## Expectation Maximization Algorithm

I. Number of dusters = number of Gaussian distributions K

A Gaussian distribution is given as  $N(x|\mu,\alpha) = \frac{1}{\sqrt{2\pi}\alpha} e^{\frac{1}{2}\sqrt{2}(x-\mu)^2}$ 

Important is the so-valled expectation value of the log-likelihood function

 $Q(0,0)^{(t-1)} = \boxed{ } \log p(\vec{x}_i,\vec{z}_i|\vec{\theta})$ 

iteration 1 log-likelihood number expectation value

Here @ are the parameter, which we want to estimate ( in and i), X; the data, and Z; refers to unknown For a Gaussian distribution this quantity as rewritten as Q(0,0(t-1)) = probability that point belongs = \langle \langle \rangle \ran

 $r_{ik} = p(z_i = k | x_i, \theta^{(t-1)})$ 

I. 
$$E - step$$
:

 $q_k p(\vec{x}_i | \vec{\theta}_k)$ 
 $f_{ik} = \frac{q_k p(\vec{x}_i | \vec{\theta}_k)}{\sum_{k'} q_{k'} p(\vec{x}_i | \vec{\theta}_{k'})}$ 

II.  $M - step$ :

Look at part of  $Q$ , which depends on  $\mu_k$  and  $\vec{\alpha}_k$ ;

 $\sum_{k'} r_{ik} log[p(\vec{x}_i | \vec{\theta}_k)] = \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{1}{2} \sum_{i} r_{ik} [log[\sum_{k'} + (\vec{x}_i - \mu_k)(\vec{x}_i - \mu_k)] - \frac{$ 

This gives the update

\[ \frac{1}{\sum\_{\text{ik}} \times\_{\text{ik}}} = \frac{\sum\_{\text{rik}} \times\_{\text{rik}}}{\sum\_{\text{rik}} \times\_{\text{rik}} \times\_{\text{rik}}} \]

\[ \frac{1}{\sum\_{\text{rik}} \times\_{\text{rik}} \times\_{\text{