3.7.4

a) Yes, as it will have a tighter fit

b) No. It may overfit

c) Polynomial Regression more flexible than linear fit & so will reduce train error

d) Due to bias-Variance tradeoff, for test data, a definitive answer can't be given. We need a model with decent fit & moderate flexibility so it does not overfit

4.1.3

$$p_k(x) = \frac{\frac{\pi_k}{\sqrt{2\pi}\,\sigma_k} e^{\left(\frac{-1}{2\sigma_k^2}(x-\mu_k)^2\right)}}{\sum \pi_l \frac{1}{\sqrt{2\pi}\,\sigma_k} e^{-\frac{1}{2\sigma_l^2}(x-\mu_l)^2}}$$

$$\log(p_K(x)) = \frac{\log \pi_k + \log\left(\frac{1}{\sqrt{2\pi}\,\sigma_k}\right) + \left(\frac{-1}{2\sigma_k^2}(x-\mu_k)^2\right)}{\log\left(\sum \frac{\pi_l}{\sqrt{2\pi}\,\sigma_l} e^{-\frac{1}{2\sigma_l^2}(x-\mu_l)^2}\right)}$$

Thus

$$\delta(x) = \log \pi_k + \log\left(\frac{1}{\sqrt{2\pi}\,\sigma_k}\right) - \frac{1}{2\sigma_k^2}(x-\mu_k)^2$$

So quadratic

4.7.7

$$p_k(x) = \frac{\frac{\pi_k}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(x-\mu_k)^2}}{\sum \pi_l \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(x-\mu_l^2)}}$$

So

$$p(yes|x) = \frac{\pi_{yes} e^{-\frac{1}{2\sigma^2}(x-\mu_{yes})^2}}{\pi_{yes} e^{-\frac{1}{2\sigma^2}(x-\mu_{yes})^2} + \pi_{No} e^{-\frac{1}{2\sigma^2}(x-\mu_{No}}}$$

$\pi_{yes} = 0.80$ $\quad x = 4$ $\quad \mu_{No} = 0$

$\pi_{No} = 0.20$ $\quad \mu_{yes} = 10$

So $p(yes|x=4) = 75.2\%$

on solving