

MATH 569 Statistical Learning

Part VII: Model Inference

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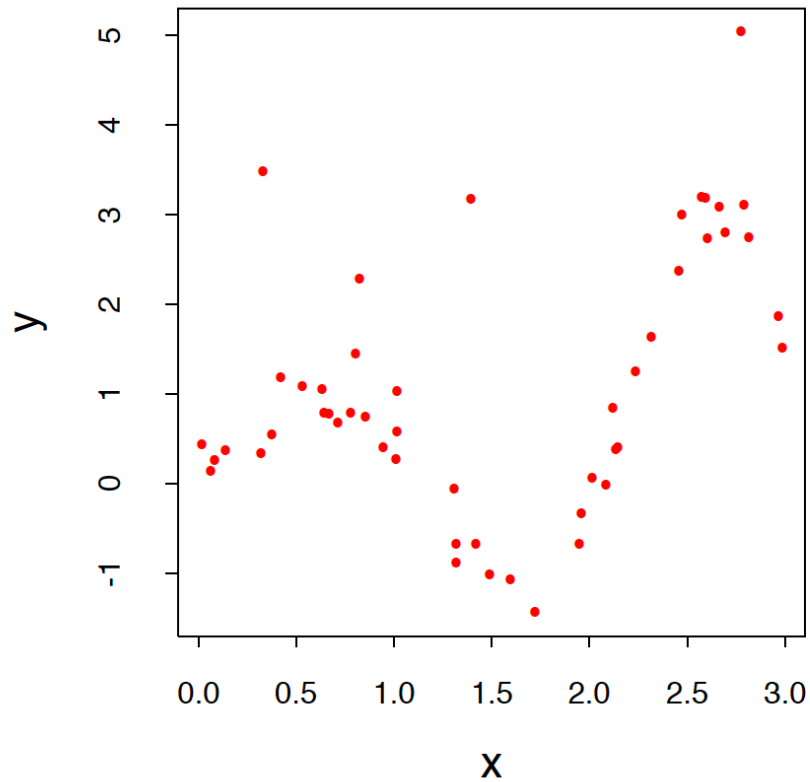
Fig 8.1

Use cubic splines to fit the data (3 knots)

$$4 \times 4 - 3 \times 3 = 7$$

$$\mu(x) = \sum_{j=1}^7 \beta_j h_j(x)$$

Data to fit



Set of seven B-spline basis functions

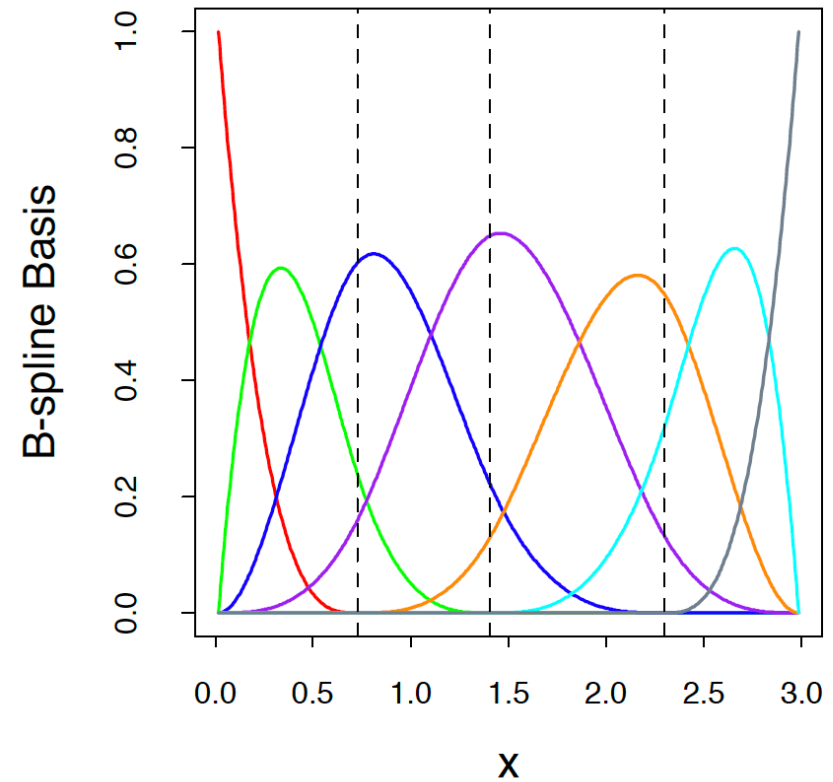
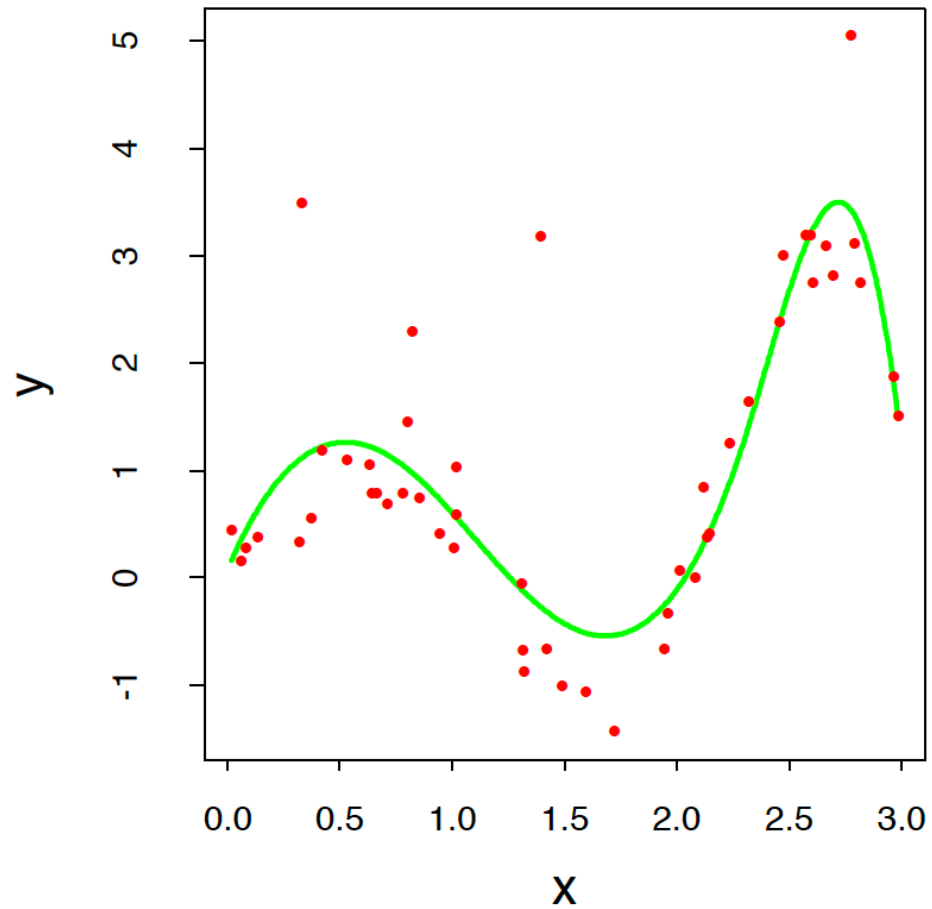


Fig 8.2

B-spline smooth of data



B-spline smooth of data with
95% point-wise confidence band

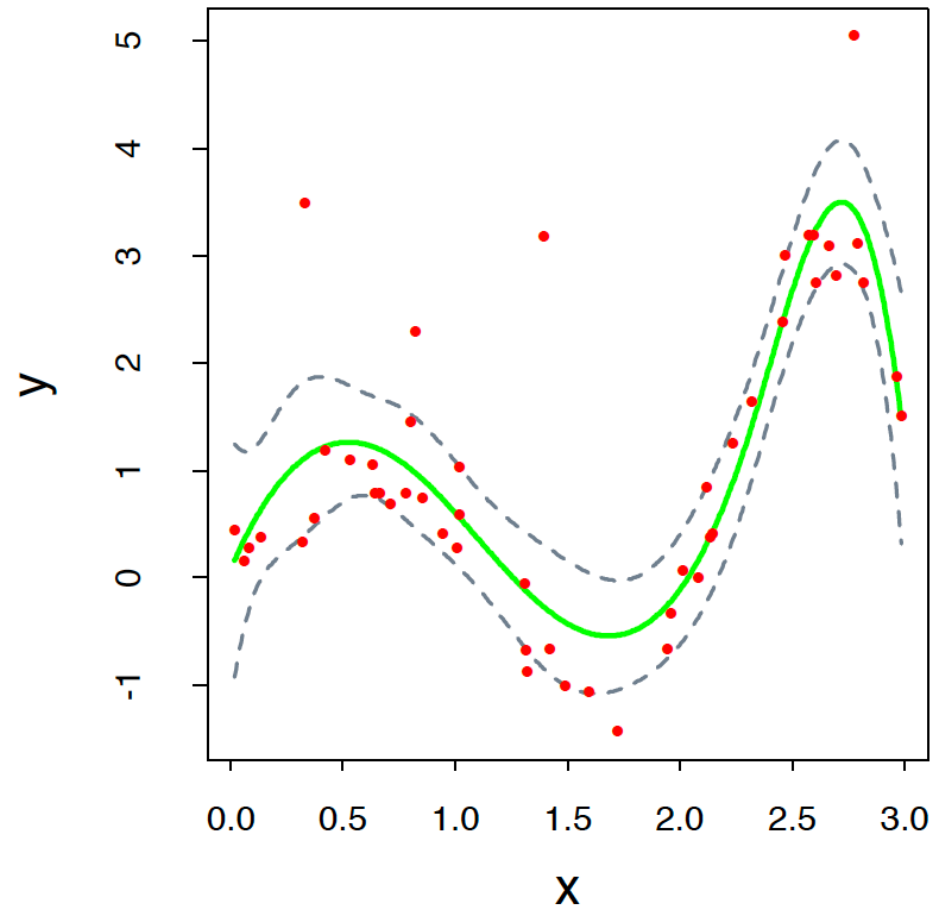
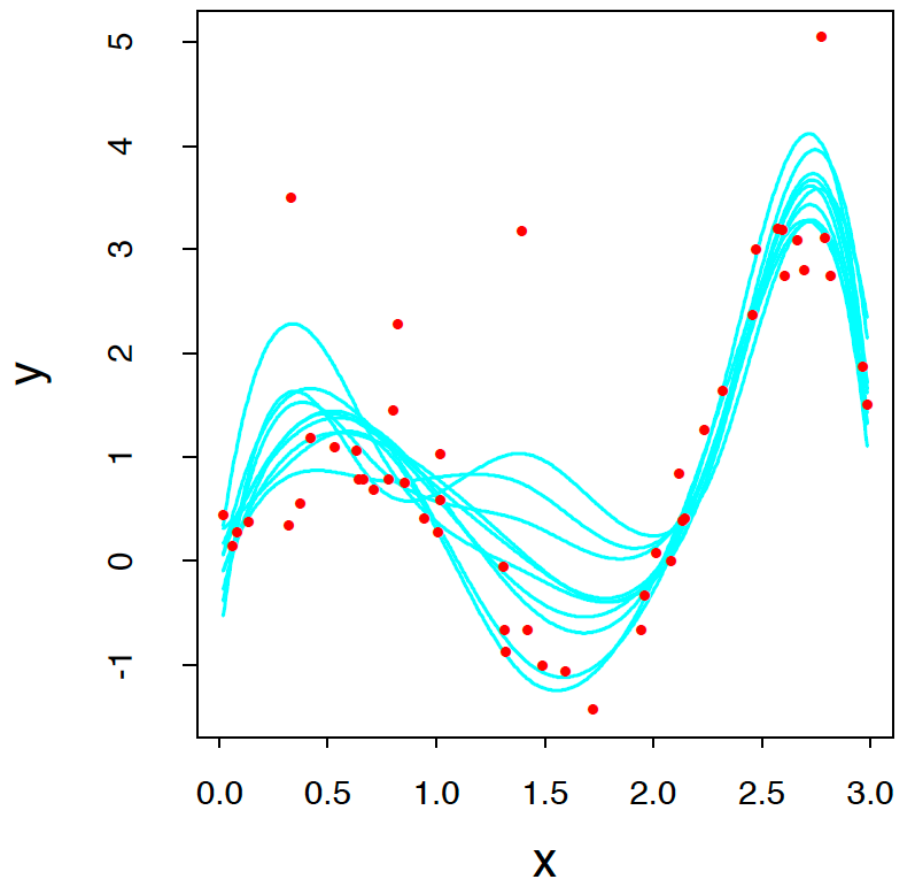


Fig 8.2

B-spline smooth of each of the 10
bootstrap datasets ($B=10$)



95% standard error bands computed
from the bootstrap distribution

With $B=200$, $2.5\% \times 200 = 5$
The band: The 5th largest and
smallest at each x

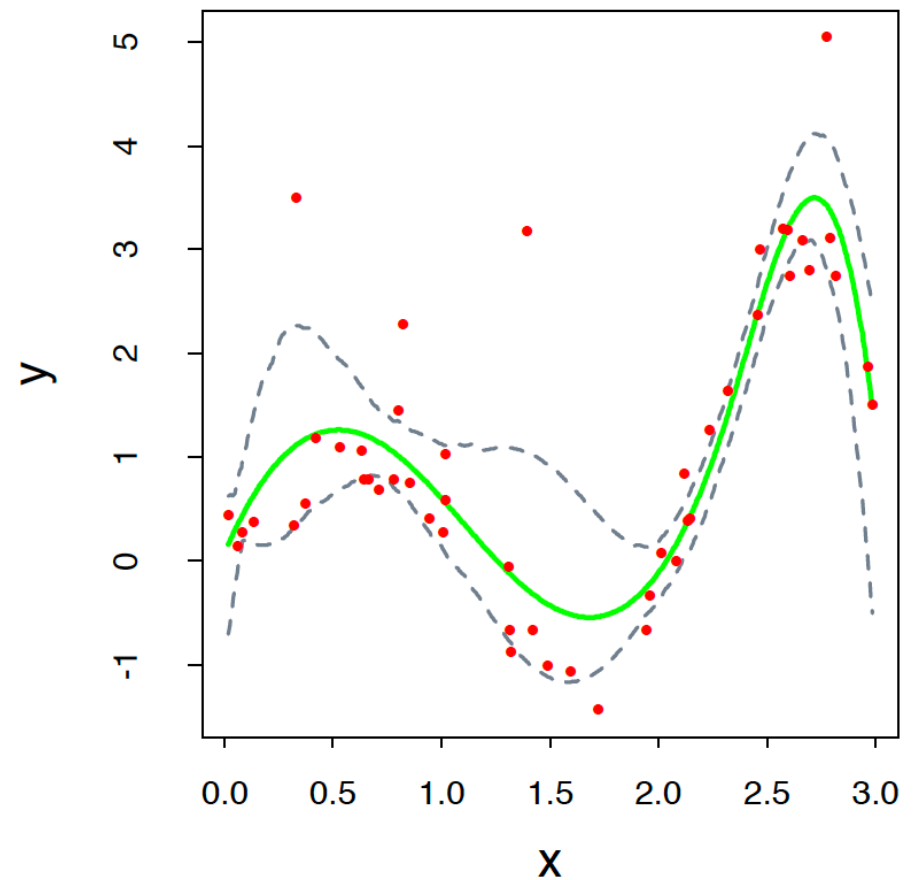


Fig 8.3

Smoothing example: Ten draws from the Gaussian prior distribution for the function $\mu(x)$.

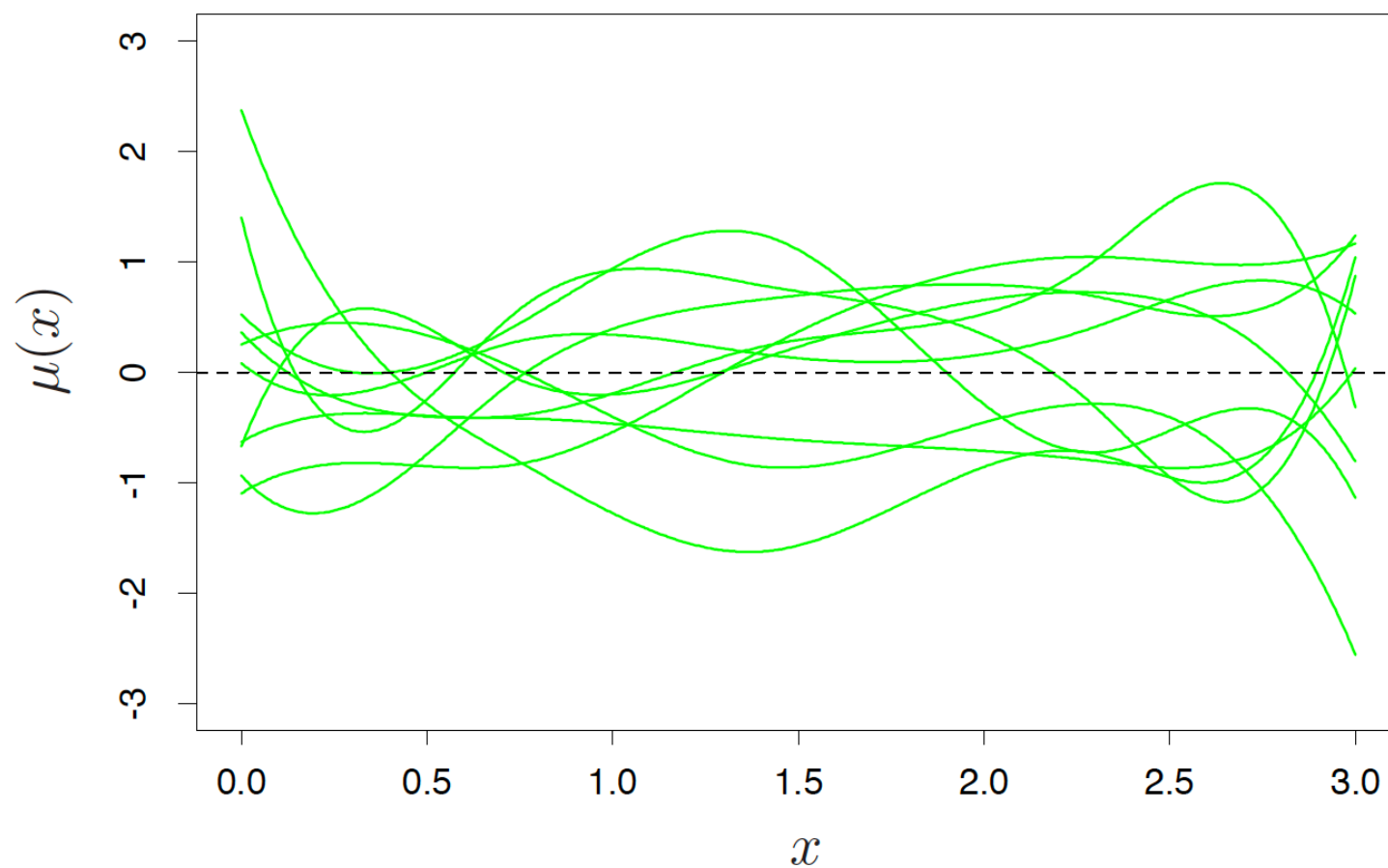


Fig 8.4 Ten draws from the posterior distribution for the function $\mu(x)$.
The purple curves are the posterior means.

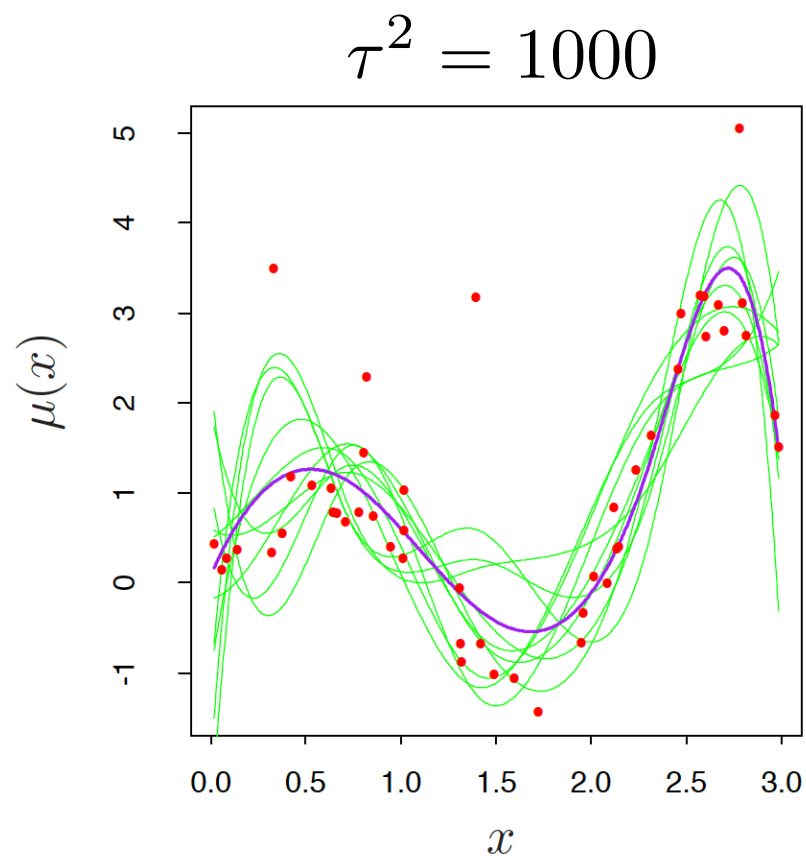
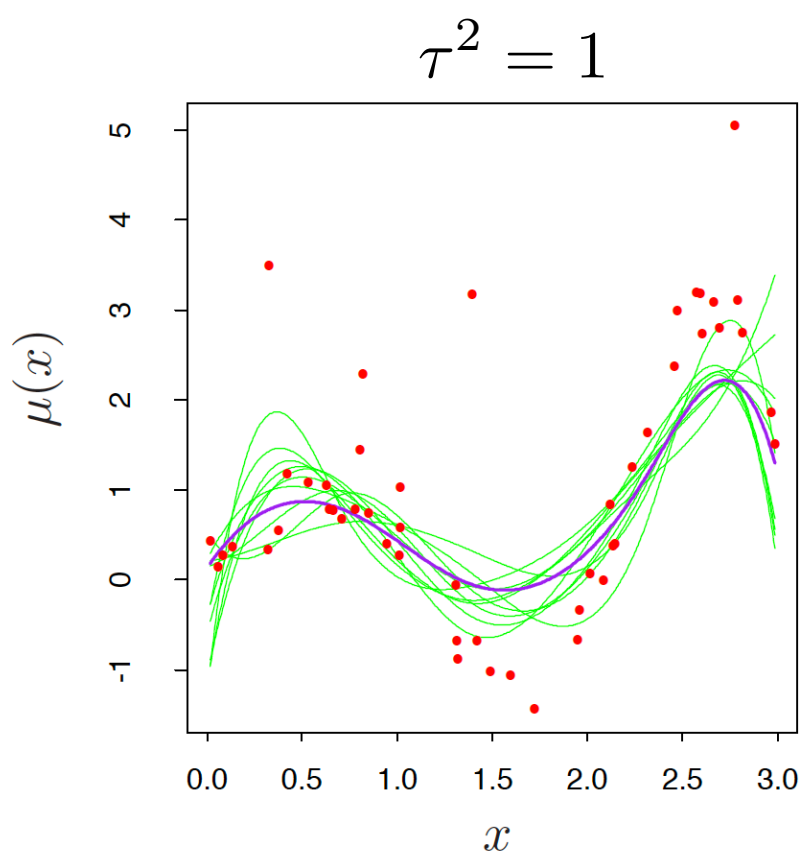
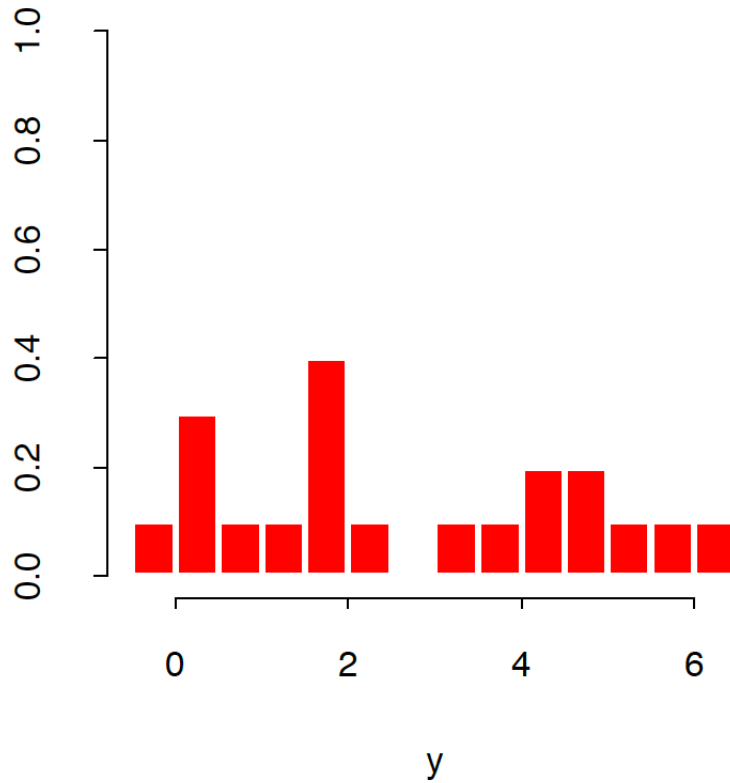


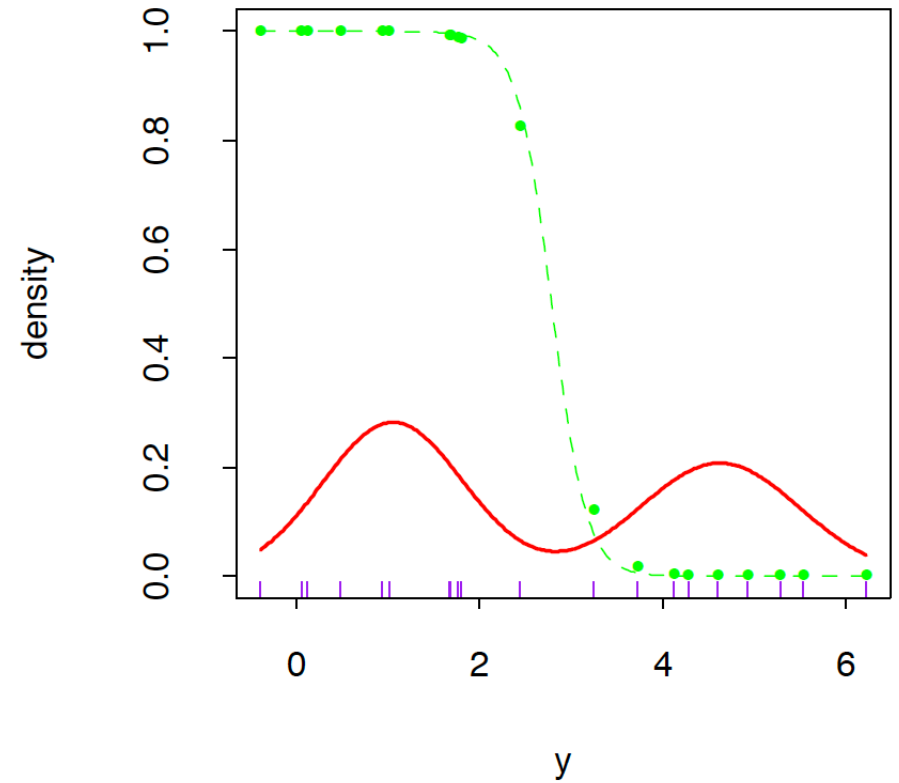
Fig 8.5

Gaussian Mixture Model with Two Components

Histogram



Maximum likelihood fit of Gaussian densities (red)
Responsibility (green)



$$\hat{\mu}_1 = 4.62, \hat{\sigma}_1^2 = 0.87$$

$$\hat{\mu}_2 = 1.06, \hat{\sigma}_2^2 = 0.77$$

$$\hat{\pi} = 0.546$$

Algorithm 8.1 *EM Algorithm for Two-component Gaussian Mixture.*

1. Take initial guesses for the parameters $\hat{\mu}_1, \hat{\sigma}_1^2, \hat{\mu}_2, \hat{\sigma}_2^2, \hat{\pi}$ (see text).
2. *Expectation Step*: compute the responsibilities

$$\hat{\gamma}_i = \frac{\hat{\pi} \phi_{\hat{\theta}_2}(y_i)}{(1 - \hat{\pi}) \phi_{\hat{\theta}_1}(y_i) + \hat{\pi} \phi_{\hat{\theta}_2}(y_i)}, \quad i = 1, 2, \dots, N. \quad (8.42)$$

3. *Maximization Step*: compute the weighted means and variances:

$$\begin{aligned} \hat{\mu}_1 &= \frac{\sum_{i=1}^N (1 - \hat{\gamma}_i) y_i}{\sum_{i=1}^N (1 - \hat{\gamma}_i)}, & \hat{\sigma}_1^2 &= \frac{\sum_{i=1}^N (1 - \hat{\gamma}_i) (y_i - \hat{\mu}_1)^2}{\sum_{i=1}^N (1 - \hat{\gamma}_i)}, \\ \hat{\mu}_2 &= \frac{\sum_{i=1}^N \hat{\gamma}_i y_i}{\sum_{i=1}^N \hat{\gamma}_i}, & \hat{\sigma}_2^2 &= \frac{\sum_{i=1}^N \hat{\gamma}_i (y_i - \hat{\mu}_2)^2}{\sum_{i=1}^N \hat{\gamma}_i}, \end{aligned}$$

and the mixing probability $\hat{\pi} = \sum_{i=1}^N \hat{\gamma}_i / N$.

4. Iterate steps 2 and 3 until convergence.
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The General EM algorithm

Algorithm 8.2 *The EM Algorithm.*

1. Start with initial guesses for the parameters $\hat{\theta}^{(0)}$.
2. *Expectation Step*: at the j th step, compute

$$Q(\theta', \hat{\theta}^{(j)}) = \mathbb{E}(\ell_0(\theta'; \mathbf{T}) | \mathbf{Z}, \hat{\theta}^{(j)}) \quad (8.43)$$

as a function of the dummy argument θ' .

3. *Maximization Step*: determine the new estimate $\hat{\theta}^{(j+1)}$ as the maximizer of $Q(\theta', \hat{\theta}^{(j)})$ over θ' .
 4. Iterate steps 2 and 3 until convergence.
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