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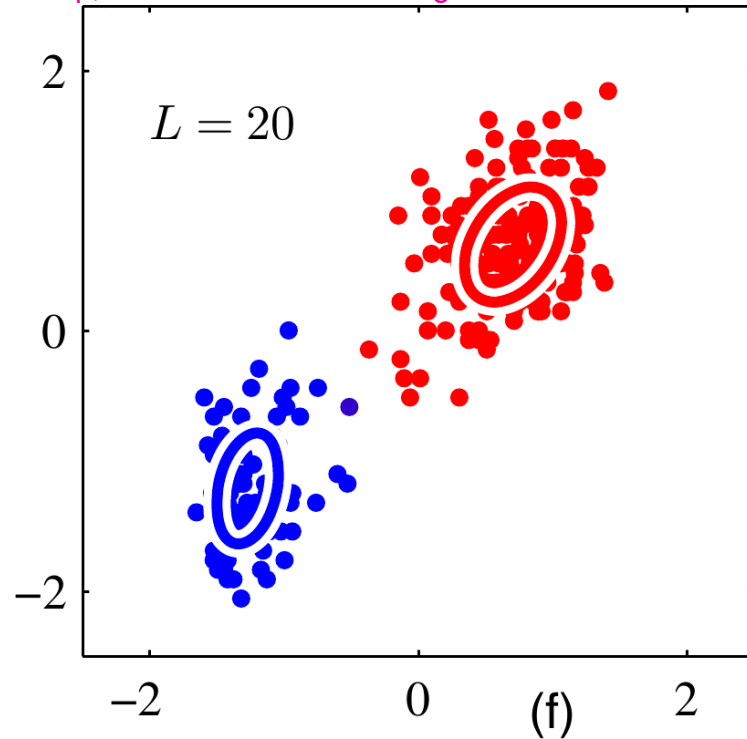
EM for Gaussian Mixtures

- **Given:** $\mathbf{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$, a set of N observations
- **Model:** $p(\mathbf{X} | \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \prod_{i=1}^N \sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}_i | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)$
- **Parameters:** 3 sets of parameters: $\boldsymbol{\mu}, \boldsymbol{\Sigma}, \boldsymbol{\pi}$
- **Initialisation:** $\boldsymbol{\mu}, \boldsymbol{\Sigma}, \boldsymbol{\pi}$: Estimate initial value of log-likelihood
- **E-step (Expectation):** $\gamma_j(\mathbf{x}_i) = \frac{\pi_j \mathcal{N}(\mathbf{x}_i | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}_i | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}$: Evaluate responsibilities using current parameter values
- **M-step (Maximisation):** Re-estimate parameters using current $\gamma_j(\mathbf{x}_i)$'s. $N_j = \sum_{i=1}^N \gamma_j(\mathbf{x}_i)$ Estimation:
 - $\boldsymbol{\mu}_j^{new} = (1/N_j) \sum_{i=1}^N \gamma_j(\mathbf{x}_i) \cdot \mathbf{x}_i$
 - $\boldsymbol{\Sigma}_j^{new} = (1/N_j) \sum_{i=1}^N \gamma_j(\mathbf{x}_i) \cdot (\mathbf{x}_i - \boldsymbol{\mu}_j^{new})(\mathbf{x}_i - \boldsymbol{\mu}_j^{new})^T$
 - $\pi_j^{new} = N_j/N$
- **Eval log-likelihood:** $\log p(\mathbf{X} | \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sum_{i=1}^N \log \sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}_i | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)$; Check for convergence of log-likelihood or parameters. Else, E-step

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EM for Gaussian Mixtures

[C. M. Bishop, Pattern Recognition and Machine Learning]



- **Initialisation:** Use K-Means to initialise: μ (sample means), Σ (sample Covs), π (rel. proportions)

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Stauffer-Grimson BG Subtraction

- The colour/grey value at a pixel is given by a distrn: modelled as a **mixture** of **adaptive** Gaussians

$$p(\mathbf{x}) \triangleq \sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j) \quad \mathbf{x}: [r \ g \ b]^T / \text{grey value}$$

<https://upload.wikimedia.org/wikipedia/en/4/4b/Fifty-Gray-poster.jpg>



- K : 3-5, empirically
- **mixture**: multiple entities can appear
- **adaptive**: with lighting conditions
- Given $\{\mathbf{x}^1, \dots, \mathbf{x}^t, \dots, \mathbf{x}^\tau\}$: history of colour/grey values at a pixel $t \in \{1, \tau\}$
- Heuristic at a pixel: to decide which Gaussians most likely to contribute to the background
- Pixels not matching BG Gaussians: foreground
- FG pixels grouped: 2-D ConnComp/ K -Means