CS 274A Homework 6

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Due Date: Wednesday March 12th in class

Solution to Problem 1

Solution to Problem 1, Part 1

Using Bayes rule we will start with the following

$$p(c_1|x) = \frac{p(x|c_1)p(c_1)}{p(x|c_1)p(c_1) + p(x|c_2)p(c_2)}$$

We will find when that is equal to 0.5 as that is the decision boundary. This occurs when

$$\frac{1}{2} = \frac{1}{1 + \frac{p(x|c_2)p(c_2)}{p(x|c_1)p(c_1)}}$$

After some simple manipulation

$$\frac{p(x|c_2)p(c_2)}{p(x|c_1)p(c_1)} = 1$$

$$\frac{p(x|c_2)}{p(x|c_1)} = \frac{p(c_1)}{p(c_2)}$$

Let

$$K_1 = \frac{1}{\sigma_1\sqrt{2\pi}}$$

$$K_2 = \frac{1}{\sigma_2\sqrt{2\pi}}$$

$$f_1(x) = \frac{(x-\mu_1)^2}{\sigma_1^2}$$

$$f_2(x) = \frac{(x-\mu_2)^2}{\sigma_2^2}$$

We now have to solve the following

$$\frac{K_2 \cdot e^{-f_2(x)/2}}{K_1 \cdot e^{-f_1(x)/2}} = \frac{p(c_1)}{p(c_2)}$$

Let

$$Q = \frac{p(c_1)K_1}{p(c_2)K_2} = \frac{p(c_1)\sigma_2}{p(c_2)\sigma_1}$$

Then we have to solve the following

$$\frac{e^{-f_2(x)/2}}{e^{-f_1(x)/2}} = Q$$

After some algebraic manipulation

$$e^{f_1(x)-f_2(x)} = Q^2$$

$$f_1(x) - f_2(x) = 2log(Q)$$

$$\frac{(x-\mu_1)^2}{\sigma_1^2} - \frac{(x-\mu_2)^2}{\sigma_2^2} = 2log(Q)$$

Let $S = 2log(Q)\sigma_2^2\sigma_1^2$ then it holds that

$$\sigma_2^2(x-\mu_1)^2 - \sigma_1^2(x-\mu_2)^2 = S$$

Expanding and then collecting terms together we get

$$x^2(\sigma_1^2 - \sigma_2^2) + 2x(\mu_1\sigma_2^2 - \mu_2\sigma_1^2) + (\sigma_1^2\mu_2^2 - \sigma_2^2\mu_1^2 - S) = 0$$

We now let

$$a = \sigma_2^2 - \sigma_1^2$$

$$b = 2(\mu_2\sigma_1^2 - \mu_1\sigma_2^2)$$

$$c = \sigma_2^2\mu_1^2 - \sigma_1^2\mu_2^2 - S$$

Then the solutions are the roots of the quadratic equation $ax^2 + bx + c = 0$ which are as follows

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

Solution to Problem 1, Part 2

For this problem we will be using

$$p(x|c_1) = \frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}}$$

$$p(x|c_2) = \frac{1}{\sqrt{6\pi}}e^{-\frac{(x-3)^2}{6}}$$

To get the decision boundaries we will solve the quadratic equation with

$$a = 2$$

$$b = 6$$

$$Q = \sqrt{3}$$

$$S = 2log(Q)3 = 3log(3)$$

$$c = -9 - 3log(3)$$

After putting this all into Matlab, we end up with the following plot

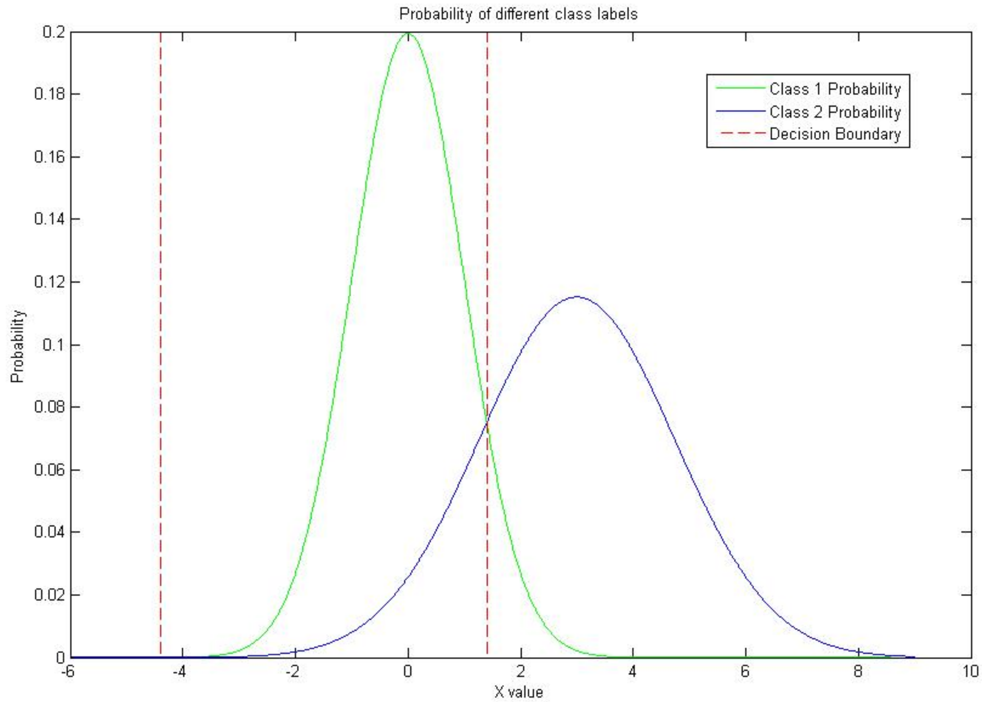

Figure 1: Probability of Class Labels with decision boundaries marked

Solution to Problem 1, Part 3

For this case, if we let a and b be the decision boundaries and E be the error, then

$$E = \int_{-\infty}^{a} p(c_1|x)p(x)\,dx + \int_{a}^{b} p(c_2|x)p(x)\,dx + \int_{a}^{\infty} p(c_1|x)p(x)\,dx$$

For our case we can simplify this to

$$E = \int_{-\infty}^{a} p(x|c_1)p(c_1)\,dx + \int_{a}^{b} p(x|c_2)p(c_2)\,dx + \int_{a}^{\infty} p(x|c_1)p(c_1)\,dx$$

$$E = 0.5(\int_{-\infty}^{a} p(x|c_1)\,dx + \int_{a}^{b} p(x|c_2)\,dx + \int_{a}^{\infty} p(x|c_1)\,dx)$$

For this case, according to the Matlab computation, we have $a = -4.3979$ and $b = 1.3979$. According to Wolfram Alpha

$$\int_{-\infty}^{a} p(x|c_1)\,dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{-4.3979} e^{-x^2/2}\,dx = \frac{0.0000136991}{\sqrt{2\pi}} = 5.46515 \cdot 10^{-6}$$

$$\int_{a}^{b} p(x|c_2)\,dx = \frac{1}{\sqrt{6\pi}} \int_{-4.3979}^{1.3979} e^{-(x-3)^2/6}\,dx = \frac{0.77055}{\sqrt{6\pi}} = 0.177480$$

$$\int_b^\infty p(x|c_1)\,dx = \frac{1}{\sqrt{2\pi}}\int_{1.3979}^\infty e^{-x^2/2}\,dx = \frac{0.203216}{\sqrt{2\pi}} = 0.0810715$$

Summing these three together we get the following estimate

$$E = 0.1293$$

Solution to Problem 1, Part 4

To get the decision boundaries we will solve the quadratic equation with

$$a = 2$$

$$b = 6$$

$$Q = 9\sqrt{3}$$

$$S = 2log(Q)3 = 6log(Q) = 6log(9\sqrt{3}) = 12log(3) + 3log(3) = 15log(3)$$

$$c = -9 - 15log(3)$$

After putting this all into Matlab, we end up with the following plot

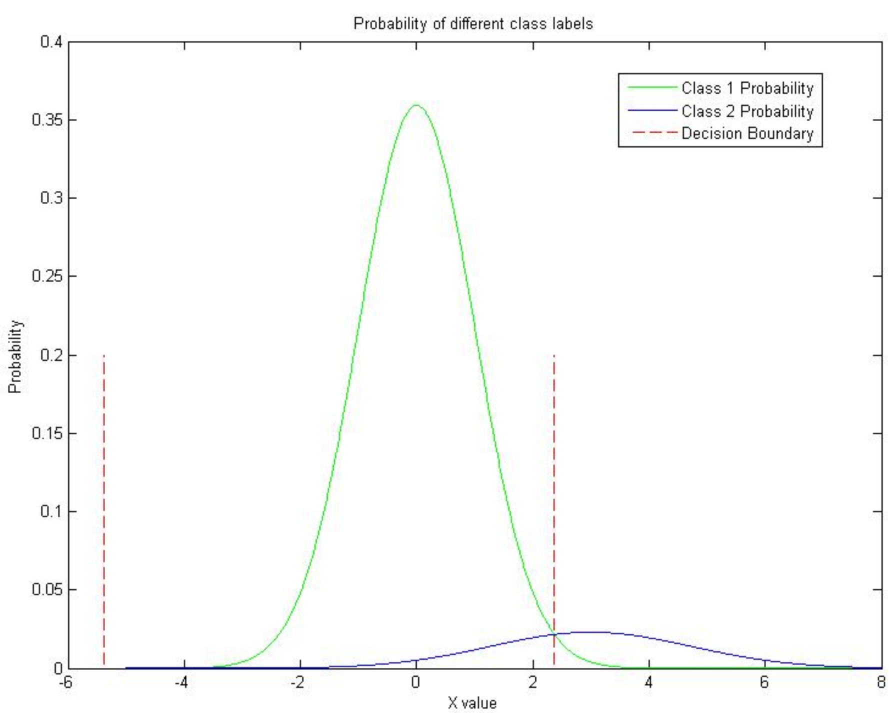

Figure 2: Probability of Class Labels with decision boundaries marked

For this case, if we let a and b be the decision boundaries and E be the error, then

$$E = \int_{-\infty}^{a} p(c_1|x)p(x)\,dx + \int_{a}^{b} p(c_2|x)p(x)\,dx + \int_{a}^{\infty} p(c_1|x)p(x)\,dx$$

For our case we can simplify this to

$$E = \int_{-\infty}^{a} p(x|c_1)p(c_1)\,dx + \int_{a}^{b} p(x|c_2)p(c_2)\,dx + \int_{a}^{\infty} p(x|c_1)p(c_1)\,dx$$

$$E = 0.9\int_{-\infty}^{a} p(x|c_1)\,dx + 0.1\int_{a}^{b} p(x|c_2)\,dx + 0.9\int_{a}^{\infty} p(x|c_1)\,dx$$

For this case, according to the Matlab computation, we have $a = -5.3716$ and $b = 2.3716$. According to Wolfram Alpha

$$\int_{-\infty}^{a} p(x|c_1)\,dx = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{-5.3716} e^{-x^2/2}\,dx = \frac{9.781\cdot 10^{-8}}{\sqrt{2\pi}} = 3.90205\cdot 10^{-8}$$

$$\int_{a}^{b} p(x|c_2)\,dx = \frac{1}{\sqrt{6\pi}}\int_{-5.3716}^{2.3716} e^{-(x-3)^2/6}\,dx = \frac{1.55592}{\sqrt{6\pi}} = 0.358374$$

$$\int_{b}^{\infty} p(x|c_1)\,dx = \frac{1}{\sqrt{2\pi}}\int_{2.3716}^{\infty} e^{-x^2/2}\,dx = \frac{0.0221978}{\sqrt{2\pi}} = 0.00885564$$

Summing these three together we get the following estimate

$$E = 0.0438$$

Solution to Problem 2

Solution to Problem 2, Part 1

Starting from one of the first steps of the last problem, we have to solve

$$\frac{p(x|c_2)}{p(x|c_1)} \leq \frac{p(c_1)}{p(c_2)}$$

Given our values this becomes

$$\frac{p(x|c_2)}{p(x|c_1)} \leq 1$$

$$p(x|c_2) \leq p(x|c_1)$$

That is when it is optimal to choose c_1
Inserting the function this occurs when

$$exp(-x) \leq 0.5$$

$$x \geq log(2)$$

However, we can only choose c_1 for $2 \leq x \leq 4$. Our condition is satisfied in that region, thus the decision regions are as follows:

c_1 if $2 \leq x \leq 4$

c_2 otherwise

Solution to Problem 2, Part 2

After putting this all into Matlab, we end up with the following plot

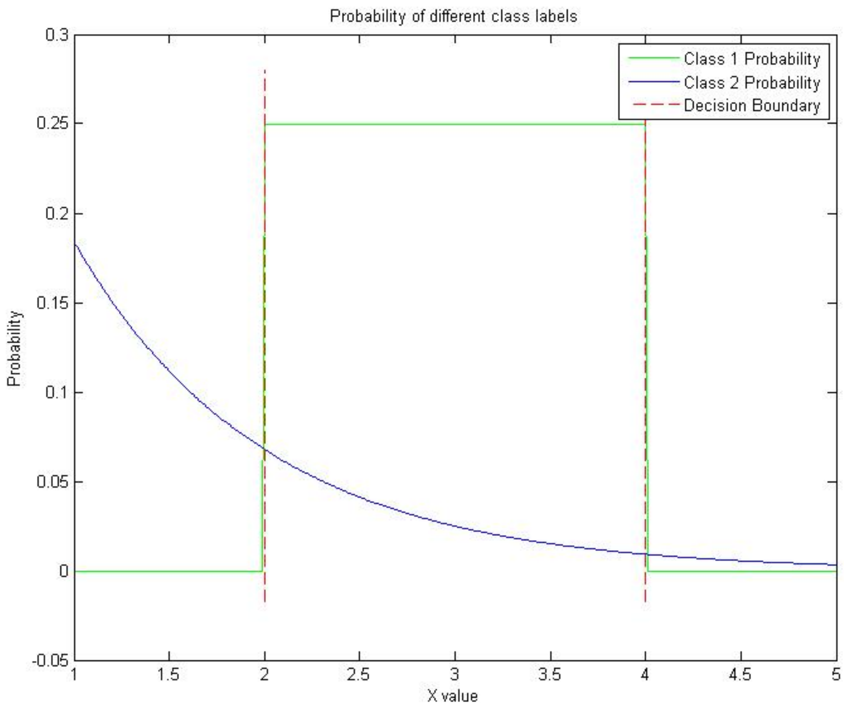

Figure 3: Probability of Class Labels with decision boundaries marked

Solution to Problem 2, Part 3

For this case, if we let a and b be the decision boundaries and E be the error, then

$$E = \int_{-\infty}^{a} p(c_1|x)p(x)\,dx + \int_{a}^{b} p(c_2|x)p(x)\,dx + \int_{a}^{\infty} p(c_1|x)p(x)\,dx$$

For our case we can simplify this to

$$E = \int_{-\infty}^{a} p(x|c_1)p(c_1)\,dx + \int_{a}^{b} p(x|c_2)p(c_2)\,dx + \int_{a}^{\infty} p(x|c_1)p(c_1)\,dx$$

$$E = 0.5\int_{-\infty}^{a} p(x|c_1)\,dx + 0.5\int_{a}^{b} p(x|c_2)\,dx + 0.5\int_{a}^{\infty} p(x|c_1)\,dx$$

For this case we have $a = 2$ and $b = 4$.

$$\int_{-\infty}^{a} p(x|c_1)\,dx = 0$$

$$\int_{a}^{b} p(x|c_2)\,dx = \int_{2}^{4} e^{-x}\,dx = e^{-2} - e^{-4} = 0.1170$$

$$\int_b^\infty p(x|c_1)\,dx = 0$$

Summing these three together we get the following estimate

$$E = 0.0585$$

Solution to Problem 2, Part 4

From previous problem we have to solve

$$\frac{p(x|c_2)}{p(x|c_1)} \le \frac{p(c_1)}{p(c_2)}$$

Given our values we have

$$\frac{p(x|c_2)}{p(x|c_1)} \le 1$$

$$p(x|c_2) \le p(x|c_1)$$

That is when it is optimal to choose c_1. This occurs when

$$exp(-x) \le 0.05$$

$$x \ge log(20) = 2.9957$$

However, we can only choose c_1 for $2 \le x \le 22$. Thus our decision boundaries are as follows:

c_2 if $x \le log(20)$

c_1 if $log(20) \le x \le 22$

c_2 if $x \ge 22$

After putting this all into Matlab, we end up with the following plot

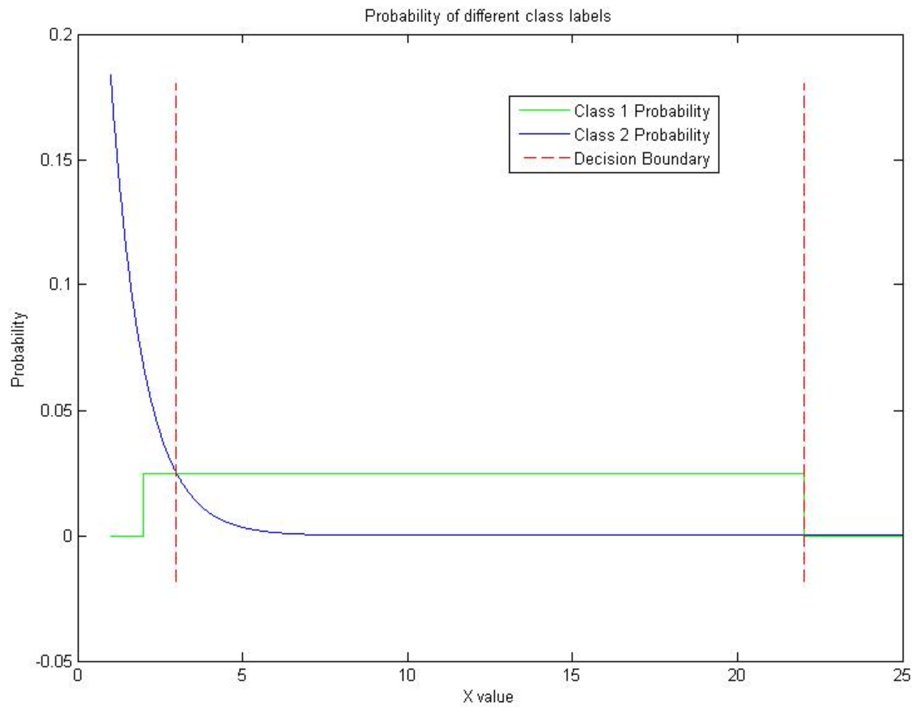

Figure 4: Probability of Class Labels with decision boundaries marked

For this case, if we let a and b be the decision boundaries and E be the error, then

$$E = \int_{-\infty}^{a} p(c_1|x)p(x)\,dx + \int_{a}^{b} p(c_2|x)p(x)\,dx + \int_{a}^{\infty} p(c_1|x)p(x)\,dx$$

For our case we can simplify this to

$$E = \int_{-\infty}^{a} p(x|c_1)p(c_1)\,dx + \int_{a}^{b} p(x|c_2)p(c_2)\,dx + \int_{a}^{\infty} p(x|c_1)p(c_1)\,dx$$

$$E = 0.5\int_{-\infty}^{a} p(x|c_1)\,dx + 0.5\int_{a}^{b} p(x|c_2)\,dx + 0.5\int_{a}^{\infty} p(x|c_1)\,dx$$

For this case we have $a = log(20)$ and $b = 22$.

$$\int_{-\infty}^{a} p(x|c_1)\,dx = \int_{2}^{log(20)} 0.05\,dx = (0.05)(log(20) - 2) = 0.0498$$

$$\int_{a}^{b} p(x|c_2)\,dx = \int_{log(20)}^{22} e^{-x}\,dx = \frac{1}{20} - e^{-22} = 0.0500$$

$$\int_{b}^{\infty} p(x|c_1)\,dx = 0$$

Summing these three together we get the following estimate

$$E = 0.0499$$

Solution to Problem 3

Solution to Problem 3, Part 1

First, we will let

$$K = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}}$$
$$f_1(x) = (x-\mu_1)^T\Sigma^{-1}(x-\mu_1)$$
$$f_2(x) = (x-\mu_2)^T\Sigma^{-1}(x-\mu_2)$$

then it holds that

$$g_1(x) = log(K) - \frac{1}{2}f_1(x) + log(p(c_1))$$
$$g_1(x) = -log((2\pi)^{d/2}|\Sigma|^{1/2}) - \frac{1}{2}f_1(x) + log(p(c_1))$$
$$g_1(x) = -\frac{1}{2}(d \cdot log(2\pi) + log(|\Sigma|) + f_1(x)) + log(p(c_1))$$

By the same token

$$g_2(x) = -\frac{1}{2}(d \cdot log(2\pi) + log(|\Sigma|) + f_2(x)) + log(p(c_2))$$

Solution to Problem 3, Part 2

By some algebraic manipulation, it holds that

$$g(x) = g_1(x) - g_2(x) = -\frac{1}{2}f_1(x) + \frac{1}{2}f_2(x) + log(p(c_1)) - log(p(c_2))$$
$$g(x) = \frac{1}{2}(f_2(x) - f_1(x)) + log(p(c_1)) - log(p(c_2))$$

Let $v = 2(log(p(c_2)) - log(p(c_1)))$ then we have to solve

$$v = f_2(x) - f_1(x)$$
$$(x^T\Sigma - \mu_2^T\Sigma^{-1})(x-\mu_2) - (x^T\Sigma^{-1} - \mu_1^T\Sigma^{-1})(x-\mu_1) = v$$
$$(x^T\Sigma^{-1}x - \mu_2^T\Sigma^{-1}x - x^T\Sigma^{-1}\mu_2 + \mu_2^T\Sigma^{-1}\mu_2) - (x^T\Sigma^{-1}x - \mu_1^T\Sigma^{-1}x - x^T\Sigma^{-1}\mu_1 + \mu_1^T\Sigma^{-1}\mu_1) = v$$

Collecting terms we end up with

$$(\mu_1^T\Sigma^{-1} - \mu_2^T\Sigma^{-1})x + x^T(\Sigma^{-1}\mu_1 - \Sigma^{-1}\mu_2) + \mu_2^T\Sigma^{-1}\mu_2 - \mu_1^T\Sigma^{-1}\mu_1 = v$$

If we let

$$u = v - \mu_2^T\Sigma^{-1}\mu_2 + \mu_1^T\Sigma^{-1}\mu_1$$

Then after some factoring we have

$$(\mu_1^T - \mu_2^T)\Sigma^{-1}x + x^T\Sigma^{-1}(\mu_1 - \mu_2) = u$$

If we let $\mu_0 = \mu_1 - \mu_2$ then we further have

$$\mu_0 \Sigma^{-1} x + x^T \Sigma^{-1} \mu_0 = u$$

If we let $m = \mu_0^T \Sigma^{-1}$ then because Σ^{-1} is symmetric, $m^T = \Sigma^{-1} \mu_0$. We thus have

$$mx + x^T m^T - u = 0$$

This is the same as

$$dot(m, x) + dot(m, x) - u = 0$$

Thus we can further say that

$$2mx - u = 0$$

Thus finally let

$$w = 2m$$

$$w_0 = -u$$

then we have the linear decision boundary as described.

Solution to Problem 3, Part 3

If $p(c_1) = p(c_2)$ then $v = 0$ in the above equations, thus they would end with

$$f_1(x) = f_2(x)$$

After substituting the equation back in, we have

$$(x - \mu_1)^T \Sigma^{-1} (x - \mu_1) = (x - \mu_2)^T \Sigma^{-1} (x - \mu_2)$$

The decision boundary is thus when the two MH distances are equal so the class will end up taking on the value of whichever mean is closer.

Solution to Problem 4

Solution to Problem 4, Part 1

Using problem 3, but where $v = 0$, we will use the following variables to simplify our problem

$$u = \mu_1^T \Sigma^{-1} \mu_1 - \mu_2^T \Sigma^{-1} \mu_2$$

$$\mu_0 = \mu_1 - \mu_2$$
$$m = \mu_0^T \Sigma^{-1}$$

For our purposes, we have $\mu_1 = (1, 1)$ and $\mu_2 = (4, 4)$, thus $\mu_0 = (-3, -3)$. Additionally

$$\Sigma^{-1} = \frac{1}{3} \begin{pmatrix} 4 & -1 \\ -1 & 1 \end{pmatrix}$$

After computing these out, we get the following numbers

$$u = -15$$

$$m = (-3, 0)$$

This leads us to the following numbers for the line

$$w = (-6, 0)$$

$$w_0 = 15$$

This leads us to the following linear equation

$$-6x_1 + 15 = 0$$

$$x_1 = 2.5$$

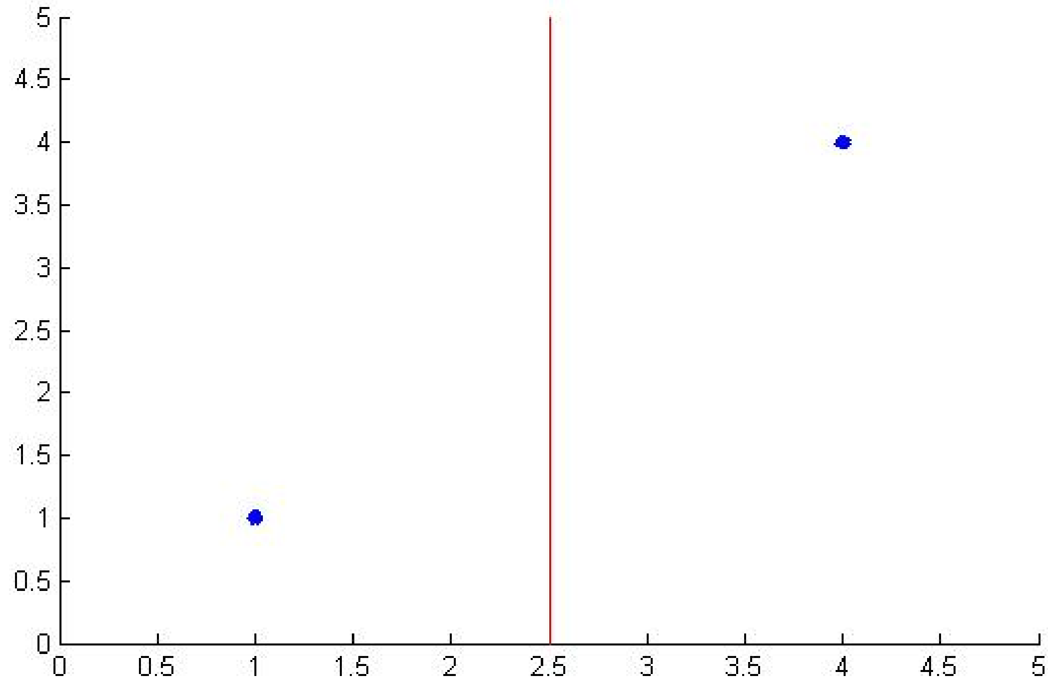

Figure 5: The decision boundary with the means

Solution to Problem 4, Part 2

The vector for w will be the same as Part 1. The vector for u will be different. We have already found that $u = -15$ when $v = 0$, thus for our case, $u = v - 15$ so we just need to calculate v. By Problem 3,

$$v = 2(log(p(c_2)) - log(p(c_1)))$$

Thus after plugging in the values

$$v = 2(log(0.2) - log(0.8))$$

$$v = 2(log(\frac{1}{5}) - log(\frac{4}{5}))$$

$$v = 2(-log(5) - (log(4) - log(5)))$$

$$v = -2log(4)$$

This means that $u = -2log(4) - 15$ and thus of course $w_0 = 15 + 2log(4)$. Our equation for the decision boundary will then become

$$-6x_1 + 15 + 2log(4) = 0$$

$$x_1 = \frac{15 + 2log(4)}{6} \approx 2.9621$$

Because class 1 is weighted higher in this case, its decision region will be bigger, thus the decision boundary will shift toward the mean for class 2, as shown in the below graph.

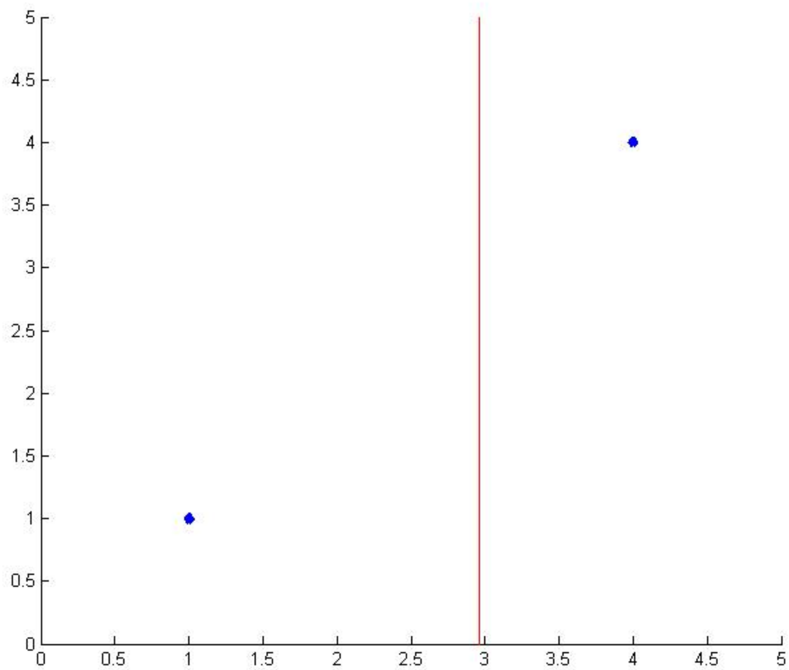

Figure 6: The decision boundary with the means

Solution to Problem 5

First, you would figure out a probability on the class labels given the parameters of the model, so you need $p(c|\hat{\theta}, M_1)$ and $p(c|\hat{\phi}, M_2)$. You would also attach a prior to the parameters if desired, so you would want $p(\hat{\theta}|M_1)$ and $p(\hat{\phi}|M_2)$. If desired, you would also want a probability assigned to the model's correctness, so you would find $p(M_1)$ and $p(M_2)$. To figure out the class probability we will say that

$$p(c|x) = \frac{p(x|c)p(c)}{p(x)}$$

We can treat $p(x)$ as a normalization constant because it will be the same for both classes, thus

$$p(c|x) \propto p(x|c)p(c)$$

By law of total probability and adding in the parameters of the model, we can further say that

$$p(c|x) \propto p(x|c, \hat{\theta}, M_1)p(c, \hat{\theta}, M_1) + p(x|c, \hat{\phi}, M_2)p(c, \hat{\phi}, M_2)$$

We can factor out the c values in order to use the probability of the class label. This yields

$$p(c|x) \propto p(x|c, \hat{\theta}, M_1)p(c|\hat{\theta}, M_1)p(\hat{\theta}, M_1) + p(x|c, \hat{\phi}, M_2)p(c|\hat{\phi}, M_2)p(\hat{\phi}, M_2)$$

We can then factor out the probability of the parameters in order to use the prior on the parameters and the prior on the model, finally yielding

$$p(c|x) \propto p(x|c, \hat{\theta}, M_1)p(c|\hat{\theta}, M_1)p(\hat{\theta}|M_1)p(M_1) + p(x|c, \hat{\phi}, M_2)p(c|\hat{\phi}, M_2)p(\hat{\phi}|M_2)p(M_2)$$

Do this for both classes c and see which one yields a greater probability.

Solution to Problem 6

For this problem, we are assuming that at each pair of points, there is a Gaussian distribution for y given x where the mean $\mu_y = ax + b$ and the variance is σ^2.
We will then define $\theta = (a, b, \sigma)$ and assert that

$$L(D|\theta) = \prod_{i=1}^{N} \frac{1}{\sigma\sqrt{2\pi}} exp(-\frac{(y_i - (ax_i + b))^2}{2\sigma^2})$$

Taking the log to get log-likelihood we have

$$l(\theta) = -\frac{N}{2} log(2\pi\sigma^2) + \sum_{i=1}^{N} -\frac{(y_i - (ax_i + b))^2}{2\sigma^2}$$

Simplifying further we have

$$l(\theta) = -\frac{N}{2} log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - (ax_i + b))^2$$

Expanding out the square we have

$$l(\theta) = -\frac{N}{2} log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} y_i^2 - 2y_i(ax_i + b) + (ax_i + b)^2$$

Expanding out the square again

$$l(\theta) = -\frac{N}{2} log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} [y_i^2 - 2ay_ix_i - 2by_i + a^2x_i^2 + 2abx_i + b^2]$$

We will find $\hat{a}_{ML}$ and $\hat{b}_{ML}$ by first taking the partials

$$\frac{\partial l}{\partial a} = -\frac{1}{2\sigma^2} \sum_{i=1}^{N} [-2y_ix_i + 2ax_i^2 + 2bx_i]$$

$$\frac{\partial l}{\partial b} = -\frac{1}{2\sigma^2} \sum_{i=1}^{N} [-2y_i + 2ax_i + 2b]$$

Setting both equal to zero we end up having to solve the following equations

$$\sum_{i=1}^{N} [-y_ix_i + ax_i^2 + bx_i] = 0$$

$$\sum_{i=1}^{N} [-y_i + ax_i + b] = 0$$

Rearranging the sums and putting into a linear system form, we have the solve the following

$$a \sum_{i=1}^{N} x_i^2 + b \sum_{i=1}^{N} x_i = \sum_{i=1}^{N} y_i x_i$$

$$a \sum_{i=1}^{N} x_i + b \cdot N = \sum_{i=1}^{N} y_i$$

For shorthand, we will now let

$$A = \sum_{i=1}^{N} x_i^2$$

$$B = \sum_{i=1}^{N} x_i$$

$$C = \sum_{i=1}^{N} y_i x_i$$

$$D = \sum_{i=1}^{N} y_i$$

Then we are left with solving

$$\begin{pmatrix} A & B \\ B & N \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} C \\ D \end{pmatrix}$$

After doing the matrix inverse, we have the following

$$\begin{pmatrix} a \\ b \end{pmatrix} = \frac{1}{AN - B^2} \begin{pmatrix} N & -B \\ -B & A \end{pmatrix} \begin{pmatrix} C \\ D \end{pmatrix}$$

Thus finally we can say that

$$\hat{a}_{ML} = \frac{NC - BD}{AN - B^2}$$

$$\hat{b}_{ML} = \frac{AD - BC}{AN - B^2}$$

We now want to find $\hat{\sigma^2}_{ML}$. If we let

$$K = \sum_{i=1}^{N} (y_i - (ax_i + b))^2$$

then we will have after letting $v = \sigma^2$

$$l(\theta) = -\frac{N}{2} log(2\pi v) - \frac{K}{2v}$$

Taking the derivative with respect to v we have

$$l'(\theta) = -\frac{N}{2v} + \frac{K}{2v^2}$$

Setting it equal to zero we have to solve

$$Kv = Nv^2$$

We can assume a non-zero variance thus we can assert that

$$v = \frac{K}{N}$$

Substituting the formula back in using the max likelihood estimates, we finally have

$$\hat{\sigma^2}_{ML} = \frac{1}{N}\sum_{i=1}^{N}(y_i - (\hat{a}_{ML}x_i + \hat{b}_{ML}))^2$$