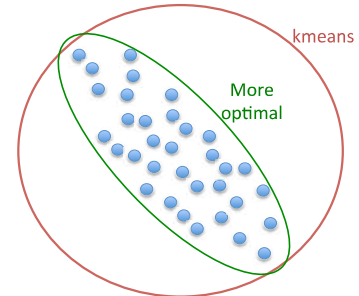


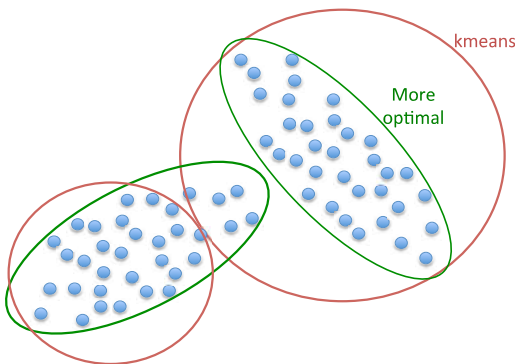
## Disadvantages of Kmeans

- Assumes spherical variance

## Expectation Maximization



Easy to see how kmeans could make a mistake here

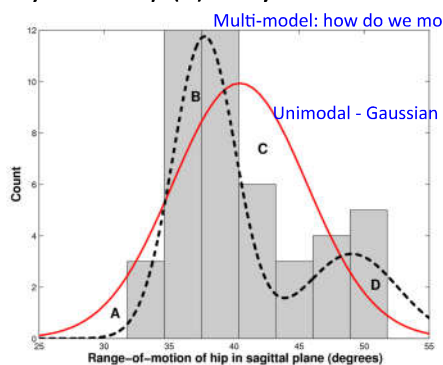


## Soft Clustering

- K means does a hard assignment of points to clusters.
- Might also like to know the probability of belonging to a cluster
- Model each cluster with a probability distribution
  - Normal with params  $\mu, \Sigma$

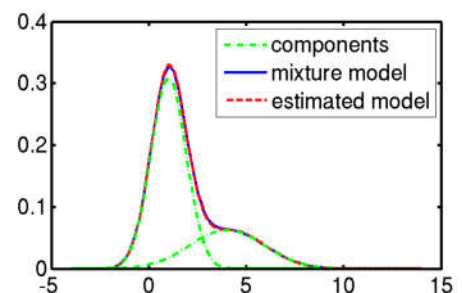
## Mixture Model

- A density model  $p(x)$  may be multi-modal.



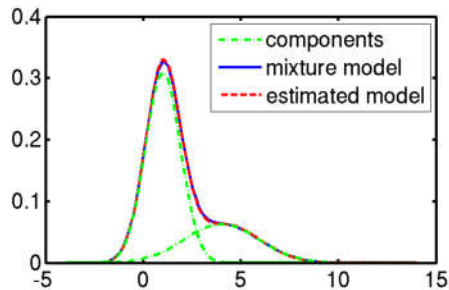
## Mixture Model

- We may be able to model it as a mixture of uni-modal distributions (e.g., Gaussians).
- Each mode may correspond to a different sub-population (e.g., male and female).



## Mixture Model

- We observe the mixture
- Can we recover the components?



## The Model

- Probability of a point  $x$  given

$$\Theta = \{\theta_1 \dots \theta_K\}$$

$$\theta_j = \{\mu_j, \Sigma_j\}$$

$$p(x|\Theta) = \sum_{j=1}^K w_j p_j(x|\theta_j)$$

- $w_j$  is probability any  $x$  belongs to cluster  $j$   
– Note: does not depend on  $i$

## The Model

- Extend this to all points

$$\begin{aligned} p(X|\Theta) &= \prod_{i=1}^N p(x_i|\Theta) \\ &= \prod_{i=1}^N \sum_{j=1}^K w_j p_j(x|\theta_j) \end{aligned}$$

## Univariate Normal Case

$$\begin{aligned} p_j(x|\theta) &= p_j(x|\mu, \sigma) \\ &= \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \end{aligned}$$

## Example Mixture

- Two univariate gaussians with
  - $\mu_1=4, \mu_2=-4,$
  - $\sigma_1 = 2, \sigma_2 = 2,$
  - $w_1 = 0.5, w_2 = 0.5$

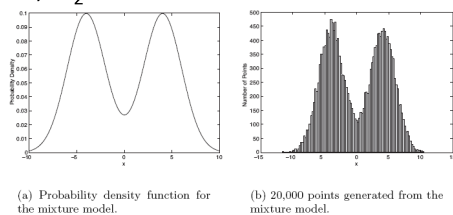


Figure 9.2. Mixture model consisting of two normal distributions with means of -4 and 4, respectively. Both distributions have a standard deviation of 2.

## How to Estimate the Params?

- Calculate the MLE!
- Turns out to be the sample mean and sample standard deviation

$$\begin{aligned} \mu &= \frac{1}{m} \sum_{i=1}^m x_i \\ \sigma &= \sqrt{\frac{1}{m} \sum_{i=1}^m (x_i - \mu)^2} \end{aligned}$$

## We're Missing Some Info

- Can't calculate the mean and std without knowing which  $m$  points belong to which cluster
- But we can't assign points to clusters without knowing the mean and std of the clusters
- EM handles this circularity

## EM Algorithm

- Select initial set of parameters
  - i.e. Set  $\mu$  and  $\sigma$  randomly, set all  $w = 1/K$
- Repeat:
  - E-step: for each object, calculate the probability that it belongs to each distribution  $p(\text{dist } j | x, \Theta)$
  - M-step: given probs from e-step, calculate new estimates of params that maximize the expected likelihood
- Until the params don't change too much

## E-step (example with K=2 clusters)

- Find probability for belonging to each cluster
  - e.g. with two clusters:

$$p(\text{dist } j | x_i, \theta) = \frac{w_j p(x_i | \theta_j)}{w_1 p(x_i | \theta_1) + w_2 p(x_i | \theta_2)}$$

- (by Bayes rule)

## M-step

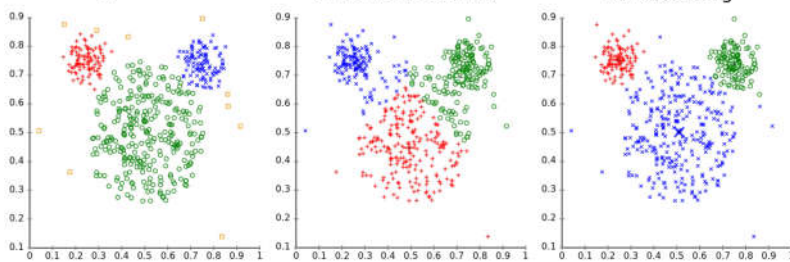
$$w_j = \frac{1}{N} \sum_{i=1}^N p(\text{dist } j | x_i, \theta)$$

$$\mu_j = \frac{\sum_{i=1}^N p(\text{dist } j | x_i, \theta) x_i}{\sum_{i=1}^N p(\text{dist } j | x_i, \theta)}$$

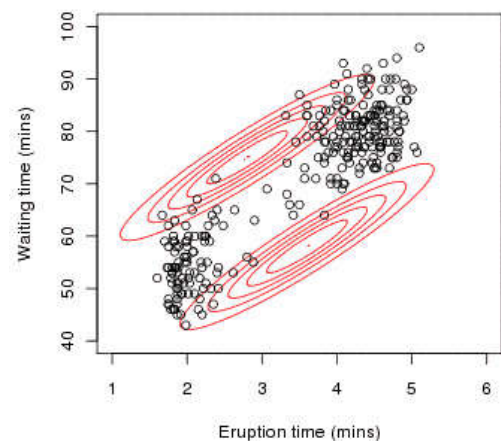
$$\sigma_j = \frac{\sum_{i=1}^N p(\text{dist } j | x_i, \theta) (x_i - \mu_j)^2}{\sum_{i=1}^N p(\text{dist } j | x_i, \theta)}$$

## K Means vs EM

Different cluster analysis results on "mouse" data set:  
Original Data      k-Means Clustering      EM Clustering



Waiting time vs Eruption time  
Old Faithful geyser



# Differences in Density

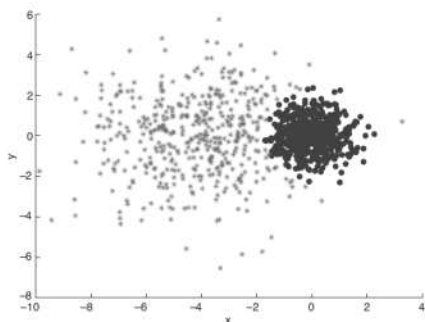


Figure 9.5. EM clustering of a two-dimensional point set with two clusters of differing density.

# Non-spherical data

