:** something to evaluate how likely a data sample is generated from a certain class. **It is like your observed evidence.**

$$p(y | x = i) = \mathcal{N}(y | \boldsymbol{\mu}_i, \Sigma_i) \text{ (likelihood function)}$$

- ▶ **Posterior probability:** based on what **you see (likelihood)** and **you know, (prior probability)** what is the probability of a data sample y belonging to certain class label. **It is like the estimate of the missing data.**

$$p(x = i | y) \quad \{i = 1, \dots, k\} \text{ (posterior probability)}$$

Some review of probabilistic theory

- ▶ Where do we start? $\alpha_i = p(x = i)$ (prior probability) $p(y | x = i) = N(y | \mu_i, \Sigma_i)$ (likelihood function)

- ▶ Joint probability

$$p(x, y) = p(y | x) p(x)$$

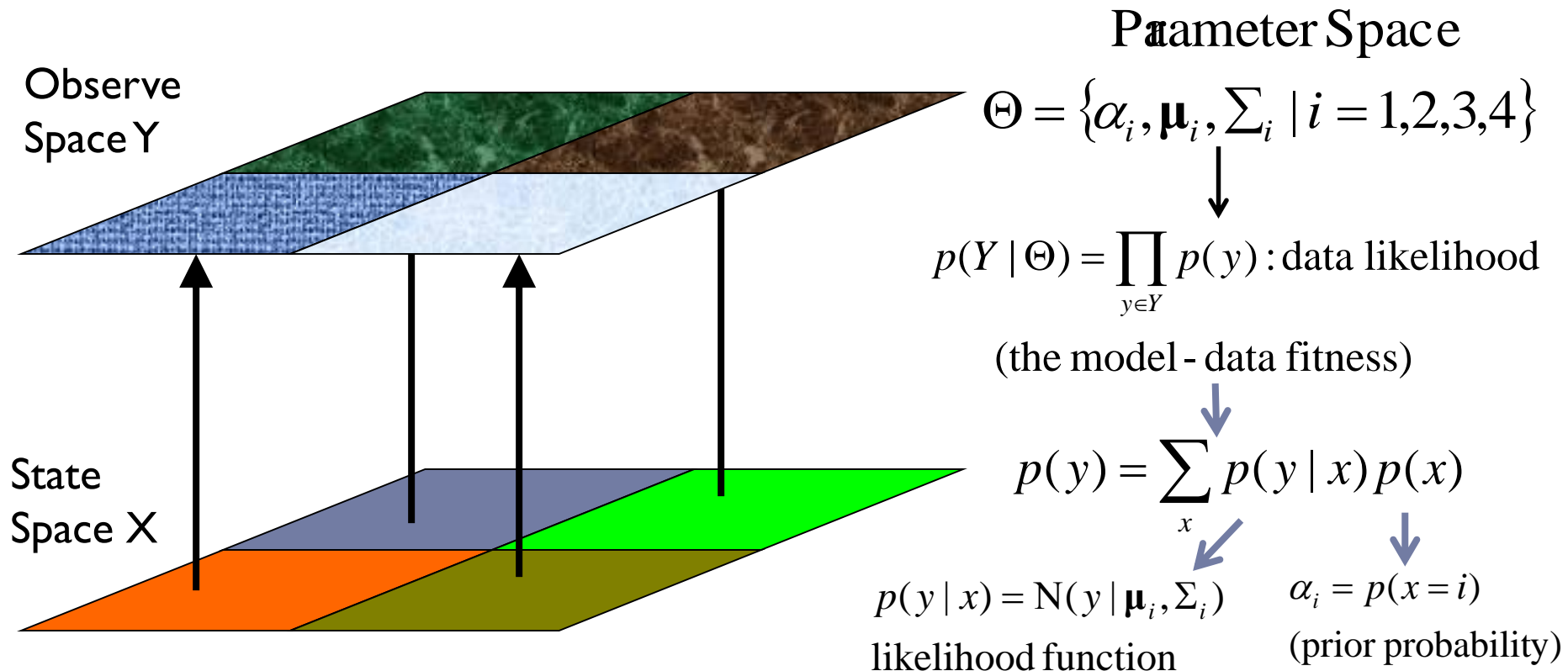
- ▶ Bayes' Law of posteriori probability

$$p(x | y) = \frac{p(x, y)}{p(y)} = \frac{p(y | x) p(x)}{p(y)} \quad (\text{Bayes' law})$$

- ▶ Marginalization probability

$$p(y) = \sum_x p(x, y) = \sum_x p(y | x) p(x)$$

Issue (1) Parameter Estimation



$$\Theta^* = \arg \max_{\Theta} p(Y \mid \Theta) \quad (\text{parameter estimation})$$

To find the parameter Θ that can best explain the current observation Y .

Issue (2) Data Classification

- ▶ To classify data, we need to compute the probability of data sample y belonging to class x , i.e., the posterior probability $p(x|y)$, which is computed during parameter estimation.

$$\alpha_i = p(x = i)$$

(prior probability)

$$p(y | x = i) = \mathbf{N}(y | \boldsymbol{\mu}_i, \Sigma_i)$$

(likelihood function)

$$p(x | y) = \frac{p(x, y)}{p(y)} = \frac{p(y | x) p(x)}{\sum_{i=1}^k p(y | x = i) p(x = i)} \quad \text{(posterior probability)}$$

(Bayes' law)

$$x^* = \arg_{x \in X} \max p(x | y) \quad \text{(maximum } a \text{ posteriori or MAP)}$$